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Equipment Detection and Maintenance in Mechanical Workshop Based on Anomaly Detection Algorithm

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Abstract: With the development of the times, people have higher requirements for information quality, data transmission and processing. Timely fault detection and maintenance of mechanical equipment in the workshop can reduce the loss of the factory. In order to prove that data processing plays an important role in practical application, this paper studies the advantages of anomaly detection algorithm in equipment detection and maintenance of mechanical workshop. This paper mainly uses the methods of experiment and comparison to obtain the accuracy of the relevant detection algorithm model by changing the variable record data. The experimental results show that the accuracy of DBM model is more than 99% when the number of hidden layers is 2. With the increase of hidden layers, the recognition accuracy of DBN model decreases.

1. Introduction

Because many enterprises do not pay attention to the inspection and maintenance of the equipment in the mechanical workshop, there are often machine failures and injuries. This is not only the economic loss of the factory, but also a threat to the safety of workers. The anomaly detection algorithm can find defects, timely repair system vulnerabilities and prevent accidents. In order to ensure the normal operation of enterprises and improve economic efficiency and safety, it is necessary to timely find hidden dangers of mechanical equipment and carry out maintenance. Therefore, it is necessary to inspect and maintain the equipment in the mechanical workshop.

There are many theories about the research of anomaly detection algorithm and the research of equipment detection and maintenance in mechanical workshop. For example, some experts believe that frequent failures of mechanical equipment will lead to abnormal operation of mechanical equipment. Therefore, mine management personnel must pay close attention to relevant situations and strictly inspect and maintain equipment [1-2]. Other experts believe that the fixed invariant feature analysis algorithm has a large error, so they propose a mechanical anomaly detection algorithm to extract local features [3-4]. Some scholars also put forward the concepts of anomaly detection and anomaly detection based on statistical theory. By detecting the abnormal state of the processing system, the degree of abnormal deviation of the processing system can be quantified [5-6]. These studies show that anomaly detection algorithm plays an important role in equipment fault detection. The normal operation of mechanical equipment ensures the economic and social benefits of operators.

Firstly, this paper studies the anomaly detection algorithm of the Gaussian process model, and finds that the Gaussian process has a very flexible non parametric property, which can be applied to data anomaly detection with high accuracy. Secondly, the main contents and methods of equipment inspection and maintenance are described. After that, the platform design of the testing equipment is carried out, and the PHM technology is proposed. Finally, the final conclusion is drawn through the system experimental design of equipment inspection and maintenance in the mechanical workshop.

2. Inspection and Maintenance of Mechanical Workshop Equipment Based on Anomaly Detection Algorithm

2.1. Anomaly Detection Algorithm Based on Gaussian Process Model

Many anomaly detection methods for data streams are mainly the optimization and improvement of traditional anomaly detection technologies on data streams. Distance based anomaly detection methods are widely used in various outlier mining and anomaly analysis. The distance based outlier detection does not need to know the distribution of the data in advance, but only needs to determine whether the point is an outlier by the distance between the data object and the nearest neighbor. The density based detection method considers that the anomaly of a data point is usually related to the density of the point and the average density of its nearest neighbor. In order to improve the effectiveness, density based modeling is more complex and computational complexity is higher. At the same time, it also has problems [7-8].

Anomaly detection of data streams requires real-time and accurate feedback information. And data streams, as a typical dynamic continuous data set, often have the problem of concept transfer. That is, with the passage of time, the concepts of frequent data events and small probability events often change.

In some practical applications, such as anomaly detection, defect location, fault detection and other problems, it is often difficult to obtain abnormal training samples. Although the traditional classification method is feasible, the effect is not very ideal. Gaussian processes have very flexible non parametric characteristics, and can obtain high accuracy in data anomaly detection [9-10].

The characteristic of Gaussian process is that it does not need any fixed parameter settings. A posteriori of the category label of an unlabeled sample can be derived from the marginal potential function value, and the formula is as follows:

$$\mathrm{q}(b_*|A,b,a_*)=\int_S^{+\infty} q(g_*|A,b,a_*)q(b_*|g_*)cg_* \tag{1}$$

Where, a is the training sample, representing the feature vector, and b is the second class label. The prior of potential function g can be modeled as a Gaussian process with mean value of 0 and covariance function of L:

$$L(\mathrm{a},a')=\exp\left(-\frac{1}{2\Im^2}\|a-a'\|^2\right) \tag{2}$$

The correlation of function values is modeled by the similarity of input samples calculated by kernel functions.

The Gaussian process model is applied to the problem of data anomaly detection_ GPM algorithm can be divided into the following three steps: Gp_ GPM model is established, and appropriate kernel function and super parameter are selected. Gp_ GPM model training to determine the optimal parameters and probability distribution. Gp_ GPM model test, and test results are given. In order to achieve anomaly detection of data samples, model testing is conducted on the test data set [11-12].

For the anomaly detection algorithm, in addition to the determination of the evaluation index, another important index is the threshold. Therefore, after the training of the Gaussian process model, it is necessary to set the threshold of three evaluation indexes on the training dataset according to the multiple training results and provide them for the use of the testing process, so as to accurately give the class label of the observation samples of the test dataset.

2.2. Equipment Inspection and Maintenance

At present, equipment maintenance is mainly divided into perfect maintenance and imperfect maintenance. Perfect maintenance mainly refers to the restoration of the equipment to a new state after the equipment is shut down for maintenance. Imperfect maintenance means that after the equipment has been maintained, the equipment reliability is between the new state and the state reliability before maintenance. Reliability function refers to that the equipment can complete the specified operation within a certain time, and it is necessary to ensure that the equipment has no fault. Failure rate refers to the loss of function of equipment under specified conditions. During the operation of the equipment, the equipment will always be shut down due to internal or external reasons. After each equipment failure, the maintenance personnel must analyze the failure of the equipment shut down [13-14].

With the continuous development of sensor technology, the detection technology has also been constantly improved. The traditional manual offline detection has developed into online detection through sensors. The equipment obtains data through sensors for analysis and processing to obtain the operating state of the equipment. This detection belongs to non-destructive testing.

In view of the production bottleneck caused by the different operating efficiency of the equipment in the multi equipment series production system, which leads to the sudden decline of the equipment reliability caused by the change of the equipment production rate, equipment detection is introduced to find the change of the equipment reliability in a timely manner. At present, most enterprises still adopt the strategy of equal cycle maintenance to implement equal cycle maintenance on the equipment, which is easy to ignore the failures and equipment operation conditions in the process of equipment operation. As a result, unplanned downtime and product quality damage occur during the use of equipment, which increases the additional cost of the enterprise [15-16].

2.3. Detection and Fault Diagnosis Network Service Platform

Nowadays, the world is developing towards informatization, networking and datalization. All data resources rely on Internet technology to achieve real-time resource sharing and services. Users can search for the information they want anytime and anywhere through the network. The platform also provides technical services related to equipment detection and fault diagnosis for the machinery workshop with the help of internet technology and computer technology.So that business owners can master the operation and use of equipment in real time, monitor and maintain equipment in a timely manner, and avoid unnecessary losses [17-18].

PHM technology adopts appropriate algorithms for monitoring, diagnosis and prediction, and provides intelligent maintenance management technology for maintenance support decision-making. Equipment condition monitoring technology is a technology to evaluate equipment health by comparing equipment parameters with corresponding normal conditions. Signal processing and analysis technology is a technology to extract effective device state attributes through appropriate signal processing and analysis methods. Equipment fault diagnosis technology is to judge whether the equipment is abnormal through appropriate identification or prediction algorithm [19-20].

PHM technology is applied to modern enterprise equipment management, mainly to ensure the safety of enterprise production, reduce the probability of equipment failure, and shorten the emergency time in the production process. This can reduce equipment investment, provide high-quality products to customers in time, save enterprise management and operating costs, and improve enterprise competitiveness.

3. System Experiment Design of Equipment Inspection and Maintenance in Mechanical Workshop

3.1. Experimental Design

In order to compare the accuracy of fault diagnosis of each depth model, four schemes are proposed for verification and analysis. In all experimental schemes, 80% of the samples randomly selected are used for training, and the remaining 20% are used for testing. The equipment fault diagnosis process based on deep learning mainly includes three parts: equipment vibration signal acquisition, signal analysis and fault diagnosis.

Input the following parameter data for fault identification: extract the original vibration signal of the equipment, which is represented by A1. 64 time-frequency domain features of equipment vibration signal are extracted and represented by A2. Six time-domain characteristics and 124 frequency-domain characteristics of equipment vibration signals are extracted and represented by A3. Six time-domain characteristics, 124 frequency-domain characteristics and 64 time-frequency characteristics of the extracted equipment vibration signal are represented in A4.

3.2. Experimental Data

The experiment set up 6 kinds of equipment with different health states. Each data acquisition channel can collect 270 data sets, and because there are two sensors to collect the vibration data of the equipment, 540 data sets are collected in the end. For A1, 20 samples are randomly selected from 540 collected equipment vibration signal data sets, so 10800 samples are generated in total, and the sampling duration of each sample is 0.04 seconds, so the length of each sample is 2000 data points. For A2 to A4, 10 samples are randomly selected from 540 collected equipment vibration signal data sets, so 5400 samples are generated in total.

3.3. Vibration Signal Feature Extraction

The accuracy of equipment fault identification and residual life prediction is affected by whether the extracted features can represent the health status of equipment. Extract the time-domain, frequency-domain and time-frequency domain features of the collected samples. Integrate them according to the requirements of A2 to A4. Finally, according to the requirements of the scheme, equipment fault diagnosis based on deep learning is carried out. The depth Boltzmann machine (DBM) and the depth belief network (DBN) can be represented in Figure 1:

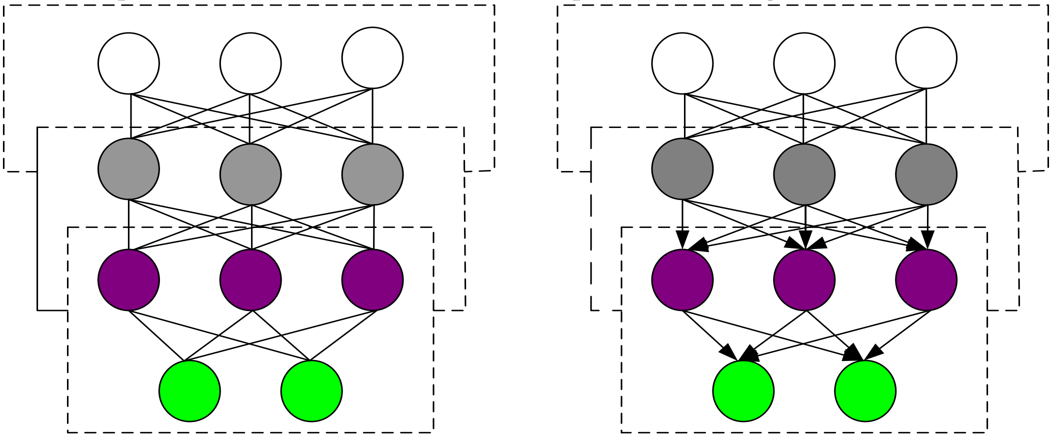

Figure 1. Structural composition of the DBM and DBN models

The training process of DBM includes two stages, namely bottom-up unsupervised learning and top-down supervised fine-tuning. The training process of DBN is a process of greedy learning layer by layer.

4. Analysis of Experimental Results

4.1. A2 Recognition Accuracy of Three Models with Changed Hidden Layers

By changing only the number of hidden layers under the default parameters, the influence of changing the number of hidden layers on the fault identification results of the three depth models is mined. When A2 is used, for SAE and DBM models, with the increase of the number of hidden layers, the fault identification of SAE and DBM models increases first and then decreases.

Table 1. A2 recognition accuracy of the three models with an altered number of hidden layers

	SAE	DBN	DBM
1	85	95	80
2	98	90	95
4	96	60	50
8	70	55	17

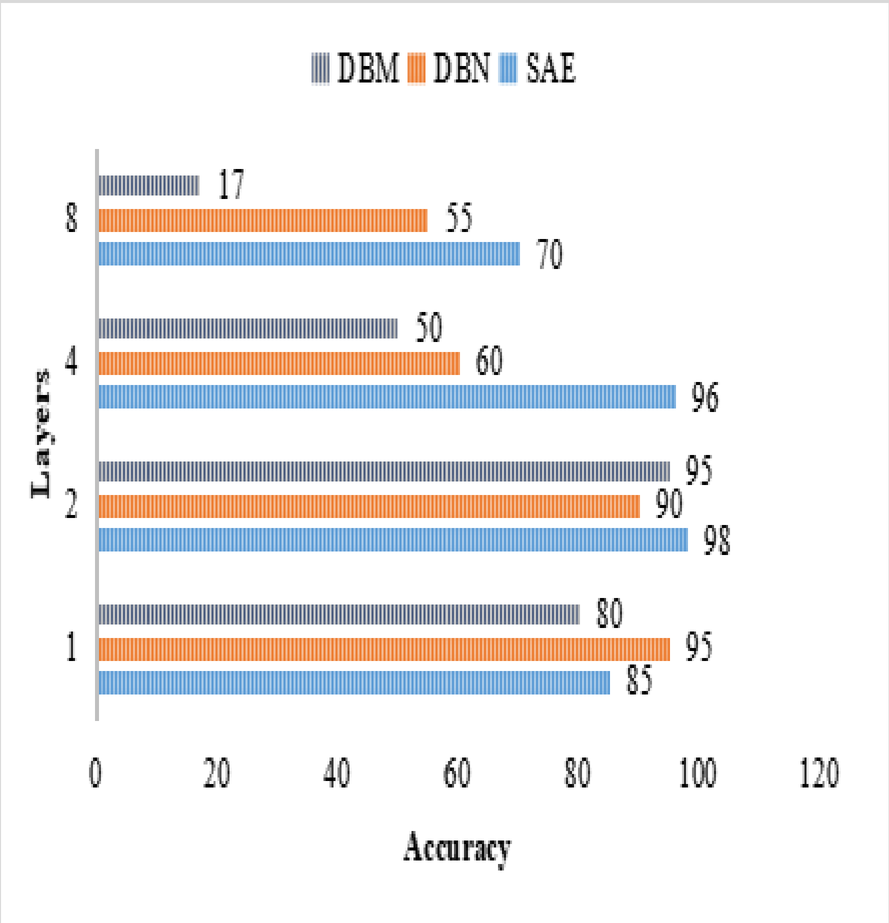

Figure 2. A2 recognition accuracy of the three models with an altered number of hidden layers

As shown in Figure 2, we can see that when the number of hidden layers is 2, the accuracy of SAE and DBM models reaches the highest, 98% and 95% respectively. For the DBN model, the recognition accuracy of the DBN model decreases with the increase of the number of hidden layers. Therefore, when the number of hidden layers is 1, the highest fault recognition rate is 95%.

4.2 Recognition Accuracy of Three Models with A4 Hidden Layers Changed

When A4 is adopted, for SAE model, with the increase of hidden layers, the bearing fault identification rate of SAE model remains unchanged, and the identification accuracy is more than 99%. In addition, when the hidden layer is 8, the recognition accuracy of DBN and DBM models is very low. See Table 2 for details:

Table 2. A4 recognition accuracy of the three models with an altered number of hidden layers

	SAE	DBN	DBM
1	99.7	99.7	99.6
2	99.8	99.8	99.9
4	99.8	96	96.8
8	99.5	72	13

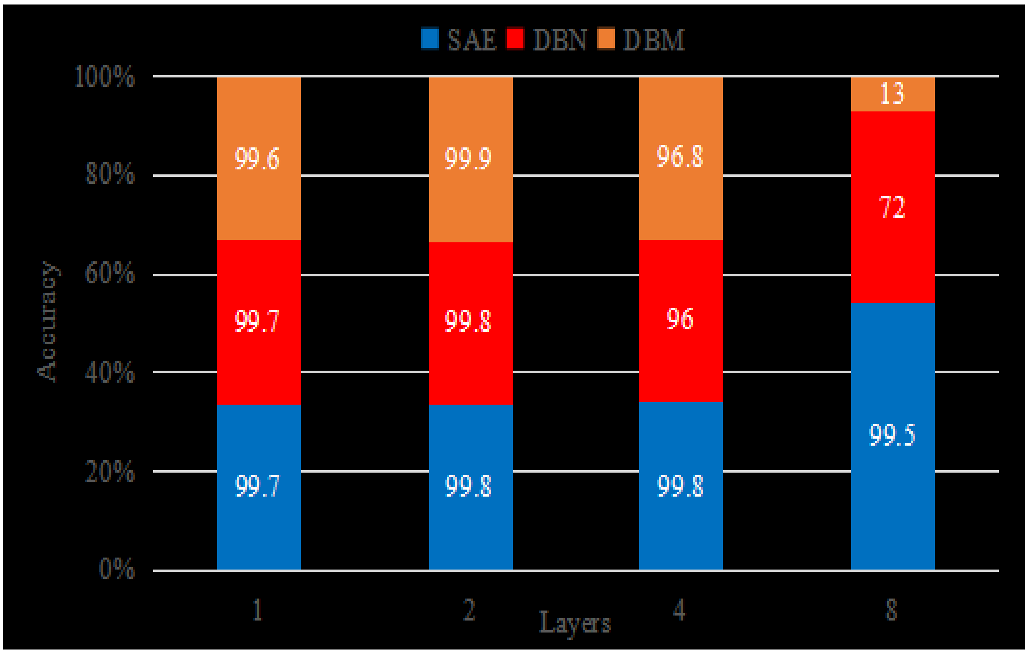

Figure 3. A4 recognition accuracy of the three models with an altered number of hidden layers

As shown in Figure 3, when the number of hidden layers is 2, the highest recognition accuracy is 99.8%. With the increase of the number of hidden layers, the fault identification rate of DBM model and DBN model increases slightly first and then decreases. The reason why A4 can obtain the highest fault identification rate is that A4 combines the characteristics of time domain, frequency domain and time-frequency domain of vibration signals, which hide more fault information, so that the model can fully learn potential information.

5. Conclusion

With the continuous development of China's industry, the requirements for product quality, production safety, equipment reliability and other aspects are getting higher and higher. Because of the low operating efficiency and human factors of traditional manual methods, it is particularly difficult to detect and maintain the system. Therefore, a new real-time monitoring method is proposed for dependency anomaly detection algorithm. This paper mainly studies the dependency anomaly detection algorithm, combining with the actual experimental data, analyzes its feasibility in depth learning. The experiment shows that the fault can be judged better by combining the characteristics of detection time domain, frequency domain and time-frequency domain. Because my level is insufficient, the measurement method of noise parameters needs to be further refined.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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