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Detection of Rolling Bearing Damage Based on Anomaly Error Reconstruction of Vibration Sample

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Abstract
-Bearings are one of the critical components in rotary machines such as motors, wind turbines, helicopters, automobiles, and gearboxes. Most machine failures are caused by bearing faults. Thus, bearing fault detection can help provide machine failure prediction, maintenance plan scheduling, and avoid catastrophic machine failures. This paper aims to detect bearing failure by anomaly detection on bearing vibration data samples. We proposed an Autoencoder model to detect anomaly using its reconstruction error of the input sample. Result shows that Autoencoder successfully detect bearing failure by doing anomaly detection. However due to non-specific and general terms of reconstruction error, the human interference still needed to know which bearing was failing
Keywords: *Anomaly Detection, Autoencoder, Bearing*

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I. INTRODUCTION

Rolling bearings are one of the critical components in rotary machines such as motors, wind turbines, helicopters, cars, and gearboxes [7]. Often machine failure is caused by damage to rolling bearings [8][10]. Therefore, the detection of rolling bearing damage can help estimate engine damage, plan maintenance schedules, and avoid major engine damage [7].

In general, the rolling bearings are installed on the machine in good condition and have gone through the previous qualification and testing stages. However, mechanical errors such as errors in the installation process, or errors in the manufacturing process can result in relatively high vibration levels at the beginning of the rolling bearings installed. After the rolling bearing and other components interact with each other for a certain duration of time, the vibration of the rolling bearing will decrease and remain at a low vibration level. After long-term use of rolling bearings, the condition of rolling bearings begins to wear out, resulting in significant degradation of rolling bearings. Therefore, the rolling bearing life can be divided into three parts, namely the run-in period, the service life period, and ending with the wear period.

This study aims to detect rolling bearing damage by detecting anomaly of rolling bearing vibration data. Anomaly detection refers to problems in finding data patterns that do not match expectations or normal conditions [3]. In this study, an Autoencoder artificial neural network model is used to detect rolling bearing vibration data anomalies by utilizing the reconstruction error value obtained from the difference between the input and output of the Autoencoder. The rolling bearing vibration data was obtained from the IMS Bearing dataset provided by the University of Cincinnati, USA and released by NASA through the PCoE Datasets page in 2014 [13]. The number of rolling bearings in the dataset is four bearings, where in each rolling bearing an accelerometer sensor is installed to read the amount of vibration in the bearing.

The scope of this research is the development of an Autoencoder model to solve the problem of detecting rolling bearing damage based on anomaly of bearing vibration data without the development of a real-time detection system. The resulting reconstruction error value is general, representing the four rolling bearings so that the output results solely represent the anomalies of the four rolling bearings without knowing in detail the number of rolling bearings that are problematic.

1.2 THE SIMULATION METHOD

A. Mean Absolute Deviation (MAD)

Mean Absolute Deviation (MAD), often also referred to as the mean deviation, is the average of the absolute deviations of the entire sample from the sample mean. MAD provides an overview of the variability of the sample. MAD is more appropriate to use than the standard deviation in the presence of outliers in the sample [5].In general, MAD is defined as follows:

$$\frac{1}{n}\sum_{i=1}^{n}|x_i - m(X)| \quad (1)$$

Where is the sample to , and is the average of the samples.

B. Mean Squared Error (MSE)

Mean Squared Error (MSE) measures the average of the squared differences between the predicted and actual values. The result of MSE is always positive [9], regardless of the sign of the predicted value and the actual value with a perfect value is 0. MSE is available natively as a loss function in the Tensorflow library.

C. Min-Max Scaler

Min-Max Scaler is a normalization function that transforms the sample linearly [1]. The Min-Max Scaler processes each feature so that it falls within a given range, for example in the ranges 0 and 1. The Min-Max Scaler function is available natively in the Scikit-learn library. In general, the Min-Max Scaler is defined as follows:

$$\frac{x_i - min(x)}{max(x) - min(x)} * (newMax - newMin) + newMin \quad (2)$$

Where is the smallest value in the set (rolling bearing vibration sample), is the largest value in the set, and , as the desired new range of values.

D. **Reconstruction Error Value (RE**)

The general definition of the reconstructed error value is the difference between the original data and the projection. In this study, the value of the reconstruction error is the difference between the input and the results of the Autoencoder reconstruction. The reconstruction error value is obtained by using the Mean Square Error (MSE) equation.

E. IMS Bearing Dataset

The IMS Bearing dataset was generated from the endurance trials of a test rig by the University of Cincinnati, USA and was released by NASA via the PCoE Datasets page in 2014 [13]. The IMS Bearing dataset is commonly used in various studies and has been published in various literatures. Many studies use IMS datasets to illustrate the remaining useful life (RUL) based on statistical indicators [6]. In this study, data from the second trial of the rig test were used in 2004 with a recording interval of 10 minutes.

F. Block Diagram

The input block consists of a rolling bearing vibration sample dataset to be processed. The dataset has passed the initial processing stage in order to facilitate the Autoencoder process in detecting anomalies.

The process block consists of the Autoencoder model programmed in the Tensorflow Python platform. The process block will receive data from the input block and process it through the training and test stages. At the training stage, the model is optimized using the loss function as a reference. The training stage generates a threshold value that determines whether the input sample is normal or anomalous. After going through the training stage, a test stage is carried out to detect the presence of anomaly.

G. Scikit-learn

Scikit-learn is an open-source machine learning library for the Python programming language supporting supervised and unsupervised learning [11]. Scikit-learn provides a wide range of features such as classification, regression, and clustering and is designed to work with the NumPy and SciPy numeric libraries. Most of Scikit-learn is written in the Python programming language, and uses NumPy in linear algebra and array operations. Scikit-learn also provides functions used for data preprocessing.

H. Autoencoder

Autoencoder is a simple learning circuit that aims to reconstruct inputs with a similar shape and the possibility of small distortion [2]. Although conceptually simple, Autoencoder has an important role in machine learning. The autoencoder was first introduced in 1986 by Honton and the PDP group [4] to overcome the problem of "backpropagation without a teacher" by using the input sample as a training reference. In general, Autoencoder consists of two parts, namely Encoder and Decoder, which can be defined as transitions and , so that :

$$\phi : \mathcal{X} \rightarrow \mathcal{F}$$
$$\psi : \mathcal{F} \rightarrow \mathcal{X}$$
$$\phi, \psi = \underset{\phi,\psi}{\arg\min} \|X - (\psi \circ \phi)X\|^2$$

Where is the input sample, is the latent space. The latent space contains a compressed representation of the input, also known as Code. The code is generated by the encoder and will be reconstructed into its original form by the decoder.

II. RESULT AND DISCUSSION

A. Preparation and Pre-processing of Data

The second experimental IMS Bearing dataset was used in this study. The second experimental Bearing IMS dataset contains rolling bearing vibration signals which are taken every 10 minutes and stored in one file for one week, resulting in a total file which in each file contains 1-second vibration signal samples. The vibration signal is generated from the accelerometer sensor mounted on the four rolling bearings with a sample rate of 20 kHz, producing 20,480 data samples per every second. Mean Absolute Deviation (MAD) is calculated for each rolling bearing vibration signal in each beam.

The MAD calculations that have been carried out can finally produce a 4-dimensional vector (according to the number of bearings) of each processing performed in a single file. The final result of the preprocessing stage is dataset $D = \{x^{(1)}, x^{(2)}, \ldots, x^{(n)}\}, x^{(i)} \in R^4$

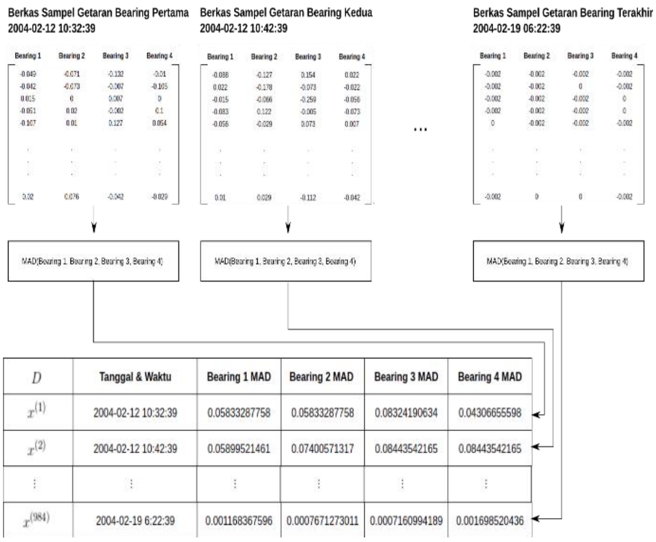

Figure 1Visual representation of the file processing stage into a D . dataset

B. Separation of Training and Test Sets

The autoencoder studies the reconstruction of the sample set that represents the normal state of the rolling bearing, so that when the Autoencoder receives an anomalous sample input, the reconstruction error value of the sample will increase. From the graph of the dataset, it can be seen that there was a significant degradation of the rolling bearing on the sample dated 2022-02-17 07:12:39 until in the end there was major damage to the sample on the date 2022-02-19 05:02:39

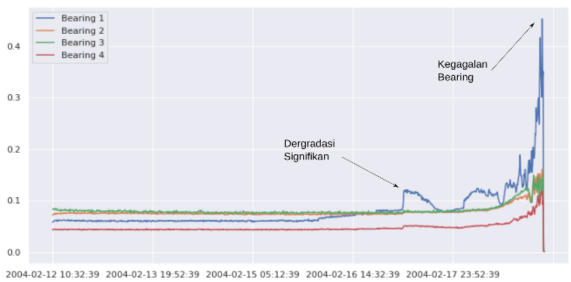

Figure 2. Dataset Grafik

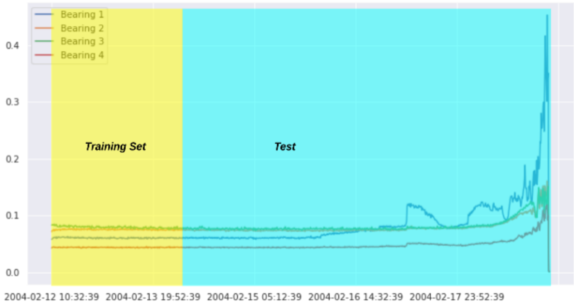

Figure 3. Separation of practice and test sets

Sample 2022-02-13 23:52:39 represents the normal state of rolling bearing vibration so that it is used as a training set. While the samples in the range of 2022-02-13 23:52:39 to the last sample represent both normal and anomalous conditions (rolling bearing failure) so that they are used as test sets.

C. Data Normalization Process

All samples were normalized prior to the training and testing process to ensure that the samples had the same range. The normalization function used in this study is the Min-Max Scaler. The normalization process is carried out twice, the first is the normalization of the training set and the second is the normalization of the test set.

D. Autoencoder Training Process

The training process is carried out with training sets that have been processed by the previous stage. In the Autoencoder training process, Mean Squared Error (MSE) is used as the loss function and Adam as the optimizer.

In its implementation, the training process requires two input hyperparameters, namely the number of epochs and batch size. In this study, 100 epochs and a batch size of 10 were used. The training process was carried out on the Tensorflow Python platform, running on an NVIDIA GeForce 930MX GPU with CUDA 10.2 support on an ASUS A442UR Laptop computer, Intel i5-8250u @ 1.60 Ghz Processor, and 12 GB RAM.

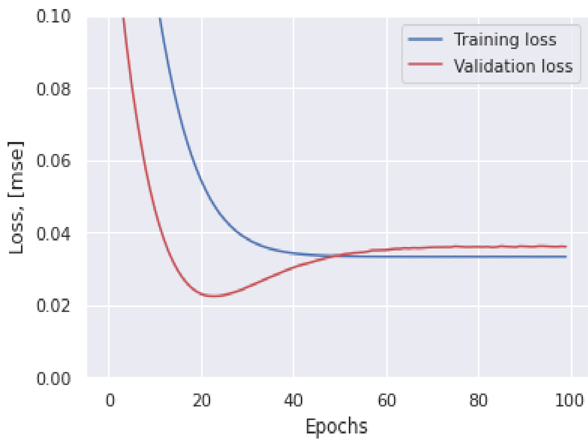

Figure 4 Graph of loss value in the training process with epoch = 100

After the Autoencoder training process is carried out, it is continued by entering the training set into the Autoencoder to get the distribution of the reconstruction error values from the training set. The distribution of the error values for the reconstruction of the training set shows that there is no value exceeding 0.3 so that the number is appropriate to be used as a threshold value that determines whether or not a sample is normal (anomaly).

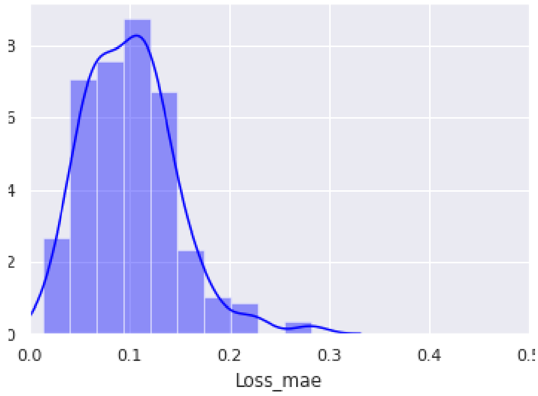

Figure 5. Distribution of training set reconstruction error values

After obtaining the threshold value, then processing the test set with the Autoencoder so as to produce a set of reconstructed error values from the test set. The processing results show that the reconstruction error value in the test set fluctuates beyond the threshold value in the sample range 2022-02-15 05:52:39 to the sample 2022-02-16 02:22:39 and in the end exceeds the threshold value completely.

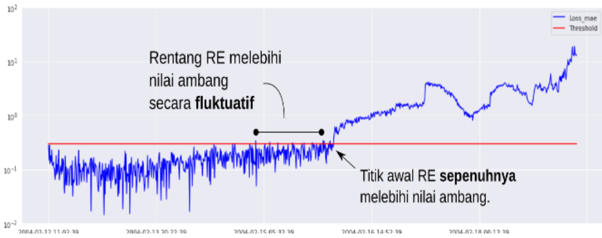

Figure 6Graph of dataset reconstruction error values (training and test sets)

If a comparison is made between the reconstruction error value and the rolling bearing sample data, it can be concluded that the increase in rolling bearing degradation 1 is the main cause of a significant increase in the reconstruction error value

Figure 7Rolling bearing sample chart

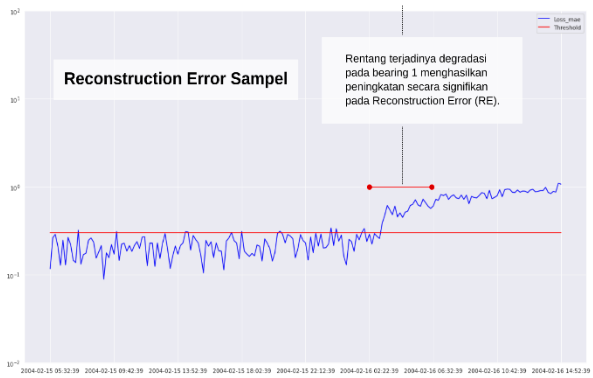

Figure 8Reconstruction error value graph

III. CONCLUSION

Based on the graph of the dataset reconstruction error value, the Autoencoder has succeeded in detecting rolling bearing damage by detecting anomalies in the bearing vibration data. The sample is considered an anomaly when the reconstruction error value of the sample exceeds the threshold value. This happens because the Autoencoder is trained to reconstruct normal samples, so that when there is an anomalous sample input, the Autoencoder's performance in reconstructing it is not good, resulting in a high reconstruction error value.

Based on the comparison graph of the rolling bearing sample and the reconstruction error value, it can be seen that the rolling bearing 1 is the main cause of a significant increase in the reconstruction error value. However, because the value of the reconstruction error is general, it is necessary for humans to know specifically the number of damaged bearings.

Research results can be more accurate by adding trial data. To get a different comparison, other types of Autoencoder devices can be used, such as Variational Autoencoder (VAE) to calculate the value of the vibration sample reconstruction error

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