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Vibration Data Feature Extraction and Deep Learning-Based Preprocessing Method for Highly-accurate Motor Fault Diagnosis

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Abstract

The environmental regulations on vessels being strengthened by the International Maritime Organization (IMO) has led to a steady growth in the eco-friendly ship market. Related research is being actively conducted, including many studies on the maintenance and predictive maintenance of propulsion systems (including electric motors, rotating bodies) in electric propulsion vessels. The present study intends to enhance the artificial intelligence-based failure diagnosis rate for electric propulsion vessel propulsion systems. To verify the proposed AI-based failure diagnosis algorithm for electric motors, this study utilized the vibration data of mechanical equipment (electric motors) in an urban railway station. Securing and preprocessing high-quality data is crucial for improving the failure diagnosis rate, in addition to the performance of the diagnostic algorithm. However, the conventional wavelet transform method, which is generally used for machine signal processing, has a disadvantage of data loss when the data distribution is abnormal or skewed. This study, to overcome this shortcoming, proposes an AI-based DAE method that can remove noise while maintaining data characteristics for signal processing of mechanical equipment.

This study preprocessed vibration data by using the DAE method, and extracted significant features from the data through the feature extraction method. The extracted features were utilized to train the one-class support vector machine model and to allow the model to diagnose the failure. Finally, the F-1 score was calculated by using the failure diagnosis results, and the most meaningful feature extraction method was determined for the vibration data. In addition, this study compared and evaluated the preprocessing performance based on the DAE and the wavelet

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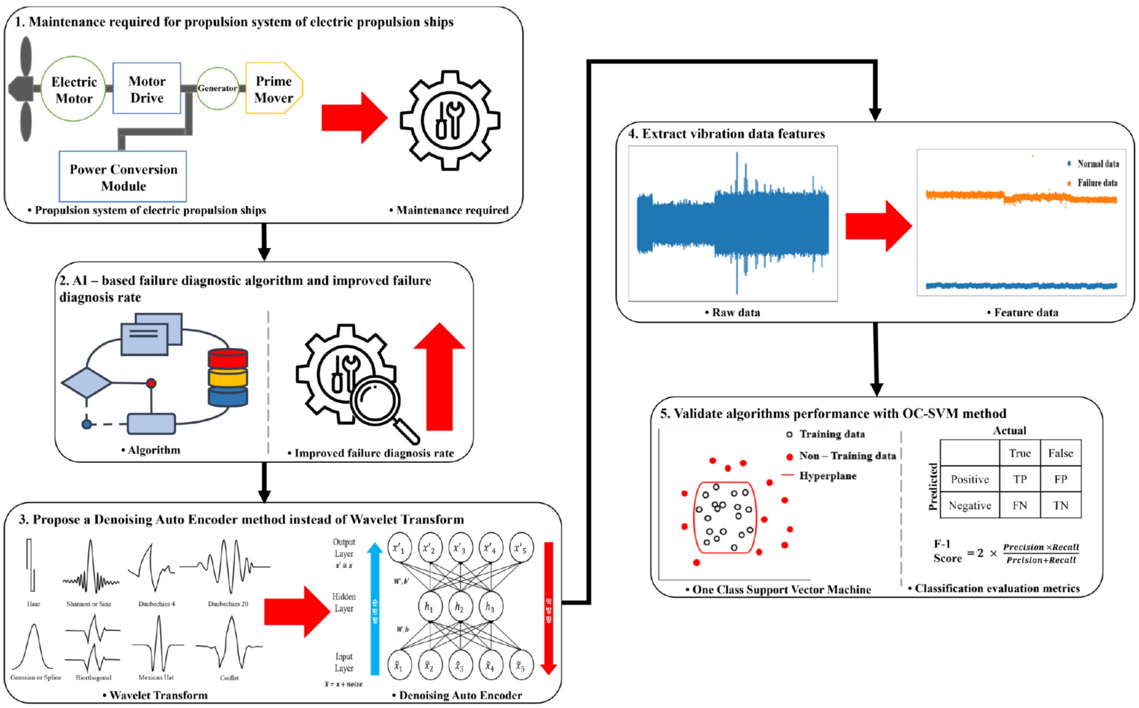
transform methods.

Graphical abstract



Keywords: Prognostics and Health Management (PHM), Denoising Auto Encoder (DAE), Wavelet Transform, OC-SVM (One-Class Support Vector Machine), Vibration Data

Highlights

- There is a need for investigating maintenance and predictive of propulsion systems in electric propulsion vessels.
- Proceeded to improve the AI-based failure diagnosis system and failure diagnosis rate of the motor.
- To overcome the shortcomings of the wavelet conversion method, a DAE is proposed for preprocessing.
- Applies the feature extraction method to the preprocessed data to extract features of the data.
- Apply the OC-SVM method to determine the performance of the proposed signal processing method..

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1. Introduction

1.1. Background and Necessity of Research

Around 90% of global goods are shipped by sea transport, accounting for about 4% of the global greenhouse gas emission (Yu *et al*., 2018). The total greenhouse gas emission from international shipping should be reduced by 50% in 2050 compared to 2008 levels, resulting from the environmental regulations established by the International Maritime Organization (IMO) in recent years. Accordingly, the market for eco-friendly vessels powered by liquefied natural gas or electric propulsion has grown significantly. The market size of electric and hybrid vessels is expected to grow to USD 1.24 billion by 2029.

Efficient maintenance and safe operation of vessels requires planned management of the propulsion system, including equipment and engines mounted on each vessel, necessitating a system that can diagnose and prevent ship defects (Park *et al*., 2015, Park *et al*., 2017). This study was aimed to improve the failure diagnosis rate of electric motors and rotating bodies, which are key elements in the propulsion system of electric propulsion vessels. Prior to the main research, there are several limitations in securing or using the data measured from the actual ship in operation. Thus, this study utilized the vibration data measured from the mechanical equipment (electric motors) in the Daejeon Metropolitan City urban railway station, a product of a project of the National Information Society Agency.

Among several factors, such as the performance of the diagnostic algorithm, it is crucial to secure high-quality data and pre-process it to improve the failure diagnosis rate. Because vibration data of mechanical equipment is measured, mixed with noise, depending on various operating environments, preprocessing is essential to extract meaningful signal features from the data (Hwang *et al*., 2018). Although many existing studies handling vibration data remove noise through the wavelet transform method, this induces data loss when the data distribution is abnormal or skewed (Lim & *Bae*, 2020). To overcome this disadvantage, this study utilized the denoising auto encoder (DAE) method, which is an artificial intelligence-based preprocessing method that induces no data loss, for removing noise from the vibration data of mechanical equipment. The DAE method is widely used to remove noise from images, and it has the advantage of removing noise while maintaining data characteristics. Thus, this study proposes the DAE method as a method to remove noise from the machine equipment data. Furthermore, the performance of the DAE method was evaluated in comparison to the performance with the wavelet transform method, which is generally used for machine signal processing.

The research is organized as follows: the statistical features of data were extracted through data preprocessing using two techniques. Failures were diagnosed by learning the one-class

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support vector machine through the feature-extracted data. The F-1 score was calculated, which was one of the indicators of classification performance evaluation based on the diagnosis results, thereby evaluating and comparing the preprocessing performance of the DAE. Section 1 presentsthe background and needs of the study along with the related study status. Section 2 includes a description of employed datasets and datasets used in the motor fault diagnosis system in this study, preprocessing of the fault diagnosis system, feature extraction, and techniques used in anomaly detection. In Section 3, the case study of the previous related studies, preprocessing, feature extraction, results of anomaly detection, and preprocessing performance evaluation are analyzed. In Section 4, conclusions and future studies are described.

1.2 Related Research Status

The vibration data of mechanical equipment are inevitably mixed with noise in the measurement process (Hwang *et al*., 2018). For this reason, it is essential to remove the noise included in the data in research using vibration data, and various methods are applied to do so.

Song et al. utilized IMS-Rexnord Bearing vibration data to predict equipment failure based on vibration data, and removed the noise from the data through Cepstrum analysis during the noise removal process (Song et al., 2018). Lu et al. sought to resolve the interference issue with vibration data by noise through frequency analysis, and removed noise from vibration data through wavelet transform (Lu & Mei, 2021). Moreover, Yang et al. predicted the trend of hydroelectric power generation devices by removing noise from vibration data through wavelet transform (Yang *et al*., 2021). Park et al. measured data through a vibration sensor installed on the output shaft of a planetary gear reducer to diagnose the failure of a planetary gear reducer for an unmanned aerial vehicle (UAV) using an artificial neural network model, and applied a band-pass filtering method to remove noise (Park *et al*., 2021). Jia et al. proposed a new noise removal method by combining the ensemble empirical mode decomposition method, and grey theory to remove noise from vibration signals (Jia *et al*., 2021).

There have been many studies on Machine signal processing through wavelet transform in many fields. Lee utilized vibration data to estimate the state of bearings, which are core parts of electric vehicles, and extracted features from the data by using wavelet transform (Lee, 2021). Lee et al. utilized IMS-Rexnord Bearing vibration data to develop a bearing failure prediction algorithm using a machine learning algorithm, and used wavelet transform to remove noise from the data (Lee *et al*., 2019). Kim et al. utilized the wavelet packet decomposition method to extract data characteristics in their study regarding diagnosis of the failure of rotating bearings, and decomposed the data into high-frequency and low-frequency components (Kim & Kim, 2021).

The DAE method is widely utilized to remove noise from data—in particular, noise from

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images—through more enhanced restoration capability than auto encoder. Dashdondov et al. used the DAE method to remove noise from hospital prescription images (Dashdondov *et al*., 2019). Song et al. utilized the convolutional DAE method to remove the noise from the images damaged by Gaussian noise, impulse noise, and speckle noise (Song *et al*., 2020). These studies verified the performance of the DAE in the image preprocessing process. Based on these results, this study proposes the DAE to effectively overcome the disadvantages of wavelet transform in machine signal processing.

2. Dataset and Motor Fault Diagnosis System

2.1 Dataset

The key element to a vessel's electric propulsion is a motor-rotating body. In the current circumstance, we aim to verify our study effect using data from a rotating body, which is similar to a motor instead of measuring and using data from expensive equipment like a vessel. Based on the verified results, we will conduct a study using the operational data of real vessels in the future. Thus, we used motor load data of mechanical equipment, which was built in 2020 by the Daejeon Metropolitan City Railway Corporation, as the project deliverable of the National Information Society Agency. Table 1 presents both vibration and current data, which are variably developed from 2.2kW to 55kW according to the load of the motor. In addition, four types of failures (rotating imbalance, belt loose, shaft misalignment, and bearing failure) were measured, and normal data were built separately for each failure type. In this study, data of intermediate and maximum loads (11kW and 55kW) out of the constructed data were used, and failure data of belt loose type were used in this study.

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Table. 1: Data amount (by load).

kW	Build amount (Current / Vibration) (Unit: 1,000ea)							
	Failure data						Normal data	
	Rotating imbalance	Belt loose	Shaft misalignment	Bearing failure	Total		Total	
					ea	Ratio	ea	Ratio
2.2	30	60	30	40	160	15.5%	270	15.5%
3.7	30	-	30	40	100	9.7%	100	9.3%
3.75	-	-	30	-	30	2.9%	30	2.8%
5.5	30	30	30	40	130	12.6%	120	11.1%
7.5	-	30	30	40	100	9.7%	80	7.4%
11	30	30	30	40	130	12.6%	150	13.9%
15	30	30	-	40	100	9.7%	80	7.4%
18.5	-	30	-	40	70	6.8%	60	5.6%
22	30	30	30	-	90	8.7%	70	6.5%
30	-	-	30	-	30	2.9%	30	2.8%
37	-	-	30	-	30	2.9%	30	2.8%
55	30	30	-	-	60	5.8%	60	5.6%
Total Sum	210	270	270	280	1,030		1,080	
Total Ratio	20.4%	26.2%	26.2%	27.2%	100%			

The target data were measured at a sampling rate of 4,000 Hz, and the amount and time of measurement vary depending on each data. This study performed data sampling for reasons, such as a reduction in the training time. 7,800,000 pieces of data were selected for each data type, and the portion with a change in amplitudes was selected from failure data. Fig. 1 and 2 show visualization of each sampled data.

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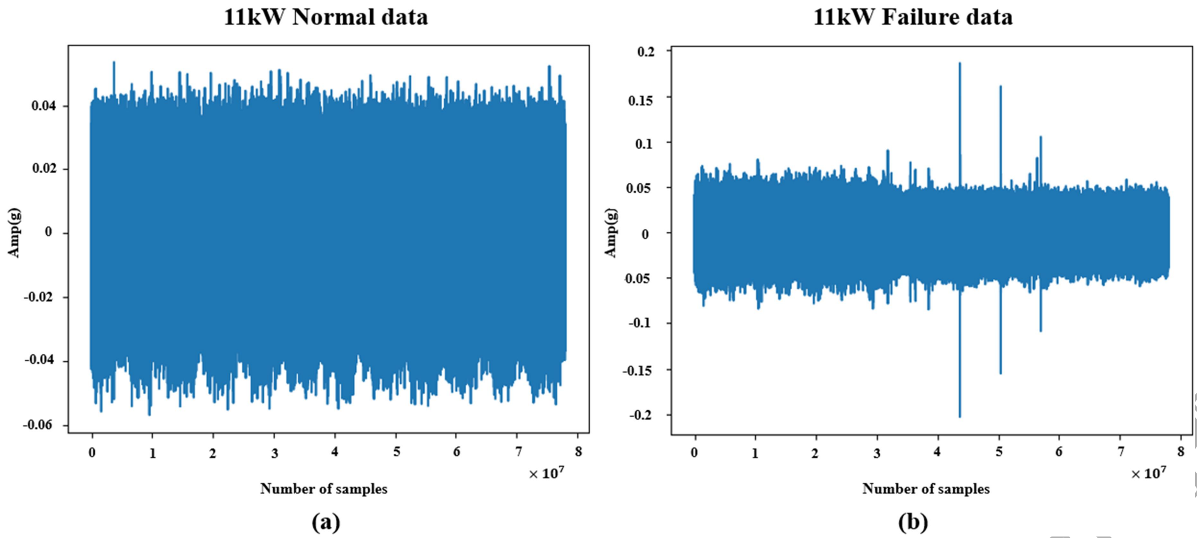

Fig. 1: (a) 11kW Normal Data, (b) 11kW Failure Data.

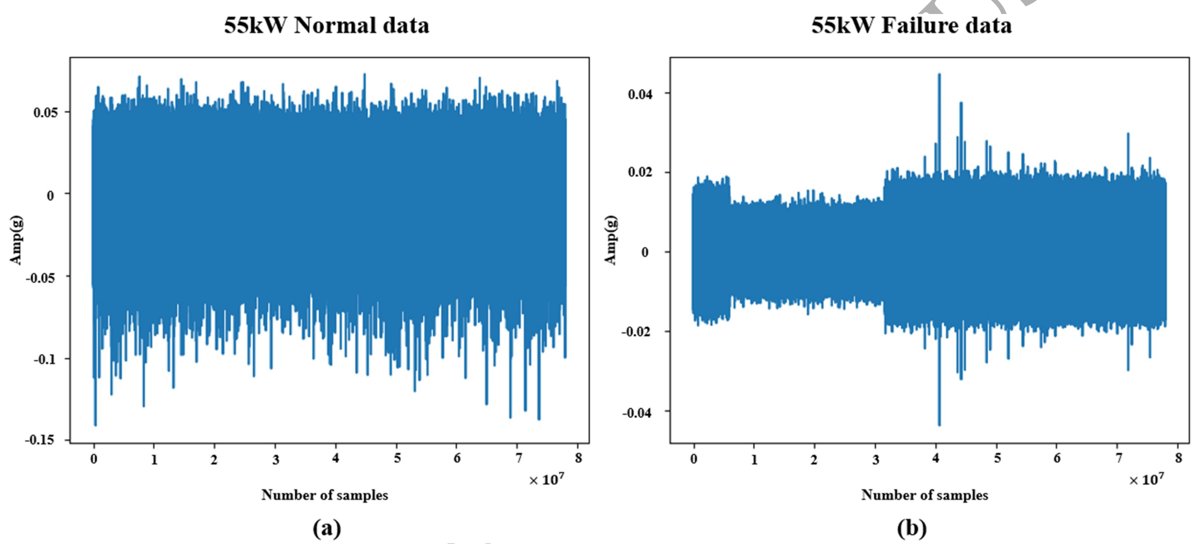

Fig. 2: (a) 55kW Normal Data, (b) 55kW Failure Data.

A crucial goal in data sampling is to maintain the characteristics of the original data while sampling. In this study, fast Fourier transform (FFT) analysis accomplished this goal. As shown in Fig. 3, FFT analysis is a method to convert complex signals from the time domain into the frequency domain.

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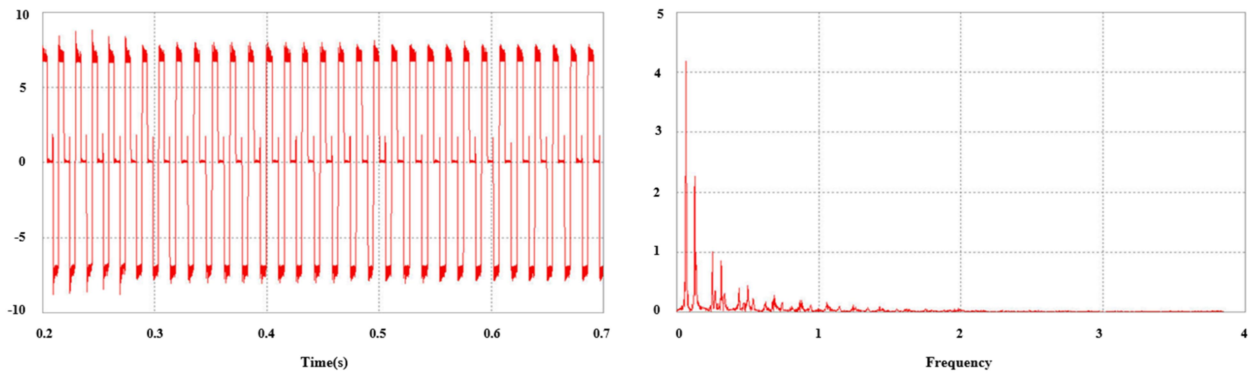
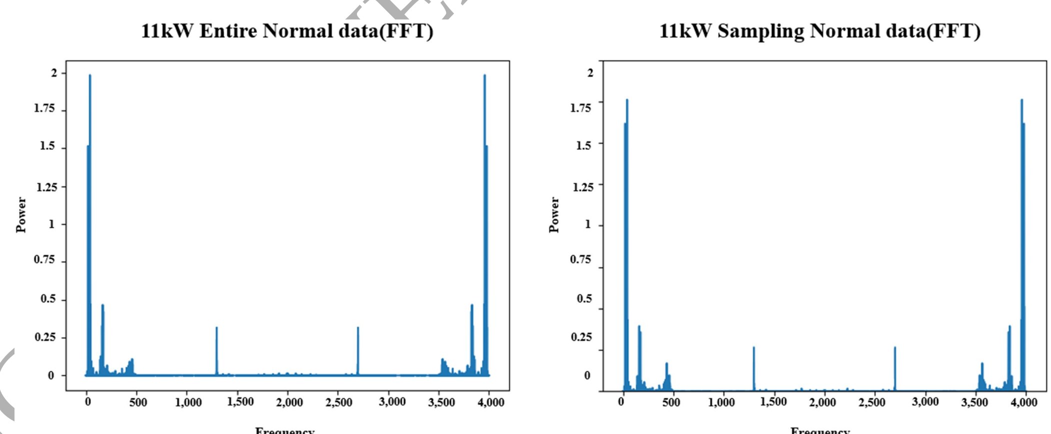


(a) (b)

Fig. 3: Fast Fourier Transform (FFT) Analysis (Yoon, 2019)

– (a) Time domain Data, (b) Frequency Domain Data.

FFT analysis provided insight into the frequency characteristics of both the machinery vibration data as well as the failure and normal data. As shown in Figs. 4 to 7, the results verified that failure data had an unusual distribution from 1,500 Hz to 2,500 Hz in contrast with normal data. In addition, we confirmed that the characteristics of the original data were maintained by comparing the frequency band of the original and sample data. The results verified that data sampling was conducted while maintaining the frequency band in all data. Furthermore, we calculated the failure diagnosis rate using the extracted frequency domain data, but we did not derive a significant result as the difference in the frequency distribution between normal and failure data was not significant. Thus, we verified the failure frequency in the frequency band according to many references and diagnosed failures using the data in the time domain (Cao *et al*., 2022), (Han *et al*., 2020), (Han *et al*., 2019), (Jung & Choi., 2022), (Song *et al*., 2018), (Tahir *et al*., 2018), (Niu *et al*., 2022).



(a) (b)

Fig. 4: (a) 11kW Normal Data(FFT), (b) 11kW Normal Data(FFT).

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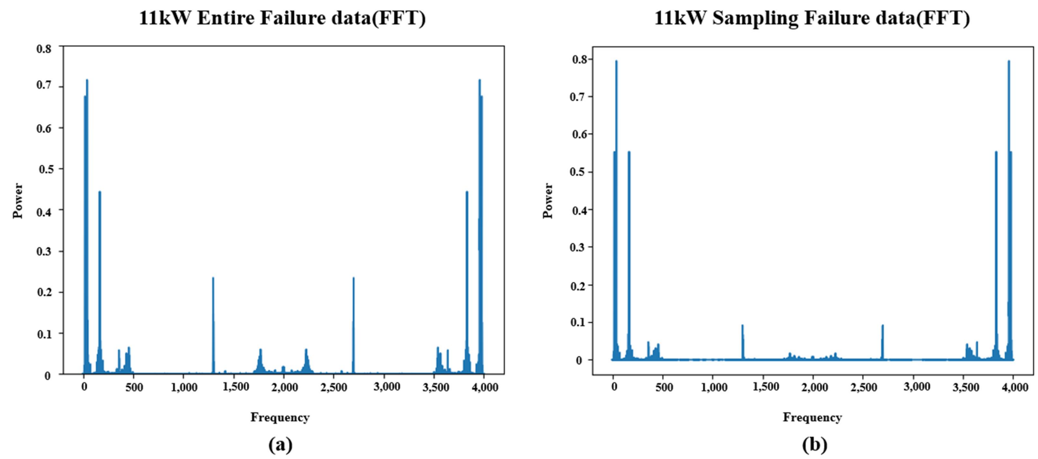

Fig. 5: (a) 11kW Failure Data(FFT), (b) 11kW Failure Data(FFT).

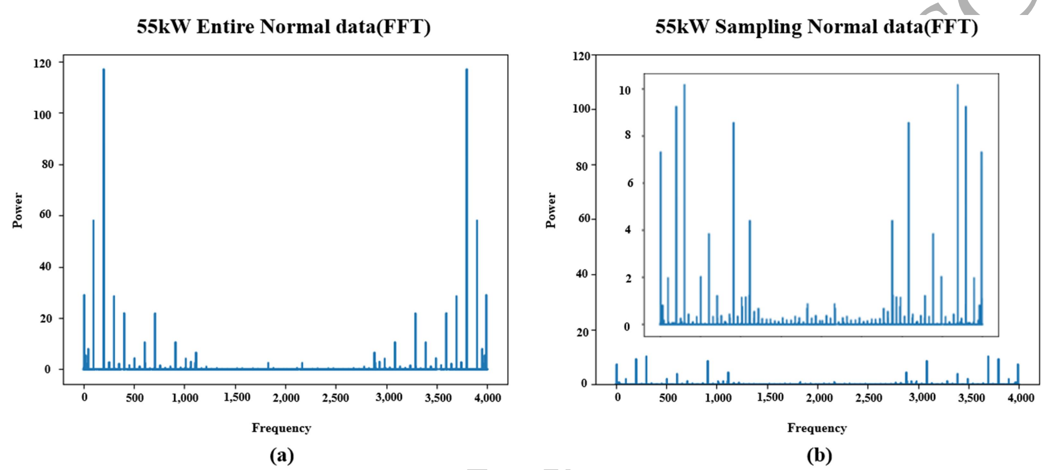

Fig. 6: (a) 55kW Normal Data(FFT), (b) 55kW Normal Data(FFT).

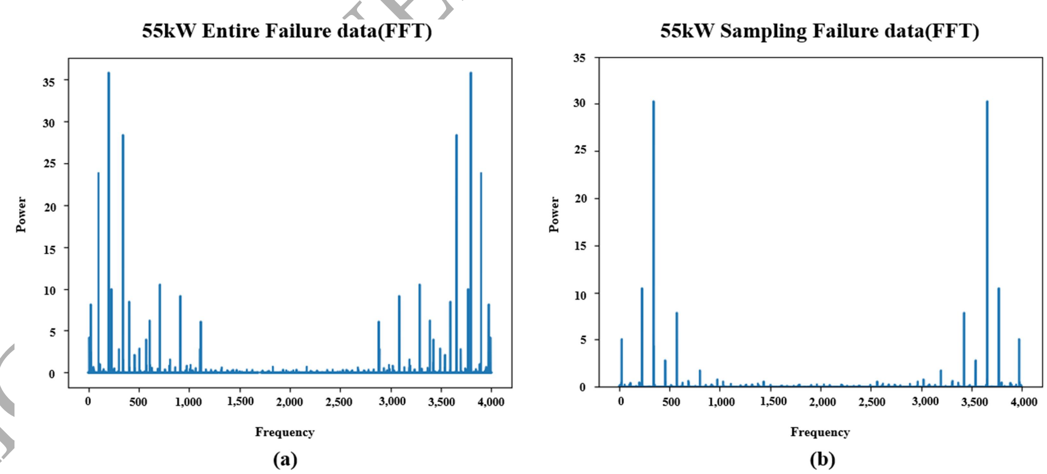

Fig. 7: (a) 55kW Failure Data(FFT), (b) 55 kW Failure Data(FFT).

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2.2 Data Preprocessing

The most important element in research regarding machine condition-based failure diagnosis is to obtain high-quality data. However, the data of mechanical equipment are mixed with noise during measurement. Numerous studies have utilized the wavelet transform method to remove the noise from mechanical equipment. However, wavelet transform has the disadvantage of inducing data loss when the data distribution is abnormal or skewed (Lim & Bae, 2020). Thus, this study proposes a method of applying the DAE method to the preprocessing of machine vibration data to overcome this issue.

2.2.1 Wavelet Transform

Wavelet transform is a conventional method widely used to remove noise from mechanical equipment, overcoming the shortcoming of Fourier transform in converting signals with the sine function and the cosine function alone. Wavelet transform, as shown in Fig. 8, analyzes and converts signals by using various wavelet functions for the time and frequency domains of the original signal (Yang *et al*., 2015). Wavelet transform has the advantages of simultaneously analyzing the time and frequency domains of the target signal, and analyzing discontinuous signals, such as mechanical vibration (Yang *et al*., 2015).

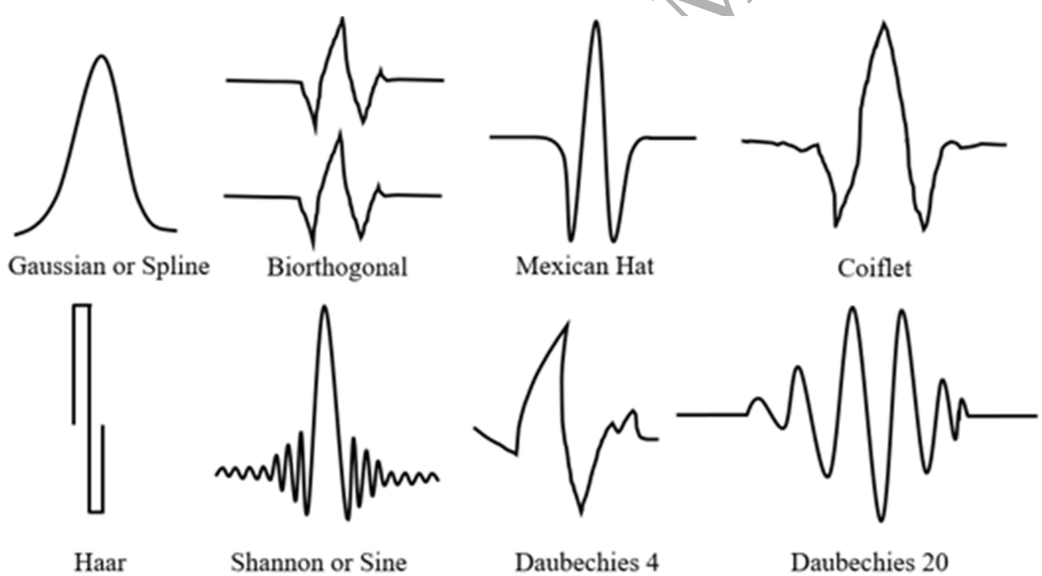

Fig. 8: Wavelet function (Al-geelani *et al*., 2016).

Wavelet transform-based noise removal is performed based on the wavelet threshold method. The wavelet threshold method is performed according to the principle of recognizing and removing noise when the wavelet coefficient calculated through wavelet transform is smaller

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than a predetermined threshold value. This method is divided into hard thresholding and soft thresholding, shown in Equations 1 and 2, respectively.

$$T_{\lambda}^{hard} = \begin{cases} \mu \; if \; |\mu \geq \lambda| \\ 0 \; otherwise \end{cases} \tag{1}$$

$$T_{\lambda}^{soft} = \begin{cases} (\mu - sign(\mu)\lambda) \; if \; |\mu \geq \lambda| \\ 0 \qquad\qquad\qquad\qquad otherwise \end{cases} \tag{2}$$

A setting of threshold λ in the above equation has a great influence on noise removal. In most studies, threshold λ is determined as in Equation 3 (Chan & *Peng*, 2003), where σ and n refer to the standard deviation of the input data, and the number of samples, respectively.

$$\lambda = \sqrt{2logn}\sigma \tag{3}$$

The largest difference between these two methods, as shown in Fig. 9, is that the hard thresholding value has a stepped shape at threshold λ, while soft thresholding does not.

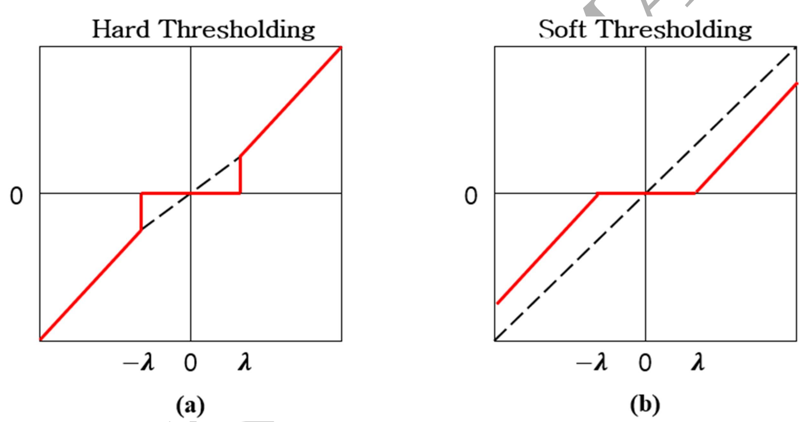

Fig. 9: (a) Hard Thresholding, (b) Soft Threshold (Ahn *et al*., 2015).

2.2.2 Denoising Auto Encoder

Auto encoder is a type of unsupervised learning that trains a network to ignore signal noise (Jeong *et al*., 2021). The types of models vary in this Auto Encoder method, depending on the number of hidden layer layers, and the number of nodes (Jeong *et al*., 2021). The DAE method is one of the methods devised from the auto encoder method, as shown in Fig. 10, which is a method to train the model to restore the input data to which random noise has been added, to the ones before addition of (Song *et al*., 2020).

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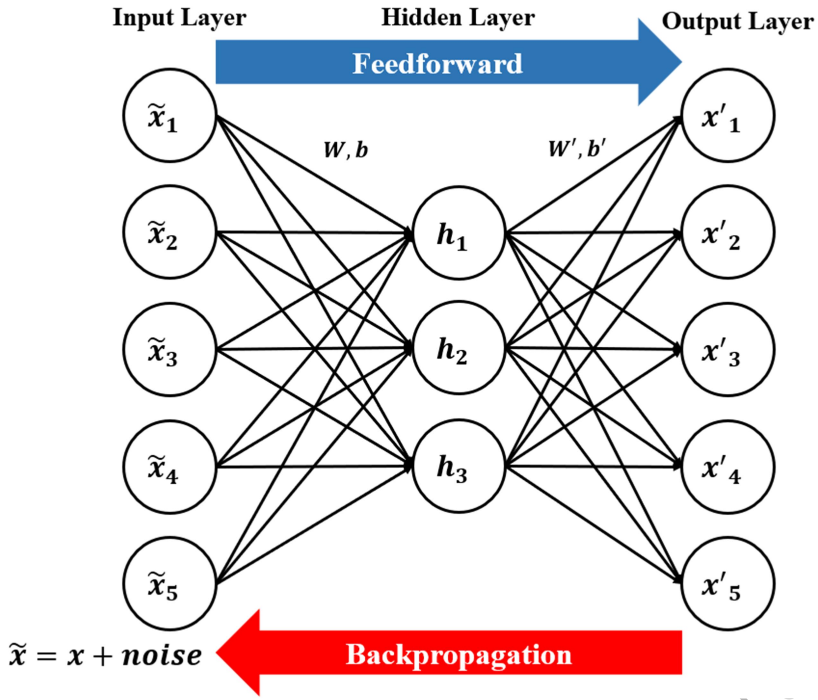

Fig. 10: Denoising Auto Encoder (Jang *et al*., 2021).

The training method of this DAE method is shown in Equations 4 to 7 (Jang *et al*., 2021).

(1) Add random noise to the original data x.

$$\tilde{\boldsymbol{x}} = \boldsymbol{x} + \boldsymbol{noise} \tag{4}$$

(2) Encode the data created by adding noise as input data.

$$\boldsymbol{h} = \boldsymbol{f_\theta}(\tilde{\boldsymbol{x}}) = \boldsymbol{f}(\boldsymbol{W}\tilde{\boldsymbol{x}} + \boldsymbol{b}) \tag{5}$$

(3) Produce a model which learns the output value most similar to the original data x by decoding the encoded results.

$$\boldsymbol{x}' = \boldsymbol{g_\theta}(\boldsymbol{h}) = \boldsymbol{f}(\boldsymbol{W}'\boldsymbol{h} + \boldsymbol{b}') \tag{6}$$

$$\mathbf{min}_{\boldsymbol{W,b,W',b'}}\, \boldsymbol{L}(\boldsymbol{x}, \boldsymbol{x}') = \frac{\mathbf{1}}{\mathbf{2}}\|\boldsymbol{x} - \boldsymbol{x}'\|^{\mathbf{2}} \tag{7}$$

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2.3 Feature Extraction

A failure diagnosis may be challenging with only vibration data consisting of time domain (Kim *et al*., 2021). Thus, the study was conducted by extracting the characteristics of the signal to be trained on the model; as shown in Table 2, it extracted features by utilizing the statistical features of the signal, such as mean, root mean square (RMS), standard deviation, skewness, and kurtosis.

The feature extraction method can be utilized to acquire all the features necessary to determine whether there is a failure in the time and frequency domains of the data (Kim *et al*., 2021). This study extracted the features in the time domain, aiming at real-time fault diagnosis in the future.

Table. 2: Feature Extraction.

Statistical Features	Formula
Mean	$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$
RMS	$x_{rms} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$
Standard Deviation	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}$
Skewness	$\beta_1 = \frac{\frac{1}{N}\sum_{i=1}^{N} x_i^3}{\sigma^3}$
Kurtosis	$\beta_2 = \frac{\frac{1}{N}\sum_{i=1}^{N} x_i^4}{\sigma^4}$

2.4 Anomaly Detection

Anomaly data refers to data that are, to a significant degree, either small or large compared to the observed values among the given data. Anomaly detection is detection of anomalous data, or data that deviate significantly from the trained dataset during the detection and classification process (Jun, 2008). The probability of a failure occurring during the

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manufacture and operation of the mechanical equipment is significantly low due to the improved reliability of the actual manufacturing site or the mechanical equipment in operation. In this case, a significantly low proportion of failure data to normal data, among the measured data, results in data imbalance. This data imbalance adversely affects training. Thus, this study trained normal data alone, and applied the OC-SVM method to detect failure data.

2.4.1 One Class - Support Vector Machine (OC-SVM)

OC-SVM is a type of unsupervised learning algorithm proposed by B. Schölkopf et al. in 2001, training unlabeled data of a single class, unlike the conventional support vector machine (Schölkopf et al., 2001).

OC-SVM, as shown in Fig. 11, detects anomalies by determining a hyperplane that separates training and non-training data (Jang *et al*., 2021). Moreover, it can employ linear classification as well as non-linear classification by utilizing kernel functions, as shown in Fig. 12. Because it is impossible to linearly classify vibration data due to their characteristics, this study applied a nonlinear classification by using a kernel function (Jang *et al*., 2021).

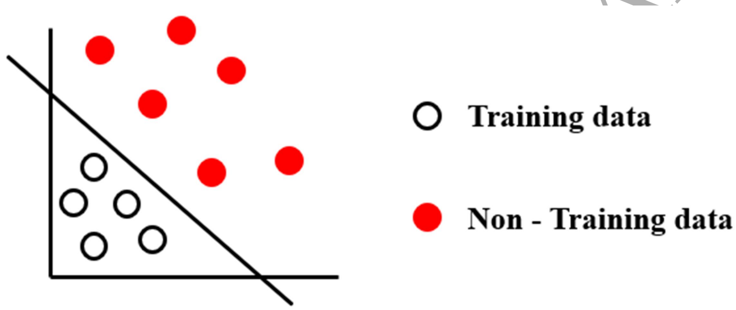

Fig. 11: One Class Support Vector Machine (Jang *et al*., 2021).

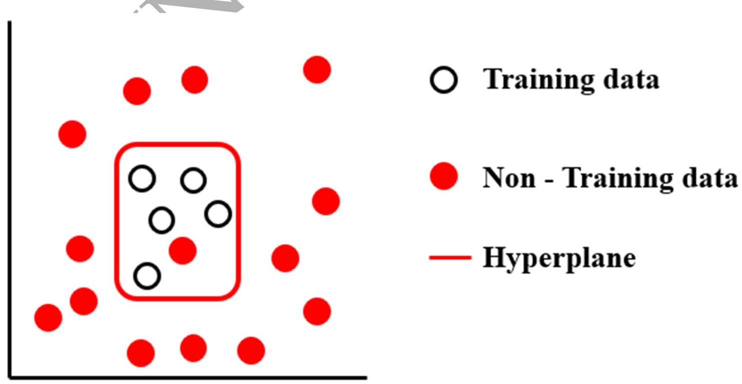

Fig. 12: Non-linear One-Class Support Vector Machine (Jang *et al*., 2021).

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2.5 Classification Evaluation Metrics

A confusion matrix that evaluates the the trained classification model's performance can be developed (Kim *et al*., 2020). Out of the components in the confusion matrix, True Positive (TP) refers to a model case that predicts normal for normal data while True Negative (TN) refers to a model case that predicts failure for failure data. Both cases mean the model predicts correctly. In contrast, False Negative (FN) refers to a model case that predicts failure for normal data while False Positive (FP) refers to a model case that predicts normal for failure data. Both cases imply that the model predicts incorrectly.

This confusion matrix is analyzed to calculate the performance metrics of a model, such as precision, recall, and F1 score (Kim *et al*., 2020). Each of the metrics is defined as in Equations 8 to 10. Precision and recall are important metrics for the failure and vibration of mechanical equipment, and performance evaluation was conducted through the F-1 score, which is the harmonic average of precision and recall.

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}} \tag{8}$$

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \tag{9}$$

$$\boldsymbol{F-1\ Score} = \boldsymbol{2} \times \frac{\boldsymbol{Precision \times Recall}}{\boldsymbol{Precision+Recall}} \tag{10}$$

3. Case Study

3.1 Analysis on Prior Studies

A prior related study is provided in the References (Jang *et al*., 2021). Similarly, the prior study utilized 2.2 kw load data to improve the failure diagnosis rate. Ultimately, the case where the DAE method was applied to preprocessing showed higher failure diagnosis rate and F-1 score than the case with wavelet transform.

As shown in Tables 3 and 4, another study adding the working load of electric motor (11 kW, 55 kW) showed low failure diagnosis rate and F-1 score. The prior study extracted 100,000 pieces of normal data, and 100,000 pieces of failure data as two sections. The reasons for the low failure diagnosis rate and F-1 score are that the vibration data of normal and failure showed a similar distribution between 11 kW and 55 kW data, compared to the 2.2 kW data, and that raw

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data without the feature extraction process was utilized. Thus, this study added the feature extraction process of the data to improve the failure diagnosis rate.

The flow chart of this study is shown in Fig. 13. After conducting preprocessing of vibration data using two methods, five statistical feature extractions for each data are performed. Using the feature-extracted normal data, the OC-SVM model is learned to detect failure. Finally, the F1-score is calculated to evaluate the performance based on the detected result, thereby evaluating and comparing the preprocessing performance of vibration data. The results of each stage are described below.

Table. 3: A Prior study confusion matrix of Denoising Auto Encoder (11 kW).

Denoising Auto Encoder (11 kW)		Actual answer (unit: case(s))		
		Normal	Failure (1)	Failure (2)
Classification results	Normal	92,802	66,673	27,320
	Failure	7,198	33,327	72,680

Table. 4: A Prior study confusion matrix of Denoising Auto Encoder (55 kW).

Denoising Auto Encoder (55 kW)		Actual answer (unit: case(s))		
		Normal	Failure (1)	Failure (2)
Classification results	Normal	90,454	60,572	61,391
	Failure	19,546	39,428	38,609

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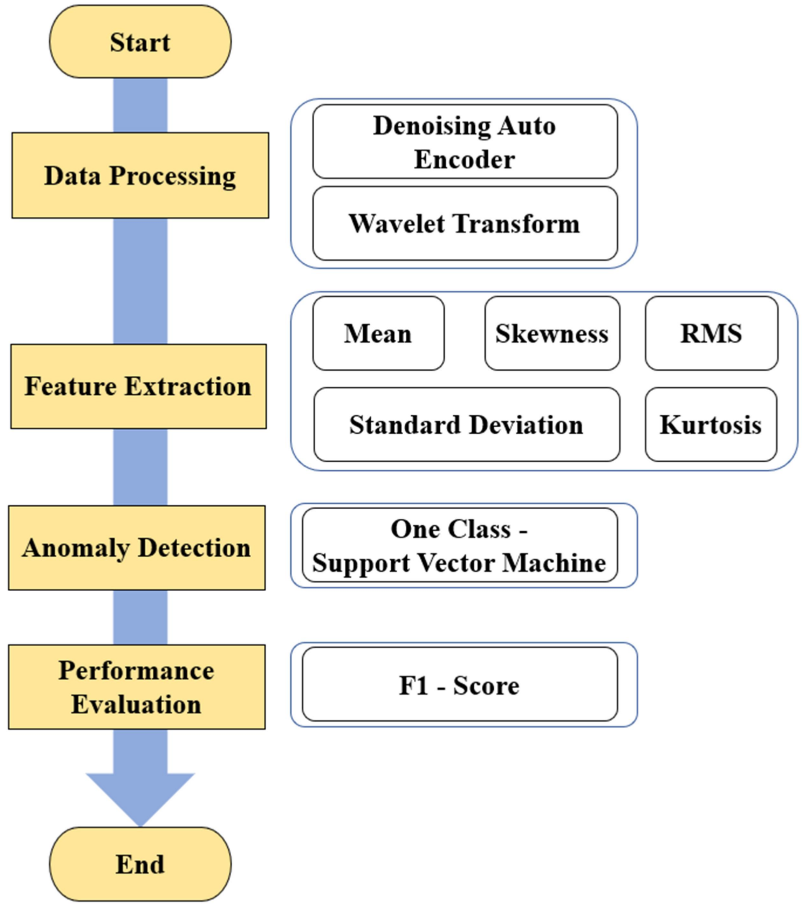

Fig. 13: Flow Chart.

3.2 Result of Data Preprocessing

The two preprocessing methods described in Sections 2.2.1 and 2.2.2 were applied to remove noise from the data.

Matlab's Wavelet Tool Box was used for preprocessing based on wavelet transform. Because the wavelet function must be similar to the type of data to remove noise, the db4 function, which is a wavelet function similar to vibration data, was utilized, involving a total of four conversion steps. The soft thresholding method more frequently applied to related research, was adopted from the wavelet thresholding methods, and noise was removed by applying it to each conversion step.

The data noise removal process using the DAE technique employs the following steps. The Gaussian noise, which was similar to the vibration data noise, was added to the original data (Jahagirdar *et al*., 2018). After this, the DAE model was produced as shown in Fig. 14 to generate a model that recovered noise-added data into the original data. The noise was removed

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by putting the data whose noise is removed into the produced model. Fig. 15a demonstrates the noise-removed result of 11kW failure data through Denoising Auto Encoder and Fig. 15b is result of wavelet transform.

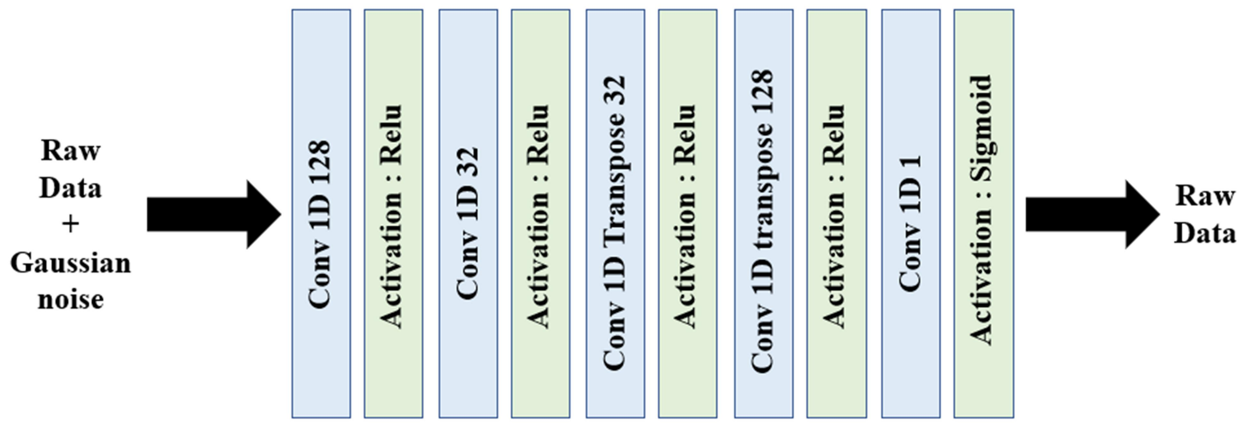

Fig. 14: Denoising Auto Encoder Architecture.

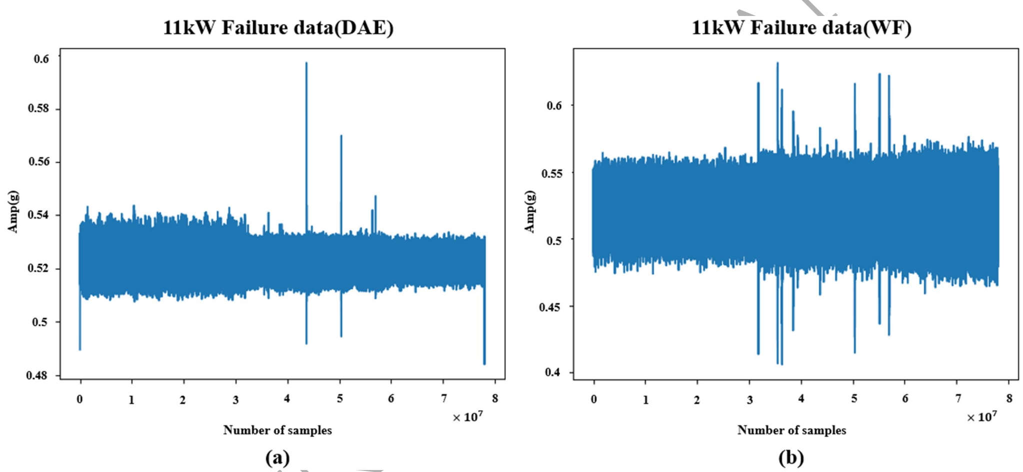

Fig. 15: (a) 11 kW Noise Reduction Failure data (DAE),

(b) 11 kW Noise Reduction Failure data (WF).

3.3 Result of Feature Extraction

The process of feature extraction after removing data noise uses the methods described herein. In the segmentation process of 7,800,000 records of sampling normal data and failure data, 1,000 records of data were set to a single segment. thereby producing 7,800 segments. The normalization between zero and one was conducted for learning stabilization of the future

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anomaly detection model after converting the produced segments through each statistical feature extraction equation. Figs. 16 to 25 reveal feature extraction-applied results, which differ significantly according to the used preprocessing technique. The results indicated that wavelet transform could not separate normal and failure data due to the drawback of signal loss under specific conditions, when compared to that of feature extraction through the DAE-based preprocessing technique.

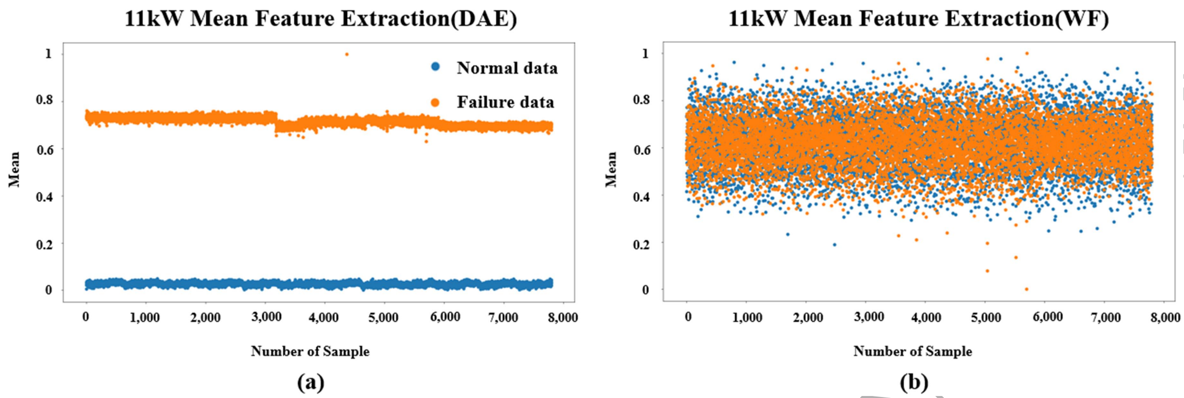

Fig. 16: (a) 11kW Data Mean Feature Extraction (DAE),

(b) 11kW Data Mean Feature Extraction (WF).

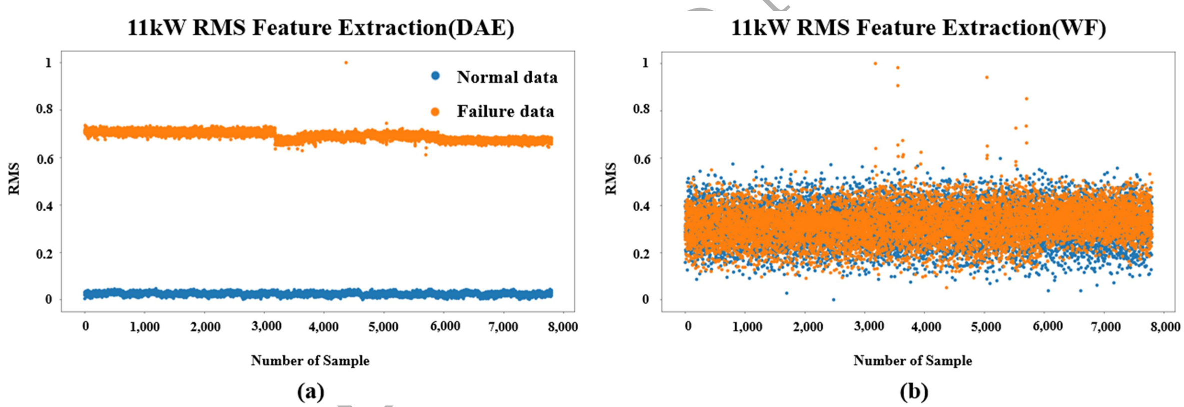

Fig. 17: (a) 11kW Data RMS Feature Extraction (DAE),

(b) 11kW Data RMS Feature Extraction (WF).

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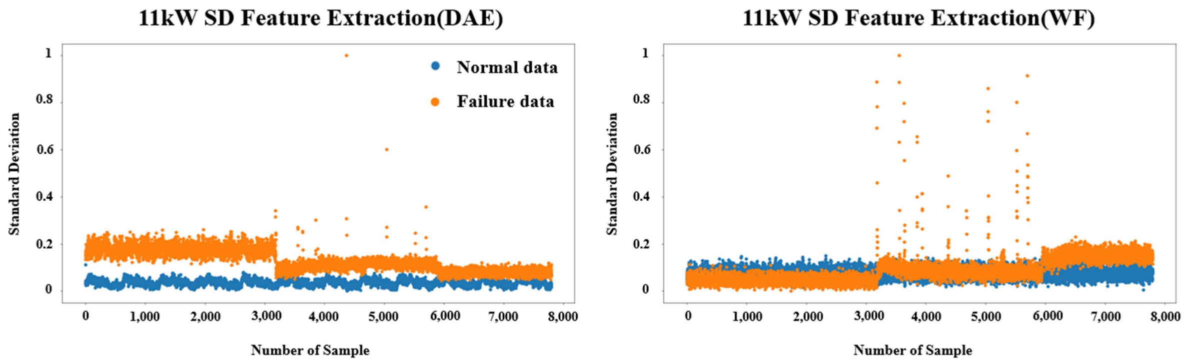
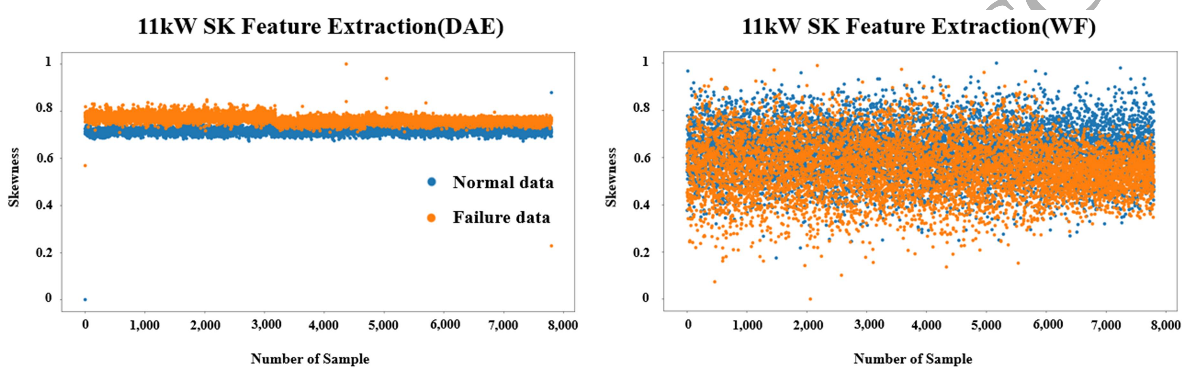


(a) (b)

Fig. 18: (a) 11kW Data Standard Deviation Feature Extraction (DAE),

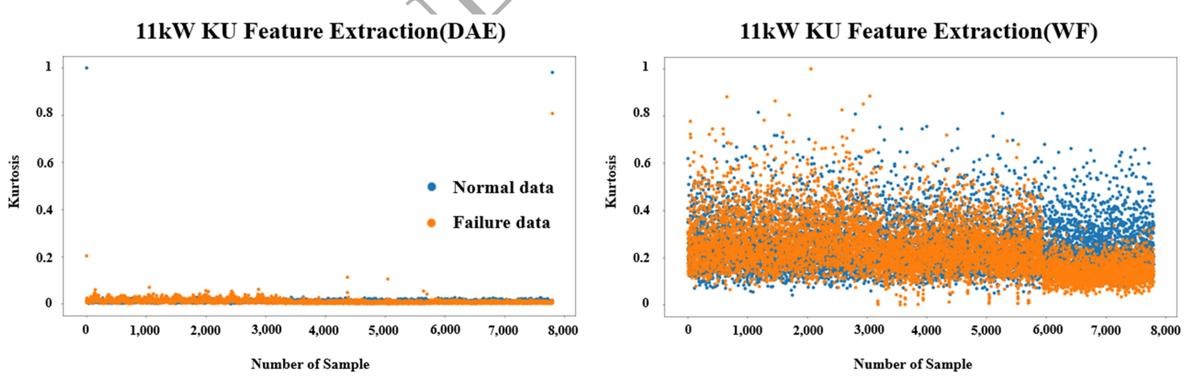
(b) 11kW Data Standard Deviation Feature Extraction (WF).



(a) (b)

Fig. 19: (a) 11kW Data Skewness Feature Extraction (DAE),

(b) 11kW Data Skewness Feature Extraction (WF).



(a) (b)

Fig. 20: (a) 11kW Data Kurtosis Feature Extraction (DAE),

(b) 11kW Data Kurtosis Feature Extraction (WF).

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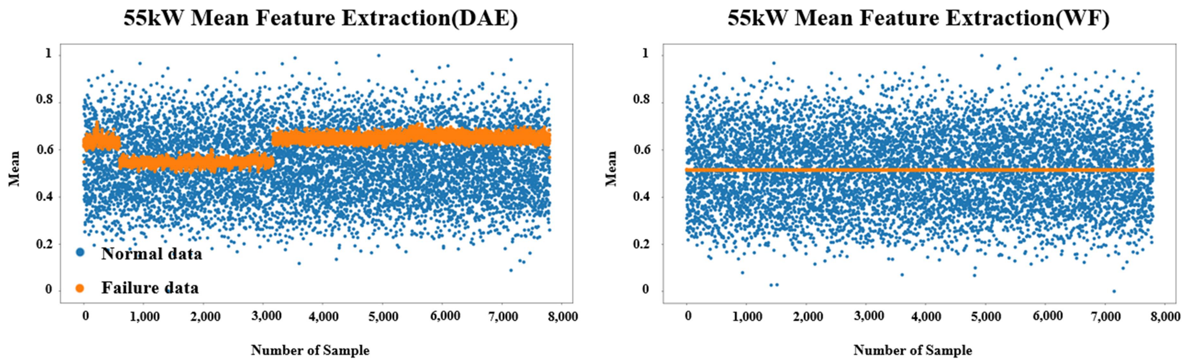
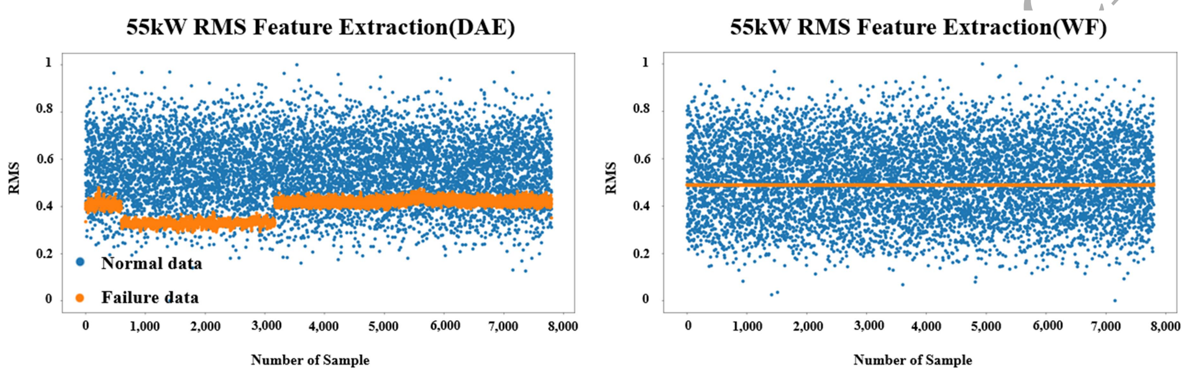


(a) (b)

Fig. 21: (a) 55kW Data Mean Feature Extraction (DAE),

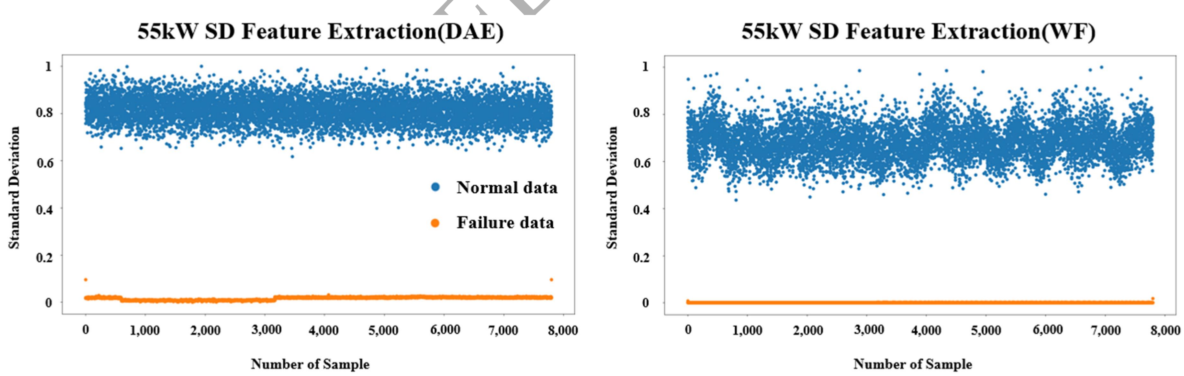
(b) 55kW Data Mean Feature Extraction (WF).



(a) (b)

Fig. 22: (a) 55kW Data RMS Feature Extraction (DAE),

(b) 55kW Data RMS Feature Extraction (WF).



(a) (b)

Fig. 23: (a) 55kW Data Standard Deviation Feature Extraction (DAE),

(b) 55kW Data Standard Deviation Feature Extraction (WF).

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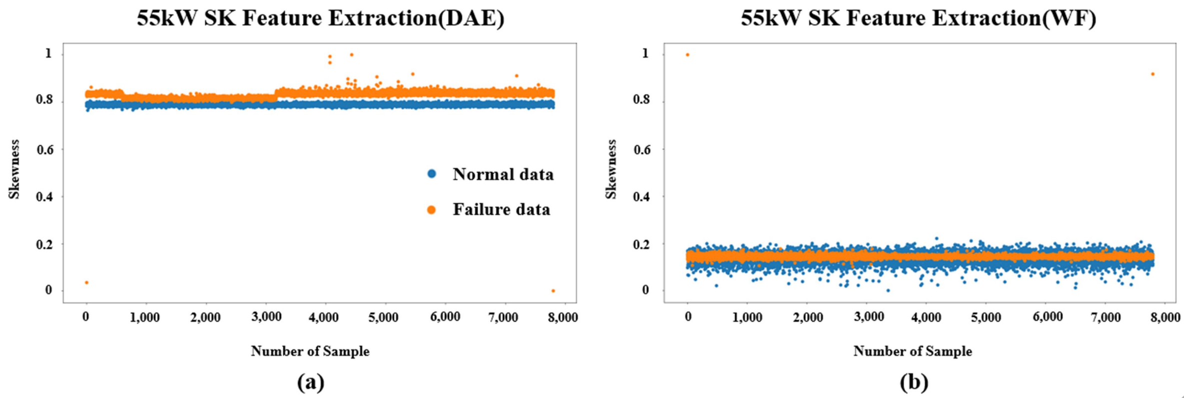

Fig. 24: (a) 55kW Data Skewness Feature Extraction (DAE),

(b) 55kW Data Skewness Feature Extraction (WF).

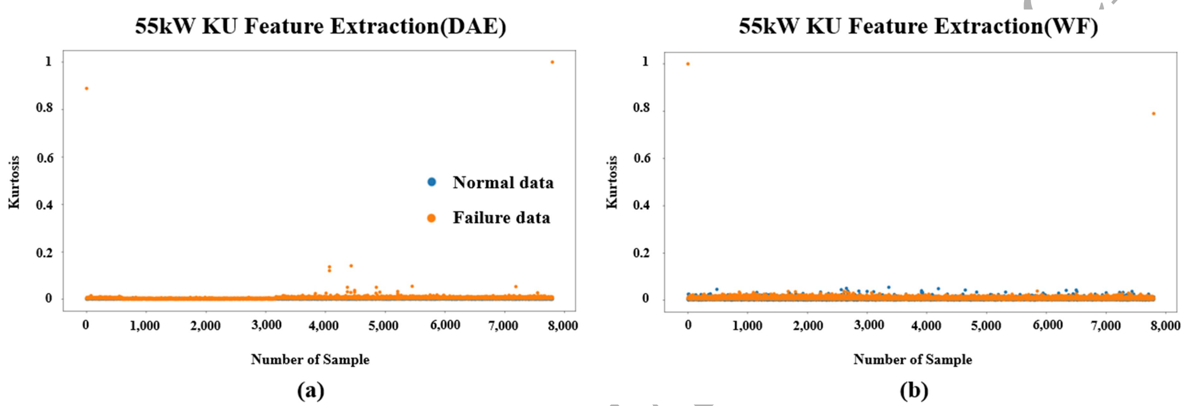

Fig. 25: (a) 55kW Data Kurtosis Feature Extraction (DAE),

(b) 55kW Data Kurtosis Feature Extraction (WF).

3.4 Result of Anomaly Detection

The OC-SVM model was produced after the preprocessing and feature extraction processes, using normal data. The model was constructed with the goal of around 90% learning rate of normal data by combining hyperparameters of OC-SVM and varying the number of cases; the highest running rate model was selected. Tables 5 and 6 present the hyperparameters derived from the number of cases. After constructing the model, failure data were added to the model to diagnose failures. Tables 7 to 10 present the normal data learning rate and failure diagnosis results of the OC-SVM model for each preprocessing and feature extraction. The running and failure rates refer to normal data learning and failure diagnosis rates.

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Table. 5: Hyper parameter of OC-SVM(11kw).

Feature	Denoising Method	Nu	Gamma	Running rate	Failure Rate
Mean (11kW)	Denoising Auto Encoder	0.05	500	**93.63%**	**100%**
			1000	91.31%	100%
		0.01	500	93.55%	100%
			1000	90.91%	100%
	Wavelet Transform	0.05	500	63.59%	60.12%
			1000	59.43%	72.84%
		0.01	500	59.71%	61.12%
			1000	56.36%	73.53%
		0.03	2	**96.99%**	**1.41%**
RMS (11kW)	Denoising Auto Encoder	0.05	500	**93.49%**	**100%**
			1000	91.42%	100%
		0.01	500	93.47%	100%
			1000	91.07%	100%
	Wavelet Transform	0.05	500	65.73%	53.32%
			1000	61.89%	67.02%
		0.01	500	60.91%	55.31%
			1000	58.22%	66.94%
		0.08	45	**90.6%**	**9.3%**
Standard Deviation (11kW)	Denoising Auto Encoder	0.05	500	93.56%	98.73%
			1000	91.57%	98.93%
		0.01	500	**93.59%**	**98.69%**
			1000	91.27%	98.93%
	Wavelet Transform	0.05	500	**91.24%**	**51.86%**
			1000	84.73%	63.36%
		0.01	500	90.08%	53.27%
			1000	82.81%	63.53%
Skewness (11kW)	Denoising Auto Encoder	0.05	500	**93.76%**	**95.77%**
			1000	90.66%	96.76%
		0.01	500	93.63%	95.76%
			1000	90.5%	96.75%
	Wavelet Transform	0.05	500	64.19%	65.1%
			1000	60.12%	76.67%
		0.01	500	60.14%	65.36%
			1000	57.25%	76.84%
		0.05	17	**93.68%**	**10.92%**
Kurtosis (11kW)	Denoising Auto Encoder	0.05	500	**93.4%**	**40.88%**
			1000	91.04%	45.46%
		0.01	500	92.79%	40.97%
			1000	90.14%	45.47%
	Wavelet Transform	0.05	500	66.76%	56.54%
			1000	62.83%	71.91%

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		0.01	500	61.47%	58.18%
		0.06	10	**93.88%**	**11.63%**

Table. 6: Hyper parameter of OC-SVM(55kw).

Feature	Denoising Method	Nu	Gamma	Running rate	Failure Rate
Mean (55kW)	Denoising Auto Encoder	0.05	500	62.85%	63.27%
			1000	57.94%	76.28%
		0.01	500	58.86%	64.38%
		0.057	35	**88.54%**	**14.65%**
	Wavelet Transform	0.05	500	62.35%	37.36%
			1000	58%	82.04%
		0.01	500	57.82%	67.14%
			1000	56.56%	81.42%
		0.08	16	**90.81%**	**35.76%**
RMS (55kW)	Denoising Auto Encoder	0.05	500	62.65%	67.55%
			1000	58.85%	81.42%
		0.01	500	25.26%	67.69%
			1000	56.94%	81.46%
		0.07	7	**92.83%**	**6.92%**
	Wavelet Transform	0.05	500	61.9%	64.17%
			1000	58.17%	78.99%
		0.01	500	57.95%	64.18%
			1000	56.35%	78.82%
		0.06	10	**93.49%**	**9.71%**
Standard Deviation (55kW)	Denoising Auto Encoder	0.05	500	72.46%	100%
			100	**92.29%**	**100%**
		0.01	500	65.36%	100%
			1000	60.31%	100%
	Wavelet Transform	0.05	500	70.86%	100%
			50	**92.49%**	**100%**
		0.01	500	64.09%	100%
			1000	60.83%	100%
Skewness (55kW)	Denoising Auto Encoder	0.05	500	**93.64%**	**99.97%**
			1000	91.22%	99.97%
		0.01	500	93.24%	99.97%
			1000	91.04%	99.97%
	Wavelet Transform	0.05	500	**89.04%**	**8.54%**
			1000	80.63%	22.08%
		0.01	500	86.59%	9.53%
			1000	76.91%	24.62%
Kurtosis (55kW)	Denoising Auto	0.05	500	85.77%	70.73%
			1000	83%	73.41%

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	Encoder	0.01	500	71.46%	72.17%
		0.09	1641	**90.99%**	**71.15%**
	Wavelet Transform	0.05	500	9014.%	28.73%
			1000	86.41%	36.12%
		0.01	500	86.92%	29.18%
		0.06	10	**93.72%**	**8.3%**

Table. 7: Confusion matrix of Wavelet Transform (11 kW).

Wavelet Transform (11 kW)			Actual answer (unit: case(s))		Running Rate	Failure Rate
			Normal	Failure		
Classification results by feature	Mean	Normal	7,565	235	**96.99%**	1.41%
		Failure	7,690	110		
	RMS	Normal	7,066	733	**90.6%**	9.63%
		Failure	7,049	751		
	Standard Deviation	Normal	7,117	683	**91.24%**	51.86%
		Failure	3,755	5,045		
	Skewness	Normal	7,307	493	**93.68%**	10.92%
		Failure	6,948	852		
	Kurtosis	Normal	7,323	477	**93.88%**	11.63%
		Failure	6,893	907		

Table. 8: Confusion matrix of Denoising Auto Encoder (11k W).

DAE (11 kW)			Actual answer (unit: case(s))		Running Rate	Failure Rate
			Normal	Failure		
Classification results by feature	Mean	Normal	7,303	497	**93.63%**	**100%**
		Failure	0	7,800		
	RMS	Normal	7,292	508	**93.49%**	**100%**
		Failure	0	7,800		
	Standard Deviation	Normal	7,300	500	**93.59%**	**98.69%**
		Failure	102	7,698		
	Skewness	Normal	7,313	487	**93.76%**	**95.77%**
		Failure	330	7,470		
	Kurtosis	Normal	7,254	546	**93%**	26.22%

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		Failure	5,755	2,045		

Table. 9: Confusion matrix of Wavelet Transform (55 kW).

Wavelet Transform (55 kW)			Actual answer (unit: case(s))		Running Rate	Failure Rate
			Normal	Failure		
Classification results by feature	Mean	Normal	7,083	717	**90.81%**	35.76%
		Failure	5,011	2,789		
	RMS	Normal	7,292	508	**93.49%**	9.71%
		Failure	7,043	757		
	Standard Deviation	Normal	7,214	586	**92.49%**	**100%**
		Failure	0	7,800		
	Skewness	Normal	6,965	835	**89.04%**	8.54%
		Failure	7,142	658		
	Kurtosis	Normal	7,310	490	**93.72%**	8.3%
		Failure	7,152	648		

Table. 10: Confusion matrix of Denoising Auto Encoder (55 kW).

DAE (55 kW)			Actual answer (unit: case(s))		Running Rate	Failure Rate
			Normal	Failure		
Classification results by feature	Mean	Normal	6,892	908	**88.54%**	14.65%
		Failure	6,518	1,282		
	RMS	Normal	7,241	559	**92.83%**	6.92%
		Failure	7,260	540		
	Standard Deviation	Normal	7,199	601	**92.29%**	**100%**
		Failure	0	7,800		
	Skewness	Normal	7,304	496	**93.64%**	**99.97%**
		Failure	2	7,798		
	Kurtosis	Normal	6,901	899	**88.47%**	**69.92%**
		Failure	2,346	5,454		

Based on the above preprocessing and classification results, precision, recall, and F-1 score, which are classification evaluation metrics, were calculated, and the results are indicated

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in Tables 11 to 14.

Table. 11: F-1 Score of Wavelet Transform (11 kW).

Wavelet Transform (11 kW)		Precision	Recall	F-1 Score
Classification evaluation metrics	Mean	0.986	0.496	0.66
	RMS	0.904	0.501	0.644
	Standard Deviation	0.587	0.3657	0.62
	Skewness	0.896	0.513	0.652
	Kurtosis	0.89	0.515	0.652

Table. 12: F-1 Score of Denoising Auto Encoder (11 kW).

Denoising Auto Encoder (11 kW)		Precision	Recall	F-1 Score
Classification evaluation metrics	Mean	0.936	1	**0.967**
	RMS	0.935	1	**0.966**
	Standard Deviation	0.936	0.986	**0.96**
	Skewness	0.938	0.957	**0.947**
	Kurtosis	0.93	0.558	**0.697**

Table. 13: F-1 Score of Wavelet Transform (55 kW).

Wavelet Transform (55 kW)		Precision	Recall	F-1 Score
Classification evaluation metrics	Mean	0.908	0.586	**0.712**
	RMS	0.935	0.509	0.659
	Standard Deviation	0.925	1	**0.96**
	Skewness	0.893	0.494	0.636
	Kurtosis	0.937	0.505	0.657

Table. 14: F-1 Score of Denoising Auto Encoder (55 kW).

Denoising Auto Encoder (55 kW)		Precision	Recall	F-1 Score
Classification evaluation	Mean	0.884	0.514	0.65
	RMS	0.928	0.499	0.65

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metrics	Standard Deviation	0.923	1	**0.96**
	Skewness	0936	0.1	**0.967**
	Kurtosis	0.885	0.746	**0.81**

3.5 Comparison Analysis on Results

When the data that had completed all preprocessing were applied to the anomaly detection model, the target level of normal learning rate was obtained in all cases. In the case of failure diagnosis rate on 11 kW data, the case of preprocessing based on the DAE method showed a higher failure diagnosis rate than that based on wavelet transform. However, in the case of feature extraction using kurtosis, the failure diagnosis rates of the preprocessing methods remained at approximately 11% and 26%, respectively, indicating poor results. The F-1 score calculated based on the failure diagnosis results was determined to be high in all feature extractions based on the DAE method.

Feature extraction from 55 kW data by using mean and RMS showed poor results for both preprocessing methods, having a failure diagnosis rate of approximately 7 to 35%. However, in the other three feature extractions, DAE showed an equivalent or significantly higher failure diagnosis rate compared to wavelet transform method. The F-1 score based on these results showed similar results. Furthermore, standard deviation was utilized to determine the method having the highest failure diagnosis rate and F-1 score in all five cases of statistical feature extraction applied to the data. These results show that standard deviation showed the most significant result among the characteristics applied to the vibration data of the electric motor.

4. Conclusion

The maintenance of motors among electric propulsion vessels was investigated in this study as the associated market grows as a result of IMO environmental regulations. We aimed to select data which had the same principle as the motor rotating bodies as key elements in the propulsion system of electric propulsion vessels. Thus, the study results were derived using the vibration data of the rotating body, which was similar to the motor's driving principle. Our final future research goal is to conduct a study by acquiring equipment data used in real vessels. In this study, the DAE technique was proposed to overcome the drawbacks of the wavelet transform technique, which was used universally in existing machine signal processing, and improve the preprocessing performance for the enhancement of the failure diagnosis rate. Data noise was removed using each of the preprocessing techniques, and feature extraction techniques were

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applied to extract significant features of data. Failures were diagnosed with the OC-SVM technique using the feature-extracted data, and the F-1 score was calculated based on the diagnosis results to compare and evaluate the performance of preprocessing techniques. The performance evaluation results showed that the failure diagnosis rate of preprocessing technique based on DAE had comparable or better performance in most cases than that of the wavelet transform. In addition, it also showed a better performance based on the F-1 score. Thus, the results proved the performance of preprocessing of machine vibration data and the improvement of failure diagnosis rate when using the DAE technique.

This study utilized the normal data of mechanical equipment (electric motors) and the data of the belt looseness failure type for verifying the preprocessing performance of the DAE method, and improving the failure diagnosis rate. Follow-up studies will proceed by adding failure type data, such as rotating body imbalance, bearing defects, and shaft misalignment, beyond one failure type (i.e., belt looseness). In addition, the generative adversarial network (Tad-GAN) and variation auto encoder (VAE) methods, which have been applied in many studies during the process of diagnosing failure data, should be used to verify the performance of the DAE method.

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