GAN-AE BASED FAULT DIAGNOSIS METHOD FOR ROTOR MACHINE

PROJECT REPORT

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FATHIMA S

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Dr. Aneesh G Nath

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Kerala

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Dept. of Computer Science & Engineering

C E R T I F I C A T E

This is to certify that this report titled ***GAN-AE Based Fault Diagnosis Method For Rotor Machine*** is a bonafide record of the **Project** presented by **FATHIMA S (TKM20CSCE06)**, under our guidance and supervision, in partial fulfillment of the requirements for the award of the degree, **M.Tech in Computer Science & Engineering** in **APJ Abdul Kalam Technological University** .

Coordinator	Supervisor	Head of the Department
Dr. Ansamma John	Dr. Aneesh G Nath	Dr. Dimple A Shajahan
Professor	Associate Professor	Associate Professor
Dept. of CSE	Dept. of CSE	Dept. of CSE
TKMCE	TKMCE	TKMCE

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Abstract

The rotor fault diagnosis plays an important role in rotating machinery system by early detection and avoiding dangerous situations of rotating machinery system. Accurate fault diagnosis of rotor machine ensures reliability and security of rotor mechanical systems. There are many existing methods for the rotor fault diagnosis, in these methods have a problem of data deficiency. To solve the problem of data deficiency and improving efficiency of model, introduced a method is called GAN-AE based rotor fault diagnosis. The data deficiency problem of existing methods are solved by using a Generative Adversarial Network (GAN) model, GAN model generating a series of new synthetic samples from the original data samples and they are similar to the original data sample and it aim to expand the original raw sample . The generated synthetic samples are utilized as the training samples to train the classifier and to identify the unknown faults. The GAN generated signal combined to the original dataset and then it given to the Auto Encoder (AE) model. These complete data is given to the auto encoder model and it extracts the signal features and it provides better accuracy than the Auto Encoder model. In this work, GAN model is combining with AE model for the rotor fault diagnosis. GAN-AE method solve insufficient fault samples problem in more complex mechanical system with agreeable fault classification accuracy. The GAN-AE method can offer better capability of extracting features, and the accuracy of fault diagnosis of rotating machines. MAFAULDA database is used as the base experimental dataset. Experimental results and analysis show that this GAN-AE based rotor fault diagnosis has better performance.

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List of Abbrevations

GAN .... Generative Adversarial Network
AE .... Auto Encoder
DTW .... Dynamic Time Wrapping
GAN-AE .... Generative Adversarial Network-Auto Encoder
RDF .... Rotor Fault Diagnosis
FDPM .... Failure Detection and Predictive Maintenance
SRT .... Structural rotor faults
FEM .... Finite Element Method
SAE .... Stacked Auto Encoder
SHAP .... Shapley Additive Explanations
ACGAN .... Auxiliary classifier GAN
DRVAE .... Deep Regularized Variational Auto Encoder
VAE .... Variational Auto Encoder
DCGAN .... Deep Convolutional Generative Adversarial Network
MFS .... Machinery Fault Simulator
ABVT .... Alignment Balance-Vibration
CSV .... Comma Separated Values
TP .... True Positive
FP .... False Positive
TN .... True Negative
FN .... False Negative
Improved DCGAN ... Improved Deep Convolutional Generative Adversarial Network

Chapter 1

Introduction

In the rotating machinery systems rotor fault diagnosis (RFD) [2] plays an important role in the modern manufacturing industry by early detection and avoiding dangerous situations of rotating machinery system. Accurate rotor fault diagnosis of rotor machines ensures security of rotating machinery systems. Accurate RFD guarantees reliability and security of mechanical systems. Rotor faults, more than any other failures in rotating machinery, have attracted the attention of the research community in terms of employing fault specific traits in its feature engineering.

In the modern manufacturing sector, diagnosis of machinery faults is extremely important because early detection might help to prevent some dangerous scenarios and prevent the failure of the system. The rotating machinery system aims for the Failure Detection and Predictive Maintenance (FDPM) [1]. The Failure detection and predictive maintenance is an vital component of industry 4.0. The Industry 4.0 defined as the intelligent networking of machines and its processes for industry with help of information and communication technology [16]. The industry 4.0 has the benefits of self-configuration, self-optimization, early awareness, decision making, and predictive maintenance capabilities [10]. By rotor fault diagnosis the rotating machines Failure detection and predictive maintenance is done and the some of the aims of industry 4.0 are achieved. The FDPM helps to achieve optimum cost, safety, avail ability, and reliability, by this it helps to preventing the chances of catastrophic failures, serious accidents, and unexpected shutdowns of the whole system.

The rotating machinery system can mainly classified into rotor faults, bearing faults and gear faults [1]. The rotor faults are the import cause of rotating machinery system faults. The rotor faults can mainly classified into Structural rotor faults (SRF), Shaft faults and Broken rotor faults. The An example of fault categorization of rotating machinery is shown in Figure 1.1. In rotating machinery system, Structural rotor faults are the root cause or the primary cause of rotating machinery system faults so in the rotating machinery system the rotor faults diagnosis is very important in the rotating machines. So there is a need of accurate rotor fault diagnosis of rotating machinery systems. There are many existing methods are available for the fault diagnosis in these models have a problem of data insufficiency (data deficiency). To solve the problem of data insufficiency and improving efficiency of model, introduced a method is called GAN-AE (Generative Adversarial Network- Auto Encoder) based rotor fault diagnosis.

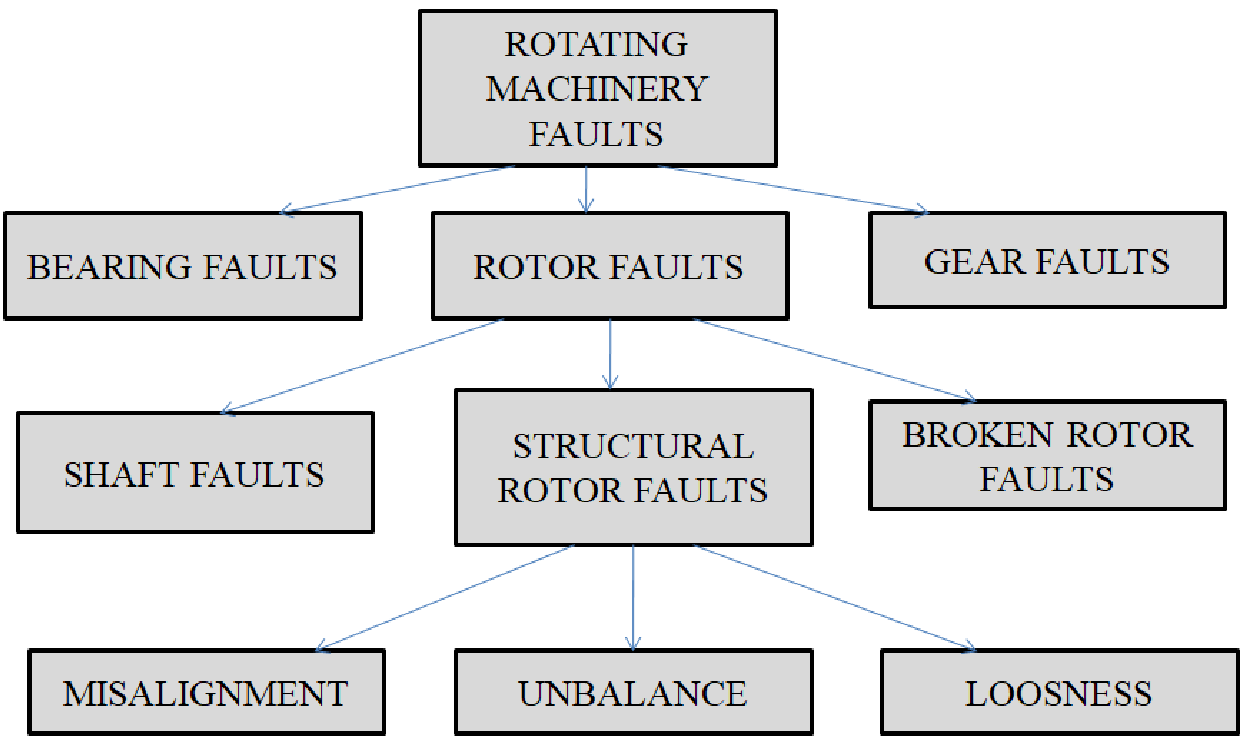

Figure 1.1: Categorization of rotating machinery faults.

GAN-AE method is used for rotor fault diagnosis by this the problem of data insufficiency is solved and classification accuracy of the model increased. Data Insufficiency problem is solved by using a model is called Generative Adversarial Network (GAN) ([2], [11], [12]). The GAN model is used to generating new synthetic samples from the existing original raw sample. The main aim of GAN is to expand the samples. The GAN model generating series of new synthetic samples that looks like the original raw sample. The original input dataset MAFULDA dataset [20] used to input into the GAN model and generating a series of synthetic samples looks similar to the original dataset. Generated synthetic samples utilized as training samples to train AE and to identify unknown faults. Auto Encoder (AE) ([3], [15]) used for fault diagnosis and to identify unknown faults. GAN-AE model extracts the signal features and it provides better accuracy than the existing methods.

GAN has outstanding performance in producing new similar samples from the raw samples and that are similar to the original input signal. GAN model mainly contain two parts a Generator and a Discriminator. The generator is used to generating new samples from the original input and the discriminator discriminating its real or fake. The generator and discriminator of GAN network is trained and a feedback is given to the generator and discriminator. Feedback is an error function that is the difference between the generated samples and the original sample and it given to the generator and discriminator. The training is repeated and the generator and discriminator reaches an equilibrium position further no change in the error value. By using GAN expand input fault samples that are similar to the original raw input sample.

Auto Encoder is used as the classification model, the AE associated with the GAN network and it create GAN-AE model and it used to improve the accuracy of the model. The synthetic signals generated by the GAN and the original signal combined as the input and given to the AE for the classification. Synthetic samples utilized as training samples to train AE model classifier to identify unknown faults. AE provides data with much detailed and promising feature information. This Used to train classifier and find better accuracy than training with raw data. AE mainly contain two parts an Encoder part and a Decoder part. Encoder for encoding the data that is compressing the input data. Decoder is to decode the data from the encoded representation and reconstructing the input data. After training this model is able to classify the data and the faults are analyzed.

The objective of this work is to Implement and Analyse the performance of GAN-AE based rotor fault diagnosis method. For that, a GAN network used to generating new synthetic samples and they are given to the AE model and it used for rotor fault diagnosis.

The remainder of this report is organized as follows. Chapter 2 recalls some related works used as reference for completing this study. Chapter 3 includes all background information used to carry out this study. Chapter 4 presents the dataset used for conducting the experiment and results of the study. Finally, conclusion and future works are provided in chapter 5.

Chapter 2

Related Works

The detection of machinery defects is extremely crucial in the modern industrial sector because early detection may help to prevent some dangerous situations of rotating machines. An accurate rotor defect identification of rotating machines guarantee the safety of rotating systems. There are numerous methods available for fault identification and they mainly face a problem of lack of data samples and a need of effective method for fault diagnosis. The rotor fault diagnostic of GAN-AE method refers to the process of creating a model to solve this issues of insufficiency and provide a high degree of accuracy.

Yun Gao et al.[2] presented a artificial intelligent method, a hybrid of FEM simulations and generative adversarial networks to classify faults in rotor bearing systems'. This method is combining Finite Element Method (FEM) with generative adversarial networks (GAN) to classify rotor bearing faults. FEM simulator is used to calculate the missing fault samples as additional sources of missing fault samples. GAN acquire abundant synthetic samples generated from the simulation and measurement samples. GAN aims to expand the simulation samples and generating new synthetic samples. Complete fault samples including simulation, measurement and their corresponding synthetic samples generated by GAN are utilized as training samples to train typical classifiers and to identify unknown faults. The hybrid model created samples using as the training sample to train classifiers to classify faults in rotor bearing system.

Hui Han et al.[3] presented GAN-SAE based fault diagnosis method for electrically driven feed pumps. The method combining generative adversarial networks (GAN) with Stacked Auto Encoder (SAE). GAN for generating synthetic samples from the original data samples and SAE for the fault diagnosis. In the practical process of electrically driven feed pump fault diagnosis, the running state is in normal state for a long time, occasionally with faults so it makes the fault data very rare in the monitoring of data and makes it difficult to extract the internal fault features than the original time series data, the deep learning theory is used the imbalance between the fault data and the normal data occurs in the operation data set. This can be solved by using GAN network. Then Stacked Auto Encoder method used to extract the signal features. Stacked Auto Encoder is used as the classifier to classify the faults.

Yu Ding et al.[4] proposed a Generative Adversarial Network-Based Intelligent Fault Diagnosis Method for Rotating Machinery under Small Sample Size Conditions. GAN is used to generate fault data and expand the training sample. The effectiveness and performance are validated using bearing and gearbox datasets.

Aneesh G. Nath et al.[1] presented a comprehensive review on the topic role of artificial intelligence in rotor fault diagnosis. It reviewed and defined the role of Artificial Intelligence (AI) in RFD and provides an all review of rotor faults for the researchers and academics. This paper present three unique ideas first it emphasizes the use of fault specific characteristic features with AI, then it is grounded in fault wise analysis rather than component-wise analysis with appropriate fault categorization, and finally it portrays the current research and analysis in accordance with different phases of an AI-based RFD framework. It also analysed detailed to the Machine learning based approaches to rotor fault diagnosis and Deep learning based approaches to rotor fault diagnosis.

Guifang Liu et al.[5] proposed a method to solve gearbox fault diagnosis by an effective deep learning method known as stacked auto encoder (SAE). This method extract salient features from frequency domain signals and eliminating exhausted features by introducing dropout technique and RELU activation function.

Lucas C. Brito et al.[6] proposed an explainable artificial intelligence approach for unsupervised fault detection and diagnosis in rotating machinery. The fault detection is done on unsupervised manner based on anomaly detection algorithms. The fault diagnosis is based on black box model is called Shapley Additive Explanations (SHAP). For fault diagnosis unsupervised classification and root cause analysis are used.

Siyu Shao et al.[7] proposed a framework of Auxiliary Classifier GAN (AC-GAN) based network learn from original data and to generate realistic data from the original mechanical signals (data). The GAN mainly contain two parts, generator and discriminator. To avoid the problem of gradient vanishing during training, Batch normalization is performed within generator and category labels are used as the auxiliary information in this network to train the model. This approach produces realistic synthesized samples and it used as augmented data. The data augmentation is done by using GAN model.

Xiaoan Yan et al.[8] proposed a deep learning model for intelligent faults diagnosis called Deep Regularized Variational Auto Encoder (DRVAE). The regularized VAE is conducted to capture more discriminative fault information and the hyper parameters of DRVAE are determined adaptively by Bird Swarm Algorithm (BSA). In this a variety of regularised strategies, the loss function of the Variational Auto Encoder (VAE) is appropriately appended with regular terms in the new model. This fixes the over-fitting issue with the original VAE and improves the network model's capacity to learn new features. DRVAE method is identifying automatically fault categories and severities of rotor bearing system.

Shucong Liu et al.[12] proposed an Improved Deep Convolutional Generative Adversarial Network (Improved DCGAN) for gas turbine signals. In the gas turbines, the collected turbine fault data are limited and it creates data deficiency and it affects the accuracy of the method. So a intelligent fault diagnosis method is important for the monitoring of health of the gas turbine. With improved DCGAN large number of new datas created from the original small data

Alec Radford et al.[13] proposed an unsupervised representation learning with Deep Convolutional Generative Adversarial Networks (DCGANs) with some architectural constraints and they strong candidate for unsupervised learning. Using unsupervised DCGAN, building good image representations and reused the parts of generator and discriminator networks as feature extractors for supervised tasks. The trained discriminators used for image classification tasks. This GAN provide an attractive alternative to maximum likelihood techniques.

There are numerous methods are available for fault identification of rotating machines. These methods mainly facing the problem of lack of data samples and a need of effective method for fault diagnosis. The rotor fault diagnosis of GAN-AE method refers to the process of creating a model to solve this issues of insufficiency and provide a high degree of accuracy.

Chapter 3

Methodology

The rotor fault diagnosis on vibrational signal based on Generative adversarial network- Auto encoder (GAN-AE) method is introduced in this work. Firstly the Generative adversarial network is used for generating synthetic samples from raw sample ie, from the input dataset. This GAN helps to solve the problem of data deficiency (data sufficiency) by generating signals from the input dataset that are similar to the original dataset. Then these generated synthetic samples included to the original dataset and the complete data is classifying by training the Auto encoder and in the testing the rotor faults are analysed, by this an effective rotor fault diagnosis model is generated. The GAN generated signals are utilized as training samples to train Auto encoder and to identify unknown faults of rotor machines.

The proposed GAN-AE based rotor fault diagnosis method is depicted in Figure 3.1. In data acquisition the datas are collected using some sensors and these collected datas are used as the input dataset. In this method 'MAFAULDA' [20] dataset is used as the input data sample. The input samples given to the GAN network and generating a series of new synthetic samples with similar to the original data sample. These generated signals fuses with the original dataset and it given to the AE model and training the model based on this complete samples and AE testing some random samples and fault diagnosis is done by the method.

3.1 Generative Adversarial Network (GAN)

Generative Adversarial Network (GAN) used for sample generation to obtain complete fault samples. Generative adversarial networks (GAN) have attention to its outstanding performance in producing new similar samples from the original sample [2]. GAN is learned from the raw sample, it generating a series of new synthetic samples with similar statistical characteristics of

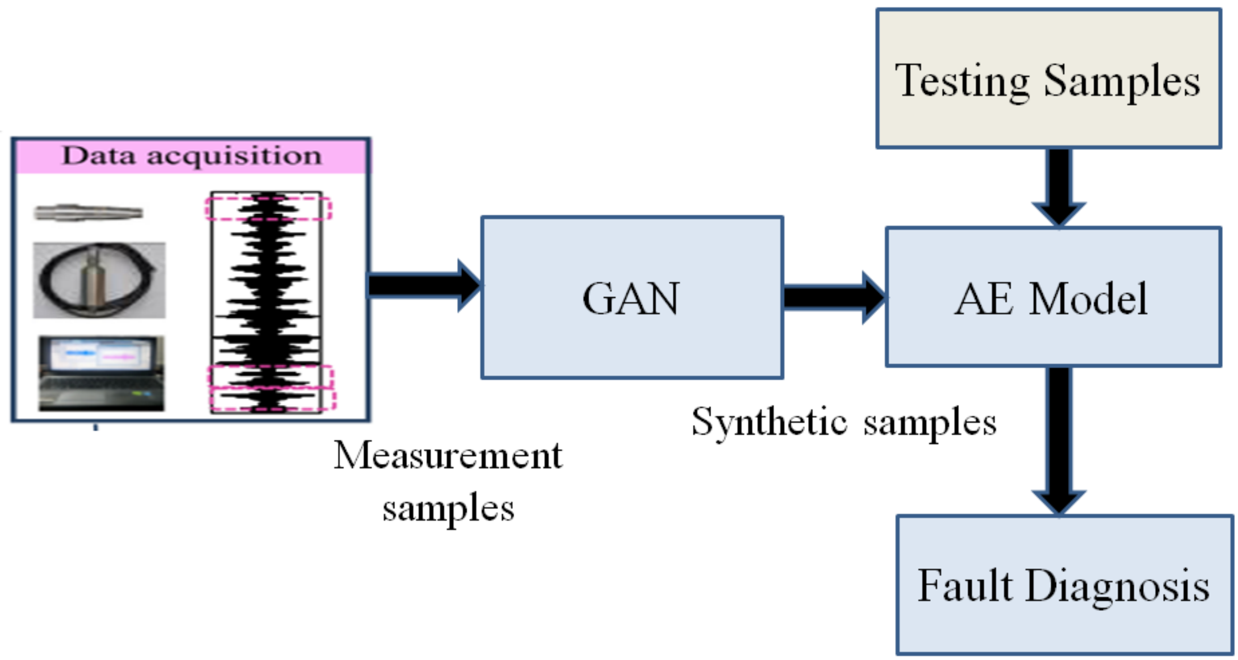

Figure 3.1: Flowchart of GAN-AE based rotor fault diagnosis method.

the raw sample. This GAN network helps to improving faulty classification accuracy of the model. This GAN model is a solution to the data deficiency problem.

GAN model mainly contain two parts a Generator and a Discriminator. The generator is used to generating new samples from the original input and the discriminator discriminating it is real or fake. The generator and discriminator of GAN network is trained and a feedback is given to the generator and discriminator. Feedback is an error function that is the difference between the generated samples and the original sample and it given to the generator and discriminator. The training process is repeated until the generator and discriminator reaches an equilibrium position, further there is no change in the error value. The GAN is used to expand fault samples that are similar to the original input sample.

The generative adversarial network's [2] training process can describe as follow. Here, the variable z is sampled using a random noise vector and G(z) is the variable's generated samples. Real samples x are fed into D to determine if the input samples are x or generated samples G in order to improve D's capacity to discriminate between the two (z), the value of D(G(z)) is more closer to 1, then it more likely from real samples. That implies that D may consider the samples generated by G(z) as "real samples."

Consequently, Equation 3.1 displays the objective of D.

$$D_{goal} = maxD(G(z)) \tag{3.1}$$

For G, G makes every effort to discover the latent statistical properties of x and provide new samples G(z), which can fool D. Alternatively put, D was unable to identify G(z) as "false samples".

Consequently, G's objective is to reduce the difference between x and G(z), as represented in Equation 3.2.

$$G_{goal} = 1 - maxD(G(z)) \tag{3.2}$$

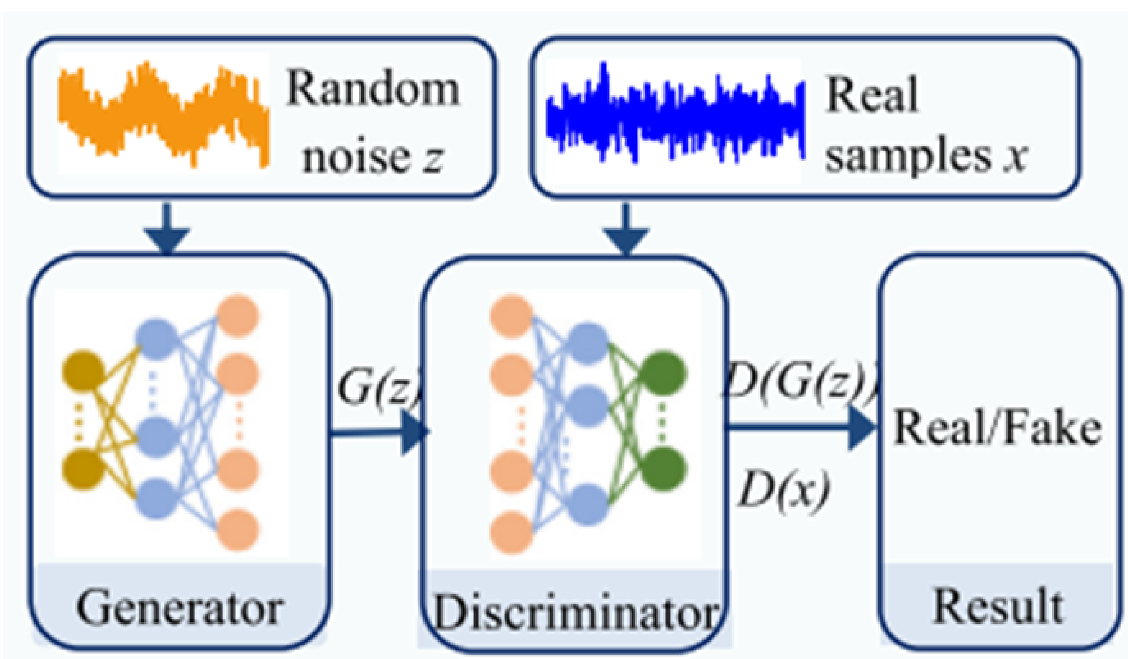

Figure 3.2: The Architecture of GAN.

Through an adversarial learning mechanism, G and D constantly challenge one another to get better performance.

From the input samples, GAN is used to produce a large number of fault samples. In particular, vibrational signals are used as training data for GANs, which in turn produce a large number of synthetic samples. As shown in Figure 3.2, the architecture of GAN mainly includes a generator G and a discriminator D.

3.1.1 Training steps of GAN

Training steps of GAN is summarised as follow

- **Train Discriminator on real data:** Initially training the discriminator on real data
- **Generator generate fake inputs:** Some random noise is adding and generator generating fake input samples.
- **Train Discriminator on fake data:** Training the discriminator on fake samples generated by the generator.
- **Train Generator with the output of Discriminator:** Training generator with the output of discriminator and generating generating fake samples that are similar to the original input samples.

Training for D and G will be halted once their Nash equilibrium is reached [15]. After training is finished, GAN is creating a large number of new synthetic samples with properties statistically close to those of the real samples.

3.2 Auto Encoder Model (AE Model)

Training AE model [9] as the classifier and to classify the rotor faults. Input fault samples and GAN generated samples combined together to train AE model. Testing is done for numerous unknown faults and the faults are diagnosed. Complete samples is used to demonstrate the effectiveness of the proposed GAN-AE method. This AE provides data with much detailed and promising feature information. This GAN-AE method has greater accuracy than training with raw data and it used to train classifier.

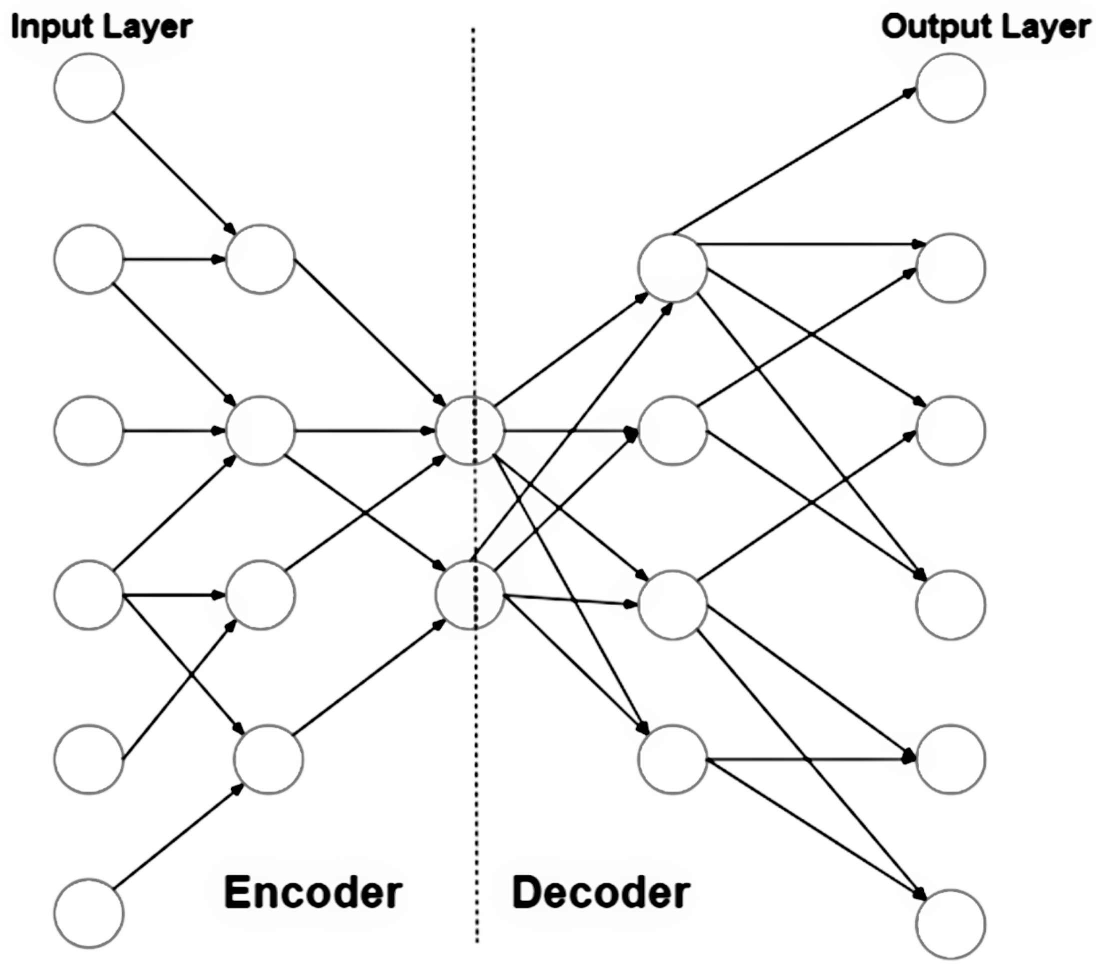

Figure 3.3: Structure of an AE.

The AE network makes an attempt to reconstruct the input from the extracted features and outputs an approximation of the input. The training process has an error computation and backpropagating this error to the network. This process is reiterated several times until there is no change in the error function.

The General structure of an AE is in the figure 3.3. AE mainly contain two parts Encoder and Decoder. The encoder part is encoding the input data into encoded data. Encoder part of the network has decreasing number of hidden layers. The decoder part of network is decoding the encoded data into output, ie, reconstructing the data. In this part increasing the number of hidden layers. Decoder tries to reconstruct the input data. AE always makes an attempt to reconstruct the input from the extracted features and outputs an approximation of the input.

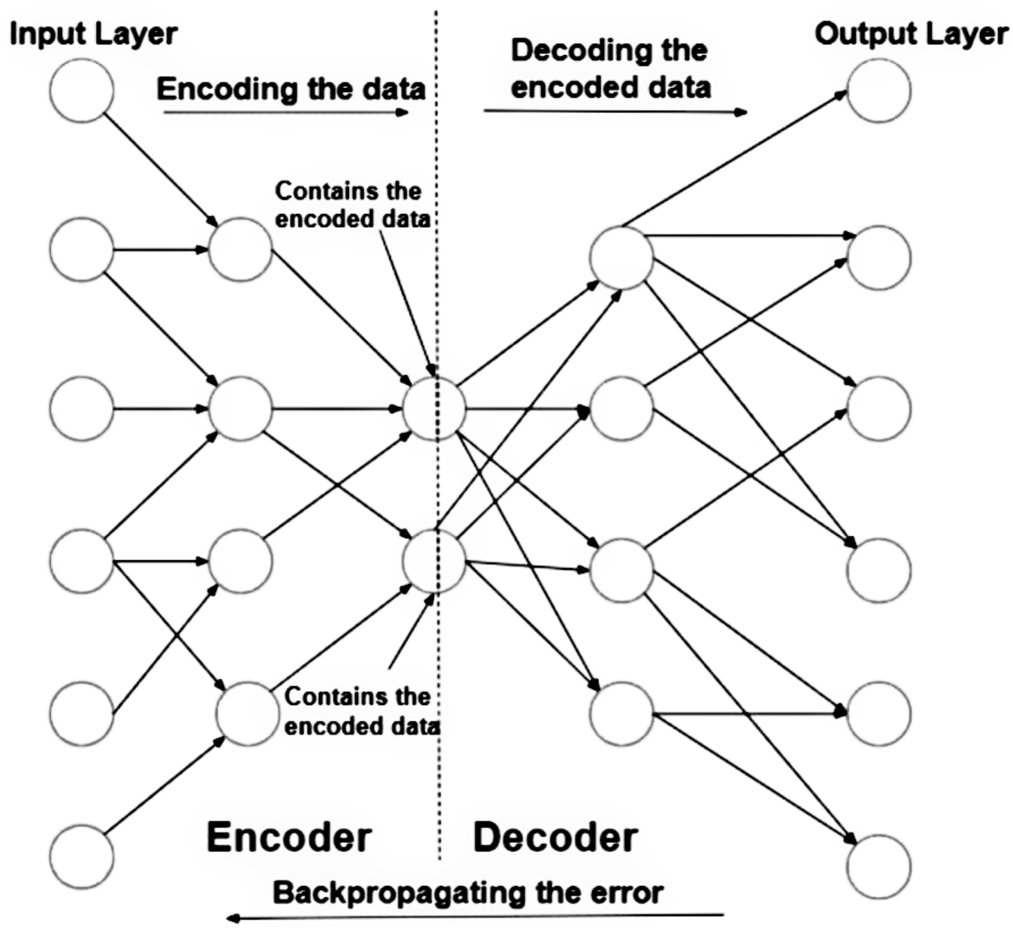

Figure 3.4: Training steps of an Auto-encoder.

3.2.1 Training steps of an Auto Encoder

- **Step 1: Encoding the input data:** AE tries to encode the input data using the initialized weights and biases.
- **Step 2: Decoding the input data:** AE tries to reconstruct the original input from the encoded data to test the reliability of the encoding.
- **Step 3: Back propagating the error:** After reconstruction (decoding), the error function is computed and is back propagated to minimizing the error and update the weight with labeled training to achieving fine tuning.

The each neuron of Auto Encoder network uses a fully connected network. From the schematic diagram of AE structure in figure 3.6. The input vector X = $(x_1, x_2, ., ., x_n)$ with weights is added to the bias and activation function applied to obtain the encoded vector Y = $(y_1, y_2, ., ., y_m)$ of hidden layer. In reconstruction the encoded vector is reconstructed to the output vector $\hat{X} = (\hat{x_1}, \hat{x_2}, ., ., \hat{x_n})$. In AE, the input and output layers are as similar as possible, the weights adjusted and optimized with the goal of minimizing the reconstruction error.

The mathematical expression of the Auto Encoder network is as follows:

$$Y = \sigma_a(W_a \cdot X + b_a) \tag{3.3}$$

$$\hat{X} = \sigma_s(W_a \cdot Y + b_s) \tag{3.4}$$

$$minL(\theta) = ||\hat{X} - X||_2 \tag{3.5}$$

$$\theta = [W_a, b_a; W_s, b_s] \tag{3.6}$$

The encoder part weight: W_a, bias: b_a and activation function: σ_a.

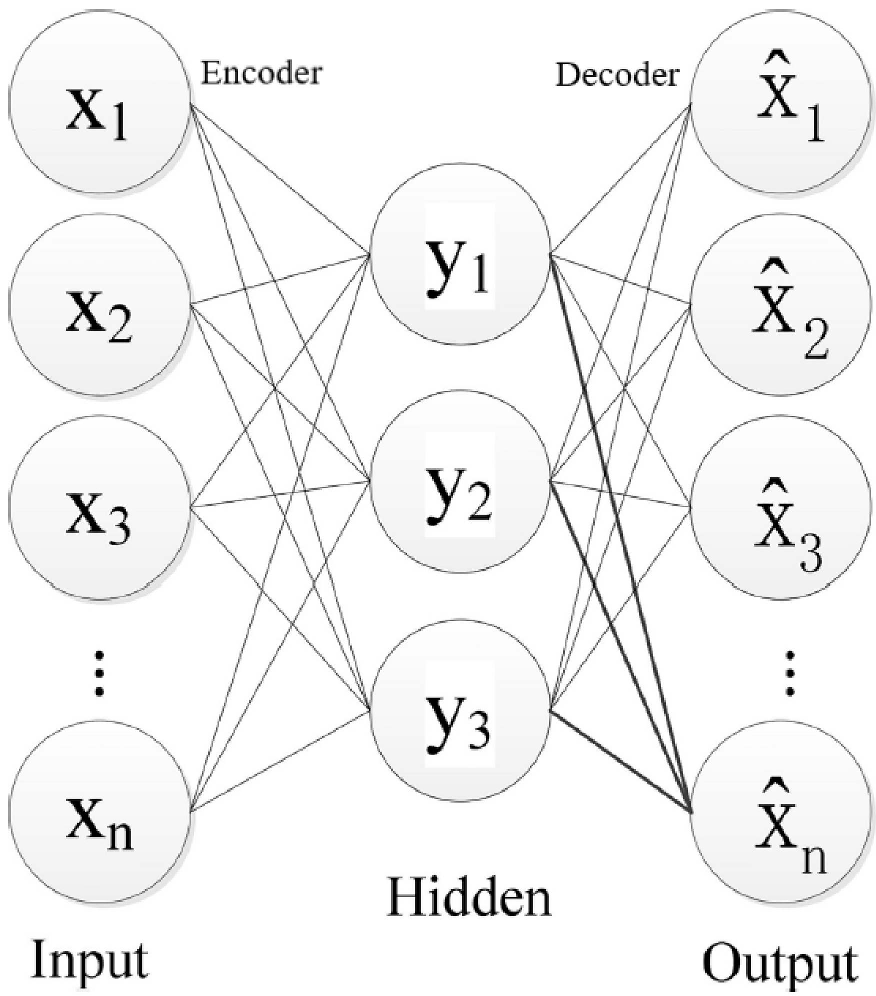

Figure 3.5: Schematic diagram of AE structure.

The decoder part weight: W_s, bias: b_s and activation function: σ_s.

The training process is reiterated several times until an acceptable level of reconstruction is reached. The error function is calculating and it back propagated to the network until an equilibrium position reached.

After the training process, only encoder part of the AE is retained to encode a similar type of data used in the training process. After training in the testing phase, only the encoder part is performed and classifying the rotor faults based on the trained data.

In GAN-AE based method GAN generating synthetic samples that are similar to the original input sample and AE classifier classifying the rotor faults by this rotor faults are analysed. GAN-AE method is effective method for rotor fault diagnosis. The experimental results are presented in the following chapter.

Chapter 4

Experimental Results and Discussions

4.1 Experimental Data

The MAFAULDA Machinery Fault Database [20] is used as the experimental data. This database composed of 1951 multivariate time-series vibrational data, the data acquired by sensors on a Spectra Quest's Machinery Fault Simulator (MFS) Alignment-Balance-Vibration (ABVT). These multivariate time series contain six different simulated states are:

- Normal function
- Imbalance fault
- Horizontal misalignment faults
- Vertical misalignment faults
- Inner bearing faults
- Outer bearing faults

Each sequence was generated at a 50 KHz sampling rate during 5 s, totaling 2,50,000 data samples in each. The summary of each type of sequence is described in the table 4.2.

The database is composed by several CSV (Comma Separated Values) files, each one of CSV file with 8 columns, one column for each sensor, according to:

- **Column 1:** Tachometer signal that allows to estimate rotation frequency

Sequence	Measurements
Normal	49
Horizontal misalignment	197
Vertical misalignment	301
Imbalance	333
Underhang bearing	
Cage fault	188
Outer race	184
Ball fault	186
Overhang bearing	
Cage fault	188
Outer race	188
Ball fault	137
Total	1951

Table 4.1: Summary of each type of sequence

- **Columns 2 to 4:** Underhang bearing accelerometer (axial, radiale tangential direction)
- **Columns 5 to 7:** Overhang bearing accelerometer (axial, radiale tangential direction)
- **Column 8:** Microphone.

From database selecting Normal function, Horizontal misalignment and Overhang outer race CSV files and it used for the model training and testing. From the selected dataset 70 % of data are selected as the training set, and the remaining 30 % selected for testing set.

4.2 GAN Synthetic signal generation

GAN is generating synthetic samples from the original raw samples. Using GAN synthetic samples are generated for Normal, Horizontal misalignment and Overhang ball_fault. In the GAN, generator is generating synthetic samples after the training of the GAN model. The generated signals are more close to the original data sample. GAN generated signals of Normal, Horizontal misalignment and Overhang ball_fault are displayed in Figure 4.1, Figure 4.2, Figure 4.3 respectively. In each Figure training signals and GAN generated signals are captured.

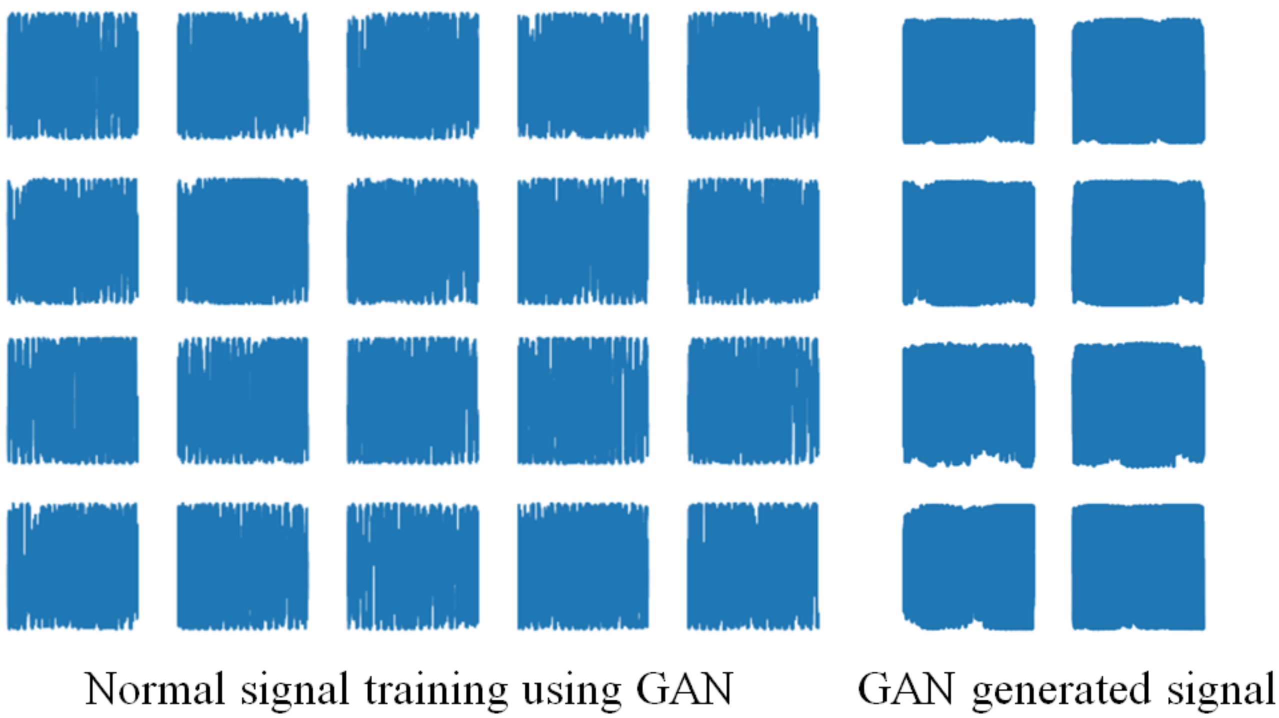

Figure 4.1: GAN signals of Normal signal.

4.2.1 Performance analysis of GAN

The performance of GAN can be analysed by using a method called Dynamic Time Wrapping (DTW) ([17], [18]). DTW is used for finding similarity measure in time series analysis ([14], [19]). Here measuring similarity distance between two signals, the distance between the original signal & GAN generated signal is calculated. The DTW distance between the original signal & GAN generated signal is shown in Table 4.2.

4.3 Generative Adversarial Network-Auto Encoder Model (GAN-AE Model)

Auto Encoder model is used as the classifier to analysing the rotor faults. Input fault samples and GAN generated samples combined to train AE model.

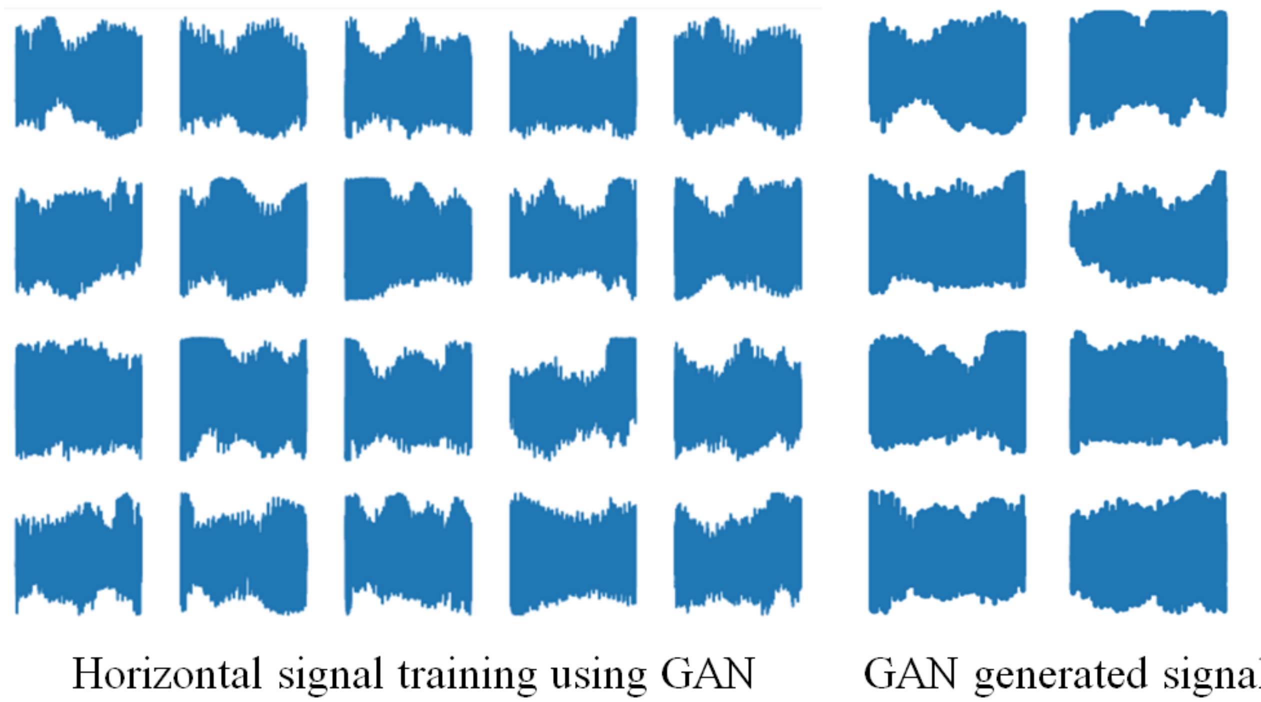

Figure 4.2: GAN signals of Horizontal misalignment.

Sigal	DTW distance
Normal	141.71552814515636
Horizontal misalignment	114.89212011176107
Overhang ball_fault	137.20050709642715

Table 4.2: Performance comparison of GAN

Testing is done for numerous unknown faults and the faults are analysed.

4.3.1 Performance analysis of GAN-AE model

The Performance analysis of GAN-AE model and AE model is done. The confusion matrix is calculated and shown in figure 4.4. The accuracy is calculated based on the equation 4.1.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.1}$$

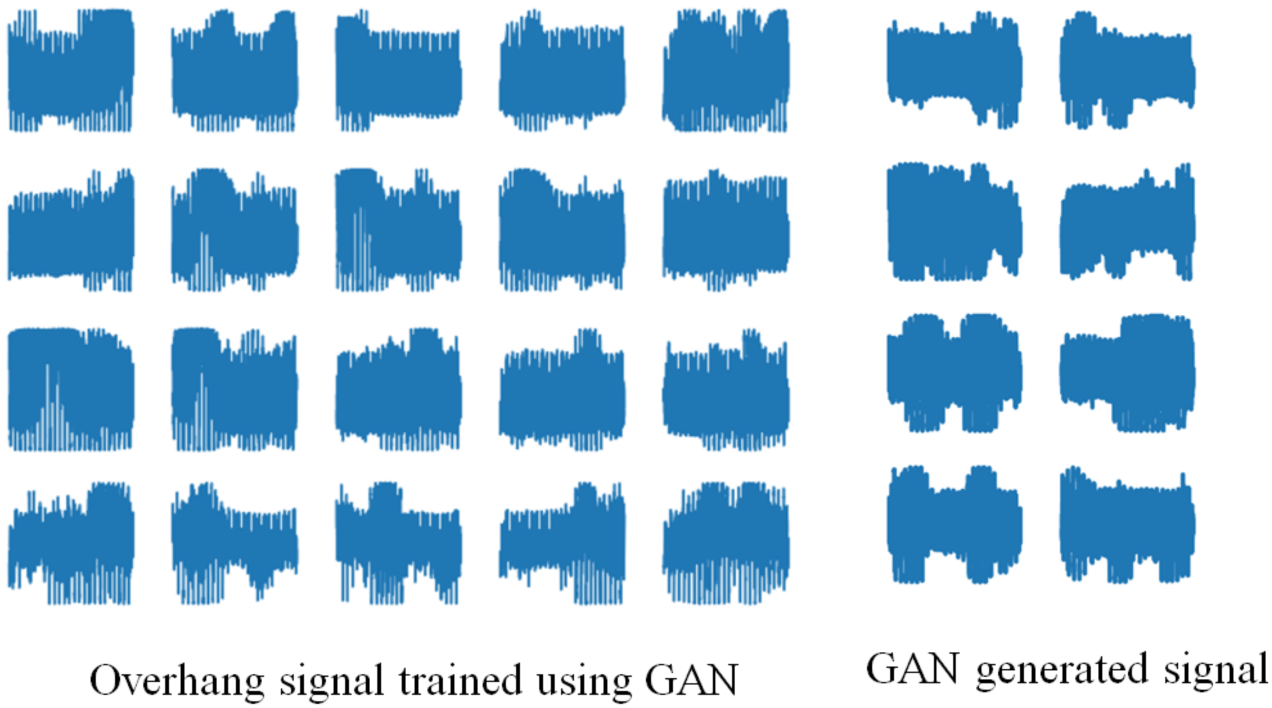

Figure 4.3: GAN signals of Overhang ball_fault.

Model	Accuracy
AE model	81.28%
GAN-AE model	91.01%

Table 4.3: Performance comparison of GAN-AE with AE

AE model fault diagnosis and the proposed method GAN-AE based rotor fault diagnosis is done. As from the results it is observed that the GAN-AE method has the higher accuracy than the AE model. GAN-AE model solved the problem of data deficiency and higher accuracy is obtained for this proposed model.

- **Accuracy of AE method: 81.28%**
- **Accuracy of GAN-AE method: 91.01%**

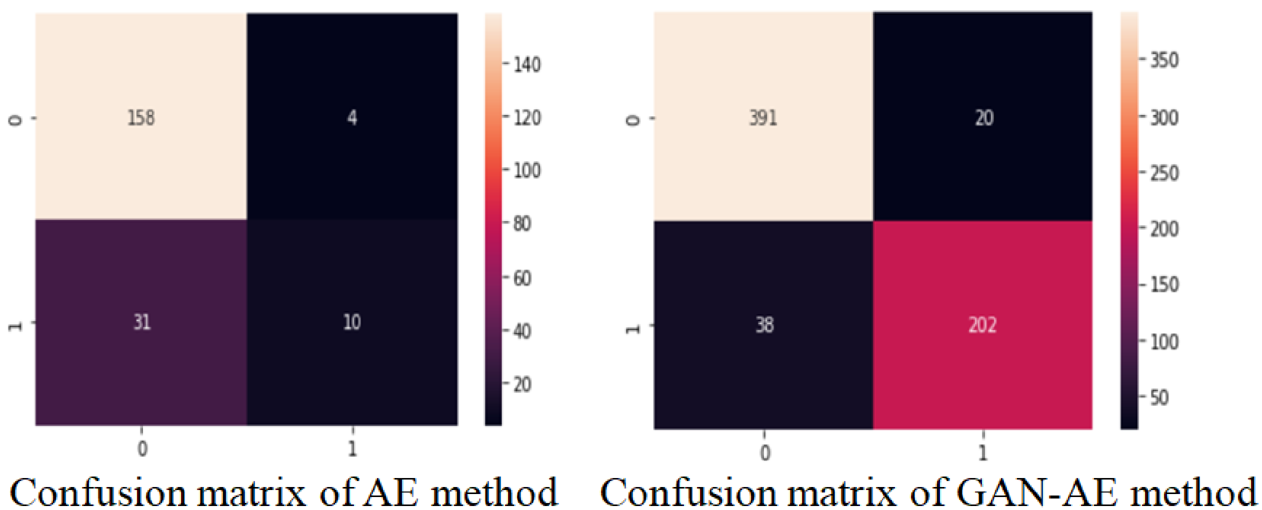

Figure 4.4: Confusion matrix of AE and GAN-AE model

Chapter 5

Conclusion

Accurate fault diagnosis helps the rotating machinery system by it guarantees reliability and security of rotating mechanical systems. The goal of this project is to solve the problem of data deficiency by using Generative Adversarial Network (GAN) and GAN generating synthetic samples that has the statistical characteristics of the original data samples. The generated GAN signals is analysed based on Dynamic Time Wrapping (DTW) distance measure. The generated GAN signals fused with original data sample and given to the Auto Encoder (AE) model and the GAN-AE method has better feature extraction capabilities and thereby improving the classification accuracy of the classifier. The AE method, which can complete the data dimensionality reduction and feature extraction tasks. GAN-AE method has improved accuracy of 91.01%. This GAN-AE method has better performance at experiments were conducted on MAFULDA database and GAN-AE method is compared with Auto Encoder model and the proposed GAN-AE method has better accuracy than the other methods.

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