People's Democratic Republic of Algeria

Ministry of Higher Education and Scientific Research

University M'Hamed BOUGARA – Boumerdès

Institute of Electrical and Electronic Engineering

Department of Power and Control

Final Year Project Report Presented in Partial Fulfilment of the Requirements of the Degree of

'MASTER'

In Electrical and Electronic Engineering

Option: **Control**

Title:

Machine Learning-Based Fault Diagnosisof Rotating Machinery using Acoustic data

Presented By:

- **Souhaib Boulenache**
- **Rayane Belal**

Supervisor:

Dr. Lahcene Rouani

Co-Supervisor:

Hamza Ouazene

Toufik Bettaher

Registration Number:……./2024

Abstract

The industrial advancement has promoted the development of machine learning based intelligent fault diagnosis methods for condition-based maintenance. Various condition-monitoring techniques can be used. However, the most reliable approaches require complex and high-cost data acquisition setups. This led to the use of acoustic signals for fault diagnosis in this study. The study presents a machine-learning fault classification approach that leverages features extracted from the decomposed acoustic signals using Empirical Mode Decomposition (EMD) and Maximal Overlap Discrete Wavelet Packet Transform (MODWPT) decomposition methods. The classification is performed using algorithms consiting of Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Decision Trees, and Ensemble Bag. These machine-learning algorithms have been tested through different experiments to evaluate the proposed approach on two datasets, MAFAULDA Machinery Fault and the Air Compressor datasets. The results revealed that SVM exhibited superior accuracy and outperformed other classifiers in most evaluation metrics. Also, it demonstrated robustness in noisy environments, and exhibited the fastest prediction time. Decision tree demonstrated that it is the most storage-efficient model.

Keywords: Acoustic analysis, Condition monitoring, Rotating machinery, Fault diagnosis, MODWPT, Machine learning, Classification, Feature extraction.

Dedication

With the deepest gratitude, I dedicate this work to **my mother and father** who have been the cornerstone of my success, **my brothers Khalil and Yasser**, **my sisters**, and **all my family**, Your unwavering support and belief in me have been the guiding light on my path toward knowledge and accomplishment. To **my treasured friends**, Their presence illuminated my journey with your energy and vitality.

This accomplishment would not have been possible without your support. thank you.

Souhaib

I dedicate this work to : **To my beloved parents**, whose unwavering love, support, and guidance have been the foundation of my achievements. **To my siblings**, who have been my constant companions, offering encouragement and laughter along the way. **To my precious nieces and nephews**, whose innocent smiles and boundless energy have been a source of joy and inspiration. **To my dear friends, near and far**, whose presence has brightened my journey, and whose friendship has been a constant reminder of the beauty of human connection. I dedicate this work to you all, for without your love and support, this accomplishment would not have been possible.

Rayane

Acknowledgements

Above everything, thanks to Allah, the Almighty and Most Merciful giving us the wisdom, persistence, and potency to complete this project.

We would like to sincerely thank Dr. Rouani Lahcene, our supervisor, and Mr. Hamza Ouazene, our co-supervisor, for their important advice and assistance academically and professionally during the entire process of performing and completing this master's thesis. their continuous encouragement, perceptive advice, and unshakable support have greatly influenced the direction of our research.

We would like to express our deepest appreciation to Toufik BETTAHAR and Nassim MAALLEM for their invaluable assistance when we began the project. Their guidance in outlining the project's pipeline and providing the right mindset has been crucial to our progress. Additionally, Toufik's and Nassim's willingness to share their wisdom and offer advice has been instrumental in advancing our study.

Finally, we would like to express our heartfelt gratitude to our friends and families for their unwavering support and encouragement. Their faith in our abilities and constant motivation has been crucial in our pursuit of academic excellence.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

CBM	Condition-Based Monitoring
CM	Condition Monitoring
DL	Deep Learning
DAQ	Data Acquisition
EMD	Empirical Mode Decomposition
FDD	Fault Detection and Diagnosis
FN	False Negative
FP	False Positive
IMF	Intrinsic Mode Function
KNN	K-Nearest Neighbors
LS-SVM	Least Squares Support Vector Machine
MAFAULDA	Machinery Fault Database
MCSA	Motor Current Signature Analysis
MODWPT	Maximal Overlap Discrete Wavelet Packet Transform
PCA	Principal Component Analysis
PdM	Predictive Maintenance
SNR	Signal-to-Noise Ratio
SVM	Support Vector Machine
TCMS	Transmitted Sound Condition Monitoring System
TP	True Positive
TN	True Negative

General Introduction

In the industry landscape, the efficient operation of rotating machinery is important in all different sectors. However, the occurrence of faults and failures in critical machines in the process leads to heavy economic losses for the companies. Therefore, effective fault diagnosis systems are essential to ensuring the machine's reliability and optimal performance.

Traditional maintenance strategies have become less reliable for modern and complex rotating machines. As a result, industry leaders focus on implementing advanced diagnosis systems as part of a condition-based maintenance strategy. The advent of Industry 4.0, which emphasizes the integration of data and the Internet of Things in manufacturing, further drives the adoption of data-driven analysis as condition-based maintenance. The convergence of data availability with the increasing need for advanced fault diagnosis systems highlights the importance of artificial intelligence as a vital tool in addressing this gap, with its ability to learn complex patterns in data-driven analysis.

Various signals of condition monitoring have been employed; the reliable ones require an advanced and costly acquisition setup. Acoustic signals can be leveraged effectively when combining signal preprocessing with machine learning and building a reliable and early-detection fault diagnosis model.

This thesis focuses on building a reliable model based on machine learning using acoustic signals. The primary objectives are to develop a robust classification model, investigate the effectiveness of acoustic analysis, and evaluate different signal preprocessing techniques on two datasets. structuring this thesis as follows:

- **Chapter 1** begins by exploring maintenance philosophies, different fault diagnosis techniques, and various condition monitoring strategies. concluding on the importance of approaching condition-based predictive maintenance.

- **Chapter 2** starts by exploring the 3 acoustic domains of time, frequency, and time-frequency. And their significance in data-driven techniques for diagnosis. Emphasizing the signal's feature extraction to obtain the most informative insight from the data, as they enable the identification of the underlying pattern within the signal.

- **Chapter 3** covers the methodology of the building classification model, starting with an explanation of the dataset and data acquisition, then moving on to data preprocessing, including signal decomposition using EMD and MOD-WPT, then arrangement, and ending the chapter by describing the machine learning models and hyperparameter tuning.

- **Chapter 4** this chapter discusses the results obtained and evaluates the models' performance using various metrics. Furthermore, a comparative analysis with related literature that used the same dataset is conducted. After that, the impact of noise on model performance is also investigated through noise testing at different signal-to-noise ratios (SNRs) added to the raw signal. The chapter analyses the strengths and weaknesses of the approaches taken and provides insights into the efficacy of the proposed fault diagnosis method.

Chapter I

Overview of Maintenance

I.1 Introduction

Detecting and diagnosing faults in rotating machines is vital for ensuring reliable operation and minimizing downtime. These machines, which include motors, generators, pumps, and turbines, often operate under harsh conditions and are prone to mechanical stress. Effective fault diagnosis helps prevent breakdowns and enhances safety. This chapter will discuss the maintenance strategies, such as reactive, preventive, condition-based, and predictive maintenance. It delves also into different approaches for fault detection and diagnosis. And, focuses on Acoustic analysis. Acoustic signals are discussed as a key method for diagnosing issues in rotating machines, covering signal representation, acquisition, and monitoring techniques used in industrial applications.

I.2 Basic Terminology

I.2.1 Fault

A fault is an unpermitted deviation of at least one characteristic property (feature) of the system from the acceptable, usual, standard condition [1].

I.2.2 Failure

A failure is a permanent interruption of a system's ability to perform the required function under specified operating conditions[1].

I.2.3 Malfunction

A malfunction is an intermittent irregularity in the fulfillment of a system's desired function.
Development of events "failure" or "malfunction" from a fault is illustrated in the figure below:

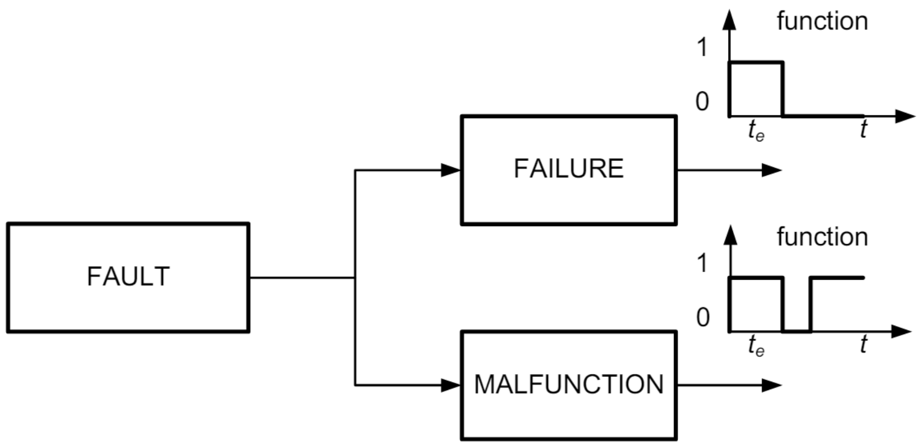


Figure I.1: Progression of fault toward failure or malfunction.

I.2.4 Reliability

"Ability of a system to perform a required function under stated conditions, within a given scope, during a given period of time." reliability is quality for some time; the reliability can be affected by malfunctions and failures[1].

I.2.5 Availability

"Probability that a system or equipment will operate satisfactorily and effectively at any period of time." fault detection and fault diagnosis can improve the availability by early fault detection in combination with maintenance on demand and by fast and reliable diagnosis (smaller MTTR)[1].

I.3 Maintenance Philosophies

Maintenance involves the integration of various actions throughout the entire lifespan of an item. These actions are aimed at preserving the item's health condition to perform its function adequately.

The leading idea in maintenance is to part ways with costly reactive maintenance to preventive and predictive maintenance, called also smart maintenance. Throughout the industrial revolutions, as shown in Figure 1.2, maintenance strategies have undergone a gradual evolution and it is currently a continuous process[2].

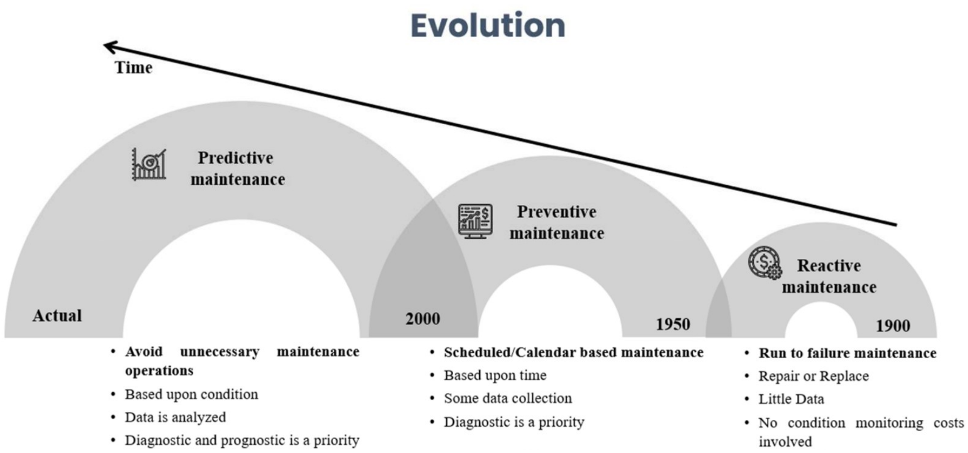


Figure I.2: Evolution of maintenance activities and methods[2].

There are various Maintenance approaches, the figure below will highlight the strategies discussed.

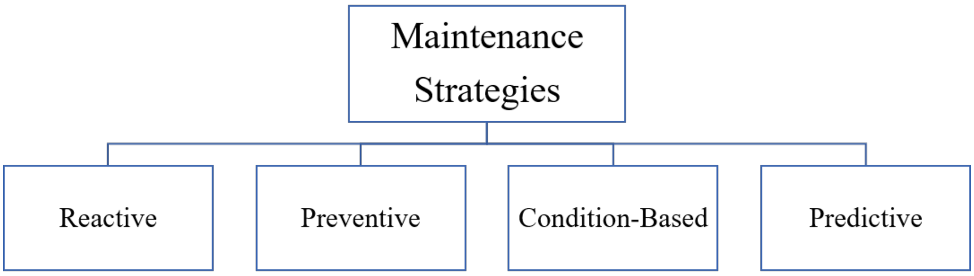


Figure I.3: Maintenance Approaches.

I.3.1 Reactive Maintenance

Reactive maintenance, or as some may call it, the "run-to-failure" approach to maintenance. Equipment, as the description suggests, is allowed to run until failure. Then the damaged equipment is repaired or replaced. The cons of this approach include unpredictability and fluctuating production capacity, higher levels of out-of-tolerance and scrap output, and an overall increase in maintenance costs to repair the failures[3].

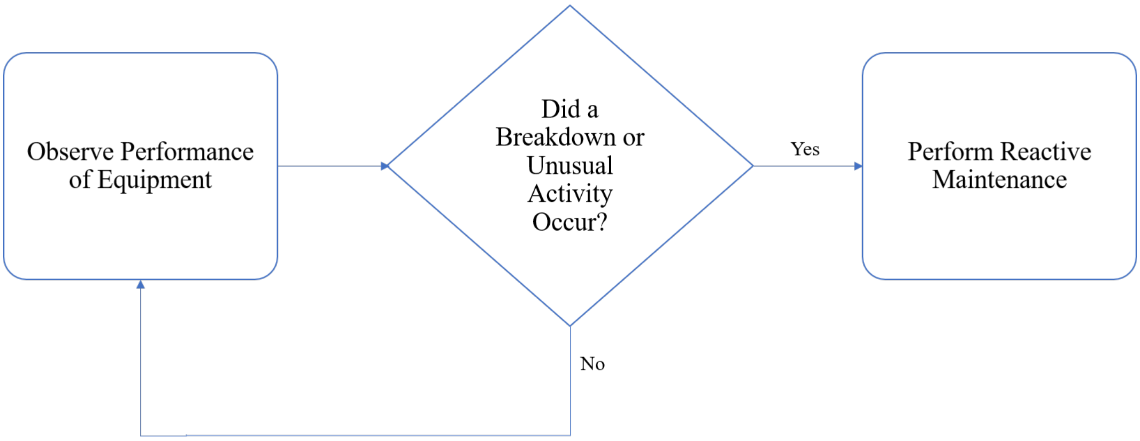


Figure I.4: Reactive Maintenance Workflow

I.3.2 Preventive Maintenance

Preventive maintenance, also known as "Scheduled" maintenance, is periodic maintenance required to keep equipment in a specific condition; its technique is built on the earliest expected failure time of similar machines. It includes, for example, periodic inspections, condition monitoring, critical item replacements, and calibration and servicing requirements such as lubrication and fueling[4].

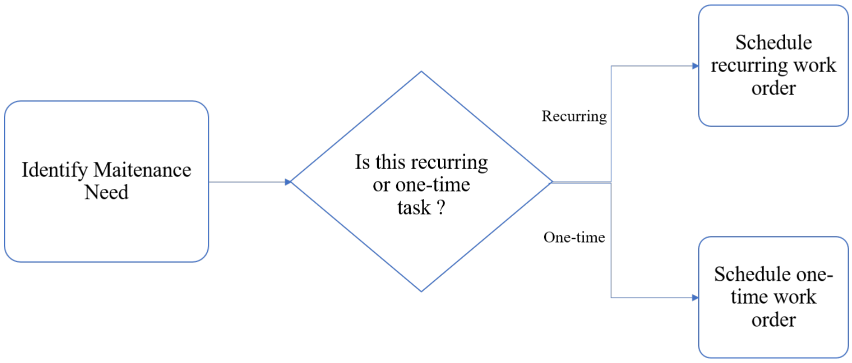


Figure I.5: Scheduled Maintenance Workflow

I.3.3 Condition-Based Monitoring

Condition-based monitoring (CBM) is a maintenance strategy that involves maintenance decisions based on the information collected throughout condition monitoring. It has three main steps:

1. Data acquisition step (information collecting): to acquire data relevant to system health.

2. Data processing step (information handling): to handle and analyse the data or signals collected in step 1 for better understanding and interpretation of the data.

3. Maintenance decision-making step (decision-making): to recommend efficient maintenance policies.

Diagnostics and prognostics are two crucial aspects in a CBM program. Diagnostics deals with fault detection, isolation and identification when it occurs.Prognostics deals with fault prediction before it occurs[5].

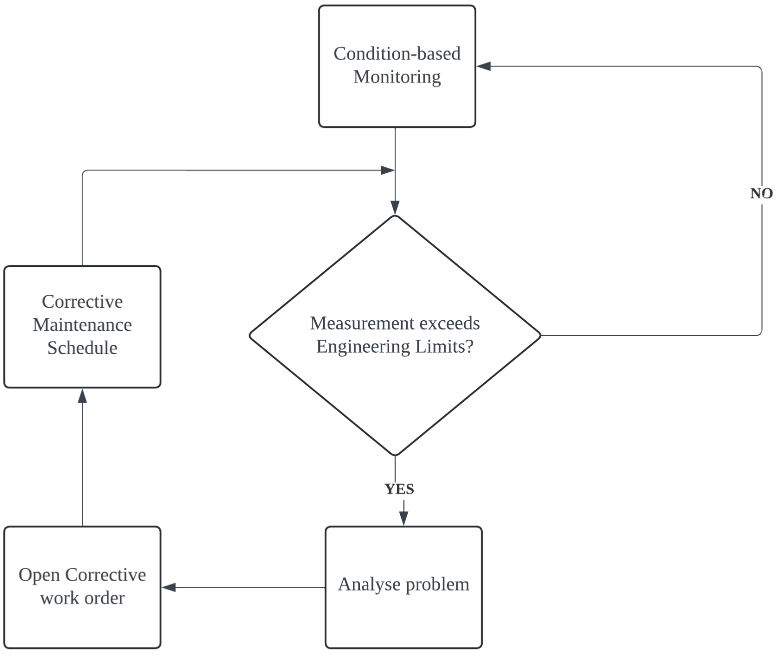


Figure I.6: Diagram of Condition-Based Monitoring

I.3.4 Predictive Maintenance

Where maintenance is performed based on an approximation of the health status of a piece of equipment, PdM systems consist of prediction tools based on historical data, health factors, statistical inference methods, and engineering approaches. These attributes allowed for advanced detection of pending failures and enabled timely pre-failure interventions[6].

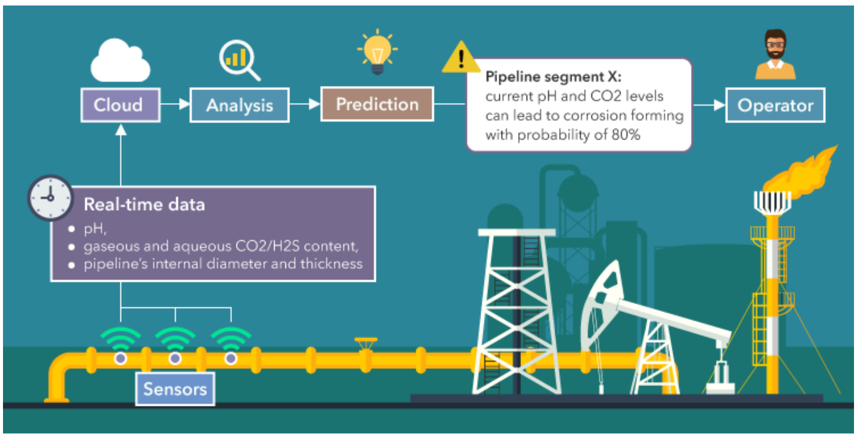


Figure I.7: example of PdM in an Oil and Gas Company [7]

I.4 Rotating Machines

Rotating machinery refers to machines with a rotating component that transfers energy to a fluid or vice versa. It is commonly used in industrial applications in order to transfer one energy form to another. Here are some examples :

I.4.1 Electrical Machines

An electrical machine is a device that can convert mechanical energy to electrical energy or vice versa. When such equipment is used to convert mechanical energy to electrical energy, it is referred to as a generator. When it converts electrical energy to mechanical energy, it is referred to as a motor. Any given electrical machine can convert power in either direction. Thus, any machine can be employed as either a generator or a motor[8].

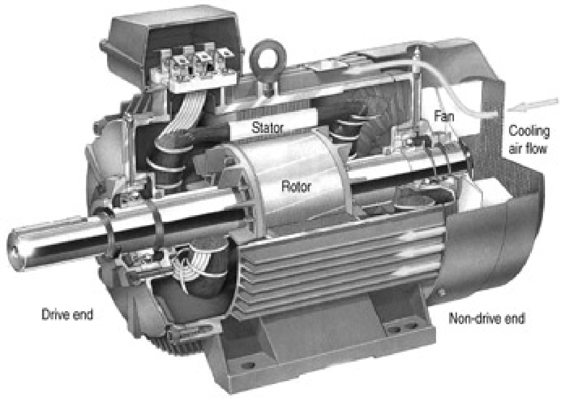


Figure I.8: Electrical Machine[9].

I.4.2 Turbomachinery

Turbomachinery refers to a type of machine that incorporates a rotating component to facilitate the transfer of energy to or from a fluid. As a result, there is dynamic interaction between the fluid and the rotor, enabling energy transfer. In general, when the energy is transferred from the rotor to the fluid, the machine is referred to as a pump or a fan.Conversely, when the energy transfer occurs from the fluid to the rotor, the machine is known as a turbine[10].

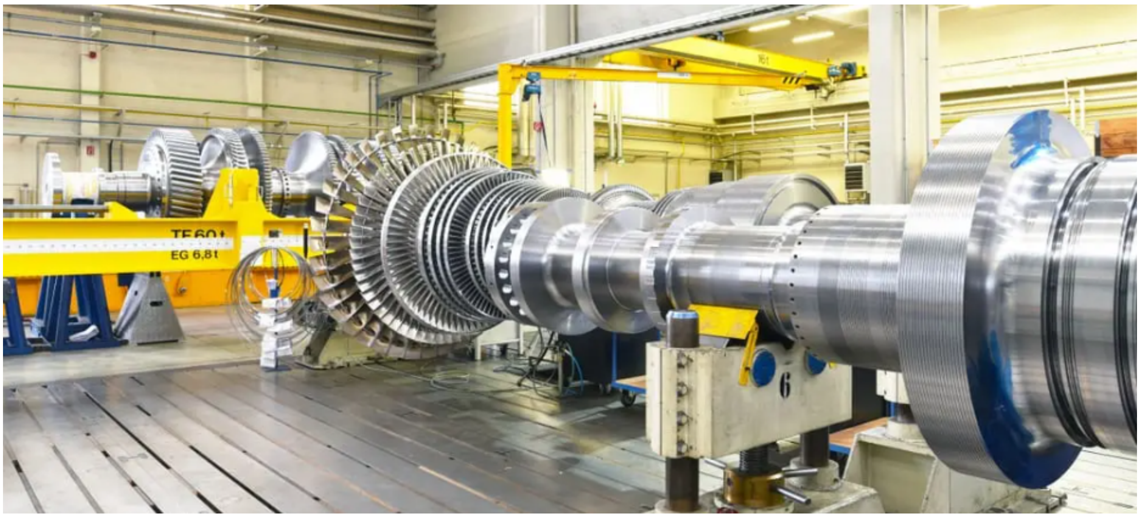


Figure I.9: Example of Turbomachinery[11].

I.5 Fault Detection and Diagnosis

Fault detection plays an important role in high-cost and safety-critical processes. Early detection of process faults can help avoid abnormal event progression. Fault detection can be accomplished through various means.

I.5.1 Fault Detection

Fault detection determines the occurrence of fault in the monitored system. It consists of detection of faults in the processes, actuators and sensors by using dependencies between different measurable signals. Related tasks are also fault isolation and fault identification. Fault isolation determines the location and the type of fault whereas fault identification determines the magnitude (size) of the fault. Fault isolation and fault identification are together referred as fault diagnosis. The task of fault diagnosis consists of the determination of the type of the fault, with as many details as possible such as the fault size, location, and time of detection[1].

I.5.2 Fault Diagnosis

Fault diagnosis is a comprehensive process that extends beyond fault detection, involving the determination of the specific type, location, magnitude, and other relevant details of detected faults within a system. It encompasses fault isolation, which involves identifying the location and type of fault, and fault identification, which focuses on determining the magnitude or size of the fault. Fault diagnosis aims to provide a deeper understanding of the root causes and implications of detected faults, enabling effective mitigation strategies. By characterizing faults with as much detail as possible[12].

I.5.3 Approaches of Fault Diagnosis

The approaches to fault diagnosis encompass traditional manual techniques, model-based methods, and data-driven approaches.

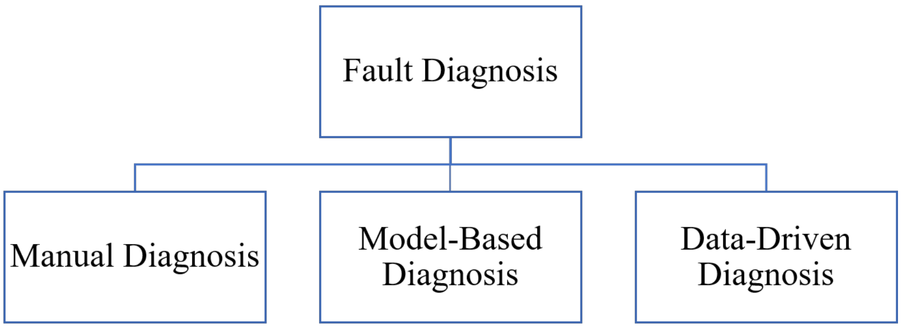


Figure I.10: Fault Diagnosis Approaches.

I.5.3.1 Manual Diagnosis

Human specialists utilize observation, testing, and analysis to diagnose faults, drawing upon their expertise and knowledge.

I.5.3.2 Model-Based Diagnosis

This method involves comparing real measurements with predictions from mathematical models. Residual analysis, derived from the variance between predicted and actual outputs, aids in fault detection and diagnosis. However, accurate representation of the system through mathematical equations or first principles is crucial for its effectiveness.

I.5.3.3 Data-Driven Diagnosis

Leveraging modern information technology, data-driven methods utilize statistical, mathematical, and signal processing techniques. Intelligent sensors gather industrial data, which is then analyzed to establish input-output models, enabling real-time monitoring and facilitating fault diagnosis objectives.

Table I.1: Comparison of fault diagnosis approaches

Approaches	Advantages and Disadvantages
Statistical approaches	• Advantages: – Do not require condition monitoring – Population characteristics information enable longer-range forecast – Can be trained to recognize the types of faults • Disadvantages: – Only provide general, overall estimates for the entire population of identical units
Model-based approaches	• Advantages: – Can be highly accurate – Require less data than data-driven approaches • Disadvantages: – Real-life system physics is often too stochastic and complex to model – Simplifying assumptions need to be examined – Various physics parameters need to be determined
Data-driven approaches	• Advantages: – Do not require assumption or empirical estimation of physics parameters – Do not require a priori knowledge • Disadvantages: – Generally require a large amount of data to be accurate

I.6 Condition Monitoring Techniques for Rotating Machinery

Progress in technology has contributed in the effectiveness and reliability of condition monitoring (CM), especially in bearings and gears in rotary machines. The accuracy of fault diagnosis is heavily dependent on the appropriate data selection techniques and signal analysis methods. CM techniques like acoustic emission measurement, vibration measurement, oil analysis, and thermography are potentially applicable to rotating machinery, with considerations given to their capabilities[13].

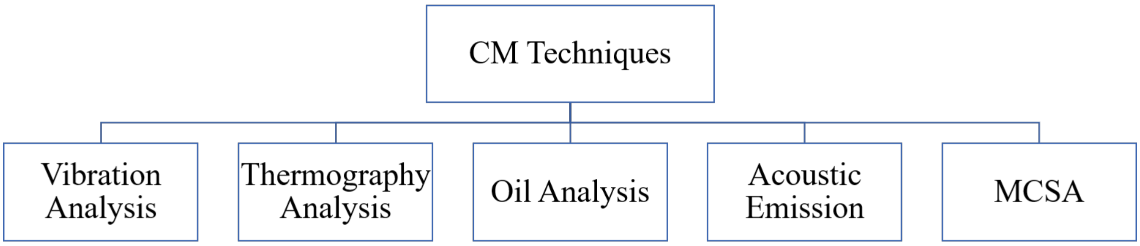


Figure I.11: Condition Monitoring Techniques.

I.6.1 Vibration Analysis

Vibration is considered the most frequently measured parameter in CM of rotary machines; it is utilized in numerous industrial applications such as material handling, aerospace, and power generation. This is because vibration is easy to sense as an effect of faulty machine components. These machines generate vibration signals through the interaction between the rolling elements and a damaged. area. Thus, vibration measurement can be a functional tool for diagnosing faults in bearings, shafts,and gearboxes, and for all kinds of machine faults[13].

I.6.2 Thermography Analysis

Temperature data is integral for the health status of mechanical equipment. Researchers are increasingly focusing on using temperature changes for fault diagnosis in rotating machinery, often employing thermocouples or resistance temperature detectors to detect abnormalities. unusual vibration and temperature fluctuations are regular indicators of machinery issues during process. Thus, thermography has emerged as a harmful testing technique for measuring temperature changes. It offers several advantages such as non-contact operation, high efficiency, and provision of infrared thermal images for indirect equipment condition monitoring[14].

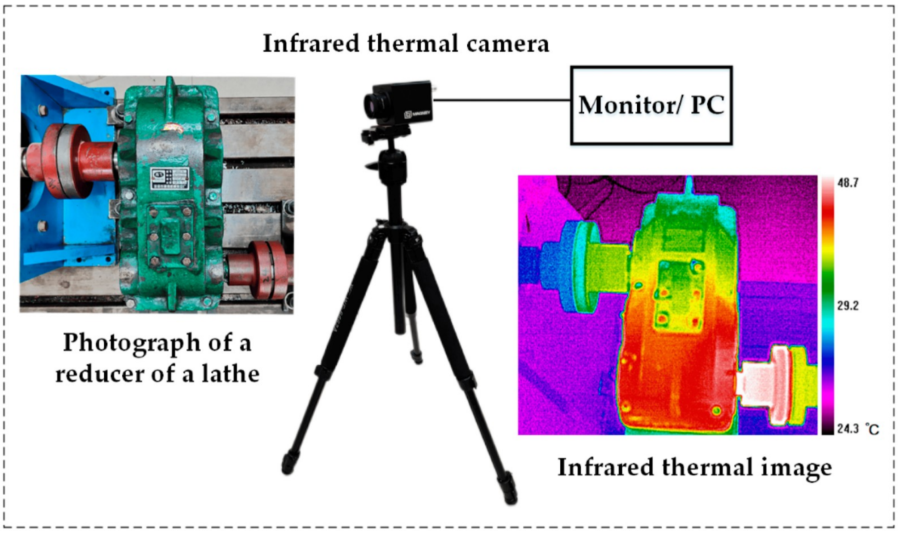


Figure I.12: The schematic diagram of Infra Red Thermography experimental device[14].

I.6.3 Oil Analysis

This method is widely used in machinery operations reliant on oil. It serves the purpose of giving out information about machine wear, lubricant contamination, and lubricant condition. Oil condition monitoring is utilised to evaluate the state of engine oils, lubricating oils, and other fluids. Thus, it is a very useful technique for predictive maintenance[15].

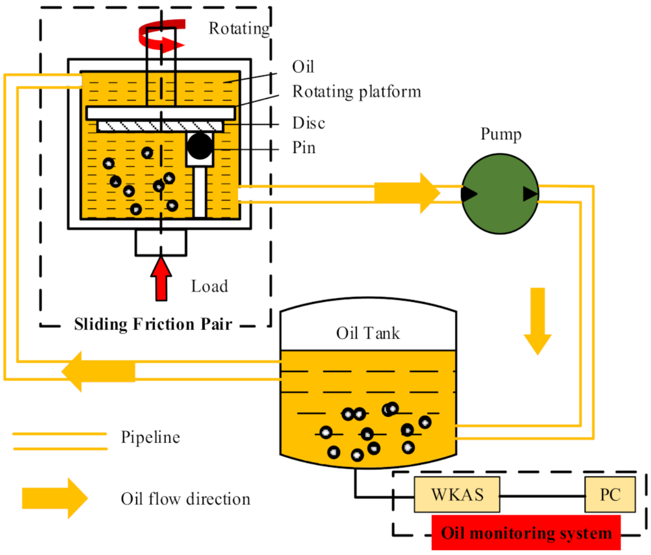


Figure I.13: Functional diagram of offline oil monitoring experiment [16].

I.6.4 Acoustic Emission

This technique detects equipment wear and tear by using sensors to pick up sound waves, some of which are beyond human hearing (ultrasonic frequencies). There are two main sensor types:

- **Airborne Sensors (Microphones):**They are notoriously sensitive to background noise and to anything standing in the path between the sensor and the object being monitored.
- **Structure-Borne Sensors (Piezoelectric Accelerometers):**These convert vibrations into electrical signals. Their effectiveness is dependent on the chosen material and how they are installed. Since sensor performance is influenced by the equipment and environment, careful selection and installation are essential for accurate monitoring[17].

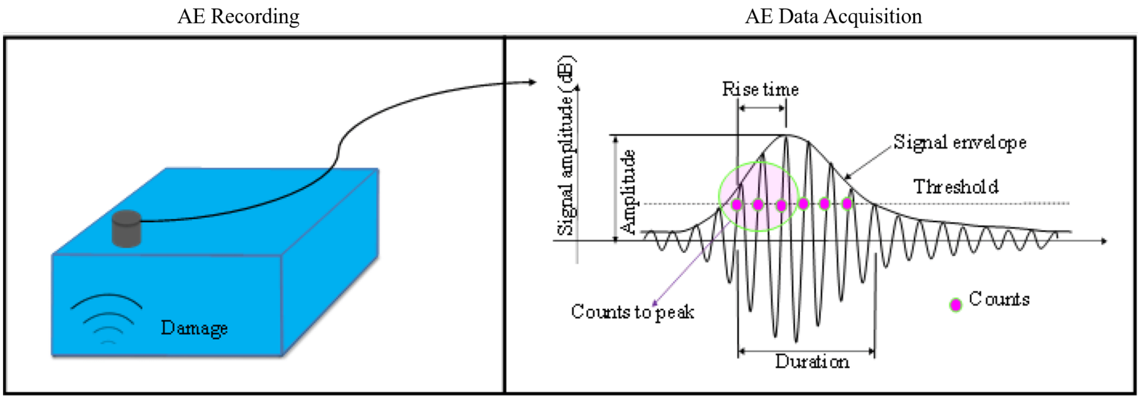


Figure I.14: Acoustic emission monitoring [18].

I.6.5 Motor Current Signature Analysis (MCSA)

Motor current signature analysis can be described as a method that aids in distinguishing the induction motor's operating condition without interrupting the process. In other words, it senses an electrical signal that has current components and determines the faults in the initial stage. Therefore, it plays an integral role in preventing damage and diagnosing motor failure[19].

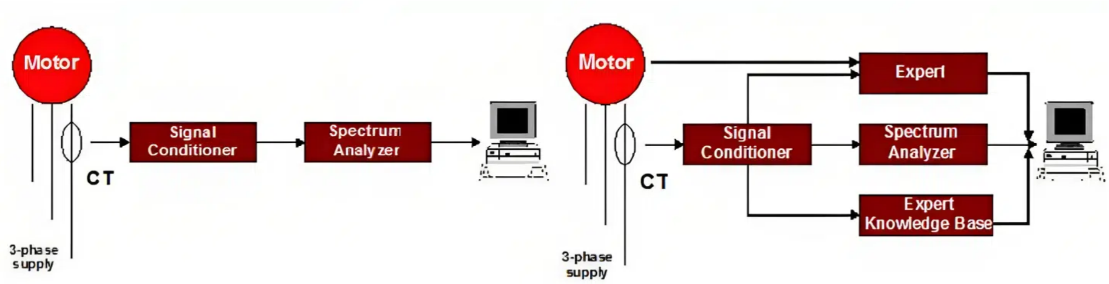


Figure I.15: Monitoring System for Motor Current Signature Analysis[20].

I.7 Acoustic Analysis

In this thesis, the focus is on utilizing Acoustic analysis as a mean of diagnosing machines. Therefore, this section will introduce transmitted sounds as a parameter for condition monitoring.

I.7.1 Definition

Before carrying on with the review of transmitted sound technique, it is integral to distinguish it from acoustic emission monitoring. many researchers over the last 50 years have been focusing on vibro-acoustic techniques. the most well-researched monitoring way is acoustic emissions(AE)[21].

Acoustic emission refers to generation of transient elastic waves produced by fast energy release from a localized source within the material. There are different causes for the occurrence of acoustic emission as compared to the natural events like earthquakes or rocks cracks during the slip and disruption movements. It also has fracture, fatigue, crack transmission, melting and material phase conversion[22].

Transmitted sound and acoustic emission share the same sources, in conjunction with airborne noise from the surrounding environment. The range to consider this audible sound is typically from 50 Hz to 20 kHz. and is measured using microphones. The most useful advantage of using transmitted sound for monitoring is its ability to be used remotely. This ability might make it feasible for TCMS to be used outside of the laboratory, in harsh industrial environments and in the tight spaces of micro-machining operations[21].

I.7.2 Acoustic Signal Representation

An acoustic signal is observed as a continuous-time function s(t) where t is a continuous variable representing time. In Fig.Fig I.16 some examples of continuous acoustic signals such as a pure tone, a room impulse response and speech are shown. The objects of acoustic signal processing include controlling the sound field, identifying acoustic systems and synthesizing the spoken word.

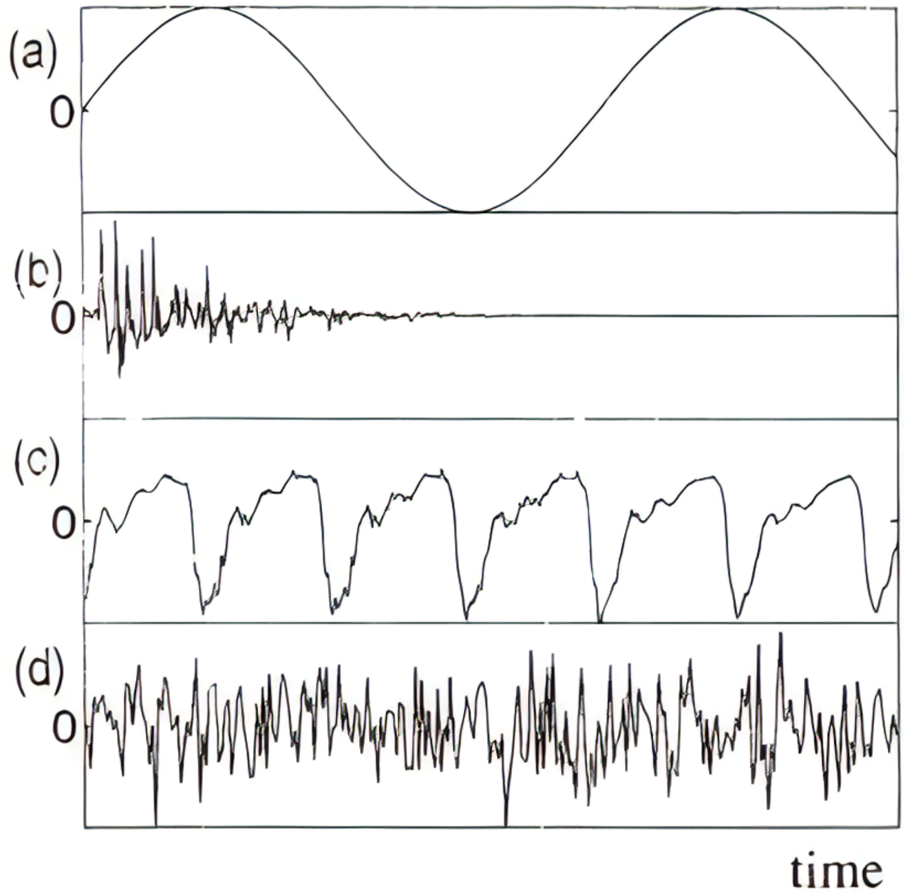


Figure I.16: Examples of acoustic signals: (a) pure tone (periodic signal); (b) room impulse response; (c) speech (vowel) and (d) white noise.

I.7.3 Acoustic Data Aquisition

During a process, sound signals will be picked up by a microphone (or microphone arrays) [23].Array systems will provide the ability of measuring sound contributions and locating the sound sources in space. This enables an effective tool for removing background noise from the signal by focusing only on the data emanating from the source of interest[21].

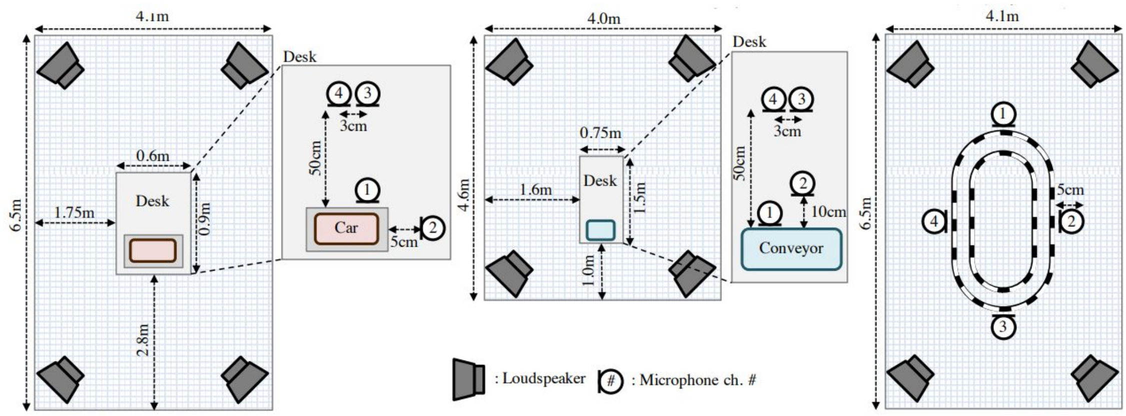


Figure I.17: Schematic of microphone installation setup for miniaturised machines (a) toy car (b) toy conveyor (c) toy train[24].

I.8 Conclusion

In summary, the maintenance techniques of CBM and PdM have been regarded widely as the better maintenance philosophies, especially the latter. Practice has shown it to have a proven track record of minimising unnecessary machine downtime[23]. This chapter extensively explores different fault diagnosis techniques and various condition monitoring methods. Placing specific emphasis on acoustic analysis and the systems used for acquiring and monitoring acoustic data in modern acoustic analysis practices.

Chapter II

Acoustic Analysis and Fault Diagnosis

II.1 Introduction

Acoustic analysis has become one of the most powerful techniques used in the field of condition monitoring (CM) and fault diagnosis demonstrating its effectiveness in early detection of faults and abnormal acoustic patterns in rotating machinery, assisting the engineers diagnosis the root of the fault such as misalignment, imbalance, and faults in bearing. This chapter will provide an overview of acoustic signal analysis for fault diagnosis including manual analysis technique as well as various method of data-driven analysis as shown in Fig II.1 [25, 26].

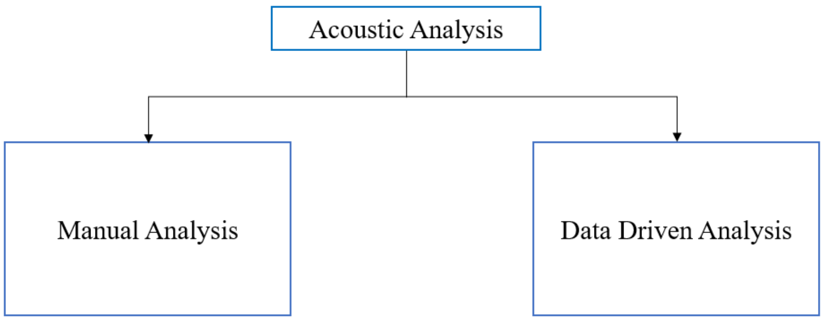


Figure II.1: Acoustic signal analysis approaches

II.2 Acoustic Analysis for Fault Diagnosis

Acoustic Analysis involves utilizing acoustic signals to detect irregularities in the patterns of a particular object. Any variation in the acoustic pattern can be an indication of a modification in the physical characteristics of the object. Expert analysts can detect abnormal patterns through various frequency and time plots such as time domain and frequency spectrum analysis as the diagram in Fig II.2 presents. Once a deviation from the normal pattern is identified, a root cause analysis is conducted to pinpoint the cause of the change. This process falls under the category of knowledge-based fault diagnosis[27].

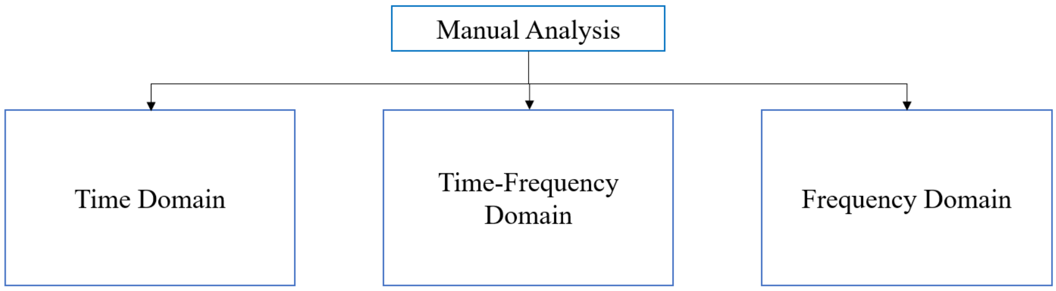


Figure II.2: Manual Signal Analysis.

II.2.1 Time Domain Analysis

Evaluating the raw signal data over time to identify and interpret patterns that indicate potential faults. This approach is fundamental in condition monitoring as it provides direct insights into the behavior of machinery. Among the most commonly used techniques in time domain analysis are waveform inspection and statistical measures.

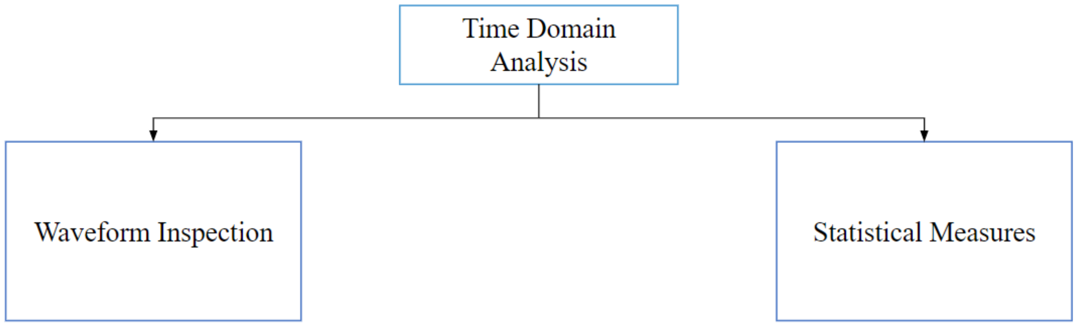


Figure II.3: Time Domain Analysis.

II.2.1.1 Waveform Inspection

Waveform time domain analysis involves examining the raw signal by plotting signal amplitude against time to extract valuable information and insights. Fig II.3 presents two time domain analysis used. This technique focuses on understanding the characteristics and patterns within the signal to derive meaningful conclusions about the operational state of machinery. Waveform analysis is particularly crucial for identifying transient events such as impact sounds, scrape noises, and impulsive bursts. These transient events often indicate faults in machinery components, including bearings and gears [28]. waveforms in Fig II.4 showcase patterns of different states of a rotating machine.

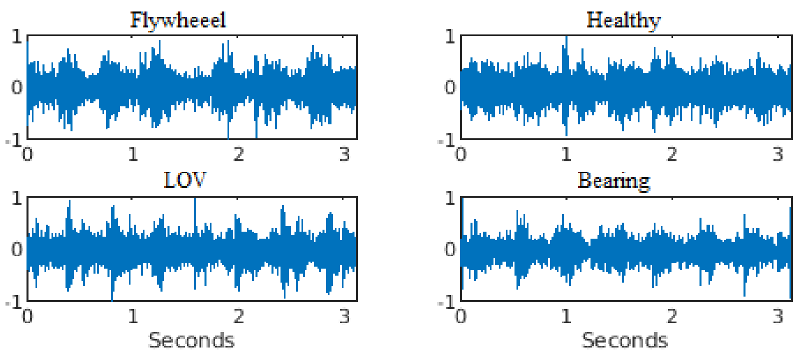


Figure II.4: Time domain plots of four acoustic recordings of different states of a single-stage reciprocating-type air compressor.

II.2.1.2 Statistical Measures

The application of statistical analysis in the time domain involves measuring many features from the signal, like mean, variance, root mean square (RMS), standard deviation, peak-to-peak factor, skewness, and kurtosis. Providing the summary of the signal as characteristic information. These features are calculated on segmented windows of the acoustic signal, Analyzing how these features change over time helps us detect faults by examining how these features deviate from normal operating conditions or exceed established thresholds in these features [29].

II.2.2 Frequency Domain Analysis

Frequency domain analysis involves transforming the signal from the time domain to the frequency domain using techniques like the Fourier Transform. Frequency-domain analysis shows how the signal's energy is distributed over a range of frequencies. This reveals the frequency content of the signal and how much of the signal is contained within certain frequency bands, as it enables the identification of characteristic frequencies associated with specific faults[29]. the Fig II.5 showed some of the frequency domain analyses that have been used for diagnosis.

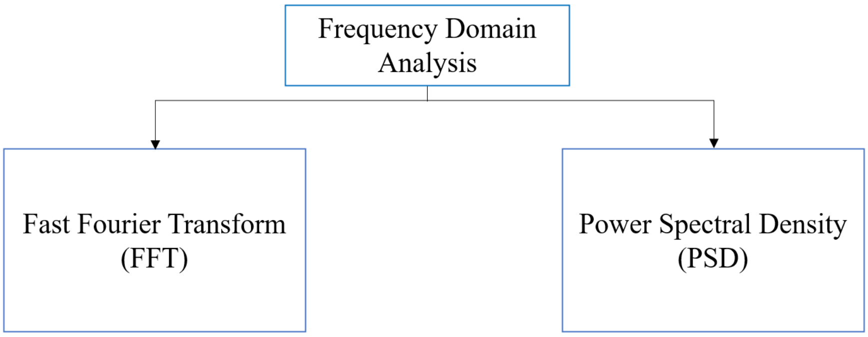


Figure II.5: Frequency Domain Analysis.

II.2.2.1 Fast Fourier Transform

The Fast Fourier Transform (FFT) is an algorithm that computes the Fourier transform of a discrete-time signal. It is an efficient implementation of the Fourier transform, reducing the computational complexity from $O(N^2)$ to $O(N \log N)$, making it much faster and more practical to use. The FFT is used extensively in signal processing and data analysis applications, such as audio and video processing, image processing, and spectral analysis. FFT is represented mathematically by the equation:

$$X_k = \sum_{n=0}^{N-1} x_n e^{\left(\frac{-\mathrm{i}2\pi\mathrm{kn}}{\mathrm{N}}\right)}, k = 0, \ldots, N-1 \tag{II.1}$$

The FFT is particularly useful for analyzing signals that contain multiple frequency components, it allows engineers to identify the individual frequency components and their amplitudes, which can be used to diagnose faults or analyze the behavior of complex systems.Fig II.6 shows an example of detecting a fault from the frequency Spectrum.

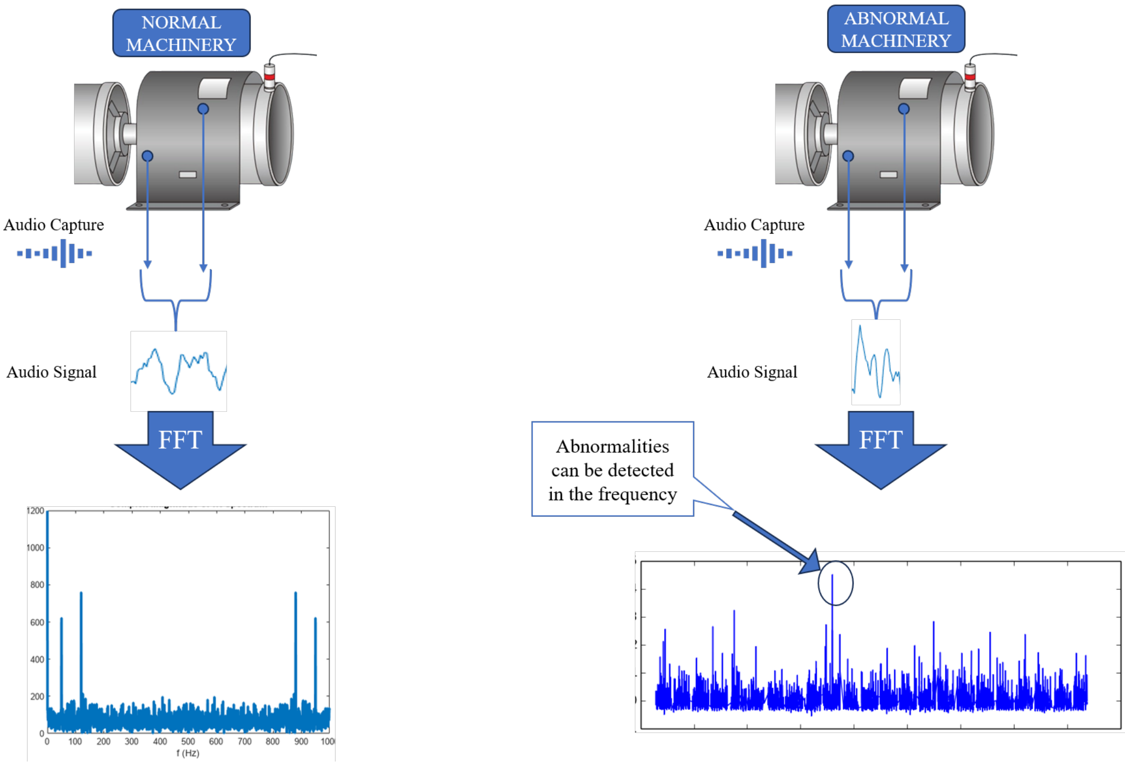


Figure II.6: Example of abnormality appearance in the frequency Spectrum.

II.2.2.2 Power Spectral Density

Power Spectral Density (PSD), is a fundamental concept used in signal processing to measure how the average power or the strength of the signal is distributed across different frequency components. The Average Power referred to is known as the mean amount of the energy transferred or distributed throughout a given time range. PSD has several characteristics that assist in fault diagnosis[30], such as :

- It describes the power distribution or the strength of the signal over a range of frequencies.
- The shape of the plot gives an important characteristic like a narrower peak describing that most of the power of the signal is concentrated at this particular frequency whereas a broader peak describes that most of the power of the signal is distributed over a wide range of frequencies.

- The peak value in the plot represents the frequencies having higher or greater power levels.

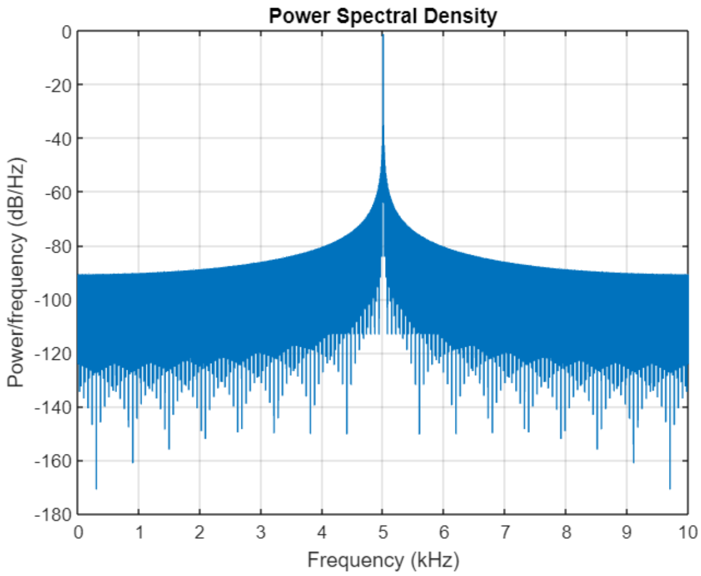


Figure II.7: Example of Power Spectral Density Curve [30].

II.2.3 Time-Frequency Domain Analysis

To overcome the limitations of time domain and frequency domain analysis for non-stationary acoustic signals, time-frequency domain techniques are used. These include Wavelet Transform, the Short-Time Fourier Transform (STFT), Hilbert-Huang transform (HHT), and empirical mode decomposition (EMD). Time-frequency analysis provides both time and frequency information by analyzing the signal in windowed segments. This allows identifying how the frequency content changes over time, which is useful for diagnosing faults in rotating machinery [29, 31].

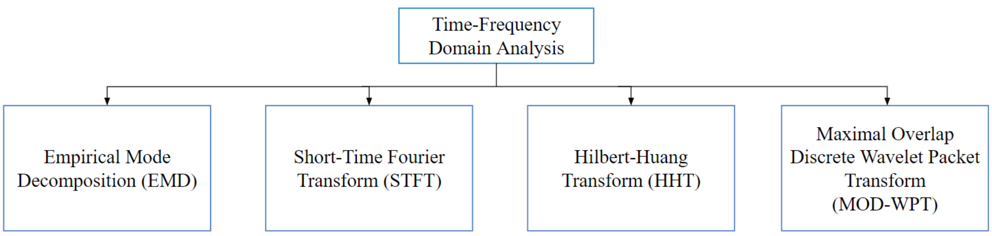


Figure II.8: Time-Frequency domain analysis.

II.2.3.1 Empirical Mode Decomposition (EMD)

Empirical Mode Decomposition (EMD) is a signal analysis technique that decomposes a signal into its underlying oscillatory components, called Intrinsic Mode Functions (IMFs) which are obtained through a process called sifting. The sifting process is the core of the EMD algorithm, where each Intrinsic Mode Function (IMF) is extracted from the signal. In this process, all the local maxima and minima of the signal are identified and connect to form the upper and lower envelopes, respectively. Then, the mean of the two envelopes is obtained as the local mean. this local mean is subtracted from the original signal to obtain an oscillatory component called an IMF [32].

EMD has been used in a variety of applications, including signal denoising, feature extraction, and trend analysis. It is particularly effective in analyzing non-stationary signals, where the frequency content of the signal varies over time.

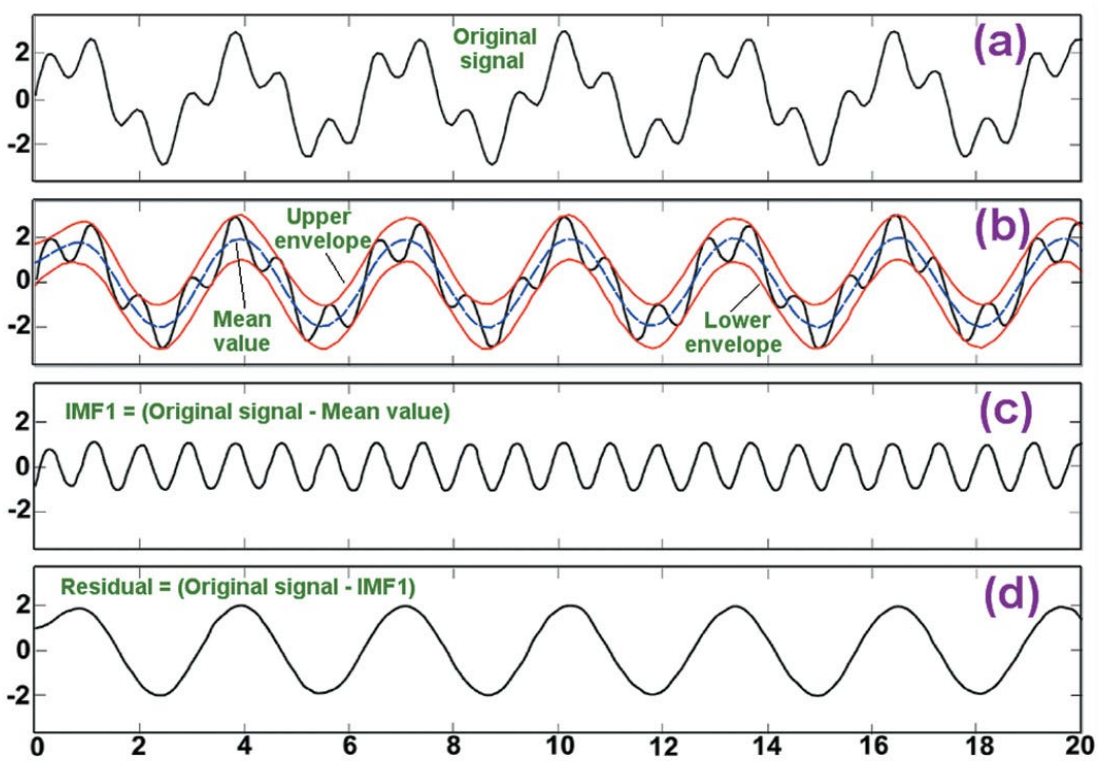


Figure II.9: Example of Emperical Mode Decomposition (EMD)[33].

II.2.3.2 Maximal Overlap Discrete Wavelet Packet Transform (MODWPT)

MODWPT is a time-invariant powerful time-frequency signal analysis technique in the time-frequency domain, it decomposes the signal into coefficients with equal pass-band periods. The input signal passes through high-pass filter and low-pass filter, these coefficients also passes through low-pass and high-pass filters to produce numerous levels of decomposition. MODWPT is ideal for analyzing non-stationary signals, since unlike Discrete Wavelet Packet Transform (DWPT), MODWPT avoids down-sampling, resulting in a representation that captures more signal details. Thus, resulting more detailed time-frequency decomposition [34].

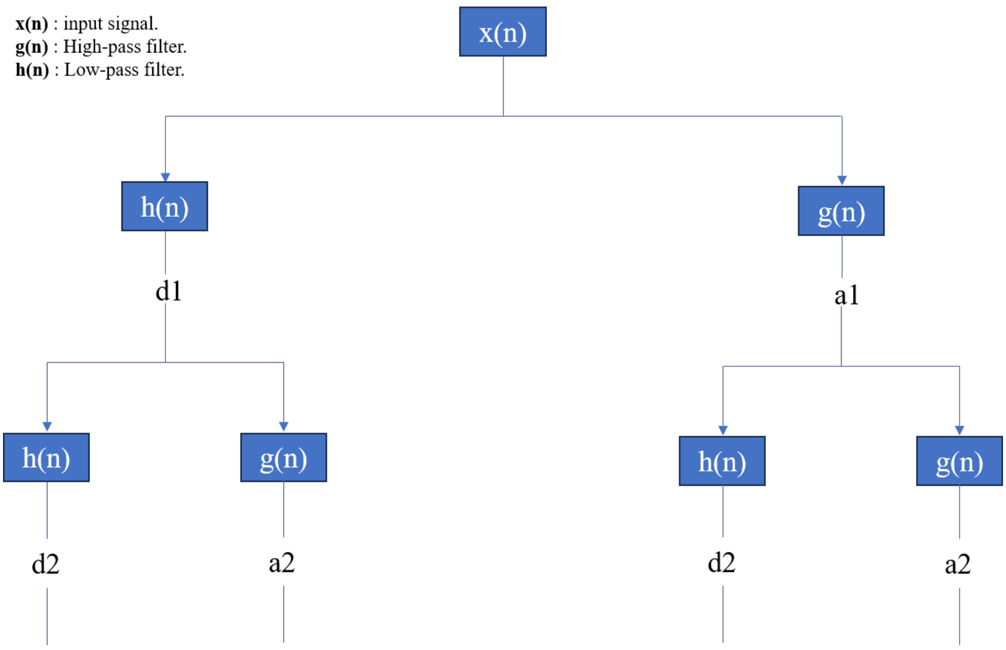


Figure II.10: Two levels of the MODWPT decomposition.

II.3 Data Driven Analysis

Data-driven acoustic analysis involves utilizing data processing techniques to extract valuable insights and patterns from acoustic signals for various applications. This approach leverages advanced algorithms and computational methods to analyze large volumes of acoustic data efficiently and accurately. By applying artificial analysis, statistical analysis, and signal processing techniques to acoustic signals, data-driven acoustic analysis can uncover hidden patterns, trends, and anomalies that aid in fault diagnosis, environmental monitoring, and other acoustic-related tasks.

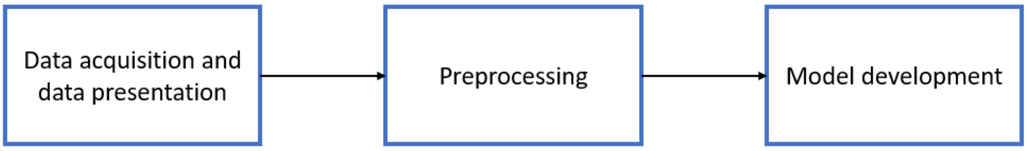


Figure II.11: Data driven approach procedure

II.3.1 Data Acquisition

The efficacy of the model depends on the quality of the data acquired from the acoustic signal. As it needs careful consideration when choosing the right acquisition setup, such as:

- The selection of appropriate acoustic sensors to ensure the capture of the relevant frequency range of the targeted faults.
- Strategic sensor placement that allows to collect the most informative acoustic signatures from the faulty part of the machine.
- A suitable DAQ system with a proper sampling rate and resolution ensures capturing the details of the acoustic signal without distortion.

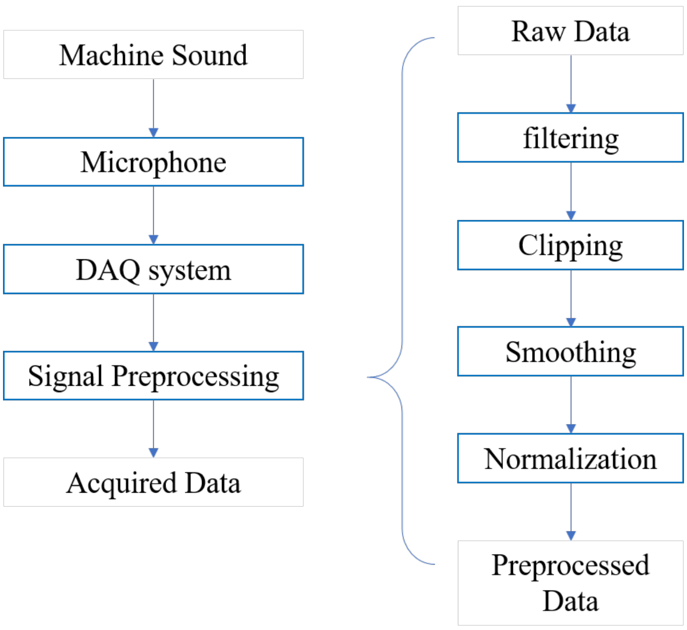


Figure II.12: Data acquisition process.

II.3.2 Preprocessing

Preprocessing is an important step in building models for acoustic signal diagnosis. It involves using techniques to prepare the signal data and extract important information from it. This is essential because acoustic data is often beset with significant levels of noise and has unnecessary information that can make the model perform poorly. the Preprocessing can be used to remove unwanted disturbances resulting in cleaner and more reliable datasets. This clean data is essential for accurate modeling, predictions, and other advanced data analysis tasks. In previous studies, researchers have used different methods to Preprocess acoustic data such as noise reduction which is a big challenge that faces signal processing engineers, also feature extraction in order to get the most important information from the signal. as we will explore in detail in chapter 3.

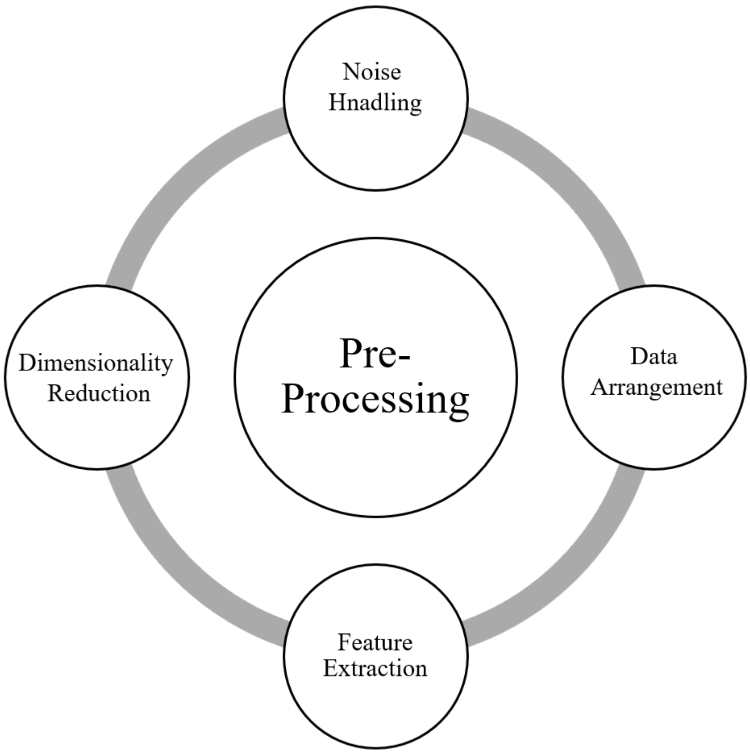


Figure II.13: Preprocessing Techniques.

II.3.2.1 Noise Handling

There exist many techniques of noise reduction and handling such as filtering (low-pass, high-pass, band-pass, band-stop), spectral subtraction, and wavelet denoising. Smoothing is a common technique to handle noise by reducing the impact of these random fluctuations. However, it is important to be careful to not remove any significant signal details.

II.3.2.2 Feature Extraction:

Calculating various statistical features in the time domain provides valuable insights into the behavior of a time series[35].

- **Mean:** gives the central tendency of the data, providing an overall idea of the data's level.
- **Variance:** measures the spread or dispersion of the data points around the mean.
- **Skewness:** quantifies the asymmetry of the distribution, indicating whether the data is predominantly spread out on one side.
- **Kurtosis:** measures the thickness of the tails of the distribution, characterizing the presence of extreme values.

II.3.2.3 Principal Component Analysis (PCA)

PCA is a statistical technique used to reduce the dimensionality of a dataset, by transforming a large set of variables into a smaller one that still contains most of the information in the large set [36]. Its goal is to extract the important information from the original data, to represent it as a set of new orthogonal variables called principal components[37].

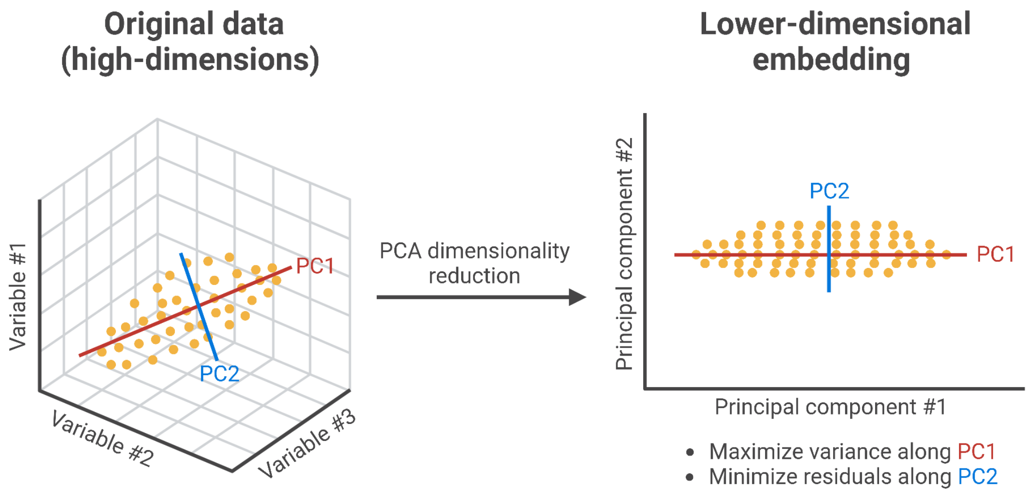


Figure II.14: Principal Component Analysis (PCA) Transformation[38].

II.3.3 Model Development

Acoustic fault diagnosis models are revolutionizing the field of condition monitoring by leveraging the power of Artificial Intelligence (AI) and Machine Learning (ML) techniques. These models analyze acoustic signal data to detect and classify faults within machinery and equipment. This section explores the development process of such models, focusing on the two primary learning paradigms: supervised and unsupervised learning.

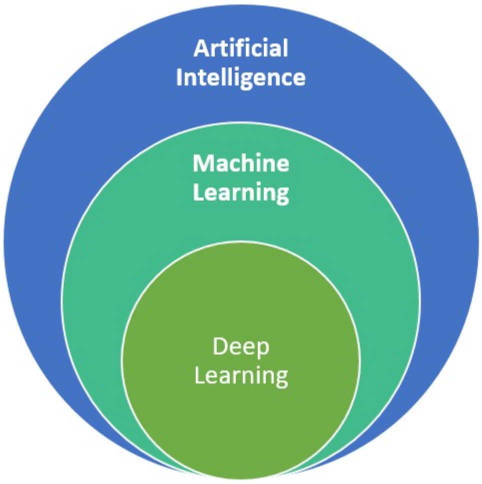


Figure II.15: representation of the relationship between AI - ML - DL [39].

II.3.3.1 Machine Learning

Machine learning is a subfield of artificial intelligence that involves the development of algorithms and statistical models that enable computers to improve their performance in tasks through experience. These algorithms and models are designed to learn from data and make predictions or decisions without explicit instructions [40].

II.3.3.2 Deep Learning

Deep learning is a branch of machine learning which is based on artificial neural networks. It is capable of learning complex patterns and relationships within data. It has become increasingly popular in recent years due to the advances in processing power and the availability of large datasets. Because it is based on artificial neural networks (ANNs), it is also known as deep neural networks (DNNs). These neural networks are inspired by the structure and function of the human brain's biological neurons, and they are designed to learn from large amounts of data[41].

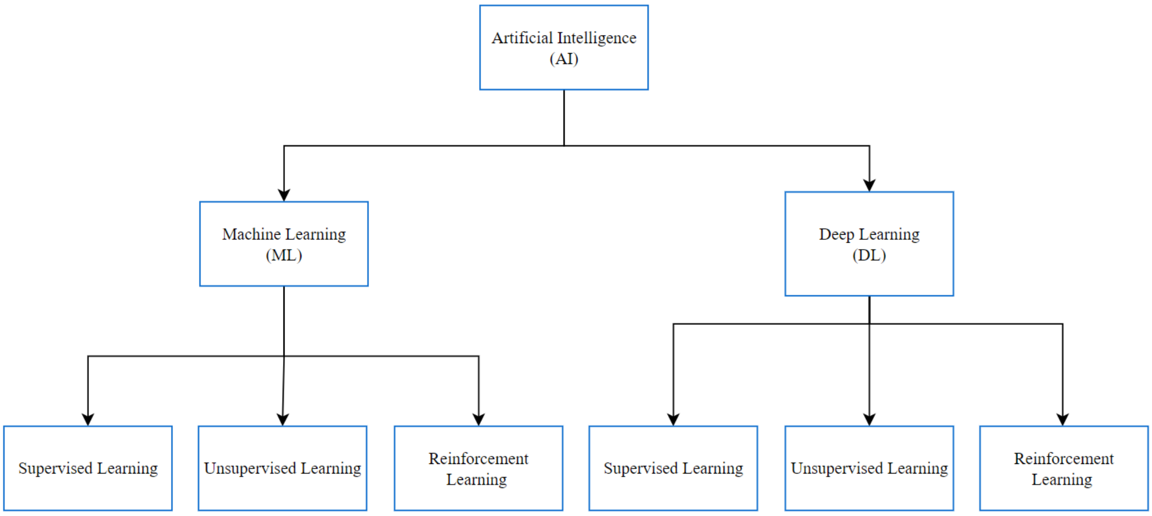


Figure II.16: Hierarchical Structure of AI, ML, DL

Table II.1: Comparison of Deep Learning and Machine Learning for Fault Diagnosis

Aspect	**Deep Learning**	**Machine Learning**
Dataset Requirement	Requires a large dataset (data-hungry)	Can work with smaller datasets
Computation Power	Consumes significant computation power	Requires less computation power
Feature Engineering	Automatically extracts features	Often requires manual feature engineering
Complexity Handling	Capable of handling highly complex and nonlinear relationships	May struggle with very complex and high-dimensional data
Training Time	Typically longer training times due to deep architectures	Generally faster training times
Performance	Potential for higher accuracy with sufficient data	Performance may plateau with increasing complexity

II.3.3.3 Supervised Learning

The predominant approach for acoustic fault diagnosis models utilizes supervised learning. This method involves training the model on a labeled dataset containing acoustic signals that have been Preprocessed and categorized according to the specific fault types present. Supervised models are generally considered to provide higher accuracy than unsupervised methods because they can capture interdependencies between variables.

II.3.3.4 Unsupervised Learning

Unsupervised learning trains without labeled data, aiming to discover hidden patterns or intrinsic structures within the data. offers an alternative approach for fault diagnosis, particularly in scenarios where labeled data for specific fault types might be limited. Here, the model analyzes the acoustic data without prior knowledge of specific fault categories. The focus is on detecting anomalies and deviations from the normal operating sound signature of the machinery.

Table II.2: Comparison of Supervised Learning and Unsupervised Learning for Fault Diagnosis

Aspect	**Supervised Learning**	**Unsupervised Learning**
Data Labeling	Requires labeled data	Works with unlabeled data
Training Objective	Learns to predict specific output labels	Identifies hidden patterns and structures
Fault Detection	Effective at identifying specific known faults	Good for anomaly detection and discovering new, unknown fault patterns
Accuracy	High accuracy with sufficient labeled data	Accuracy can be lower due to the lack of labeled training data
Complexity	Can handle complex problems with well-labeled datasets	Often simpler but powerful in discovering hidden patterns
Implementation Time	Implementation can be time-consuming due to the need for labeled data	Faster to implement as it doesn't require labeled data

II.4 Conclusion

This chapter explored the approaches in acoustic analysis for fault diagnosis, with emphases on manual and data-driven techniques. The significance of Time domain, Frequency domain, and Time-Frequency domain analysis was highlighted, focusing on their roles in extracting valuable details from the acoustic signals.
Time domain analysis allows for the identification of abnormal events through waveform inspection and statistical measures. Additionally, frequency domain analysis provides the signal's frequency content, which is important for diagnosing faults associated with specific frequency components. Also, advanced time-frequency domain such as Empirical Mode Decomposition (EMD) and Maximal Overlap Discrete Wavelet Packet Transform (MODWPT) add more details on non-stationary signals, which characterise acoustic signals.
The chapter drifts towards the data-driven technique, which involves utilising advanced analytical models that can detect and classify faults within machinery and equipment. Preprocessing techniques were discussed, highlighting the significance of feature extraction to organise the data. Finally, the topic of model development was discussed, focusing on the AI models that can learn from the Preprocessed data to accurately detect and diagnose faults.

Chapter III

Methodology

III.1 Introduction

This chapter will examine the steps involved in building fault diagnosis classification models, starting from data description and visualization. After that, the chapter will shift towards the preprocessing the data in preparation for feature extraction. Furthermore, a comprehensive description of the Machine Learning Algorithms used to build our models is highlighted.

III.2 Experimental Framework

In this study, we utilized various datasets from diverse applications and environments to test our model under different conditions and noise levels to establish a reliable model.

III.2.1 MAFAULDA Machinery Fault Dataset

The first dataset used in this study was selected from MAFAULDA Machinery Fault Database [42]. it is a database that was created to imitate the failure scenarios that occur in rotating machinery due to misalignment, imbalance, and bearing issues. The database contains 1951 data files that represent different fault situations for six distinct operating states: Normal, imbalance, horizontal and vertical misalignment, underhang, and overhang bearings. The Signals, Multimedia, and Telecommunication Laboratory developed the database using the SpectraQuest Alignment/Balance Vibration Trainer (ABVT) machine fault simulator.

III.2.1.1 Data Acquisition System

The experimental setup used to acquire this data is shown below in

Table III.1: Experimental Bench Specifications[42]

Specification	Value	Unit
Motor	1/4 CV DC	
Frequency range	700-3600	rpm
System weight	22	kg
Axis diameter	16	mm
Axis length	520	mm
Rotor	15.24	cm
Bearings distance	390	mm
Number of balls	8	
Balls diameter	0.7145	cm
Cage diameter	2.8519	cm
FTF	0.3750	CPM/rpm
BPFO	2.9980	CPM/rpm
BPFI	5.0020	CPM/rpm

Continued on next page

Table III.1 – continued from previous page

Specification	Value	Unit
BSF	1.8710	CPM/rpm

The sensors' utilized to acquire the data

- **Three IMI Sensors, Model 601A01:** accelerometers on the radial, axial and tangencial directions.

Figure III.1: IMI Sensor, Model 601A01

- Sensibility : (±20%) 100 mV per g (10.2 mV per m/s2);
- Frequency range : (±3 dB) 16-600000 CPM (0.27-10.000 Hz);
- Measurement range : ±50 g (±490 m/s2).

- **IMI Sensor triaxial accelerometer, Model 604B31:**

Figure III.2: IMI Sensor, Model 604B31

- Sensibility : (±20%) 100 mV per g (10.2 mV per m/s2);

  - Frequency range : (±3 dB) 30-300000 CPM (0.5-5.000 Hz);
  - Measurement range : ±50 g (±490 m/s2).

- **Monarch Instrument MT-190**: Analog tachometer.

Figure III.3: Monarch Instrument MT-190

- **Two National Instruments NI 9234:** 4 channel analog acquisition modules, with sample rate of 51.2 kHz.

Figure III.4: NI 9234.

- **Shure SM81:** A high-quality, unidirectional condenser microphone that is widely used for professional audio recording, broadcasting, and sound reinforcement. It captures wide range of frequency (20-20.000 Hz). Also, it has low-self noise [43].

Figure III.5: Shure SM81.

III.2.1.2 Raw Data Description

A variety of faults were collected during the acquisition phase. Each sequence was generated at at a 50 kHz sampling rate during 5 seconds, totaling 250.000 samples, they are described below :

- **Normal sequence:** There are 49 sequences without any fault, each with a fixed rotation speed within the range from 737 rpm to 3686 rpm with steps of approximately 60 rpm.

- **Imbalance faults:** Measured with ranging loads from 6g to 35g coupled with the rotor. With limited rotation frequencies for loads above than 30g. Totalling 333 sequences.

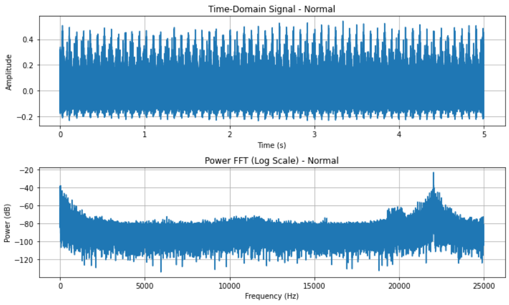
- **Horizontal Parallel Misalignment:** The motor shaft was shifted horizontally by f 0.5 mm, 1.0 mm, 1.5 mm, and 2.0 mm. Totalling 197 sequences.

- **Vertical Parallel Misalignment:** The motor shaft was shifted vertically 0.51 mm, 0.63 mm, 1.27 mm, 1.40 mm, 17.8 mm and 1.90 mm. Totalling 301 sequences.

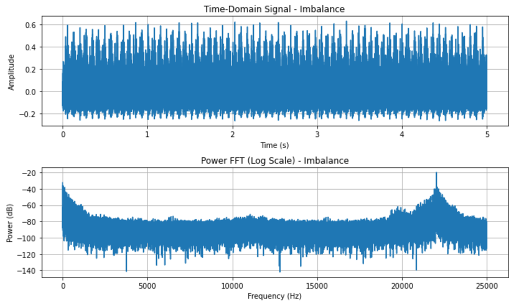
- **Bearing faults:** Three defective bearings, each one with a distinct defective element (outer track, rolling elements, and inner track), that were placed one at a time in two different positions, resulting in 558 Underhang sequence and 513 Overhang sequence. Three masses of 6 g, 20 g, and 35 g were added to induce a detectable effect. The dataset was origanised in CSV (Comma-Separated Values) files, each one with 8 columns. Our concern is the 8th column which contains the microphone acoustic signal.

III.2.1.3 Data Visualization

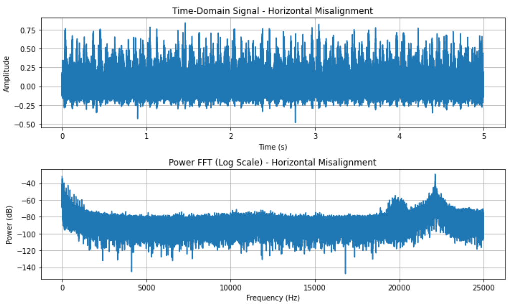
To comprehend the structure and format of the data we used MATLAB to plot the Fig III.6 below of the time-domain to identify any trends or patterns, and the frequency domain by applying the one-sided power spectral density plot to identify the dominant frequency components and understanding the distribution of power in the signal across different frequencies.



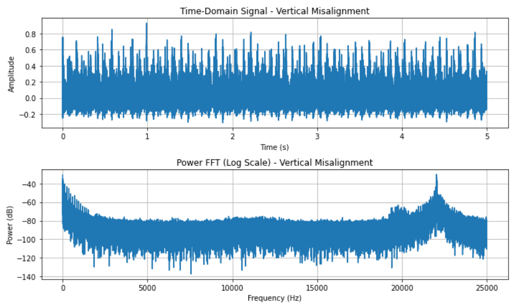
Healthy



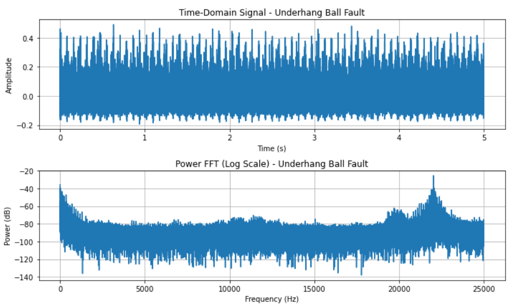
Imbalance



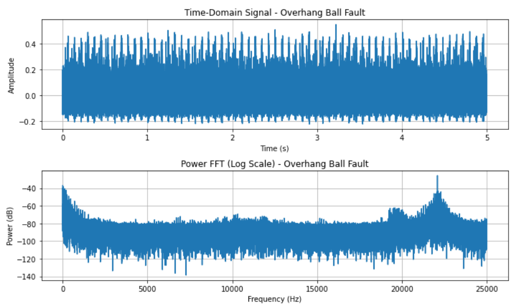
Horizontal misalignment



Vertical misalignment



Underhang



Overhang

Figure III.6: Visualization of spectral and waveform plots of the data.

In comparing the frequency distributions of healthy and faulty states from Fig III.6 , it is observed that the overall shapes of all plots are similar, with the majority of power concentrated around lower frequencies and different distributions of power across various frequencies. For example, the imbalance has some power around 0 Hz. Also, the misalignment plots show less prominent peaks at the harmonics of the peak frequency in the healthy state. In conclusion, the similarity in the plots suggests the unreliability of spectrum graphs in analysing the machine's conditional state. Therefore, utilising alternative methods, such as machine learning-based techniques, may be preferable in this scenario.

III.2.2 Air Compressor Dataset

The dataset consists of acoustic recordings collected on a single-stage reciprocating-type air compressor. The data are sampled at 16 kHz. Specifications of the air compressor are as follows:

- **Air Pressure Range**: 0-500 lb/m2, 0-35 Kg/cm2
- **Induction Motor**: 5HP, 415V, 5Am, 50 Hz, 1440rpm
- **Pressure Switch**: Type PR-15, Range 100-213 PSI

III.2.2.1 Data Acquisition System

Data acquisition is the first step of fault diagnosis where machine characteristics are measured and recorded for further analysis. Data are collected using microphones placed at many positions around 1.5 cm away from the machine. The data acquisition setup is shown in Fig III.7 and Fig III.8 [44].

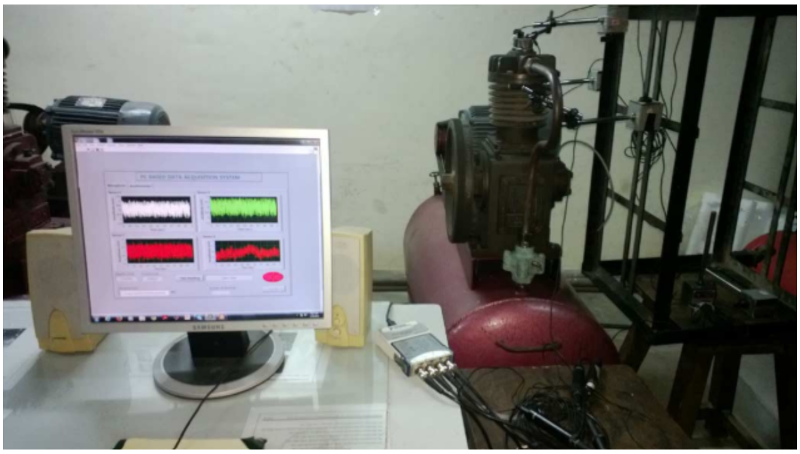


Figure III.7: data acquisition setup.

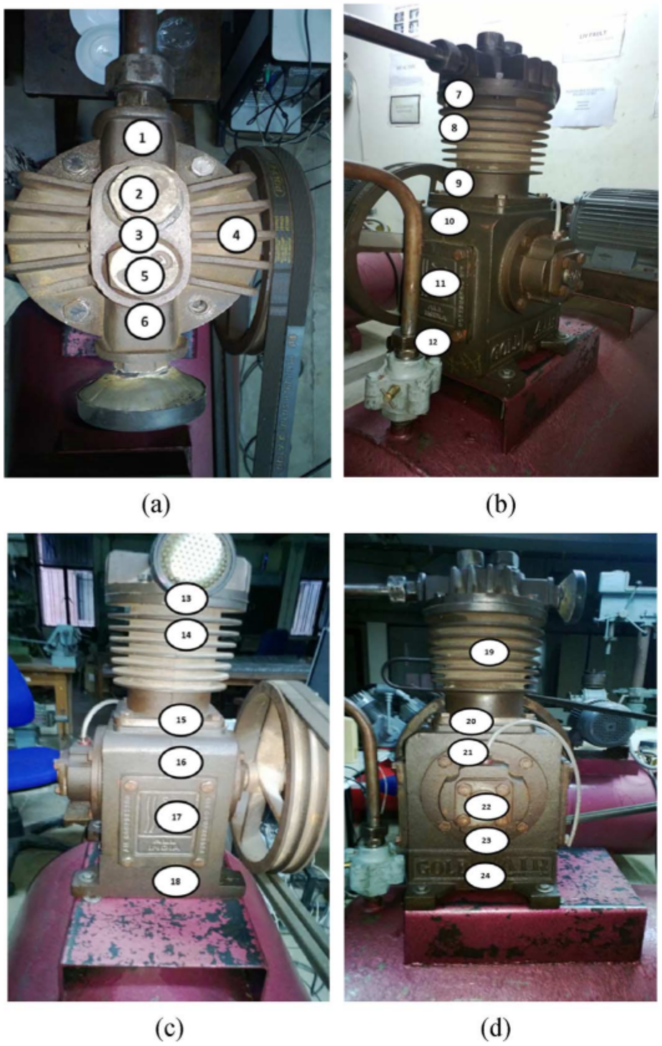


Figure III.8: Positions taken on each side of the air compressor: (a) Top of Piston, (b) NRV side, (c) Opposite NRV side, and (d) Opposite Flywheel side [44].

The microphones used are unidirectional. These microphones pick up less environmental noise. The process of recording from these microphones is done using a single NI 9234 data acquisition (DAQ) hardware unit with multiple ports, an NI-9172 USB interface, and a LabVIEW-based data acquisition interface. The NI 9234 is used to sample the data. The sampled signal is then stored on a computer using NI 9172 and a LabVIEW interface [44].

- **NI 9172:** or cDAQ-9172 is an 8-slot USB Compact DAQ chassis, designed for creating small and portable sensor measurement systems.
  - USB connectivity: It simplifies connection to a computer using a standard USB interface.
  - Plug-and-play functionality: Easy connection of various sensors and elec-

trical measurement devices.

- Timing and synchronization control: Manages timing, synchronization, and data transfer between C Series I/O modules and the computer.

Figure III.9: NI-cDAQ-9172.

- **LabVIEW:** is a graphical programming environment simplifies data acquisition by offering drag-and-drop tools for hardware configuration, real-time data visualization, and basic analysis

  - Graphical Programming: LabVIEW's intuitive approach replaces traditional text-based coding with drag-and-drop blocks.
  - Instrument Connectivity: It seamlessly connects to various instruments, regardless of manufacturer, simplifying data acquisition from diverse test equipment.
  - Integrated User Interfaces: LabVIEW allows for building user interfaces directly within the program, creating a cohesive test system environment.

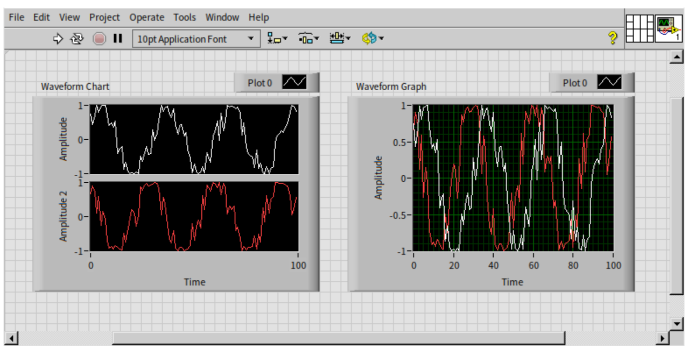


Figure III.10: labview waveform graphical interface.

III.2.2.2 Raw Data Description

Acoustic recordings were taken from the single stage reciprocating type air compressor in 8 different designated states. These 8 states include a healthy state, and 7 faulty states:

a) **Healthy** is the state where the air compressor is healthy, and is free from all faults.

b) **LIV fault** is the state that occurs when the inlet valve of the air compressor is damaged. Hence, while the piston compresses the air, the air accordingly leaks through the inlet valve.

c) **LOV fault** is the state that occurs when the outlet valve of the air compressor is damaged.

d) **NRV fault** is the state that occurs when the non-return valve of the air compressor is damaged, which creates air leakage from the tank. The leaked air puts an additional load on the air compressor; hence, this fault can be especially dangerous while the air compressor runs.

e) **Piston ring fault** is the state that occurs due to loosening of the piston ring on the piston head, which results in leakage of air in the compressor.

f) **Flywheel fault** is the state in which wear on the flywheel causes a flywheel fault.

g) **Rider-belt fault** is the state that occurs when the Rider-belt is not properly aligned with the pulley.

h) **Bearing fault** is the state due to cracks in bearings.

each signal is recorded over 3.125 sec with 16kHz sampling frequency and saved as .wav file with 50k samples. A total of 225 recordings were collected for each of 8 categories, for all compressor states giving a total of 1800 recordings. The acoustic recordings were taken while the air compressor operated within a pressure range of 10 to 150 PSI [44].

III.2.2.3 Data Visualization

The following figures from Fig III.11 to Fig III.18 display the time domain and power FFT of a signal from each category.

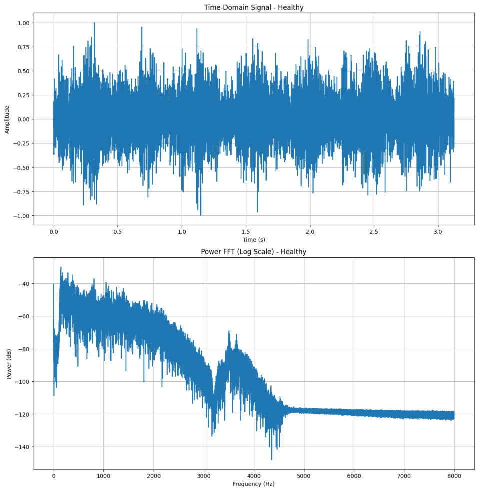


Figure III.11: healthy

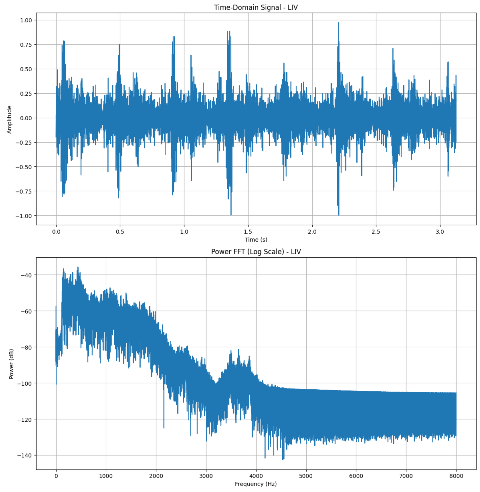


Figure III.12: LIV

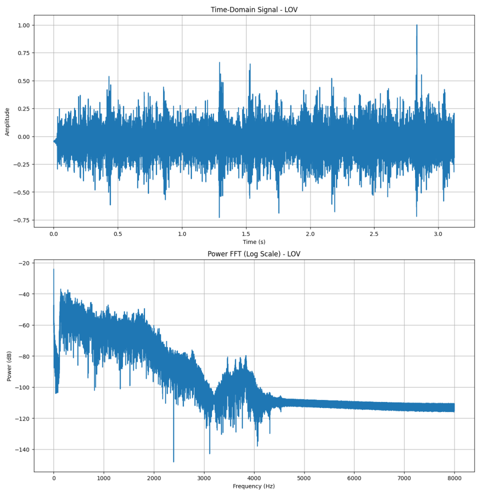


Figure III.13: LOV

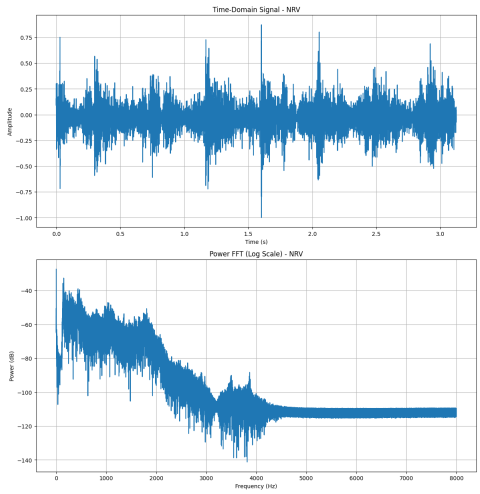


Figure III.14: NRV

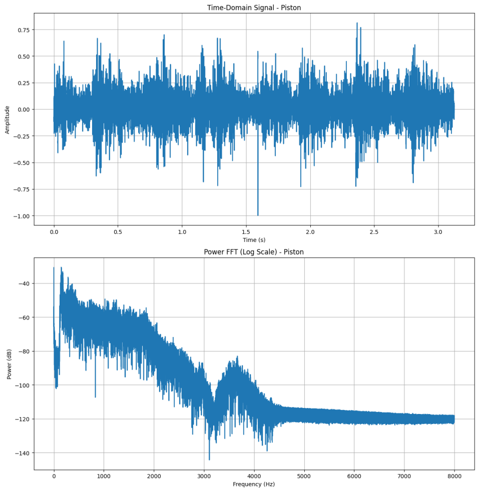


Figure III.15: Piston

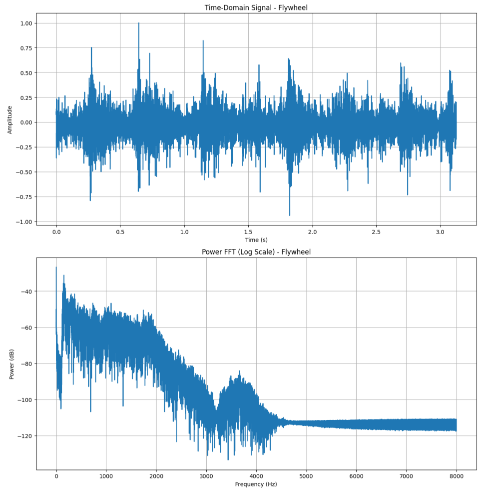


Figure III.16: Flywheel

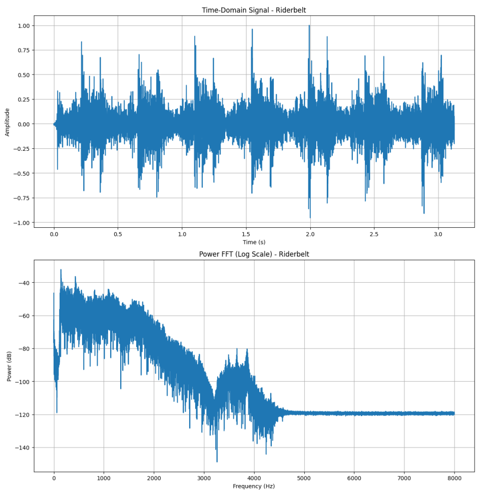


Figure III.17: Rider-belt

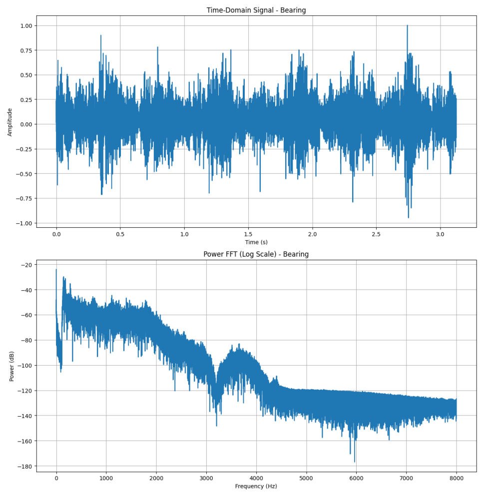


Figure III.18: Bearing

The time-domain signals show fluctuations in amplitude over time, with no clear distinguishable patterns that the human can identify the faults. from the power FFT side, it exhibits a similar overall shape with a broad distribution of power across frequencies. The peaks and troughs in the plots are not significantly distinct enough for a human observer to easily differentiate between the states. the general trend shows a decrease in power with increasing frequency, with some variations in the power levels at certain frequencies. The plots indicate that it is challenging for humans to visually distinguish between the healthy state and the various faulty states, a data-driven approach using machine learning models is essential. Machine learning algorithms can analyze and detect patterns within the data more effectively than human observation, allowing for accurate detection and classification of faults.

III.3 Preprocessing

This section will delve into the preprocessing techniques utilized to obtain a model matrix for the classification model, starting from the decomposition of each signal using MODWPT and EMD. Then, the features extracted from each IMF obtained.

III.3.1 Signal Decompositon

Decomposing the signal is highly effective in signal processing, particularly for FDD, as it emphasizes localized time-frequency information as it identifies and analyzes the underlying patterns and characteristics that are not easily discernible in the raw signal. in this study, we tested two decomposition techniques EMD and MODWPT.

Each signal from each class is decomposed to 10 IMFs using EMD and to 16 IMFs using MODWPT. the comparison between the two decomposition techniques is analyzed in the fourth chapter.

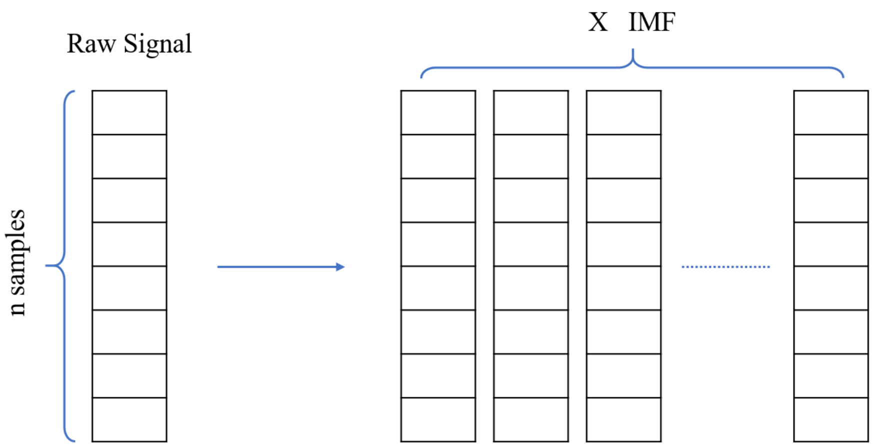


Figure III.19: Decomposing each signal to IMFs

III.3.2 Feature Extraction

After decomposing each signal into Intrinsic Mode Functions (IMFs), the following statistical features are extracted from each IMF. This process enhances the understanding of the characteristics of each IMF, helps in emphasizing the informative parts of the IMFs, minimizes the impact of noise of the original signal, enabling machine learning algorithms to detect patterns associated with specific faults and improve the model's performance and reliability.

- **Root Mean Square (RMS):** Depicts the IMF's average energy content. Changes in RMS over different IMFs can indicate variations in the machine's operating conditions.

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{III.1}$$

- x_i: sample values of the signal.

- N: The total number of samples in the signal.

- **Max-to-RMS Ratio:** Compares the peak amplitude of the IMF to its overall energy level (RMS). A high ratio might suggest impulsive events.

$$\text{Max-to-RMS} = \frac{\max(x)}{\text{RMS}} \tag{III.2}$$

- **Peak-to-Peak Value:** Indicates the variation in the IMF's amplitude values from maximum to minimum

$$\text{Peak-to-Peak} = \max(x) - \min(x) \tag{III.3}$$

- **Skewness:** Measures the asymmetry of the probability distribution of the signal.

$$\text{Skewness} = \frac{E[(x-\bar{\mu})^3]}{s^3} \tag{III.4}$$

-x: Sample values of the signal.

- μ: Mean (average) of the signal.

- σ: Standard deviation of the signal.

- $E[(x-\mu)^3]$: Expected value (or mean) of the cubed deviations from the mean.

- **Kurtosis:** Measures the "tailedness" of the probability distribution of the signal.

$$\text{Kurtosis} = \frac{E[(x-\mu)^4]}{\sigma^4} \tag{III.5}$$

- $E[(x-\mu)^4]$: Expected value (or mean) of the fourth power of deviations from the mean.

- **Entropy:** Measures the randomness or complexity of the signal.

$$\text{Entropy} = -\sum p(x)\log p(x) \tag{III.6}$$

- $p(x)$: Probability distribution of the signal's values.

- **Mean:** Average value of the signal.

$$\text{Mean} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{III.7}$$

- **Standard Deviation:** Measures the amount of variation or dispersion of the signal.

$$\text{Standard Deviation} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{X})^2} \tag{III.8}$$

- **Variance:** Measures the spread of the signal values.

$$\text{Variance} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{X})^2 \tag{III.9}$$

- **Peak-to-RMS Ratio (Alternate):** Another measure of the peak value relative to the RMS value.

$$\text{Peak-to-RMS} = \frac{\max(x)}{\text{RMS}} \tag{III.10}$$

- **Root Sum of Squares (RSSQ):** Sum of the squares of the values, square rooted. Similar to RMS but summed before taking the root.

$$\text{RSSQ} = \sqrt{\sum_{i=1}^{N} x_i^2} \tag{III.11}$$

- **Maximum Value:** Maximum value of the signal.

$$\text{Max} = \max(x) \tag{III.12}$$

- **Minimum Value:** Minimum value of the signal.

$$\text{Min} = \min(x) \tag{III.13}$$

The features selected for fault diagnosis were chosen based on previous research on fault diagnosis using acoustic signals and vibration signals [45, 46].

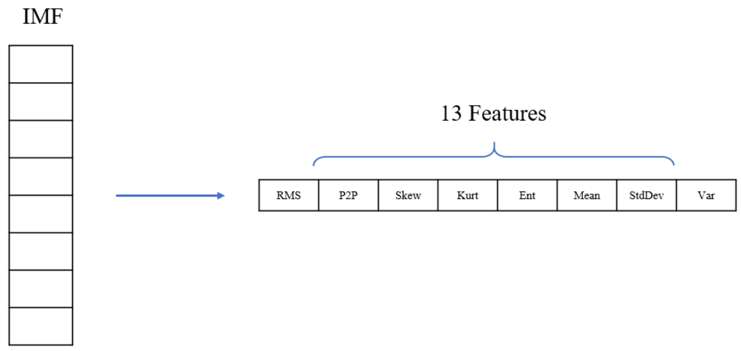


Figure III.20: extracting features from each IMF

III.3.3 Data Arrangement

For the data arrangement, the following structure is applied: each dataset consists of n classes (e.g., the air compressor dataset contains 8 classes). Each class comprises m acoustic signals. Each signal is decomposed into X Intrinsic Mode Functions (IMFs), and 13 features are extracted from each IMF. The labeling vector is filled with the class number corresponding to each signal.

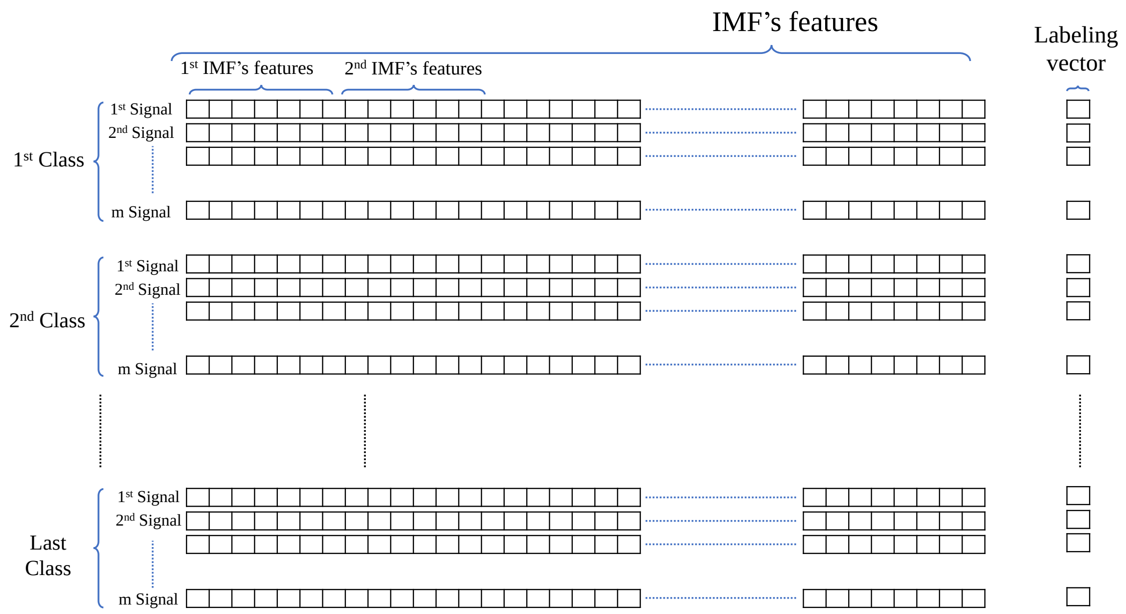


Figure III.21: Model matrix

III.3.4 Data Splitting

The Data was randomly split into train and test sets, with ratios of 80% and 20% respectively. Applying 5 fold cross validation essential for assessing the generalization of a model by training and validating it on multiple subsets of the data, thereby mitigating the risk of overfitting.

Table III.2: Data Splitting

Dataset	Class	Train 80%	Test 20%
MAFAULDA	Normal	39	10
	Imbalance	158	39
	Horizontal parallel misalignment	267	66
	Vertical parallel misalignment	161	40
	Underhang Bearing	446	112
	Overhang Bearing	410	103
Air Compressor	Healthy	180	45
	LIV	180	45
	LOV	180	45
	NRV	180	45
	Piston Ring	180	45
	Flywheel	180	45
	Rider-Belt	180	45
	Bearing	180	45

III.4 Algorithms and Hyperparameters

III.4.1 Support Vector Machine

SVM is a machine learning algorithm used for classification, regression, and outlier detection tasks. It aims to fit an optimal separating hyperplane (OSH) between classes. OSH is strategically placed such that it focuses on the samples that lie at the boundaries of the class distributions; these data points are called support vectors[47].

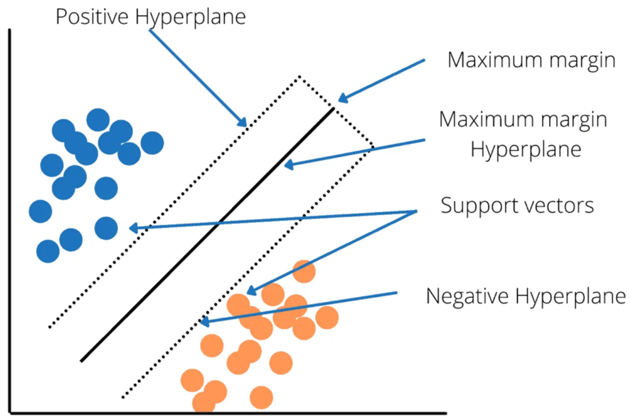


Figure III.22: Data separation in SVM [48].

The SVM formulation aims to solve optimization problem, with a general equation being:

$$\min \left[\frac{\|\boldsymbol{w}\|^2}{2} + C \sum_{i=1}^{r} \xi_i \right] \tag{III.14}$$

Under the constraints of :

$$\boldsymbol{y}\left(\boldsymbol{w} \cdot \boldsymbol{x}_i + \boldsymbol{b}\right) > 1 - \xi_i. \tag{III.15}$$

Where:

- $\boldsymbol{w}$ is the weighted vector that makes the decision boundary.
- $\boldsymbol{C}$ is a parameter in SVM that helps control the trade-off between the training error and the margin
- $\boldsymbol{\xi}$ is the slack variable for linearly separable classes.
- $\boldsymbol{xi}$ is an input vector (training example) that corresponds to a label $\boldsymbol{yi}$.
- $\boldsymbol{b}$ is the bias term.

The Support Vector Machines can vary to two different types:

- **Linear SVM :** If the data is linearly separable,i.e: the data can be classified into different classes using a simple straight line, then Linear SVM is recommended for usage.

- **Non-Linear SVM :** If the dataset cannot be separated into different classes, thus it is a non linearly separable. Then, one should use Non-Linear SVM.

One of the main advantages of SVM is that since SVM only needs support vectors in the establishment of the decision surface, unlike other classifiers. Therefore, a small sample size dataset is sufficient to make get good classification results [47]. Also, it has very excellent capability of dealing with high dimensional data and non-linearly separable datasets.

III.4.2 K-Nearest Neighbors (KNN)

K-NN is a machine learning algorithm that determines the class of a certain training data point. The prediction approach of this technique is known as the majority rule, which is done by identifying K objects in the training set that are the closest to the unclassified data point. Then, according to the predominant class, a label is assigned to this data point. K-NN is a flexible classification approach, it handle various datasets since it does not need to make any assumption about the data. Also, the error rate of a K-NN algorithm tends towards being very minor [49].

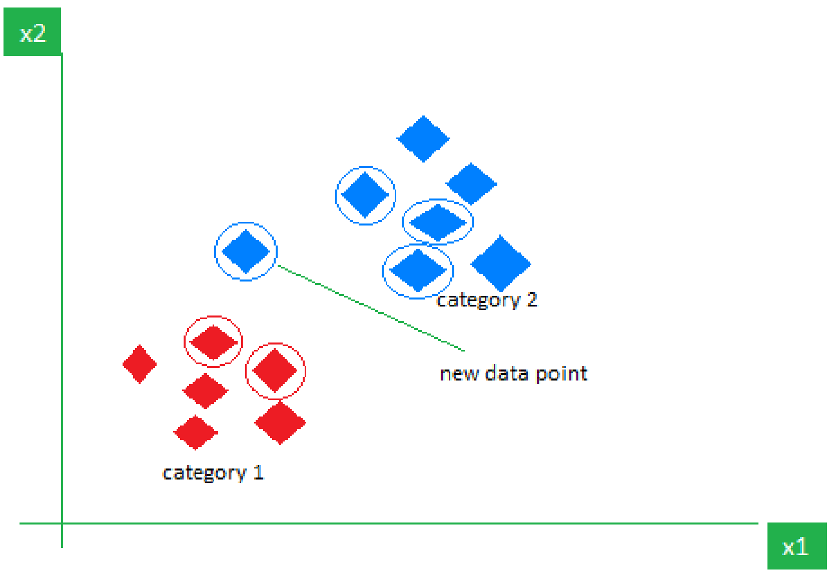


Figure III.23: KNN Algorithm working visualization [50].

The distance metrics used in K-NN are various, some of which include:

- **Eucledean distance :** in simple terms it is the length between two points irrespective of their dimensions.

$$\text{distance}(x, X_i) = \sqrt{\sum_{j=1}^{d}(x_j - X_{ij})^2} \tag{III.16}$$

- **Manhattan Distance :** It is used if our interest is the total distance covered rather than the displacement. It sums absolute difference between the coordinates of the points in n-dimensions.

$$d(x, y) = \sum_{i=1}^{n} |x_i - y_i| \tag{III.17}$$

III.4.3 Decision Tree

Decision tree is a flow-chart tree structure, its concept as mentioned in [51] takes as input an object or situation described by a set of properties, and outputs a yes/no decision. Decision trees therefore represent Boolean functions'. Each node in the tree denotes a feature, branches denotes the regulations and leafs denotes the result of the algorithm [52].

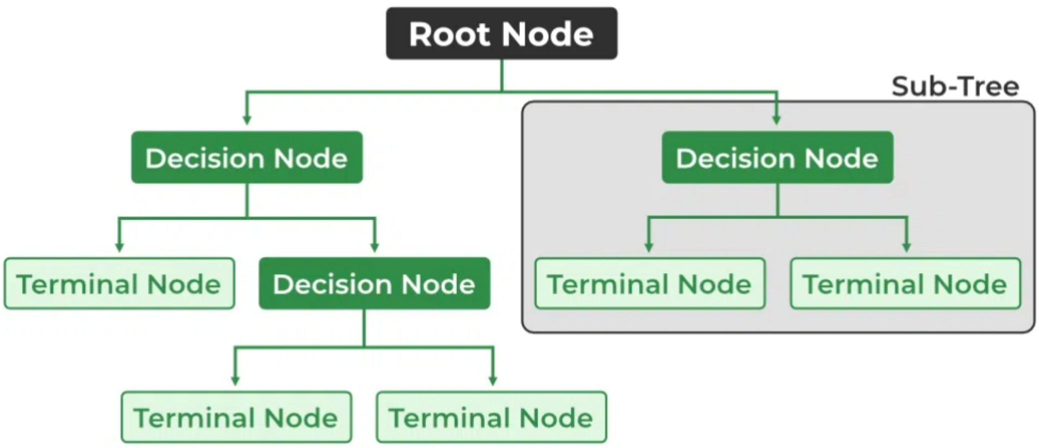


Figure III.24: Decision Tree Flowchart [52].

III.4.4 Ensemble Bag

Ensemble Bag is a machine learning model, which trains multiple decision tree simultaneously. Each tree is built around randomness (random section of data is set to measure a random section of feature). The final prediction is typically the average or majority vote of the predictions made by individual trees. It is widely known for their ability to handle complex data and reduce overfitting [53].

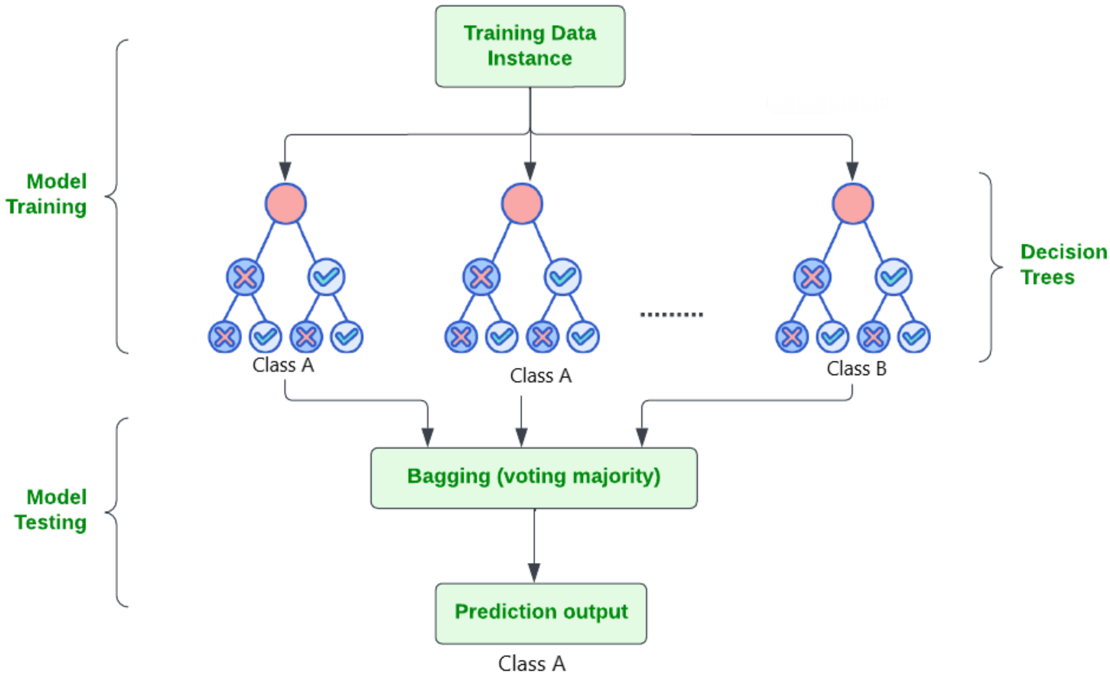


Figure III.25: Ensemble Bag Flowchart[53].

III.4.5 MATLAB Classification Learner App

Classification Learner is a tool that helps you with supervised machine learning tasks for classification problems. It give you access to explore data, select features, determine validation schemes, train numerous models, and evaluate their performance. Also, there is an option that allows for automated training, which aids in finding the optimized models [54].

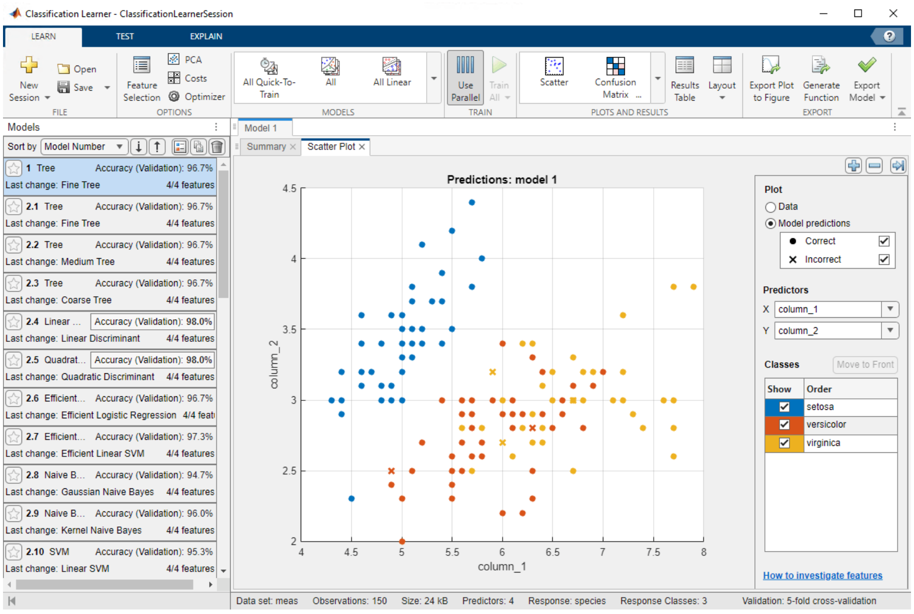


Figure III.26: MATLAB's Classification Learner App

III.5 Hyperparameters Tuning

Hyperparameters tuning is a critical step in achieving the best model for the model. The Classification Learner app provides algorithms that facilitate the optimization of the models' configurations.

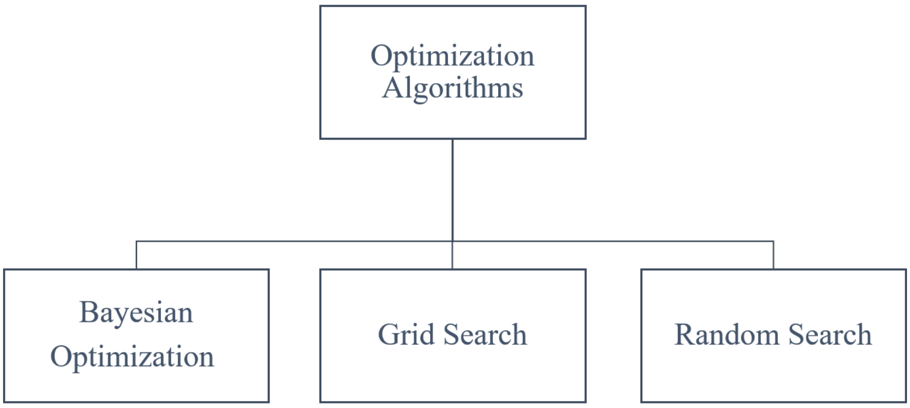


Figure III.27: Optimization Algorithms provided by The Classification App.

The optimized hyperparameters selected for the Air Compressor dataset, for both decomposition techniques are provided in Table III.3.

Table III.3: The Optimized hyperparameters for the Air Compressor's Dataset.

	Classifier	**Optimized Hyperparameters Obtained**
EMD	Decision Tree	Maximum number of splits: 458, Split criterion: Maximum deviance reduction
	SVM	Box constraint level: 447.8129, kernel: Linear, Kernel Scale: auto, Standardize data: true, Multiclass coding: One-vs-One
	KNN	Number of neighbors: 17, Distance metric: Cosine, Distance weight: Squared Inverse, Standarize data: no
	Ensemble Bag	Number of learners: 261, Maximum number of splits: 1274, Number of Predictors to sample: 81
MODWPT	Decision Tree	Maximum number of splits: 124, Split criterion: Maximum deviance reduction
	SVM	Box constraint level: 998.9011, kernel: Linear, Kernel Scale: auto, Standardize data: true, Multiclass coding: One-vs-All
	KNN	Number of neighbors: 1, Distance metric: Correlation, Distance weight: Inverse, Standarize data; true
	Ensemble Bag	Number of learners: 440, Maximum number of splits: 1221, Number of Predictors to sample: 56

The optimized hyperparameters selected for the MAFAULDA dataset, for both decomposition techniques are provided in Table III.4.

Table III.4: The Optimized hyperparameters for MAFAULDA's Dataset.

	Classifier	Optimized Hyperparameters Obtained
EMD	Decision Tree	Maximum number of splits: 95, Split criterion: Maximum deviance reduction
	SVM	Kernel function: Linear, Box constraint level: 35.9494, Kernel Scale: auto, Standardize data: false, Multiclass coding: One-vs-All
	KNN	Number of neighbors: 1, Distance metric: City block, Distance weight: Squared Inverse, Standarize data: false
	Ensemble Bag	Number of learners: 256, Maximum number of splits: 1406, Number of Predictors to sample: 36
MODWPT	Decision Tree	Maximum number of splits=58, Split criterion=Twoing rule
	SVM	kernel function: Linear, Box constraint level =996.8985, , Multiclass coding= One-vs-All, Standardize data=false
	KNN	neighbors=7, Distance metric=correlation, Distance weight=Squared inverse, Standardize data=true
	Ensemble Bag	Number of learners=355, Maximum number of splits=110, Number of Predictors to sample = 84

III.6 Conclusion

In conclusion, this chapter outlines the methodology for building a fault diagnosis classification model, initiating with understanding the data and selecting the best hyperparameters.

Firstly, the datasets of the air compressor and MAFAULDA were discussed, starting with description and visualization, concluding on the limitations of the classical approach to fault diagnosis and the need to introduce the data-driven approach using machine learning combined with signal preprocessing in order to obtain an improved model that can capture complex patterns and accurately diagnose anomalies.

Next, we delved into signal preprocessing. This includes Empirical Mode Decomposition (EMD) and Maximal Overlap Discrete Wavelet Packet Transform (MODWPT) signal decomposition, which emphasize localized time-frequency information and identify underlying patterns that are not easily detectable in the raw signal. Then feature extraction to identify the informative insight of the signal and the data arrangement for the machine learning models.

Furthermore, we emphasized the implementation of several classification models using the Classification Learner Toolbox including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, Ensemble Bag, and Extra Tree classifiers. Ending the chapter with hyperparameter tuning helps the models achieve the best possible accuracy.

Chapter IV

Results & Discussion

IV.1 Introduction

This chapter presents the study's results, evaluating and analyzing the model's performances and outcomes. Several fault diagnosis metrics are investigated in order to examine the accuracy of the techniques implemented in the study. Also, this evaluation includes a comparison with previous research findings. After that, an evaluation of the model on real world scenarios through noise test is implemented. All of these aspects combined provides a comprehensive study on the model, giving us a deep understanding of the model's strength and weaknesseses in the context of fault diagnosis.

IV.2 Model Performance Evaluation

The dataset is split into a training set and a test set. The model is then trained, tested, and evaluated. The chosen classifiers consist of SVM, KNN, Decision Tree, and Ensemble Bag. The evaluation process is done by choosing metrics aligned with the specific goals of our applications. In the case of fault diagnosis, specific metrics are selected.

- **Accuracy:** The ratio of correctly predicted samples to the total samples in the dataset
$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{IV.1}$$

- **Precision:** Measures the accuracy of the positive predictions made by the model. It is the ratio of true positive predictions to the total predicted positives.
$$\text{Precision} = \frac{TP}{TP + FP} \tag{IV.2}$$

- **Recall:** (Or Sensitivity) is the proportion of true positives to the total actual positives. It measures the ability to capture all positive samples.
$$\text{Recall} = \frac{TP}{TP + FN} \tag{IV.3}$$

- **F1-Score:** The harmonic mean of Precision and Recall, provides a single metric that balances the trade-off between Precision and Recall. It is useful for imbalanced datasets.
$$F1 - \text{ score } = \frac{2 \times \text{ Precision } \times \text{ Recall}}{\text{Precision } + \text{ Recall}} \tag{IV.4}$$

TP,TN,FP and FN are respectively the true positives, the true negatives, the false positives and false negatives data samples.

IV.2.1 Performance Metrics

The results of the metrics are summarized in Table IV.1.

Table IV.1: Performance Evaluation Metrics

Dataset	Decomposition	Classifier	Accuracy	Precision	Recall	F1 Score
MAFAULDA	MODWPT	Linear SVM	**98.92**	**98,96**	**98,84**	**98,92**
		KNN	93.05	93.74	90.82	89.73
		Decision Tree	92.70	89.39	90,61	89.18
		Ensemble Bag	97.30	97.41	96.46	96.41
	EMD	Linear SVM	**98.92**	**98.91**	**97.89**	**98.31**
		KNN	97.03	94.92	93.94	94.72
		Decision Tree	90.00	80.05	83.66	82.01
		Ensemble Bag	96.76	97.2	93.10	94.63
AIR COMPRESSOR	MODWPT	Linear SVM	**99.72**	**99.73**	**99.72**	**99.72**
		KNN	88.61	89.04	88.61	88.62
		Decision Tree	85.83	86.52	85.83	85.85
		Ensemble Bag	98.61	98.36	98.6	98.47
	EMD	Linear SVM	**88.89**	89.02	**88.9**	**87.54**
		KNN	54.44	54.5	54.5	54.7
		Decision Tree	81.39	82.4	81.4	81.6
		Ensemble Bag	88.61	**89.1**	88.6	87.4

For the MAFAULDA dataset, SVM with a linear kernel with both MODWPT and EMD decomposition techniques achieved the highest accuracy of 98.92%. The MODWPT decomposition with linear SVM also yielded the best precision (98.96%), recall (98.84%), and F1 score (98.92%). Ensemble Bag demonstrated close results with accuracy of 97.30%, KNN and Decision Tree under mMODWPT decomposition exibited slightly lower accuracies, with 93.05% and 92.70%, respectively. However, under EMD decomposition, KNN showed an increase in accuracy of 97.03%, yielding better results than Ensemble Bag with 96.76%.

For the Air Compressor Dataset, SVM with a linear kernel demonstrated higher results across all metrics under MODWPT decomposition, with an accuracy of 99.72%. Assembly Bag is a close second (98.61% accuracy). Under EMD decomposition, linear SVM showed reliable results in all metrics, with only Ensembla Bag having superior precision (89.1%), while KNN experienced a significant drop. The decision tree classifier exhibited relatively lower performance compared to MODWPT decomposition.

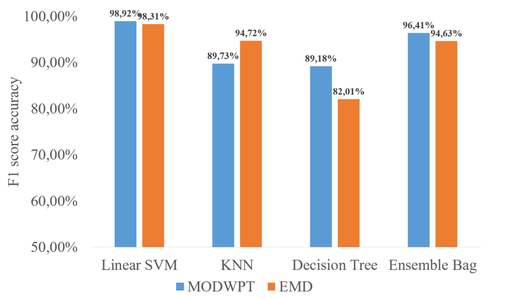


Figure IV.1: Air compressor - MODWPT-EMD comparison.

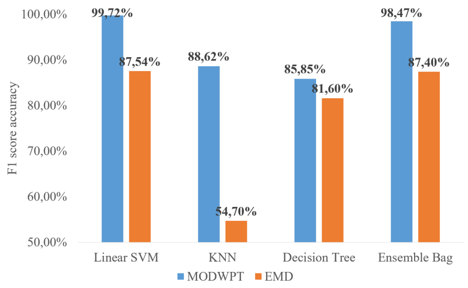


Figure IV.2: MAFAULDA - MODWPT-EMD comparision.

Based on the findings for both datasets, it is evident that the combination of MODWPT decomposition and linear SVM consistently outperformed other classifiers, implying its capability to accurately classify faulty samples and detect healthy samples. The remaining three methods demonstrated slightly lower results compared to linear SVM, but they still performed fairly well across all metrics.

IV.2.2 Prediction Speed

For real-world fault diagnosis, it is essential for fast predictions, which enable the early detection of faults. Table IV.2 compares the classifiers used in terms of their capacity to process a high number of observations per second.

Table IV.2: Models' Prediction Speed.

Classifier	Prediction speed (obs/sec)	
	Mafaulda	Air compressor
Linear SVM	**20000**	14000
KNN	3300	2300
Decision Tree	11000	**15000**
Ensemble Bag	970	900

In the case of the MAFAULDA dataset, it is shown that SVM has the highest prediction speed with 20000 (obs/sec), followed by Decision Tree with 11000 (obs/sec). KNN showcased a prediction speed of 3300 (obs/sec), while Ensemble Bag is the slowest with 970 (obs/sec). However, in the case of the air compressor dataset, Decision Tree was the classifier with the highest prediction speed with 15000 (obs/sec), followed closely by SVM with 14000 (obs/sec), KNN showcased approximately the same result, and Ensemble Bag is the slowest once again with

900 (obs/sec).

In summary, the table provides valuable insights into the suitability of different classifiers for real-time fault diagnosis, where prediction speed is a critical factor.

IV.2.3 Model Size

For real-world fault diagnosis, effenciency and storage is essential, especially if the working enviroment offers limited storage. Table IV.3 highlights a comparison of the models' compact size.

Table IV.3: Models' compact size.

Classifier	Model size (kB)	
	Air Compressor	Mafaulda
Linear SVM	314	223
KNN	2000	2000
Decision Tree	**62**	**45**
Ensemble Bag	33000	18000

With compact sizes of 62 kB and 45 kB, respectively, Decision Tree is the most storage-efficient model in both datasets. SVM is next, with compact sizes of 314 kB and 223 kB. While Ensemble Bag can be as big as 18 MB and up to 33 MB in size, KNN and Ensemble Bag require more storage. KNN remained consntant at 2 MB in size.

IV.3 Noise Test

Noise testing is a common technique used to evaluate the machine learning model's reliability in noisy conditions. In our study, we simulated a real-world scenario by adding artificial noise to the acoustic data using the noise-to-signal ratio (SNR), ranging from 10 dB to -4 dB. The SNR is calculated using the following formula:

$$\text{SNR} = 10 \log \frac{P_{\text{signal}}}{P_{\text{noise}}} \tag{IV.5}$$

- $P_{\textbf{signal}}$: The power of the original signal.
- $P_{\textbf{noise}}$: The power of the added noise.

The noise is random values generated from a normal distribution with zero mean and unit variance. A high SNR indicates a low noise level added to the signal, whereas a low SNR means that the signal is heavily obscured by added noise.

In our study, we obtained very good model performance results even though we trained the models without any noise handling, which yielded very good results. The reason behind not filtering the noise is based on: first, the complexity of filtering the noise of a signal without knowing the recording environment, and also the risk of filtering or removing valuable signal information from the raw signal. Second, machine learning models have the capability to focus on intrinsic features of the signal that are not obscured by noise, making them effective for classification tasks. Table IV.4 and Table IV.5 illustrates the accuracy of four machine learning models (SVM, KNN, Ensemble, and Decision Tree) at various levels of SNR, on both datasets.

Table IV.4: Air compressor - Noise Test Accuracy (%)

	10 dB	**0 dB**	**-2 dB**	**-4 dB**
SVM	99.72	99.44	95.28	94.86
KNN	81.11	76.94	67.50	65.35
Ensemble Bag	92.78	91.94	84.17	84.44
Decision Tree	84.44	84.44	78.06	73.61

Table IV.5: MAFAULDA - Noise Test Accuracy (%)

	10 dB	**0 dB**	**-2 dB**	**-4 dB**
SVM	98,2	96,97	96,96	93,93
KNN	87,49	76,76	70,7	67,35
Ensemble Bag	92,13	91,84	90,9	87,76
Decision Tree	88,31	82,82	81,63	75,28

Fig IV.3 and Fig IV.4 below shows the accuracy of four machine learning models (SVM, KNN, Ensemble, and Decision Tree) at various levels of signal-to-noise ratio (SNR):

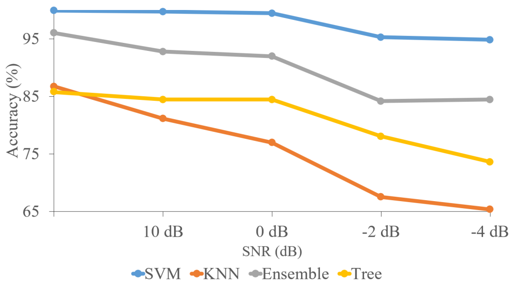


Figure IV.3: Air compressor - Accuracy results under noise test.

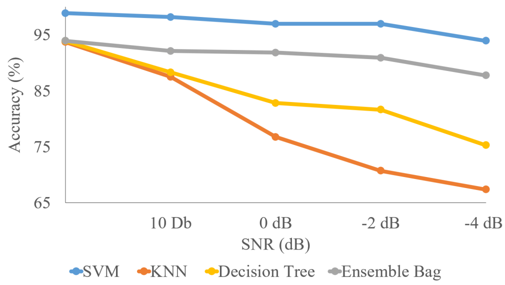


Figure IV.4: MAFAULDA - Accuracy results under noise test.

Histograms from Fig IV.5 and Fig IV.6 below, illustrate how much the accuracy of each model drops on each SNR levels

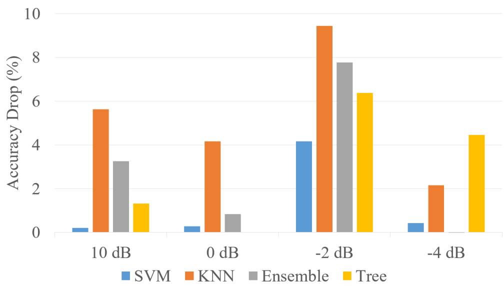


Figure IV.5: Air compressor - Model's Accuracy Drop at Different SNR Levels.

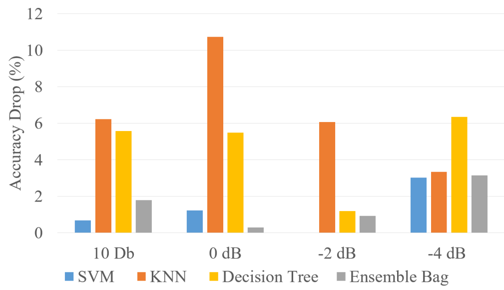


Figure IV.6: MAFAULDA - Model's Accuracy Drop at Different SNR Levels.

Histograms from Fig IV.7 and Fig IV.8 below, illustrate total accuracy of each model drops from no noise added to -4dB

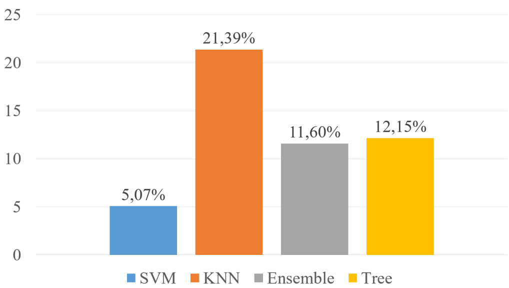


Figure IV.7: Air compressor - Model's Total Accuracy Drop.

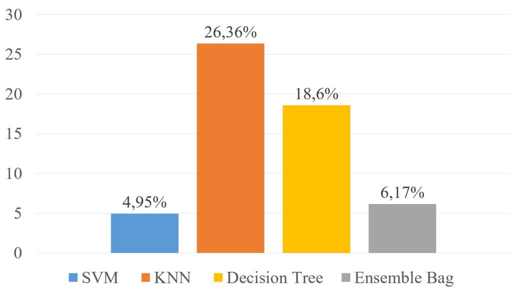


Figure IV.8: MAFAULDA - Model's Total Accuracy Drop.

For both datasets, the results were relatively equal when considering the noise impact. The results demonstrate that classifiers respond differently to the introduced noise in the data. The charts show how the noise levels are affecting the model.

The SVM performance shows a minimal accuracy drop across all noise levels, maintaining above 93% accuracy even at -4 dB, indicating its robustness. On the contrary, the KNN model exhibits significant accuracy drops as noise levels increase, which implies it is the most sensitive model in this study, with a total drop of over 21% from (no noise added) to -4 dB. Both the Ensemble and Decision Tree models display similar total accuracy drops. However, the Ensemble model consistently achieves higher accuracy than the Decision Tree, but the DT shows high resilience to noise up to 0 dB, with only a 1% drop.

Decomposing the signal into multiple IMFs helped in isolating the noise within certain IMFs while allowing the machine learning models to focus on the unobscured IMFs. also, Feature extraction from each IMF and feeding the machine learning model with informative insights is more effective than using the raw signal, which contains noise fluctuations. Additionally, a larger dataset improves model performance by enabling better diagnosis and reducing overfitting, which is a primary concern for data scientists. Overfitting occurs when the model learns to recognize noise patterns rather than the underlying signal. From this test, the robust model between the others is SVM degraded by 5% with -4dB SNR added, we conclude that our model of diagnosing faults using acoustic signals is robust to the introduced noise. The suggested enhancement is augmenting the data with many levels of noise and then training the model with this augmented data. This approach is expected to yield a model with slightly less accuracy but greater robustness.

IV.4 Comparison with Prior Research

Several researchers have invested in the use of artificial intelligence for fault detection and classification, using the same acoustic air compressor dataset.

C.Rahmoune et al. [45]. conducted a study with the premise of enhancing air compressor multi-fault classification using new criteria for the Harris Hawks optimisation algorithm in tandem with MODWPT and the Least Squares SVM (LS-SVM) classifier. While S.Dixit et al. [55] proposed a novel Conditional Auxiliary Classifier Generative Adversarial Network (CACGAN) Framework, which is a data augmentation method, then classified using SVM.

Table IV.6 showcases the results obtained when using the same classifiers.

Table IV.6: Accuracy (%) Comparison with related studies.

Author	SVM	KNN	DT	Ensemble BAG
Our study	**99.72**	**88.61**	85.83	**98.61**
C.Rahmoune et al.	97,81	86,28	**89,02**	97,02

Table IV.7 showcases the proposed models and their respective accuracy.

Table IV.7: Comparison between proposed models.

Author	Proposed Model	Accuracy(%)
Our study	MODWPT-Linear SVM	$\boxed{\textbf{99.72}}$
Rahmoune et al. (2023)	MODWPT-Least Square SVM	99.55
Sonal Dixit et al.(2021)	CACGAN-SVM	98.89

As seen in Table IV.6 above, the resulting accuracies of the common classifier techniques used in our study exibited greater accuracy than the resulting accuracies of C. Rahmoune et al.'s study, except for the Decision Tree classifier, where our study resulted in slightly lower accuracy.

However, as seen in Table IV.7, the C. Rahmoune et al. approach yielded an accuracy of 99.55%, while S. Dixit et al. showcased lower results with an accuracy of 98.89%. In comparison with previous studies, our proposed model showcased superior results, with an accuracy of 99.72%, emphasising the efficacy of our model in diagnosing faults.

IV.5 Conclusion

Our findings demonstrate that the SVM classifier, especially with a linear kernel, achieved the highest accuracy, notably 99.72% for the Air Compressor dataset using MODWPT. Ensemble Bagged Trees also performed well but were slower in prediction speed. Decision Tree showcased its compactness in size. Noise testing showed that SVM maintained relatively high accuracy even at high SNR levels, indicating robustness, while KNN was most sensitive to noise. A comparative analysis with prior research was done, with our proposed model showcasing high resulting accuracy, emphasizing its efficiency in fault diagnosis.

Feature extraction from decomposed signals significantly improved fault diagnosis accuracy. The combined use of EMD, MODWPT, and SVM proved highly effective for fault diagnosis in rotating machinery.

General Conclusion

In conclusion, this thesis's primary objective was to build a data-driven, early-detection fault diagnosis model using acoustic signals as a parameter of condition-based monitoring in order to prevent failures in the industry process that may result in heavy economic losses and unscheduled downtime. This study investigates different preprocessing techniques on two datasets: the rotating machine MAFAULDA and the Air compressor. Time-frequency analysis was used to obtain more underlying patterns in the signal, namely MODWPT and EMD decomposition methods. Also, features were extracted from each IMF to get the signal's informative characteristics. To classify these fault patterns, we employed four machine learning algorithms : Support Vector Machines (SVM), k nearest neighbours (KNN), Decision Trees, Ensemble Bag. The performance of each model was assessed and evaluated using a comparative analysis on significant metrics used to evaluate fault diagnosis models.Additionally , noise testing was conducted.

The results of the analysis revealed that SVM exhibited superior accuracy and outperformed other classifiers in most evaluation metrics, on both datasets and decomposition methods. It demonstrated robustness in a noisy environments, and it exhibited the fastest prediction time. Decision tree demonstrated that it is the most storage-efficient model. MODWPT-based models outperformed EMD-based models, indicating the effectiveness of MODWPT in capturing the underlying information from acoustic signals.

While acoustic signals are generally considered late indicators of faults compared to ultrasonic or vibration signals, the combination of signal preprocessing techniques with machine learning significantly improved their early detection capabilities.

For future improvement, it is better to find the optimal acoustic data acquisition setup that can capture more detailed information. It is also recommended to enhance the model's sensitivity to noise. Additionally, this study could be extended by using deep learning models, given their ability to detect features and patterns of faults without human intervention. Finally, enhancing the model's ability to generalise the diagnosis process using data from many other similar machines.

Bibliography

[1] R. Isermann, *Fault-diagnosis systems: an introduction from fault detection to fault tolerance.* Springer Science & Business Media, 2006.

[2] M. Achouch, M. Dimitrova, K. Ziane, S. S. Karganroudi, R. Dhouib, H. Ibrahim, and M. Adda, "On predictive maintenance in industry 4.0: Overview, models, and challenges," *Applied Sciences*, vol. 12, p. 8081, AUG 2022.

[3] L. Swanson, "Linking maintenance strategies to performance," *International Journal of Production Economics*, vol. 70, pp. 237–244, APR 2001.

[4] N. M. Paz and W. Leigh, "Maintenance scheduling: Issues, results and research needs," *International Journal of Operations amp; Production Management*, vol. 14, pp. 47–69, AUG 1994.

[5] A. K. Jardine, D. Lin, and D. Banjevic, "A review on machinery diagnostics and prognostics implementing condition-based maintenance," *Mechanical Systems and Signal Processing*, vol. 20, pp. 1483–1510, OCT 2006.

[6] G. A. Susto, A. Schirru, S. Pampuri, S. McLoone, and A. Beghi, "Machine learning for predictive maintenance: A multiple classifier approach," *IEEE Transactions on Industrial Informatics*, vol. 11, pp. 812–820, JUN 2015.

[7] A. Grizhnevich, "A comprehensive guide to IoT-based predictive maintenance," 6 2024. [Online]. Available: https://www.scnsoft.com/blog/iot-predictive-maintenance-guide

[8] S. J. Chapman, *Electric Machinery Fundamentals*, 5th ed. New York: McGraw-Hill, 2011.

[9] K. K. Kumar, S. R. Sasikanth, and L. P. Dinesh, "Simulation of sensorless induction motor based on model reference adaptive system (mras)," 2012. [Online]. Available: https://api.semanticscholar.org/CorpusID:6889432

[10] G. Hailu, *Rotating Machinery.* BoD–Books on Demand, 2020.

[11] S. Eagle, "Identify defects in gas turbine rotors," https://www.screeningeagle.com/fr/inspection/identify-defects-in-gas-turbine-rotors, accessed: May 2024.

[12] C. Ly, K. Tom, C. S. Byington, R. Patrick, and G. J. Vachtsevanos, "Fault diagnosis and failure prognosis for engineering systems: A global perspective," in *2009 ieee international conference on automation science and engineering*. IEEE, 2009, pp. 108–115.

[13] A. Althubaiti, F. Elasha, and J. A. Teixeira, "Fault diagnosis and health management of bearings in rotating equipment based on vibration analysis–a review," *Journal of Vibroengineering*, vol. 24, no. 1, pp. 46–74, 2022.

[14] R. Wang, X. Zhan, H. Bai, E. Dong, Z. Cheng, and X. Jia, "A review of fault diagnosis methods for rotating machinery using infrared thermography," *Micromachines*, vol. 13, no. 10, 2022.

[15] N. Mackos, M. Baybutt, C. A. Palmer, and J. D. Tario, "Providing embedded, in-situ oil quality monitoring for improved maintenance and on-board diagnostics in trucking and automotive applications," *SAE International Journal of Commercial Vehicles*, vol. 1, no. 2008-01-2614, pp. 260–267, 2008.

[16] Z. Liu, Y. Liu, H. Zuo, H. Wang, and H. Fei, "A lubricating oil condition monitoring system based on wear particle kinematic analysis in microfluid for intelligent aeroengine," *Micromachines*, vol. 12, no. 7, 2021.

[17] S. Jagers. (29/04/2020) Samotics, acoustic emission analysis (everything you need to know). [Online]. Available: https://samotics.com/blog/acoustic-emission-analysis

[18] L. Ai, S. Flowers, T. Mesaric, B. Henderson, S. Houck, and P. Ziehl, "Acoustic emission-based detection of impacts on thermoplastic aircraft control surfaces: A preliminary study," *Applied Sciences*, vol. 13, no. 11, 2023.

[19] Artesis. (April 25, 2021) Motor current signature analysis. [Online]. Available: https://www.artesis.com/motor-current-signature-analysis/

[20] Sensemore, "Motor current signature analysis (mcsa) for predictive maintenance," 2024, accessed: June 2024. [Online]. Available: https://sensemore.io/motor-current-signature-analysis-mcsa-for-predictive-maintenance/

[21] V. G. Cook, "Acoustic monitoring of machine tool health using transmitted sound," in *Proceedings of the 2012 International Conference on Industrial Engineering and Operations Management, Istanbul*, 2012, pp. 1831–1839.

[22] Y. H. Ali, R. A. Rahman, and R. I. R. Hamzah, "Acoustic emission signal analysis and artificial intelligence techniques in machine condition monitoring and fault diagnosis: A review," *Jurnal Teknologi*, vol. 69, p. Not available, JUN 2014.

[23] J. Coady, D. Toal, T. Newe, and G. Dooly, "Remote acoustic analysis for tool condition monitoring," *Procedia Manufacturing*, vol. 38, pp. 840–847, 2019.

[24] G. Jombo and Y. Zhang, "Acoustic-based machine condition monitoring—methods and challenges," *Eng*, vol. 4, no. 1, pp. 47–79, 2023.

[25] A. K. S. Jardine, D. Lin, D. Banjevic, N. Haddaway, and D. McKeown, "A review on machinery diagnostics using artificial neural networks," *Mechanical Systems and Signal Processing*, vol. 20, no. 7, pp. 1483–1510, 2006.

[26] P. D. McFadden and J. D. Smith, "Model for the extraction of characteristic acoustic signals from noisy rotating machinery data," *Transactions of the ASME. Journal of Vibration and Acoustics*, vol. 106, no. 3, pp. 276–282, 1984.

[27] C. Scheer, W. Reimche, and F. Bach, "Early fault detection at gear units by acoustic emission and wavelet analysis," https://www.ndt.net/?id=13345, 2012, accessed: May 2024.

[28] F. Alharbi, S. Luo, H. Zhang, K. Shaukat, G. Yang, C. A. Wheeler, and Z. Chen, "A brief review of acoustic and vibration signal-based fault detection for belt conveyor idlers using machine learning models," *Sensors*, vol. 23, no. 4, p. 1902, 2023.

[29] S. Misra, S. Kumar, S. Sayyad, A. Bongale, P. Jadhav, K. Kotecha, A. Abraham, and L. A. Gabralla, "Fault detection in induction motor using time domain and spectral imaging-based transfer learning approach on vibration data," *Sensors (Basel)*, vol. 22, no. 21, p. 8210, Oct 2022, pMID: 36365909; PMCID: PMC9655596.

[30] mathivananshivam- GeeksforGeeks. (2024, Feb.) Power spectral density. GeeksforGeeks. [Online]. Available: https://www.geeksforgeeks.org/power-spectral-density/#what-is-power-spectral-density-psd

[31] Z. Han, X. Zhang, B. Yan *et al.*, "The time-frequency analysis of the acoustic signal produced in underwater discharges based on variational mode decomposition and hilbert–huang transform," *Sci Rep*, vol. 13, p. 22, 2023.

[32] A. Maverick, "What is empirical mode decomposition - ai maverick - medium." [Online]. Available: https://samanemami.medium.com/what-is-empirical-mode-decomposition-3ec89115db6b

[33] S. Gopalakrishnan, "Decomposing signal using empirical mode decomposition: Algorithm explanation for dummy," Towards Data Science, 2019, accessed: 2024-06-12. [Online]. Available: https://bit.ly/3cgT8pq

[34] N. H. M. M. Shrifan, M. F. Akbar, and N. A. M. Isa, "Maximal overlap discrete wavelet-packet transform aided microwave nondestructive testing," *NDT & E International*, vol. 119, p. 102414, 2021.

[35] DataCamp, "A data scientist's guide to signal processing," https://www.datacamp.com/tutorial/a-data-scientists-guide-to-signal-processing, 2023, accessed: May 2024.

[36] J. Zakaria. (2024, 02) A step-by-step explanation of principal component analysis (pca). https://builtin.com/data-science/step-step-explanation-principal-component-analysis. Accessed: [May 2024].

[37] H. Abdi and L. J. Williams, "Principal component analysis," *Wiley interdisciplinary reviews. Computational statistics*, vol. 2, no. 4, pp. 433–459, 7 2010.

[38] BioRender, "Principal component analysis (pca) transformation," 2024, accessed: May 2024. [Online]. Available: https://www.biorender.com/template/principal-component-analysis-pca-transformation

[39] A. M. Iesc. (2018, 04) Artificial intelligence, machine learning, and deep learning: Same context, different concepts - master intelligence economique et stratégies compétitives. https://bit.ly/3WEQZDD. Accessed: [May 2024].

[40] GeeksforGeeks, "An introduction to Machine Learning," 7 2023. [Online]. Available: https://www.geeksforgeeks.org/introduction-machine-learning/

[41] "Introduction to deep learning," 4 2023. [Online]. Available: https://www.geeksforgeeks.org/introduction-deep-learning/

[42] F. Ribeiro, "Mafaulda machinery fault database," Online, 2023, available: https://www02.smt.ufrj.br/~offshore/mfs/page_01.html, Accessed March 2024.

[43] Shure, "Shure sm81," 2024, accessed: May 2024. [Online]. Available: https://www.shure.com/en-US/products/microphones/sm81?variant=SM81-LC

[44] N. K. Verma, R. K. Sevakula, S. Dixit, and A. Salour, "Intelligent condition based monitoring using acoustic signals for air compressors," *IEEE transactions on reliability*, vol. 65, no. 1, pp. 291–309, 3 2016.

[45] C. Rahmoune, M. A. Sahraoui, F. Gougam, M. Zair, and I. Meddour, "Enhancing air compressors multi fault classification using new criteria for harris hawks optimization algorithm in tandem with modwpt and lssvm classifier," *Advances in Mechanical Engineering*, vol. 15, no. 12, p. 16878132231216208, 2023.

[46] T. Bettahar, R. Chemseddine, and D. Benazzouz, "Faults' Diagnosis of Time-Varying Rotational Speed machinery based on vibration and acoustic signals features extraction, and machine learning methods," *Journal of vibration engineering technologies*, vol. 11, no. 5, pp. 2333–2347, 9 2022.

[47] A. Mathur and G. M. Foody, "Multiclass and binary svm classification: Implications for training and classification users," *IEEE Geoscience and Remote Sensing Letters*, vol. 5, no. 2, pp. 241–245, 2008.

[48] B. Alam, "Svm python easy implementation of svm algorithm," https://hands-on.cloud/svm-python-tutorial/, 01 2022, accessed: May 2024.

[49] S. Zhang, "Challenges in knn classification," *IEEE Transactions on Knowledge and Data Engineering*, vol. 34, no. 10, pp. 4663–4675, 2022.

[50] GeeksforGeeks. (2023) K-nearest neighbours. Accessed: 15 May 2024. [Online]. Available: https://www.geeksforgeeks.org/k-nearest-neighbours/

[51] S. J. Russell and P. Norvig, *Artificial intelligence: a modern approach.* Pearson, 2016.

[52] GeeksforGeeks. (October 2023) Decision tree. Accessed: 15 May 2024. [Online]. Available: https://www.geeksforgeeks.org/decision-tree/?ref=header_search

[53] Geeksforgeeks. (2024,02) random forest. https://bit.ly/3XoT8JQ. Accessed: 15 May 2024.

[54] MathWorks, "Matlab documentation," 2023, accessed: 15 May 2024. [Online]. Available: https://www.mathworks.com/help/stats/classificationlearner-app.html

[55] S. Dixit, N. K. Verma, and A. K. Ghosh, "Intelligent fault diagnosis of rotary machines: Conditional auxiliary classifier gan coupled with meta learning using limited data," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–11, 2021.