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DIAGNOSIS OF FAULTS IN ELECTRO-MECHANICAL DEVICES FROM VIBRATION MEASUREMENTS

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NEAR EAST UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

DEPARTMENT OF MECHANICAL ENGINEERING

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Nicosia

February, 2023

Approval

We certify that we have read the thesis submitted by Binnur Demir Erdem titled **"DIAGNOSIS OF FAULTS IN ELECTRO-MECHANICAL DEVICES FROM VIBRATION MEASUREMENTS"** and that in our combined opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Mechanical Engineering.

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Declaration

I hereby declare that all information, documents, analysis and results in this thesis have been collected and presented according to the academic rules and ethical guidelines of Institute of Graduate Studies, Near East University. I also declare that as required by these rules and conduct, I have fully cited and referenced information and data that are not original to this study.

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Abstract

Diagnosis of Faults in Electro-Mechanical Devices from Vibration Measurements

Demir Erdem, Binnur

MA, Department of Mechanical Engineering

February, 2023, 75 pages

Owing to the fact that, computer and computer-related communication technologies have been developed very rapidly in the last thirty years. Artificial Intelligence which is commonly known as AI is being viewed as a critical component of Industry 4.0. Since its establishment, it has provided several opportunities as well as problems for various businesses. AI is usually defined as an emerging technology that combines both theoretical and practical studies extending human intelligence. Usually, AI involves disciplines such as bioscience, psychology, cognitive science, etc with computer and software engineering.

Since science and technology have been progressing in an enormous continuation, mechanical engineering is also changing from traditional engineering concepts to modern electronic mechanical engineering concepts. With new enhancements and developments, mechanical engineering got into a new stage of enhancement where the combination of artificial intelligence technology and mechanical engineering has become a hotspot.

We frequently see mechanical and electronic engineering's perception of artificial intelligence. This can utilize computers' sophisticated data processing capabilities, solving a variety of complicated problems while also increasing the amount of automation in mechanical and electronic engineering. The main issue with traditional mechanical fault detection is that, because technical circumstances are so difficult and complex, only minor errors can be recognized by machines. As a result, the usage procedure is inconvenient. This tendency demands that equipment fault diagnosis technologies be continuously improved. This research work combines some machine learning algorithms to analyze the rate of diagnosis of faults in Electro-Mechanical devices from vibration measurements. According to the results obtained, the Random Forest algorithm has achieved the highest rate of 88.6%.

Keywords: mechanical engineering, vibrations, faults, artificial intelligence, machine learning.

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List of Abbreviations

TRNC:	Turkish Republic of North Cyprus
MNE:	Ministry of National Education
AI:	Artificial Intelligence
ANN:	Artificial Neural Network
ML:	Machine Learning
SVM:	Support Vector Machines
DT:	Decision Tree
LR:	Logistic Regression
GNB:	Gaussian Naive Bayes
KNN:	k-Nearest Neighbour
GB:	Gradient Boosting
BPNN:	Back Propagation Neural Network
RF:	Random Forest
SL:	Supervised Learning
UL:	Unsupervised Learning
RL:	Reinforcement Learning

CHAPTER I

Introduction

This chapter includes the problems, aims, importance, limitations and related descriptions of the research.

Artificial Intelligence (AI), the magic word, has altered both our personal and professional lives. Because of its potential benefits, AI adoption is being viewed as a critical component of Industry 4.0. Since its establishment, it has provided several opportunities as well as problems to various businesses. As a result, a slew of AI-powered technologies has been developed with the potential to improve the economy while also increasing people's quality of life. (Dhanabalan Thangam, 2018). Artificial Intelligence, to better comprehend the nature of human intelligence and develop a clever machine that can respond to and solve problems in the same way that humans can, artificial intelligence models the process of data interaction in human thinking. AI covers a wide range of additional topics and techniques that enable us to complete our activities faster than humans. Machine learning is a component of AI. It is how the computer trains itself to think for itself.

With the development of science and technology, mechanical engineering is always changing and evolving, from classical mechanical engineering to electronic mechanical engineering. It has also advanced to a new stage of development as a result of continually rising levels of automation and intellectualization, creating a hotspot for the fusion of artificial intelligence technology and mechanical and electrical engineering. (Huang, 2017).

We frequently see mechanical and electrical engineering's perception of artificial intelligence. It can utilize the full computers' significant data processing capabilities, solving a variety of complicated issues while also raising the level of automation in engineering, mechanical and electronic. Furthermore, in the twenty-first century, every nation is working to advance mechanical and electronic engineering, not only to boost productivity but also to encourage the field's development in the intellectualization direction and to advance its networking and adaptability.

Mechanical and electronic engineering, as well as artificial intelligence, have been organically intertwined since the turn of the century.

In the coming decades, it is expected that mechanical and electronic engineering will continue to merge with artificial intelligence (AI). In current history, artificial intelligence (AI) has been used in power systems, which has resulted in enhanced solutions across a wide range of applications.

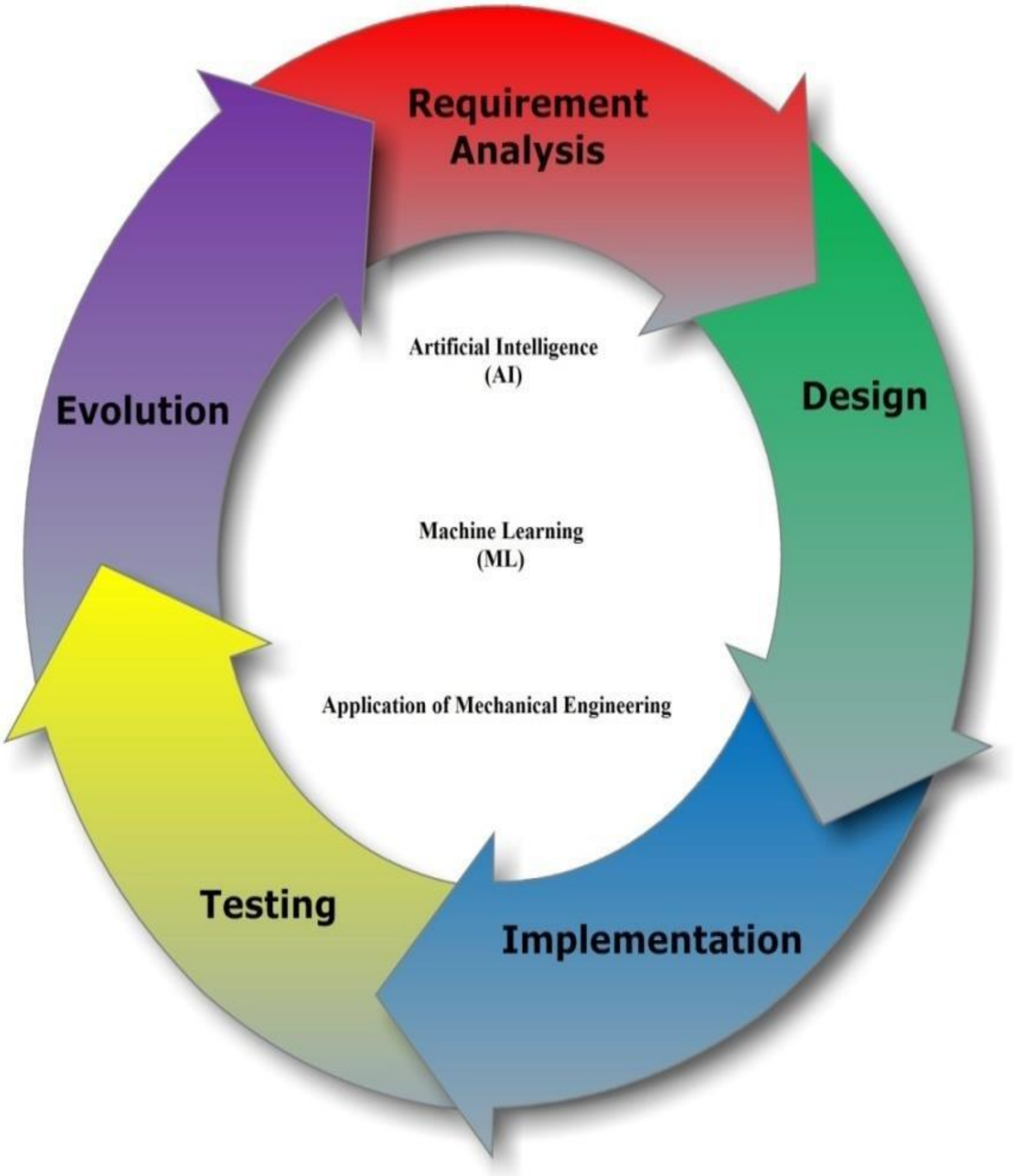
According to Chen et al. (2019), AI approaches have been widely employed in power system transient stability research. They have been identified as the most successful strategies for forecasting post-fault transient stability status using phasor measurement unit data.

More and more emphasis is being given to artificial intelligence in the current age of technology. It has been utilized in robots, control systems, simulation systems, and economic and political decision-making (Tingting,2020). Advances in artificial intelligence (AI) have accelerated the creation and use of autonomous vehicles (AVs) in the transportation industry. AI has become a crucial component of mechanical devices, fueled by huge data from diverse sensing devices and powerful computational resources (Ma, Wang, Yang, & Lin Yang, 2020).

Artificial intelligence, particularly machine learning (ML) algorithms, is quickly becoming a valuable tool in mechanical engineering and materials science, thanks to its capacity to make new materials, predict the properties of current ones, and detect novel, less obvious systems.

Figure 1.1

Application of Mechanical Engineering using ML.



As the structural similarities of unique materials increase, the material design challenge to optimize mechanical behaviors' may include broad design areas that are intractable for current techniques. In response to this obstacle, ML models built from enormous material datasets that integrate structure, features, and functionality at various hierarchical levels have created new possibilities for the rapid exploration of design spaces.

Under the assumption of current industrial automation and ongoing development, modern mechanical equipment is always moving toward automation, modernization, and continuous development. Traditional mechanical equipment has fallen behind in the evolution of modern mechanical equipment. It introduces a slew of new problems into the fault diagnosis system. Furthermore, intelligent technology is a key indicator of the direction and strategy of growth for emerging sectors. It is particularly useful for dealing with circuit integration, cost planning, and circuit troubleshooting. It considerably simplifies traditional mechanical fault diagnostic techniques (Tingting, 2020). With China's ability to manufacture machinery and equipment continually improving, present mechanical equipment is evolving into larger, more advanced, and automated equipment. This development is essential to China's achievement of high efficiency and high quality. The mechanical components are drawing ever closer together. If there is a failure when the equipment is in use, the mechanical equipment will also fail. As a result, mechanical equipment defect detection and processing have become extremely important.

Since conventional mechanical equipment fault processing depends heavily on the work processing skills of maintenance personnel, it is imperative to update the device fault detection method who are ill-equipped to handle the current mechanical equipment (Zhu, 2021).

Machine fault diagnostics is a branch of mechanical engineering that focuses on identifying flaws in machines. Several methods, including thermal imaging, vibration analysis, sound signal analysis, and inspection of oil particles, are used to identify the most prevalent defects that lead to failure. The most popular techniques used when machinery maintenance requires analysis of sound and vibration signals which provide the essential information.

For more accurate classification than decision tree classification, different techniques were used in the machine learning approach for fault classification.

The creation of informative resources for an expert system devoted to troubleshooting electromechanical devices should be automated. These targets will be achieved by the prototype system, which is an architecture based on an integrated deductive research methodology that has been developed and extensively conducted by F. Bergadano (1990).

Any machine with rotating parts will inevitably cause its parts to vibrate in different ways. As long as their amplitude is controlled, these vibrations, which are inevitable during appropriate machine functioning, are safe. When a machine fault happens, new, anomalous vibrations appear along with other manifestations. Predictive maintenance seeks to identify issues (still in the early stages) and assess the severity of those defects by a procedure called mechanalysis, which examines these vibrations. Mechanalysis basically entails performing a Fourier analysis on the vibrations produced accurately on the machine's supporting component parts at pre-set and identified points. The technician measures the global vibration's intensity and speed for each support in the vertical, horizontal, and axial axes using a dedicated analyzer. The technician can get the same data for each harmonic component of the vibrations as well. It is also possible to evaluate the vibration amplitude qualitatively.

Problem Statement

Modern firms use increasingly complex, automated, and up-to-date equipment. Even though the equipment is expensive, if there is a problem, it will not operate well, reducing output effectiveness and resulting in heavy casualties for the firm. The main issue employing conventional mechanical faults is the process of detection because technical circumstances are so difficult and complex, only minor errors can be recognized by machines. As a result, the usage procedure is really inconvenient. This tendency demands that equipment fault diagnosis technologies be continuously improved (Tingting, 2020).

The service life of the equipment will be extended if the problem can be detected and remedied using the equipment promptly. Because of the variety of artificial, it is impossible to collect the most exact technical data, which is currently the major difficulty with traditional mechanical fault diagnostics. This problem is solvable through the use of artificial intelligence technology and prudent budget allocation.

Aims and objectives

- To identify useful AI techniques in mechanical engineering.
- To propose selected ML techniques that may be used in mechanical engineering.
- To utilize ML techniques to detect mechanical faults.
- To test the accuracy of ML techniques in detecting mechanical faults.

Scope of Study

In this study, we will research AI methods in mechanical engineering. The main aim of this study is to employ ML techniques for the classification of mechanical failure analysis. The obtained dataset will be used to analyze the ML techniques.

Methodology

We utilized the NEU library online database to find articles that are related to our work. Most of the literature review in this work has been written by answering the following research questions:

RQ1: What are the mechanical faults that affect mechanical equipment?
RQ2: What is the mechanical equipment impacted by these faults?
RQ3: What mechanical measures were taken to minimize these faults?
RQ4: Were there any AI solutions to support the mechanical measures?

Different engineering problems and processes are becoming smarter through the application of artificial intelligence as the world improves in every way possible.

It is important to assess and comprehend each AI technique's applicability and performance when it is tried in a variety of mechanical engineering applications, including fault detection, autonomous vehicles, manufacturing, smart buildings, etc. Adaboost, BPNN, decision tree, gaussianNB, GBA, KMeans, KNN, logistic regresion, random forest, and support vector machines will be applied to train the dataset.

The dataset used in this investigation came from https://archive.ics.uci.edu/ml/datasets/Mechanical+Analysis.

Expected results

It is expected that at the end of this thesis, we will have:

- identified useful AI techniques in mechanical engineering.
- proposed selected ML techniques that may be used in mechanical engineering.
- utilized selected ML techniques to detect mechanical faults.
- tested the accuracy of ML techniques in detecting mechanical faults, and decided which ML technique is most suitable for detecting mechanical faults.

Machine Fault Diagnosis Analysis

Machinery fault diagnostics is a key technique for stopping the propagation of abnormal occurrences, reducing downtime, estimating residual life, and limiting productivity loss. These, in consequence, can reduce the likelihood of catastrophic system breakdowns.

The essential components of mechanical equipment will eventually develop numerous faults of varying degrees due to difficult and challenging situations like a heavy load, a high temperature, and a rapid speed. demonstrate a few possible problem modes in various transmission system machine components, including wind turbines, hot strip milling production lines, and helicopters. Errors with damaging effects can occur even in sophisticated mechanical systems.

The currently accessible literature includes a broad range of analytical methods, artificial intelligence, statistical methodologies, and four core study areas of machinery fault diagnosis.

These four routes are the four main steps in machine defect diagnosis. Before mechanical fault detection employing various approaches, the fundamental cause of fault formation in light of the fault mechanism is initially explored.

Before performing mechanical fault diagnostics using various methodologies, the underlying cause of fault formation is first investigated from the aspect of the fault mechanism. For instance, when determining the cause of a bearing problem, the characteristic frequencies must be computed.

For example, it is necessary to compute the characteristic frequencies while diagnosing a bearing issue. Signal acquisition using multiple sensors is the second phase. To minimize the size of the raw data and retrieve useful information representing defects, signal processing,and feature extraction must then be used. The reliability of mechanical problem diagnosis is greatly influenced by the chosen signal processing methods and suitable feature extraction. Finally, using intelligent methods for fault detection and identification, a mapping relationship between the fault-sensitive features and specific faults can be constructed.

In industrial rotation and transport machinery applications, the three main rotating components namely, bearing, gear, and rotor play a significant role. These parts, however, are prone to failure. Rolling element bearings are among the most frequently utilized and critical mechanical components. Defects in bearings act as alerts for other potential problems in spinning machinery. For instance, misalignment or imbalance may cause bearing flaws.

Dynamic modelling of rolling element bearings supports both the identification of the vibration generation process in a problematic rolling element bearing and the enhancement of vibration-based status monitoring and fault detection (Xuefeng CHEN, 2017).

It is essential to provide consistent performance, high efficiency, and extended durability in tough settings for the advancement of mechanical engineering (extremes of temperature, pressure, corrosion, vibration, etc.). The characteristics of the component in harsh conditions are directly influenced by the mechanical qualities of the materials used to produce the component.

Most modern intelligent fault diagnostic techniques for mechanical faults have good classification performance for fault pattern recognition.

The considerable similarity across monitoring signals, however, makes diagnosing fault severity more challenging and necessitates enhancing diagnosis tools' sensitivity, stability, and accuracy.

The majority of machinery diagnosis research focuses on vibration signal analysis. Audio-based CM, on the other hand, has not developed as swiftly. This is because the sound signal is contaminated by adverse sources such as other machines, noisy environments, and structural vibration from the machine itself. In this case, obtaining the machine's signature is difficult (Patricia Henr´ıquez, 2014).

Systems that automatically detect faults improve security when monitoring crucial infrastructures, such as industrial settings and electrical substations. Additionally, they save maintenance expenses, eliminate machine downtime, and guard against accidents that can have dire implications. Signal acquisition, signal processing, decision support, and fault diagnosis are all elements of automatic fault detection systems.

Immense of mechanical applications employ rotating machinery systems in some capacity. Due to the relative motion between coupling surfaces, equipment parts are particularly vulnerable to damage in rotating machinery. Therefore, locating and diagnosing defects is essential to maintaining the functionality of machinery.

Finding flaws and their patterns is the main challenge in maintaining the health of machinery. Early failure detection is essential since undesired machine downtime can lead to large financial losses. Industrial wireless sensor networks provide a more adaptable means of information transfer and communication to the targeted site.

Different techniques have been developed for the diagnosis of defects in rotating machinery, including bearings, gearboxes, and many others. One of the most effective systems involves the extraction of extremely sensitive features, the identification of malfunction symptoms, and the analysis of historical trends. Measurement is one of a fault's symptoms. Numerous other approaches, such as the testing of thermal properties, acoustic, and vibration factors, have also been considered as measures of the condition of spinning systems.

Considering each of these elements, the vibrational signal Sensors that measure the state of the spinning system have been found to be the most reliable monitoring devices.

In recent years, the field of vibration sensor signals has undergone study on several sensitive aspects for defect detection. In the time, frequency, and time-frequency domains, most systems extract features.

As smart industries grow, existing industrial processes are evolving and adopting multiple smart devices for automation. The most important duty in industrial operations is maintaining the required performance, which can be affected by a variety of issues. Maintaining high throughput from industrial activities depends on implementing precise, quick, and effective fault detection and its diagnosis method for improving the performance of the complete machinery and systems. Due to the many major advantages that may be derived from the reduction in process and cost variables while also offering better quality and productivity, fault detection and diagnostic systems have attracted a lot of interest from academia and entrepreneurs alike.

There have previously been a lot of theoretical and experimental studies on different defect detection techniques for different industrial processes. You can further categorize defect detection methods into data-driven, knowledge-based, and model-based methods.

To protect machinery from further damage in industrial automation, problem detection and diagnosis are essential. Therefore, real-time machine health monitoring is essential for fault identification and diagnosis, which aids in mitigating future fault occurrences (Nan, 2015).

Any spinning machinery must have bearings, gears, pulleys, belt drives, and other rotating mechanical parts. Machine downtime and decreased output arise from the failure of these components. The unexpected failure of these parts will cause considerable financial losses.

Belt drives are used in a lot of industrial gear. It's critical to recognize the early belt drive malfunction symptoms.

One of the parameters used for belt drive condition monitoring and problem-solving is the vibration signal.

Thus, the utilization of vibration signals for machinery maintenance decisions and the potential for predictive maintenance processes are discussed.

Techniques for signal processing can be utilized to detect modifications in vibration signals brought on by faults. It can be applied to gauge the overall condition of the equipment. It is possible to identify the issue's nature and scope as well as the failure's likely timing by evaluating the vibration signal.

An indication of a machine malfunction is carried by the vibration signal. Early discovery of fault is possible through examining these vibrating signals. Various signal processing methods are used to process these. Machines' moving parts force them to vibrate and make noise.

Depending on the equipment's state and design, each machine part emits a recognizable vibration signal. The signal fluctuates together with the machine part's status. By changing a vibration signature, the nascent issue could be identified and resolved before failure. The main benefit of condition monitoring is this.

The expense of preserving the and serious risk of unlucky events employing condition monitoring can decrease. Noise effects of numerous different components both present the signal of vibration captured from a running machine The signal connected to the component being monitored must be recognized and selected.

The vibration signals are often recorded in this case. The problem's type and presence will be determined at the beginning of development, and its evolution will be followed and estimated to determine the machine's remaining life. This facilitates planning suitable maintenance. Vibration in belt drives is typically caused by out, and to the side of slack belt situations.

The condition monitoring system employs methods for signal processing. Analyzing these signals is essential because there are many different types of problems. An optimum strategy must be selected based on the properties of the acquired signal:

i. Time domain analysis is the study of temporal time series of physical signals or data. Using a time-domain graph, it is possible to see how a signal changes over time.

ii. The approach known as "frequency domain analysis" entails examining time series of data or physical signals about their frequency.

It shows the quantity numbers that are dispersed throughout a range of frequencies and fall within the chosen frequency band.

iii. Methods that are applied simultaneously in the time and frequency domains are included in the period analysis in the frequency domain. This analysis includes an examination of two-dimensional signals.

Rotating machines are an essential part of the bulk of modern mechanical systems. Therefore, to ensure safety and reduce downtime, it is crucial to regularly and precisely monitor their health. Vibration-based fault diagnostics is one of the trusted and widely accepted techniques for evaluating the condition of a rotating machine. The more time there is for a thorough study and maintenance planning, the sooner the defect is found.

The conventional technique of measuring the vibration on the bearing pedestals has proven to be applicable in the vast majority of cases of machine structures and configurations.

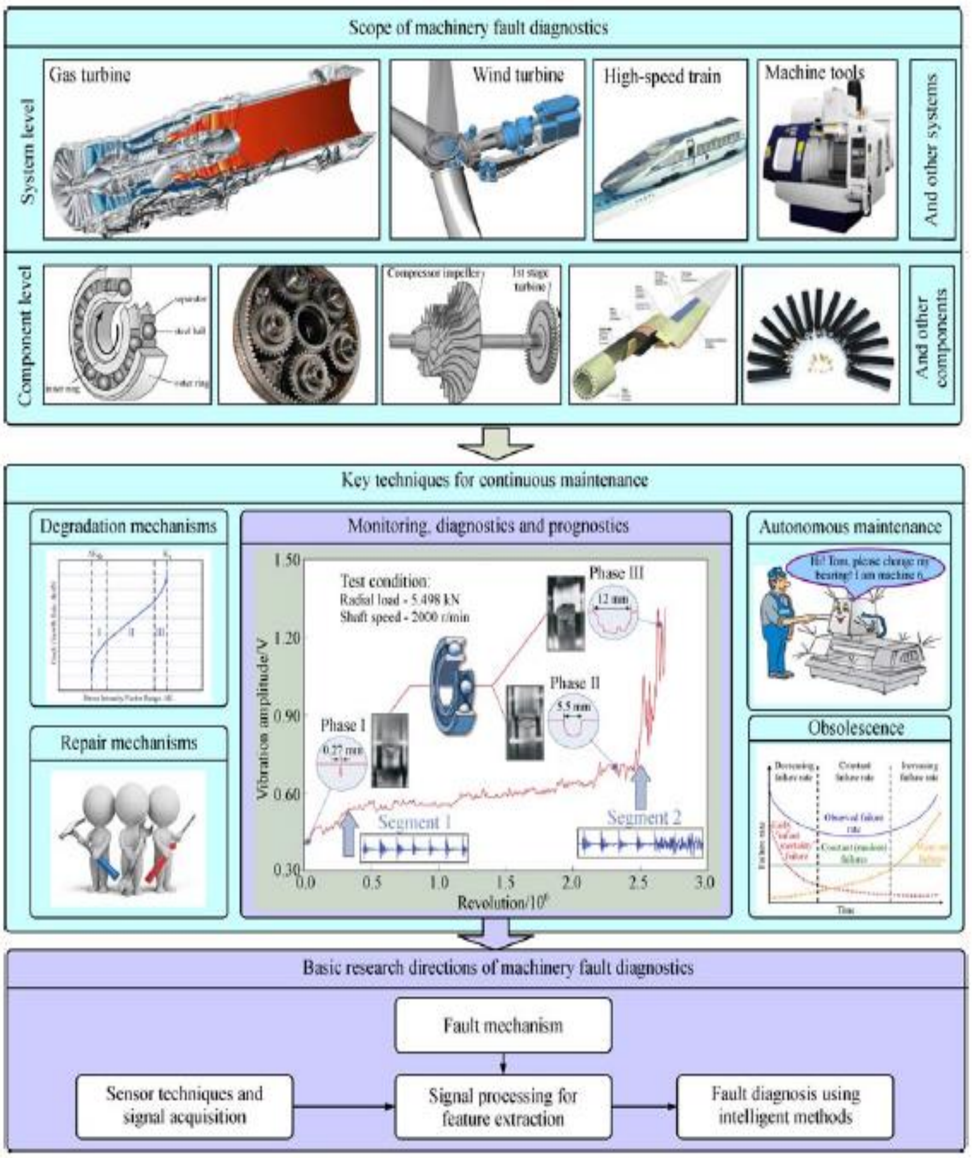
Vibration-based condition monitoring of rotating machines begins with gathering as much vibration data from the machine as is practical and then continuously monitors changes in a few selected parameters based on the analysis technique being used (time, frequency, time-frequency,...).

The appropriate analysis is then carried out to monitor their behavior over time. Continuous monitoring makes it feasible to spot growing flaws early.

A definition of fault detection is the deviation of a measured parameter from a range thought to represent normal operation. One or more parameters can be used to accurately characterize the machine state. different criteria from different sectors.

Figure 1.2

Scope and fundamental directions for machine fault diagnosis research



Any modification to a part or component of a piece of machinery that prevents it from carrying out its function properly or the loss of an item's capacity to carry out its intended function can be referred to as a machine defect.

The usual steps before the final defect— inchoative fault, hardship degradation, and harm—all lead to the segment or element becoming unstable or unreliable ongoing use.

The elements that lead to failure are divided into three categories:

i. Inherent defects in the material, design, or manufacturing;

ii. Abuse or applying force in the wrong direction; and

iii. Gradual deterioration is brought on by wear and tear, stress fatigue, corrosion, and other factors.

Antifriction bearing failure in rotating machinery is a significant contributing factor. There are two types of antifriction bearing faults: localized and distributed. Localized faults on rolling surfaces include pits, spalls, and fatigue cracks. Some of the surface waviness, misaligned races, and off-size rolling are examples of distributed defects.

Those imperfections might be a result of manufacturing processes or abrasive wear. Early machine problem detection can avoid costly emergency repairs and output losses costing millions of dollars. The gears and bearings of many machines are crucial.

Early fault identification is crucial for damage avoidance because it can prevent collateral damage to other machine parts or even the full failure of the enormous system it is attached to. Machine fault identification is to prevent future failure incidents and to guarantee the dependability, safety, and maintainability of machinery.

Vibration signature analysis is the method that is most frequently used to locate machine defects. Every part of the system vibrates, hence vibration monitoring is based on this notion. A machine's vibration is minimal and steady when it's in good working order, but when problems arise and some of the dynamic processes alter, the vibration spectrum will shift.

In light of previously published research, it has been recognized that faults in gears, bearings, and couplings are the primary study issues in fault signature analysis research.

Rolling or ball bearings are used in the majority of industrial machinery. These vibration signals gathered from the range of a bearing assembly extensive the bearing status details regarding.

Most academics have used methodologies for analyzing vibration signatures to identify rolling element bearing problems when a single defect arises on a bearing component.

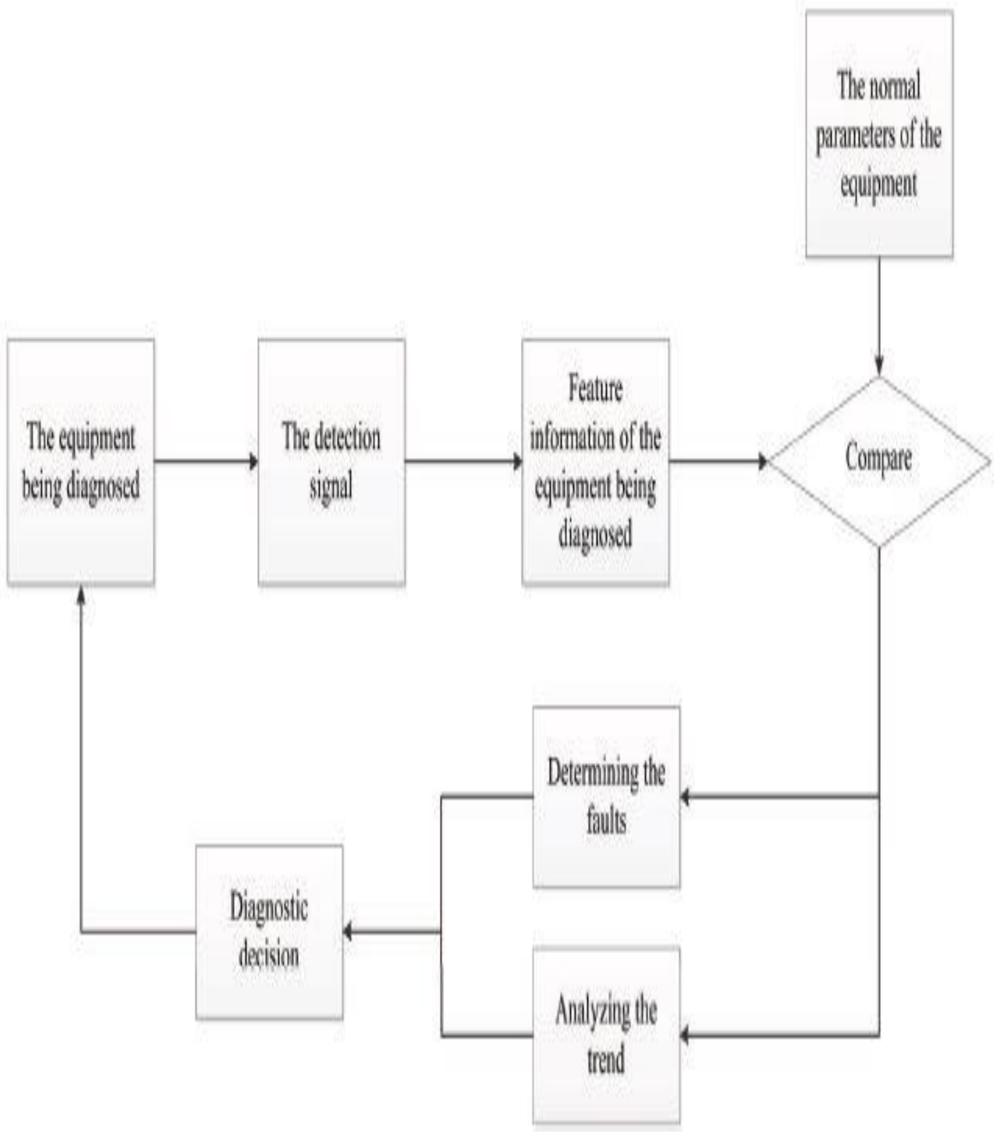
Although vibration analysis in the time- and frequency-domain methods have been examined, it is not always simple to diagnose a bearing's condition accurately. Researchers have developed expert diagnostics systems for identifying bearing failures utilizing wavelet transforms, fuzzy logic, artificial neural networks, and other methods in addition to time-frequency domain analysis.

The requirement for various machine failure signature analysis approaches is reviewed in this work, along with their discussion.

Rolling element bearing vibration signature analysis is given primary emphasis, even if other approaches are also described by (Pratesh Jayaswal, 2008).

Figure 1.3

Flowchart of mechanical fault diagnosis.



Mechanical fault diagnosis is the process of determining the mechanism, sources, and locations of a mechanical fault. We can determine the type and position of the defect using the mechanical system's abnormal state equipment and fault detection technology, which will allow all to increase the degree of mechanical design.

Furthermore, mechanical fault identification is essential for minimizing unplanned machine downtime and averting catastrophic disasters. The development of sophisticated fault characteristics, which are among the most challenging and complex difficulties in modern mechanical engineering, depends in particular on the ability to identify mechanical issues.

However, the feature analysis of the acquired signals is crucial for the circumstances of fault diagnosis of equipment. Otherwise, the signals produced by devices are frequently noisy mixed, non-stationary a non-linear.

The distracting background noise could obscure the valuable flaw features. Furthermore, developing problems' weaker elements typically get lost in background noise. This study's objective is to create a novel machine learning-based technique for identifying mechanical flaw.

CHAPTER II

Literature Review

Electromechanical systems are essential in industrial systems. On the other hand, electromechanical drivetrains typically confront hostile, unpredictable conditions and experience failure.

It is prone to failure because of the challenging working circumstances and wide range of load variations. Defects in the drivetrain system can badly injure the entire piece of machinery, so it's critical to recognize any potential problems as soon as they arise.

Longer downtime is frequently the result of failures of gearboxes, bearings, and other drivetrain components, which raises the cost of drivetrain maintenance. To overcome the problems with fault categorization, many academicians have become interested in machine learning and deep learning technologies (Zhao-Hua Liu, 2019), including Decision Trees, Logistic Regression, Random Forest, Adaboost, Gaussian Navie Bayers (GNB), K-Nearest Neighbour (KNN), Support Vector Machine (SVM), Back-Propagation Neural Network (BPNN), KMeans, and Gradient Boosting (GB) in recent years.

Although the majority of fault detection problems may be resolved by these ML algorithms without professional manual assistance as with conventional as it does, they still require a substantial quantity of prior knowledge and a sizable amount of training sets with labels.

This can be difficult to acquire enough labeled data for a viable diagnosis model to be trained in the majority of engineering applications. It can be tough to get enough trustworthy diagnostic methods in the majority of engineering applications.

According to Zhao-Hua Liu (2019). The distributions among data sets from the same operation may differ in real-world contexts due to the stochastic nature of electromechanical systems' operating environments, outside noise, the quality of their outputs, and other considerations. Additionally, in the absence of labeled training data, it is necessary to reliably forecast the labels of new data using past labeled data (source domain) (target domain).

However, this knowledge transfer may lead to a distribution disparity between the testing samples, the training data, and the target domain (the source domain), which dramatically reduces how well the diagnostic performs.

In a nutshell, it is a tricky problem with current ML-based techniques for fault diagnosis.

These two types of fault diagnosis methodologies are analytical-based on fault detection and hardware-based defect finding The method of analytical redundancy roughly falls. Since the 1980s, fault diagnosis research has been categorized into three categories: model-based fault diagnosis, signal-based fault diagnosis, and knowledge-based fault diagnosis.

The designer has access to a model of a system that defines the connection between the system parameters for model-based fault diagnostic approaches. Based on the model, algorithms, or fault diagnosis plans are developed and then put into use online for real-time system or process monitoring and diagnosis. It is done by comparing the gained underlying knowledge to the actual system characteristic deduced from the online monitored data (Zhiwei Gao, 2015).

Recently, sophisticated techniques for the use of machine learning (ML) developed to enhance the identification of faults in electromechanical systems. Electromechanical systems operate under a variety of operating conditions because, In the target domain, the distribution of the test data is different from the distribution of the data from training used to train. An ML technique's diagnosis performance may consequently suffer for practical applications.

AI in Mechanical Engineering

According to (S. Anush Lakshman, 2020) concerning a task T and a performance metric P, If a computer program's performance on T, as determined by P, increases with experience E, the program is said to learn from that experience.

To further comprehend, think of a human example. Imagine a learner learning linked lists, for example. Task T is this.

Performance P is lower since learning requires more time for to subject. Assume he has acquired experience and finished five linked list programs. He will take less time and perform better if he goes over the basics of linked lists again (T).

Three main categories can be used to further divide machine learning:

Supervised Learning (SL)

Its name, "supervised machine learning," refers to the fact that at least some of these method requirees human supervision. Most of the available information is unlabelled, raw information. For data to be appropriately labeled and ready for supervised learning, human input is typically necessary.

Unseen data is categorized into pre-existing categories using supervised machine learning, and predictive models are employed to predict trends and future change. Through supervised machine learning, a model can be trained to recognize objects and the attributes that categorize them. Additionally, supervised machine learning methods are frequently used to train predictive models. Supervised machine learning algorithms can forecast results from fresh, unforeseen data by identifying patterns between input and output data.

A set of predetermined operations are provided to the software as examples to teach it how to carry out a specific activity (i.e., sample inputs and outputs). When a fresh batch of data is provided, it displays the output depending on the training examples that were provided. Take a straightforward illustration.

When I give a computer two new numbers and teach it how to add using a series of training examples, the software will combine the two new numbers. However, employing this kind of program is only permitted for addition; multiplication and division are not permitted.

Unsupervised Learning (UL)

All that is given to the software is a collection of data. The application's goal is to identify relationships and interconnections among the provided collection of data. Assume that stock market information from the preceding month has been loaded into the computer. It is now possible to calculate and anticipate the stock market closure for the following day or the upcoming week. More details provided by you (E) increase the accuracy of stock market forecasts (P) (T).

Reinforcement Learning (RL)

When a reward must be earned, this style of learning necessitates a decision-making process. Think of a maze where a rabbit must navigate and overcome particular challenges to reach its young. To make the process easier, RL algorithms are applied in this scenario.

The design and production of mechanical systems can benefit from the use of artificial intelligence technologies. The task must be completed following the pertinent drawings, whether designing or producing items. To guarantee that various parts can work together effectively, it is also vital to understand the components of the parts. The dimensions of the pieces must then be precisely measured to guarantee each part's specifications. Artificial intelligence technology may be used to measure each component's size and decrease the inaccuracy that is produced during the measuring process. Additionally, numerical control technology may be integrated with artificial intelligence technology to more precisely identify equipment defects (Zhu, 2021).

Classification Algorithms

Decision Trees

Machine learning is most frequently used for predictive data mining (ML). The two basic ways that ML classification fulfillment can be separated are model development and model evaluation.

The same set of attributes is used to describe each instance across all datasets used by ML methods. They could be categorical, continuous, or binary. If cases are recognized with recognized labels, learning is said to be supervised (correct outputs).

A function is inferred via supervised learning in machine learning from categorized training data. However, each data input object has already been given a class label. The basic objective of supervised algorithms is to create a model that, when applied to fresh data, produces the same labeling as the input data as efficiently as possible.

The basic objective of supervised algorithms is to create a model that, when applied to fresh data, produces the same labeling as the input data as efficiently as possible. This is where classification algorithms' main focus lies.

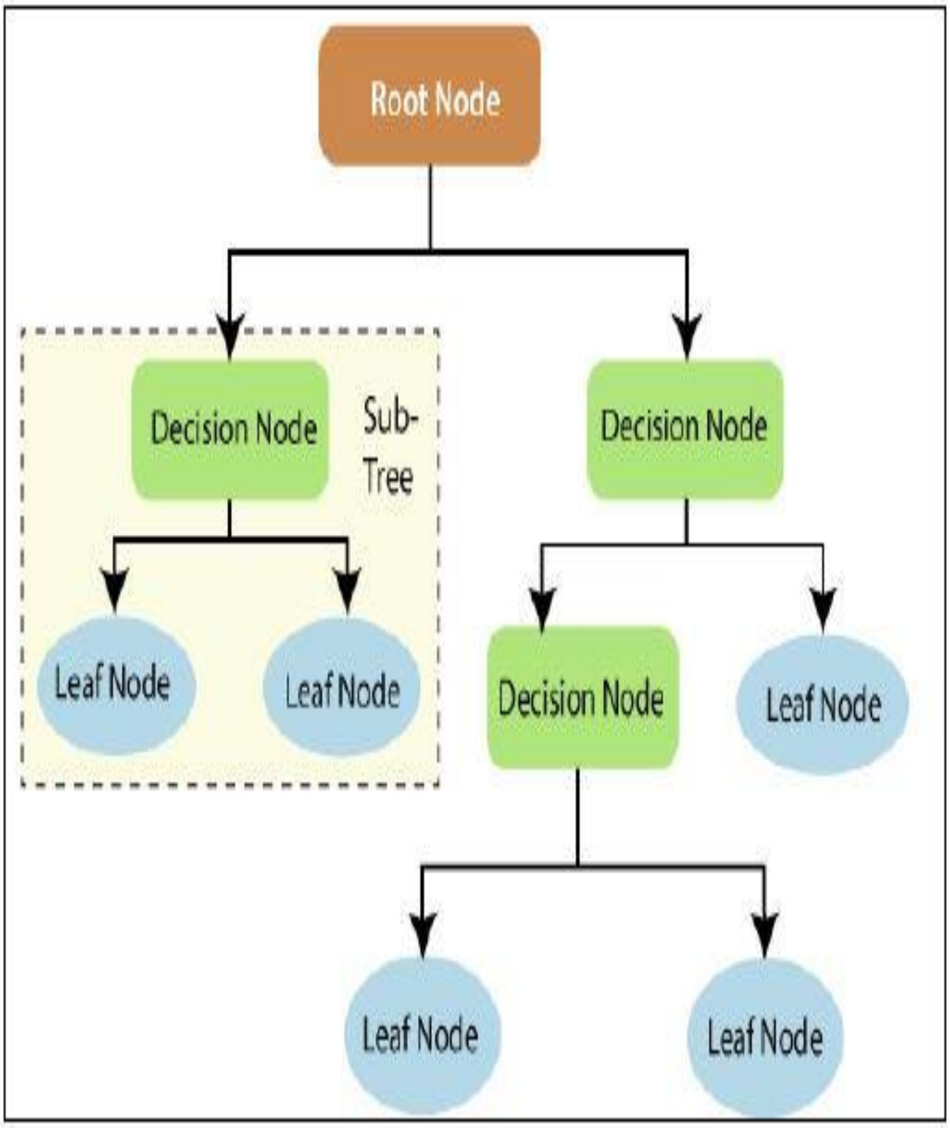
The classification algorithm determines the connection between the input attribute and the output attribute to create a model that is a training process.

A huge amount of data is gathered in data mining environments. The decision tree method works best when the data set is accurately categorized and has the fewest number of nodes possible.

A decision tree is a tree-based approach where each path leading from the root is marked by a data separation process up until a Boolean result is obtained at the leaf node .

Figure 2.1

Decision Tree



The decision tree is one of the efficient tools that is frequently used in a range of fields, including pattern recognition, image processing, and machine learning. In each test, the DT (Decision Tree) model, which successfully and convincingly integrates several core tests, compares a numerical property to a threshold value.

The conceptual concepts are easier to build in the neural network of connections between nodes than the numerical weights. Decision Trees (DT) are frequently used for grouping purposes.

Every branching path starting at the root of a decision tree from there is marked by a data separation step until a Boolean result is obtained at the leaf node. It is an organized representation of the links and nodes that make up knowledge. Relationships are used to categorize, and nodes specify purposes. Something that should be done is to create a model that forecasts the goal variable using several input variables.

Decision trees are simple visual tools for classifying examples. Assume for this section that the objective feature is "classification" and that each input feature has a finite discrete domain.

Each part of the categorization domain is referred to as a class. A decision tree or classification tree labels each internal (non-leaf) node with an input characteristic.

On these arcs that originate from a node that has been assigned to label an input feature, each of the target feature's potential values is labeled. Alternatively, the arc may go to a decision node that is subordinate to the node that has been assigned to label the input feature .

KMeans Algorithm

The most popular simple clustering technique is K-means. For a range of high dimensional numerical data, it gives an efficient technique of clustering related data together. In this work, a bi-layer k-means algorithm and a portion of the multi-k-means method are proposed. Outliers, noisy data, and initial cluster centers can affect the-means technique. To get around these, use tri-level k-means. (Shyr-Shen Yua, 2018).

According to (GechengChen, 2019), the identification of faults is a crucial part of process monitoring in industrial operations. The majority of conventional fault classification techniques work on the premise that the amount of data in each class is roughly the same. But in practice, most of the information gathered from industrial processes is normal information, and very little of it is defective information (minority). In other words, the unbalanced data classification issue, which has not yet been solved in this field, might be seen as the root cause of fault classification. The K-means technique is provided to handle the imbalanced fault classification issue.

Unlabelled data can be categorized in an unsupervised manner using K-means clustering by attributes instead of pre-established categories.

The element K indicates how many classifications or groupings were created The purpose is to partition information into K distinct groups to identify the mass centers of every cluster. The closed center of mass can then be used to assign a cluster (class) to a new data point.

The key benefit of this strategy is that it removes analysis-related human bias. Instead of letting a researcher create clusters using real data rather than conjecture, the machine creates clusters on its own (DeepAI, n.d.).

To optimize the coordinates of the centroids, K-means is an algorithm used in data mining. initially randomly chooses a primary group of centroids that act as the origins of each cluster. Construction and optimization of clusters halt when either of these takes place. The centroids have remained steady, displaying no change in their values, indicating that the clustering was successful. The predetermined number of iterations has been finished (Garbade, 2018).

Support Vector Machines

The most well-known approach to learning a computer is SVM. SVM, or support vector machine, has become a powerful classification paradigm.

According to (Mayank Arya Chandra, 2021), SVM is the most effective classification and regression mathematical model.

This sound mathematical base opens up a new field of inquiry into the broad area of categorization and regression.

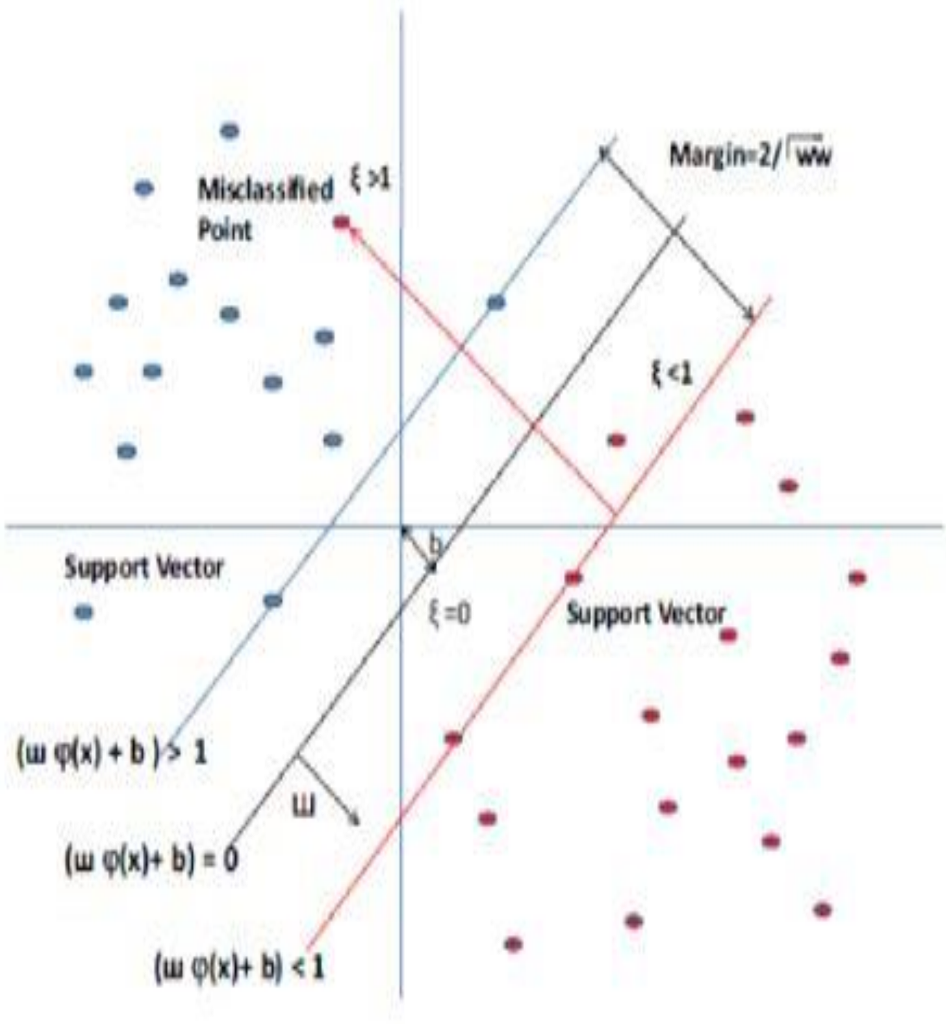
The mathematical computer model known as SVM is effective for classification jobs. SVM is a supervised approach used in regression and classification problems. It works well and has a solid statistical foundation. Dimensional elevation, which involves a non-linear transformation to assign points from the input space into a higher dimensional space, is the most crucial step in the SVM classification process.

The nonlinearly separable points of the initial sample are transformed with a large margin into linearly separable points in the new feature space in these high-dimensional domains. To create the ideal hyperplane, SVM employs an iterative training procedure with the primary objective of decreasing an error function. Kernels that are linear, Gaussian, and sigmoid are a few of the popular forms.

With the SVM technique employed in this example, a C parameter is used to regulate the trade-off between rigid margins and training mistakes, resulting in a soft margin that allows some misclassification.

Figure 2.2

SVM Separable Problem in 2-Dimensional Space



Since faulty events are frequently the most expensive to collect and analyze, defective signal datasets are uncommon in the field of fault diagnosis using SVM. The dataset of large-scale normal samples becomes unbalanced when incorrect cases are present.

The classic SVM method always yields biased results when the dataset is uneven, and the classifier may easily display excellent performance for the class that is overrepresented and subpar performance for the class that is underrepresented. An improved SVM technique that considers data unbalance is presented for the diagnosis of steering actuator defects in electromechanical devices to address the aforementioned problems.

Logistic Regression

Created for statistics, the categorization method known as logistic regression has been adapted for use in machine learning.

Identification is the main goal of logistic regression. a statistical technique called logistic regression is used to examine datasets when a result is influenced by one or more independent factors. Utilizing the model that most accurately depicts the connection between the dependent and independent variables.

In machine learning, logistic regression is a categorization technique. Using a logistic function, the dependent variable is represented. There are just two valid classes as a result of the dependent variable's dichotomous form, e.g., whether the cancer is malignant or not.

In recent years, numerous to anticipate landslides, statistical and artificial intelligence (AI) tools have been created and put to use.

These methods include both quantitative data-driven and qualitative knowledge-driven approaches. Although Each technique has benefits and drawbacks, the majority of academics have favoured the Logistic Regression (LR) model approach. The advantage of logistic regression is that variables can be discrete or any combination of types; they do not need to have a regular distribution. To estimate the likelihood that an event will occur, the logistic regression (LR) employs a supervised classification estimate function.

The logistic regression model's premise is that qualities have a linear connection with one another. Logistic regression does not support a nonlinear attribute-attribute connection. This implies that logistic regression will have a substantial bias if the data contains a non-linear decision boundary.

One can add attribute interactions to address this problem, but the interaction that is added must be carefully considered.

The inclusion of every possible interaction may also considerably increase the danger of model overfitting. Assume that domain knowledge already exists, for example in the form of qualitative multi-criteria decision models .

Back Propagation Neural Network

One machine learning technique that makes predictions based on the current data is the backpropagation neural network approach. The Backpropagation Neural Network Technique (BPNN), a supervised learning approach, modifies the weights assigned to the neurons in the hidden layer using a multi-layer perceptron.

The backpropagation neural network type looks to be the most popular and often used neural network type (BPNN). Utilizing the supervised learning technique known as BPNN, multilayer feedforward neural networks are trained. By adjusting the weights, a BPNN is trained using the gradient or steepest descent method.

Changing the numerical weights is intended to decrease the network error between the target and the output.

A multilayer network is used in the BPNN algorithm's network architecture. The BPNN architecture's essential components are the hidden layer, the output layer, and the input layer.

The input layer does not do any computations, but rather transfers the input signal to the hidden layer at the input layer. Based on particular activation functions, the size of the output from the hidden and output layers is calculated, and the hidden and output layers' weights and biases are computed.

K - Nearest Neighbors

By using k-NN, the function is just locally approximated and all computation is delayed until after it has been assessed. If the characteristics reflect many physical units or have vastly different scales, normalizing the training data can greatly improve accuracy because this technique relies on distance for classification. A strategy for making uncertain decisions is the certainty factor, while a method for classifying data that is comparable to a near neighbor is K-Nearest Neighbor. Each student in this study received a career recommendation based on their interests, skills, and exam scores.

The K-Nearest Neighbor and Certainty Factor algorithms are used to create the Student Career Prediction System.

These two-way analyses were expected to provide students with more knowledge to aid them in making their career decisions. The KNearest Neighbor technique was given value by the Certainty Factor, which proved useful for predicting career projections.

For example, in recognition and information collection for arranging, the KNN method, which is well known for its simplicity and low mistake rate, is frequently utilized.

The general rule of the algorithm states that a question point qi can be classified as belonging to a certain class if a bigger proportion of the k examples in the component space that are most similar to it have a place with that classification. This method is also known as the K Nearest Neighbour algorithm since distance in the component space can be utilized to assess comparability.

Random Forest

According to Chenco (2020), the homogeneous ensemble method is used in the supervised machine learning algorithm random forest. Different decision trees act as fundamental students. A non-parametric supervised learning technique is a decision tree.

By learning straightforward rules derived from the features, it can be utilized to forecast the value of the output variables. It can be used to solve classification and regression issues. Binary and multiclass scenarios can be classified using a decision tree-based classifier.

Frequently used supervised machine learning techniques include random forest utilized when solving classification and regression issues. It creates decision trees from several samples, categorizing them based on their average, and regressing them based on a majority vote.

The Random Forest Algorithm's ability to handle data sets with both continuous variables, as in regression, and categorical variables, as in classification, is one of its key characteristics. Produces better results when it comes to classification problems.

Recently, numerous engineering sectors have used the categorizing technique Random Forest (RF) for diagnosis.

Among the most precise machine learning methods currently accessible is RF, it works well when there are a lot of input features and few available examples. RF has been used to detect issues with mechanical devices.

With the help of numerous Random Forest is a powerful classifier that builds sets of decision trees (CART) by randomly choosing a selection of variables and a portion of bootstrap samples from the input data. Variance and overfitting are decreased by integrating the concepts of bagging and this kind of random feature selection. By adding up the votes from each tree's response, the class that is highlighted for each sample is chosen using a random forest. Each tree contributes a sorting.

The residual data are referred to as out-of-bag observations, whilst the input data used to construct the trees are referred to as data in the bag .

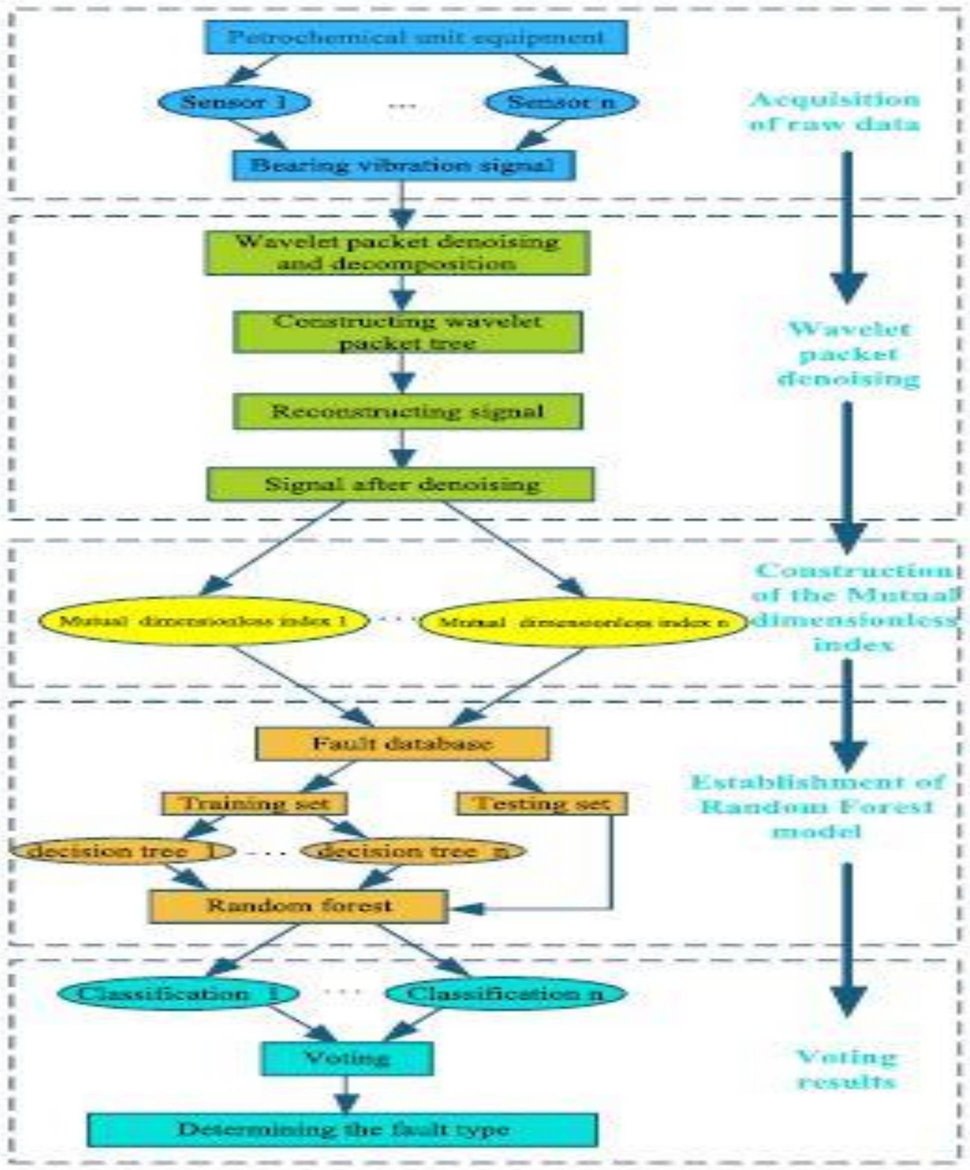
Random Forest RF is a decision tree-based ensemble-based machine learning model that excels on low-dimensional datasets. High inaccuracy, large volatility, and over-fitting are all considered decision tree downsides because a decision tree is a non-linear technique.

To considerably reduce variation and increase the power capabilities that RF approaches, The average of hundreds or thousands of decision trees is constructed from numerous bootstrapped data sets. Additionally, a small number of characteristics are randomly selected at each stage of the tree-building process, frequently by cross-validation. As a result of decorrelating the input trees, the model becomes more accurate.

The rating of the importance of each feature in a dataset using RF has a significant positive impact on model inference (a feature ranking). RF is a method that uses to train multiple trees, separate bootstrap samples, or random samples, of the training sample, are used. RF is utilized as a subset of features for training the individual trees in addition to bootstrap samples.

Figure 2.3

Flowchart of Fault Diagnosis Method based on Random Forest



Gaussian NB

Naive Bayes is a straightforward method for building classifiers. These models apply class labels to issue circumstances, which are represented as vectors of feature values, by choosing one from a finite set of class labels.

There is a group of algorithms predicated on the idea that, given the class variable, one feature's value is unrelated to the value of any other feature that is used to train such classifiers rather than a single technique. For instance, if the fruit is spherical, red, and around 10 cm in diameter, it can be referred to as an apple.

A naïve Bayes classifier, taking into account any potential correlations between the variables of color, roundness, and diameter, assumes that each of these properties independently adds to the likelihood that this fruit is an apple.

A family of straightforward probabilistic classifiers known using a standard classification algorithm, the Naive Bayes (NB) classifier is the presumption that, given the category variable, all features are independent of one another. What sets different NB classifiers apart from one another is the assumptions they make about the distribution of features.

The assumption on the distribution of attributes is made by the event models of the NB classifier. For discrete attributes, multinomial or Bernoulli distributions are typically utilized. These assumptions, which are commonly jumbled up, result in two different models. When dealing with continuous features, the Gaussian distribution is a key definition.

Each data piece is essentially assigned to the class to which it is most comparable by the procedure. In contrast to using the Euclidean distance from the class means, the GNB establishes that nearness by considering both the distance from the mean and how it relates to the class variance.

The z-score for each dimension is created by dividing the variation by dividing the mean by the standard deviation (only one is shown in the graphic). The classifier assumes that the distributions of the classes are Gaussian. the average deviations. As seen in Fig., this enables the conversion of each z-score distance into a p-value.

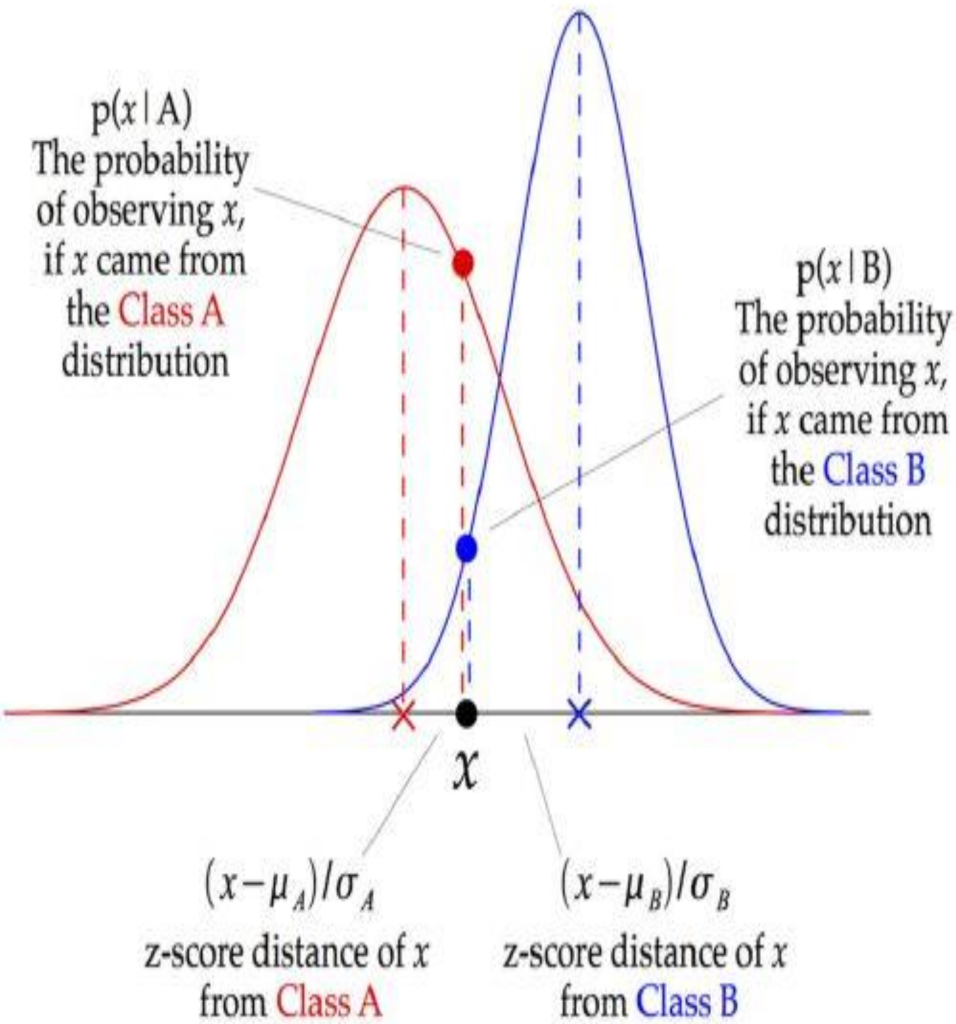
This p number represents the likelihood that a certain data point, x, would be identified if it were randomly selected from the distribution of a particular class.

But rather than the likelihood of the information for a specific class what we truly want is the potential to utilize our observed data, of a class.

The "Bayes" portion currently of Gaussian Naive Bayes takes hold because it is possible to determine each one from the others using Bayes' Theorem.

Figure 2.4

An example of the operation of a Gaussian Naive Bayes (GNB) classifier.



Gradient Boosting Algorithm

Gradient boosting is one kind of boosting technique that enhances boosting algorithms. The first boosting algorithm is called Adaboost. Initialization marks the beginning of The algorithm giving each sample the same weight.

Then again, To put it another way, each sample is equally important at first. After each training model, logarithmic stronghold estimates will be produced. Break the mold.

The outcome of each phase needs to be addressed. weight, and the processing method is making the fault worse. the weight of the samples' categorization. Reduce the samples' suitable classification weight while you wait. As a result, the samples are certain to be often misclassified, given a lot of weight, and labeled as "seriously concerned."

N simple basic learners will be created after N iterations. They can either be given the choice to vote on the final model or weighted (a base learner with a greater mistake once they are all combined, (a base learner with a higher error rate has a smaller weight value; a base learner with a lower error rate has a greater weight value) once they have all been integrated.

AdaBoost

The AdaBoost algorithm is one of the well-known methods for building a group classifier from ineffective member classifiers. With the help of several weak classifiers, the AdaBoost approach creates a powerful classifier. Weak classifiers and weight modifications are combined with repetition in AdaBoost while maintaining the integrity of the initial training set. One of the elements that contribute to the AdaBoost algorithm's effective performance is the diversity of weak classifiers. To evaluate process variety, there isn't a clear benchmark, nevertheless.

The AdaBoost method transforms weak classifiers into powerful classifiers. The AdaBoost ensemble classifier includes the weak classifiers. AdaBoost employs cycle-by-cycle adaptive weight adjustment to create a collection of weak classifiers from its constituents.

Weights for training samples that a weaker classifier used today misclassified are raised, whereas training sample weights that were correctly identified are lowered.

AdaBoost is a useful method for building ensemble classifiers, however, it occasionally fails to generate classifiers with a small enough size to lower the generalization average error. The AdaBoost algorithm performs effectively because it may generate a growing diversity. To improve performance, the final ensemble consists of a range of weak classifiers.

Summary of Related Works

Numerous articles have presented problem diagnostic systems for circuit breakers for high voltage based on vibration indication analysis because high voltage circuit breakers' mechanical vibration signals provide a wealth of information.

We are all aware that the closer the measurement point for the vibration signal is to the vibration source, the less energy is lost during transmission and the more accurately the operation state of the testing apparatus is reflected.

Research Questions for Mechanical Fault Analysis

RQ1: What are the mechanical faults that affect mechanical equipment?

RQ2: What is the mechanical equipment impacted by these faults?

RQ3: What mechanical measures were taken to minimize these faults?

RQ4: Were there any AI solutions to support the mechanical measures?

Table 2.1

Mechanical fault analysis

Reference	Mechanical Faults/Aim	Mechanical Equipment	Mechanical Measure	AI Solution
(Hu et al. 2020)	to determine the mechanical components' state of health	Rolling bearings and gears	redefined dimensionless indicators (RDIs) and minimum redundancy maximum relevance (mRMR)	Adaboost
(M.E.Elnady, 2014)	to analyze the vibration fault.	Bearing, gear, and bent shafts	Vibration analysis methods; FFT, STFT, EA	Artificial Neural Networks (ANN) & Deep Learning (DP)
(Bahgat, 2015)	vibration monitoring detects a problem with a piece of machinery	rotating parts	Dynamics Monitoring	Support Vector Machines (SVM)
(M.E.Elnady, 2014)	to determine the bearing vibrations	Bearing Vibration fault	Vibration signals calculated	RF and ANNs are two types of artificial neural network
(D.H.Pandya, 2014)	examining the rolling motion	Rolling Bearing	Measured the rolling vibration	Logistic Regression (LG)
(Sujesh Kumar M. L., 2018)	to determine vibration signals due to fault	Drives, pulleys, and bearings	identify the signal which is related to the component under observation	Artificial Neural Networks (ANN)

(M.E.Elnady, 2014)	to analyze vibration fault	Rotating shaft	measuring the rotating shaft vibrations fault	Nearest neighbor
(Nan, 2015)	solve the mechanical fault diagnosis problem	Shaft Crack, Bearing fault	using the algorithms to solve the fault	SVM
(Xianzhen Xu, 2020)	to analyze the fault diagnosis	rotating machinery	using the algorithms to solve the fault	Neural Network
(Alireza Zabihi-Hesari, 2018)	vibration signature analysis	fault detection on the engine parts	measuring the signal to detect the fault	Fast Fourier Transform, Artificial Neural Network

Mechanical faults that affect mechanical equipment

Mechanical equipment is impacted by defects when there is an excess of vibration, which fails the equipment's operating principles. The equipment is also damaged by vibration and noise.

Influence of mechanical faults on mechanical equipment

Equipment such as bearings, rotating shafts, and bearings will be damaged by vibration, which will result in system failure.

Mechanical measures are taken to minimize mechanical faults

The equipment reliability of these systems can be considerably increased by performing regular maintenance and repairs on the machines. The Dominion urged that firms make careful to have a regular timetable to adhere to for preventive upkeep. important administrators personnel ought to first select crucial computers to be included as a part of this process, in these strategies.

The schedule must contain information on the sorts of maintenance that need to be done on each system, as well as how frequently these fixes need to be made.

To build this strategy, administrators can rely on the guidance and expertise of important personnel who regularly operate with this technology, as well as on manufacturer suggestions. Establish a maintenance schedule.

According to Lifetime Reliability, businesses should create a plan for preventive maintenance as well as work to eliminate any potential machine defects that could lead to failure. To uncover any equipment defects that could lead to downtime, plant managers and operators should research the equipment employed in their facilities.

People can prevent these flaws such as harming by investigating previous failures of the same machines reported by other customers as well as any manufacturer's notices, they can improve their business. Using the condition monitoring system to learn about the health of important assets is one of the greatest strategies to prevent equipment breakdown. This technique offers the chance to undertake preventative maintenance before bigger problems develop and incorporates sensors to measure important components. This technology can increase equipment reliability and facility uptime overall, making it a wise investment.

AI solutions to support the mechanical measures in mechanical faults

The majority of research also conducts comparison evaluations between several machine learning algorithms to highlight the benefits of the suggested approach or to choose the most suitable algorithm. In the latter scenario, this review will only include the chosen (or best-performing) algorithms.

These algorithms include: AdaBoost; back-propagation neural network (BPNN); classification and Support vector machines (SVM), k-nearest neighbors (K-NN), logistic regression (LR), decision tree (DT), and k means (KMeans).

CHAPTER III

Methodology

Different engineering problems and processes are becoming smarter through the application of artificial intelligence as the world improves in every way possible. It is important to assess and comprehend each AI technique's applicability and performance when it is tried in a variety of mechanical engineering applications, including fault detection, autonomous vehicles, manufacturing, smart buildings, etc.

The following sections in this chapter describe the workflow of this research thesis.

Dataset and Patterns

The dataset in this research thesis was collected from https://archive.ics.uci.edu/ml/datasets/Mechanical+Analysis. As an example, Bergadano et al. (1989) applied the dataset in the ENIGMA system for electromechanical device malfunction diagnosis issues.

The ENIGMA system uses an integrated inductive/deductive paradigm to learn structured information from examples and a domain theory. The outcomes are contrasted with those attained by an expert system created for the same task, whose knowledge base was generated via the conventional technique of expert interviewing.

There are several parts to each instance, and each part has eight properties. This database's instances vary in the number of components they contain. One instance could not be placed on a single line. It is challenging to FTP these because he initially had one instance per file (just try ftp'ing 222 or so files!). The 209 instances were combined into one data file and each was prefixed with the line.

Programming languages and Libraries Used

The Python programming language is most suitable for implementing machine learning algorithms. The following Python libraries were used to train and test the selected machine-learning algorithms for this research:

Numpy

For critical research calculations, NumPy is a Python library that can process a sizable collection of arrays using a wide range of complex mathematical operations. It is incredibly useful because of its proficiency with numerical values, and linear programming. NumPy is used implicitly by sophisticated tools and features like TensorFlow to manipulate tensors.

Scipy

Because it contains several modules for data analytics, discrete mathematics, and optimization. The prominent SciPy programming language is packaged for having an interest in artificial intelligence. The SciPy library and stack are different from one another. SciPy is one of the crucial aspects of the SciPy stack. SciPy is an excellent tool for images manipulation.

Scikit-learn

One of the most well-liked software programs for traditional ML techniques is Scikit-learn. The fundamental Python modules serve as the foundation for this package (SciPy and NumPy). The vast majority of ML techniques are supported by Scikit-learn.

As it can be used for data analysis and mining, Scikit-learn is a great tool for an individual who is just learning machine learning.

Theano

Multi-dimensional array-based mathematical equations can be effectively defined, evaluated, and optimized using Theano.

By maximizing CPU and GPU utilisation, it is accomplished. Theano may be employed to detect and identify different kinds of issues during unit testing and self-verification.

This library may be categorized as an extremely potent one that has been used in severe, computationally demanding sophisticated scientific activities yet is simple and usable for users to use it for their projects.

TensorFlow

TensorFlow is a popular open-source toolkit for high-performance numerical calculation that was developed by the Google Brain team. As its name suggests, TensorFlow is a framework that makes it possible to define and carry out tensor-based calculations. It can train and control AI algorithms, which can be used to build a wide range of AI technologies.

Keras

Collecting, integrating, and filtering data, it comes with a number of built-in methods. Keras is a high-level neural network API that is compatible with Theano, CNTK, and TensorFlow. The CPU and GPU can both run without any problems. A neural network can be easily built and designed using Keras. Prototyping is made simple and rapid with Keras, which is one of its best characteristics.

PyTorch

An open-source machine learning framework called Torch was developed. The core of PyTorch, a well-known data analysis tool, is written in C with a wrapper in Lua. It works with a variety of machine learning (ML) programs, processing of natural language (NLP), computer vision, and many others. It assists in the creation of computational graphs and provides GPU-accelerated Tensor computations for developers.

Pandas

Pandas are mainly used for data analysis, and they have nothing especially related to machine learning. Since everyone are conscious that the dataset must be prepared prior to training. Due to its creation as a tool primarily for data pretreatment and extraction, Pandas is advantageous in this case. It provides a wide range of high-level data structures and data analysis tools. It comes with a number of integrated methods for collecting, integrating, and filtering data.

Matplotlib

Matplotlib is particularly advantageous when a coder needs to recognize the patterns in the data. It is a 2D charting library used to produce 2D graphics and graphs. Pyplot is a module that makes it simple plotting of data programmers due to it offers tools to adjust font properties, line styles, formatting axes, etc. It offers a variety of plots and graphs for visualizing data, including scatter plots, unreliable charts, bar charts, and line graphs.

CHAPTER IV

Findings and Discussion

This chapter presents the findings based on the collected data.

The dataset that has been used contains a total number of 14290 observations or variables. These variables may be classified into six classes, from F_1-F_6, as seen in Table 4.1.

Table 4.1

Classes and Definitions

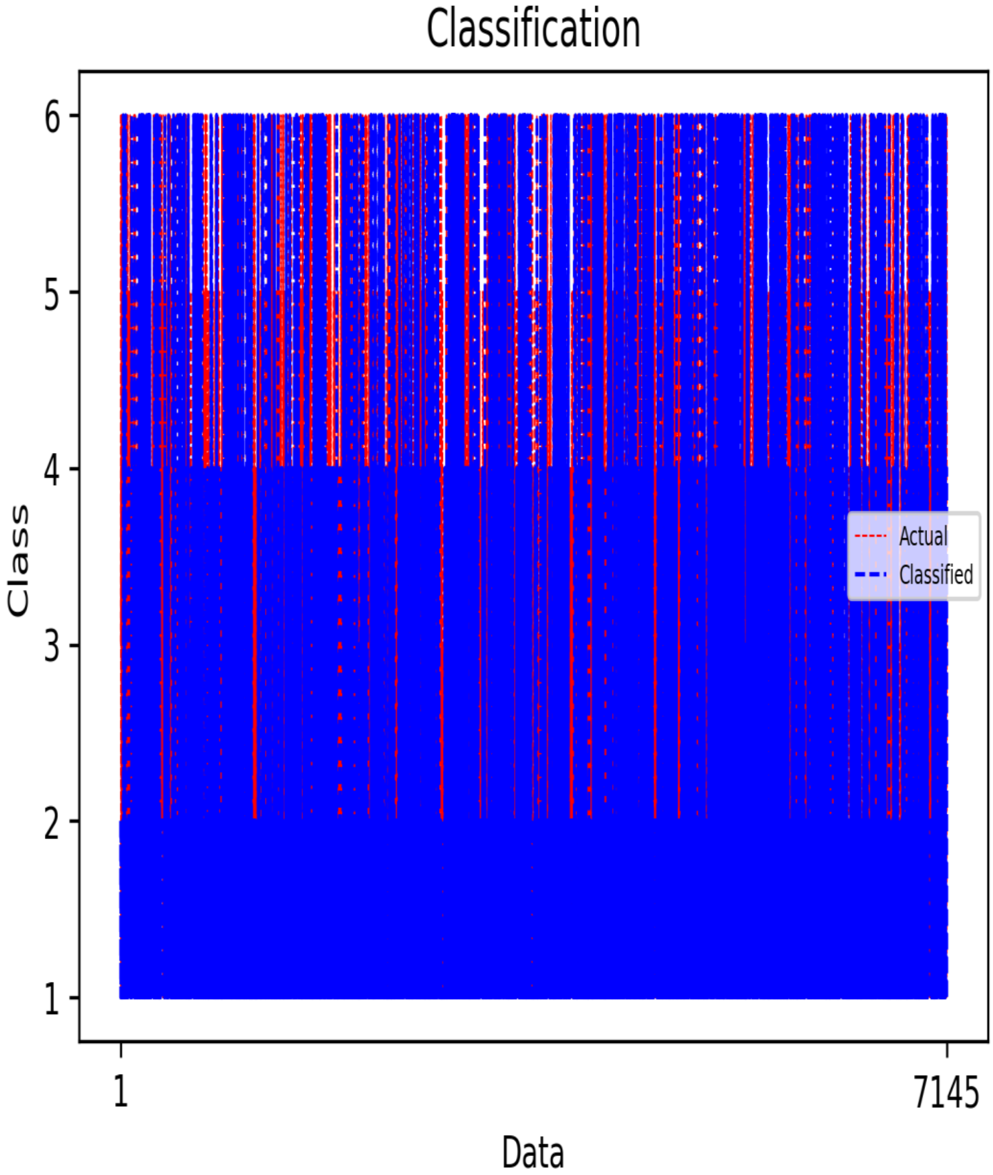
Classes	Definition
F_1	Faults related to the joint
F_2	Faults in the bearings
F_3	Loosened machine parts
F_4	Base related faults
F_5	Mechanical instability
F_6	Required operating states

The ML algorithms that have been selected for this work include Adaboost, BPNN, decision tree, GBA, KNN, logistic regression, KMeans, random forest, gaussianNB, and support vector machines. Considering different test ratios, from 0.2 to 0.8, the Adaboost algorithm obtained the most efficient result of 88.6%, as seen in Table 4.2 Figures 4(a-b) describe the plot analysis based on the 6 classes defined in Table 4.1 above.

Figure 4.1 gives the graphical classification of the Adaboost algorithm. It classifies all types of machine faults, as defined in table 4.1 above.

Figure 4.1

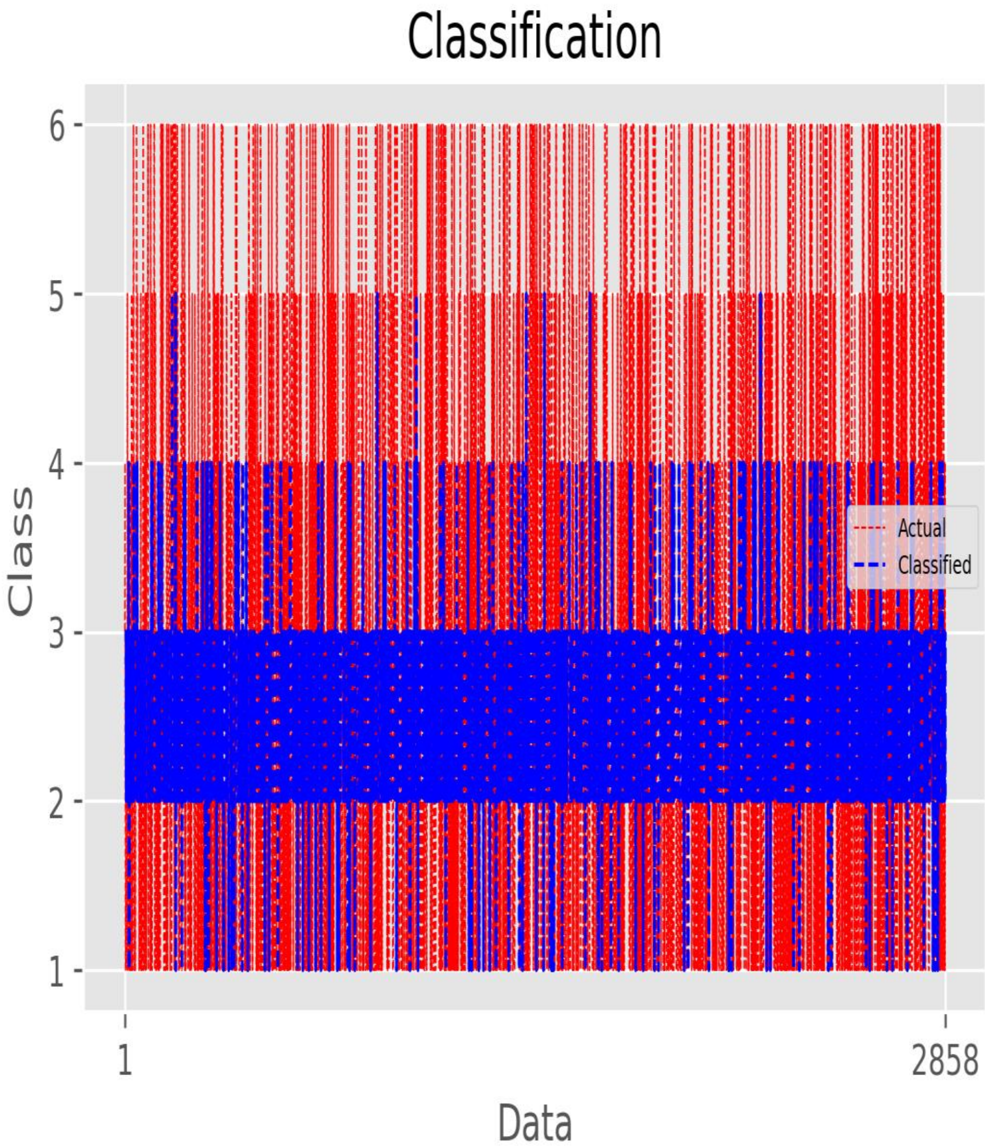
Adaboost Classifier Results



The BPNN algorithm adequately classifies faults from the C_2-C_3 level, as seen in figure 4.2 below.

Figure 4.2

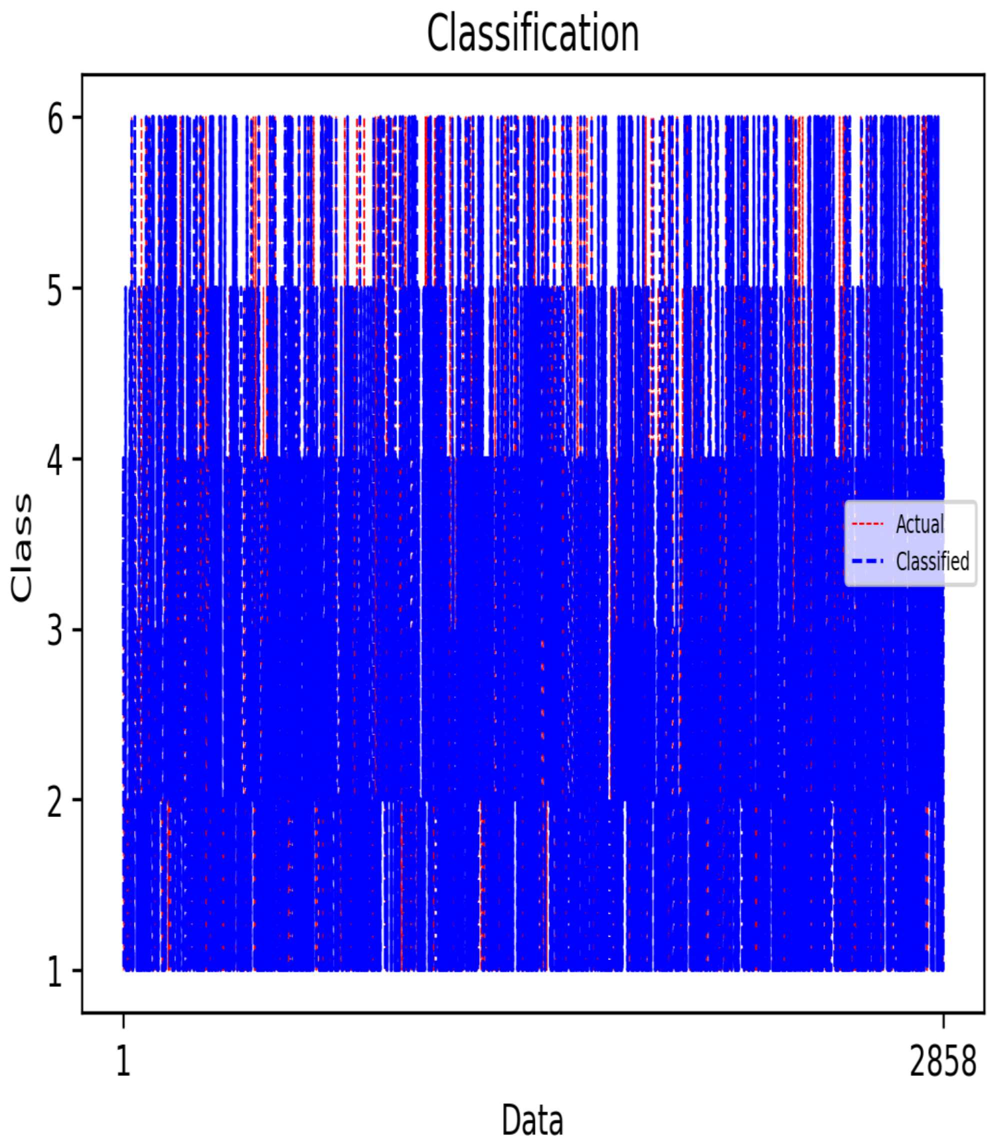
BPNN Classifier Results



The decision tree algorithm is the first selected algorithm to attempt to classify all types of machine faults fairly, and this can be seen in figure 4.3 below.

Figure 4.3

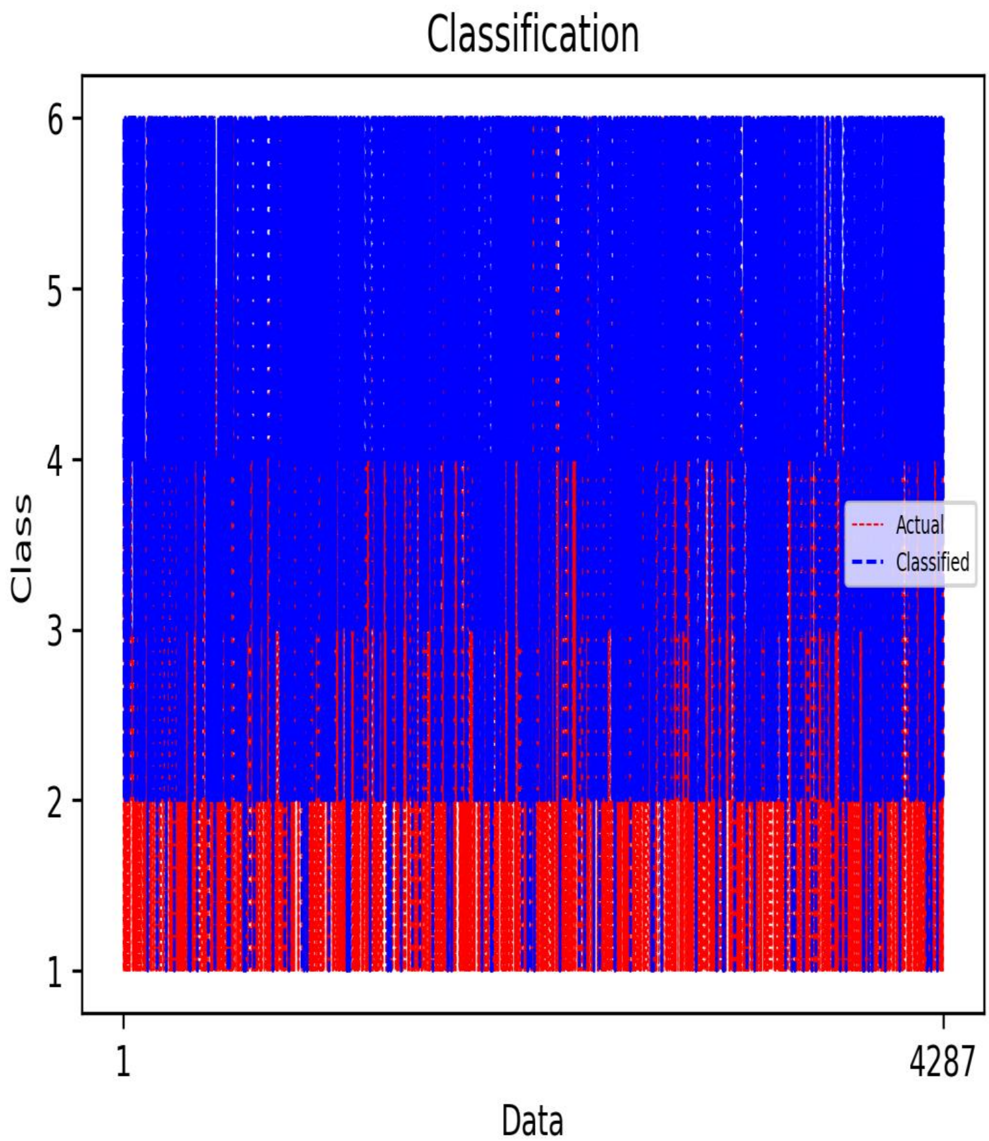
Decision Tree Classifier Results



GaussianNB mainly classified 5 types of machine faults, as seen in figure 4.4 below.

Figure 4.4

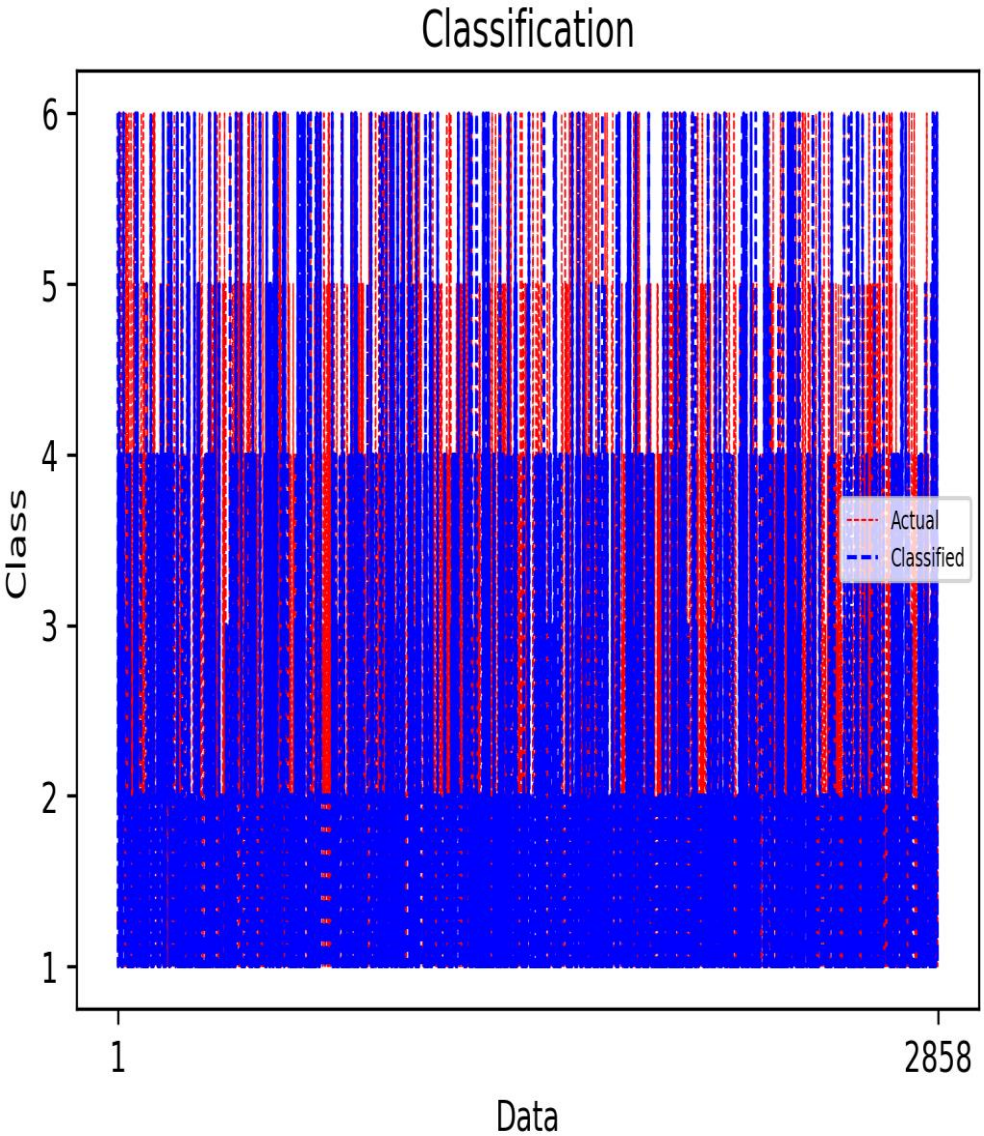
GaussianNB Classifier Results



The GBA algorithm classified all 6 types of machine faults as seen in figure 4.5.

Figure 4.5

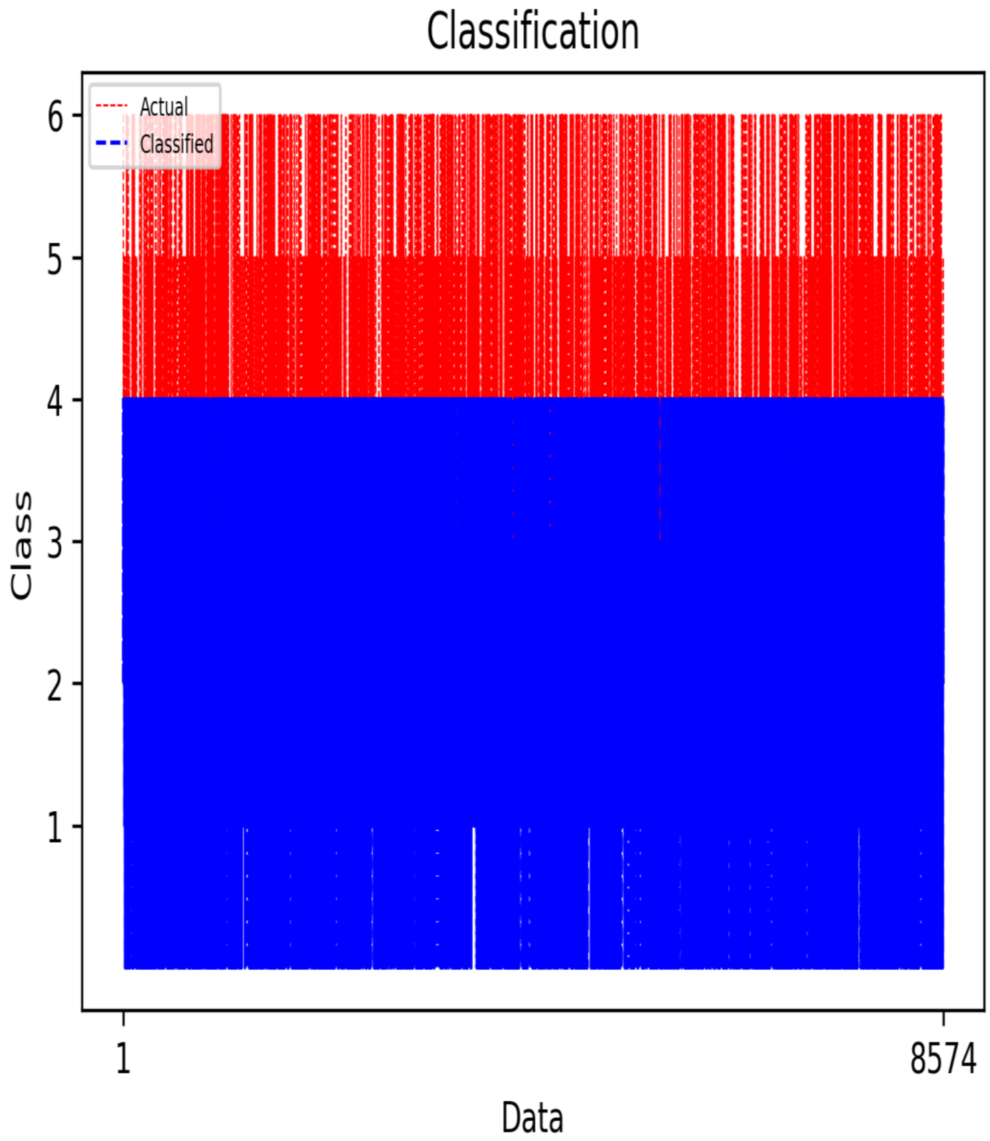
GBA Classifier Results



The KMeans algorithm classified up to 4 machine faults.

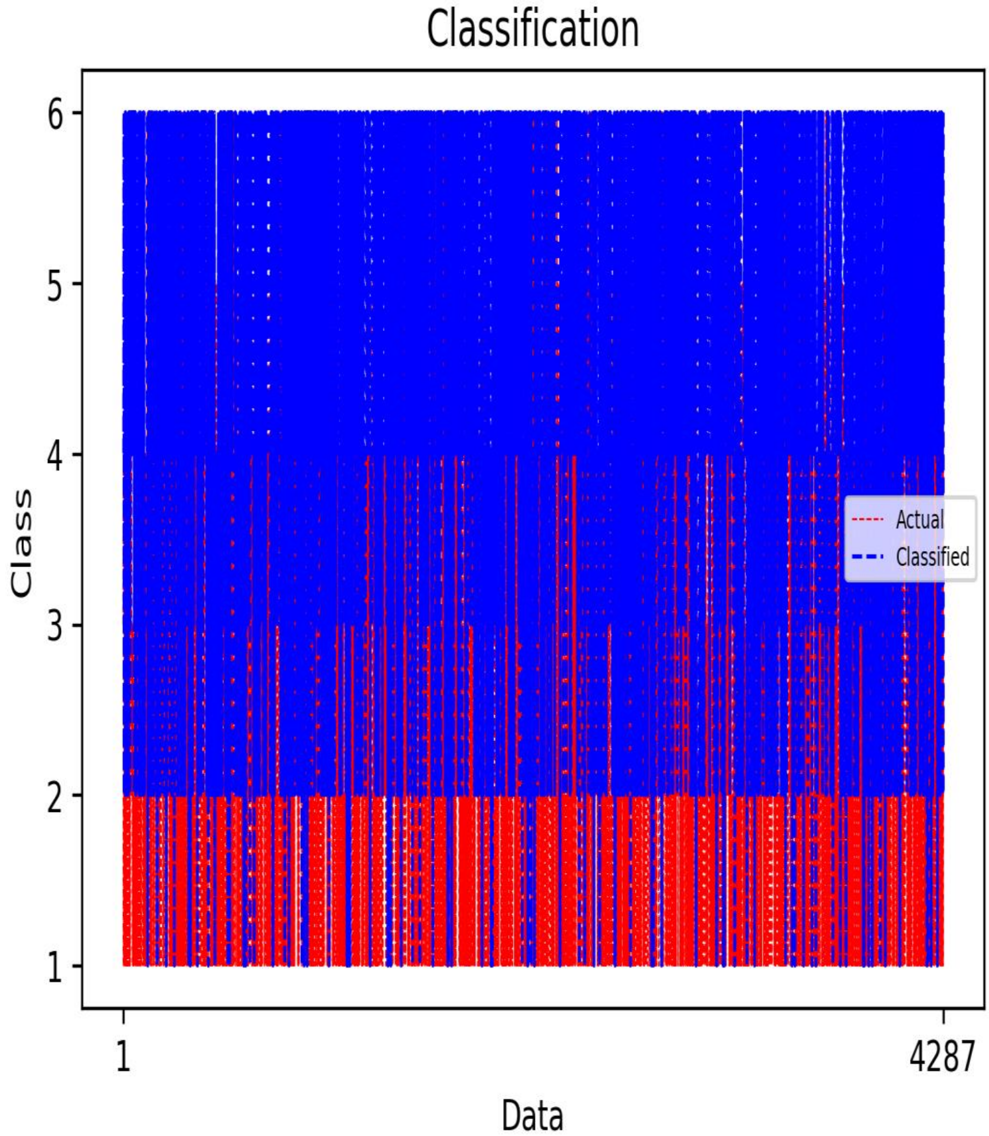
Figure 4.6

KMeans Classifier Results



As seen in figure 4.7, we can say that the KNN algorithm could classify up to 5 classes of machine faults.

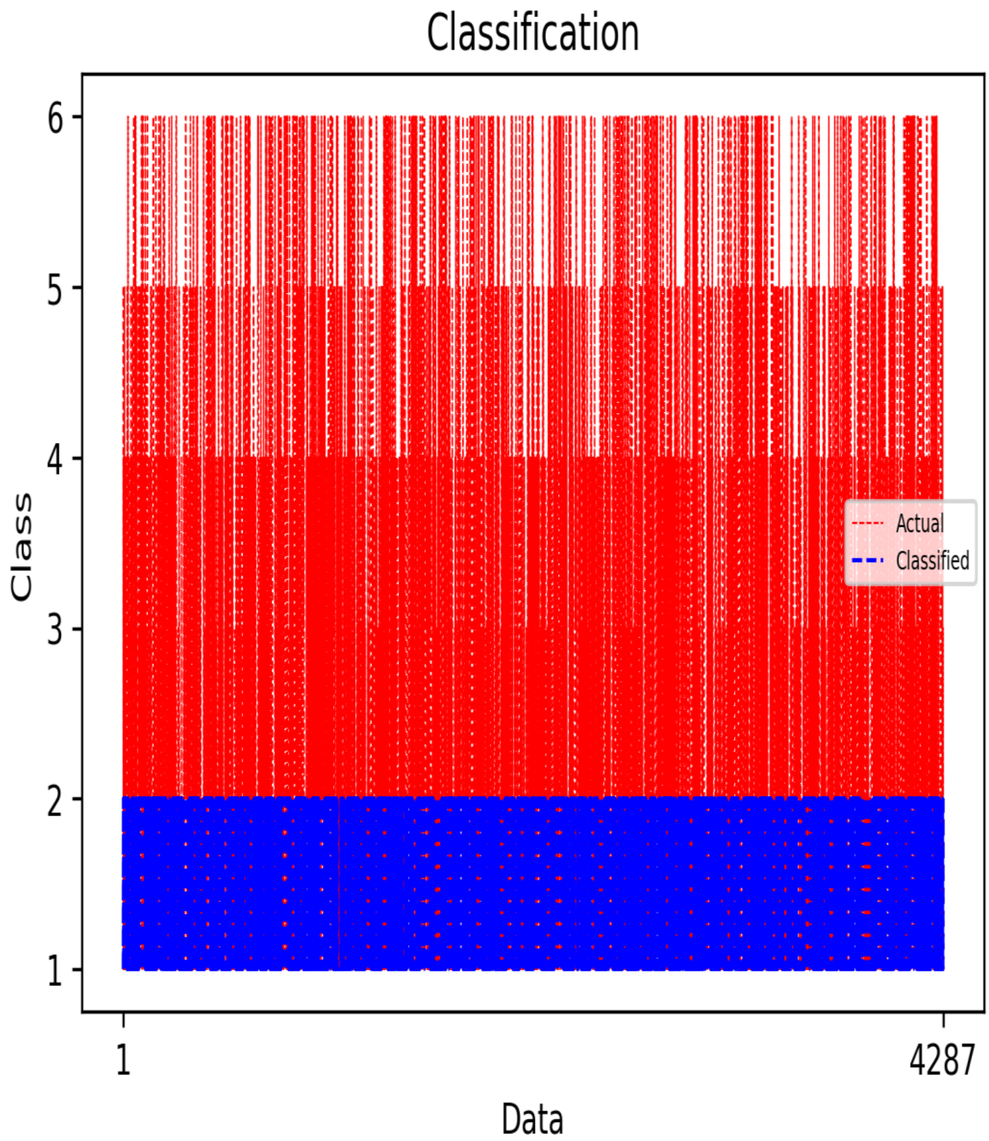
Figure 4.7
KNN Classifier Results



Logistic regression classified just two classes of machine faults.

Figure 4.8

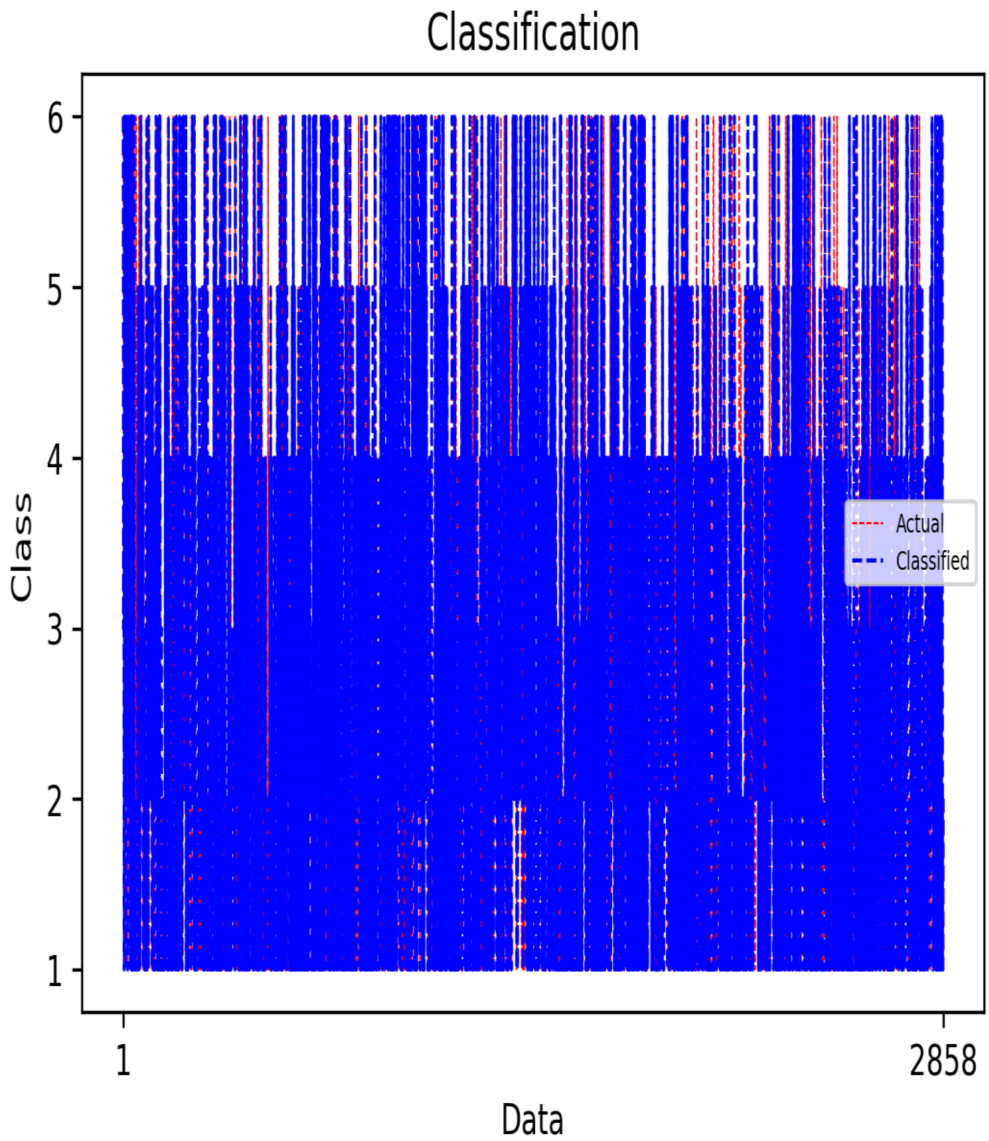
Logistic Regression (LR) Classifier Results



The random forest algorithm classified all 6 classes fairly, as seen in figure 4.9

Figure 4.9

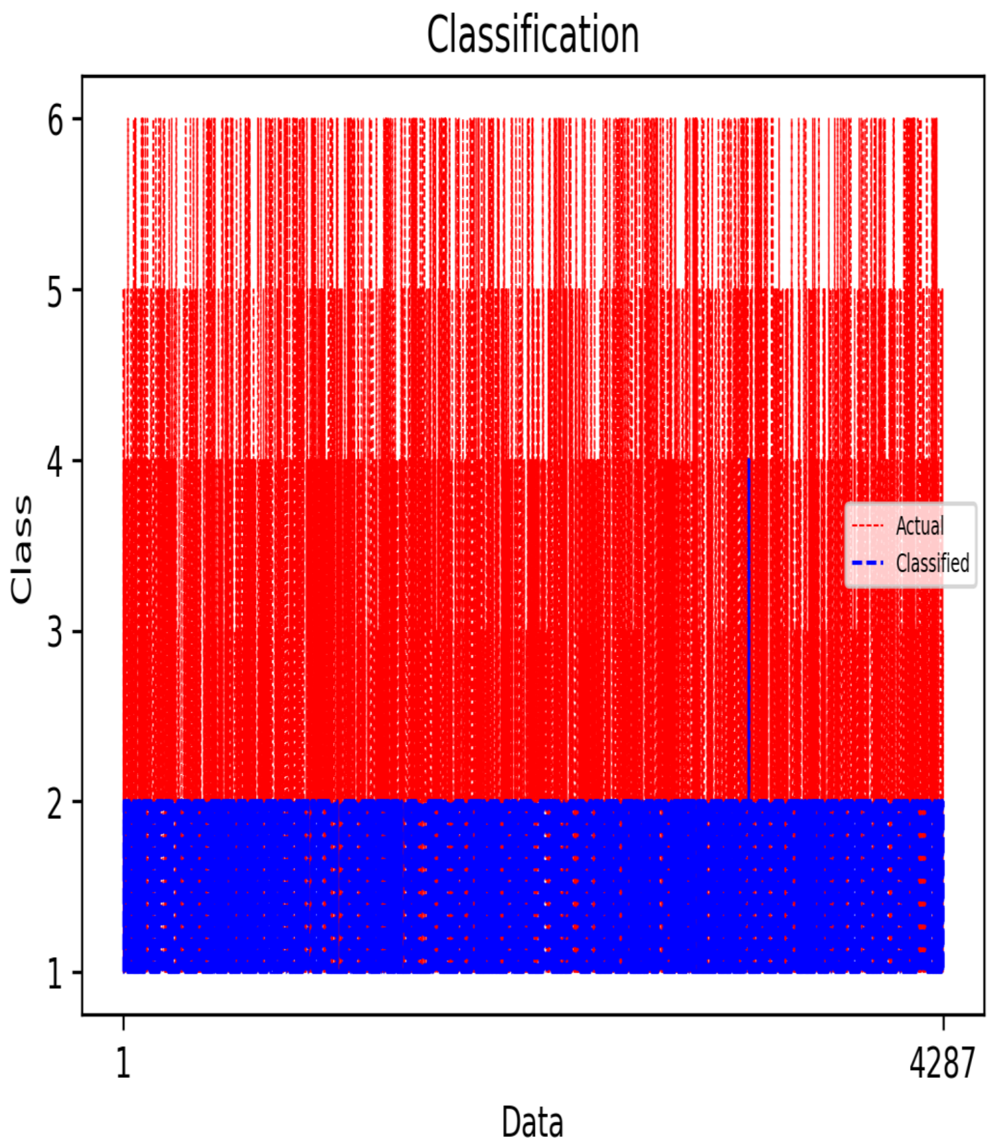
Random Forest (RF) Classifier Results



The SVM algorithm classified faults into 2 classes, as seen in figure 4.10.

Figure 4.10

Support Vectors Machines (SVM) Classifier Results



The overall outcome shows that the random forest algorithm obtained the best results. After considering the different test ratios, the random forest algorithm was most stabilized after considering the mean of the test ratios from 20% to 80%. The results are well analyzed in Table 4.2 below, as mentioned earlier.

Table 4.2

Ratio of obtained results

RESULTS							
Training Data / Classifiers	0.2 (% 20)	0.3(% 30)	0.4 (% 40)	0.5 (% 50)	0.6 (% 60)	0.7 (% 70)	0.8 (% 80)
Adaboost Class	0.460	0.457	0.479	0.499	0.495	0.459	0.479
BPNN Class	0.274	0.228	0.231	0.250	0.257	0.234	0.225
Decision Tree	0.874	0.831	0.790	0.745	0.701	0.655	0.591
Gaussian NB	0.310	0.314	0.310	0.302	0.301	0.301	0.300
GBA	0.589	0.588	0.587	0.583	0.579	0.577	0.568
KMeans	0.244	0.285	0.292	0.256	0.296	0.235	0.215
KNN	0.310	0.314	0.310	0.302	0.301	0.301	0.300
Logistic Regression	0.496	0.498	0.494	0.498	0.495	0.495	0.495
Random Forest	0.886	0.844	0.809	0.774	0.732	0.635	0.685
SVM	0.506	0.509	0.506	0.509	0.505	0.506	0.507

The Kmeans algorithm obtained the least results after considering the mean of the test ratio, resulting in a 24%. BPNN achieved a result of 27.4%. This is followed by the KNN and GaussianNB. Both algorithms obtained 31%, for a 20% test ratio. The Adaboost algorithm obtained 46%, Logistic regression with 49.6%, support vector machines with 50.6, the gradient boosting algorithm with 58.9%, the decision tree with 87.4%, and finally, random forest with 88.66%.

Conclusion

As degrees of automation and intellectualization rise steadily, mechanical engineering has reached a new stage of growth.

The procedure of detection is the primary concern when using conventional mechanical flaws. Artificial intelligence technology can be used to solve this issue.

In our research, we have selected some machine learning algorithms for the diagnosis of faults in electro-mechanical devices from vibration measurements.

The random forest algorithm produced an optimal result of 88.6%. Other machine learning algorithms will be tested and compared to the used ML algorithms in this research for future work.

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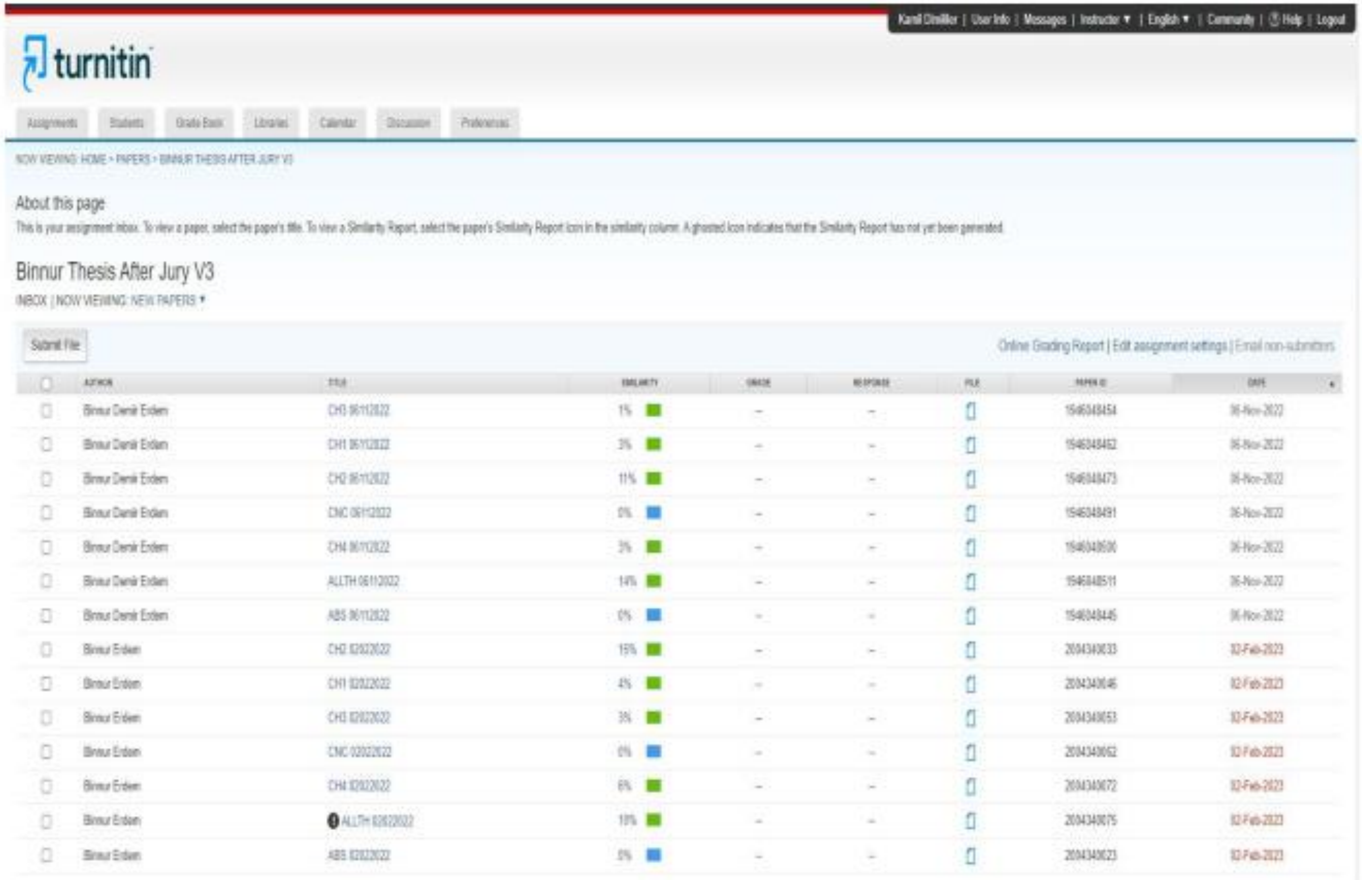

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