Reliability Estimation of Induction Motor Through Vibration Trend Analysis

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MASTER'S THESIS WORK

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Declaration

I, Safi Ur Rehman declare that thesis titled "***Reliability Estimation of Induction Motor Through Vibration Trend Analysis***" is self-work, solely presented by the author. All related material in this regard has been properly acknowledged and referred.

Safi Ur Rehman

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DEDICATION

“This thesis is dedicated to my family who instilled in me the virtues of perseverance and relentlessly encouraged me to strive for excellence”

Abstract

Vessels and installed subsystems on board require global planning, performance, and regular maintenance in the maritime industry. The goal of maintenance is to limit the frequency of failures in subsystems and avoid frequent breakdowns that cause operational disruptions. Preventive and corrective maintenance are quiet prominent and used in the marine industry. Mechanical systems, including plants, machinery, and equipment (PME) parts/ constituents, are replaced or renovated after specific intervals. Marine mechanical system components may need to be replaced during the scheduled interval or defined maintenance even though they are still operational, which results in exorbitant repair and maintenance costs. Similar to this, it's possible that PME components reached the end of their useful lives prior to the maintenance or scheduled period. Mechanical systems may malfunction as a result, necessitating corrective maintenance. As a result, the dependability, safety, and maintainability of maritime mechanical systems are being improved using traditional maintenance techniques to fail. The gaps left by the earlier maintenance techniques can be filled with predictive maintenance.

Predictive maintenance refers to the use of data, machine learning strategies, and statistical algorithms to foresee the most likely failure consequence of systems. In order to minimize maintenance costs and downtime, the data collected by sensors (wired or wireless) on machinery is processed to produce a reliable prediction on when a specific section or piece of equipment should be maintained or replaced. A subset of condition-based maintenance (CBM), which is characterized as a maintenance strategy that recognizes and tolerates system failure while it is occurring, is predictive maintenance. This tactic is becoming more popular in a number of contexts where modern signal processing and monitoring techniques are improbable. Due to contemporary maintenance trends, mechanical PME system performance and wear and tear can be quickly identified.

Electric motor drives have become widely used in marine applications, and their operational availability is always seen as important to ensuring that systems work smoothly and effectively. The usable life of the motors has a significant impact on the overall reliability of operational systems. Because electric drives are widely used, it is critical to assess the reliability of drive motor systems throughout both the design and operating phases. The reliability of the motor drive system is critical in process identification. Any little changes or failures in a system might occur owing to human mistake or environmental factors, resulting in significant losses in terms of system downtime, material and labour costs.

In this study, a predictive maintenance system for maritime boats will be built utilizing machine learning techniques. Using real-time data. Machine Learning will be used to estimate the reliability of induction motors used in industrial and home applications.

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Chapter No 1: Introduction

1.1 Background of Maritime Industry

For decades, the marine industry has played an important role in worldwide trade, transportation, and commerce. It includes a wide range of maritime industries such as shipping, shipbuilding, port operations, logistics, and marine services. The significance of the business arises from its role in facilitating international trade by providing a cost-effective way of carrying products and commodities across oceans and continents. The marine business has a long history, dating back to ancient civilizations when waterways were essential for trade and cultural exchange. Maritime activities evolved with developments in navigation skills, ship design, and maritime infrastructure, beginning with the usage of rafts and rudimentary boats and progressing to the introduction of sophisticated sailing vessels. With the introduction of steamships in the nineteenth century and the subsequent move to motorized vessels, marine transportation witnessed dramatic transformations, increasing efficiency and worldwide connectedness.

The marine industry thrives in the modern period, acting as a backbone for worldwide trade and economic development. According to the United Nations Conference on Trade and Development (UNCTAD), maritime routes transport almost 80% of world trade by volume and more than 70% by value. This reliance on sea transportation emphasizes its vital role in maintaining global availability and accessibility of goods. However, the maritime industry faces its own set of issues. Vessels and onboard equipment face tough environmental conditions such as corrosive seawater, intense weather, and high operational demands. These circumstances can cause wear and tear, mechanical failures, and significant safety hazards, necessitating effective maintenance practices to maintain safe and dependable operations. [1]

1.2 Induction Motor

An induction motor (IM) is a category of asynchronous AC motor that uses electromagnetic induction to drive spinning machinery. Nikola Tesla created the first induction motor with a wrapped rotor in France in 1882. [2]. Tesla established the scientific basis for comprehending the operation of the motor through his research. About a year later, in Europe, Mikhail Dolivo-Dobrovolsky invented the induction motor with a cage. The difference in size between a 100 horsepower (74.6 kW) motor from 1976 and a 7.5 horsepower (5.5 kW) engine from 1897 shows how far technology has come. Cage rotor motors are currently the most popular type of induction motor (Figure 1). In its rotor, an electric motor transforms electrical energy into mechanical energy. It's possible to power the rotor. While an induction motor induces this power inside the rotating machinery, a DC motor's armature receives it directly from a DC source. Since the stator serves as the transformer's main side and the rotor serves as its secondary side, an induction motor is occasionally referred to as a spinning transformer. Induction motors are frequently used in industrial drives, particularly polyphase induction motors. Industrial motors are increasingly being replaced by induction motors because of their robust design, lack of brushes (which are necessary in the majority of DC motors), and controlled speed. [3]

1.2.1 Construction

Stator and rotor are the two main components of a conventional motor, much like other kinds of motors.

a. A stator that is stationary outside and has coils operated by AC to produce a revolving magnetic field.

b. A rotating field's torque is applied to an internal rotor that is connected to the output shaft.

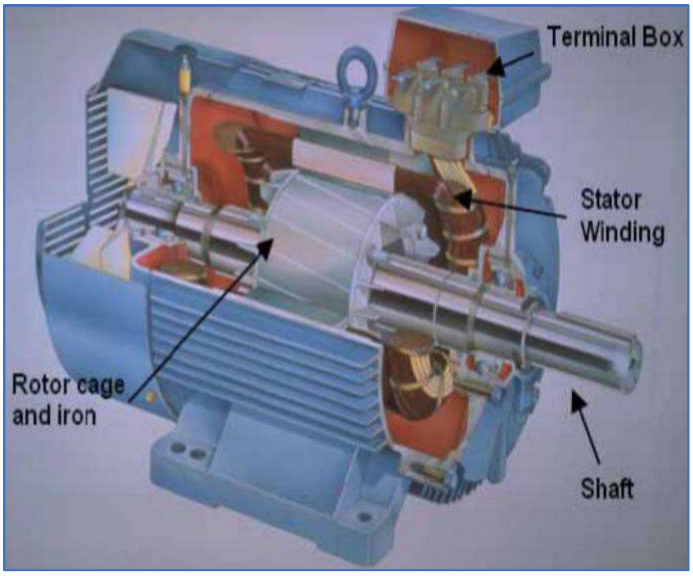

Figure 1: Construction of induction Motor

1.2.2 Stator construction

An induction motor's stator is made of a laminated iron core with slots, similar to the stator of a synchronous machine. Coils are inserted into the slots to produce a three- or one-phase winding. [4]

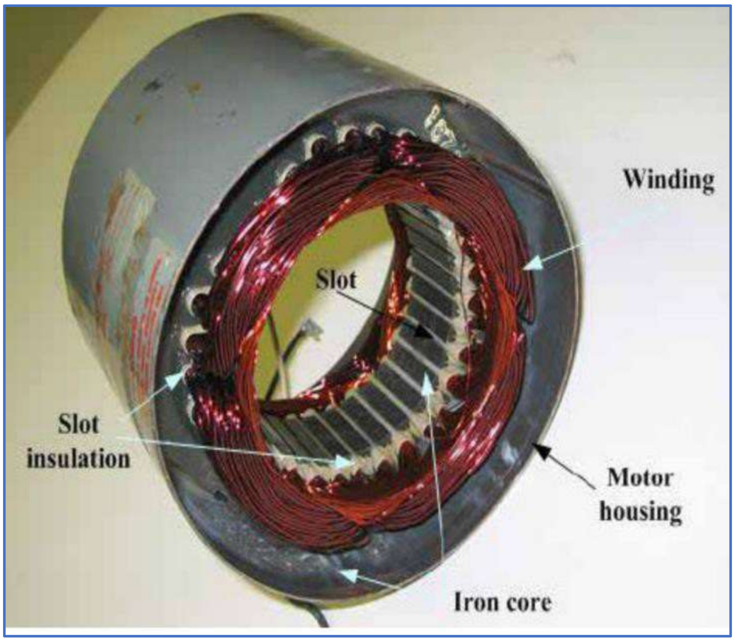

Figure 2: Single Phase Stator with Windings

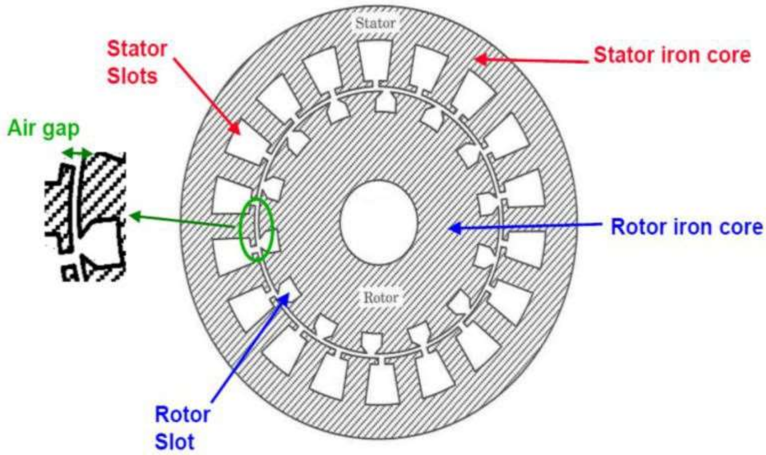

Figure 3: Induction Motor Magnetic Circuit Showing Stator and Rotor Slots

1.2.3 Type of rotors

There are two different types rotors.

a. Squirrel cage rotor

b. Wound rotor

1.2.3.1 Squirrel-Cage Rotor

Individual copper or aluminium bars that are placed into the slots and short-circuited via end rings on either side of the rotor make up the squirrel-cage rotor's winding. A squirrel-cage rotor is used by all single-phase induction motors. For the purpose of cooling the circuit, one or two fans are fastened to the side of the rotor. [5]

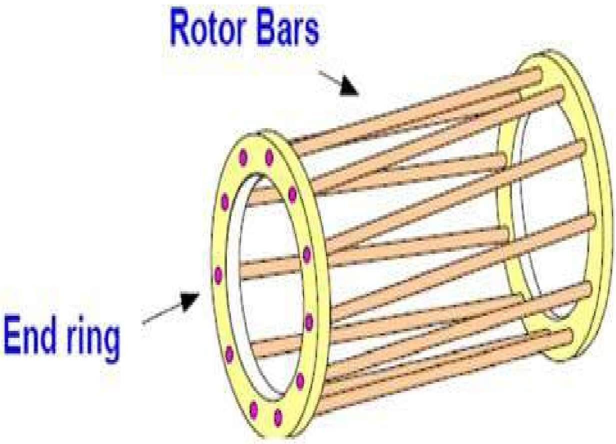

Figure 4: Squirrel Cage Rotor

1.2.3.2 Wound Rotor

An insulated 3-phase winding with the same number of poles wound as the stator is applied to the slots in the wrapped rotor. To connect it for starting or speed regulation, the ends of the star-connected rotor winding are brought to three slip rings on the shaft.

- Usually, it is used with big, three-phase induction motors.

- The end of every phase is linked to a slip ring at the rotor, which has a winding similar to that of the stator.

- Wound rotor motors are less widespread in industrial applications than squirrel cage rotors because they are more costly and need maintenance on the brushes and slip rings.

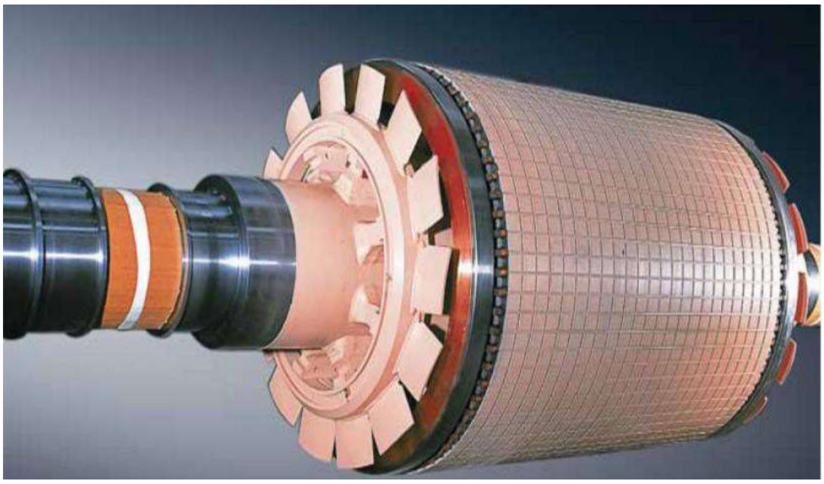

Figure 5: Wound rotor of a large induction motor

1.3 Principle of Operation

Flux is created in the stator magnetic circuit, by supplying AC to the stator armature. When the magnet is moved, this flux "cuts" the conducting bars of the rotor, causing an EMF to be generated (E = BVL (Faraday's Law)). Due to the induced EMF, current flows in the rotor circuit, resulting in a force that may be converted to torque as output. [6]

In a three-phase induction motor, the three-phase currents have identical magnitudes but 120° phase variances. Physically, each magnetic flux generated by each phase current shifts by 120°. The three fluxes are combined to create the machine's overall flow. The three ac fluxes are added to produce a rotating flux with a constant amplitude and speed. A rotating magnetic flux or rotating magnetic field (RMF) is produced when balanced three-phase currents running in the three-phase windings do so. RMF rotates without interruption (synchronized speed). Without an RMF, an induction motor cannot function. [7]

When an AC source powers the stator, RMF is formed as a result of the current delivered to the stator winding. This flux produces a rotating magnetic field in the space between the rotor and the stator. The rotor's short-circuited bars experience a voltage as a result of the magnetic field. The voltage causes the bars to conduct current (Wrong wording). A force that propels the motor and, as a result, torque is produced resulting from the interplay of the revolving flux and the rotor current. The magnetic field in the air gap rotates in the same plane as the rotor. [8]

The actual rotor's speed and the stator's rotating magnetic field's speed, nevertheless, must differ for these currents to be generated; otherwise, the magnetic field would not be moving in relation to the rotor conductors and no currents would be generated [9]. The rotor typically slows down slightly in the unlikely case that this happens until a current is reduced, at which time it resumes its typical activity. This difference in speed between the rotor and the stator's rotating magnetic field is known as slip. It is the ratio of the rotational speed of the rotating stator field (slip speed) to the relative speed of the magnetic field as determined by the rotor. The term "asynchronous machine" is sometimes used to describe an induction motor because of this.

1.4 Causes of Failure of IM and its Effects

There is a growing need to increase the availability and dependability of electrical systems in many different types of manufacturing applications. In some instances, an unexpected system failure might result in costly downtime, damage to the surrounding equipment, or even a risk to people. A modern device is more dependable and is available with tracking and failure detection. Given that many natural catastrophes deteriorate very slowly, there may be a chance for early defect discovery and corrective preservation. This prevents unexpected, widespread device failure that might have negative effects. [10]

Induction motor electric failure can be due to stator winding rapid circuit, broken quit ring, damaged rotor bar, and inverter failure. A mechanical issue with induction, Entrance of dust, bearing failure, shaft misalignment, load faults (unbalance, gearbox issue, or favored failure in the load component of the drive), and motor rotor eccentricity. The majority of errors are caused by bearing (> 44%) and winding (> 26%) defects, according to a reliability survey on large electric vehicles (> 200 horsepower) [11]. If we can eliminate these crusher application motor problems (have no idea what it means), it will significantly improve the life and performance of induction motors, resulting in less downtime for businesses and cost savings. [12]

Improve the dependability and effectiveness of electric motor operations in order to improve the marine sector's energy efficiency and reduce energy production and consumption costs. Energy consumption can be decreased while maintaining the same level of production capacity by adopting two-way, high-efficiency equipment and installing an energy management technology. Consumers, businesses, the energy sector, and governmental organizations risk making poor judgments due to ignorance about new energy-efficient motor technology, selection mistakes, and incorrect equipment use. The situation eventually reduces industrial system efficiency and causes financial losses for every link in the supply chain. The categorization and causes of electric motor failures are crucial factors to take into account for energy efficient management due to their influence on operational dependability. Another thing to remember is that not all equipment malfunctions occur abruptly and without warning. The working temperature, operating torque, damages, mechanical vibration, and other parameters are adversely impacted, which lowers the efficiency of the production system. These can occur in both degenerative and progressive manners. However, it's crucial to consider how the frequency of repairs impacts the effectiveness of the electric motor. This is due to the fact that motor losses tend to increase with time, and research indicate that each repair can reduce efficiency by up to 2%. [13].

Both scholarly as well as business communities are interested in exploring the causes of electric motor failures; current research concentrates on methods for determining and measuring defects using on-line or off-line examinations. According to the kind of failure (mechanical, electrical), the location of the problem (stator, rotor), and other factors, several writers in their studies have classified and divided motor failures into different groups. Some researchers have categorized and classified types of motor failures according to the kind of failure (electrical, mechanical), the location of the defect (stator, rotor), and several other factors.

1.5 Source of the Failures

There are two levels that may be used to categorize the sources of problems in an electric motor: internal sources and external sources. It is crucial to define what constitutes an electrical machine failure for instance, any component change that stops the machine from operating properly is considered a failure. Another way to describe it is the absence of an ingredient necessary for an anticipated activity. According to this definition, the phases of failure include impending failure, material fatigue, degeneration of the material, and the defect itself [14]. The causes of failures are classified as:

- Materials, designs, and production flaws inherent in them.
- Inappropriate use of or application of efforts.
- The degradation that occurs over time due to rust, wear and tear, or by being overworked.

In his work, Bazurto, A. J., come to the conclusion that prompt failure detection assures the machines' security, dependability, and simplicity of maintenance. According to various studies, the failures of the rotor and stator are result of a number of forces operating on both of these parts at once. Following table shows types of stress acting on stator and rotor: [15]

Stator	Thermal stress
	Electric stress
	Mechanical stress
	Environmental pressure
Rotor	Thermal Stress
	Electromagnetic Stress
	Stress residual
	Dynamic stress
	mechanical stress
	environmental stress

Table 1: Classification of Motor Stresses

A. Bonnett and C. Yung are credited with compiling survey data and identifying the top five reasons why electric motors fail, which include operational stressors and random events. [16]

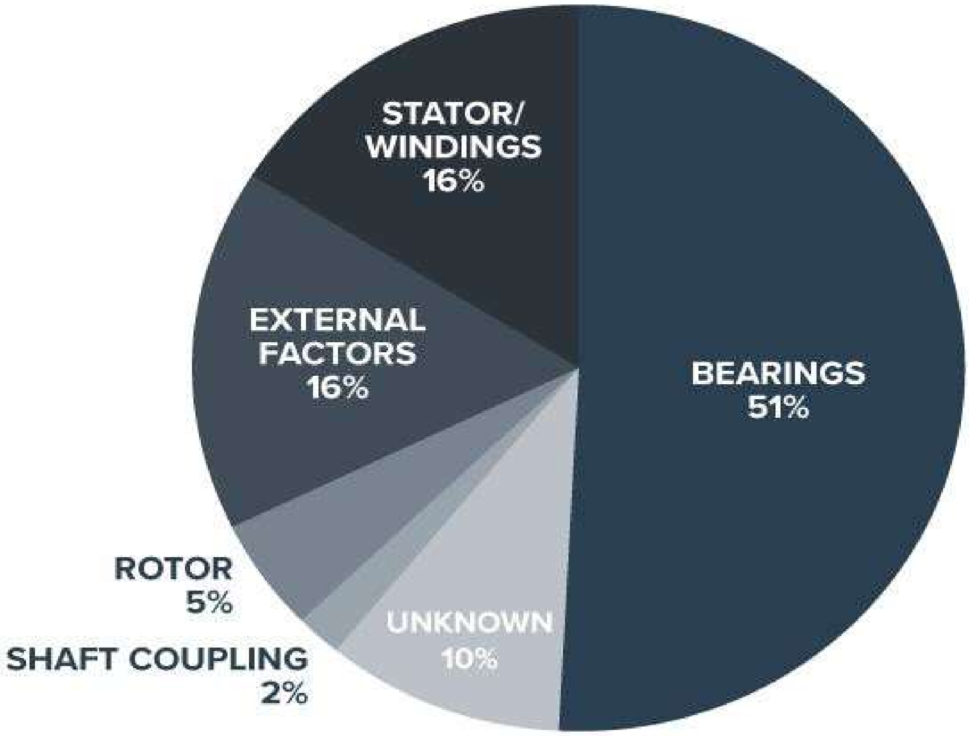

Figure 6: Different Types of Failures

1.6 Problem Identification and Significance

Thanks to the Fourth Industrial Revolution's quick development, the widespread increased usage of sensors, the creation of vast databases and analysis systems, and the implementation of artificial intelligence techniques, smart factories may automate their operations and significantly improve their efficiency and manufacturing quality. Equipment downtime and malfunctions must be maintained to a minimum as manufacturing procedures become increasingly intricate and time-consuming in order to save manufacturing costs and improve plant and employee safety. But unplanned downtime is a given in the industrial industry. For this reason, Prognostics and Health Management (PHM) is an indispensable aspect of manufacturing, responsible for monitoring and analyzing the status of equipment for suitable machine maintenance and proper functionality.

One of the biggest problems for a successful predictive maintenance plan is data availability. Machine learning depends heavily on the quantity and quality of the data used to train them. Therefore, without a considerable amount of quality data, the data driven approach is hard to perform. In this thesis, fault diagnosis of induction motor data is performed. Upon acquiring such a motor, no data existed. This fact was an impediment to selecting and progressing in the thesis. One solution to this problem was to use a public dataset with similar characteristics that can be temporarily used to train and test the models and methodology presented by Baicoianu, A., & Mathe, A. [17]

Maintenance methods have rapidly evolved from reactive maintenance, where maintenance is performed after a failure occurs, to Preventive Maintenance (PvM), where maintenance is performed at set time breaks, and onto the predictive maintenance.

Due to its benefits over other maintenance techniques, including reduced factory downtime, decreased manufacturing and maintenance expenses, increased production, safety, machinery life, and a rise in overall profit, among others, predictive maintenance is a hot topic that is gaining attention among manufacturing businesses and research institutions.

Predictive maintenance aims to detect component and equipment failure before it happens, and ultimately, predict the Remaining Useful Life (RUL) of the equipment, with the goal of allowing manufacturing companies to schedule maintenance before a failure occurs. As smart factories monitor equipment and collect more data than is possible for technicians to inspect, the opportunity for data-driven fault diagnosis methods is opened. Machine Learning (ML) makes use of neural networks with three or more layers which are able to learn from a vast amount of data. Because machine learning development rapidly increases and given the vast amount of data that is collected by condition monitoring systems deep learning appears to be a perfect candidate for processing the data and performing of fault diagnosis. The induction motor is of one the most important components in present-day manufacturing factories because of its ruggedness, reliability, and cost. It is therefore of utmost importance that proper monitoring and maintenance is performed on induction motors in order to keep manufacturing processes as lean and efficient as possible. [13]

1.7 Motivation and Objective of the Thesis

Greater safety, longer machinery life, greater machine uptime, and part-life optimization were all results of early equipment fault identification along with adequate maintenance of manufacturing machinery. The net result of all these advantages will be improved and leaner production processes at lower expenses that can be passed effectively on to the consumer and community. An increase in equipment efficiency also translates into less waste and fewer resources required.

This thesis work is exploring the vast and broad area of predictive maintenance. Given that no project specifications, requirements or metrics were provided, the thesis workload was split into two broad modules:

- Data acquisition and preprocessing
- Data processing, feature engineering, and model selection

The objective of the thesis is to explore machine learning data and driven fault diagnosis approaches for induction motor prognostics. From the study, the following research questions emerge:

- What kinds of sensor readings (temperature, vibration, pressure, etc.) have the most beneficial impact on predictive maintenance?
- How can Machine learning be used for predictive maintenance?) This should be part of next section.

1.8 Scope of Work

In the modern world, cost optimization is a key objective for industrial drives. There are fixed expenses and variable costs in all industrial facilities. The first are routine expenses for maintenance and spare components, and a sizeable portion of the latter is the unforeseen expenses for fixing faulty equipment. If, for whatever reason, an induction motor (IM) enters an incorrect operating mode that could result in equipment failure, it can result in the largest additional financial loss. Electrical machine failures must be prevented, which necessitates the development of a condition-based maintenance system to track and analyze a machine's operational state. Due to the effectiveness of the drives and the cost savings realized in this way, there has been a rise in the cost of systems that can forecast future occurrences in addition to analyzing the machine's current working condition. The efficiency of the drive is improved through early fault identification. Many methods for tracking the performance parameters of machines and identifying breakdowns before they occur have been developed thanks to modern technologies. The methods for locating faults rely on measurements of a variety of variables, including temperature, oil analysis, gas analysis, and global performance monitoring [18]. Electromechanical fault detection techniques measure currents, partial discharges, leakage flows, shock pulses, vibrations, and acoustic noise. These methods frequently rely on processing and interpreting massive amounts of data. The key issue is extracting valuable information out of the available data. The use of machine learning in data study enables a wide range of tools for comprehending the statistics immediately collected from the industrial drive.

It is important to comprehend the factors that contribute to vibration change since motor vibrations can occur even when the motor is in perfect condition. Before these issues cause shaft or bearing degeneration, vibration analysis can find misalignment and imbalance. While a machine is starting up, shutting down, or just running normally, vibration analysis provides a reliable, non-intrusive way to check on its current condition. The main benefit is that it responds immediately to changes, making it useful for both ongoing and sporadic analyses of operational conditions. Also, a key component of vibration examination is the potential for extensive usage of signal processing procedures to quickly locate problem signs that are not obvious in the original signal.

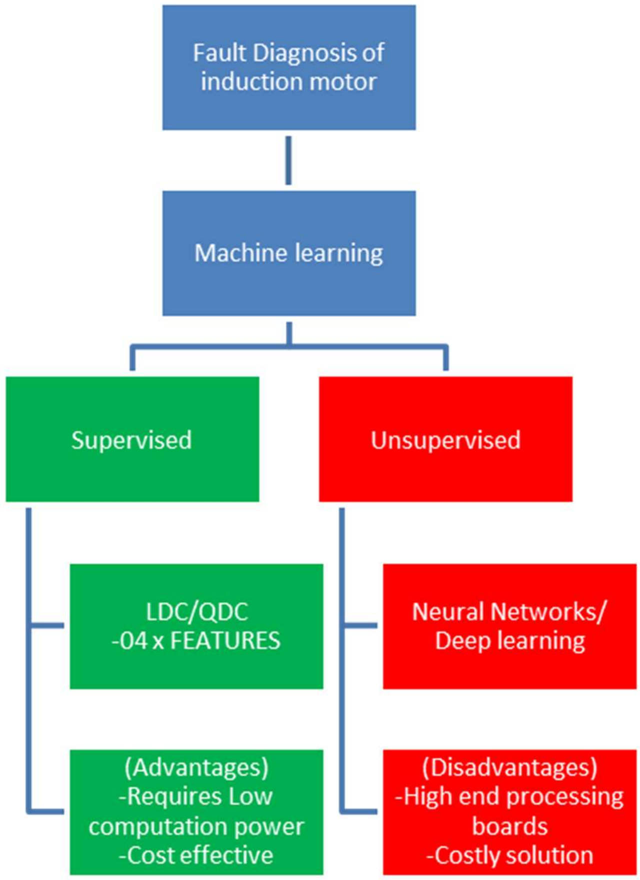

Figure 7: Comparison of Supervised and Unsupervised Machine Learning Technique

Chapter No 2: Literature Review

2.1 Significance of Machine Learning

Monitoring and analyzing a machine's operational state is required to prevent breakdowns in electrical machines, necessitating the deployment of a condition-based maintenance system. Fault diagnosis methodologies vary depending on the amount of available data Manufacturing industries rely on motors for their processes and the induction motor is the most important component of any manufacturing industry. Because of its ruggedness, reliability, and cost. Fault detection and diagnosis for moving machinery such as motors and turbines has been a topic of interest for the industry. In past decades, however, the methodologies used have mostly been model based and signal based. Given the cost of hardware, the use of well-controlled simulation motor models for testing fault diagnosis approaches is the widespread strategy under practice. Such simulations are meant to replicate the motor's dynamic behavior and electromechanical interactions. [19] [20]

Machine learning is a sub branch of Artificial Intelligence that can be defined as a set of methods used to automatically detect patterns in input data in order to make predictions on future data. Contrary to traditional programming where the designer defines the rules (program) to be used with the data in order to obtain a result, machine learning systems are trained to extract the rules based on the data and results of previous iterations. [21]

Machine Learning

Figure 8: Basic Steps of Machine Learning

2.2 Origin and Development of Reliability

Since ancient times, people have lauded reliability as a human quality. The dependability idea hasn't been used in technological systems, nonetheless, for more than 60 years. It was first used in relation to compare the operational safety of one, two, and four-engine airplanes just after World War I when it had a technological significance. The accidents per hour of flying time served as the primary metric for determining dependability. [22] [23]

The idea of reliability is well-liked and has long been praised as a positive quality in a person or a product. Far earlier than anyone would anticipate, it began modestly in 1816. Samuel Taylor Coleridge, a poet, is credited with creating the term "reliability." Reliability in statistics refers to a measurement sets or instrument's consistency, which is frequently used to define a test., Reliability as a term initiated to specify dependability or repetition prior to World War II. The U.S. military redefined the current application in the 1940s, and it developed from there to the present. At first, it came to signify a product that would function as anticipated. The definition as it stands now includes a variety of other characteristics that can apply to goods, services, software programs, or human activities. All facets of our modern, technologically advanced world now exhibit these characteristics. [24] [25]

2.3 Reliability Concept and definition

Reliability is defined as the probability that a product, system, or Service will operate in a predetermined setting without failure for a given amount of time or will sufficiently fulfil its intended function. Reliability is a property of any measure, tool, test or sometimes of a whole experiment. It entails estimating the potential degree of random error in grades that are very close to the genuine score.

To properly comprehend how reliability in a product or service is developed, it is imperative to comprehend the definition's key elements.

- Probability
- Intended function.
- Satisfactory
- Specific period
- Specified conditions.

The product development process begins with the most efficient improvement activities being taken. The designer may minimize weak points and eliminate probable failure sources based on existing experiences from the use of similar design solutions. Customer experiences sent back to the designer are no longer sufficient since failure acceptability is declining, development lead times are getting shorter, and product life cycles are getting shorter. It is necessary to employ additional trustworthy information sources. It is necessary to use statistically prepared trials to identify probable unreliability causes. Accelerated life testing is becoming more popular as a way to quickly identify significant failure causes and processes. It will become more crucial to understand the mechanics of failure to make accurate forecasts. [26]

A new design philosophy must be implemented since the production and development processes need to have shorter lead times. It is necessary for disciplines to be integrated more thoroughly. These activities are referred to as "integrated product development," "concurrent engineering," and "simultaneous engineering." In these new attitudes toward a comprehensive product life cycle point of view, reliability engineering methodologies are crucial.

Simple analytical approaches must be employed since the majority of reliability enhancement measures must be taken by the designer. FMEA, or failure mode and effects analysis, is one such tool. The question of whether FMEA should be carried out by the designer or the reliability analyst was debated in the 1970s [27]. Today, many design engineers view it as a natural tool. This tool is increasingly used in process development as well as design, where its importance is recognized. [28]

2.4 Maintenance Techniques and Tools

Maintenance is a crucial component of production since it improves the quality and dependability of equipment while reducing downtime. Depending on the methods employed, maintenance may be divided into following categories [29]:

2.4.1 Reactive Maintenance:

Often known as Run 2 Failure (R2F), is the most basic but also the most expensive and ineffective type of maintenance. After a defect has occurred, reactive maintenance entails fixing the affected equipment, which may have detrimental effects on other components as a result of the initial issue.

2.4.2 Planned Maintenance:

Maintenance actions are arranged in advance based on manufacturer recommendations, industry standards, and historical performance data in planned maintenance. This proactive method entails routine inspections, lubrication, and component replacement at predefined intervals. The purpose of planned maintenance is to avoid unexpected breakdowns, extend equipment lifespan, and ensure continuous operation.

2.4.3 Preventive Maintenance:

Preventive maintenance is comparable to planned maintenance, but it goes above and beyond the guidelines of the manufacturer. It entails continuously monitoring equipment performance and carrying out maintenance activities based on condition-based assessments. Monitoring the state of vital components allows maritime operators to identify possible issues and solve them before they become failures, lowering maintenance costs and minimizing downtime.

2.4.4 Predictive Maintenance:

Predictive maintenance is an advanced maintenance technique that predicts the condition and performance of equipment using real-time data, sensors, and machine learning algorithms. Predictive maintenance can spot anomalies and probable breakdowns by analyzing data from sensors implanted in machinery, allowing for prompt maintenance actions before problems grow. By directing resources where they are most needed, this technique optimizes maintenance schedules, saves downtime, and lowers maintenance costs.

Because of its ability to increase equipment durability, optimize maintenance practices, and improve overall operational efficiency, predictive maintenance is gaining appeal in the maritime industry. By merging data-driven insights with traditional maintenance methods, maritime enterprises may move towards a more proactive and effective maintenance approach, resulting in safer and more reliable vessel operations. [30]

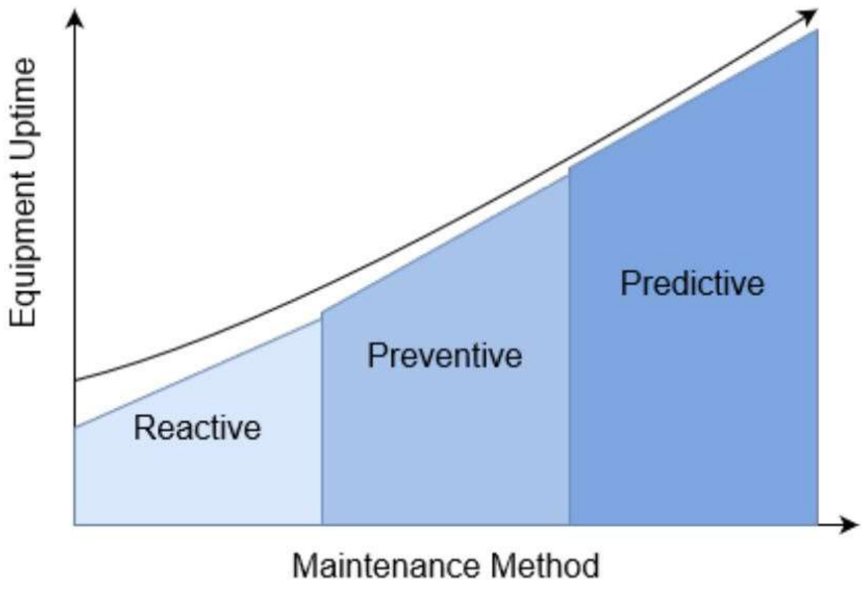

Figure 9: Equipment Uptime vs Maintenance Method

2.5 Predictive maintenance

Predictive maintenance (PdM) is a development and expansion of condition monitoring made feasible by the massive amount of data collected by sensors (CM). The industry is paying attention to predictive maintenance, which is the most effective sort of maintenance. However, if there is no previous data, predictive maintenance may be difficult to perform and costly to execute without the right hardware and analysis skills. Predictive maintenance is an example of an improvement that uses the strategies further described in this thesis to identify potential faults and correct them to prevent downtime that a failure would otherwise create. [26]

Predictive maintenance insights are a very useful tool for enhancing an operation's general maintenance and dependability. Benefits comprise:

- Reduce the number of unforeseen failures.
- Increase asset availability and reliability.
- Lower operating costs by only doing maintenance as required.
- Increase production time.
- Enhance safety.
- Maintenance costs can be decreased by lowering labour, inventory, and equipment expenditures.

In contrast to preventative maintenance, predictive maintenance bases its maintenance forecasts on the equipment's current condition instead of its average or anticipated life figures. The present condition of the system and its predicted future states are frequently determined using machine learning techniques. Some of the essential components needed to perform predictive maintenance include data gathering and preprocessing, early defect detection, fault detection, time to failure prediction, maintenance planning, and resource optimization. Another way to increase productivity and implement "just-in-time" production is through predictive maintenance, which has been referred to as one of the essential aspects in this respect.

Predictive maintenance strategies are used more frequently than conventional preventative measures in reliability-centered maintenance. When used correctly, it gives businesses a tool for obtaining the lowest asset net costs for a particular level of performance and risk. Predictive machine maintenance methods heavily rely on vibration diagnostics. Vibration diagnostics has been shown to be the most reliable way to assess the "health" of a machine. We can forecast machine problems with the use of vibration diagnostic technologies. Machine defects may be found early, and the proper course of action can be taken when predictive maintenance is used and the machines are examined routinely. By doing this, you may prevent unexpected machine shutdowns and spare components from needing to be replaced when they are still in good shape.

The performance of the equipment is assessed using condition monitoring devices. The purpose of evaluating the equipment's efficiency entails adding sensors to the machinery to collect data about the machinery. Aspects like pressure and temperature can be recorded using sensors. Without needing to open the machine, condition-monitoring sensors allow maintenance crews to have knowledge about the asset's operational state. Teams don't experience a lot of unintended downtime because to this diagnosis automation. In order to determine when equipment needs maintenance or replacement, the statistics gathered is analyzed employing predictive algorithms that spot trends. These algorithms compare the equipment's present behavior to its anticipated behavior using a set of established rules. [31]

Using this information interchange, maintenance managers are able to view all physical assets collectively, understanding what goes on with the equipment and identifying any parts that need care.

2.6 Predictive Maintenance Tools

This section discusses the different Predictive Maintenance tools that are commonly used by reliability engineers across all industries.

2.6.1 Infrared Analysis Sensors

Predictive maintenance software needs sensor data to work properly. IoT sensors collect data on a variety of machine characteristics, such as temperature, pressure, sound, and more. [32]

Infrared analysis may be employed to evaluate a variety of conditions, including those of electrical components (commonly for ARC flash analysis), process temperatures, piping, plumbing, solar panel conditions, variations in temperature of mechanical components (like motor cases), insulation conditions, etc. Infrared thermography sensors and cameras are a common investment for managers creating a PdM programme. Thermal imaging is a great way to quickly measure and contrast thermal signatures that are undetectable to the naked eye without interfering with business as usual or putting technicians in risk. Additionally, it enables staff to find anomalous circumstances that are hidden by other equipment components. [33]

2.6.2 Motor Circuit Analyzers

A PdM tool called a motor circuit analyzer aid in providing a comprehensive picture of the electrical condition of equipment's motor system. Motor circuit analysis leverage electric signature analysis (ESA) to locate these errors. ESA analyses the operational current and supply voltage of a motor to identify problems. ESA operates equally well on both AC and DC motors. Finding issues with incoming electricity and mechanical motor components requires the investigation of motor circuits. It can find faults with the stator winding, anomalies in the bearing, rotor, coupling, connected load, efficiency, and system load, among other things.

A practical method for examining the status of equipment while it is still operating is motor circuit analysis. Many motor circuit analyzer tools enable testing to be carried out in under two minutes. The full equipment chain cannot be checked; it is only utilized to inspect electrical components that are linked to other components. [34]

2.6.3 Vibration Analysis Sensors

Vibration analysis sensors analyze the vibration of the parts to find trouble signals and transmit data to a database. By contrasting current and historical data when connected to a contemporary CMMS (what is CMMS), it is feasible to detect changes over time. Moreover, CMMS machine learning groups data into useful knowledge. When it comes to rotating machinery, vibration is one of the best signs of imminent breakdowns. Increasing vibration intensity is a sign of equipment wear and tear, which without prompt repair results in asset failure.

Vibration analysis is used to find problems with alignment, mechanical looseness, gear flaws, lack of lubrication, resonance, rubbing, cavitation, corrosion, and other things. As a result, it may be used for a wide range of equipment across various sectors. The versatility of vibration analysis applications is one of its benefits. It gathers information regarding the displacement, vibration frequency, and velocity (or speed of the vibration) of an object in real-time. After a month of data collection from sensors, there is enough knowledge to take appropriate action. [35]

2.6.4 Laser-Shaft Alignment Tool

To verify precisely aligned spinning shafts in a facility, laser-shaft alignment equipment is utilized. The reason for this is because one of the most common causes of mechanical failure when equipment is put into operation is improper installation procedures.

The drive train of an asset is put under tremendous strain by misaligned components, whether they are offset or angular in nature. Often, misplaced shafts do the most damage to the bearings. Laser-shaft alignment equipment uses single laser measuring technology. The use of instruments for laser-shaft alignments is simple and effective. Mechanical faults are significantly decreased because it ensures accurate shaft alignment. Equipment may need to be halted in order to undertake analysis, which is one of the drawbacks. [36]

2.7 Vibration Analysis

The technique of continuously monitoring the vibration frequency and amplitude of machinery and employing that data to assess the state of the equipment and its components is known as vibration analysis. Even though the underlying mechanisms and math required to distinguish between various forms of vibration can be complex, the process uses accelerometer to measure vibration. Vibrations are created whenever a piece of machinery is in operation. As a machine vibrates, an accelerometer linked to it produces a voltage signal that indicates how much and how frequently it vibrates—typically, how many times per second or minute it vibrates.

The accelerometer's software either records the signal as amplitude vs. time (also referred to as a time waveform), amplitude vs. frequency (also referred as a FFT), or both. After being analysed by computer algorithms, all of this information is reviewed by engineers or certified vibration analyzers in order to determine the machine's state and identify any potential issues, including imbalance, looseness, lubrication issues, misalignment, and more. Vibration analysis can spot problems such as: [37]

- Imbalance
- Bearing malfunctions
- Mechanical slackness
- Misalignment
- Natural frequencies and resonance
- Faults in Electrical motor
- Bent shafts.
- Gearbox failures
- Cavitation, or empty space, in pumps
- Critical speeds

In this thesis, results are derived using Predictive Maintenance Tool/ Technique known as Vibration Analysis. Same is further discussed in ensuing paragraphs.

2.7.1 Vibration Analysis Methodology

Accelerometers being the most common instrument for gathering vibration data, yet non-contact, high-speed laser sensors may now be able to detect issues that accelerometers are unable to. This broadens the use of the vibration analysis methodology and makes it possible for a more precise and targeted investigation. The features and operating conditions of the vibrating elements are covered in detail by each vibration analysis concept. [38]

2.7.1.1 Time Domain

A waveform is an oscilloscope's display of a vibration signal that has been recorded by a transducer. The temporal domain is displayed when amplitude versus time is plotted. The majority of machine vibration issues are discovered using spectral analysis, though some are simpler to identify in waveforms. [39]

2.7.1.2 Frequency Domain

A graph of frequency vs. amplitude or spectrum is produced after the waveform from earlier has undergone spectrum analysis. The spectrum exists in the frequency domain, much like a vibration. The most research on equipment vibration is calculated in the frequency domain or spectrum analysis. [40]

2.7.1.3 Time-Frequency Domain

The simultaneous computation of several spectra may be useful since vibration signals evolve over time. In present study wavelet decomposition is used to analyze signal. [41]

2.7.2 Modal analysis

The modal analysis uses a part of equipment's measured frequency response functions to build a computer model. The computer model may display animations of each of the numerous vibration modes. The model can be altered to see the effects by adding or removing stiffness or mass components. In addition to these four core ideas, many more aspects of vibration analysis are identified using various forms of analysis, calculations, and algorithms. Among them are: [42] [43]

2.7.2.1 Time Waveform

An acceleration vs. time graph or table is called a time waveform. Time waveforms show a quick time sample of raw vibration and provide information about the condition of the equipment that isn't always obvious from the frequency spectrum. A method for using time waveform vibration signals as a tool for vibration analysis is called FFT.

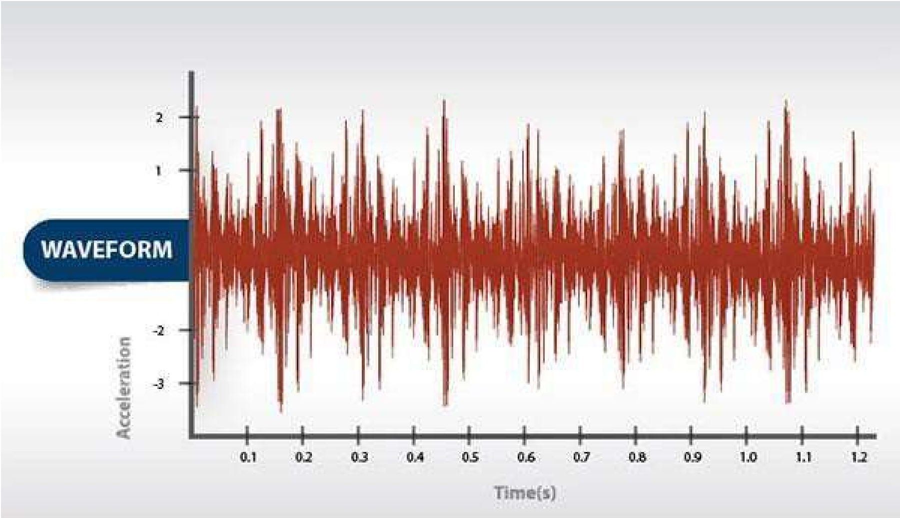

Figure 10: Vibrational Wave Form

2.7.2.2 Fast-Fourier Transform (FFT)

A spectrum can be produced from a time waveform using the FFT method. In other words, a signal is divided into all of its frequencies using a calculation. The FFT transforms a signal from the time domain to the frequency domain, as was clear from the earlier discussion of time domain and frequency domain. Quick Fourier transform is frequently used to identify issues with machine alignment or balance [44].

2.7.3 Categories of Vibration Measurement

Vibration measurement can be categorized in following:

2.7.3.1 Overall level of vibration

A "coarse inspection" of a machine is comparable to measuring the overall vibration level. Touching a machine with bare hand can give you a general idea of whether it is operating roughly across a widespread frequency range. For this initial evaluation, rotating machinery is ideal, especially high-speed machinery. Typically, it can't be used by reciprocating machines.

2.7.3.2 Spectral analysis of vibration

Spectral analysis, a process of transforming a signal from the time domain to the frequency domain. For this, FFT is frequently employed. The signal is carefully examined to identify any significant frequencies origination from machine's parts. Where the frequency signal peaks is where the vibration is most likely to come from. Spectral analysis is frequently used to determine the speed of a shaft's rotation or how frequently a set of gear wheels mesh.

2.7.3.3 Discrete frequency monitoring

To monitor a specific component inside a machine, discrete frequency monitoring looks at the vibration level being produced at a certain frequency that that component would be likely to emit. For instance, if you want to concentrate on a specific shaft, you can set the monitoring to the machine's rotational speed. Discrete frequency is calculated using the FFT method.

2.7.4 Vibration Analysis Measurement Parameters

Three key characteristics are identified by each of these vibration analysis methods: acceleration, velocity (RMS), and displacement. Each of these characteristics highlights specific frequency ranges in a different way, and they may be used to detect problems. Let's examine each parameter individually.

- **Acceleration:**

  High frequencies become more crucial during acceleration. Although it is exclusive, an acceleration signal is not. Velocity or displacement can be created from the acceleration signal.

- **Displacement:**

  Similar to how acceleration emphasizes high frequencies more than low ones, displacement focuses on low frequencies. Displacement measurements are often only employed when analyzing mechanical vibrations in their entirety. Due to a substantial quantity of displacement at the machine's shaft's rotational frequencies, you might utilize displacement to detect imbalance in a spinning part.

- **Velocity:**

  The most crucial metric is velocity since it is connected to the vibration's destructive force. Both high and low frequencies are equally valued in this system. The greatest indicator of how severe a vibration is is often the RMS value of velocity, which is recorded between 10 and 10,000 Hz. By dividing the peak amplitude by 0.707, RMS is computed.

Figure 11 shows how the same signal may display velocity, displacement, and acceleration. Although appearing at the same frequency, different peaks have different amplitudes. This is a good example of the varying values assigned to frequency ranges by each parameter.

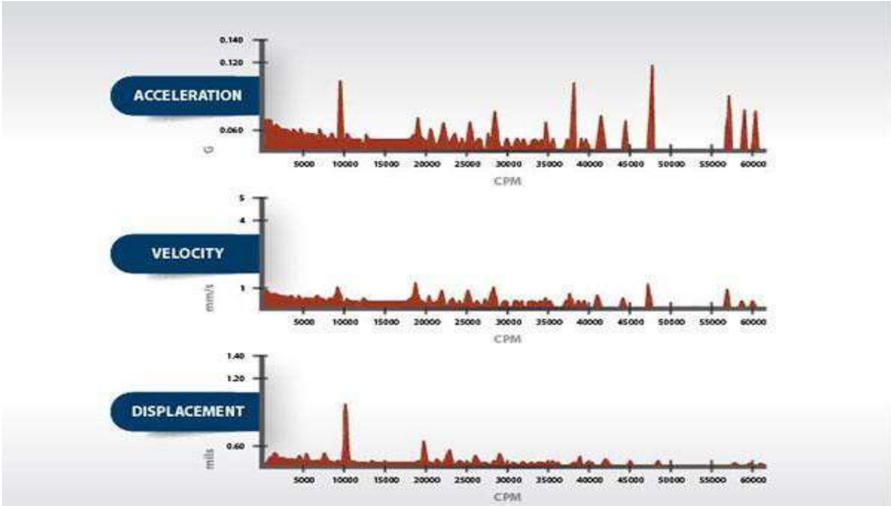

Figure 10: Vibration Analysis in Acceleration, Velocity and Displacement

2.7.5 Benefits of Continuous Vibration Monitoring

The methods and technologies discussed in this article are great for diagnosing problems with equipment or machinery in a reactive manner, but they can also be employed in a proactive manner to find issues before they cause significant downtime. Vibration analysis and monitoring can be used to determine statistically structural fragility or looseness, rotating components looseness, and the occurrence of resonance.

If used effectively, continuous vibration monitoring assists you in optimising the performance of your gear. With today's technology, vibrations may be continually measured in real time on a number of equipment and the findings are quickly sent to a tablet, PC, or smartphone over the cloud.

2.7.5.1 Monitor critical equipment

Any piece of machinery or equipment that, should it fail, would put finances at risk is considered critical equipment. Constant vibration monitoring aids in the detection of differences in the vibration spectrum, which can identify lubrication problems and bearing flaws well in advance of serious problems.

2.7.5.2 Monitor heavily used equipment

Several plants run nonstop and only take a break for regular maintenance once or twice a year. The factory may incur large financial losses if it stops more frequently than this. Online continuous vibration monitoring assists in keeping an eye on the health of machinery that is under stress or that is frequently utilized, and it notifies users when that state changes.

2.7.5.3 Monitor difficult-to-access equipment

It is challenging to maintain equipment that is positioned in challenging-to-reach areas. Machinery operating in high-temperature environments, cooling towers, and machines on rooftops can all be continuously checked for vibration anomalies, enabling maintenance to be performed when it's most convenient. This avoids unscheduled downtime and minimizes the need for maintenance professionals to visit these locations.

2.8 Frequency Analysis

The Discrete Fourier Transformation is used to convert the data from time domain in which they were captured to frequency domain (DFT). The DFT is created by evenly distributing N frequencies over a length 2 interval in the Fourier transform of a discrete signal. [45]

2.8.1 Dominant Frequencies of Mechanical Faults

Rotor imbalance, shaft misalignment (parallel and angle), and soft foot are three mechanical defects for which vibration analysis is frequently employed as a method for fault identification. In the Table No 2, characteristic vibrational frequencies that are generally used to identify mechanical issues are defined. [46]

Type of failure	Dominant Frequency	Dominant Plane
Imbalance	1 x rpm	Radial
Angle Misalign	1 x, 2 x rpm	Radial
Parallel Misalign	1 x, 2 x rpm	Radial
Soft foot	1 x, 2 x rpm	Radial

Table 2: Dominant Frequency in Vibrational Spectra

The failures described in Table 1 are characterized by an increase in the component amplitudes in the frequency spectrum on a single or dual frequency of shaft rotation. The dual frequency signal element may be found in the majority of failures. Depending on the connection technique and the applications the motors are utilized in, experiments conducted have demonstrated that misalignment can happen in the frequency spectrum at all frequencies from one to six times the frequency of rotation. Soft foot often appears at a frequency of 1x rpm, but it can also occur at two- and three-times rpm, demonstrating once more that defect diagnosis alone by analyzing characteristic frequencies does not necessarily result in obvious conclusions. [47]

2.8.2 Data Collection

A piezoelectric accelerometer is the most used transducer for vibration analysis. Because on the way the accelerometer is built, an electric signal proportional to strain is produced using the piezoelectric capabilities of certain crystals and ceramics. This sensor's architecture makes it possible to convert a mechanical signal into an electrical signal without the need for an extra power source. The most significant benefits of this transducer are its wide frequency and dynamic range, both of which have outstanding linearity across all ranges.

2.9 Previous Research Work

Vibration analysis is frequently used given the mechanical nature of motors. Fast Fourier transform (FFT), Hilber Huang Transform (HHT), Wavelet Transformation (WT), Ensemble Empirical Mode Decomposition (EEMD), and Empirical Mode Decomposition (EMD) are some of the commonly used signal processing techniques for feature extraction. Vibration analysis proposed a vibration signal-based fault detection and diagnosis system for induction motors by converting the time-series data into a 2-D image and subsequently performing the scale-invariant feature transform (SIFT) algorithm to extract significant features. [48]

With the rise and advancement of Artificial Intelligence methods, the development of hardware platforms that enable high parallel computations, a decrease in sensor production cost, and an increase in data collection, data-driven methodologies are now of interest and explored by the academic and industrial community. Data-driven methods are those which use large amounts of data for feature diagnosis. Methods can be grouped into different categories such as statistical, machine learning, and deep learning. Statistical analysis methods include Principal Component Analysis (PCA) and Partial Least Squares (PLS). Machine learning methods are apt for big amounts of data; however, they are usually combined with signal processing techniques for highlighting the features and further feature extraction. [49] Common machine learning methods used in motor diagnosis are principal component analysis (PCA), Hilbert–Huang Transform and Support Vector Machine (SVM), Hilbert–Huang Transform with k-Nearest Neighbors (k-NN), Singular Value Decomposition (SVD) uses Random Forests for analyzing the health of a woodworking cutting machine spindle health; uses multiple classifiers with different prediction horizons approaches use SVM for evaluating different feature extract methods, proposed a Fuzzy Logic based resilient state awareness of control system for anomalous behavior detection, and used wavelet packet decomposition on sound data along with an Extension Neural Network (ENN) for fault diagnosis in an internal combustion engine.

Ehab Salem Al Fahadi worked on Lateral Vibration Analysis and Shaft Whirling due to the design of machine components, manufacturing procedures, and material choices, some machine components may react differently in mechanical engineering. It is beneficial to comprehend appropriate system modeling in order to comprehend the fundamental phenomena of any broad dynamic stressors. It is good to know that the phenomenon of lateral bending, whirling, and transverse vibration in propulsion systems is less hazardous than torsional vibration. A shaft is a rotating machine part that transfers energy from one part to another or from a machine that produces energy to a machine that absorbs energy. Shafts usually have circular cross sections. Since the physical object's dimensions are tiny in comparison to the vibration's wavelength, a lumped-parameter technique is usually the best choice. Any system with dependent variables that are functions of both time and one or more geographic variables are referred to be a distributed system. [50]

The majority of shafts are exposed to varying loads of torsion and bending paired with varying levels of stress concentration. The main issue with such shafts is fatigue loading. Engineers and academics have spent a lot of time investigating why these parts and structures fail in order to give solutions to prevent similar disasters. Whirling is typically related to fast rotating shaft speeds. Critical speed and whirling are two terms used to describe vibrations in a shaft. The shaft will suffer damage and eventually fail if the speed is maintained at the same level. Also, the shaft will continue operating safely until another event might stop it if the speed keeps rising before any other consequences manifest Moreover, even in the absence of external stresses, a shaft's rotational imbalance causes it to whirl, and at certain speeds, referred to as critical speeds, resonance happens as a result. The spinning also takes place at the same time as the resonance. The radial and centrifugal forces, which might act on the shaft as it is spinning, could cause it to deviate from its "safe" position. Moreover, the majority of machines that employ long shafts have a big issue with shafts spinning. [51]

The spinning shafts that power mechanical systems like motors, pumps, engines, and turbines rotate at various speeds. Over its service life, numerous flaws such as cross-sectional fractures, looseness, and misalignment may happen because of unforeseen operating circumstances. In order to forecast the vibration spectrum for shaft misalignment, experimental tests on a rotor-bearing system have been conducted, previously. Majority of the studies confirm that shaft misalignment has come out to be one of the most common causes of vibration. [52]

Chapter No 3: Experimental Setup

3.1 Machinery Fault Simulator (MFS)

The Machinery Fault Simulator from Spectra Quest is a ground-breaking instrument for researching the telltale signs of typical machinery flaws without affecting manufacturing output or revenues. The system is desktop-sized and weighs roughly 150 pounds. It features a modular design that offers versatility, simplicity of use, and resilience. The simulator's parts are all machined with tight tolerances so that no substantial vibrations can interfere with operation. Consequently, in a completely controlled environment, one can introduce various errors either alone or in groups, depending on the circumstance required to investigate. [53]

Misalignment can cause vibration. The primary factor in the majority of machine malfunctions is misalignment. When the machine is running normally and the rotating centre lines of the shaft are not collinear, the shaft is out of alignment. Before failure, rotating machinery typically exhibits warning indicators, such as changes in vibration intensity and pattern. The vibration signal can be used to identify these issues. By identifying these symptoms, an early attempt at correction can be made to stop the system from completely failing. However, a review of the literature revealed that employing Operational Deflection Shapes (ODS) is the best way to identify misalignment. A shape can be defined by specifying the movement of two or more points. Using a variety of frequency domain measures, ODS can be produced. Many studies have also recommended using amplitude domain measurements to describe the vibration issue. Condition-based maintenance aims to prevent failures through regular inspections so that a fault can be detected before it occurs, has replaced corrective maintenance, which is carried out as soon as a fault is discovered and attempts to restore normal operating conditions. [54]

For more than 20 years, experiments for fault simulation and detection have been carried out using the MFS, which is regarded as a condition-based maintenance tool. Despite the fact that numerous papers in recent literature have looked into the issue of identifying flaws in rotary machinery, there is no evaluation of research done on MFS machines. The Machinery Fault Simulator (MFS), shown in figure no. 11, was developed by the Spectra Quest Company. It has the ability to look into common machine faults like bearing, alignment, resonance, imbalance, and other machine component failures. The robust multi-channel DAQ and data analysis software system of the MFS makes data acquisition, analysis, and report production simple.

Figure 11: Machinery Fault Simulator – Magnum *[55]*

3.2 Inducing Defects in Motor using MFS

Misalignment is probably the most common cause of machinery malfunction. While a properly aligned machine can save an industry between 20% and 30% on energy consumption and extend equipment life, The equipment would operate much longer if it is properly aligned Despite the frequency of misalignment and the known benefits offered by proper alignment, plant managers and machine operators have a marginal understanding of its importance. Bai, C, et al [56], under various operating and design conditions, including speed, alignment level, and coupling type, tests were conducted to identify distinct vibration signatures for alignment and misalignments. The effects of shaft misalignment on the dynamic behavior of rotating machinery were demonstrated by the authors using an Operational Deflection Shape (ODS), which is created from multiple accelerometer signals distributed throughout the machine. A numerical model was developed to simulate machine issues at various locations. The authors also studied the structure and growth of cavitation in a centrifugal pump casing as well as a fractured shaft fault, AC motor faults, and those faults.

Alok Kumar Verma et al [57] determined through research into the instability of a rotating shaft mounted on journal bearings that misalignment was the cause of instability. The results were based on the shaft displacement and stator current of the misaligned machine. Michael Monte used spectral analysis to contrast various vibration signals brought on by misalignment. Measurements were taken using a variety of tools and locations. Two accelerometers were used to record vibration on the bearings, and two eddy-current probes were mounted on the shaft itself. Tristan Plante et al. used vibration signals and principle component analysis to find flaws. In the tests, an induction motor was connected to a loaded shaft that was supported by two bearings. Healthy, unbalanced, and parallel misalignment working conditions were tested [58]. The vibration data was collected using four accelerometers that were installed in various places. The database is made up of 1951 multivariate time-series that were collected by sensors on a Machinery Fault Simulator (MFS) Alignment-Balance-Vibration (ABVT) from Spectra Quest. Normal function, imbalance faults, and horizontal misalignment faults are three different simulated states included in the 1951.

When compared to imbalance and misalignment, cracked shafts make up a minor portion of rotary machinery defects. But, if a fractured shaft is not found early on, it could endanger the safety of the machine and its operators, not to mention the amount of downtime and money needed for a replacement.

José M. Machorro-López et al [59] investigated a number of methods for detecting shaft cracks in spinning machinery. The authors conducted numerical and experimental research to identify damages in both cases by examining the vibratory response in static and rotating shafts under various kinds of external excitations. Finite element models at twelve different temperatures to examine the effects of different crack types (open and breathing), fracture depths, and crack positions on the dynamic response.

Naqash Azeem et al. combined vibration spectra and phase analysis to find shaft unbalance, misalignment, cracks, and bearing issues. The elastic support properties of a spinning shaft represented by a Bernoulli-Euler beam were studied by T.A.N. Silva et al. The investigations were aimed at identifying the intrinsic frequencies and mode shapes of continuous beams while taking into account various boundary conditions. [60]

The simulator is an ideal tool to use for studying the vibration signature that occurs when two mating shafts are misaligned. Using the simulator to study misalignment enables you to achieve the following:

- Practice and learn different methods of alignment.
- Determine the vibration spectra that occur due to different levels of angular and parallel misalignment
- Study the relationship between vibration and several parameters: coupling stiffness, shaft speed, machinery dynamics stiffness, resonance, and soft-foot
- Determine the effects of misalignment on power consumption.
- Develop an understanding of why misalignment produces axial vibration.
- Develop strategies to differentiate misalignment spectra from the other sources of vibration
- Calculate the savings that can be achieved by frequently checking the alignments of machinery.

3.3 Shaft Alignment

The MFS is ideal for addressing shaft alignment issues and functioning identically. Although the motor side does not provide convenient features to assist in movement, the motor can be adjusted horizontally and vertically. If the rotor side becomes "bolt bound then you will have to reposition the motor. Otherwise, alignments are conducted rotor side with the benefit of jack bolts. With the motor side considered "fixed", the rotor side can be jacked horizontally: vertically, and axially. Shims are generally used to perform vertical movements to simulate the real world. "A" size standard, precut stainless shims will fit this machine as an option, one can cut brass or plastic shims. Cutting shims requires more time and effort. Plastic shims are not as stable as they tend to compress a bit but are acceptable for training purposes and are much safer. Inexperienced individuals must be warned that metal shims (particularly stainless) can inflict a cut as easily as a razor blade! Enough cannot be said about the hazard of thin (say 0.001" through 0.005") shims. Many a mechanic has injured himself badly on an exposed shim and kept the accident quiet to avoid the hassle of reporting it (perhaps the injury statistics are a bit biased). In a nutshell, handle thin shims carefully and avoid positioning them so that they create an exposed knife edge. Also, when stacking shims under a machine foot, arrange them like a sandwich where the thickest is on the outside. This practice will prevent the thin ones from being as exposed and possibly curling to where they become a hazard. Shims that extend beyond the rotor deck and interfering with the belts should be inserted from beneath the deck. Please refer to the photograph inserted at the end of this procedure. The axial adjustment is used to load couplings for vibration measurements. Some styles of couplings must be allowed space for growth and float. If they are subject to axial loading, unusual wear patterns develop, and unwanted vibration can be transmitted across the coupling. Dial indicators, lasers, optical devices, etc. are very precise measuring tools that will reflect tiny movements imperceptible to the human eye. [61] [62]

As a result, to obtain a good alignment, all unwanted motion and vibration must be kept to a minimum. What appears to be an acceptable, sturdy machine may not be so rigid when examined carefully. When performing shaft alignments, be alert to the effect of a bent shaft, excessive runout, loose/worn bearings, and a poor foundation. All these parameters and more) can interfere with obtaining a quality alignment. Do not attempt to align the simulator using the aluminum resonance shaft. This shaft is flexible to promote resonance at a lower shaft speed. It can be easily bent as well contributing to alignment problems. Fundamentally, it is not possible to obtain a rigid shaft arrangement. As a result, whereas with a steel shaft, unwanted indicator movement is held to a minimum (say 1 to 2 mils when leaning hard on the machine) with the aluminum shaft, the movement is on the order of 5 mils. Of course, this situation may not be all that bad as such unwanted movement is present on some real-world machines. Where possible, simply avoid leaning on or climbing on the machinery that you are aligning in order to avoid the possibility of disturbing your measurements.

Alignment changes due to thermal growth can be significant and are sometimes a major factor in mysterious machinery problems (along with resonance) At this time, the MFS is not set up to create thermal growth simulations. However, you should be aware of the contribution of thermal changes. Also, contrary to some machinery operating and servicing manuals, the growth is not always linear. Namely, the movement may not be straight and may not follow the calculation for linear expansion and contraction. Most mechanics live in the real world, so it pays to be patient with their concerns. [55]

3.3.1 Methods for Inducing Horizontal Misalignment.

Prior to beginning this activity, the MFS has to be aligned. Install a rigid shaft coupling to increase the vibration's amplitude. Make sure the motor's electricity is turned off.

a. Remove the T-handle alignment pins, step 1.

b. Tighten the horizontal jack bolts until they touch the base plate of the rotor.

c. Turn the four plastic dials' outer rings until the index line lines up with the zero mark.

d. Choose the desired level of horizontal misalignment. You might want to introduce 10 mils (0.010 inches), for instance.

e. Remove the four socket head cap screws holding the base plate of the rotor to the support channels.

f. Unscrew the jack bolts to the predetermined number of turns on the back side (the side away from you).

g. On the front side of the machine (the side that is directly in front of you), the jack bolts should be advanced or screwed in to the preset depth. For there to be a parallel misalignment, both ends of the rotor base must be shifted out of alignment by the same amount. This requirement will guarantee that the shafts of the motor and rotor remain parallel.

h. Tighten the cap screws with socket heads on the rotor base plate's attachment to the support channels.

i. Close the safety cover.

j. Turn on the motor and the MFS. As needed, collect vibration data.

k. By loosening the socket head cap, the shafts can be roughly realigned. Screws that hold the rotor base plate in place and reverse the jacking movements to reset the dials.

3.4 Shaft Balancing

The simulator 1s a perfect tool for examining the impact of machine imbalance in a controlled environment. Using the simulator for this study enables you to do the following:

- Learn about vibration spectra due to an unbalance force in a single plane or a multiplane
- Learn about overhung unbalance
- Learn about phase relationship due to coupled unbalance force
- Develop an expertise for balancing rotors in a single plane or multiplane, and/or overhung
- Measure the location (phase) and estimate the magnitude of unbalance force
- Develop an understanding of interaction between unbalance force, speed, and machine dynamics
- Practice the use of commercial balancing software & hardware.

3.4.1 Procedures for Testing Balancing

To test for imbalance, you need to introduce to one or more of the rotors disks a force that creates imbalance. The following steps explain how to complete this procedure:

a. Weigh a few (a dozen) 1/4-20 screws, nuts, and washers of various lengths. Each item should have a label, and weights should be noted in a notebook.

b. Screw a 1/4-20 screw into a rotor disk's tapped hole. Put a nut on the screw, then tighten it firmly. There is an imbalance force created by the additional weight.

c. Attach accelerometers to the fault simulator at various places, then take vibration readings. The two bearing housings, the motor, the gearbox, and the base in the X, Y, and Z directions are suggested locations for the accelerometer installation.

d. Alter the motor speed while measuring the vibration levels universally.

e. Chart vibration levels versus speed to observe how speed affects unbalance force.

f. Repeat steps 1 through 5 using various weights, at various locations on the shaft. Using two or more rotors, add various weights at various angles. The weights do not need to be at the same angle, so specifically place them on the rotors so that one weight may be at 0° and the other at 45°.

g. Apply the same steps to the overhung rotor.

h. Experiment with various arrangements of each concept listed above. Specifically, combine weights and angles in any way that resembles a real-world scenario.

Chapter No 4: Methodology

4.1 Scope and Objective of Chapter

This chapter presents the methodology used for the classification of induction motor data using supervised learning. Four features - Coefficient of Variation (CVA), Entropy, Mean, and Fast Fourier Transform (FFT) have been used with two classifiers, Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA).

4.2 Comparison of Supervised and Unsupervised Learning

Advantage of supervised learning is that the model is trained on labeled data that provides a clear signal for the correct output, supervised learning has the potential to be more accurate than unsupervised learning. Because labeled data enables the model to learn more quickly and accurately than unsupervised learning, which may require more trial and error to find patterns in the data, supervised learning can be more effective than unsupervised learning. The ability to solve specific tasks, like classification or regression, where the objective is to predict a specific output based on input features, is another benefit of supervised learning. In these scenarios, the labeled data offers a clear objective for the model to optimize, whereas unsupervised learning may not have a clear objective or performance metric. Comparison of supervised and unsupervised learning is given below:

Supervised Learning	Unsupervised learning
Labelled data is necessary for supervised learning algorithms, which means that each data point in the training set must be associated to a relevant label or target value. As a result, supervised learning is better suited for applications where labelled data is present.	Employs unlabeled data: Unsupervised learning techniques use data that has no corresponding labels or target values. Unsupervised learning is therefore more suited for issues when labelled data is lacking.
Supervised learning, which employs input information to forecast the value of a target variable. The objective is to create a model that can correctly forecast the target value from new, unrecognized data.	The goal of unsupervised learning is to identify patterns and structures in the data itself. When performing tasks like clustering, where the objective is to put similar data points together, this can be helpful.
Findings that are easy to interpret: considering that supervised learning is based on labelled data, the model that is created often yields comprehensible results. For instance, it is simple to visualize and comprehend a decision tree model, and it is simple to explain the rules that are used to create predictions.	Less interpretable results: Since unsupervised learning is based on unlabeled data, the model that is produced may be more challenging to understand. For instance, a clustering model might combine data points based on imprecise, hard-to-understand patterns.

Table 3: Comparison of Supervised and Unsupervised Learning *[63] [64]*

4.2 Data Collection and Pre-processing

The primary step in the methodology is data collection. The data may contain numerous parameters such as motor current, voltage, temperature, vibration, and other pertinent operational parameters. The collected data is formerly pre-processed to eradicate any noise or outliers. The pre-processing step is critical to warrant usage of the data for classification to be accurate and reliable.

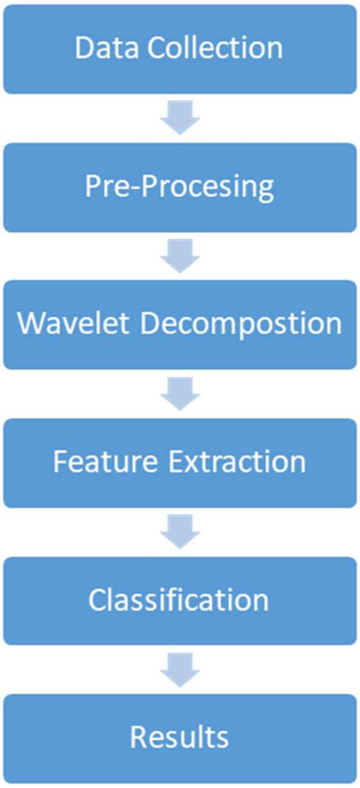

Figure 11: Data Collection Flow Chart

4.3 Wavelet decomposition

In many fields, such as speech recognition, image and audio analysis, and biomedical signal processing, wavelet decomposition is a widely used technique for signal processing and feature extraction. It involves using a set of wavelets, which are functions that oscillate around zero and have a finite duration, to divide a signal into various frequency bands. The Daubechies wavelet, which has a few variations including the db 4 and db 7 wavelets, is one of the wavelets that is frequently used for decomposition. The smoothness and regularity of the wavelet function are determined by the number of vanishing moments present in each of these wavelets as shown in figure below. In the current study db 4 and db 7 have been used at wavelet level 7,8,9. [65]

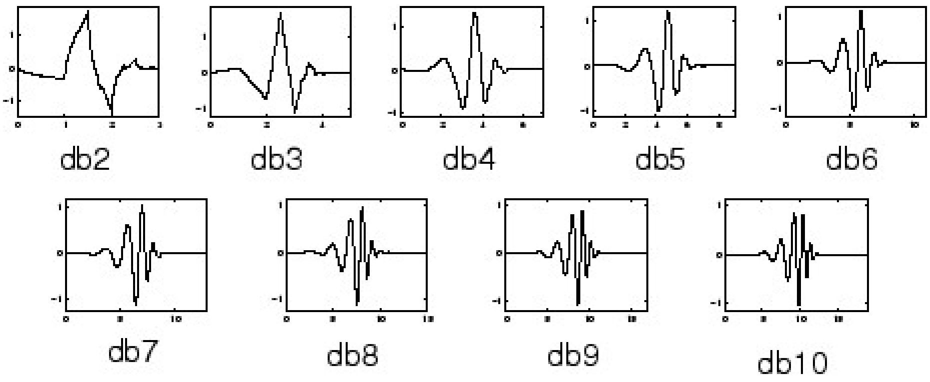

Figure 12: The Daubechies Wavelet

4.4 Selection of Mother Wavelet

To select specific mother wavelet for signal analysis of induction motor faults following characteristics is deem feasible:

4.4.1 Orthogonality and Smoothness:

Daubechies wavelets are acknowledged for orthogonality and smoothness behavior. The selection of db4 and db7 is compelled by their aptitude to capture both high and low-frequency components of a signal efficiently. These wavelets offer a steadiness between time and frequency localization, which is crucial for analyzing complex signals as in case of induction motors.

Vanishing Moments allows Daubechies to approximate polynomial signals of a certain degree precisely. The higher the number of vanishing moments, results in enhanced wavelet for representing signals with smooth variations. Db4 has 4 vanishing moments. This property provide advantage when dealing with motor signals as behavior of signal varies as degrees of smoothness.

4.4.2 Multi-Resolution Analysis

Discrete wavelet transform (DWT) for multi-resolution analysis uses Daubechies wavelets. The DWT divides a signal into numerous scales, enables to study the varying levels. For locating certain frequencies or characteristics in induction motor signals, this is quite helpful.

4.4.3 Accuracy and Complexity Trade-Off

Wavelet analysis entails a complexity and accuracy trade-off. Although more complex wavelets may be more accurate in capturing signal properties, they also run the risk of adding noise or artifacts. Db4 and db7 are good options for motor signal analysis because they establish a compromise between complexity and accuracy. Moreover, Daubechies wavelets have compact support, which restricts the range across which they are nonzero. When working with signals that have well defined beginning and ending timings, such as transient signals in motors, this trait is helpful.

4.4.4 Selection of Wavelet Levels

Wavelet level 1 to 5 does not hold relative signal information as shown in figure below. Whereas, wavelet level 7 ,8 ,9 entails significant information.

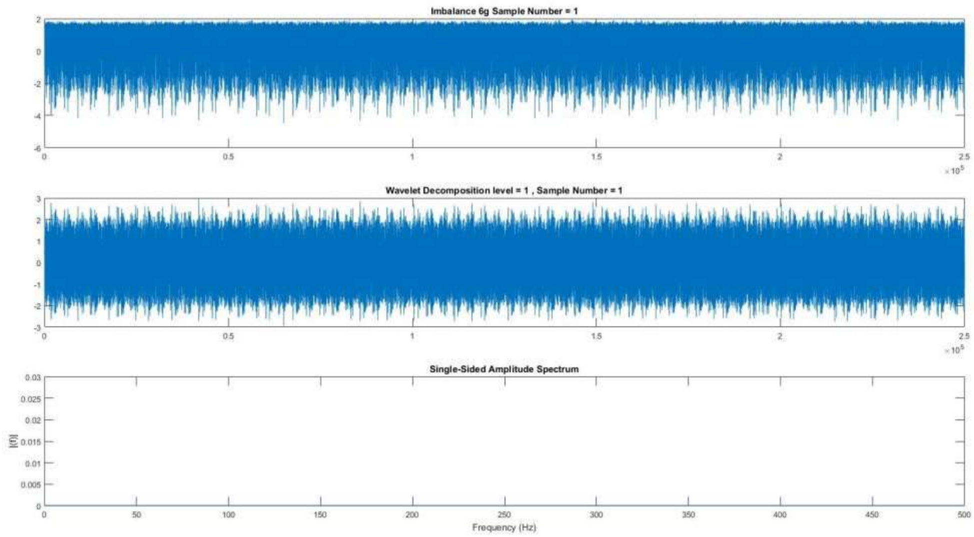

Figure 13: Wavelet Level 1 (Imbalance)

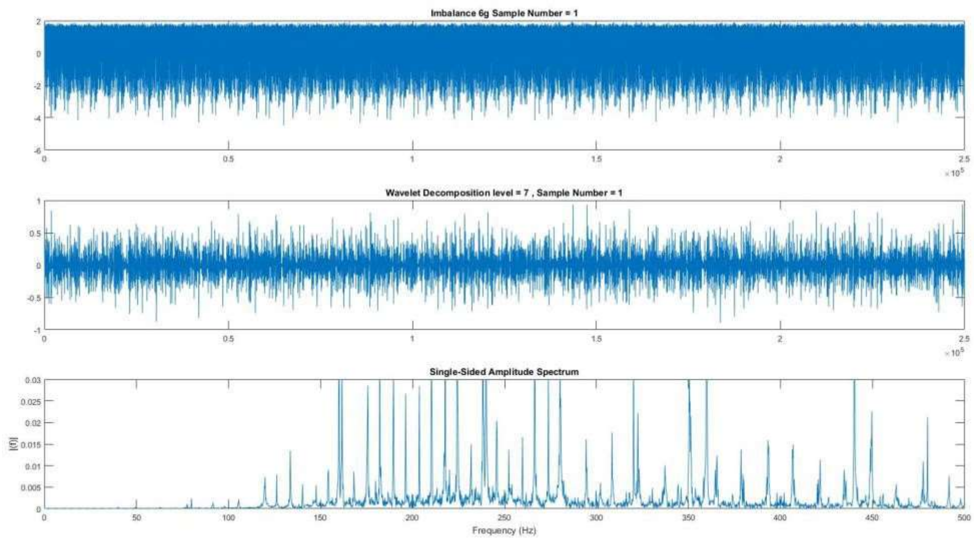

Figure 14: Wavelet Level 7 (Imbalance)

4.5 Feature Selection/Extraction

Feature extraction is executed for identification of the best relevant features which contributes meaningfully for classification of data. Numerous feature selection procedures are employed to extract maximum accuracy. In this study, feature selection is performed using a combination of domain knowledge and statistical methods to identify the most important features that are highly correlated with the motor health condition.

Subsequently, the features are extracted from the pre-processed data. Four features are selected for this study: CVA, Entropy, Mean, and FFT. CVA is a measure of the variation of a feature, calculated as the ratio of the standard deviation to the mean. Entropy is a measure of the randomness or disorder in a feature. Mean is a simple statistical measure that represents the average of a feature. FFT as already discussed, providing information about the frequency components present in the signal. These features are calculated from the pre-processed data for each motor sample. [66] [67]

4.6 Classification Models

Two classifiers, Linear Discriminant Analysis LDA and Quadratic Discriminant Analysis QDA, are used for the classification of induction motor data. LDA is a linear discriminative model that finds a linear combination of features that best separates the classes. QDA, on the other hand, is a quadratic discriminative model that finds a quadratic decision boundary to classify the data. Both LDA and QDA are supervised learning algorithms that require labeled data for training. [68]

4.6.1 Model Training

The classification models are trained by means of the pre-processed data using selected features. The data is distributed into training and testing sets to assess the performance of the classifier. The training set is used to train the models, while the testing set is used to validate the classifier performance. Performance metrics such as true detection, false detection and accuracy are used to evaluate the classification models performance.

4.6.2 Model Validation

After training and optimizing the model, they are validated using unseen data to assess their performance. The models are tested with set of new motor samples, and the classification results are compared with the actual motor health condition to validate the accuracy of the models.

Chapter No 5: Results and Discussion

5.1 Scope and objective of Chapter

This chapter presents a comprehensive discussion and interpretation of the findings obtained from the data analysis of induction motors induced with imbalance and horizontal misalignment faults. The discussion begins with a summary of the key results, highlighting data sets used and significant findings, followed by an in-depth analysis of the results in relation to the research objectives. The implications of the classification are also discussed, including their theoretical, and practical implementation. Overall, this chapter aims to provide a thorough and meaningful interpretation of the study's findings, contributing to the understanding of the results and paving the way for future research directions.

5.2 Datasets Test and Train Split

In present study, a commonly used ratio of 70:30 was used. This means 70% of samples was used for training whereas 30% of samples were used for testing in following breakdown:

a. Total sample space : 240 samples
b. Samples used for Training : 168 samples
c. Samples used for Testing : 72 samples

5.3 Classifier Performance Parameters

Classifier performance was evaluated on the basis of few parameters. In this research work, classifier performance has been evaluated at wavelet level '7' & '8'. Following performance indicators have been used:

5.3.1 True Detection (TD)

Total number of samples classified correctly from each class can be defined as:

$$\boldsymbol{TD = TP + TN}$$

Where,

TP: True Positive
TN: True Negative

5.3.3 False Detection (FD)

Total number of samples classified from each class can be defined as:

$$\boldsymbol{FD = FP + FN}$$

Where,

FP: False Positive
FN: False Negative

5.3.4 Accuracy (ACC)

It is correctly classified samples from overall number of samples and can be written as:

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \; X\, 100$$

5.4 Feature Extraction Results

As discussed in earlier section, four features are used for classification using Linear discriminant classifier (LDC) and quadratic (QDC). Four features were extracted from data set. After applying features resultant feature vector depicts the data boundary for classifier. Behavior pattern from each feature are as follows:

5.4.1 Co-efficient of Variation of Amplitude (CVA)

Co-efficient of variation of amplitude (CVA) performed best as shown in figure no 12. After applying CVA on dataset feature values are distinct from each other as shown in figure below. Hence, best performance has been achieved using this feature.

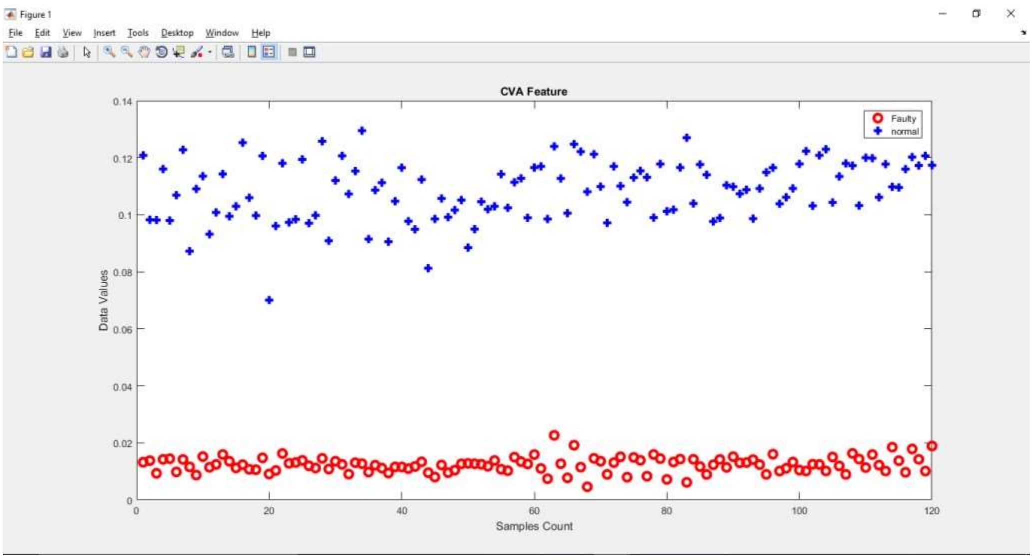

Figure 15: Co-efficient of Variation of Amplitude (CVA)

5.4.2 Wavelet Entropy

Wavelet entropy performed average as shown in figure below. This feature was not able to classify each class in a refined manner. Hence resulted in average classification results.

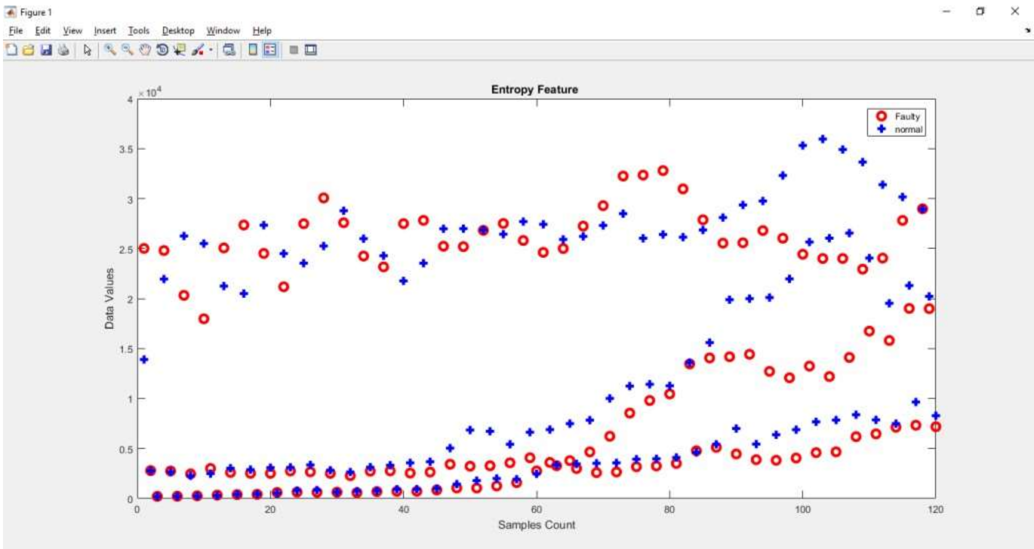

Figure 16: Wavelet Entropy

5.4.3 Mean

Mean feature data values is shown in figure below. It can be seen that this feature was not able to discriminate between the data of each class significantly. Hence performance of classifier using this feature remained average.

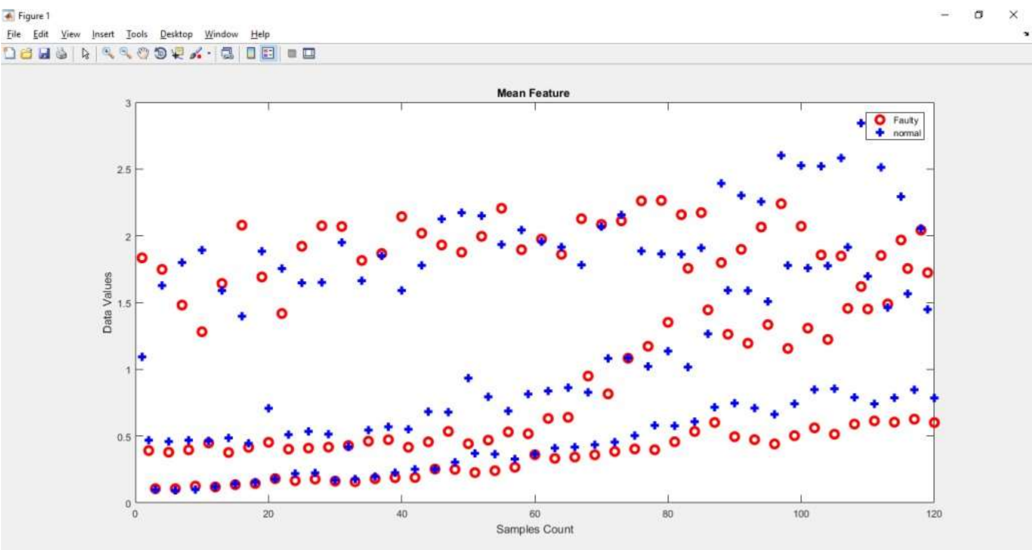

Figure 17: Mean

5.4.4 Fast-Fourier Transform (FFT)

Similarly, FFT performance was lowest as can be seen in figure below, the data point is not discriminant for the classifier.

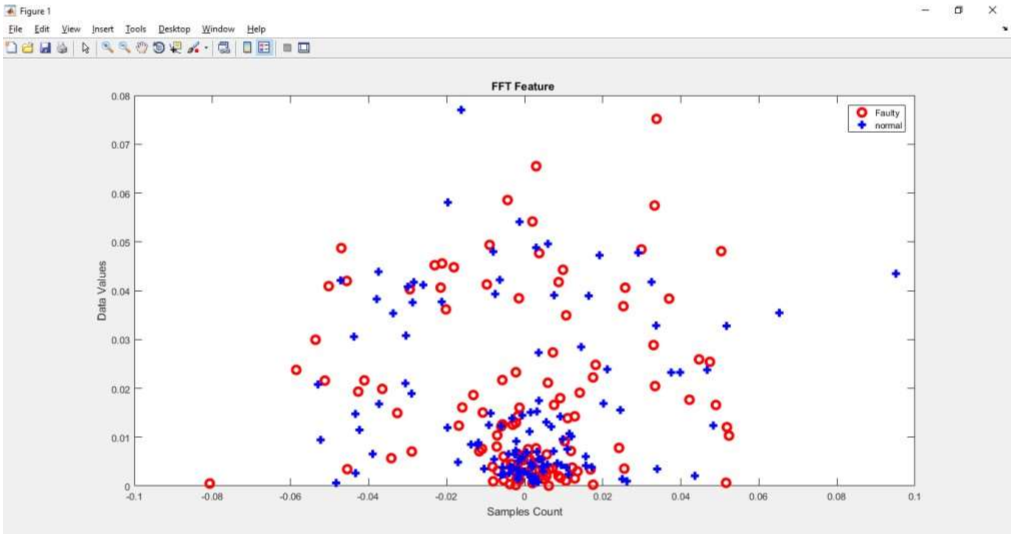

Figure 18: Fast-Fourier Transform (FFT)

As shown in figures above, it is evident that after applying CVA data from each class is highly discriminative as compared with other features. Hence it is predicable that CVA classification results came out to be the best amongst all. Therefore, fault detection is better using CVA.

5.5 Classifier Parameter Results

5.5.1 Linear Discriminant Classifier (LDC)

Maximum accuracy was achieved by CVA. It gave maximum accuracy of 100% at wavelet levels (7-9) using both mother wavelet 4,7 Daubechies. Whereas entropy performed at (36%-66.6%). Mean gave (50%-66.6%). FFT was lowest performing feature (37.5-43%). Ensuing sections shows all the results.

LDC Classifier for Imbalance at NDE (6g) (120 SAMPLES)					
Features	**Wavelet Level**	**Mother Wavelet**	**TD**	**FD**	**ACC**
CVA	7	DB-4	72	0	100
		DB-7	72	0	100
	8	DB-4	72	0	100
		DB-7	72	0	100
	9	DB-4	72	0	100
		DB-7	72	0	100
ENTROPY	7	DB-4	48	24	66.6
		DB-7	48	24	66.6
	8	DB-4	48	24	66.6
		DB-7	48	24	66.6
	9	DB-4	27	45	37.5
		DB-7	26	46	36.1
MEAN	7	DB-4	48	24	66.6
		DB-7	48	24	66.6
	8	DB-4	44	28	61.1
		DB-7	47	25	65.2
	9	DB-4	37	35	51.3
		DB-7	36	36	50
FFT	7	DB-4	31	41	43
		DB-7	31	41	43
	8	DB-4	27	45	37.5
		DB-7	27	45	37.5
	9	DB-4	38	34	52.7
		DB-7	40	32	55.5

Table 4: LDC Classifier for Imbalance at NDE (6g)

LDC Classifier for Imbalance at NDE (20g) (120 SAMPLES)					
Features	**Wavelet Level**	**Mother Wavelet**	**TD**	**FD**	**ACC**
CVA	7	DB-4	72	0	100
		DB-7	72	0	100
	8	DB-4	72	0	100
		DB-7	72	0	100
	9	DB-4	72	0	100
		DB-7	72	0	100
ENTROPY	7	DB-4	45	27	62.5
		DB-7	45	27	62.5
	8	DB-4	36	36	50
		DB-7	36	36	50
	9	DB-4	36	36	50
		DB-7	36	36	50
MEAN	7	DB-4	36	36	50
		DB-7	37	35	51.3
	8	DB-4	36	36	50
		DB-7	36	36	50
	9	DB-4	36	36	50
		DB-7	36	36	50
FFT	7	DB-4	40	32	55.5
		DB-7	38	34	52.7
	8	DB-4	30	42	41.6
		DB-7	36	36	50
	9	DB-4	31	41	43
		DB-7	35	37	48.6

Table 5: LDC Classifier for Imbalance at NDE (20g)

LDC Classifier for Imbalance at DE (6g) (120 SAMPLES)					
Features	**Wavelet Level**	**Mother Wavelet**	**TD**	**FD**	**ACC**
CVA	7	DB-4	72	0	100
		DB-7	72	0	100
	8	DB-4	72	0	100
		DB-7	72	0	100
	9	DB-4	71	1	98.6
		DB-7	70	2	97.2
ENTROPY	7	DB-4	35	37	48.6
		DB-7	35	37	48.6
	8	DB-4	36	36	50
		DB-7	36	36	50
	9	DB-4	37	35	51.3
		DB-7	37	35	51.3
MEAN	7	DB-4	35	37	48.6
		DB-7	35	37	48.6
	8	DB-4	36	36	50
		DB-7	36	36	50
	9	DB-4	36	36	50
		DB-7	36	36	50
FFT	7	DB-4	35	37	48.6
		DB-7	37	35	51.3
	8	DB-4	36	36	50
		DB-7	36	36	50
	9	DB-4	40	32	55.5
		DB-7	34	38	47.2

Table 6: LDC Classifier for Imbalance at DE (6g)

LDC Classifier for Imbalance at DE (20g) (120 SAMPLES)					
Features	**Wavelet Level**	**Mother Wavelet**	**TD**	**FD**	**ACC**
CVA	7	DB-4	72	0	100
		DB-7	72	0	100
	8	DB-4	72	0	100
		DB-7	72	0	100
	9	DB-4	70	2	97.2
		DB-7	70	2	97.2
ENTROPY	7	DB-4	35	37	48.6
		DB-7	35	37	48.6
	8	DB-4	36	36	50
		DB-7	36	36	50
	9	DB-4	35	37	48.6
		DB-7	35	37	48.6
MEAN	7	DB-4	37	35	51.3
		DB-7	35	37	48.6
	8	DB-4	36	36	50
		DB-7	36	36	50
	9	DB-4	36	36	50
		DB-7	34	38	47.2
FFT	7	DB-4	40	32	55.5
		DB-7	38	34	52.7
	8	DB-4	33	39	45.8
		DB-7	37	35	51.3
	9	DB-4	37	35	51.3
		DB-7	35	37	48.6

Table 7: LDC Classifier for Imbalance at DE (20g)

LDC Classifier for Horizontal Misalignment at NDE (0.5mm & 2.0mm) (120 SAMPLES)								
Features	**Wavelet Level**	**Mother Wavelet**	**TD**	**FD**	**ACC**	**TD**	**FD**	**ACC**
			0.5mm			**2.0mm**		
CVA	7	DB-4	72	0	100	72	0	100
		DB-7	72	0	100	72	0	100
	8	DB-4	72	0	100	72	0	100
		DB-7	72	0	100	72	0	100
	9	DB-4	72	0	100	72	0	100
		DB-7	72	0	100	72	0	100
ENTROPY	7	DB-4	35	37	48.6	48	24	66.6
		DB-7	34	38	47.2	48	24	66.6
	8	DB-4	36	36	50	45		62.5
		DB-7	36	36	50	46	26	63.8
	9	DB-4	36	36	50	36	36	50
		DB-7	36	36	50	35	37	48.6
MEAN	7	DB-4	36	36	50	43	29	59.7
		DB-7	36	36	50	42	30	58.3
	8	DB-4	36	36	50	34	38	47.2
		DB-7	36	36	50	35	37	48.6
	9	DB-4	35	37	48.6	32	40	44.4
		DB-7	39	33	54.1	31	41	43
FFT	7	DB-4	35	37	48.6	35	37	48.6
		DB-7	36	36	50	36	36	50
	8	DB-4	34	38	47.2	27	45	37.5
		DB-7	32	40	44.4	28	44	38.8
	9	DB-4	32	40	44.4	31	41	43
		DB-7	31	41	43	31	41	43

Table 8: LDC Classifier for Horizontal Misalignment at NDE (0.5mm & 2.0mm)

LDC Classifier for Horizontal Misalignment at DE (0.5mm & 2.0mm) (120 SAMPLES)								
Features	**Wavelet Level**	**Mother Wavelet**	**TD**	**FD**	**ACC**	**TD**	**FD**	**ACC**
			0.5mm			**2.0mm**		
CVA	7	DB-4	72	0	100	72	0	100
		DB-7	72	0	100	72	0	100
	8	DB-4	72	0	100	72	0	100
		DB-7	72	0	100	72	0	100
	9	DB-4	71	1	98.6	71	1	98.6
		DB-7	70	2	97.2	70	2	97.2
ENTROPY	7	DB-4	36	36	50	35	37	48.6
		DB-7	36	36	50	35	37	48.6
	8	DB-4	36	36	50	36	36	50
		DB-7	36	36	50	36	36	50
	9	DB-4	36	36	50	36	36	50
		DB-7	36	36	50	35	37	48.6
MEAN	7	DB-4	35	37	48.6	35	37	48.6
		DB-7	36	36	50	35	37	48.6
	8	DB-4	36	36	50	36	36	50
		DB-7	36	36	50	36	36	50
	9	DB-4	36	36	50	36	36	50
		DB-7	36	36	50	36	36	50
FFT	7	DB-4	35	37	48.6	37	35	51.3
		DB-7	35	37	48.6	35	37	48.6
	8	DB-4	38	34	52.7	38	34	52.7
		DB-7	39	33	54.16	38	34	52.7
	9	DB-4	35	37	48.6	34	38	47.2
		DB-7	34	38	47.2	36	36	50

Table 9: LDC Classifier for Horizontal Misalignment at DE (0.5mm & 2.0mm)

5.5.2 Quadratic Discriminant Classifier (QDC):

Maximum accuracy was achieved by CVA. It gave maximum accuracy of 100% at wavelet levels (7-9) using both mother wavelet 4,7 Daubechies. Whereas entropy performed at (48%-66.6%). Mean gave (51%-56%). FFT was lowest performing feature (48-52%). Table below shows all results.

QDC Classifier for Imbalance at NDE (6g) (120 SAMPLES)					
Features	**Wavelet Level**	**Mother Wavelet**	**TD**	**FD**	**ACC**
CVA	7	DB-4	72	0	100
		DB-7	72	0	100
	8	DB-4	72	0	100
		DB-7	72	0	100
	9	DB-4	72	0	100
		DB-7	72	0	100
ENTROPY	7	DB-4	48	24	66.6
		DB-7	48	24	66.6
	8	DB-4	48	24	66.6
		DB-7	48	24	66.6
	9	DB-4	30	42	41.6
		DB-7	31	41	43
MEAN	7	DB-4	48	24	66.6
		DB-7	48	24	66.6
	8	DB-4	48	24	66.6
		DB-7	48	24	66.6
	9	DB-4	43	29	59.7
		DB-7	31	41	43
FFT	7	DB-4	38	34	52.7
		DB-7	37	35	51.3
	8	DB-4	37	35	51.3
		DB-7	36	36	50
	9	DB-4	33	39	45.8
		DB-7	35	37	48.6

Table 10: QDC Classifier for Imbalance at NDE (6g)

QDC Classifier for Imbalance at NDE (20g) (120 SAMPLES)					
Features	**Wavelet Level**	**Mother Wavelet**	**T D**	**FD**	**ACC**
CVA	7	DB-4	72	0	100
		DB-7	72	0	100
	8	DB-4	72	0	100
		DB-7	72	0	100
	9	DB-4	72	0	100
		DB-7	72	0	100
ENTROPY	7	DB-4	48	24	66.6
		DB-7	48	24	66.6
	8	DB-4	44	28	61.1
		DB-7	45	27	62.5
	9	DB-4	35	37	48.6
		DB-7	35	37	48.6
MEAN	7	DB-4	43	29	59.7
		DB-7	44	28	61.1
	8	DB-4	41	31	56.9
		DB-7	41	31	56.9
	9	DB-4	37	35	51.3
		DB-7	37	35	51.3
FFT	7	DB-4	38	34	52.7
		DB-7	37	35	51.3
	8	DB-4	36	36	50
		DB-7	37	35	51.3
	9	DB-4	36	36	50
		DB-7	35	37	48.6

Table 11: QDC Classifier for Imbalance at NDE (20g)

QDC Classifier for Imbalance at DE (6g) (120 SAMPLES)					
Features	**Wavelet Level**	**Mother Wavelet**	**TD**	**FD**	**ACC**
CVA	7	DB-4	72	0	100
		DB-7	72	0	100
	8	DB-4	72	0	100
		DB-7	72	0	100
	9	DB-4	72	0	100
		DB-7	72	0	100
ENTROPY	7	DB-4	35	37	48.6
		DB-7	35	37	48.6
	8	DB-4	35	37	48.6
		DB-7	36	36	50
	9	DB-4	38	34	52.7
		DB-7	38	34	52.7
MEAN	7	DB-4	36	36	50
		DB-7	35	37	48.6
	8	DB-4	36	36	50
		DB-7	36	36	50
	9	DB-4	36	36	50
		DB-7	36	36	50
FFT	7	D B-4	35	37	48.6
		DB-7	38	34	52.7
	8	DB-4	35	37	48.6
		DB-7	35	37	48.6
	9	DB-4	38	34	52.7
		DB-7	33	39	45.8

Table 12: QDC Classifier for Imbalance at DE (6g)

QDC Classifier for Imbalance at DE (20g) (120 SAMPLES)					
Features	**Wavelet Level**	**Mother Wavelet**	**TD**	**FD**	**ACC**
CVA	7	DB-4	72	0	100
		DB-7	72	0	100
	8	DB-4	72	0	100
		DB-7	72	0	100
	9	DB-4	72	0	100
		DB-7	71	1	98.6
ENTROPY	7	DB-4	36	36	50
		DB-7	36	36	50
	8	DB-4	36	36	50
		DB-7	39	33	54.1
	9	DB-4	37	35	51.3
		DB-7	38	34	52.7
MEAN	7	DB-4	41	31	56.9
		DB-7	40	32	55.5
	8	DB-4	37	35	51.3
		DB-7	38	34	52.7
	9	DB-4	37	35	51.3
		DB-7	36	36	50
FFT	7	DB-4	41	31	56.9
		DB-7	37	35	51.3
	8	DB-4	33	39	45.8
		DB-7	38	34	52.7
	9	DB-4	38	34	52.7
		DB-7	37	35	51.3

Table 13: QDC Classifier for Imbalance at DE (20g)

QDC Classifier for Horizontal Misalignment at NDE (0.5mm & 2.0mm) (120 SAMPLES)								
Features	**Wavelet Level**	**Mother Wavelet**	**TD**	**FD**	**ACC**	**TD**	**FD**	**ACC**
			0.5mm			**2.0mm**		
CVA	7	DB-4	72	0	100	72	0	100
		DB-7	72	0	100	72	0	100
	8	DB-4	72	0	100	72	0	100
		DB-7	72	0	100	72	0	100
	9	DB-4	72	0	100	72	0	100
		DB-7	72	0	100	72	0	100
ENTROPY	7	DB-4	35	37	48.6	48	24	66.6
		DB-7	36	36	50	48	24	66.6
	8	DB-4	35	37	48.6	48	24	66.6
		DB-7	35	37	48.6	48	24	66.6
	9	DB-4	31	41	43	36	36	50
		DB-7	36	36	50	34	38	47.2
MEAN	7	DB-4	36	36	50	45	27	62.5
		DB-7	29	43	40.2	44	28	61.1
	8	DB-4	33	39	45.8	43	29	59.7
		DB-7	32	40	44.4	43	29	59.7
	9	DB-4	36	36	50	35	37	48.6
		DB-7	32	40	44.4	34	38	47.2
FFT	7	DB-4	36	36	50	38	34	52.7
		DB-7	36	36	50	38	34	52.7
	8	DB-4	32	40	44.4	37	35	51.3
		DB-7	32	40	44.4	37	35	51.3
	9	DB-4	36	36	50	35	37	48.6
		DB-7	36	36	50	39	33	54.1

Table 14: QDC Classifier for Horizontal Misalignment at NDE (0.5mm & 2.0mm)

QDC Classifier for Horizontal Misalignment at DE (0.5mm & 2.0mm) (120 SAMPLES)								
Features	**Wavelet Level**	**Mother Wavelet**	**TD**	**FD**	**ACC**	**TD**	**FD**	**ACC**
			0.5mm			**2.0mm**		
CVA	7	DB-4	72	0	100	72	0	100
		DB-7	72	0	100	72	0	100
	8	DB-4	72	0	100	72	0	100
		DB-7	72	0	100	72	0	100
	9	DB-4	72	0	100	72	0	100
		DB-7	72	0	100	72	0	100
ENTROPY	7	DB-4	36	36	50	36	36	50
		DB-7	36	36	50	36	36	50
	8	DB-4	38	34	52.7	36	36	50
		DB-7	39	33	54.1	38	34	52.7
	9	DB-4	37	35	51.3	35	37	48.6
		DB-7	36	36	50	35	37	48.6
MEAN	7	DB-4	38	34	52.7	36	36	50
		DB-7	38	34	52.7	36	36	50
	8	DB-4	38	34	52.7	35	37	48.6
		DB-7	38	34	52.7	36	36	50
	9	DB-4	36	36	50	36	36	50
		DB-7	35	37	48.6	35	37	48.6
FFT	7	DB-4	33	39	45.8	34	38	47.2
		DB-7	37	35	51.3	33	39	45.8
	8	DB-4	41	31	56.9	39	33	54.1
		DB-7	41	31	56.9	39	33	54.1
	9	DB-4	33	39	45.8	34	38	47.2
		DB-7	36	36	50	37	35	51.3

Table 15: QDC Classifier for Horizontal Misalignment at DE (0.5mm & 2.0mm)

5.6 Classifier Accuracy

When two distinct classification techniques, such Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA), provide the same accuracy for a particular feature, it suggests that the feature may have certain properties that make it equally acceptable for both techniques. Following are the causes:

a. **Separation of Features:** The CVA feature clearly outperforms different classes, enabling both LDA and QDA to differentiate targets. Both LDA and QDA performed well as the feature values for lasses are sufficiently identical as shown in figure 15.

b. **Feature Distribution:** Both linear and quadratic discriminant analysis benefit from the distribution of Coefficient of Variation of Amplitude (CVA). While QDA accepts that the covariance matrices for each class, LDA presupposes that the data inside each class & follows a multivariate Gaussian distribution with equal covariance matrices for all classes. Similar performance results are extracted if both assumptions are supported by the distribution of CVA feature.

c. **Low Dimensionality:** LDA works best when there are fewer features per sample than there are samples per feature. Both LDA and QDA can perform similarly if the dataset has a sufficient number of samples and a sufficient number of features. Hence, in this study 20 samples as explained above has been used.

d. **Redundancy of Features:** If a feature is redundant, it may have a comparable impact on the classification performance of both LDA and QDA.

e. **Noise Levels:** Consistent performance across various classifiers results same if the feature is not greatly impacted by noise or outliers. As wavelet decomposition has discarded the noise band consistent performance is achieved.

5.7 Confusion Matrix

The confusion matrix is a useful tool for assessing the effectiveness of classification algorithms in the area of condition monitoring and problem diagnosis of induction motors. It offers a thorough breakdown of the classifier's predictions as well as the actual class labels. Researchers can learn more about the defect diagnostic process's accuracy, precision, and general efficacy by examining the confusion matrix. The performance of a classification method is represented by the confusion matrix, which is a square matrix. True positive (TP), false positive (FP), true negative (TN), and false negative (FN) are its four main parts. These elements are obtained by comparing the actual fault classes of the induction motor with the projected fault classes. [69]

5.7.1 Interpreting the Confusion Matrix

Several performance measures that assess the efficiency of the defect detection procedure for induction motors may be obtained by looking at the numbers in the confusion matrix which are as follows:

5.7.1.1 Accuracy

Accuracy gauges how accurately the categorization method is working overall. It is determined by dividing the total number of instances by the sum of TP and TN. Better categorization ability is indicated by an increase in the accuracy value.

5.7.1.2 Precision

Precision is the classifier's capacity for accurately identifying true positives while minimizing false positives. It is determined by dividing TP by the total of TP and FP. Fewer false positives are indicative of higher precision.

5.7.1.3 Sensitivity or True Positive Rate

Sensitivity or True Positive Rate gauges a classifier's accuracy in identifying genuine positives while reducing false negatives. It is determined by dividing TP by the total of TP and FN. Fewer false negatives are indicated by higher recall.

Specificity (genuine Negative Rate) assesses a classifier's accuracy in identifying genuine negatives while reducing false positives. It is determined by dividing TN by the total of TN and FP. Less false positives are indicated by higher specificity. However, confusion matrix of all feature at wavelet levels 7,8 and 9 corresponding to db 4 and 7 would provide excessive information in this particular study. Therefore, only Non drive end HM 2.0 dataset in order to demonstrate confusion matrix and analyze classifier behavior. The resulting confusion matrix of aforesaid dataset is appended below:

Wavelet Level - 7			db - 4		db - 7	
CVA	True Class	Positive	36	0	36	0
		Negative	0	36	0	36
ENTROPY	True Class	Positive	12	24	12	24
		Negative	0	36	0	36
MEAN	True Class	Positive	12	24	12	24
		Negative	5	31	6	36
FFT	True Class	Positive	31	5	31	5
		Negative	32	4	31	5
			Predicted Positive	Predicted Negative	Predicted Positive	Predicted Negative
			Pridicted Class		Pridicted Class	

Table 16: Confusion Matrix - Wavelet Level 7

Wavelet Level - 8			db - 4		db - 7	
CVA	True Class	Positive	36	0	36	0
		Negative	0	36	0	36
ENTROPY	True Class	Positive	12	24	12	24
		Negative	3	33	2	34
MEAN	True Class	Positive	12	24	12	24
		Negative	14	22	13	23
FFT	True Class	Positive	24	12	24	12
		Negative	33	3	32	4
			Predicted Positive	Predicted Negative	Predicted Positive	Predicted Negative
			Pridicted Class		Pridicted Class	

Table 17: Confusion Matrix - Wavelet Level 8

Wavelet Level - 9			db - 4		db - 7	
CVA	True Class	Positive	36	0	36	0
		Negative	0	36	0	36
ENTROPY	True Class	Positive	12	24	12	24
		Negative	12	24	13	23
MEAN	True Class	Positive	13	23	12	24
		Negative	17	19	17	19
FFT	True Class	Positive	22	14	25	11
		Negative	27	9	30	6
			Predicted Positive	Predicted Negative	Predicted Positive	Predicted Negative
			Pridicted Class		Pridicted Class	

Table 18: Confusion Matrix - Wavelet Level 9

5.8 Receiver Operating Characteristic (ROC)

When assessing the effectiveness of the non-intrusive defect detection system for induction motors, the Receiver Operating Characteristic (ROC) curve analysis proved to be a crucial tool. The trade-off between true positive rate (sensitivity) and false positive rate (1-specificity) across various categorization thresholds was comprehensively visualized via the ROC curve. The discriminative power of the created fault detection system might be measured by analyzing the area under the ROC curve (AUC). The ROC study showed that the Coefficient of Variation (CVA) feature produced an excellent AUC when combined with wavelet decomposition, demonstrating its superior ability to recognize and categorize problems in induction motor data. [70]

The study's credibility is increased by the ROC curve's distinct delineation of the system's performance, which also makes it simple to compare the results with those of other defect detection techniques. The study's primary finding is that the CVA feature, when combined with wavelet decomposition, excels as the top feature for classification, enables more efficient and reliable non-intrusive problem detection in induction motors, is reaffirmed by the ROC curve analysis. ROC Curve for only Non drive end HM 2.0 dataset is appended below in order to demonstrate classifier behavior.

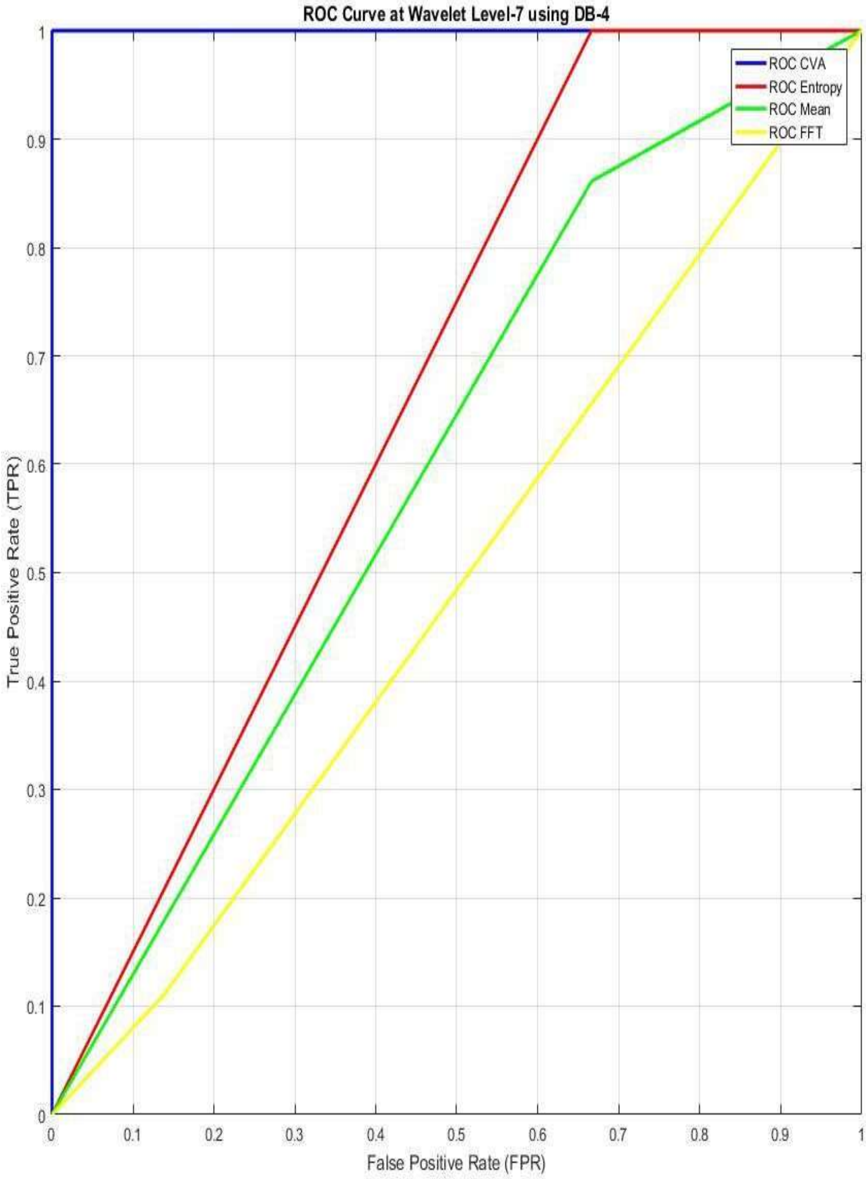

Figure 19: ROC Curve at Wavelet Level-7 using DB-4

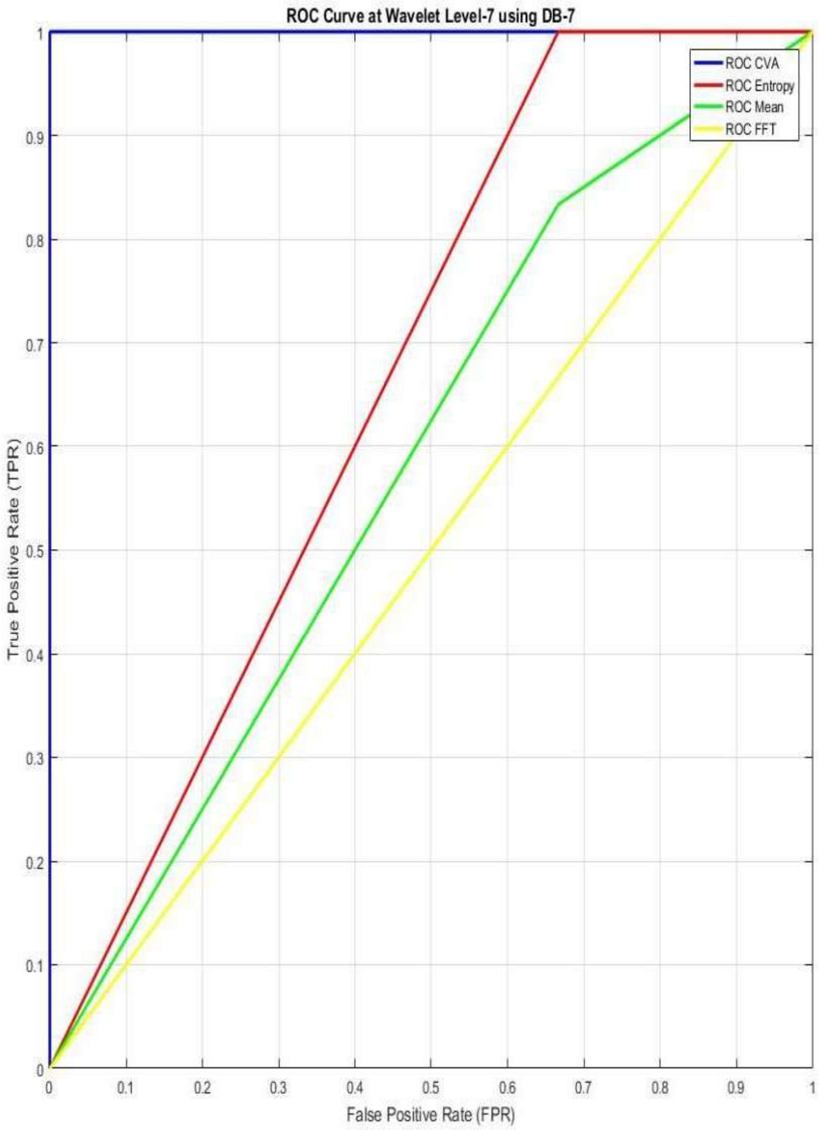

Figure 20: ROC Curve at Wavelet Level-7 using DB-7

5.8.1 ROC Behavior

Threshold Effect, used to get variable TPR and FPR values, ROC curves are commonly produced by altering the model's classification threshold. It could result in a straight line if the threshold values are discrete. The written given code builds and presents ROC curves for LDC & QDC classifiers. For classification threshold values, ROC curves provide a graphical depiction of the trade-off between the true positive rate (sensitivity) and the false positive rate (1 - specificity) as shown in figure below:

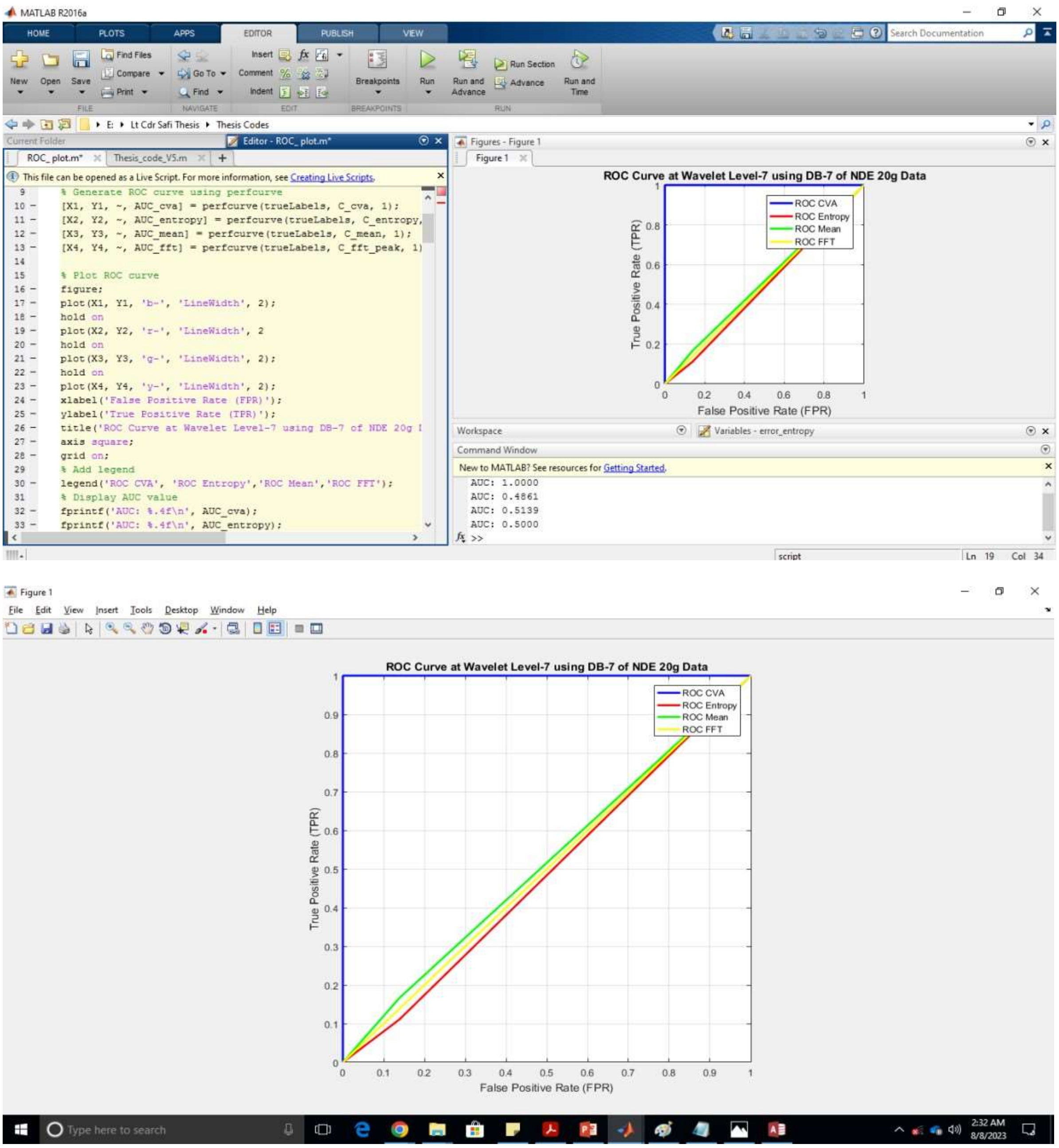

Figure 21: ROC Curve using Perfcurve

5.9 Validation of Results

The written code is performing the validation of different classification results against a true (actual labels) for dataset. It assesses the correctness of the predictions made by LDC & QDC classifiers and calculates various metrics related to error such as true detections (TP), and false detections (FD) using a confusion matrix. Break down of code step by step is as follows:

a. Group Verification: group_verify is a matrix that contains the true labels or f the samples. It is formed by combining the true labels of two groups (normal , faulty).

b. Error Calculation: The code calculates the error for each classifier by comparing their predictions (C_cva, C_entropy, C_mean, C_fft_peak) with the true labels (group_verify). The result of this comparison is a binary matrix (error_cva, error_entropy, error_mean, error_fft_peak) where each element is 1 if the prediction is correct (true) and 0 if the prediction is incorrect (false).

c. Error Validation: The code then finds the indices where the errors occurred (where the binary matrix is 0) for each classifier. This provides insight into which samples were misclassified.

d. True Detections (TP): The code finds the indices where the predictions match the true labels (where the binary matrix is 1) for each classifier. This represents the true positive (TP) instances, which are correctly detected by each classifier.

e. False Detections (FD): The code finds the indices where the predictions do not match the true labels (where the binary matrix is 0) for each classifier. This represents the false positive (FP) instances, which are incorrectly detected by each classifier.

f. Confusion Matrix Calculation: The code calculates the confusion matrix for each classifier using the confusionmat function. The confusion matrix provides a comprehensive summary of the classifier's performance, showing the counts of true positive, true negative, false positive, and false negative instances.

g. Metrics Calculation: The lengths of true detections (TP) and false detections (FD) are calculated for each classifier, providing insight into their performance.

h. Overall, code is a part of the validation process for assessing the performance of different classifiers. It calculates and presents information about correct and incorrect predictions, which can be used to evaluate the effectiveness of the classification methods and to fine-tune them if necessary. The confusion matrices and the TP/FD counts can help in understanding the strengths and weaknesses of each classifier in terms of its predictive accuracy and error.

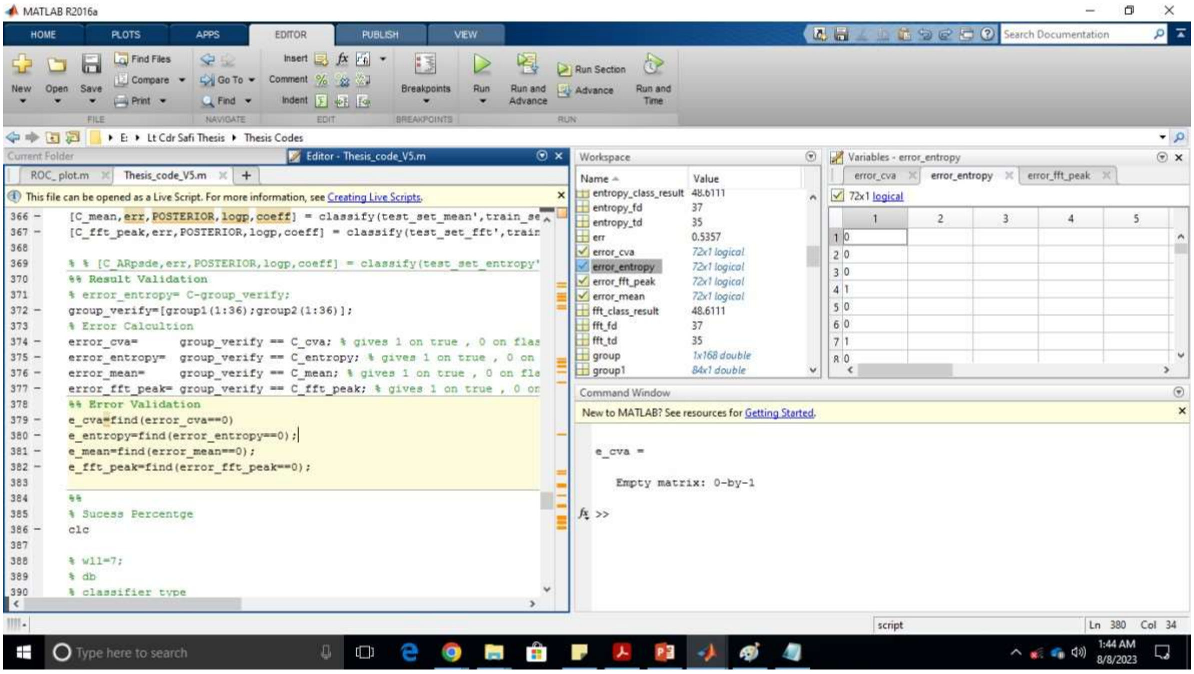

Figure 22: Error Validation

Chapter No 6: Conclusion and Recommendations

6.1 Summary of Research Findings

We investigated the application of supervised learning and wavelet decomposition for non-intrusive fault identification in induction motors in this study. To classify motor data into distinct health categories, the study used four features - Coefficient of Variation (CVA), Entropy, Mean, and Fast Fourier Transform (FFT) - and two classifiers, Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA). The following are the important conclusions of the study:

a. Wavelet Decomposition for Feature Extraction: Wavelet decomposition was quite useful in identifying meaningful features from motor data. The choice of mother wavelet (4 and 7 Daubechies) and wavelet levels (7, 8, and 9) had a substantial impact on classifier performance.

b. CVA effectiveness: The Coefficient of Variation (CVA) feature outperformed all other wavelet levels in successfully classifying induction motor data. The ability of CVA to capture changes in data variance over time proved to be extremely useful in finding flaws and anomalies in motor behavior.

c. Classifier Performance: In categorizing induction motor data, both Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) produced promising results. However, in most circumstances, LDA outperformed QDA, especially when paired with the CVA function.

d. Potential Applications: The created classification models have a lot of promise for real-time defect detection and condition monitoring of induction motors in a variety of sectors. Accurate defect identification can lead to enhanced reliability, reduced downtime, and better maintenance practices.

6.2 Achievements of the Study

The research contributed significantly to the field of non-intrusive failure detection in induction motors. We were able to construct classification models with good accuracy in recognizing motor health issues by using machine learning approaches and wavelet decomposition. The research effectively addressed the goals of improving defect diagnosis methods and increasing overall induction motor reliability.

Furthermore, the research revealed the usefulness of supervised learning algorithms in industrial contexts. The inclusion of CVA as a fundamental feature in defect identification emphasized the significance of statistical techniques in detecting fluctuations in motor data. The findings of this study establish the groundwork for future advances in predictive maintenance and condition-based monitoring of induction motors.

6.3 Implications and Applications

This research has far-reaching benefits and has potential applications in a variety of sectors that rely on induction motors for vital operations. To improve defect detection capabilities, the created classification models can be integrated with current motor monitoring systems. These improved fault diagnosis techniques can help industries such as manufacturing, power generation, transportation, and maritime. Among the practical applications of this research are:

a. Predictive Maintenance: By deploying non-intrusive problem detection technologies, industries can shift from reactive to proactive maintenance practices. Early defect detection enables for prompt response and avoids costly breakdowns.

b. Increased Reliability: Induction motors are essential in many industrial processes. The danger of motor failure and unscheduled downtime is considerably decreased by precisely recognizing defects, resulting in better overall system reliability.

c. Savings on maintenance and energy: Effective defect detection and condition monitoring can lead to cost savings on maintenance and energy consumption. Improved energy efficiency is aided by timely maintenance and optimized motor performance.

d. Enhancement of Safety: The dependability of induction motors has a direct impact on the safety of employees and equipment. Early fault identification guarantees that necessary safety actions to prevent accidents are implemented.

6.4 Limitations of the Study

While this study provides vital insights into non-intrusive defect detection in motors with induction, it is important to recognize the limits encountered:

a. Size of the data set: A larger and more diversified dataset could have boosted the classification algorithms' performance even more.

b. Data Variability: Variations in operational circumstances and external factors may have an impact on fault detection accuracy. More comprehensive datasets with varied operational circumstances could improve the models' robustness.

c. Generalization: The classification models built in this study were unique to the dataset presented. Additional validation and testing would be required to generalize these models to diverse motor types and operating circumstances.

d. Feature Selection: While CVA outperformed other features in this investigation, other characteristics may be useful in different fault detection circumstances. Exploring more features may result in improved categorization accuracy.

6.5 Future Research Directions

The study establishes the framework for a number of intriguing future research directions in the realm of non-intrusive failure detection in induction motors. Among the possible directions are:

a. Incorporating data from several sensors, including as temperature, vibration, and sound sensors, could provide a more comprehensive view of motor health conditions and improve fault detection accuracy.

b. Exploring the mix of supervised and unsupervised learning approaches may provide unique insights into recognizing complicated and unknown defects in induction motors.

c. Online defect Detection: Creating real-time defect detection algorithms capable of continually monitoring induction motors while they are in operation would be a beneficial addition to predictive maintenance practices.

d. Examining the transferability of the created classification models to various motor types and sectors may result in more generalized and adaptable fault detection systems.

6.6 Recommendations

Following recommendations based on the research findings and limitations are proposed:

a. Enhanced Data Collection: To enable robust model development and validation, industries should focus on collecting more vast and diversified datasets.

b. Sensor Integration: Using a variety of sensors for motor monitoring can provide richer data and enhance fault detection accuracy.

c. Continuous Model Updating: As new data becomes available, the established models should be updated and revalidated on a frequent basis to ensure their effectiveness.

d. Collaboration and Data Sharing: Industries and researchers should work together to produce larger and more complete datasets that will help the overall area of motor defect detection.

6.7 Conclusion

The study effectively investigated the use of supervised learning and wavelet decomposition (Time-frequency analysis) for non-intrusive fault identification in induction motors. The study highlighted the utility of the Coefficient of Variation (CVA) feature, as well as the importance of wavelet decomposition in extracting important information from motor data. The generated classification models performed well in diagnosing motor health issues, especially when paired with Linear Discriminant Analysis (LDA).

The implications of this research extend across other industries, providing prospects for preventive maintenance, increased reliability, cost savings, and greater safety. However, it is critical to acknowledge the study's limitations and encourage additional research in the field to overcome these limits and explore new possibilities.

Finally, this study advances defect detection methods in induction motors and lays the path for more complex and effective predictive maintenance practices. As enterprises transition to smart manufacturing and Industry 4.0, the integration of fault detection systems will be important in guaranteeing the smooth and reliable functioning of critical industrial processes.

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