M.Tech (Signal Processing and Digital Design) SONALIKA BHANDARI 2023

MECHANICAL FAULT ANALYSIS AND DETECTION USING NON STATIONARY DECOMPOSITION FOR VIBRATION SIGNALS

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CANDIDATE'S DECLARATION

I, Sonalika Bhandari, Roll No. 2K21/SPD/13, student of M.Tech (Signal Processing and Digital Design), hereby declare that the project dissertation titled "Mechanical Fault Analysis and Detection using Non Stationary Decomposition for Vibration Signals " which is submitted by me to the Department of Electronics and Communication Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirements for the award of degree of Master of Technology in Signal Processing and Digital Design, is original and not copied from any source without citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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CERTIFICATE

I hereby certify that the project dissertation titled "Mechanical Fault Analysis and Detection using Non Stationary Decomposition for Vibration Signals", which is submitted by Sonalika Bhandari, Roll No. 2K21/SPD/13, Department of Electronics and Communication Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirements for the award of degree of Master of Technology in Signal Processing and Digital Design is a record of the project work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this university or elsewhere.

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ABSTRACT

Machine health monitoring plays an increasingly crucial role in automated industries, particularly in the context of meeting Industry 4.0 standards. One significant aspect is the detection and diagnosis of faults in rotating machines by implementing continuous machine health monitoring systems. These systems can proactively detect and classify issues related to rotating elements in real-time, allowing for timely maintenance and repairs.

Bearing faults and shaft imbalances are common problems that accounts for 50% of motor failures. This can significantly impact machine performance and lead to premature failures. Through continuous monitoring and analysis of vibration patterns, temperature fluctuations, stator current, acoustic noise or any other relevant parameters, an early sign of bearing faults and shaft imbalances can be identified. This will enable timely corrective actions to prevent catastrophic assembly line failures. Integrating machine health monitoring with advanced analytics and predictive maintenance algorithms, can help achieve higher levels of efficiency, productivity, and cost savings by minimizing unplanned downtime and extending the lifespan of critical machinery.

There has been significant contribution in this field but a major challenge remains in terms of fault detection and severity identification under varying load and rotational speed. The changing speed impacts frequency content and pattern changing the fault characteristic frequency which hinders consistent fault detection. To overcome this challenge robust algorithm incorporating speed information or extracting features which are independent of speed is essentially an area of research. This thesis presents a

comprehensive investigation of the rolling bearing faults and shaft unbalance faults, including their characteristics and fault signatures in the vibrational signals.

The presented work proposes two methods based on non-stationary signal decomposition to tackle variational speed problem. The first work introduces an intelligent framework for fault detection using a single sensor. It utilizes Gramian-multi-resolution dynamic mode decomposition to process vibration signals. Initially, the vibration signals are transformed using a gram matrix, which converts the one-dimensional data into a snapshot matrix that evolves with time, preserving the temporal variation. This transformed data is then subjected to spatial temporal decomposition through multi-resolution dynamic mode decomposition (MrDMD). It decomposes the system dynamics into hierarchically evolving fast and slow modes, enabling the identification of transient fault characteristics. To handle noise from sensors and the environment, a robust least square dynamic mode decomposition algorithm is applied at each level of MrDMD. The resulting mode matrix is further processed by colour coding, effectively converting it into an image format for analysis and classification.

The second work fuses vibration signals from sensors placed at three different locations in the frequency domain. This fusion process ensures that maximum spectral information is retained, enabling a more comprehensive analysis. The fused signal is then subjected to decomposition using an energy-preserving maximum overlap discrete wavelet transform, resulting in a multi-scale matrix. Further, to evaluate the severity of the shaft unbalance the decomposed scale matrix is encoded into a contour plot, using the mean absolute deviation of individual scales as iso-reference lines. Finally, the images generated from both the methods are used for classification using different convolutional neural networks. The proposed methodology is evaluated on publicly

available datasets, from University of Ottawa for bearing fault identification and Fraunhofer Institute for Integrated Circuits for shaft unbalance and severity detection. The results show an overall classification accuracy of 96.83% for bearing fault characteristic and accuracy of 97.05% for unbalance severity detection.

The effectiveness of the method is evaluated by comparing the accuracy of fault detection and analysing the performance metrics such as sensitivity and specificity. The finding and result demonstrates the potential of the proposed methodology in improving the reliability and maintenance practices of rotating machinery systems, ultimately leading to enhanced operational efficiency and reduced downtime. The performance surpasses the results achieved by previous studies in terms of adaptability of real-time operation and accuracy.

ACKNOWLEDGEMENT

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LIST OF SYMBOLS, ABBREVIATIONS AND NOMENCLATURE

1. **MrDMD –** Multi Resolution Dynamic Mode Decomposition
2. **AI –** Artificial Intelligence
3. **DL –** Deep Learning
4. **ML –** Machine Learning
5. **MODWT –** Maximum Overlap Discrete Wavelet Transform
6. **GMrDMD –** Gramian Multi Resolution Dynamic Mode Decomposition
7. **DMD –** Dynamic Mode Decomposition
8. **FCF –** Fault Characteristic Frequency
9. **RT-CMS –** Real Time Condition Monitoring System
10. **CNN –** Convolutional Neural Network
11. **STFT –** Short Time Fourier Transform
12. **CWT –** Continuous Wavelet Transform
13. **DWT –** Discrete Wavelet Transform
14. **SVM –** Support Vector Machine
15. **DNN –** Deep Neural Network
16. **OT –** Order Tracking
17. **EMD –** Empirical Mode Decomposition
18. **VMD –** Variational Mode Decomposition
19. **TF –** Time Frequency
20. **FFT –** Fast Fourier Transform
21. **LMD –** Local Mean Decomposition

CHAPTER 1

INTRODUCTION

1.1 GENERAL

The reliable functioning of rotating machine is of paramount importance across industries such as manufacturing, construction, power plants and also in the drivetrains of electric vehicles. In the context of this thesis is a motor is being referred as rotating machine. Among the crucial components of motor, bearings and shafts assume a pivotal role in supporting and transferring power to rotating elements. Nevertheless, faults in these components can lead to significant ramifications, including diminished performance, extended downtime, and potential safety hazards. Hence, the implementation of a condition monitoring system for rotating machine elements like bearings and shafts holds great significance across diverse industries.

The industrial advancement and the need for health monitoring of rotating elements go hand in hand. The foundation of Industry 4.0 revolves around automating processes and remotely monitoring the condition of systems in large-scale factories [1]. It encompasses the integration of digital technologies and automation in manufacturing, leveraging concepts from artificial intelligence (AI) and the Internet of Things [2]. Similarly, a real-time monitoring and alert system is designed to continuously monitor and track the status of machine components, and promptly alerting operators of any anomalies or deviations from standard operation.

Precise identification and detection of faults in these elements are crucial to avoid catastrophic failures and promote optimal performance and durability of machinery. Over time, mechanical fault analysis and detection techniques have experienced substantial advancements, incorporating sophisticated methodologies and technologies such as vibration analysis, acoustic emission, temperature monitoring, along with advanced signal processing algorithms and data-driven decompositions [3]. By utilizing advanced technologies and methodologies, the system continuously monitors the condition of bearings and shafts, promptly identifying early indicators of wear, misalignment, lubrication problems, and abnormal vibrations. The information about the health of these components is delivered in real-time, enabling the condition monitoring system to proactively raise alarms for maintenance measures.

1.2 MOTOR COMPONENTS: SIGNIFICANCE AND RELIABILITY

1.2.1 Overview

Motors are widely used in various sectors due to their cost-effective and energy-efficient design for converting electrical energy into mechanical power. They consist of stationary and rotating parts, with crucial elements such as bearings and shafts as shown in Figure 1.1 supporting their proper functioning. These components form the foundation of the motor's mechanical system [4], ensuring smooth rotation and proper alignment. Understanding their significance is essential for optimizing motor performance, reliability, and longevity. However, these components are subjected to various stress profiles, leading to non-deterministic abrasions and the emergence of different faults within the motor. This study focuses on the development of fault diagnosis methods for bearings and shafts. The operational importance of these components is outlined below.

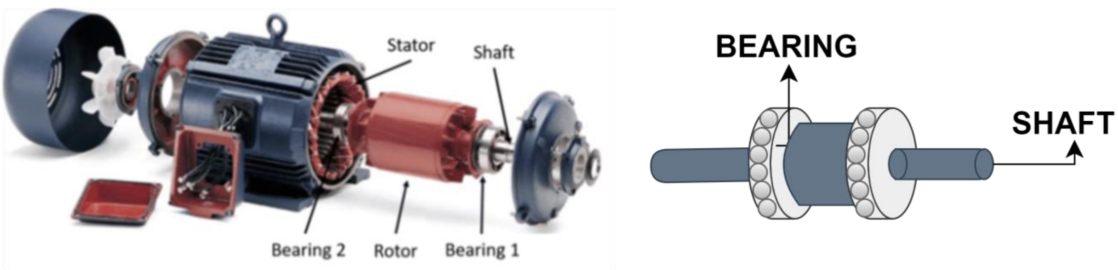

Figure 1.1 Components of motor.

1. **Bearings:** Bearings facilitate smooth rotational movement in motors by reducing friction by supporting axial and radial loads. They guide and support rotating shafts, allowing them to rotate with minimal resistance. By distributing the load evenly, bearings prevent wear and damage to the shaft and other components [5]. Proper selection, lubrication, and maintenance of bearings are essential to minimize friction, extend the motor's lifespan, and ensure efficient operation.

2. **Shafts:** Shafts are essential components that transmit power from the motor to connected machinery or devices. In motors, the shaft connects the rotating part, known as the rotor, to the driven load. It transfers torque [6] and rotational motion, enabling the motor to fulfil its intended function. Achieving optimal performance and reliability requires careful consideration of shaft design and construction, including factors such as material selection, diameter, length, and shaft alignment.

The reliable functioning of bearings, shafts, and rotating parts is crucial for the performance of motors in diverse industries. Any issues or failures in these components can result in reduced efficiency, increased energy consumption, or mechanical damage. Therefore, proactive monitoring and timely replacement of these critical components are essential to ensure optimal motor reliability and minimize downtime.

1.2.2 Types of Faults

Electric motors can encounter various faults [7] that have the potential to affect their performance and reliability. These faults can be broadly classified based on the nature into two groups namely electrical fault or mechanical fault as shown in Figure 1.2. Electrical faults primarily involve problems related to the electrical components and systems within the motor. These include issues with the electrical wiring, insulation breakdown, short circuits, open circuits, electrical overloads, voltage fluctuations, and component failures such as capacitors, or switches. While mechanical faults, on the other hand, pertain to issues concerning the mechanical components and systems of the machinery. These faults can involve problems with bearings, gears, shafts, belts, lubrication, misalignment, unbalance, resonance, structural defects, and wear and tear of mechanical parts.

Electrical faults can arise from various factors, including insulation degradation, moisture or contamination, overheating, electrical surges, overloading, poor wiring or connection quality, aging of electrical components, and inadequate maintenance. To detect these faults in motors, a range of electrical measurements and monitoring techniques are employed [8]. These methods involve analysing parameters such as voltage, current, power factor, harmonic distortion, insulation resistance, and thermal imaging to identify any abnormalities or deviations from normal electrical behaviour. Electrical faults in motors can have significant repercussions, including equipment malfunctions, electrical failures, circuit breakdowns, power outages, and the risk of electrical fires. They can also lead to damage to electrical components, disrupt operations, pose safety hazards, and jeopardize personnel safety. Remedial actions for electrical faults in motors typically involve repairing or replacing faulty electrical components, improving insulation, ensuring proper grounding, addressing wiring or connection issues, and implementing effective electrical protection measures such as circuit breakers or fuses.

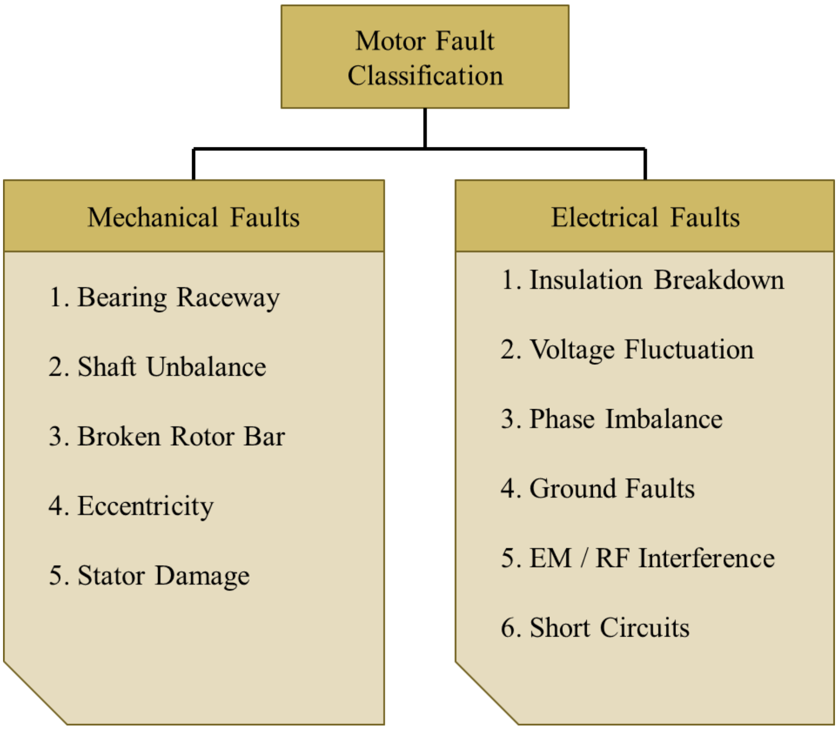

Figure 1.2 Classification of Motor faults.

Mechanical faults in motors can arise from various factors, including excessive loads, inadequate lubrication, misalignment, unbalanced forces, fatigue, improper installation or assembly, environmental conditions, wear and tear, and insufficient maintenance practices. Detecting these faults requires the use of techniques such as vibration analysis, acoustic monitoring, thermography, oil analysis, and visual inspections. These methods are employed to identify irregularities in vibration patterns, temperature distributions, lubrication quality, noise emissions, and the physical condition of mechanical components [9]. The consequences of mechanical faults in motors can be severe, leading to increased friction, excessive wear, loss of accuracy, unexpected downtime, decreased efficiency, increased energy consumption, and even catastrophic failures. These faults [10] can cause production delays, higher maintenance costs, safety risks, and damage to other components within the motor system. Remedial actions for mechanical faults often involve repairing or replacing damaged parts, realigning or balancing components, optimizing lubrication practices, implementing preventive maintenance schedules, conducting equipment overhauls, and adopting condition-based monitoring strategies to detect faults early.

It's important to note that electrical and mechanical faults can coexist and impact motor performance. By understanding the specific characteristics and detection methods associated with both types of faults, appropriate remedial actions can be taken to ensure the reliable and efficient operation of electric motors. In this thesis, the focus is on providing a detailed exploration of two specific mechanical faults: bearing raceway faults and shaft unbalance faults.

1.3 FAULT MONITORING

1.3.1 Evolution

Machine fault diagnosis has emerged as a critical field in industrial maintenance and reliability, and understanding its historical context is essential. The roots of machine fault diagnosis can be traced back to the early stages of industrialization when machines became increasingly complex and integral to various industries. The smooth operation and prevention of unexpected failures became a significant concern.

Bearings and shafts play crucial roles in ensuring the smooth and efficient operation of machinery by providing support to rotating elements and transmitting power in automated industries, renewable energy plants, and intelligent vehicles. However, these components operate under diverse conditions in the industrial sector, making them susceptible to various faults [11], including wear, misalignment, unbalance, lubrication issues, and others. Periodic quality checks are necessary to ensure proper operation and mitigate the detrimental effects of these faults.

In the past, fault monitoring on rotating machine components relied primarily on manual inspection and rudimentary techniques. Technicians would physically inspect the machines, looking for visible signs of wear, damage, or misalignment. This involved observing and listening to the machines while in operation, checking for unusual vibrations, noises, or excessive heat. However, these traditional monitoring methods had limitations. They heavily relied on human expertise, were subjective in nature, and often required machines to be taken offline for inspection. Consequently, this reactive maintenance approach often led to unexpected breakdowns and cost inefficiency.

These limitations prompted the development of more advanced and automated fault monitoring approaches in subsequent years. The advancements in electrical engineering, electronics, computing, and sensing technology played a significant role in this progression. Early diagnostic methods began to emerge, such as infrared thermography and vibration spectrum analysis.

Infrared thermography [12] involved the use of infrared cameras to capture the thermal patterns emitted by the machines. Experts would then analyse these patterns for any variations in temperature distribution, which could indicate issues like overheating or friction. On the other hand, vibration spectrum analysis [13] involved studying the vibration spectrum of rotating machines. By analysing the spectral characteristics of recorded vibration signals, experts could then identify early signs of faults such as imbalances, misalignments, bearing defects, and shaft damage based on characteristic frequency.

Today, machine fault diagnosis continues to evolve rapidly, driven by advancements in machine learning, AI, data driven analytics, and connectivity [14]. Researchers are exploring the potential of AI techniques, such as expert systems and neural networks, to automate fault detection and diagnosis processes. These approaches aimed to replicate human expertise and decision-making in analysing and identifying potential faults. Additionally, the integration of cloud-based platforms and digital twins is allowing remote monitoring and diagnosis of faults.

Overall, the field of fault monitoring in bearings and shafts demonstrates the evolution from manual inspection to data-driven [15], proactive maintenance practices. The integration of advanced signal processing methods along with smart decision making through AI has revolutionized the field, providing more sophisticated tools for fault detection and contributing to safer and more reliable industrial operations.

1.3.2 Types of Signals

Condition monitoring techniques are used to assess the health and performance of machinery and equipment, including motors. Several types of sensor data are suitable for performing this task but the ultimate choice of sensors depends on the specific application and the type of fault being targeted. These sensors primary objective is to monitoring various physical parameters of motor components to detect abnormalities, faults, or potential failures. Table 1.1 presents summary of commonly used techniques and their focus on corresponding physical parameters and motor components. Detailed overview of common types of sensor data that are often used for fault diagnosis is presented below:

Table 1.1 Summary of methods used for motor fault identification

Method	**Recorded Parameter**	**Target Motor Part**
Vibration Analysis	Vibration for analysis of fault characteristic frequency.	Bearings, Shaft, rotors, stators
Temperature Sensing	Temperature for sudden increase due to friction etc.	Windings, bearings, cooling systems
Oil Analysis	Oil properties like viscosity, contaminants etc. is studied	Bearings, gears, lubrication system
Current Analysis	Electric current for abnormal spikes in usage	Windings, electrical connections
Acoustic Emission	Acoustic emissions or sound waves	Bearings, gears, electrical discharges
Motor Current Signature Analysis (MCSA)	Current waveform and harmonics	Rotor bars, stator windings, air gap
Flux Analysis	Stray flux intensity or distribution	Stator core, rotor core, magnetic circuits, Insulation degradation

1. **Vibration data:** Monitoring the vibrational behaviour of rotating machinery using vibration sensors is a common practice. By analysing the spectrum of the vibration signal, it is possible to identify fault characteristic frequencies. This analysis provides insights into the acceleration and displacement levels associated with specific faults, such as unbalance, misalignment, bearing defects, or mechanical looseness. Changes in these parameters can help diagnose and detect potential issues in the machinery [16].
2. **Current data:** Utilizing current sensors, the electrical current flowing through components or motors can be measured. Deviations from normal current patterns can be indicative of various issues [17], including motor winding faults, short circuits, or electrical imbalances. By closely monitoring the current data, such anomalies can be promptly detected, enabling necessary actions to address the underlying problems and prevent further complications.
3. **Temperature data:** Temperature sensors are used to monitor the thermal behaviour of various components and systems. They are particularly useful for detecting faults related to overheating [18], such as issues with bearings, motors, electrical connections, or cooling systems. By monitoring the temperature of these components, abnormalities or excessive temperature levels can be identified, allowing for timely intervention to prevent further damage or failures.
4. **Acoustic data:** Acoustic sensors are utilized to capture sound or noise emissions generated by machinery. Abnormal or excessive noise levels [19] can serve as indicators of potential faults such as bearing defects, gear problems, or excessive friction. By analysing the acoustic data, operators can identify these issues and take appropriate measures for maintenance and repair. However, it's important to note that acoustic monitoring may have limitations in certain environments where background noise or masking effects can affect the accuracy of fault detection. Therefore, careful consideration should be given to the operating conditions and other monitoring techniques employed in conjunction with acoustic data to ensure comprehensive and reliable condition monitoring.
5. **Oil analysis data:** In systems that employ lubricating oil, the chemical composition, contaminants, and wear debris within the oil can be monitored using oil analysis sensors [20]. Alterations in oil properties can offer valuable insights into potential issues such as bearing wear, contamination, or lubrication

problems. It is important to note, however, that oil analysis has limitations, as certain faults may not be detectable through oil analysis alone. Additionally, the interpretation of oil analysis results requires expertise and knowledge of the specific system being monitored.

6. **Speed data**: Speed sensors like tachometers are utilized to measure the rotational speed of components or systems. Deviations from the expected speed values can be indicative of various issues, including unbalance, misalignment, or mechanical faults [21]. However, it's important to note that relying solely on speed or RPM data may have limitations, especially in the case of fast-moving machines. Tachometers or speed sensors may not capture rapid variations or transient events accurately. Additionally, while speed deviations can signal potential problems, they alone cannot provide detailed information about the specific fault or its severity. Therefore, it is essential to combine speed data with other condition monitoring techniques that measure additional parameters, such as vibration, temperature, or current, to diagnose specific faults accurately.
7. **Optical Imaging Data**: Sensors such as infrared thermography or high-speed cameras play a crucial role in motor fault analysis. They capture visual or thermal images of motor components, revealing hotspots, material deformations, or abnormal surface conditions [22]. However, it is important to consider the cost of implementing these techniques as they can be relatively expensive. Additionally, optical imaging has limitations and may not detect certain types of faults, such as internal defects or faults without visible or thermal anomalies on the motor's surface. Hence, it is recommended to combine optical imaging with other condition monitoring techniques. By leveraging multiple sensor data sources and complementary techniques, the effectiveness and reliability of motor fault diagnosis and maintenance activities can be enhanced.

It is worth noting that despite the availability of various types of sensors, vibration sensor data analysis remains the most popular method for detecting faults related to bearings and shafts. Vibration data provides a unique advantage over other sensor data in detecting these faults. Not only does vibration data detect motor bearing and shaft faults, but it also has the capability to distinguish between their severity and other factors such as unbalance. By analysing various vibration parameters, such as amplitude, frequency, and phase, vibration data can provide insights into the specific characteristics of different faults. This means that it can differentiate between the severity of bearing faults, such as early-stage wear or advanced damage, and also identify the presence and magnitude of unbalance in the motor. This capability allows maintenance practitioners to prioritize and address the most critical issues, ensuring optimal motor performance and minimizing the risk of further damage or failures.

The methods discussed above serve as examples of condition monitoring techniques that analyse physical parameters and motor components to detect potential faults or degradation. By integrating multiple sensor data sources and applying suitable signal processing and machine learning techniques, the accuracy and effectiveness of fault diagnosis systems can be enhanced. This comprehensive assessment of motor health facilitates predictive maintenance and helps minimize the occurrence of unexpected issues.

1.3.3 Significance of Condition Monitoring System

Leading research institutions such as IEEE Industry and General Application, the Electric Power Research Institute, and companies like Brüel & Kjær have consistently emphasized the importance of fault monitoring. Their research suggests that up to 50% of faults in motors [23] and rotating parts are attributed to faulty bearings and shafts. Therefore, the application of real-time condition monitoring systems (RT-CMS) plays a crucial role in various industries and sectors for several compelling reasons [24], which are discussed below.

1. **Early Fault Detection:** RT-CMS enables early detection of faults, anomalies, and deviations from normal operating conditions using data from sensors like vibration, temperature, pressure, etc. A moving system works at a characteristic frequency under healthy conditions, but once a fault occurs, the behaviour of sensor data changes. Hence, implementing RT-CMS in industrial rotating machines helps to solve a fundamental problem of early fault detection.
2. **Increased Equipment Reliability:** Monitoring the condition of critical components such as bearings, shafts, gears, and motors, helps ensure the reliability and longevity of the equipment. By addressing these issues promptly,

maintenance activities can be scheduled in a planned and controlled manner, reducing the risk of unexpected breakdowns and enhancing reliability.

3. **Optimized Maintenance Strategies:** RT-CMS offers valuable insights into machinery condition and performance, enabling condition-based maintenance strategies. It replaces scheduled or reactive repairs with tailored maintenance based on real-time machine condition. This optimizes maintenance schedules and production efficiency.
4. **Reduces Cost:** Condition monitoring saves costs by preventing unplanned downtime, mitigating major failures, and emergency repairs. It enables planned repairs, minimizing production losses. It also optimizes spare parts inventory based on actual condition assessments.
5. **Improved Safety:** By detecting abnormal equipment conditions, RT-CMS helps in identifying safety hazards, leading to a safer workplace and reducing the risk of accidents.
6. **Data-Driven Decision Making**: Monitoring machine parts records valuable data which can be used for optimizing processes, improving equipment design, and making informed decisions about maintenance, and repairs. This data-driven approach improves operational efficiency, reduces costs, and enhances productivity.

The main goal of RT-CMS is to detect potential failures early by analysing sensor data using intelligent AI-based classification. This helps improve equipment reliability, optimize maintenance, reduce costs, enhance safety, and enable data-driven decision-making. Continuous monitoring of machinery allows for early issue detection, proactive maintenance, and optimal performance and longevity of high cost machines.

1.3.4 Challenges

The field of fault diagnosis for mechanical faults, particularly related to bearings and motor shafts, presents significant challenges that researchers continually strive to address. The faults in these components can have severe implications for system performance, reliability, and safety. However, diagnosing these faults is a complex task due to factors such as the diverse range of possible fault types, the inherent variability in operating conditions, and the need to differentiate between normal variations and abnormal behaviour. Moreover, the increasing complexity and integration of mechanical systems introduce additional challenges in fault diagnosis. This section explores the key challenges [25] faced in the field of fault diagnosis and real-time monitoring for bearings and motor shafts as listed below.

1. **Varying operating conditions:** It presents challenges in data collection and modelling for fault diagnosis. Data collection becomes complex as it requires capturing diverse operating conditions. Traditional fault diagnosis models struggle to handle changing conditions, requiring advanced techniques like machine learning to adapt and differentiate between normal variations and actual faults. Moreover, the shifting fault frequencies with rotational speed add complexity. Signal processing and machine learning algorithms are used to track and adapt to these shifting frequencies, improving fault detection. Researchers aim to develop robust predictive monitoring systems that address these challenges and provide accurate fault diagnosis for mechanical faults.
2. **Noise in sensor data:** Noise interference is the presence of unwanted signals or disturbances that contaminate measured data, posing challenges in accurately detecting and analysing fault-related information. It can result from factors like electromagnetic interference, electrical noise, vibrations, or environmental conditions. This interference introduces additional components or frequencies in the spectrum, obscuring fault signatures and making it difficult to isolate relevant fault-related information. It masks or distorts fault-related signals, leading to false alarms or missed detections and reducing the signal-to-noise ratio. As a result, the accuracy and reliability of fault diagnosis systems are compromised, impacting their effectiveness in detecting and predicting mechanical faults.
3. **False Alarm:** A major challenge in bearing health predictive maintenance is the occurrence of false alarms, where the monitoring system incorrectly detects faults or anomalies in the bearings. False alarms can lead to unnecessary maintenance actions and disrupt operations. Factors such as noise interference, variations in operating conditions and limitations in fault detection algorithms contribute to false alarms. It is important to minimize false alarms to maintain the integrity and reliability of the predictive maintenance system. To address this challenge, advanced signal processing algorithms and accurate fault signature

analysis techniques are employed to reduce false alarms, ensuring maintenance actions are taken only when necessary, optimizing efficiency, and reducing costs.

4. **Scalability and real-time processing**: In many industrial settings, there is a need to monitor a large number of machines in real time. This requires system capable of real-time data acquisition, processing, and analysis to promptly alert and notify for essential proactive maintenance actions. Scalability becomes a challenge when dealing with a massive amount of sensor data, especially while processing it in real time. Efficient algorithms and infrastructure are required to handle the high volume, velocity, and variety of data generated by multiple machines simultaneously.
5. **Artificial Intelligence:** AI-based predictive maintenance encounters challenges that impact its effectiveness and practicality. The scarcity of labelled data impairs predictive models' accuracy in anomaly detection and overall performance. Feature extraction and selection pose another challenge in real-world scenarios, as determining the most informative features from sensor data is complex. Employing techniques for feature extraction and selection is crucial to reduce dimensionality and identify discriminative features for accurate predictions. Additionally, interpretability limitations hinder practicality of the proposed solution. Despite achieving high accuracy, complex models like deep learning lack transparency. Understanding the reasoning behind predictions or failure diagnoses is vital for building trust and making informed decisions.

In conclusion, addressing these challenges requires advancements in data pre-processing techniques, feature engineering, model development and integration with domain expertise. Continued research, development, and innovation in this field are crucial to further enhance the effectiveness and practicality of predictive fault maintenance systems, leading to significant benefits for industries across various sectors.

1.4 OBJECTIVE

The objective of this thesis is to explore mechanical fault analysis and detection, with a specific emphasis on bearing and shaft faults in rotating elements. The research aims to enhance the reliability, efficiency, and overall performance of rotating machinery systems by understanding common fault mechanisms and developing effective detection strategies. The following objectives have been identified for this thesis:

- Conduct a comprehensive literature review and analysis of various types, causes, and consequences of bearing and shaft faults in rotating elements.
- Develop a framework that focuses on fault severity assessment, aiming to accurately measure the severity and type of faults.
- Explore data-driven decomposition methods such as multi-resolution dynamic mode decomposition and time-frequency analysis using the maximum overlap discrete wavelet transform for non-stationary vibrational signals.
- Develop methods capable of handling translating fault signatures caused by variations in speed and load conditions.
- Develop a framework using only vibration sensor data for detecting bearing and shaft faults under time-varying rotational speed and discrete load conditions.
- Utilize a complementary data fusion strategy to integrate data from vibration sensors into a single signal with maximum relevance.
- Design a novel encoded statistical contour plot for signals decomposed using the maximum overlap discrete wavelet transform.
- Design a multi-level convolutional neural network (CNN) model for bearing and shaft fault identification to improve the false alarm rate.
- Perform experimental studies to validate the proposed fault detection techniques and assess their effectiveness in identifying and classifying bearing and shaft faults.

The findings and conclusions of this research are expected to contribute to the advancement of mechanical fault analysis and detection techniques, specifically for bearing and shaft faults in rotating elements. The practical implications of this work can benefit various industries by assisting in proactive maintenance management, enhancing reliability, and optimizing the performance of critical rotating machinery systems.

1.5 OVERVIEW OF PROPOSED METHODS

1.5.1 Bearing Fault Detection

The Gramian-Multi-Resolution Dynamic Mode Decomposition (GMrDMD) approach introduces fault detection in bearings using a single accelerometer sensor. The framework involves transforming vibration signals into a gram matrix to enhance spatial resolution while preserving temporal characteristics. The gram matrix undergoes spatial-temporal decomposition via MrDMD, resulting in fast and slow evolving modes that capture transient fault characteristics. To handle noise, the framework employs a robust least square DMD algorithm at each MrDMD level. The framework color-codes the resulting mode matrix and treats it as an image input for fault classification using a CNN. Experimental validation on the University of Ottawa dataset, which features five fault vibration signal types under varying rotational speed conditions, demonstrates the efficacy of the framework in early bearing fault identification.

1.5.2 Shaft Unbalance Detection

This work focuses on developing an automated algorithm for detecting unbalance faults of varying strengths at different rotational speeds. Unbalance occurs due to uneven mass distribution, causing misalignment between the shaft's centre of mass and rotation axis. The proposed approach integrates data fusion, contour plot encoding, and deep learning techniques namely CNN, offering contributions such as a complementary data fusion strategy, an encoded statistical contour plot for signal analysis, and a two-stage warning system for unbalance detection and severity analysis. The effectiveness of method is examined on the dataset by Fraunhofer Institute for Integrated Circuits for shaft unbalance and severity detection. The proposed advancements aim to enhance accuracy, enable timely actions, and reduce maintenance expenses in rotating machinery.

1.6 ORGANISATION OF DISSERTATION

The thesis is structured as follows: Chapter 1 serves as an introduction, providing a comprehensive understanding of faults, their evolution, fault monitoring techniques, sensing methods, and the associated significance and challenges in fault detection. Additionally, it offers a brief overview of the work conducted in the thesis.

Chapter 2 presents an extensive literature review on fault detection, encompassing both static and dynamic operating conditions. This chapter examines time domain, frequency domain, and time-frequency domain features utilized in fault detection, along with the latest advancements in deep learning algorithms for predictive maintenance. Chapter 3 delves into the intricacies of bearing geometry, fault characteristic frequencies, and shaft faults, including an in-depth exploration of unbalance strength. This chapter establishes the essential background knowledge necessary for comprehending the specific fault detection methodologies proposed in the thesis. Chapter 4 provides a detailed, step-by-step discussion of the proposed methodology for bearing fault detection. It encompasses the utilization of the gram matrix, multi-resolution Dynamic Mode Decomposition (DMD), and the overall methodology. Additionally, this chapter presents a description of the employed dataset and an analysis of the obtained results. Chapter 5 follows a similar structure to Chapter 4 but focuses on the proposed methodology for shaft unbalance detection and severity assessment. It introduces the application of the Maximum Overlap Discrete Wavelet Transform (MODWT) and contour plots within the proposed methodology. Furthermore, this chapter includes a detailed description of the dataset utilized and an analysis of the results obtained. Lastly, Chapter 6 concludes the thesis by summarizing the main findings and contributions. It also addresses the limitations of the proposed methodologies and proposes potential avenues for future research, aiming to further enhance fault detection techniques.

CHAPTER 2

LITERATURE REVIEW

2.1 OVERVIEW

Research in the field of bearing fault detection can broadly be categorized into methods designed for stationary working conditions and methods suitable for application under dynamic and time-varying operating conditions [26]. Each category addresses different challenges and requirements in fault detection.

For stationary working conditions, numerous studies have focused on developing techniques that assume a stable operating state. These techniques heavily rely on signal processing methods, dependent on analysis in either time domain, frequency domain, or analysis in the time-frequency domain. Work in time domain entails the computation of statistical measures [27] from the vibration signal, such as root mean square, peak value, standard deviation, skewness, kurtosis, shape factor, and impulse factor. On the other hand, analysis in the frequency domain employs techniques like FFT to examine the frequency components present in the signal or amplitude of power spectrum. Further, time-frequency analysis [28] methods like the STFT and Winner-Ville distribution etc. has been widely used for bearing fault detection these methods offers insights into time-dependent variations of characteristic frequencies. Though these signal processing methods are known to give satisfactory results but the high knowledge required for selecting frequency, mother wavelet and sub-band limit [29] its usage. Also, these methods require extensive feature selection to categorize the fault and many times these handcrafted features fail to extract all the patterns from the waveform which results in lesser accuracies for fault detection.

In contrast, the dynamic and time-varying operating conditions pose additional challenges for fault detection. Vibration signals recorded from bearings in real-world scenarios often exhibit non-stationary behaviour, consisting of periodic components, impulse components from faults or cracks, and broad-band background noise generated by other machine parts. Traditional methods like order tracking [30] and time or phase averaging-based methods [31] were used but these methods struggle with spectrum smearing caused by variable speed. To address these challenges, researchers have proposed advanced techniques that can handle non-stationary signals. These methods focus on capturing the transient nature of faults from the vibration signal. For instance, adaptive data based techniques [32], such as Empirical Mode Decomposition (EMD), Dynamic Mode Decomposition (DMD), Variational Mode Decomposition (VMD), synchro-squeezing transform (SST) and local mean decomposition (LMD) have gained popularity for their ability to analyse non-stationary signals and extract fault signatures at different scales and time intervals. These data-driven methods have shown promising results in detecting faults under dynamic operating conditions and have become foundational methods and base of future result.

In both the domains ultimately for decision-making [33], researchers have increasingly favoured machine learning and deep learning approaches over thresholding based methods. Machine learning algorithms encompass feature extraction, feature selection, and classification stages, leveraging data to improve accuracy. Commonly employed machine learning methods for bearing fault detection include optimised nearest neighbours, support vector machine (SVM), principle component analysis, and artificial neural networks. While these methods have yielded satisfactory results, the desire to automate feature extraction and minimize human intervention has spurred the adoption of deep learning techniques. Inspired by the brain's structure, deep learning models facilitate hierarchical feature learning [34] from raw data. Models such as convolutional neural networks (CNN), dense neural networks (DNN), stacked auto encoders, and recurrent neural networks have demonstrated superior accuracy compared to traditional machine learning models. Nonetheless, the process of training deep learning models can be computationally demanding and requires a substantial volume of labelled data. This creates a balance between the desired accuracy and the computational resources needed. This thesis primarily concentrates on fault diagnosis under varying speed conditions, thereby emphasizing a comprehensive literature review of existing techniques suitable for dynamic operating conditions in the subsequent section.

2.2 DETAILED REVIEW

2.2.1 Order Tracking Based Methods

Order tracking (OT) synchronizes vibration data with the rotational speed to analyse the signal in terms of order components, allowing for accurate fault detection even in varying speed scenarios. However, spectrum smearing can occur when the speed continuously changes, spreading fault-related frequencies and hindering accurate fault identification. Inaccurate OT based methods also require domain knowledge to understand signal spectrum sometimes this can lead to false alarms or missed detections. Further research is needed to overcome these limitations and develop alternative approaches for fault detection in variable speed systems.

Several studies have proposed innovative approaches to improve the analysis of order components and enhance fault diagnosis in different systems. In [35], a combination of Vold-Kalman filtering and computed order tracking is presented, demonstrating improved Fourier analysis results through numerical simulations and experimental validation. Research in [36] introduces a phase demodulation-based order tracking method that accurately measures rotation angle and time relationship for bearing and gear signals. Paper [37] discusses a technique that utilizes EMD and intrinsic cycles to simplify signal analysis, proving its effectiveness as a condition monitoring tool even without rotational speed information. Researchers in [38] have developed a tacholess order tracking method for wind turbine gearboxes, which utilizes phase reference information and resampling for analysis. Work in [39] addresses the challenge of limited sensor installation by using virtual multichannel signals in the angle domain, combining computed OT and VMD for independent component analysis. Lastly, [40] introduces an order spectrogram-based method that estimates instantaneous frequency through ridge extraction, performs resonance demodulation, and rescales the time-frequency distribution to suppress non-stationary interference caused by speed fluctuations.

2.2.2 Time-Frequency Analysis Based Methods

In the field of fault diagnosis for rolling element bearings, time-frequency analysis plays a crucial role in accurately extracting diagnostic information from vibration signals. An early work on in TF analysis is proposed in [34] which uses a three-level discrete wavelet transform (DWT) followed by the FFT of the approximate coefficient to establish unbalance detection of shaft using on spectrum visualization. Work in [41] propose a combination of a ridge extraction algorithm and an enhanced empirical wavelet transform to estimate instantaneous frequency for feature extraction. Another method proposed in [42] introduces a sparsity-promoting low-rank decomposition technique that utilizes robust principal component analysis to denoise the TF representation of signals. The method incorporates a reassignment strategy to enhance the detection of fault characteristics. In [43], researchers present a novel method known as the transient extracting transform, based on the STFT. The method yielded a concentrated TF representation, verified using quantized indicators such as Rényi entropy and kurtosis. Approach proposed in [44] uses CWT combined with Gabor wavelets with multiple Q-factors, combining sets of continuous wavelet coefficients for each Q-factor to generate a time-frequency map. Comparison of proposed method with Morlet wavelet transform and tuneable Q-factor wavelet transform (TQWT) is extensively highlighted by the researchers. A novel TF analysis method using synchrosqueezing extracting transform is introduced [45]. The method exhibits improved noise robustness and lower time consumption which is confirmed using numerical signal analysis.

2.2.3 Data Driven Decompositions

This section reviews the advancements in field of adaptive data driven methods for predictive maintenance. Work proposed in [46] focus on detecting unbalance of different strengths using EMD followed by novel dimensionality reduction, which achieves an accuracy of 98.13% with SVM under constant rotating speed. Researchers of [47] proposed a new data-driven approach for fault detection and isolation by combining EMD, envelope analysis, and a pseudo fault signal. Dominant mode function is extracted using EMD followed by envelope modulation with multiple sources and noise. Work in [48], also explores strength of by combining EMD and

VMD. The method adaptively selects sensitive IMF components based on an evaluation index and analyses them using Hilbert spectrum. To overcome problem associated with mode mixing work in [49] uses ensemble local mean decomposition and kurtogram for rotating machinery fault diagnosis. The method generates product functions which characterizes the fault impulse based on kurtosis index, and then an optimal band-pass filter.

To address the limitation of physical interpretation of extracted components dynamic mode decomposition (DMD) emerged from fluid mechanics and has gained significance through Koopman spectrum analysis. In [50], the development of DMD is discussed, offering strong mathematical and physical implications. Variations of DMD have been explored to suit different applications. For fault diagnosis, [51] proposes the use of approximate entropy applied to decomposed DMD modes. In [52], the advantages of DMD over other signal processing methods are highlighted, and a rank truncation method is introduced to extract dominant DMD modes. Additionally, [53] presents an efficient algorithm called PRLDMD that preserves the amplitude and energy of transient features in faulty signals. Another extension of DMD, known as MrDMD [54], is capable of extracting transient events through recursive application of DMD. These advancements in DMD and its variations contribute to improved understanding and analysis of signals in various domains.

2.2.4 Advance AI Networks

Significant advancements have been made in deep learning architectures for fault analysis research in [55], provides an improved autoencoder called the SN-AE. This model incorporates a speed branch to address challenges related to speed variations. Experimental evaluations conducted on various rotating machines demonstrate that the SN-AE outperforms existing autoencoder-based methods, achieving superior fault detection performance. Approach presented in [56] is based on VMD-DenseNet method, which converts vibration signals into images using Hilbert spectrum analysis through VMD and utilizes the lightweight DenseNet network for accurate image classification and prediction. The VMD-DenseNet achieves an impressive accuracy rate of 92% for common motor faults. Additionally, research in [57] introduces the deep sparse representation network (DSRNet), a novel deep learning model specifically designed to suppress noise and directly learn features from noisy vibration signals. DSRNet employs a sparse representation layer to filter out impulsive components and reduce noise, followed by an adaptive densely stacked convolutional structure for effective feature extraction. Experimental results on gearbox cases validate the superiority of DSRNet in terms of feature learning and signal denoising performance when compared to popular deep learning networks.

Research in [58], proposes a novel DL architecture called the Deep Interpolation ConvNet which incorporates specialized layers, such as sub-ConvNet units, weight units, and fusion units, to effectively extract fault features and handle the influence of working conditions. To enhance the architecture's performance, a ConditionSenseNet (CSN) module is introduced, which dynamically represents crucial features while suppressing the impact of unknown working conditions.

Authors in [59] introduce a decision-level fusion approach that utilizes an ensemble model consisting of a convolutional residue network, auto-encoder, and deep belief network (DBN) to classify multiple faults. This ensemble model achieves an impressive accuracy of 98.08% for data collected under various speeds. Transfer learning is explored in [60], where a pre-trained VGG19 model is employed to analyse Mel frequency spectrogram images of vibration signals obtained under a fixed unbalance strength of 3.2gm. Transfer learning has gained attention in the field of deep learning for bearing fault diagnosis in rotating machinery as it addresses the time-consuming process of constructing and training convolutional neural network (CNN) models and reduces the need for extensive prior knowledge [61]. Notable advantage of transfer learning methods is demonstrated in, where a pre-existing AlexNet model is utilized. In this approach, only the last fully connected layer needs to be replaced, resulting in time and knowledge savings. Despite this simplicity, the method achieves effective feature extraction and condition classification. By transforming raw acceleration signals into time-frequency images, the model can process diverse input forms. Experimental validation using standardized images generated through various time-frequency analysis methods confirms the effectiveness of this approach. These findings underscore the practical applicability of the method in real-world scenarios.

2.3 MOTIVATION

This thesis is motivated by the research gaps identified in the field of rotor fault detection and severity assessment, specifically regarding single sensor type methods under time-varying rotational speed. Existing approaches in AI have high time complexity, and incur moderate processing costs. The aim is to develop innovative algorithms that strike a balance between accuracy, time complexity, and processing cost. Additionally, most work focuses only on bearing health monitoring, but from the mechanical standpoint, the stress caused by unbalanced faults extravagate bearing faults. This research focus on use of data-driven methods for feature extraction of bearing fault signatures from vibration signals.

CHAPTER 3

FAULTS OVERVIEW

3.1 ROLLING ELEMENT BEARING

3.1.1 Structure

The mechanical structure of a rolling element bearing consists of several key components that work together to facilitate smooth rotational motion and support axial and radial loads. The main components of a rolling element bearing are as shown in Figure 3.1. The mechanical structure of a rolling element bearing consists of an outer ring (outer race), inner ring (inner race), rolling elements (balls or rollers), and a cage. The outer ring provides support, the inner ring rotates and transmits the load, and the rolling elements enable smooth motion. Ball bearings have spherical balls for low-friction rotation, while roller bearings use cylindrical, tapered, or spherical rollers for higher load capacities. The cage separates the rolling elements, maintaining proper spacing [62].

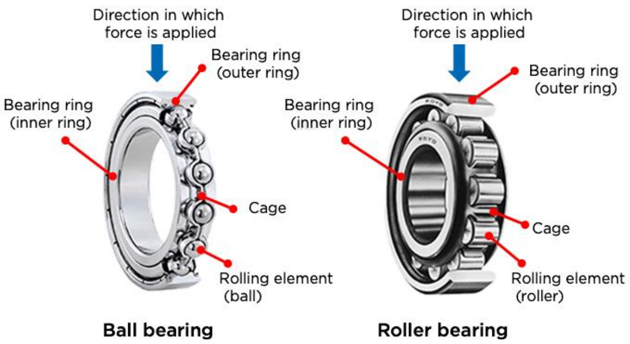

Figure 3.1 Components of a rolling bearing element.

3.1.2 Types of Defect And Causes

Bearing faults can be categorized into distributed faults and localized faults:

1. Distributed faults:

- Fatigue Spalling: Small cracks and surface fatigue due to repeated loading and unloading.
- Brinelling: Dents or indentations caused by excessive static or impact loads.
- Fretting corrosion: Microscopic wear and corrosion due to slight movement or vibration [63].

2. Localized faults:

- Inner raceway fault: Cracks, pitting, scoring, or wear on the inner ring.
- Outer raceway fault: Similar types of damage as the inner raceway fault on the outer ring.
- Ball fault: Pitting, spalling, cracking, or wear on the rolling elements [64].
- Combined fault: Multiple types of faults occurring simultaneously in the bearing.

Bearing faults can occur due to various factors. Inadequate lubrication, whether it's due to insufficient lubricant or using the wrong type, can lead to increased friction, heat, and wear on the bearing surfaces. Contamination by foreign particles or contaminants can also accelerate wear and damage the raceways and rolling elements. Misalignment or unbalance between the bearing and the rotating shaft or housing can result in excessive loads and uneven force distribution, leading to localized faults. Operating the bearing under loads beyond its design capacity can cause fatigue and accelerated wear. Additionally, improper installation practices, such as excessive interference fit or incorrect clearances, can contribute to bearing faults. Addressing these factors is vital to ensure optimal performance and durability of bearings.

3.1.3 Mathematical Analysis

Fault characteristic frequencies (FCF) in bearing are specific frequencies that are generated as a result of the faulty conditions within the bearing. These frequencies are derived from the impulse generated during interaction between the rolling elements and the faulted areas on the inner and outer raceways of the bearing. The calculation of these characteristic frequencies depends on the bearing's geometry and the shaft's rotational speed. As a result, additional processing techniques are necessary to effectively handle and analyse the time-varying FCF for accurate diagnosis of bearing faults in such situations [65]. FCF can be calculated as mentioned below where f is the frequency of rotation in Hz, m is the number of ball elements, γ is the angle of contact, d_b is the diameter of the ball and d_c is cage diameter [66] as shown in Figure 3.2.

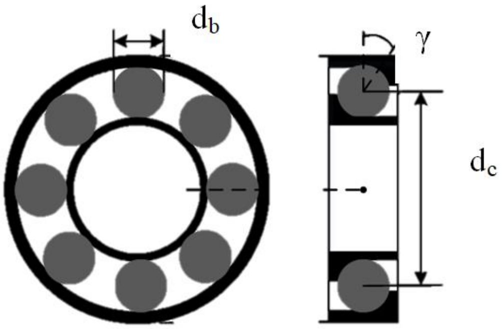

Figure 3.2 Mechanical drawing of bearing structure [66].

- **Cage Frequency (FTF):** FTF is the frequency at which the cage or retainer that holds the rolling elements rotates.

$$FTF = \frac{f}{2}\left[1 - \frac{d_b}{d_c} cos\gamma\right] \tag{3.1}$$

- **Ball Pass Inner (BPI):** BPI is the frequency at which the rolling elements pass over the inner raceway fault.

$$BPI = \frac{mf}{2}\left[1 + \frac{d_b}{d_c} cos\gamma\right] \tag{3.2}$$

- **Ball Pass Outer (BPO):** BPO is the frequency at which the rolling elements pass over the outer raceway fault.

$$BPO = \frac{mf}{2}\left[1 - \frac{d_b}{d_c} cos\gamma\right] \tag{3.3}$$

- **Ball Spin frequency (BSF):** It is associated with the spinning of the rolling.

$$BSF = \frac{d_c f}{2d_b}\left[1 - \left[\frac{d_b}{d_c} cos\gamma\right]^2\right] \tag{3.4}$$

By analysing the vibration signals of the rotating machinery using techniques such as spectral analysis or Fourier transform, these characteristic frequencies can be identified. The presence and intensity of these frequencies indicate the presence and severity of specific bearing faults, allowing for early detection, diagnosis, and appropriate maintenance actions to be taken.

The bearing fault-induced signal can be viewed as the impulse response s(t) of a one-degree-of-freedom mass-spring-damper system [67] as shown in Equation 3.5, the vibration system determines the excited resonance frequency ω, while the amplitude A and damping coefficient β further characterize the system.

$$s(t) = Ae^{-\beta t}\sin(\omega t)u(t) \tag{3.5}$$

Hence the bearing fault signal x(t) can be modelled as repeated impulse response as shown below, where M is the total number of impulses which is determined by the signal length T and the fault characteristic frequency fc, Am is the amplitude of the m^{th} fault impulse response, T_p is the reciprocal of fc and τi is the random slippage during each T_p [68] as shown in Figure 3.3.

$$x(t) = \sum_{m=1}^{M} A_m\, e^{-\beta(t-mT_p-\sum_{i=1}^{m}\tau_i)}\sin(\omega(t-mT_p-\sum_{i=1}^{m}\tau_i))u\left(t-mT_p-\sum_{i=1}^{m}\tau_i\right) \tag{3.6}$$

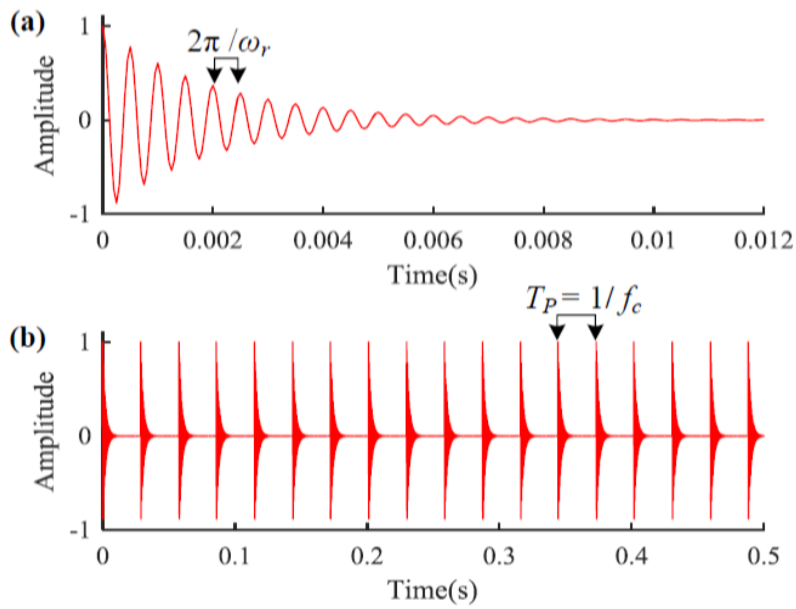

Figure 3.3 Fault induced bearing signal under constant speed.

3.2 SHAFT FAULT

A shaft in rotating machines is a cylindrical component that transmits power and rotational motion, connecting different parts of the machine. Made of durable materials, shafts support and align components, use couplings for torque transfer, and may have keyways or splines for secure connections. Balancing techniques minimize vibration, while regular maintenance and inspection ensure their integrity. Shafts are vital for efficient machine operation, enabling power transmission and interconnection of components [69]. Various standards and guidelines exist to define acceptable levels of unbalance for different types of machinery. The ISO 1940-1:2016 and ISO 10816 standards, for instance, provides specifications for balance quality requirements of rotors. It establishes tolerance limits for residual unbalance based on factors such as the machine type, rotational speed, and balance quality grade.

3.2.1 Types of Defect and Causes

Some of the common shaft faults that can occur in rotating machinery are listed below. The work in this thesis focuses on unbalance fault detection and strength of unbalance.

1. **Shaft unbalance:** It is an uneven mass distribution in rotating machinery, causing centrifugal forces, vibration, decreased performance, and potential damage.
2. **Misalignment:** Rotational axes of connected shafts are improperly aligned, leading to increased forces, vibration, bearing wear, and reduced efficiency.
3. **Bent Shaft:** Physical deformation causes the shaft to deviate from its straight form, resulting in vibration, stress on bearings, and decreased performance.
4. **Shaft Cracking:** Cracks develop due to cyclic loading, stress concentrations, fatigue, or improper maintenance, compromising structural integrity and risking catastrophic failure.
5. **Bearing Faults:** Issues like misalignment, lubrication problems, wear, pitting, or failure in bearings cause vibration, friction, noise, and reduced machinery lifespan.
6. **Shaft Eccentricity:** Centre of rotation does not coincide with the geometric center due to defects, assembly issues, or wear, leading to vibration, stress on bearings, and decreased performance.
7. **Shaft Runout:** Radial deviation from true circular path caused by uneven wear, defects, or mishandling results in vibration, stress on components, and reduced accuracy.

8. **Resonance:** Natural frequency coincides with excitation frequency, causing excessive vibration due to unbalanced masses, stiffness, or inadequate damping, leading to potential damage.

Shaft faults in rotating machinery can stem from manufacturing defects, wear and tear, debris accumulation, component damage, or incorrect assembly. It leads to adverse effects such as vibration, reduced performance, bearing and seal wear, structural damage, and noise. Detection methods include vibration analysis, portable balancing equipment, modal analysis, and infrared thermography. Balancing procedures involve static and dynamic balancing, using correction methods like adding or removing weights. By addressing shaft unbalance, the overall performance, reliability, and lifespan of the machinery can be improved while minimizing the risk of catastrophic failures.

3.2.2 Mathematical Analysis

The unbalance factor is represented as "e" or "eU," It is a measure of the severity of unbalance in a rotating component. It is defined as the ratio of the calculated centrifugal force due to unbalance to the product of the mass of the rotating component and the square of the reference speed. The unbalance factor can be expressed mathematically as [70]:

$$eU = \frac{F \times r}{m \times \omega^2} \tag{3.7}$$

where, F is centrifugal force due to unbalance, r is the distance from the centre of rotation to the centre of gravity of the unbalanced mass, m is the mass of the rotating component and ω is the rotational speed of the component.

- **Centrifugal Force (F):**

The centrifugal force is the force generated by the unbalanced mass as it rotates. It is directly proportional to the square of the rotational speed n and the unbalance factor eU [71]. Mathematically, it can be expressed as:

$$F = m \times eU \times \omega^2 \tag{3.8}$$

- **Centrifugal Moment (M):**

The centrifugal moment is a measure of the unbalance's effect on the rotating machinery. It represents the moment generated by the centrifugal force acting at a distance from the axis of rotation. Mathematically, it is given by [71]:

$$M = F \times r \tag{3.9}$$

- **Correction Weight (W):**

To balance the rotating component, correction weights are added at specific locations to counteract the unbalance. The magnitude and position of the correction weights can be determined using the following formula [72]:

$$W = \frac{M}{eU \times r} \tag{3.10}$$

By calculating the centrifugal force, centrifugal moment, and correction weight, engineers can determine the necessary adjustments to balance the rotating machinery effectively. It's important to note that unbalance can also be expressed in terms of angular displacement or phase angle. The phase angle represents the position of the unbalance mass relative to a reference point on the rotating component. It is measured in degrees or radians and provides information about the location of the unbalance, which is crucial for accurate balancing.

Additionally, there are various methods to measure and analyse unbalance, such as vibration analysis, which involves monitoring and interpreting the vibration signals produced by the rotating machinery to assess the severity of unbalance and identify corrective actions [73]. These mathematical concepts and calculations play a vital role in diagnosing, quantifying, and rectifying unbalance-related issues in rotating machinery, ultimately ensuring smooth and reliable operation.

CHAPTER 4

BEARING FAULT DIAGNOSIS

4.1 OVERVIEW

The chapter provided detailed discussion of the approach employed for bearing fault identification. The primary goal of this work is to develop a tachometer-free method capable of identifying faults using single sensor data, while effectively addressing the translation of fault signatures resulting from variations in rotational speed.

To achieve this objective, the MrDMD framework is extended, and a novel method called GMrDMD is introduced. This method enhances the spatial resolution of vibration signals through gram matrix transformation while preserving their temporal characteristics. The GMrDMD technique involves a spatial-temporal decomposition of the gram matrix using multi-resolution dynamic mode decomposition. Subsequently, the resulting mode matrix is color-coded and utilized for fault classification, leveraging convolutional neural networks (CNNs) to eliminate the dependency on expert knowledge for feature extraction.

The proposed methodology is validated using experimental simulations with data from the University of Ottawa, covering varying rotational speeds. It is structured into three stages: signal pre-processing, feature generation, and classification, as depicted in Figure 1. Performance metrics are employed to evaluate the method's effectiveness, ensuring a comprehensive assessment of its performance. The results obtained from the experiments demonstrate the accuracy and efficiency of the approach in identifying bearing faults.

4.2 METHOD

This section is divided into three stages namely signal preprocessing, feature generation and classification Figure 4.1 shows the flowchart of the proposed method.

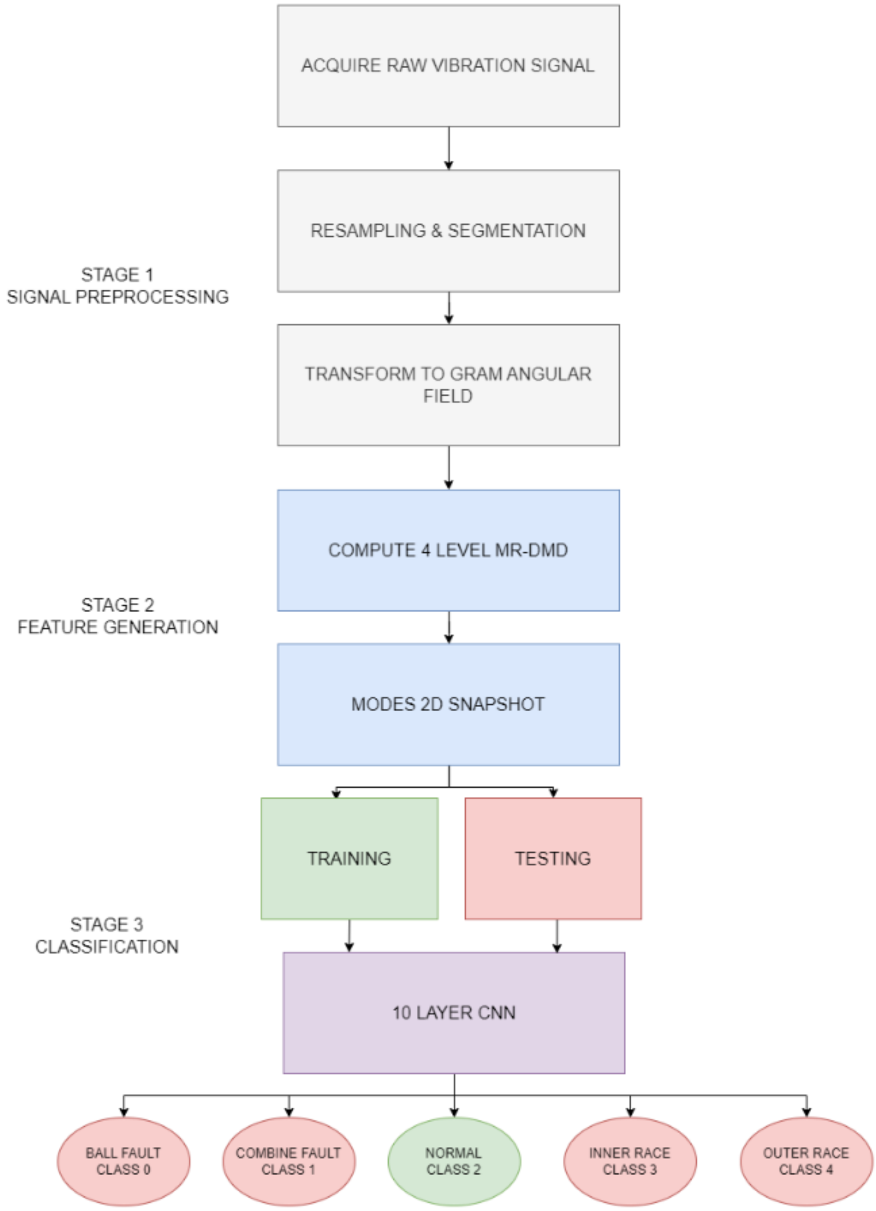

Figure 4.1 Flowchart of the proposed methodology.

4.2.1 Signal Pre-processing

4.2.1.1 Segmentation & Resampling

The raw signal is originally sampled at 200 KHz for duration of 10s. For efficient resource utilization the signal is resampled at 100 KHz and segmented without overlapping. The purpose of segmentation is to subdivide a large signal into small sections which have similar properties. The segment size varies according to the occurrence of the frequency region of interest in a signal. Then each sub-signal is transformed into a gram angular field which preserves the temporal relation of the original segment while separating inference signal.

Figure 4.2 shows the raw signals under increasing rotational speed. It can be observed that no significant information can be understood based on the raw signals except that the amplitude is increasing with time. To further analyse the signal FFT of the input signal is plotted as shown in Figure 4.3. It can be seen from the frequency spectrum that majority information is present below 50 KHz. Hence resampling of original vibration signal at 100 KHz is performed. The resampled signal is segmented into 500 sub signals such that each sub-signal has fault characteristics.

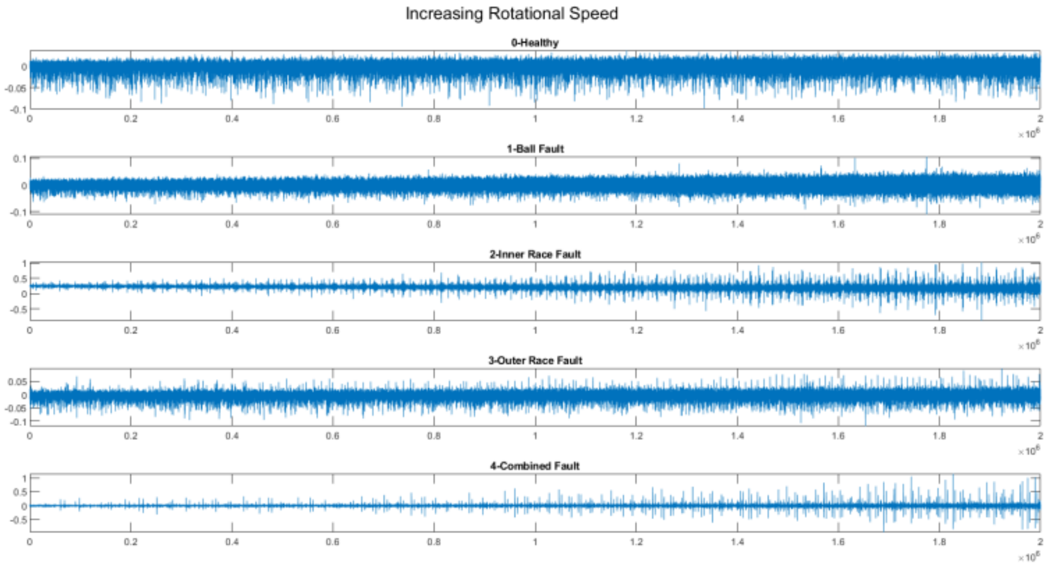

Figure 4.2 Raw vibration signals under increasing speed condition.

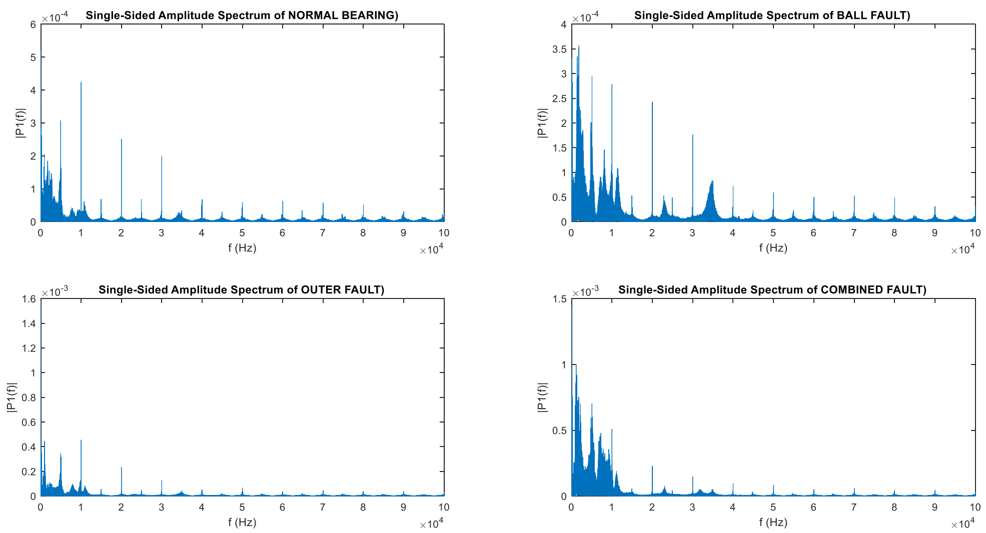

Figure 4.3 Frequency spectrum of orignal signals shown in figure 4.2.

4.2.1.2 Gram Based Transformation

In case of varying speed, it is important to preserve the temporal relation between sample points. Gram matrix is an ancient representation that calculates complete inner product space of vectors. The extension of this to gram angular field was first proposed in 2015, as a transformation of 1D time series signal to a 2D representation using polar coordinates. Since then, GAF has shown excellent results with ECG, ECoG for activity tracking, financial market tracking, fault monitoring etc. Let V be a given time series sensor data that is first rescaled to have a maximum value 1 and minimum value -1 using Equation 4.1. Then the scaled signal is transformed into polar space where the angular value is determined by taking trigonometric inverse of amplitude and the radius is calculated as the time stamp divided by number of samples as shown in Equation 4.2.Finally, the polar representation is used to calculate the G matrix Equation 4.3 whose leading diagonal represent original signal and remaining columns from top left to right represent the preserved the temporal correlation between signal. This transformation method is bijective and invertible as followed from mathematical principle of inverse trigonometric operations [74].

$$v = \frac{(v - \max(V)) + (v - \min(V))}{\max(V) - \min(V)} \tag{4.1}$$

$$f(v) = \begin{cases} cos^{-1}(v)\,, \ -1 \le v \le 1 \\ t/N, \quad t \in N \end{cases} \tag{4.2}$$

$$G = [\cos\emptyset_i - \cos\emptyset_j] \tag{4.3}$$

4.2.2 Multi-Resolution DMD

The basic idea of DMD is to form dynamic system matrix using Koopman frequency analysis [50]. The eigenvectors of this matrix form coherent spatial-temporal modes while eigenvalues depict how each mode evolves in time. The advantage of DMD is that it produces non-orthogonal single frequency modes which are used in diagnostics. Usually, DMD decompose a multivariate time signal but mechanical vibration signals are 1D time-series. The algorithm of proposed standard DMD is presented in [22] transforms mechanical signal into a m x n shift-stack Hankel matrix as shown in Equation 4.4. Considering V_1, $V_2 \ldots V_n$ as snapshots V' can be written as Equation 4.5.

$$V' = \begin{bmatrix} v_1 & v_2 & \cdots & v_n \\ \cdots & \cdots & \cdots & \cdots \\ v_m & v_{m+1} & \cdots & v_{m+n-1} \end{bmatrix} \tag{4.4}$$

$$V' = [V_1\, V_2\, V_3 \ldots\ldots V_n] \tag{4.5}$$

This V' matrix is now rearranged in the form of two snapshot matrix X and Y.

$$X = [V_1\, V_2\, V_3 \ldots\ldots V_{n-1}] \tag{4.6}$$

$$Y = [V_2\, V_3\, V_4 \ldots\ldots V_n] \tag{4.7}$$

The crux is to find A matrix such that Y = AX, the algorithm applied to find A can be found in [74]. Thus, evolution of X to Y is found using eigenvalues of A. This approach suffers from noise bias effect hence an improved framework tlsDMD [75] is used for countering the effect of noise. The tlsDMD aims to find a total least square solution for estimating error in both the matrix X and Y using Equation 4.8.

$$A\!: Y + \epsilon_y = A(X + \epsilon_x) \qquad s.t.\ argmin \left\| \begin{matrix} \epsilon_x \\ \epsilon_y \end{matrix} \right\| \tag{4.8}$$

The problem of noise tolerance is solved using tlsDMD and multi resolution DMD approach has been adopted to handle the problem of extracting transient events. The MrDMD method successively pulls out time-frequency information in a principled way. The modes with the slowest variation are extracted at each level. This gives a time frequency representation as shown in Figure 4.4 . where sampling window at each level is divided into half and slow varying modes are selected at each level for reconstructing the original signal V(t) without initial conditions as shown in Equation 4.9 where, l is the level of decomposition and M_1, M_2 ... are number of slow modes selected at each level ω is the frequency corresponding to the eigenvector φ.

$$V(t) = \left\{ \sum_{\substack{d=1 \\ l=1}}^{M_1} \varphi_d e^{(\omega_d t)} + \cdots + \sum_{\substack{d=1 \\ l=4}}^{M_2} \varphi_d e^{(\omega_d t)} \right\} \tag{4.9}$$

After completion of signal processing we get an NxN gram matrix on which a four-level multi-resolution tlsDMD is applied. This step gives two matrices namely mode and dynamic whose significance can be understood from Koopman theory [50]. At each level of decomposition, the time axis is sampled into 2^L sub-parts, where L represents the level of decomposition and tlsDMD is performed on each sub part to calculate the modes. The mathematical process of calculating modes matrix is already discussed in [75]. These modes are typically Eigen vectors corresponding to individual frequencies of the original gram matrix. Hence the collection of the entire modes into a snapshot is able to isolate the behaviour corresponding to all frequencies of original matrix. This snapshot is used as input for classification using a CNN Figure 4.5. shows the mode snapshot for the five classes under four types of varying rotational speed.

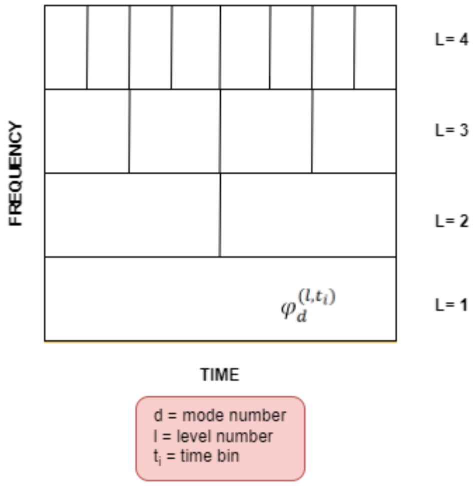

Figure 4.4 Time frequency representation generated using MrDMD.

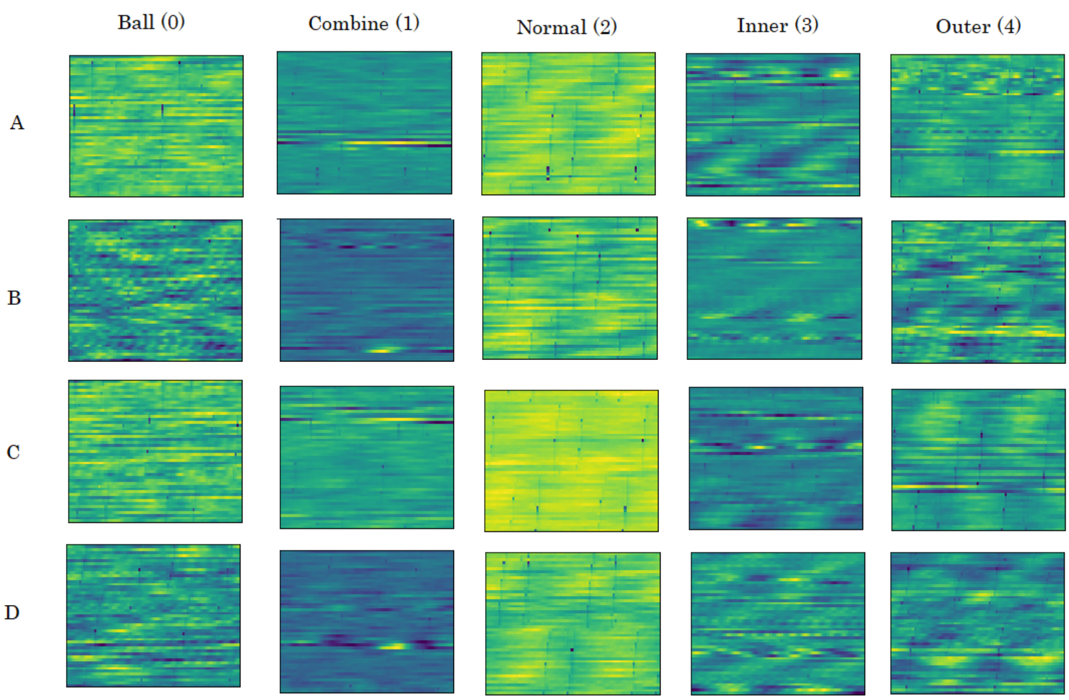

Figure 4.5 Mode snapshots generated for 5 classes under four speeds.

4.2.3 Classification

The next step after generating mode snapshot is to perform classification, in this work we used a 10 layer CNN inspired from GoogleNet architecture [24]. A CNN consists of three basic layers namely convolutional layer which strides kernel of a specified size over the input image to get a convolved output of kernel function with input image followed by pooling layer and activation layer. The proposed structure uses 4 inception blocks as shown in Figure 4.6 with different kernel sizes of (7x7, 5x5, 3x3 and 1x1) each with a single stride. The main advantage of the structure is that it gives the network an idea about the spatial resolution of the input. After each inception block filter output concatenation is performed along the depth.

Since fault characteristic require non-linear classification, hence relu is used as activation function for the proposed CNN. We have also used drop out layer with 0.2 dropping fraction which ensures that our network avoids over fitting on the training data. Figure 4.7 shows the basic block diagram of the used CNN model for fault classification.

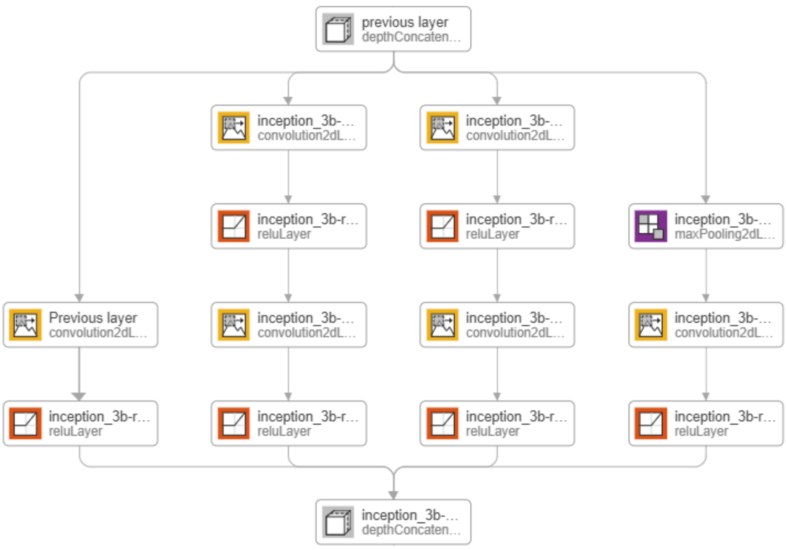

Figure 4.6 Inception module used in CNN.

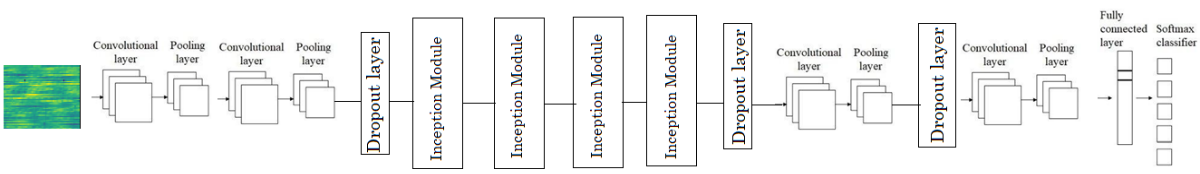

Figure 4.7 Proposed 10 layer CNN network.

4.3 EXPERIMENTAL SETUP

This section firstly describes the used dataset followed by an overview of the considered performance metrics. Lastly the results and discussion section cover the comparison of the proposed work with other relevant deep learning-based methods from literature. All the experiments are carried on Intel i5 9^{th} gen processor with 8 GB RAM.

4.3.1 Dataset

The proposed data driven fault classification method is validated using time-varying rotational speed dataset from the University of Ottawa, version 2 published in 2019 [76]. The data from university of Ottawa consists of vibration signals under four time-varying rotational speeds as mentioned in Table 4.1. The vibration data is collected for ER16K rolling element using ICP accelerometer. The experimental setup for recording signals is shown in Figure 4.8. The recorded signal length is of 10s, and has a sampling frequency of 200 KHz and for each speed condition three trials are conducted.

When the ball element of the bearing interacts with a fault region it produces a fault frequency proportional to rotational speed in Hz. This data contains vibration signals for five faults type namely ball (class-0), combined (class-1), healthy (class-2), inner raceway (class-3) and outer raceway fault (class-4).

Table 4.1 Various Speed Condition Of Dataset

Speed Condition	**Speed Value (in Hz)**
A- Increasing	14.1 to 23.8
B- Decreasing	28.9 to 13.7
C- Increasing - Decreasing	Increased: 14.7 to 25.3 Decreased: 25.3 to 21
D- Decreasing - Increasing	Decreased: 24.2 to 14.8 Increased: 14.8 to 20.6

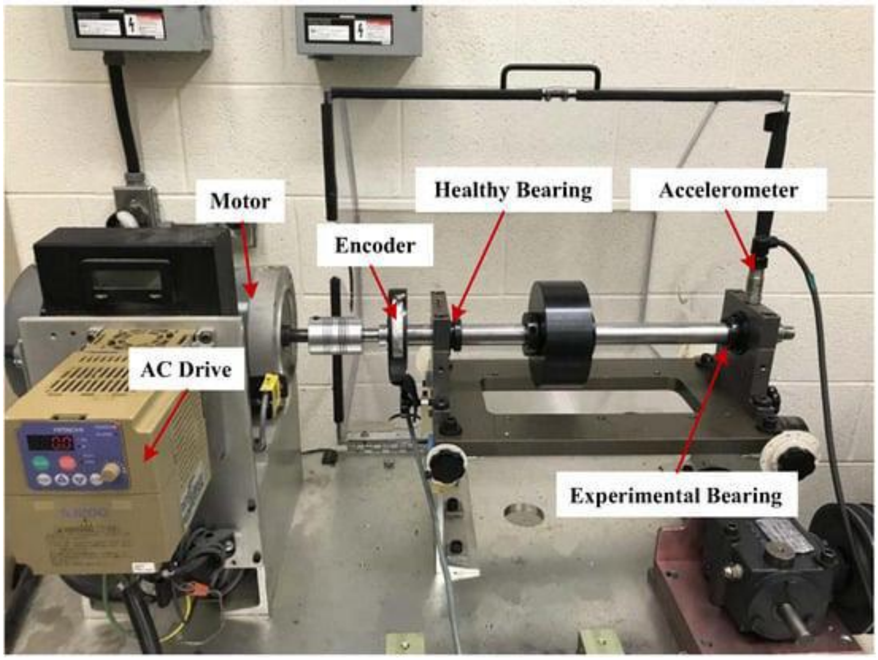

Figure 4.8 Experimental setup to record vibration data [76].

4.3.2 Performance Metrics

To evaluate the proposed GMrDMD method widely used accuracy metric and confusion plot is considered. Accuracy is the ratio of total correct classified sample to the total number of samples. It evaluates an overall average performance without considering class wise categorization. Accuracy is insightful only for a balanced class problem. Since in our dataset we have equal samples for each class accuracy gives a good idea about model performance. Another metric to understand the micro-level performance is confusion metric it gives a holistic analysis of each class. It helps in understanding which classes are closer to each other causing confusion and wrong prediction in the model.

4.4 RESULTS AND DISCUSSION

The data of trial 1 is divided into 5 datasets which are individually used for training and testing. Table 4.2 summarizes the experimental data setup for trial 1 (T1) where 80% data is used for training and 20% for testing. The remaining two trials T2 and T3 are only used as testing data for the model. The D5 dataset is most crucial for our experiment as it captures all types of speed variation.

Table 4.2 Experimental Setup of Data

Data (t1)	**Symbol**	**Total Sample**	**Train**	**Test**
A	D1	2500	2000	500
B	D2	2500	2000	500
C	D3	2500	2000	500
D	D4	2500	2000	500
(A+B+C+D)	D5	10000	8000	2000

The 500 sub signals from each class were used to generate the mode snapshots according to the methodology discussed in previous section. The snapshots obtained after GMrDMD are augmented for scale and rotational invariance. These were now given as input to a 10-layer CNN inspired from GoogleNet architecture. The CNN structure uses multiple kernel sizes of which gives network a perspective about spatial resolution of the image. A summary of accuracy obtained using the model is mention in Table 4.3. The model shows best performance for increasing speed with an average accuracy of 98.2% while, the average accuracy for all four-speed condition is 94.8%. Figure 4.9 shows the confusion matrix on dataset D5 it can be seen that class 0 corresponding to ball fault has maximum misclassification with a false detection rate of 4.8% while the class 3 corresponding to inner raceway fault has the lowest false detection rate of 0.9%. Also, it should be noted that the model raises a fault warning for 2.7% times when in reality the roller bearing is not faulty. This category of false alarm is of concern and further improvement is possible in this direction. The plot of model training accuracy and loss for dataset D5 is shown in Figure 4.10.

Table 4.3 Summary Of Accuracy Obtained On Dataset

Trial Accuracy	**Dataset**				
	D1	D2	D3	D4	D5
T1	98.67	96.81	97.17	97.43	94
T2	98.41	96.46	98.31	96.71	96.12
T3	97.52	96.9	96.48	97.24	94.28
Mean	98.2	96.72	97.32	97.12	94.8

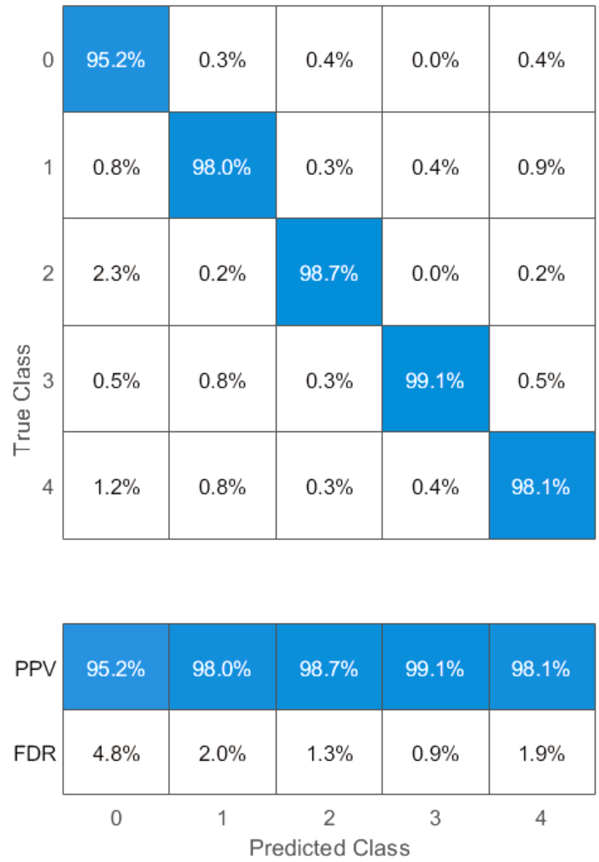

Figure 4.9 Plot of accuracy for three trials of each dataset.

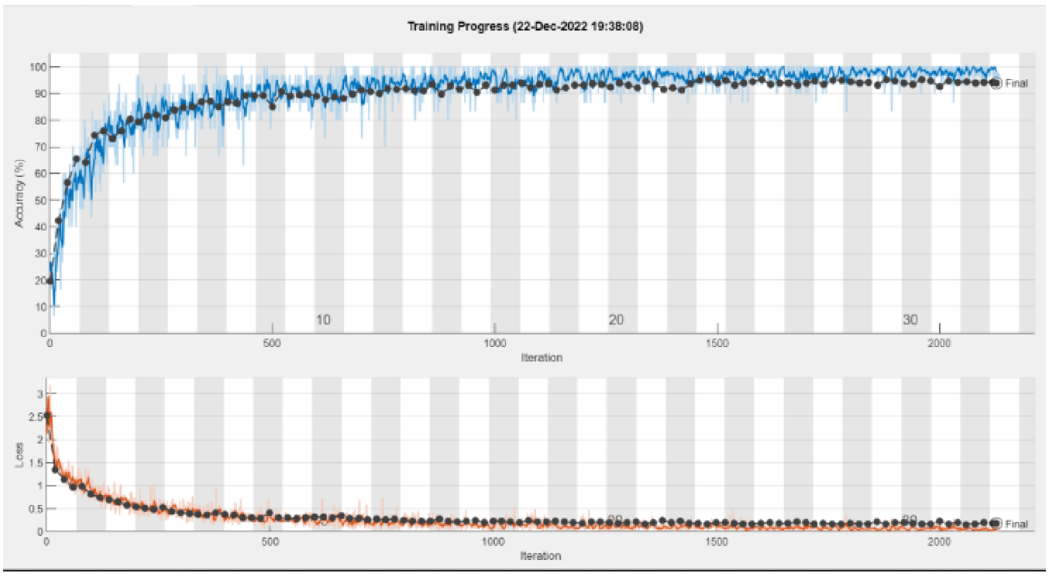

Figure 4.10 Plot of accuracy for three trials of each dataset.

We also tested the generated feature set with other state of art DNN architectures the results for the same is summarized in Table 4.4 along with other similar work done on the same dataset for fault identification. Most of the discussed work uses a standard train-test split size of 80:20. A VMD based transfer learning method [77] using Hilbert spectrum images with DeneNet is able to achieve 92% accuracy. Similar method proposed in [78] is also using IMF of VMD as an input to a deep belief network is achieving an accuracy of 93.17%. The other works proposed in [79] considers subset of fault types using a feature set based on wavelet packet transform. Research in [80] uses local mean decomposition-based data driven method to identify four fault conditions except combined and ball fault to achieve an accuracy of 95.88% with random forest classifier.

Table 4.4 Comparison with related work

Method	**Features**	**Class**	**Average Accuracy (%)**
Proposed-CNN	GMrDMD modes	3	98.89
Proposed-CNN		5	96.83
Proposed-AlexNet			84
Proposed-DenseNet			93.62
Proposed-GoogleNet			93.4
VMD-DenseNet [77]	Hilbert Spectrum	5	92
AVMD-DBM-ELM [78]	IMFs Data driven	5	93.17
WPT-MWSVD+SVM [79]	Wavelet packet	3	87.8
HPO-RF [80]	Local Mean Decomposition	3	95.88

CHAPTER 5

BEARING FAULT DIAGNOSIS

5.1 OVERVIEW

This chapter aims to address the critical fault of unbalance in rotating machinery through the development of an automated algorithm capable of detecting unbalance and analyzing its severity in real-time. The algorithm utilizes data fusion, contour encoding, and deep learning techniques to achieve its objectives. Vibration data from three sensors is integrated into a single signal to maximize its relevance. Additionally, a novel encoded statistical contour plot is introduced to decompose the signal using the maximum overlap discrete wavelet transform. The system includes a two-stage warning system to effectively detect unbalance and analyze its severity.

The proposed approach is validated using a dataset obtained from the Fraunhofer Institute for Integrated Circuits, demonstrating its effectiveness. The results show that the proposed algorithm achieves a high accuracy rate in classifying the severity of unbalance, surpassing existing methods. The distributed architecture and utilization of single modal data make the algorithm well-suited for real-time applications. To further enhance accuracy, future work can focus on refining contour encoding techniques and expanding the labeled dataset to incorporate more advanced deep neural networks.

5.2 METHODOLOGY

The work proposes a three stage method for identifying unbalance and classifying its severity based on ISO standards for small machines as mild, moderate and severe as shown in Figure 5.1. The following sub-section discusses the details of each stage.

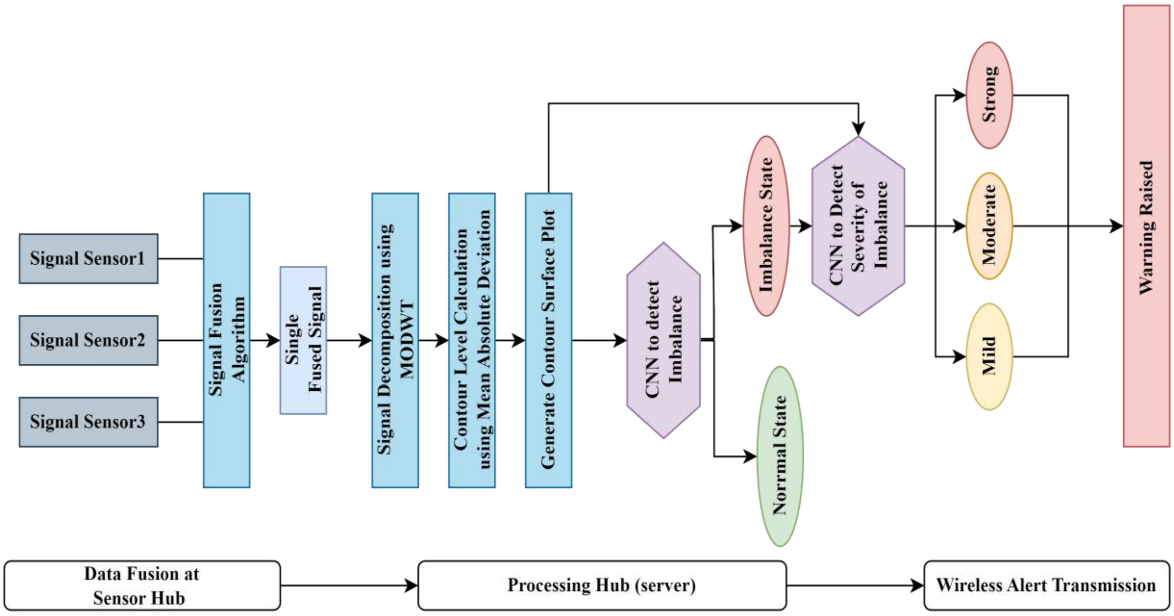

Figure 5.1 Flowchart for the proposed methodology.

5.2.1 Data fusion

Fusion refers to the process of amalgamating information from different sources. This can be done at three levels. First is the sensor level, where multi-domain sensors record data that gets processed differently, as proposed in [81]. The second type is data level, where sensor data is combined based on mathematical or domain knowledge to form a single signal with relevant and consistent information. Third is decision-level fusion involving an ensemble of multiple algorithms [82] to complement each other’s drawback in the decision-making phase.

This work uses the frequency domain for performing data level fusion of three vibration sensors. Fault signals are associated with fault characteristic frequency hence frequency domain has been chosen for data fusion. Two of the sensors are placed in an orthogonal manner at the bearing block and one at the motor mount. Firstly, FFT is calculated for signals S1, S2 and S3 to obtain frequency spectrum F1, F2 and F3, respectively. Then point wise mean is calculated and inverse FFT (IFFT) is performed to obtain the fused signal as given by Equation 5.1. The frequency domain is ideal for fusion because the region of interest for unbalanced machine fault lies at the amplitude of peak frequency. With variation in speed, the peak frequency varies and often becomes difficult to distinguish in the spectrum obtained under the real-world environment with ambient noise. The recording of individual sensors and the obtained fused signal of a signal segment of 1s is shown in Figure 5.2.

$$X_{Fused} = IFFT\left[\sum_{n=1}^{N} \frac{F1(n)+F2(n)+F3(n)}{3}\right] \tag{5.1}$$

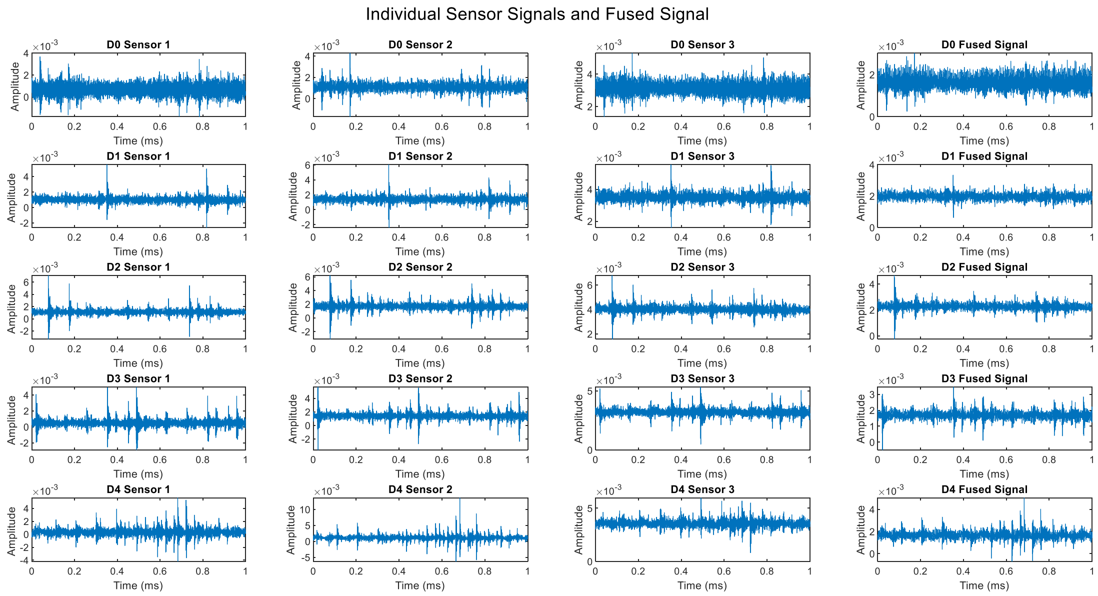

Figure 5.2 Representation of fused signals obtained for different strengths of unbalance.

5.2.2 Maximum Overlap Discrete Wavelet Transform

Wavelet-based signal decomposition [29] is among the most suitable method for the feature generation of non-stationary signals. It uses a time-shifted and scaled collection of basis functions of the selected mother wavelet. Traditionally DWT has been used for machine fault detection [34] but it suffers from an inherent disadvantage of loss of data due to down-sampling and stringent requirement of 2n samples in a signal. Owning to this MODWT was proposed as a revised version of DWT which does not decimate the decomposed signal at each scale. This makes MODWT redundant in nature as well as energy-preserving decomposition. Hence X_{Fused} can be obtained from the summation of coefficients from all scales. This work uses higher-order Daubechies asymmetrical wavelet 'db40' to ensure maximum localization [28] with non-linear phase response. The decomposition of fused signal for no unbalance and maximum unbalance is shown in Figure 5.3 and Figure 5.4, respectively.

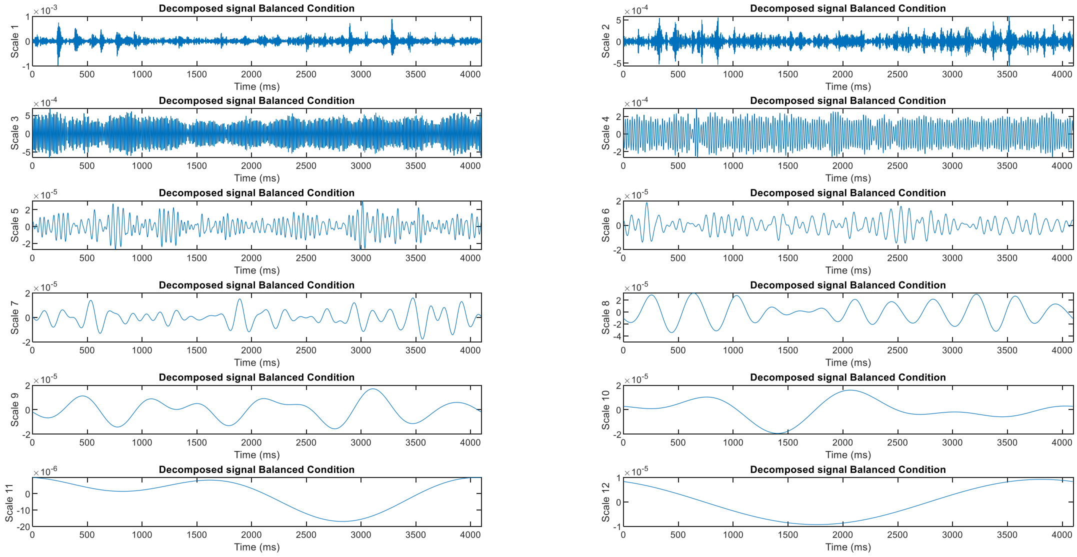

Figure 5.3 MODWT of the fused signal under no unbalance condition.

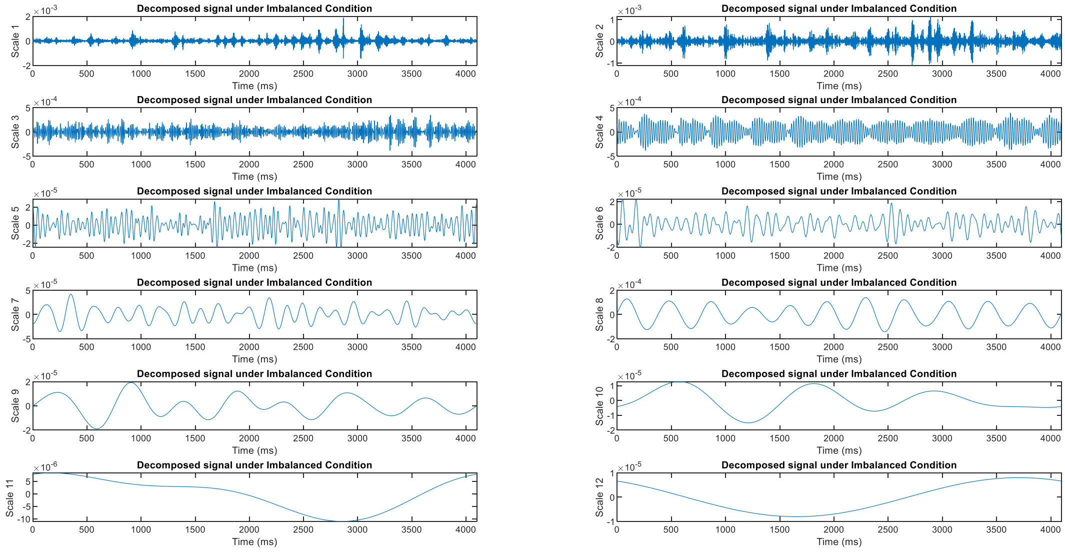

Figure 5.4 MODWT of the fused signal under maximum unbalance condition.

5.2.3 Contour Plot

The work in the literature has significantly explored time-frequency images like spectrogram, scalogram, Hilbert transform, and synchrosqueezing transform as potential options for the CNN network. In general, the computational cost of calculating wavelet-based scalograms is very high, which introduces latency in the system for real-time monitoring. To overcome this, a contour plot has been proposed using mean absolute deviation-based iso-response z slices. Historically contour plots have been widely used for elevation representation in meteorology, geology, and physics [83].

We have proposed a novel application of statistically encoded contour plot to visualise the decomposed signal by relating it with the variance at each scale. A level matrix with 13 values is created for each decomposed segment using MAD shown in Equation 5.2 where, x_m is the coefficients of a given scale μ is the mean of the scale and N is the total number of coefficients [84]. Figure 5.5 shows the zoom version of obtained contour plot for samples of individual classes for development and evaluation signals. It can be seen that with the increase in unbalance strength, the plot captures the detailed variation of the signal.

$$L = \frac{1}{N}\sum|x_m - \mu| \qquad (5.2)$$

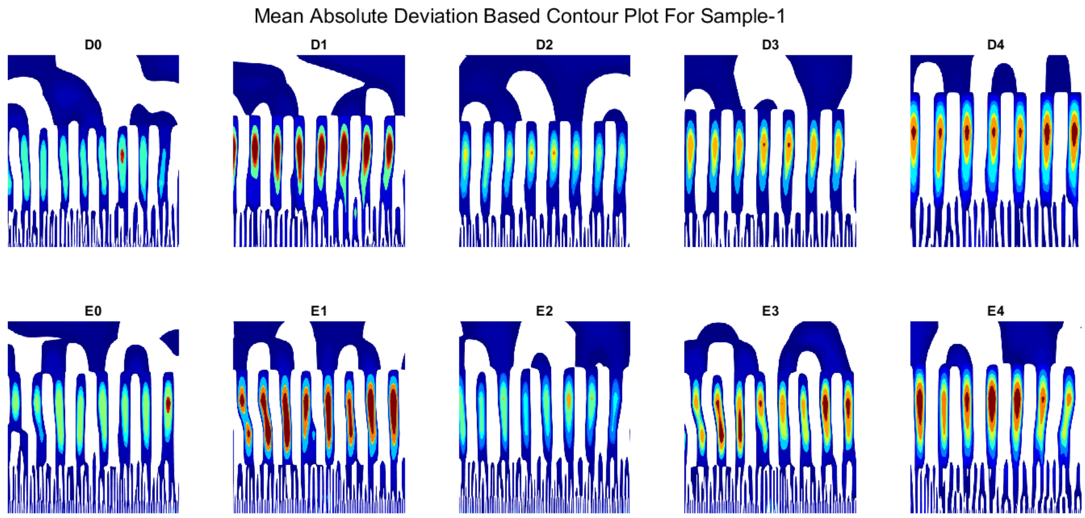

Figure 5.5 Encoded contour plot of the decomposed signal matrix for all classes.

5.2.4 Convolutional Neural Network

CNN has proved its capability for classification problems related to machine failure [85] over time. It is a popular choice among researchers because of its ability to learn contour lines from complex images using filter weights adjustment [56-58]. CNN is realised using a set of recurring units consisting of a convolutional, activation, and pooling layer. In this work, a dual-stage CNN is used to improve the accuracy of the severity-based warning system. Stage 1 is a coarse CNN structure with two convolution blocks and a dropout layer. The shallow net learns more generalized weights for classifying the rotor as balanced or unbalanced in case of unbalancing the stage 2 network triggers and raises a warning based on detected severity. The input image size for best performance is taken as 256 x 256. ‘Leaky Relu’ with alpha 0.2 is used as an activation function, while ‘softmax’ is used for classification, and ‘sparse cross entropy’ is the loss function minimized during the training process. The architecture of CNN for both stages, along with the first filter response of the convolutional layer on the input image, is shown in Figure 5.6.

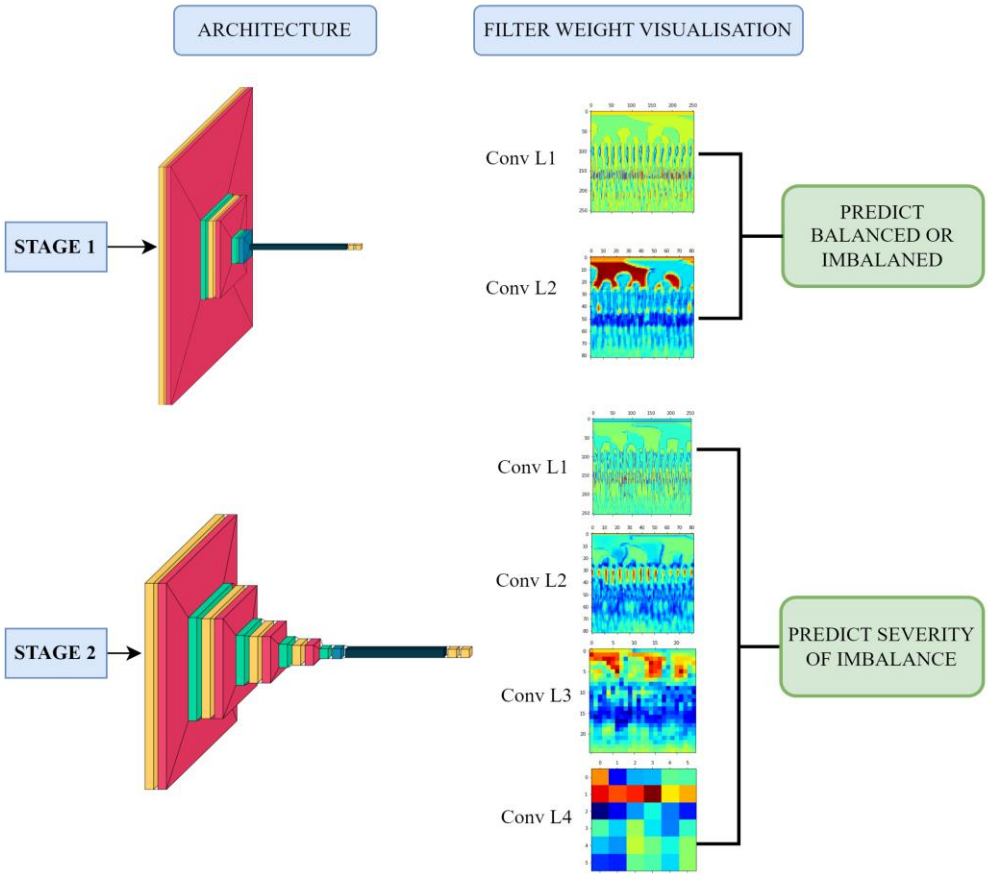

Figure 5.6 Architecture and filter weight visualization of convolutional layer of CNN.

5.3 DATASET

The method for automated detection of unbalance and severity classification is verified using a publicly available dataset from Fraunhofer Institute for Integrated Circuits [86]. The speed of the motor is varied from 550-2500 RPM for recording different datasets for development (Dx) and evaluation (Ex). The measurement setup and speed variation are shown in Figure 5.7. The setup employs a 3D printed disc to introduce unbalance of different strengths viz. 0 – no unbalance and 4 – maximum unbalance. The data is sampled at 4096 samples per second and a window of 1s is considered for segmentation. Table 5.1 summarizes the details of different conditions considered in the dataset.

Unbalance force is equivalent to the centrifugal force also it can be noted that the strength of unbalance (UF) for a point mass is proportional to the product of mass m times the radii r Equation 5.3 and its effects get amplified at higher rotational speeds ω [87].

$$F = mr\omega^2 \tag{5.3}$$

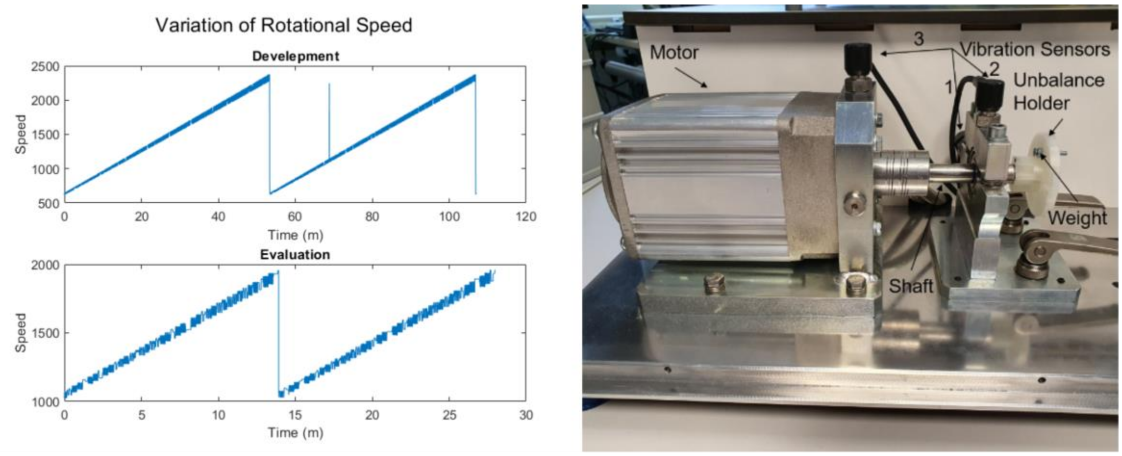

Figure 5.7 Measurement setup for recorded dataset [86].

Table 5.1 Summary of dataset from Fraunhofer Institute.

Parameter	**Severity of Fault based on ISO standard 10816**				
	Normal	**Mild**	**Mild**	**Moderate**	**Strong**
Dataset	D0 and E0	D1 and E1	D2 and E2	D3 and E3	D4 and E4
Radi (mm)	-	14	18.5	23	23
Mass (g)	0	3.281	3.281	3.281	6.614
UF (mm g)	0	45.9	60.7	75.5	152.1

5.4 RESULTS

This section discusses the results obtained from the dual-stage classification process and severity detection of unbalance. The system configuration used for the experimental study is i5 9th, 2.4GHz, and 16 GB RAM. The speed of classification using mentioned system configuration and the proposed method is approximately 2800 samples per second. The recorded wall time for generating the encoded contour image is 0.52ms, while for generating a scalogram with the same data is 2.9ms. Hence the proposed method speeds up the classification process by five times.

As mentioned above a segment of 1s length with 4096 data points from three sensors is fused in the frequency domain to form a single, decomposed signal, and a contour MAD-based input image for CNN is obtained. The data is divided into 6000 images from each development file (Dx) to form a training dataset and 1500 images from the evaluation file (Ex) to create a testing dataset. Further, the training set is split into two parts, with 4800 and 1200 from all individual files. This is used for training and validation, respectively.

Evaluation for two stages is conducted where stage 1 is a general qualitative analysis using coarse CNN to detect an unbalanced or balanced rotor operation state. Accuracy in validation and test data has been considered for describing the model performance, as summarized in Table 5.2. Initially, a pairwise analysis is done to understand the distinguishability between the two classes. It is observed that the unbalance strength of 45.9mm g is the most difficult to distinguish from the balanced case, and it shows the lowest test accuracy of 98.3%. The final test accuracy all samples from 1E, 2E, 3E, and 4E are considered as unbalance class. In contrast, 0E as the balanced class gives an accuracy of 99%, comparable to the other methods summarized in Table 5.3.

The second stage involves quantitative analysis of severity as mild (1E & 2E), moderate (3E), and severe (4E) based on ISO standards to raise the alarm. It is seen that the proposed method is capable of raising a correct warning with a test accuracy of 98.42% which is significantly higher compared to the literature for datasets with varying rotational speeds. The confusion matrix for the overall warning system obtained by evaluating the complete two-stage method end-to-end using test data of all classes (0E, 1E, 2E, 3E, and 4E) is shown in Figure 5.8. The observed accuracy for the 4-layer CNN model with batch normalization and dropout layer neither over fits nor under fits the data. Also, the results establish that the MAD iso-reference-based contour plot of the MODWT decomposed signal is a good representation of localized information. The study conducted in this paper is limited in the selection of iso-reference where options like energy, median frequency, etc., can also be explored.

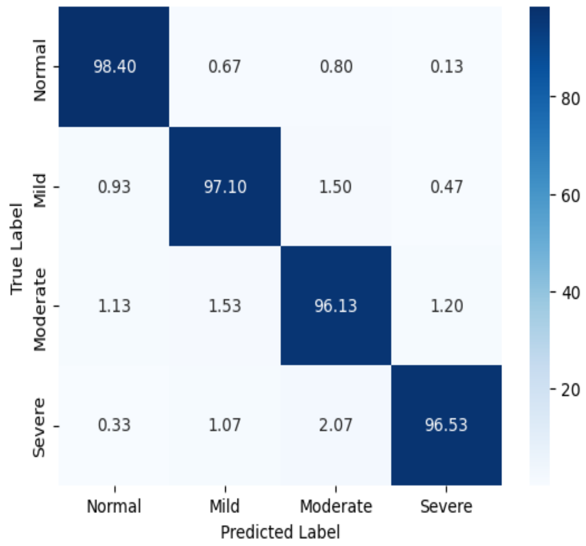

Figure 5.8.Confusion matrix for overall warning system using test data.

Table 5.2 Summary of accuracy obtained for different classification tasks.

STAGE 1 - CNN (2 Class - Balance/Unbalance Detection)			
Train Dataset	**Validation Accuracy**	**Test Dataset**	**Test Accuracy**
0D + 1D	98.67	0E + 1E	98.3
0D + 2D	99.24	0E + 2E	98.62
0D + 3D	99.84	0E + 3E	99.39
0D + 4D	100	0E + 4E	99.45
0D + (1D + 2D + 3D + 4D)	99.46	0E + (1E + 2E + 3E + 4E)	99
STAGE 2 - CNN (3 Class - Severity Detection)			
Train Dataset	**Validation Accuracy**	**Test Dataset**	**Test Accuracy**
(1D +2D) + 3D + 4D	99.7	(1E + 2E) + 3E + 4E	98.42
Overall Warning Accuracy (4 Class - Normal/Mild/Moderate/Severe)			**97.05**

Work addressing the two-class problem on the same dataset is presented in [86]. It compared the performance of multiple algorithms where maximum accuracy of 98.6% is obtained using a single sensor data for FFT-based fully connected neural network (FCN) with two hidden layers for unbalance detection. Other summarized works use personal datasets like research in [90] that combines three statistical features from both the time and frequency domain to feed into an SVM classifier. The results showed the accuracy was a vital function of operating speed, and the method is unsuitable for classification at lower speeds. Work in [91] uses data recorded at multiple speeds to develop and test classification and regression trees using dynamic-based features (D-CART). The method achieved 90% accuracy for qualitative analysis of severity detection. Research in [92] used heterogeneous information from vibration signals and shaft orbital plots to extract features using a deep belief network (DBN) automatically. The method showed an accuracy of up to 100% using both sensor data and only 75% using the vibration sensor under constant motor speed.

Table 5.3 Comparison of work with existing methods in the literature.

Classification Method	**Features**	**Classes**	**Speed**	**Average Accuracy (%)**
Proposed CNN	**MODWT-MAD-Contour Images**	**2**	**Time-Varying**	**98.72**
		4		**97.05**
SVM [59]	Frequency spectrum	2	Constant	94
FCN [86]	FFT (single sensor)	2	Time-Varying	98.6
1D-CNN [86]	Raw vibration signal	2	Time-Varying	93.6
CNN [88]	TF Image angular domain	2	Time-Varying	98.1
SVM [89]	Raw time / frequency domain	2	Multiple Speeds	91.66
D-CART [90]	Dynamics	4	Multiple Speeds	90
SVM [91]	Hybrid features	4	Constant	93.2 - 98.2
Multi-DBN [92]	Raw vibration signal	4	Constant	75
	Fused orbit plots + vibration			86.46 - 100

CHAPTER 6

CONCLUSIONS AND FUTURE SCOPE

This thesis undertakes a comprehensive study aimed at advancing mechanical fault analysis and detection techniques, with a specific focus on bearing and shaft faults in rotating parts. Extensive literature review was conducted to explore the different types, causes, and consequences of mechanical faults in rotating elements. This review served as the foundation for identifying the research objectives, resulting in the development of novel methodologies and a framework for an early warning system.

The key aspect of this research is to accurately measure the severity and type of faults in order to enable timely actions and reduce maintenance expenses. By integrating data-driven decomposition methods, such as MrDMD and time-frequency analysis using the MODWT, non-stationary vibrational signals can be effectively analyzed. Furthermore, the research aims to address the challenges posed by translating fault signatures caused by variations in speed and load conditions. By developing methods capable of handling these variations, the proposed framework ensures accurate detection of bearing and shaft faults under time-varying rotational speed and discrete load conditions.

The first part of this work presents a fault detection framework for bearings using GMrDMD and CNN, addressing the challenge of using only a single type of sensor for fault detection under varying rotational speeds. The method utilizes a gram matrix-based transformation to convert vibration signals into time-evolving snapshot matrices, preserving temporal relations. These matrices are decomposed using MrDMD, isolating transient fault characteristics. The GMrDMD approach offers preservation of spatial and temporal information, aiding fault identification, especially for transient events. The CNN architecture with inception modules enhances fault classification accuracy using multiple-size kernels. This work contributes to fault detection advancements, offering an innovative approach applicable across industries to enhance reliability and performance optimization of bearings in rotating machines.

Another contribution of this research relates to shaft unbalance and severity detection by utilizing a complementary data fusion strategy. The approach integrates data from vibration sensors into a single signal with maximum relevance, enhancing the accuracy and reliability of fault detection. Additionally, a novel encoded statistical contour plot is designed for signals decomposed using the maximum overlap discrete wavelet transform. This contour plot provides a visual representation of fault characteristics, enabling effective analysis and classification. To further improve fault identification and reduce the false alarm rate, a multi-level CNN model is developed specifically for shaft fault identification. The CNN model leverages the power of deep learning techniques to effectively analyse the encoded contour plots and classify faults with high accuracy.

The proposed fault detection techniques were validated through experimental studies using real-world datasets, including the University of Ottawa dataset and the dataset provided by the Fraunhofer Institute for Integrated Circuits. These datasets encompassed various fault vibration signal types and rotational speed conditions. The results demonstrated the effectiveness of the proposed methodologies, achieving an impressive 96.83% accuracy for distinguishing fault characteristics in bearing faults using the GMrDMD-CNN method, and an overall classification accuracy of 97.05% for unbalance fault detection.

The findings and conclusions of this research significantly contribute to the advancement of mechanical fault analysis and detection techniques, specifically for bearing and shaft faults in rotating elements. There are potential areas for further exploration, such as adaptive level encoding for contours, which could enhance the accuracy and robustness of fault detection methodologies. Additionally, increasing the labelled data for more advanced deep neural networks can further improve the performance and applicability of the proposed methods. Alternative options for iso-reference selection, such as energy or median frequency, can also be investigated to expand the capabilities of the fault detection framework.

Future research in mechanical fault analysis and detection can focus on refining the false alarm rate of the GMrDMD method, improving fault classification algorithms, optimizing threshold values, and incorporating additional features or data analysis methods. It is essential to test the methodologies on dynamic load variation to ensure their robustness and accuracy in real-world scenarios. Integration of multiple sensor data, such as temperature or acoustic sensors, can provide a comprehensive understanding of system health and enhance fault detection capabilities. Validating the proposed methodologies on diverse industrial systems will further enhance their generalizability and practicality. Exploring adaptive level encoding for contours can improve fault identification and classification accuracy, while increasing labeled data for testing advanced deep neural networks will enable the exploration of more complex models with improved generalization capabilities. These future scopes will contribute to the continuous advancement of mechanical fault analysis and detection, optimizing the performance of rotating machinery systems in various industries.

By refining and developing these techniques, the field of mechanical fault analysis and detection can continue to evolve and drive progress in the maintenance and performance optimization of rotating machinery. The comprehensive understanding of fault mechanisms, utilization of advanced data-driven approaches, and integration of deep learning techniques hold great promise for the future of fault detection and maintenance in rotating machinery systems.

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APPENDIX A (LIST OF PUBLICATIONS)

DETAILS OF PUBLICATIONS

Below is the list of published research article in SCOPUS indexed conference proceedings along with the proofs of publications.

1) S. Bhandari, S. Taran and V. Sangwan, "An Intelligent System for Bearing Fault Identification based on Gramian Multi-Resolution Dynamic Mode Decomposition," 2023 10th International Conference on Signal Processing and Integrated Networks (SPIN), Noida, India, 2023, pp. 715-720, doi: 10.1109/SPIN57001.2023.10117292. **(IEEE XPLORE).**

2) S. Bhandari, S. Taran and V. Sangwan, " Rotor Unbalance Severity Detection using Maximum Overlap Discrete Wavelet Transform," 2023 2nd International Conference Women Researchers in Electronics and Computing (WREC), at Dr B R Ambedkar National Institute of Technology, Jalandhar, Punjab, India. **(Accepted & Presented, yet to be Published in the Lecture Notes in Electrical Engineering SCOPUS Indexed)**

2023 10th International Conference on Signal Processing and Integrated Networks (SPIN) | 978-1-6654-9099-3/23/$31.00 ©2023 IEEE | DOI: 10.1109/SPIN57001.2023.10117292

An Intelligent System for Bearing Fault Identification based on Gramian Multi-Resolution Dynamic Mode Decomposition

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***Abstract*— This work introduces a single sensor intelligent end-to-end framework for fault detection based on Gramian-multi-resolution dynamic mode decomposition (GMrDMD). Vibration signals are transformed using gram matrix followed by spatial temporal decomposition based on multi-resolution dynamic mode decomposition (MrDMD). The gram matrix converts the 1D data into time evolving snapshot matrix which retains the relation of signal with time. This forms the input to the MrDMD framework which decomposes the system dynamics into hierarchically evolving fast and slow modes capable of isolating the transient fault characteristics. To handle sensor and environmental noise a robust total least square DMD algorithm is applied at each level of MrDMD. The resultant mode matrix is color coded and fed as image to a convolutional neural network (CNN) for classification. The performance of the designed method is verified on University of Ottawa dataset which contains five type of fault vibration signal under four different time varying rotational speed condition. The results demonstrate that of the proposed data driven method is effectively able to distinguish between different fault characteristics with an accuracy of 96.83%.**

Keywords—Fault detection, DMD, Gram matrix, Convolutional neural network, Vibration signal.

I. INTRODUCTION

The foundation of industry 4.0 revolves around automation and remote condition monitoring of systems. The industrial sector inhabits some of the most complex machines which work under stochastic conditions. These machines require time to time quality check but physical inspection-based methods are not scalable. Hence the shortcoming gave rise to a broad field of intelligent machine health monitoring and prognostics. The aerospace and atomic energy are the earliest industries [1] to adopt fault monitoring systems.

Today, with the technological advancement in sensing devices, network connectivity and high-speed processors all large-scale industrial setups include early fault monitoring and warning systems. Machines are made of multiple rotating parts that house a crucial rolling element called ball bearing, which comprises of equally-spaced balls between two concentric circular races. These elements in any system are critically exposed to different stress profile, load and speed which cause non-deterministic abrasion and limit their life cycle. The early warning of faults in ball bearing elements at lower severity of abrasion saves huge resources and industrial down-time avoiding machine strip down. So, bearing fault detection is hour of need and several algorithms have been proposed for the same.

The earliest works for fault identification with varying speed condition [2] focused on order tracking based on resampling using the changing speed signal. It involves an extra sensor i.e., tachometer and additional multiple resampling needs to be performed. An improved order tracking method using virtual multichannel signals based on variational mode decomposition (VMD) has been proposed in [3] with a primary target of improving performance for detecting compound faults. Another work in [4] proposes a deep learning (DL) based speed normalization-based auto encoder method to normalize the effect of speed using speed accounting function. The effectiveness of the method is only studied for determining healthy and faulty state with 97% accuracy. The research in [5] uses a tachometer free approach which focuses on optimizing the ridge detection using time-frequency ridge estimation method but with the application of this method classification of fault requires manual efforts and domain knowledge. A DL based speed fusion network is proposed in [6] it uses multihead self-attention modules to improve accuracy for distinguishing between healthy, inner and outer race fault but details about network performance for ball and combined fault is not mentioned. Work in [7] discusses time frequency-based method improved using sparse and low rank decomposition based on robust principle component analysis for noise removal. Presently, DL architectures are being used rigorously to address variable working condition, work in [8] develops a condense sense network with emphasis on non-linear fitting functions to improve accuracy by 9% but limits the real time application due to computational complexity. To address the existing algorithms gap in terms of algorithmic complexity, sensor requirement and accuracy this work proposes Gramian-multi-resolution dynamic mode decomposition (GMrDMD).

Prominent spectrum analysis methods [9] like fast Fourier transform, short time Fourier transform, Hilbert transform and envelop detection worked best in case of datasets acquired from test-bench with constant operating conditions with less or no ambient noise. Still they are not

Rotor Unbalance Severity Detection using Maximum Overlap Discrete Wavelet Transform

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Abstract. The rotor unbalances a critical fault that increases stress at rotational parts like bearings and gears, resulting in higher power consumption and early machinery wear. The general behavior of the vibration spectrum under this fault changes with strength and rotational speed. To address this problem, the presented work proposes frequency domain data fusion of vibration signals obtained from sensors placed at three different locations. The fused signal retains maximum spectral information, which decomposes into a multi-scale matrix using energy-preserving maximum overlap discrete wavelet transform. To analyze the severity of unbalance, the decomposed scale matrix is encoded into a contour plot using the mean absolute deviation of individual scales as iso-reference lines. Finally, a two-stage classification is performed using a convolutional neural network. The proposed method is tested using a publicly available dataset from Fraunhofer Institute for Integrated Circuits. The results show an overall classification accuracy of 97.05% for unbalance severity which is significantly better than other studies using single-sensor data.

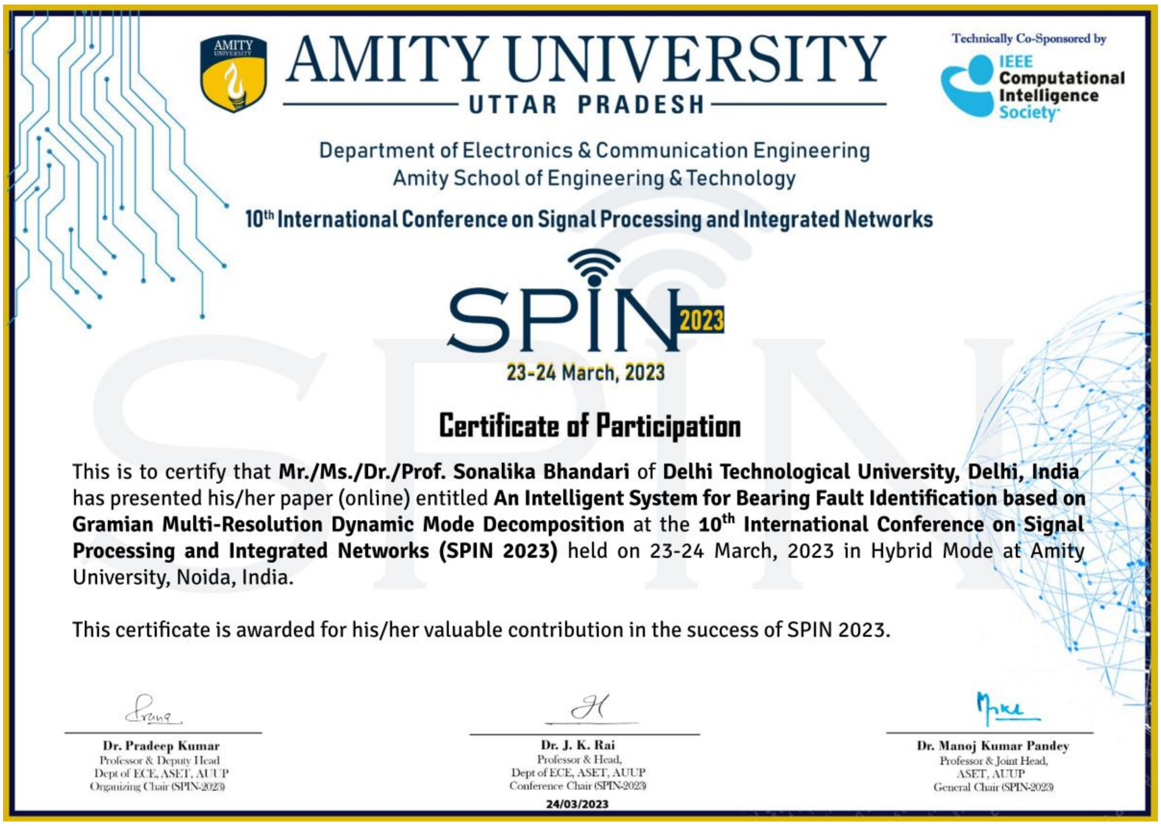
Keywords: Unbalance Fault, Data Fusion, MODWT, Contour Plot.

1 Introduction

The advancement in networks, processors, and sensors has together revolutionized multiple fields. It has opened a plethora of opportunities for the development of real-time condition monitoring systems (RT-CMS). These systems have strong use cases in areas where 24-hour supervision of all components is not possible, like automated industries, renewable energy plants, intelligent vehicles, etc. RT-CMS aims to create an early warning in case of any probable failure. This is done based on sensor data analysis and intelligent AI-based classification. A critical area of innovation lies in developing algorithms with low time complexity and moderate processing cost.

A typical drive train or rotating machine comprises shafts, gears and bearings. These parts often get worn out due to operating conditions causing misalignment, bearing, or unbalanced faults. A moving system works at a characteristic frequency under healthy conditions, but once a fault occurs, the behaviour of sensor data changes. Hence, implementing RT-CMS in industrial rotating machines helps to solve a fundamental problem of early fault detection, which scrapes downtime requirements. This work focuses on detecting unbalance faults of multiple strengths at varying rotational

1) 10th International Conference on Signal Processing and Integrated Networks



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23-24 March, 2023

Certificate of Participation

This is to certify that **Mr./Ms./Dr./Prof. Sonalika Bhandari** of **Delhi Technological University, Delhi, India** has presented his/her paper (online) entitled **An Intelligent System for Bearing Fault Identification based on Gramian Multi-Resolution Dynamic Mode Decomposition** at the **10th International Conference on Signal Processing and Integrated Networks (SPIN 2023)** held on 23-24 March, 2023 in Hybrid Mode at Amity University, Noida, India.

This certificate is awarded for his/her valuable contribution in the success of SPIN 2023.

Dr. Pradeep Kumar Professor & Deputy Head Dept of ECE, ASET, AUUP Organizing Chair (SPIN-2023)	**Dr. J. K. Rai** Professor & Head, Dept of ECE, ASET, AUUP Conference Chair (SPIN-2023) 24/03/2023	**Dr. Manoj Kumar Pandey** Professor & Joint Head, ASET, AUUP General Chair (SPIN-2023)

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APPENDIX B (PLAGIARISM REPORT)

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