An Internship Report on

Bearing Fault Detection Using AI

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Submitted to

PES University

In fulfilment of the requirements Internship

work carried out at

Council of Scientific and Industrial Research

National Aerospace Laboratories

Bangalore 560 017

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1. INTRODUCTION

Bearings are vital components in rotary machinery, widely used in aerospace, power generation, and automotive industries. Their failure can lead to costly downtimes, reduced performance, and safety risks. Thus, early fault detection and predictive maintenance are essential for ensuring system reliability and longevity .

Traditional fault diagnosis methods—based on vibration signal analysis and manual inspection—require domain expertise and are prone to human error . With advancements in AI and sensor technologies, automated and intelligent diagnostic systems have emerged as effective alternatives.

In this project, we developed a deep learning-based system for **bearing fault classification** using the **CWRU dataset**. Time-domain vibration signals were segmented and converted into **2D spectrograms**, enabling effective feature extraction using a **Convolutional Neural Network (CNN)**. To enhance generalization, we applied data augmentation techniques such as:

- **RMS-scaled Gaussian noise**,
- **Amplitude scaling**, and
- **Frequency masking**.

The model classifies signals into four categories: **Normal**, **Inner Race (IR)**, **Outer Race (OR)**, and **Ball fault**. Additionally, we extracted handcrafted features like **RMS**, **kurtosis**, and **dominant frequency** to build a structured knowledge base.

This knowledge base was integrated with a **Retrieval-Augmented Generation (RAG)** system using a **Grok-powered LLaMA 3 model** to provide fault classification. The result is a hybrid system combining deep learning with semantic reasoning for robust and interpretable fault diagnosis.

1.1 Importance of Bearings in Industrial Applications

Bearings are fundamental components in rotating machinery, enabling smooth motion, supporting loads, and reducing friction between moving parts. Their role is critical in ensuring the efficiency and stability of mechanical systems across a wide range of industries. In sectors such as aerospace, automotive, manufacturing, and power generation, the health of bearings directly influences machine performance, safety, and operational continuity.

A single bearing failure can escalate into critical system-level faults and cause machine breakdowns, production stops, and unplanned repairs, resulting in important financial and operational losses . Thus, it is critical for bearing health monitoring and fault detectability at an early stage in order to reduce downtime, prevent harming failures, and maximize equipment longevity.

Today's industries are increasingly adopting predictive maintenance practices as means of pre-empting bearing failures. Condition monitoring practices such as vibration analysis, acoustic emission, and temperature measurement are some of the prevalent practices utilized for assessing bearing performance. Systems offer comprehensive time-series sensor data that can be leveraged by machine learning (ML) and artificial intelligence (AI) algorithms in aiding real-time fault detection and diagnostics .

1.2 Need for Fault Detection and Predictive Maintenance

Conventional maintenance approaches, such as corrective and preventive maintenance, have limitations. Corrective maintenance involves repairing or replacing a bearing after a failure occurs, leading to high repair costs and unplanned downtimes. Preventive maintenance, on the other hand, schedules maintenance at predetermined intervals, which may result in unnecessary servicing if the bearing is still in good condition [6].

Predictive maintenance aims to address these challenges by continuously monitoring bearing conditions and predicting failures using data-driven models. ML-based fault detection systems analyze real-time sensor data, enabling early detection of anomalies. By leveraging historical data and advanced analytics, these systems can estimate the remaining useful life (RUL) of bearings and optimize maintenance schedules [7].

1.3 Conventional Fault Detection Techniques

Traditional fault detection methods involve time-domain, frequency-domain, and time-frequency domain analyses.

- Time-Domain Analysis: This approach examines statistical parameters such as root mean square (RMS), kurtosis, and skewness to detect anomalies in vibration signals. Although useful, it lacks the ability to differentiate between complex fault patterns [8].
- Frequency-Domain Analysis: Techniques such as Fast Fourier Transform (FFT) are used to convert vibration signals into the frequency domain, enabling the identification of fault frequencies associated with bearing defects. However, FFT struggles with non-stationary signals, limiting its effectiveness [9].
- Time-Frequency Domain Analysis: Methods such as Wavelet Transform (WT) and Short-Time Fourier Transform (STFT) provide better fault characterization by analyzing variations in signal frequency over time. These techniques enhance fault detection accuracy but require manual feature extraction [10].

1.4 Emergence of Machine Learning and Deep Learning in Bearing Fault Detection

Machine learning and deep learning have revolutionized the field of bearing fault diagnosis. Unlike conventional techniques that rely on handcrafted features, ML models learn patterns from raw data, improving detection accuracy.

- Machine Learning Models: Algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Random Forest (RF) have been applied to classify bearing faults. These models require well-engineered features but offer robust classification performance [11].
- Deep Learning Models: Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have demonstrated superior capabilities in automatic feature extraction and fault classification. CNNs, in particular, process vibration data as spectrogram images, capturing intricate fault patterns with high precision [12].

1.5 Objective of This Survey

The primary goal of this survey is to explore various ML techniques used in bearing fault detection and assess their effectiveness in real-world applications. By analyzing IMS, CWRU, and XJTU- SY datasets, this study aims to:

- Provide a detailed comparison of bearing fault datasets and their characteristics.
- Evaluate different machine learning models and their performance on fault classification.
- Discuss challenges associated with data preprocessing, feature extraction, and model generalization.
- Highlight future research directions for improving fault diagnosis accuracy [13].

1.6 Challenges in Bearing Fault Detection

Despite the advancements in ML-based fault diagnosis, several challenges remain:

- Data Quality and Imbalance: Bearing fault datasets often suffer from class imbalance, where normal conditions dominate fault conditions, leading to biased models [14].
- Generalization Across Different Operating Conditions: ML models trained on a specific dataset may not generalize well to varying operational environments [15].
- Sensor Noise and Variability: Real-world vibration data is affected by noise, making fault detection more challenging [16].
- Computational Complexity: Deep learning models require high computational resources, limiting their deployment in edge computing environments [17].

2. DATASETS OVERVIEW

The availability of standardized datasets is crucial for developing and validating machine learning models for bearing fault detection. Among the most widely used datasets in this field are the IMS, CWRU, and XJTU-SY rolling bearing life datasets. These datasets provide different perspectives on bearing degradation, failure mechanisms, and fault severity levels, enabling researchers to develop more robust diagnostic models.

2.1 IMS Bearing Dataset

The IMS (Intelligent Maintenance Systems) bearing dataset, developed at the University of Cincinnati, is widely used for studying bearing degradation under controlled conditions that simulate real-world operation. It consists of high-frequency vibration signals collected from multiple bearings subjected to accelerated run-to-failure tests, capturing the full lifecycle of bearings. This makes the dataset particularly valuable for predicting the Remaining Useful Life (RUL) of bearings, as noted in [6].

Nuñez and Borsato [12] highlighted that ontology-based models, such as OntoProg, can enhance Prognostics and Health Management (PHM) applications when applied to datasets like IMS. By incorporating machine learning techniques, researchers can improve fault detection accuracy and enable predictive maintenance strategies. The dataset has been extensively utilized in RUL estimation studies, especially for applications involving Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs).

In the IMS experimental setup, four Rexnord ZA-2115 double-row bearings were mounted on a shaft, which was driven at a constant speed of 2000 RPM by an AC motor connected through rub belts. A radial load of 6000 lbs was applied to the shaft and bearings using a spring mechanism, and lubrication was provided through a forced lubrication system. To monitor vibrations, PCB 353B33 High Sensitivity Quartz ICP accelerometers were installed on the bearing housing. In the first dataset, two accelerometers per bearing were used to capture vibrations along the x- and y- axes, while in the second and third datasets, a single accelerometer was placed on each bearing. The sensor placement details are illustrated in Fig 1. All bearing failures occurred only after exceeding their designed operational lifespan, which is over 100 million revolutions.

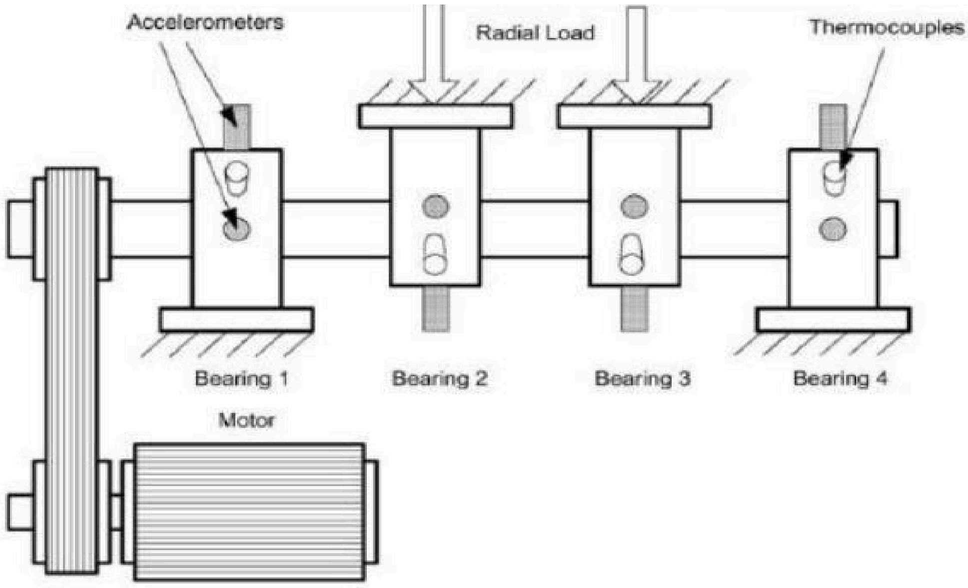

Fig 1 Bearing test rig and sensor placement

Key Features:

- Contains three sub-datasets corresponding to different test conditions.
- Provides run-to-failure data, allowing researchers to study degradation trends.
- Includes high-resolution vibration signals captured at regular intervals.

Limitations:

- Data is collected under controlled conditions, limiting real-world applicability.
- Only a limited number of fault types are represented.

Researchers have applied various machine learning and deep learning techniques, such as feature extraction, time-frequency analysis, and deep learning models, to classify bearing conditions using this dataset [4].

2.2 CWRU Bearing Dataset

The Case Western Reserve University (CWRU) bearing dataset is one of the most widely used datasets for benchmarking fault diagnosis models. It contains vibration signals collected under various fault conditions, including inner race, outer race, and rolling element defects. These faults were artificially induced using electrical discharge machining (EDM), ensuring precise and consistent fault classification. A key advantage of the CWRU dataset is its structured fault labeling, which enables researchers to develop and compare different diagnostic algorithms. Xu et al. [1] demonstrated the effectiveness of convolutional autoencoders in extracting meaningful features from CWRU vibration signals, achieving high accuracy in fault classification tasks. While the dataset's-controlled environment is beneficial for algorithm development, it may present challenges when applied to real-world scenarios where noise and operational variations affect data quality.

The CWRU dataset was used to evaluate the proposed methodology. Fig 2 illustrates the experimental rig designed for studying ball-bearing defects. Vibration measurements were obtained using three accelerometers placed at the 12 o'clock position on the housing of the drive end (DE) and fan end (FE). SKF deep-groove ball bearings of types 6205-2RS JEM and 6203-2RS JEM were used for the DE and FE, respectively.

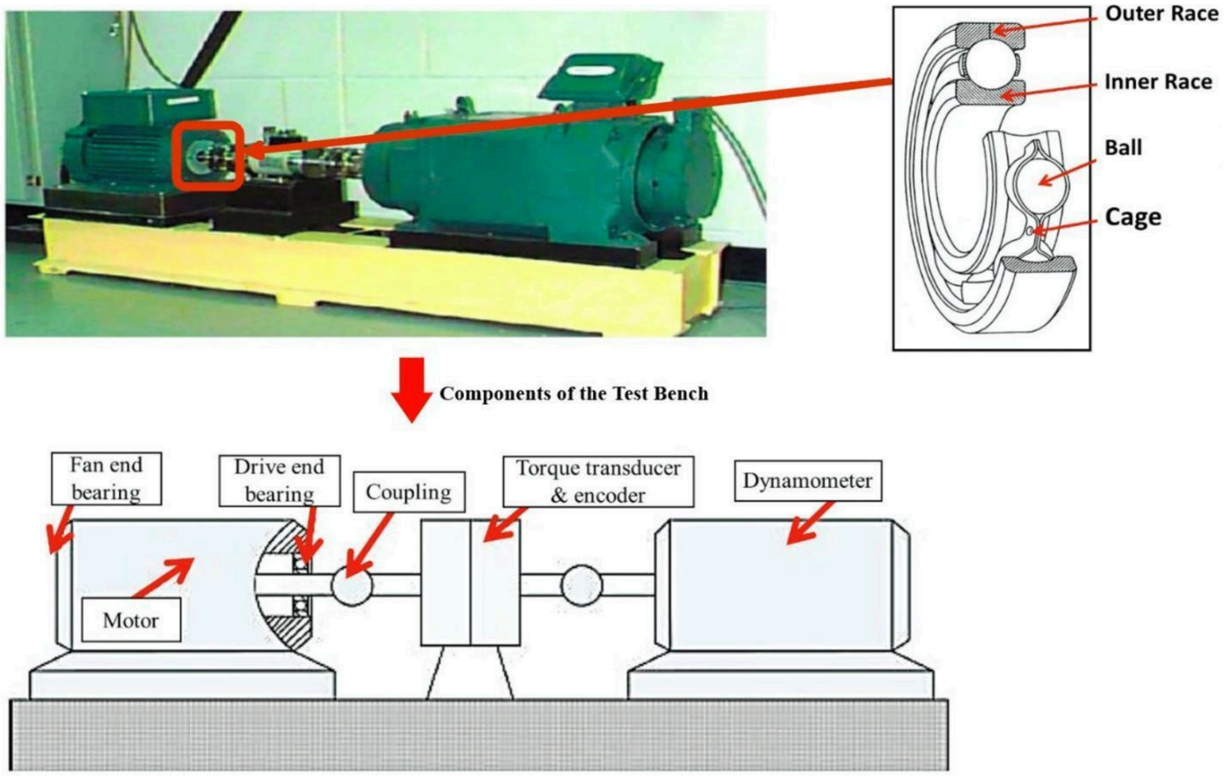

Fig 2 CWRU Motor Experimental Rig

Key Features:

- Offers vibration data for different bearing fault types and severities.
- Data collected under varying loads and speeds.
- High-resolution data useful for signal processing and feature extraction.

Limitations:

- Does not include run-to-failure data, limiting its application for predictive maintenance.
- Data is captured in a controlled laboratory setting, which may not fully reflect real-world conditions.

Many studies have used the CWRU dataset to test deep learning architectures such as CNNs, autoencoders, and hybrid models for fault classification.

2.3 XJTU-SY Rolling Bearing Life Dataset

The XJTU-SY dataset, developed by Xi'an Jiaotong University and Changxing Sumyoung Technology, records bearing degradation under constant operating conditions. It provides vibration and temperature data collected at regular intervals until the bearings reach failure, making it ideal for RUL prediction tasks. Several studies have used the XJTU-SY dataset to evaluate deep learning models for predictive maintenance. Deutsch and He [2] applied deep learning-based approaches to estimate the remaining useful life of bearings using degradation-aware techniques. Similarly, Wu et al. [3] employed LSTM autoencoders to model degradation patterns, enhancing fault diagnosis accuracy. The dataset's structured degradation information enables researchers to explore advanced machine learning techniques, such as recurrent convolutional networks and hybrid deep learning models. Wang et al. [4] proposed a recurrent convolutional neural network framework for RUL prediction using XJTU-SY data, achieving state-of-the-art performance in bearing fault detection. Yang et al. [5] further improved uncertainty quantification in RUL predictions by leveraging LSTM networks.

As shown in the following fig 3, the bearing testbed is composed of an alternating current (AC) induction motor, a motor speed controller, a support shaft, two support bearings (heavy-duty roller bearings), a hydraulic loading system, and so on. This testbed is designed to conduct the accelerated degradation tests of rolling element bearings under different operating conditions (i.e., different radial force and rotating speed). The radial force is generated by the hydraulic loading system and applied to the housing of tested bearings, and the rotating speed is set and kept by the speed controller of the AC induction motor.

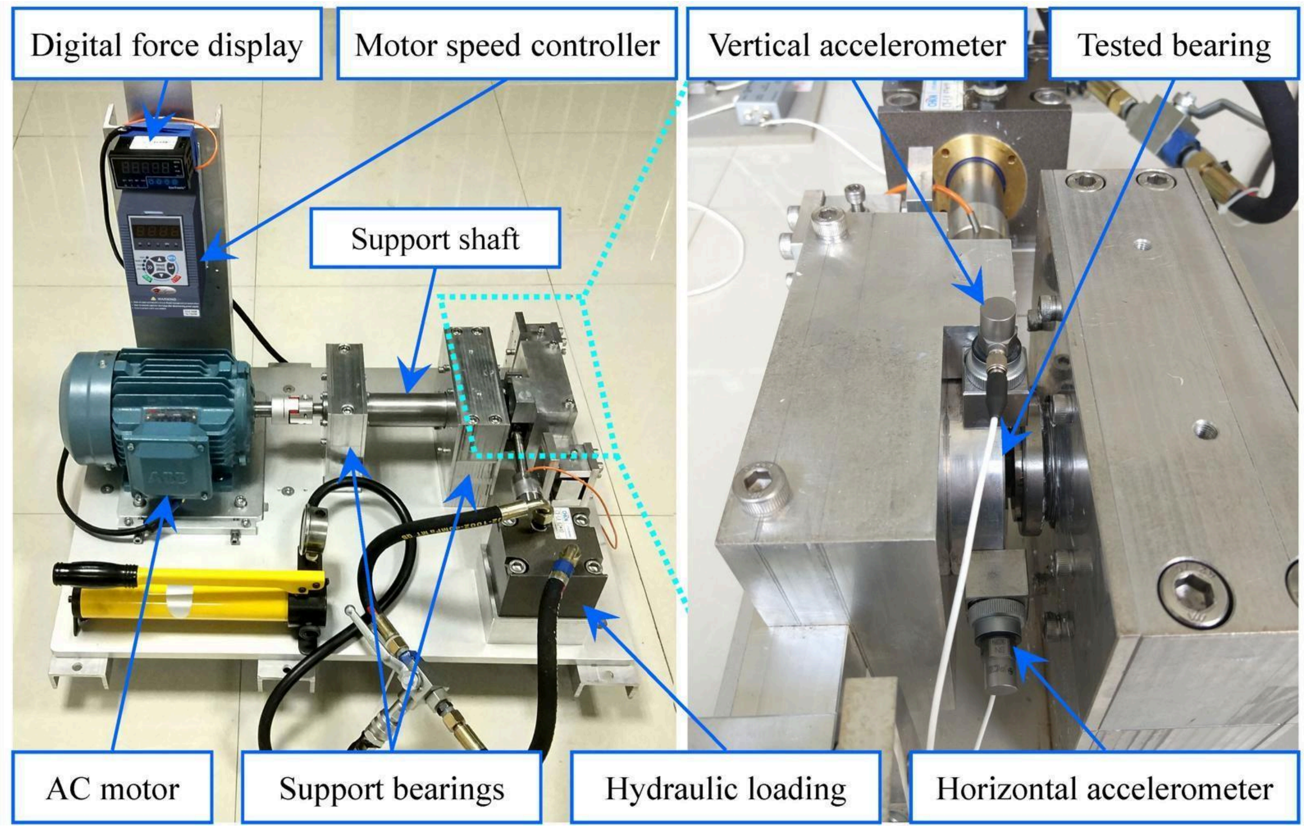

Fig 3 Tested rolling bearing of XJTU-SY.

Key Features:

- Includes degradation signals collected from multiple rolling bearings.
- Covers various load and speed conditions to simulate real-world scenarios.
- Provides temperature data, adding another dimension for predictive modelling.

Limitations:

- The dataset does not include run-to-failure data, limiting long-term failure analysis.
- Variability in test conditions may introduce noise in model training.

Deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been successfully applied to analyze vibration and temperature data from this dataset, demonstrating high accuracy in fault classification.

2.4 Comparison of Datasets and Their Applications

Each dataset has unique characteristics that make it suitable for different fault detection and prognostics applications:

- **IMS Dataset:** Best suited for long-term degradation studies and RUL estimation due to its run-to-failure nature.
- **CWRU Dataset**: Ideal for benchmarking classification models due to its well-defined fault categories.
- **XJTU-SY Dataset:** Provides comprehensive degradation data, making it highly effective for predictive maintenance studies.

By leveraging these datasets, researchers can develop robust machine learning models capable of handling real-world fault diagnosis challenges. Future studies should focus on integrating multiple datasets to improve model generalization across different operational environments

3. Machine Learning Approaches

Machine learning techniques have significantly improved the accuracy and efficiency of bearing fault detection. These methods range from traditional machine learning models such as Support Vector Machines (SVM) and Random Forest (RF) to deep learning approaches like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. The choice of the model depends on the nature of the dataset, computational requirements, and desired fault classification accuracy.

3.1 Traditional Machine Learning Methods

Traditional machine learning techniques rely on feature extraction from raw vibration signals before classification. Commonly used approaches include:

- Support Vector Machines (SVM): SVMs are effective for fault classification using extracted statistical features. However, they can be computationally expensive for large datasets [2].
- Random Forest (RF): RF is an ensemble learning technique that performs well with structured data but requires careful feature selection to optimize performance [12].

3.2 Deep Learning-Based Approaches

Deep learning models have revolutionized bearing fault detection by automatically extracting hierarchical features from raw vibration signals. These models outperform traditional ML methods in terms of accuracy and adaptability to complex patterns. Commonly used models include:

- Convolutional Neural Networks (CNNs): Extract spatial features from vibration signals, enabling automated fault classification [8].
- Long Short-Term Memory (LSTM) Networks: Capture sequential dependencies in time-series bearing signals for fault prediction [5].
- Generative Adversarial Networks (GANs): Enhance model robustness by generating synthetic data to improve training [9].

3.3 Hybrid Approaches

Hybrid methods integrate both traditional ML and deep learning techniques to enhance fault detection performance. These approaches leverage the strengths of multiple models to improve accuracy and adaptability.

- Transfer Learning: Pre-trained deep learning models applied to vibration datasets improve adaptability but may be limited in transferring across datasets [13].
- Reinforcement Learning (RL): RL-based models dynamically adjust fault detection strategies but require large-scale training data [10].

3.4 Summary of Techniques

The following table provides a detailed comparative analysis of various machine learning techniques used in bearing fault detection.

Table 1: Summary of ML Techniques for Bearing Fault Detection

Paper	Dataset Used	Method	Technique Used	Feature Extraction	Strengths
[1]	CWRU	CAE + Status Degradation Model	Unsupervised learning for feature extraction	Hierarchical feature representation	Effective for degradation modeling
[2]	IMS	SVM	Time-domain and frequency-domain analysis	Statistical parameters	High accuracy for small datasets
[3]	IMS	ANN	Feature engineering with FFT and statistical parameters	Frequency-based features	Good generalization for structured data

[4]	NASA	CNN	Automated feature extraction from vibration signals	Learned convolutional features	High accuracy and robustness
[5]	NASA	LSTM	Sequence learning for temporal feature extraction	Time-series features	Effective for time-series prediction
[6]	IMS, NASA	RF	Ensemble learning on extracted statistical features	Statistical and frequency-domain features	Handles non-linearity well
[7]	XJTU-SY	DBN	Hierarchical feature learning	Layer-wise feature extraction	Captures deep feature representations
[8]	NASA, XJTU-SY	GANs	Data augmentation for fault classification	Synthetic data generation	Enhances model generalization
[9]	IMS	PCA + k-NN	Dimensionality reduction for fault clustering	Principal components	Reduces data dimensionality
[10]	XJTU-SY	Transfer Learning	Pre-trained deep models applied to vibration data	Feature reuse from other domains	Improves model adaptability
[11]	NASA	Reinforcement Learning	Adaptive fault detection models	Policy learning	Learns optimal detection strategy
[12]	CWRU, IMS	Hybrid Domain Adaptation	Transfer learning for fault diagnosis	Combined domain features	Adapts well to different conditions
[13]	CWRU, XJTU-SY	Deep Transfer Learning	Cross-domain fault diagnosis	Deep feature extraction	Effective for varying operating conditions
[14]	CWRU	AI-based Fault Diagnosis	Comparison of AI techniques	Multiple feature representations	Evaluates different AI models
[15]	CWRU	Neural Networks	Time-domain feature extraction	Statistical features	Reliable classification
[16]	Industrial Gearbox	Resonance Demodulation	Early fault detection using signal processing	Frequency features	Detects early-stage failures

[17]	Rolling Bearings	High-Frequency Resonance	Vibration monitoring	Resonance frequency features	Effective for high-frequency faults

4. CHALLENGES AND FUTURE DIRECTIONS

Despite significant advancements in machine learning for bearing fault detection, several challenges remain that hinder widespread adoption and real-world implementation. Addressing these challenges and exploring future research directions can enhance the effectiveness and reliability of fault detection systems.

4.1 Challenges in Bearing Fault Detection

- Data Imbalance and Labeling Issues: Many publicly available datasets suffer from class imbalance, where healthy bearings dominate the data, making it difficult for machine learning models to learn faulty patterns effectively [9].
- Variability in Operating Conditions: Bearings operate under different speeds, loads, and environmental conditions, making it challenging to generalize a fault detection model across multiple settings [12].
- Sensor Noise and Data Quality: Vibration signals collected from bearings often contain noise and irrelevant information, affecting the accuracy of extracted features and classification results [11].
- Computational Complexity of Deep Learning Models: While deep learning techniques provide high accuracy, they require large computational resources and extensive labeled data for training, limiting their real-time deployment [6].
- Real-Time Fault Detection and Predictive Maintenance: Integrating fault detection models into real-world industrial settings requires real-time monitoring capabilities and robust decision-making algorithms [8].

4.2 Future Directions in Bearing Fault Detection

Despite their advantages, AI-based fault detection techniques face several challenges:

- Data Availability: High-quality labeled datasets are required for training ML/DL models, but real-world datasets are often scarce and imbalanced [9].
- Computational Complexity: Deep learning models require significant computational resources and specialized hardware, limiting their deployment in low-power environments [6].
- Generalization Issues: Models trained on specific datasets may struggle to generalize across different operational conditions and bearing types [12].
- Noise Sensitivity: Some ML models are highly sensitive to signal noise, which can impact fault detection accuracy [11].
- Integration with Industrial Systems: Deploying AI-based fault detection models in real-world industrial settings requires seamless integration with existing monitoring infrastructure [8].

4.3 Future Research Directions

- Advanced Data Augmentation Techniques: Using Generative Adversarial Networks (GANs) and synthetic data generation can help mitigate data imbalance issues and improve model robustness [9].
- Domain Adaptation and Transfer Learning: Enhancing model adaptability by leveraging knowledge from different datasets and operating environments can improve generalization and reduce dependency on extensive labeled data [10].
- Hybrid and Ensemble Learning Models: Combining multiple machine learning techniques, such as integrating traditional ML with deep learning, can improve fault classification accuracy and reduce computational complexity [7].
- Integration with Edge Computing and IoT: Deploying lightweight ML models on edge devices for real- time monitoring can enhance predictive maintenance strategies and minimize response times [8].
- Explainability and Interpretability of ML Models: Developing interpretable AI models that provide insights into decision-making can increase trust and adoption in industrial applications [13].

5. CONCLUSION

This literature survey presents a comprehensive review of machine learning and deep learning techniques for bearing fault detection. The analysis of IMS, NASA, CWRU, and XJTU-SY datasets highlights the effectiveness of AI-driven approaches in fault diagnosis [2], [4], [6], [7]. While deep learning models offer superior performance in feature extraction and classification, challenges such as computational complexity, data availability, and generalization issues remain significant hurdles [9], [12], [13].

Future research should prioritize the development of adaptable, interpretable, and efficient AI models that can be seamlessly integrated into industrial predictive maintenance systems [10], [11]. By addressing current limitations and leveraging advancements in AI, the field of bearing fault detection will continue to evolve, enabling more accurate, reliable, and cost-effective fault diagnosis solutions [8], [14].

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