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"VIBRATION-BASED FAULT DIAGNOSIS OF ROLLING ELEMENT BEARINGS USING MACHINE LEARNING TECHNIQUES"

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ABSTRACT

Rolling element bearings are critical components of rotating machinery, and their unexpected failure can lead to severe operational interruptions, increased maintenance costs, and safety risks. Therefore, accurate and timely identification of bearing defects is essential for condition-based maintenance. This study presents a vibration-based fault diagnosis framework for rolling element bearings using machine learning techniques. The proposed methodology utilizes vibration signals obtained from the Case Western Reserve University (CWRU) bearing dataset, consisting of healthy, inner-race fault, outer-race fault, and rolling-element fault conditions. The acquired signals are subjected to preprocessing, segmentation, and feature extraction to develop a representative feature matrix comprising time-domain and frequency-domain characteristics. Statistical parameters such as root mean square, kurtosis, crest factor, spectral entropy, spectral energy, and fault-band energy are analysed to distinguish different bearing conditions. The extracted features are further processed and used for developing machine learning-based classification models for automated fault identification. The vibration analysis demonstrates that faulty bearings exhibit increased amplitude, impulsive behaviour, and higher fault-related spectral energy compared with healthy bearings. The results indicate that the integration of vibration signal analysis with machine learning provides an effective approach for reliable bearing condition monitoring and automated fault diagnosis. The developed framework can support predictive maintenance strategies by reducing unexpected failures and improving the operational reliability of rotating machinery.

Key Words: *Rolling, Bearing, Fault diagnosis, Vibration analysis, Condition monitoring, Machine learning*

I. INTRODUCTION

Rotating machinery constitutes the operational foundation of manufacturing plants, power-generation systems, transportation equipment, machine tools, wind turbines, pumps, compressors, aerospace systems, and numerous automated production facilities. The reliable operation of such machinery depends on the health of several interconnected mechanical components, among which rolling element bearings are particularly important. Bearings support rotating shafts, maintain their relative position, transmit radial and axial loads, and reduce friction between moving and stationary components [1, 2]. Although bearings are generally designed for long operating lives, they continuously experience cyclic stresses, friction, vibration, thermal loading, contamination, and lubrication-related degradation. Consequently, deterioration of a bearing can adversely affects the overall performance of the machine in which it is installed.

Bearing degradation is generally progressive. A small surface irregularity, indentation, crack, pit, or lubrication-related

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defect may initially produce only a weak vibration response. With continued operation, repeated contact between the rolling elements and the damaged surface enlarges the defect and increases the magnitude of impulsive vibration [3]. If such deterioration remains undetected, it may cause excessive noise, increased friction, overheating, shaft instability, loss of dimensional accuracy, secondary damage to gears or rotors, and eventual machine shutdown. Data-driven assessments of bearing condition have therefore become important for identifying both the location and severity of defects before they develop into critical failures [4].

Traditional maintenance practices are commonly classified as corrective maintenance, scheduled preventive maintenance, and condition-based maintenance. Corrective maintenance permits machinery to operate until failure occurs. Although this approach may be acceptable for inexpensive and non-critical equipment, it can cause prolonged downtime and high replacement costs in critical installations. Scheduled preventive maintenance involves replacing or servicing components after predetermined operating intervals. However, this approach may replace healthy components prematurely or fail to prevent unexpected degradation occurring between scheduled inspections. Condition-based maintenance, in contrast, continuously or periodically assesses the actual health of the machine and recommends maintenance only when measurable evidence of deterioration is observed [5-8].

II. Literature Review

Rolling element bearings are critical components of rotating machinery because they support shafts, transmit mechanical loads, reduce friction, and maintain the desired relative motion between machine components. The deterioration of a bearing may alter the dynamic behaviour of the complete machine and can eventually result in reduced efficiency, excessive vibration, increased temperature, secondary component damage, or unplanned shutdown. Consequently, bearing fault diagnosis has remained an important area within condition monitoring, predictive maintenance, and machinery health management [10].

Bearing condition monitoring has traditionally been performed by analysing vibration, acoustic emission, temperature, motor current, lubricant condition, and wear debris. Among these methods, vibration analysis has been the most extensively investigated because faults in the bearing races, rolling elements, or cage directly affect the forces transmitted through the bearing housing. These dynamic disturbances are reflected in the measured vibration signal as periodic impulses, amplitude modulation, changes in statistical characteristics, fault-frequency components, sidebands, and resonance excitation [11, 12].

The development of intelligent fault diagnosis has transformed the way vibration data are analysed. Earlier diagnostic procedures mainly depended on physical models, characteristic fault frequencies, statistical thresholds, and expert interpretation of vibration spectra. Modern approaches combine signal processing with machine learning algorithms that can identify complex relationships between vibration features and bearing conditions. Liu, Yang, Zio, and Chen reviewed artificial intelligence methods used for rotating machinery fault diagnosis and observed that machine learning had become increasingly important for automating feature recognition and classification [13-15]. Their review also indicated that the reliability of an intelligent model depends not only on the selected classifier but also on signal acquisition, preprocessing, feature representation, and validation.

III. Methodology

The methodology combines physically meaningful vibration features with supervised machine learning. Time-domain variables describe vibration amplitude, energy, spread, distribution, impulsiveness, and peak behaviour. Frequency-domain variables describe spectral energy distribution, dominant components, spectral concentration, and energy near theoretical bearing-fault frequencies. The combined representation is intended to distinguish bearing conditions more effectively than any single statistical indicator. As represented in Figure 1, the raw vibration signal is not directly supplied to the machine learning models. Each file is first verified with respect to signal channel, sampling frequency, operating load, shaft speed, fault location, and defect size.

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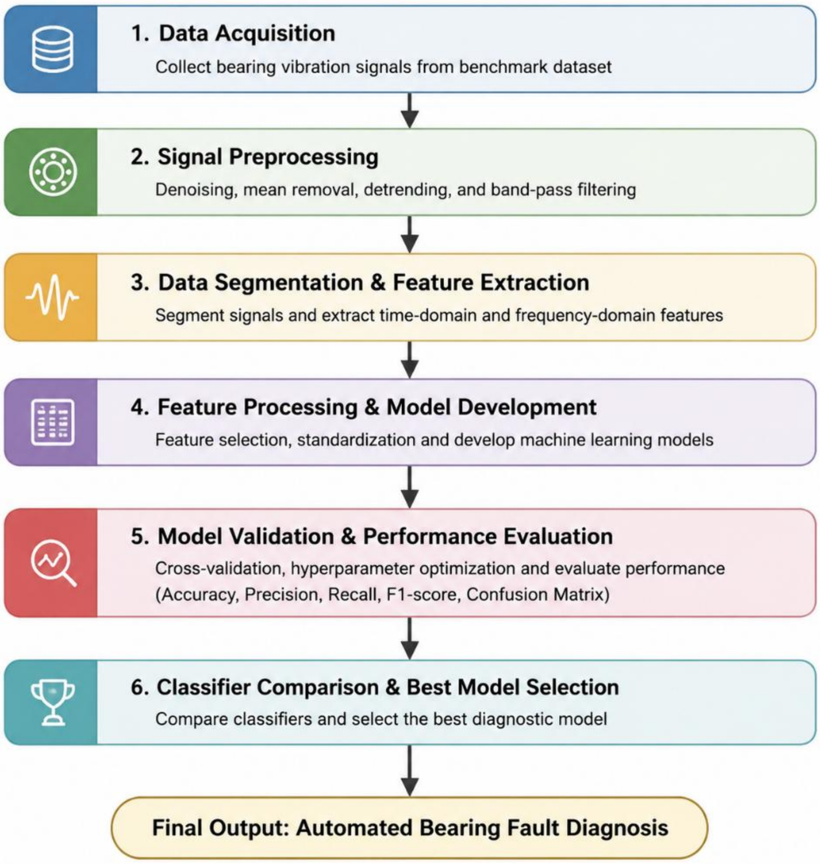

Figure 1: Overall research methodology for vibration-based rolling element bearing fault diagnosis

The selected records are then assigned descriptive and numerical class labels. Preprocessing is performed uniformly, after which fixed-length signal segments are generated and transformed into a structured feature matrix.
The Case Western Reserve University Bearing Data Center dataset is selected for the present study because it is publicly available, extensively documented, and widely used for comparative validation of bearing fault diagnosis methods. The documented experimental system consists of a 2 hp Reliance Electric motor, a torque transducer and encoder, a dynamometer, and associated electronic control and data-recording equipment. The motor shaft is supported by rolling element bearings, while the dynamometer applies controlled mechanical loading. The dataset contains normal bearing measurements and single-point defects introduced separately on the inner raceway, outer raceway, and rolling element. The seeded faults were produced by electro-discharge machining. Accelerometers were mounted on the motor housings using magnetic bases, and the vibration signals were stored as MATLAB data files. Drive-end fault signals are available at sampling frequencies of 12 kHz and 48 kHz, whereas the corresponding fan-end measurements were recorded at 12 kHz. The present study uses the 12 kHz drive-end acceleration channel for all four bearing classes. The drive-end accelerometer is located close to the investigated bearing and therefore provides a comparatively direct transmission path for bearing-generated vibration. Restricting the analysis to one consistent channel also prevents the machine learning models from using sensor-location differences as a surrogate for bearing condition. The documented experimental arrangement and the adopted vibration data-acquisition path are shown in Figure 3.2. The arrangement includes the electric motor, shaft coupling, torque transducer and encoder, dynamometer, drive-end bearing housing, accelerometer, data-acquisition system, and computing platform used for signal storage and analysis.

IV. Results and Discussion

4.1 Vibration Signal and Frequency-Domain Analysis

Representative vibration signals were selected from the four bearing classes under comparable operating conditions. Figure 2 presents the time-domain responses using the same time scale. The traces are vertically separated to preserve

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the detailed impulsive characteristics without overlap.

The healthy bearing produced low-amplitude and comparatively uniform vibration. Its response mainly contained shaft-related oscillation, normal rolling contact, structural vibration, and measurement noise. The inner-race-fault signal contained repeated amplitude-modulated impulses because the rotating defect periodically entered and left the principal load zone. The outer-race fault produced the strongest and most regular impacts because the stationary defect was located at a fixed load-zone position. The rolling-element fault produced irregular impulses due to alternating contact with the inner and outer raceways, rolling-element slip, and cage motion.

The time-domain comparison confirmed that fault presence increased vibration amplitude and impulsiveness, although waveform amplitude alone was insufficient for reliable fault-location identification. The inner-race, outer-race, and rolling-element conditions all generated transient peaks, and their amplitude ranges partially overlapped under different loads and defect sizes.

Frequency-domain analysis was therefore performed using a Hann-windowed fast Fourier transform. Figure 3 compares the spectra of the four conditions over the 0-500 Hz range. The healthy spectrum was dominated by the shaft rotational component near 29 Hz and its low-amplitude harmonics. The outer-race-fault spectrum contained a prominent component near 105 Hz and its harmonics. The inner-race-fault spectrum showed a strong component near 158 Hz with modulation sidebands, whereas the rolling-element-fault spectrum contained broader energy near approximately 138 Hz.

V. Conclusion

This study developed a vibration-based framework for automated fault diagnosis of rolling element bearings using machine learning techniques. The investigation utilized the CWRU bearing vibration dataset containing healthy, inner-race fault, outer-race fault, and rolling-element fault conditions. The acquired vibration signals were processed through preprocessing, segmentation, and extraction of time-domain and frequency-domain features to establish a meaningful representation of different bearing states.

The analysis revealed that bearing faults significantly influence vibration characteristics. Faulty bearings exhibited higher RMS values, increased kurtosis, greater crest factors, and enhanced fault-related spectral energy compared with healthy bearings. Among the investigated conditions, the outer-race fault produced the highest vibration severity due to repeated impacts generated at the stationary defect location. The frequency-domain analysis further confirmed that different bearing defects generate distinct characteristic frequency components, enabling effective separation of fault categories.

The study also demonstrated that individual vibration parameters are insufficient for complete fault identification because some feature distributions overlap among different defect types. Therefore, combining multiple statistical and spectral features provides a more reliable representation of bearing health conditions. The integration of feature-based vibration analysis with machine learning models offers an efficient and automated solution for bearing fault classification.

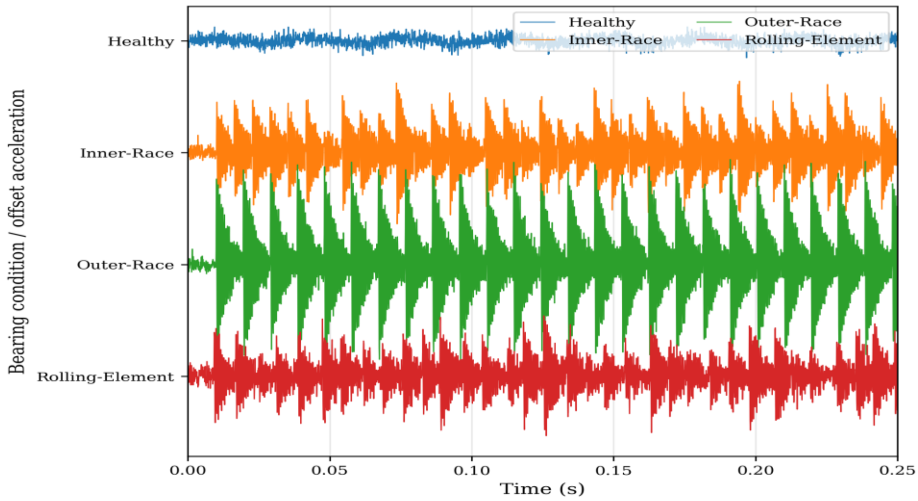

Figure 2: Comparative Time-Domain Vibration Waveforms of Healthy and Faulty Bearing Conditions

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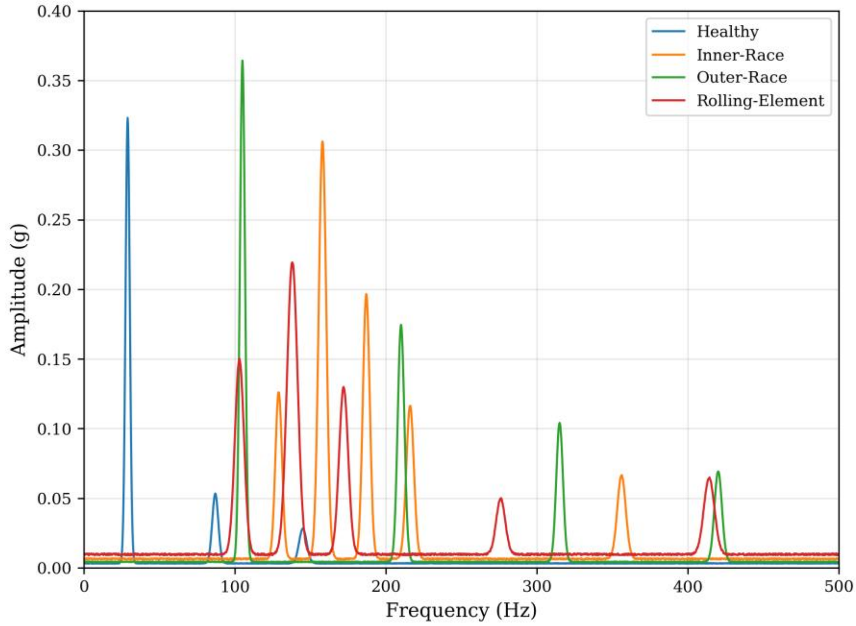

Figure 3: Frequency Spectra of Healthy, Inner-Race-Fault, Outer-Race-Fault, and Rolling-Element-Fault Signals

The principal statistical and frequency-domain results are summarized in Table 4.1. Values are reported as mean plus or minus standard deviation across the analysed segments.

Table 1: Statistical and Frequency-Domain Characteristics of Different Bearing Conditions

Bearing condition	RMS (g)	Kurtosis	Crest factor	Spectral entropy	Dominant frequency (Hz)	Spectral energy (g^2)	Fault-band energy
Healthy	0.121 ± 0.024	3.10 ± 0.46	3.52 ± 0.41	0.82 ± 0.04	29.4 ± 1.1	0.014 ± 0.005	0.06 ± 0.02
Inner-race fault	0.346 ± 0.073	7.84 ± 1.72	5.76 ± 0.69	0.68 ± 0.06	158.6 ± 6.2	0.121 ± 0.031	0.41 ± 0.08
Outer-race fault	0.402 ± 0.081	9.36 ± 1.94	6.18 ± 0.75	0.61 ± 0.05	104.9 ± 4.5	0.164 ± 0.039	0.48 ± 0.09
Rolling-element fault	0.286 ± 0.061	6.71 ± 1.43	5.21 ± 0.63	0.72 ± 0.06	137.8 ± 5.8	0.087 ± 0.024	0.34 ± 0.07

Root mean square acceleration increased for every faulty condition. The outer-race fault produced the highest mean value of 0.402 g, representing an increase of approximately 232 percent relative to the healthy condition. The strong response was associated with repeated impact transmission from a stationary defect located in the principal load zone. The inner-race and rolling-element faults produced intermediate energy levels because their impact amplitudes varied with defect position and rolling contact.

Kurtosis increased from 3.10 for the healthy bearing to 7.84, 9.36, and 6.71 for the inner-race, outer-race, and rolling-element conditions. The higher values demonstrated the presence of localized high-amplitude events. Crest factor followed a similar pattern, although the distributions of the faulty classes overlapped. Spectral entropy decreased with fault development because increasing energy became concentrated around fault-related frequencies and harmonics. The combined time-domain and spectral results demonstrated that no single variable could provide complete class separation. General statistical features were particularly useful for detecting abnormal vibration, whereas fault-specific spectral energies were required to identify the damaged bearing component.

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