



BEARING FAULT DIAGNOSIS: DATASETS, SIGNAL PROCESSING PARADIGMS, AND INTELLIGENT DIAGNOSTIC FRAMEWORKS

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ABSTRACT

Rolling element bearing faults are among the leading causes of failure in rotating machinery, leading to unexpected downtime, increased maintenance costs, and reduced system reliability. Consequently, significant research efforts have been devoted to developing effective bearing fault diagnosis techniques. This paper presents a comprehensive and structured review of bearing fault diagnosis studies, focusing on three key aspects: experimental data sources, signal analysis techniques, and expert-system-based diagnostic approaches. Both publicly available benchmark datasets and customized experimental setups reported by individual researchers are systematically examined to highlight their characteristics, fault types, operating conditions, and suitability for fault diagnosis and prognostics. The review further categorizes commonly adopted signal processing techniques applied to vibration and related signals, including time-domain, frequency-domain, and time-frequency-domain methods, with particular emphasis on feature extraction strategies used to characterize bearing defects. In addition, expert systems ranging from traditional machine learning algorithms to advanced deep learning models are reviewed and compared based on their reported usage trends and diagnostic capabilities. By consolidating fragmented research outcomes, this review provides a unified perspective on current practices in bearing fault diagnosis and identifies key directions for future research toward more reliable, generalizable, and industry-oriented diagnostic frameworks.



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I. INTRODUCTION

Rotating machines are crucial in the modern industrial system including manufacturing, petrochemical plant, aviation, and the chemical process [1]. The basic parts of these rotating machineries consist of the shaft, bearing, stator and rotor, which are the components of these machines. Bearings assist in rotating shafts and allow the smooth and efficient work. Failure in a bearing system can greatly influence the performance of a machine, leading to unwanted down time and decreased effectiveness [2]. As bearings account for a major portion of failures in rotating machinery, their condition is intimately connected with system reliability [3]. These failures may be localized, minor, or large-scale, and when ignored, could change into expensive failures. So condition-based monitoring and fault diagnosis have become important constituents of the contemporary maintenance strategies [4]. Continuous observation of equipment condition and detection of defects prior to breakdown is called condition monitoring. Vibration monitoring is among the most efficient ways of assessing the health of the bearings. The vibration signals hold data relating to the condition of the mechanical system, both in term of operating condition and presence of bearing defect [5]. The vibration data can be continuously monitored, and the defect of the bearing can be identified at the initial stage, which facilitates the routine maintenance of the bearings and reduces the risk of the catastrophic failure to a minimum [6]. Bearing fault diagnosis (BFD) involves several important steps.

First, data is collected through sensors that monitor vibration, temperature, and acoustic emissions, the most frequent one being the vibration sensor. This captured data for vibration is then pre-processed to eliminate noise and emphasize fault-relevant frequencies, often achieved through techniques like filtering or envelope analysis. The next phase is feature extraction, where both time-domain and frequency-domain characteristics such as Root Mean Square (RMS), peak-to-peak value, mean-to-peak value, and fault frequencies (e.g., BPFO, BPFI) are identified. In order to enhance the accuracy of detecting faults, statistical methods, machine learning models, or pattern recognition methods are implemented to identify the type of faults. Figure 1 illustrates the steps that are entailed in BFD.

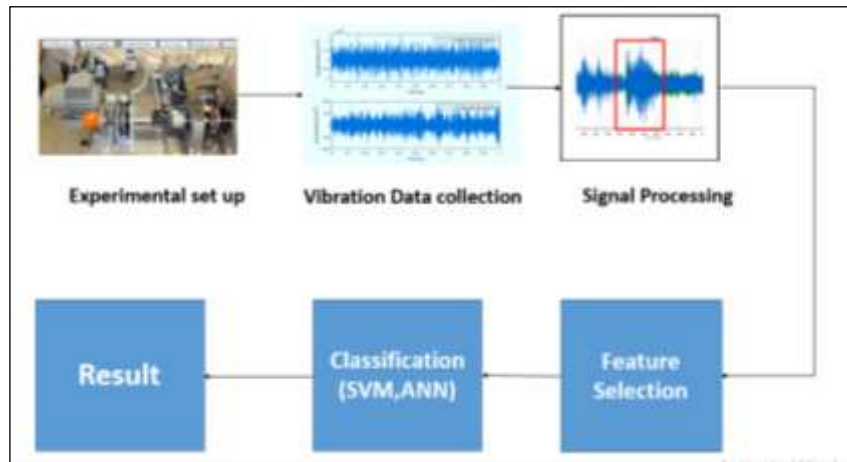


Figure 1: Step for fault diagnosis of bearing.
Source: Authors, (2026).

Even though the number of review papers on the topic is quite large, new surveys are necessary due to the constant implementation of innovative practices and technologies in this field, as well as the comparison of multiple signal processing methods and machine learning approaches with their advantages and disadvantages. The objectives of this article are to briefly introduce vibration analysis, some recent advances in experimental setups to collect data, fault diagnostics, and bear fault classification, and compare various signal processing methods and machine learning approaches. A systematic screening was performed, which involved the removal of duplicates, assessment of titles and abstracts and the full-text analysis to make sure that they are relevant and of good quality. Articles that studied bearing vibration, fault diagnosis, signal-processing techniques, datasets, as well as review articles were retained. A total of 83 papers were studied in this research. Of these, only original experimental and methodological studies are summarized in Table 2, while review articles and dataset descriptor papers are discussed separately and not included in the table. The main contributions of this review are: 1. A structured taxonomy of datasets, signal processing, and diagnostic models 2. A comparative analysis of methodological trends over the last decade; 3. Identification of key research gaps limiting industrial applicability; and 4. Future research directions toward robust and transferable diagnostic systems.

II. EXPERIMENTAL SETUP FOR DATA ACQUISITION

The quantity and quality of datasets have a direct impact on the performance of different fault detection methods. Existing studies can be broadly categorized into those utilizing publicly available benchmark datasets and those employing customized experimental setups.

II.1 Open-Source Datasets

The following are a few publicly available bearing datasets that are used to diagnose and detect bearing faults:

II.1.1 CWRU dataset

The CWRU dataset is one of the most widely used benchmarks for bearing fault diagnosis. Figure 2 shows the experimental setup for CWRU dataset. Bearing vibration signals were recorded at various motor speeds under different bearing defect conditions [7],[8].

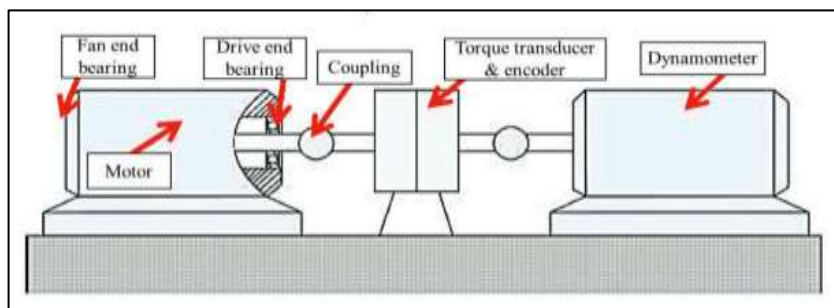


Figure 2: Practical setup for CWRU.
Source: [9].

The experiments were performed on a motor–bearing test rig consisting of a motor, a sensor, and a dynamometer. Artificial single-point defects of different diameters were created on the test bearings using EDM, with SKF-6205 and SKF 6203 bearings used for smaller faults and NTN bearings were used for larger faults. Data were recorded through a multi-channel system and processed in MATLAB, with different sampling rates (12kHz, 48 kHz). Speed and load information came from the torque transducer. Since outer race defects remain stationary, their position relative to the load zone strongly affects the vibration response. Therefore, tests were carried out with the defect located at 3, 6, and 12 o'clock positions to study this influence [7],[9]. Although the CWRU dataset is widely used and well-annotated, its reliance on artificially seeded faults under steady-state laboratory conditions limits its representativeness for real industrial fault evolution.

II.1.2 Paderborn university dataset

A dedicated test rig was constructed at Paderborn University to collect experimental data for developing condition monitoring techniques for damaged bearings using motor current signals. To examine the effects of different parameters and confirm the resilience of the condition monitoring techniques under these circumstances, the ring was operated under a variety of operating situations. The dataset includes several bearing test conditions created by varying motor speed, applied torque, and radial load [10].

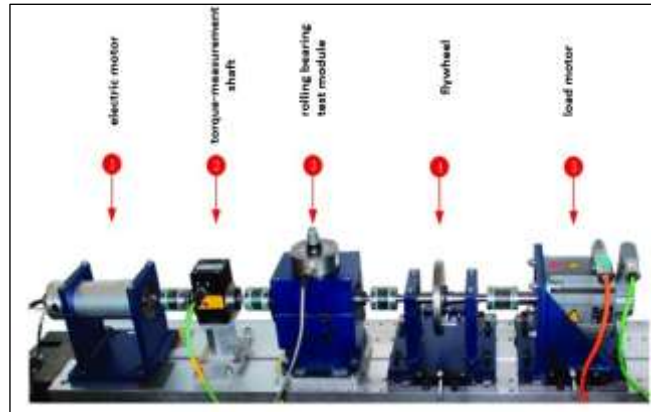


Figure 3: Practical setup for Paderborn University.
Source: [11].

The test rig runs at a 1500 rpm and force in the radial direction of 1 kN and a torque of 0.7 Nm in the basic configuration (Set No. 0). In the next set, each parameter is gradually reduced until the speed is 900 rpm, the force is 400 N, and the torque is 0.1 Nm. Twenty measurements, each lasting four seconds, were taken for every arrangement. Throughout all of the experiments, the temperature was maintained between 45 and 50 degrees Celsius. A total of 32 bearings were evaluated; 12 of these had artificial damage, and 14 of them had damage from accelerated lifetime tests. The dataset lists different faulty bearings according to where the damage occurred. Bearings labelled OR1 to OR5 outer race flaws, including plastic deformation characterized by indentation and fatigue pitting. The inner race faults of bearings with labels IR1 to IR5 are only identified by fatigue pitting [11]. While this dataset introduces natural and accelerated degradation, it is still limited by a single test rig and specific operating conditions, which may restrict generalization to other industrial machines.

II.1.3 Pronostia dataset

An experimental platform called PRONOSTIA was created to test and validate bearing defect detection, diagnosis, and prediction techniques. Its main objective is to give real-world data that follows ball bearing degradation throughout the course of their whole existence, up till failure. It was developed at the FEMTO-ST institute's AS2M department. Many trials can be carried out in a single week to speed up bearing degradation, which allows the completion of multiple studies in a shorter time period [12]. A rotating mechanism, a deterioration generation system that exerts radial load on the bearing being tested, and a measurement system are the three main parts of PRONOSTIA, as shown in Figure 4.

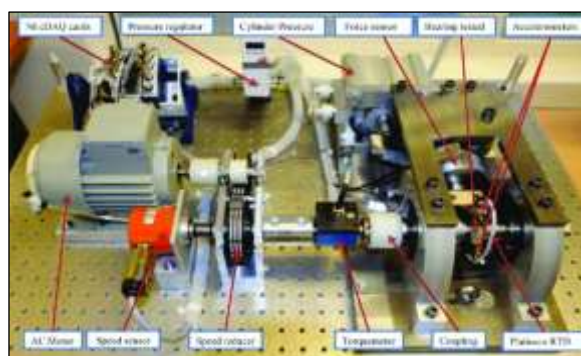


Figure 4: Practical setup for PRONOSTIA platform.
Source: [12].

The PRONOSTIA bearing dataset provides detailed information on the performance and degradation of a 6804 ball bearing under varying conditions. It records data at a high sampling frequency of 25,600 Hz, capturing the bearing's behavior at different load and speed condition. The bearing is tested for a maximum runtime of 126 minutes. The dataset focuses on natural faults, including wear in the balls or races of the bearing, which simulates real-life degradation over time. This data is valuable for studying bearing performance and predicting potential failures [12]. The main limitation of PRONOSTIA is the restricted variety of bearing types and fault modes, which may constrain the transferability of prognostic models trained on this dataset.

II.1.4 IMS dataset

In the IMS dataset, four bearings (Rexnord ZA-2115) are mounted on the shaft, which is run with the help of belt drive. A force of 26.68 kN is applied on the bearing in the radial direction with the help of a spring mechanism. Every bearing was pressure-lubricated. Two accelerometers (PCB 353B33) were installed on the housing for data collection. Figure 5 displays the location of the sensor. Breakdown occurs after the bearings have gone beyond their intended lifecycle of 100 million revolutions [13]. Although valuable for prognostics, the IMS dataset includes a limited number of bearings and fault types, which restricts its applicability for multi-fault classification studies.

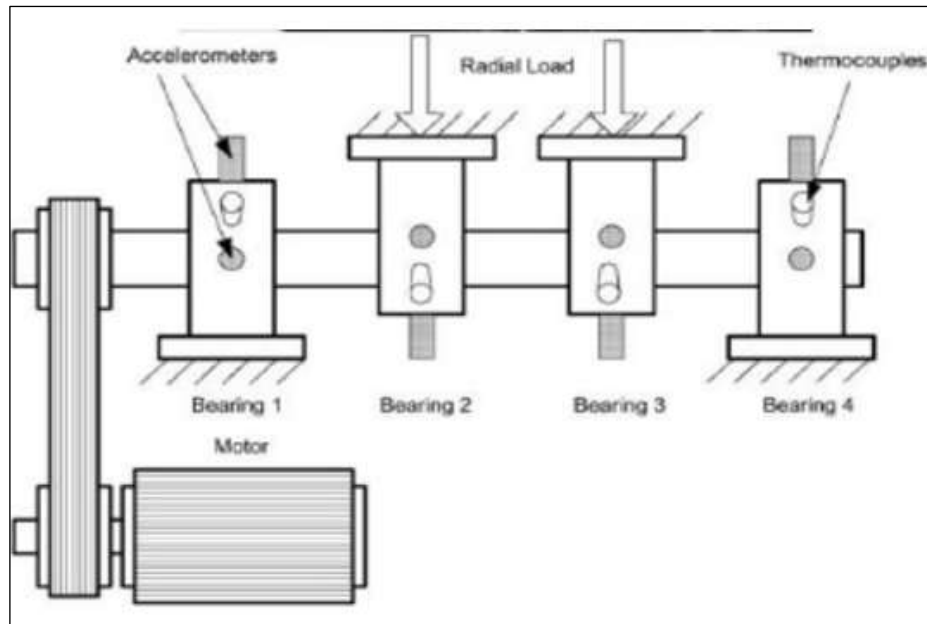


Figure 5: Practical setup for IMS dataset.

Source: [13].

II.1.5 HUST Bearing Fault Dataset

The HUST bearing fault dataset contains both artificially and naturally occurring bearing defects. However, since generating natural faults is more complex, the defects in this dataset were artificially created. The focus is on electric motors running under low loads, and the bearings used for defect creation are of types 6204, 6205, 6206, 6207, and 6208. The dataset includes only a single fault at different places, like the ball, outer race, and inner race. Combination of defects are also considered for this dataset. Figure 6 shows this defect in the bearing at different places. The initial size of the fault is a 0.2 mm microcrack created by using a wire cutting machine.

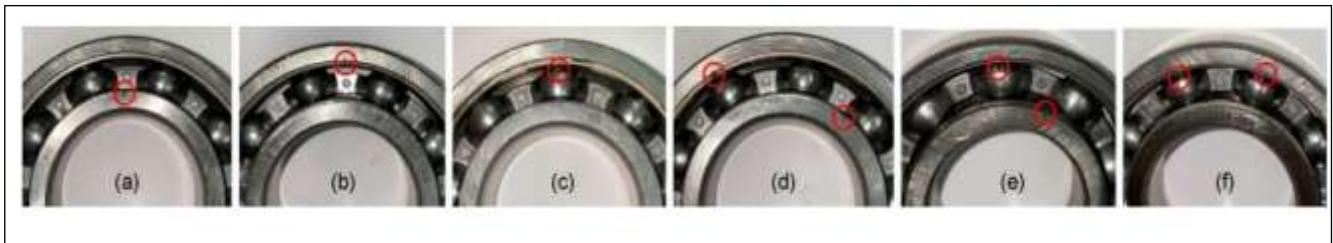


Figure 6: Bearing Defect for HUST bearing Test.

Source: [14].



Figure 7: Practical setup for HUST bearing Test.

Source: [14].

Figure 7 shows the setup for the HUST dataset. The dataset includes 30 prototype defective bearings tested under three different load variations. Additionally, the dataset includes vibration data for defective bearings during a 5-second run-up period. The vibration signals observed during run-up can help identify potential bearing issues early on, especially in high-power electric motors that require time to start. Notably, all the data was gathered at a sampling rate of 51.2 kHz, enabling precise recording of signal variations [14]. Since most defects in this dataset are artificially induced, the vibration patterns may differ from those produced by naturally evolving faults in industrial environments.

II.1.6 XJTU-SY bearing dataset

This dataset contains vibration data collected from rolling element bearings operating under three different working conditions with different rotational speeds and radial loads. The signals were measured using horizontal and vertical accelerometers with a sampling frequency of 25.6 kHz, and data were recorded every minute until the bearings failed. Unlike many datasets that use artificially introduced defects, this dataset captures the natural degradation process of bearings. Because of this, it is widely used in research on remaining useful life prediction, and it is often treated as a benchmark dataset in prognostics studies [15]. Despite its usefulness for degradation modeling, the dataset is limited by a fixed sensor configuration and controlled loading, which may not reflect complex field conditions. Figure 8 shows the experimental set up for XJTU-SY Bearing Dataset.

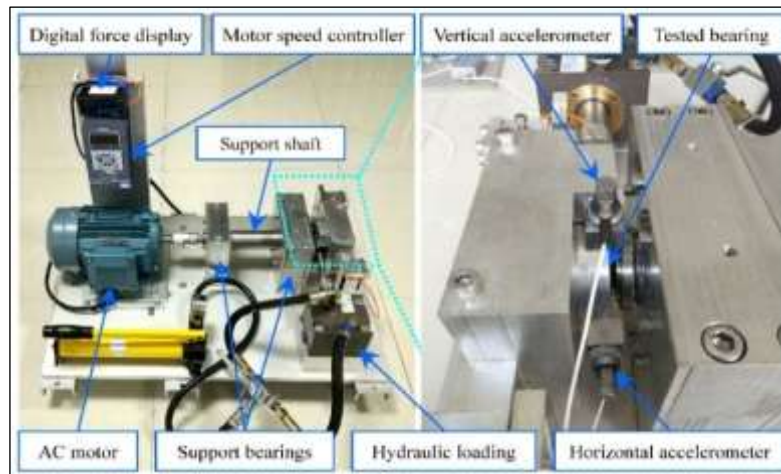


Figure 8: Experiment setup and Failure bearings XJTU-SY Bearing Dataset.

Source: [15].

II.1.7 University of Ferrara dataset

The University of Ferrara bearing dataset is a new run-to-failure dataset, which has become a focus of bearing health monitoring studies. The experimental resources (self-aligning ball bearings) were used in this setup by being run under controlled conditions of speed and load until failure, and vibration measurements were recorded during the lifetime of the bearing. The dataset provides long-term degradation signals, which are useful for studying fault progression, designing health indicators, and developing remaining useful life prediction models [16]. Due to the realistic operating conditions and the high-quality vibration measurements obtained in the experiments, the dataset is considered to be a useful benchmark to current data-driven and deep learning-based bearing prognostics research.

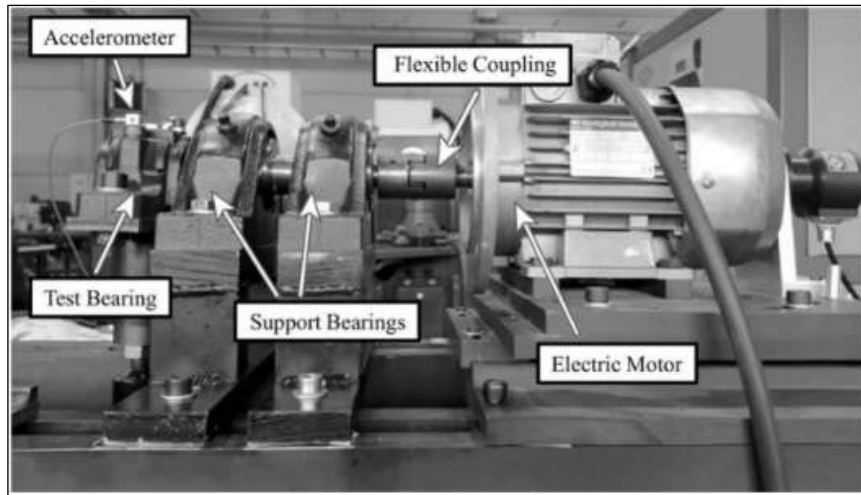


Figure 9: Experiment setup for University of Ferrara.

Source: [16].

II.1.8 Vishwakarma university, Pune dataset

In this research, a comprehensive and organized dataset was created to facilitate the diagnosis and detection of rolling bearing faults in dynamic operational conditions. The experiment was carried out at Vishwakarma Institute of Technology, Pune, with ball bearings (type 608-2RSH & SKF) for testing purposes at three different motor speeds and at two load levels (no load and full load with a 1.25 kg weight and a gearbox). The test ring for performing the experiment is shown in Figure 10. Faults with varying sizes (0.3 mm depth, 0.5 mm breadth) were produced at various locations in the bearing. Vibration data was acquired through two accelerometers of 100 mV/g sensitivity installed in horizontal and vertical positions on the bearing housing to collect vibration data comprehensively. Data collection was conducted at a sampling rate of 12 kHz at 6-second intervals for every condition by an Instruments USB-6212 DAQ system [17]. It provides real laboratory measurements suitable for fault diagnosis, feature extraction, and machine learning-based classification studies.

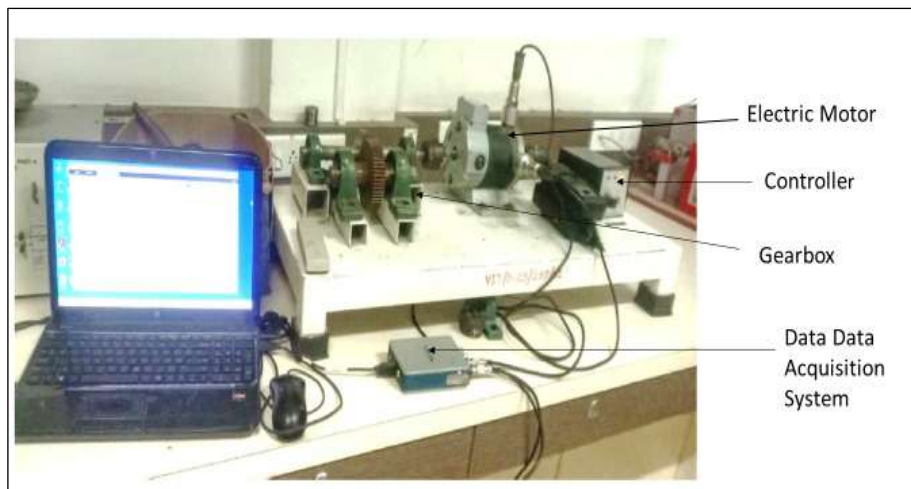


Figure 10: Experimental setup Vishwakarma University.

Source: [17].

Figure 11 presents the distribution of bearing fault diagnosis studies according to the datasets employed. The CWRU dataset is the most extensively used, reflecting its wide acceptance as a benchmark due to its availability, clear fault annotations, and controlled experimental conditions. The IMS and PRONOSTIA datasets also receive considerable attention, as they support degradation analysis and prognostics in addition to fault diagnosis. Moderate usage of the Paderborn and XJTU-SY datasets indicates growing interest in more complex and realistic operating conditions.

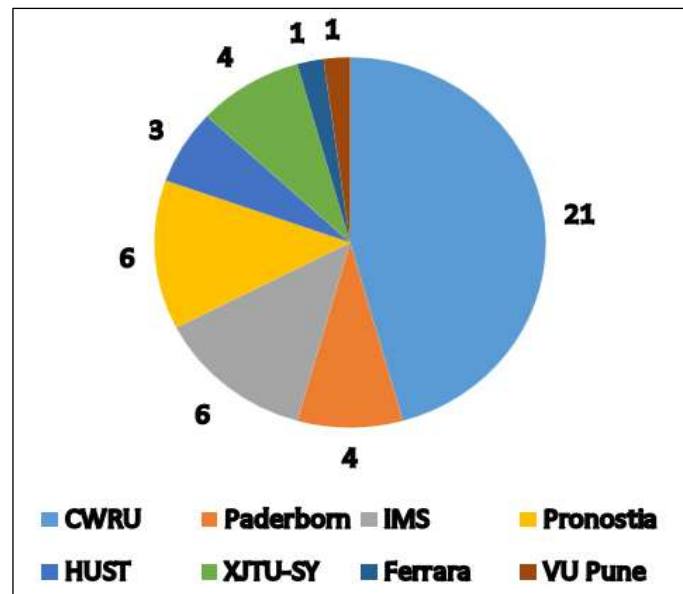


Figure 11: Dataset usage distribution.

Source: Authors, (2026).

In contrast, datasets such as HUST, Ferrara, and VU Pune are used less frequently, highlighting limited availability or narrower application scope. Overall, the distribution demonstrates a strong reliance on a small number of benchmark datasets, suggesting the need for broader validation using diverse and real-world datasets. This Table 1 summarizes the key publicly available bearing datasets by highlighting their operating conditions (speed and load), fault generation strategy, bearing type, and intended application. It clearly distinguishes datasets used mainly for fault diagnosis with localized induced defects from those designed for prognostics using run-to-failure progressive faults, helping researchers select appropriate data sources for their studies.

Table 1: Comparison of publicly available bearing datasets.

Sr.No	Dataset	Speed variation (rpm)	Load	Fault Type Category	Bearing Type	Utilization
1	CWRU	1730 to 1797	0HP, 1HP, 2HP	Localized induced faults	6205, 6203	Fault diagnosis
2	Paderborn	900 to 3000	400N,1000N, 3000N	Localized induced, Progressive continuous faults run-to-failure	6203	Prognostics, Fault diagnosis
3	IMS	2000	6000lbs	Progressive ,continuous faults run-to-failure	ZA2115	Prognostics
4	Pronostia	1550 to 1800	4kN,4.2kN,5kN	Progressive,continuous faults run-to-failure	6804	Prognostics
5	HUST	1400	0HP,200W,400W	Localized induced faults	6204 to 6208	Fault diagnosis
6	XJTU-SY	2100 to 2400	10kN, 11kN, 12kN	Progressive,continuous faults run-to-failure	LDK UER204	Prognostics
7	University of Ferrara	2400	3kN, 4kN, 4.7kN, 5kN	Progressive, continuous faults run-to-failure	1205 ETN 9	Prognostics
8	Vishwakarma University, Pune, India	950,1250,1950	1.25 kg mass and a gearbox	Localized induced faults	608-2RSH & SKF	Fault diagnosis

Source: Authors, (2026).

While benchmark datasets such as CWRU and IMS have enabled rapid methodological development, their limited variability in operating conditions and artificially seeded faults restrict generalization to industrial settings. In contrast, run-to-failure datasets like PRONOSTIA and XJTU-SY support prognostics research but are limited by cost, availability, and sensor diversity.

II.2 CUSTOMIZED EXPERIMENT SETUP USED BY RESEARCHER

In spite of these advantages, benchmark datasets are not able to exhaust all of the work related to real-life operating conditions and have encouraged numerous researchers to develop specialized experimental systems. In order to working around the shortcomings of benchmark datasets, a number of researchers have created specific experimental configurations that are unique to individual machines, operating conditions, and fault cases.

They consist of a motor, coupling, bearing housing and adjustable loading mechanism in which the speed, load and lubrication can be accurately controlled. Seeded defects are typically introduced using machining techniques to create known fault conditions to use in diagnostic studies, e.g., inner-race, outer-race, or ball defects. According to [18] use a magnetic ring to provide load and place two bearings (ER16) one healthy and one with seeded faults as shown in Figure 11(a). In [19] measures the thermal data with infrared imaging camera as depicted in Figure 11(b). In this experiment, dead weights are used in the introduction of the applied load. Patil et al. (2017) use a spring-balance system that allows varied loading conditions to be controlled. In their study, Ambrozkiwicz et al. develop a special experimental rig that will produce quality vibration data to analyze the behavior of bearings in various internal clearances [20]. Create an experimental facility, which is high-speed and not loaded at all as shown in Figure 12(c), to examine bearing dynamics at large rotational speeds [21].

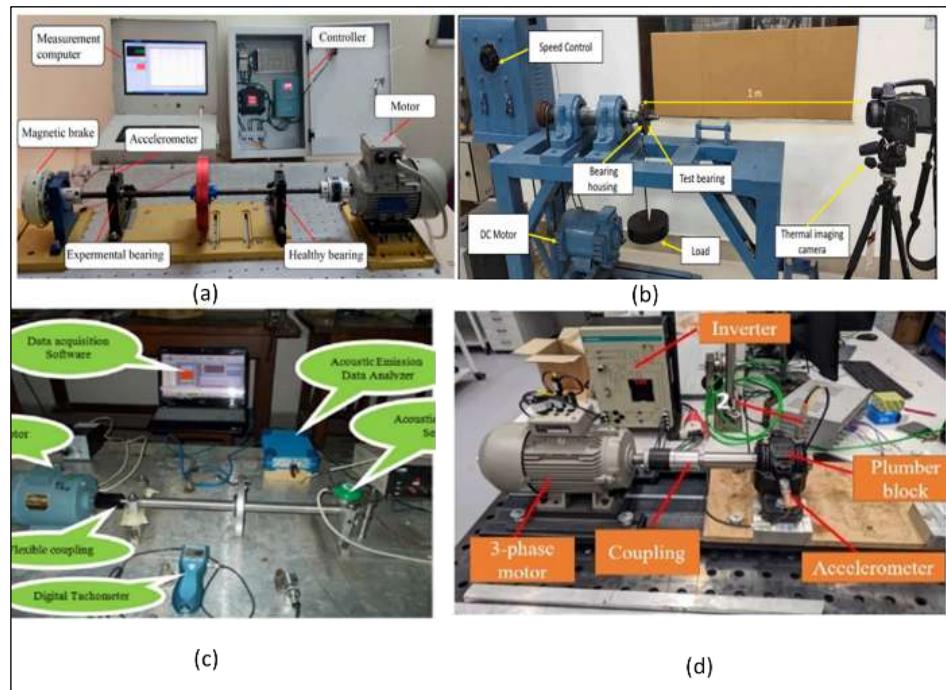


Figure 12: customized experiment setup.

Source: [18-21].

Across these studies, key experimental parameters typically include rotor speed, applied load or torque, bearing defect type, and bearing geometry, which are systematically varied to evaluate their influence on vibration characteristics and fault signatures. All in all, benchmark datasets that are publicly available have greatly aided the development of methods in bearing fault diagnosis; nonetheless, their controlled practices and lack of variability limit their applicability in the real world. In their turn, customized experimental setups are more realistic, yet have low standardization and reproducibility.

This creates a need to have more standardized, diverse, and generally open-shared industrial datasets to overcome the disconnect between laboratory work and real-world implementation. A detailed summary of the experimental conditions, feature extraction techniques, and diagnostic models used in the reviewed studies is presented in Table 2.

Table 2: Summary of reviewed bearing fault diagnosis studies.

SR No	References	Speed in rpm	Bearing condition	Type of bearing	Feature extracting and Signal Processing Technique	Expert System
1	Yang et al [22].	680 to 2460	Healthy and Artificial damage	NSK 6205 DDU	Grayscale images	Fusion Attention Network (FAN), CBMA-ViT, Swin Transformer
2	Gong et al [23].	900, 1500	Healthy, Natural Damage, Artificial damage	6203	STFT	least squares method (LSM), DT-based fault diagnosis framework
3	Geetha et al [24].	900, 1500	Healthy, Natural Damage, Artificial damage	6203	Time Domain Feature Extraction	k-NN, DT and SVM
4	Peng et al [25].	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	Variational Mode Decomposition (VMD), Canberra distance feature extraction, Symmetrized Dot Pattern (SDP) image conversion	rule-based threshold decision system

5	Siddique et al.[26]	1800	Healthy and Artificial damage	FAG NJ206-3	Mel-transformed scalograms	FOX Optimizer and ANN
6	Du, N. T. et al. [18]	780 to 1464	Healthy and Artificial damage	ER 16	Fourier-based Synchro Squeezing transform (FSST) and Principal Component Analysis (PCA).	Nearest Neighbor Classifier
7	Kiakojour et al.[27]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	cepstrum pre-whitening (CPW)	SVM, ANN
8	Singh et al. [28]	900, 1500	Healthy, Natural Damage, Artificial damage	6203	Nonlinear Mode Decomposition (NMD), Hilbert transform (HT), time-domain feature	
9	Ogaili et al. [29]	60	Healthy and Artificial damage	Ball Bearing	Time Domain Feature Extraction	ANN
10	Shi et al.[30]	2100, 2250, 2400	Healthy, Natural, continuous run-to-failure	LDK UER204	FFT	SVM ANN WDCNN
11	Zheng et al. [31]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	Legendre multi wavelet transform (LMWT), Hilbert transform	-
12	Iunusova et al. [32]	2000	Healthy and Artificial damage	Rexnord ZA-2115	Time Domain Feature Extraction	Knowledge-based approach, TSFEL and TSFESH
13	Maliuk et al. [33]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	WPT	LDA
14	Lu, J et al. [34]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	image feature extraction	Gramian angular field (GAF),
15	Ambrozkie wicz et al.[20]	3000	Healthy(different radial internal clearances)	NTN 2309SK	Variational Mode Decomposition (VMD)	Extreme. Gradient. Boosting, Light. Gradient. Boosting., Extra Trees, RF
16	Qin et al.[35]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	generalized S-transform (GST)	Two-channel CNN
17	Esaki Muthu et al. [36]	1765, 1770, 1775, 1780	Healthy and Artificial damage	Ball bearing	Wavelet Scattering Transform (WST),	CNN model.
18	Qiu et al. [37]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	waveform coding matrix (WCM),two-dimensional principal component analysis (2DPCA)	nearest neighbor classifier (NNC)
19	He, F., & Ye [38]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	Wavelet Packet Transform	Convolutional Neural Network
20	Toma et al. [39]	900, 1500	Healthy, Natural Damage, Artificial damage	6203	DWT	XGBoost, RF, ANN
21	A. Kumar et al. [40]	-	Healthy and Artificial damage	Cylindrical Roller bearing NBC: NU205E	WPT	Deep convolutional neuralnetwork (DCNN)
22	Choudhary et al. [19]	1140, 1380, 1740	Healthy and Artificial damage	bearing (BB1B4202 05) of SKF	Time Domain Feature Extraction and feature extraction from thermal images.	ANN, CNN
23	Li et al. [41]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	deep convolution residual feature extractor	deep neural-network-based diagnostic decision system
24	Nishat Toma et al. [42]	1500	Healthy and Artificial damage	Roller bearing	DWT	RF and XGBoost

25	Chen et al. [43]	1800	Healthy and Artificial damage	GB203	frequency-temporal-logic, defining the time-frequency	Bayesian neural networks
26	Zhao et al. [44]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	Weighted Euclidean Affinity Propagation	two layers of unsupervised feature extractor
27	Tang et al. [45]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	Time Domain +FFT Feature Extraction	GL-mRMR-SVM model, CNN, SVM
28	Li. G et al. [46]	2100, 2250, 2400	Healthy, Natural, continuous run-to-failure	LDK UER204	wavelet packet transform	Complex trees, , SVM, KNN
29	Dhomad et al. [47]	1500	Healthy and Artificial damage	6304 D	Motor Current Signature Analysis (MCSA)	ANN
30	Piltan et al. [48]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	Residual signal energy (time-domain based)	Decision tree-based advanced fuzzy SMO
31	Wang et al. [49]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	Continuous Wavelet Transform (CWT)	Capsule Neural Network
32	Li, S. et al. [50]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	kernel. method for K-means, Euclidean distance and approaches in Hierarchical	Hierarchical rule-based decision system
33	Li, X et al. [51]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	automatically extract features based on MMD Classifier	Multi-kernel maximum mean discrepancy with softmax classifier
34	Song et al. [52]	800	Bearing flaking at inner and outer race.	Roller Bearing of 2.2 kW power motor.	signal histogram. and genetic programming, Statistical filter.	SVM, ANN, CNN
35	Wang, R et al. [53]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	automatically extract features based on CNN	RNN, CNN
36	Zhang, A. et al. [54]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	automatically extract features based on CNN	WDCNN, SVM
37	Zheng, L. [55]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	Time Domain Feature Extraction	Kernel extreme learning machine (K-ELM)
38	Li, X. et al. [56]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	automatically extract features from deep stacking LS-SVM	SVM (LS-SVM), Deep stacking based on S-RL
39	Sadoughi et al. [57]	CASE STUDY 1 (600 to 1800)	Healthy and Artificial damage	Roller Bearing	Spectral Kurtosis (SK) , Hilbert transform)	physics-based convolutional neural network (PCNN), CNN, ANN,SVM
40	Mao et al. [58]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	frequency domain Feature Extraction	Deep Output Kernel Learning (DOKL)
41	Duong et al. [59]	500	Healthy and Artificial damage	FAG NJ206-3-TVP2	time-domain feature, Stacked Denoising Autoencoder (SDAE	SVM, NMEC-DNN (multi-label DNN)
42	Yang, Y. et al. [60]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	frequency domain feature	Deep neural network.
43	Li, K. et al. [61]	600 to 1200	Healthy and Artificial damage	Roller bearing	VMD	Improved kernel extreme learning machine
44	Yao et al. [62]	500 to 900	Healthy and Artificial damage	6203	wavelet packet transform	DT and Learning Vector Quantization (LVQ) neural network model
45	Huang et al. [63]	1800,1500,1650,	Healthy and Artificial damage	Cylindrical roller bearing of NU250E	Time-domain features, Wavelet Packet Energy, Nuisance Attribute Projection (NAP)	Back Propagation Neural Network (BPNN), Support Vector Data Description (SVDD)

46	Tong et al. [64]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	local characteristic-scale decomposition ,Redundant second-generation wavelet packet transform , energy ratio.	Extreme Learning Machine (ELM)
47	Kanai et al. [65]	1500	Healthy and Artificial damage	BALL, SKF1208ET 9	Time and frequency Domain	ANN
48	Boudiaf et al.[8]	1730, 1750, 1772, 1797	Healthy and Artificial damage	SKF 6203, SKF6205	Wavelet Transform, FFT, Envelope Analysis (EA), Cepstrum Analysis (CA)	
49	Vakharia et al.[66]	1000 to 2000	Healthy and Artificial damage	SKF 6205	Wavelet Transform, Multiscale Permutation Entropy (MPE)	SVM and self-organizing maps
50	Safizadeh et al. [67]	1000, 1200, 1600	Healthy, outer race, ball	SKF 6307	Principal Component Analysis (PCA)	KNN (K-Nearest-Neighbor)
51	Pandya et al.[5]	250 to 1500	Healthy and Artificial damage	SKF 6205	Hilbert–Huang Transform (HHT),	APF-KNN

Source: Authors, (2026).

Having reviewed the available datasets and experimental configurations, the next step in the diagnostic pipeline is signal processing and feature extraction, which transforms raw sensor data into meaningful fault indicators.

III. SIGNAL ANALYSIS AND FEATURE EXTRACTION TECHNIQUES

Signal processing and feature extraction play a key role in fault diagnosis, particularly in sensor-based monitoring systems that use vibration, temperature, and acoustic emission signals. These methods transform raw measurements into information useful in the detection, localization, and classification of faults in rotating machines like bearings, motors, and turbines. Time-domain, frequency-domain, and time–frequency analyses are commonly used as the initial steps in signal processing and are often combined with envelope analysis.

Time-domain analysis studies statistical properties of the signal, such as mean, root mean square (RMS), peak-to-mean ratio, kurtosis, and skewness, which indicate variations in the signal energy and impulsiveness [5,21]. The frequency-domain analysis, which commonly employs Fast Fourier Transform (FFT), decomposes the signal into spectral elements and aids in the detection of periodic fault patterns and characteristic bearing frequencies, e.g., BPFO and BPFI. Spectral density and dominant frequency components are commonly used to detect mechanical defects [30,58,60-59, 68-67].

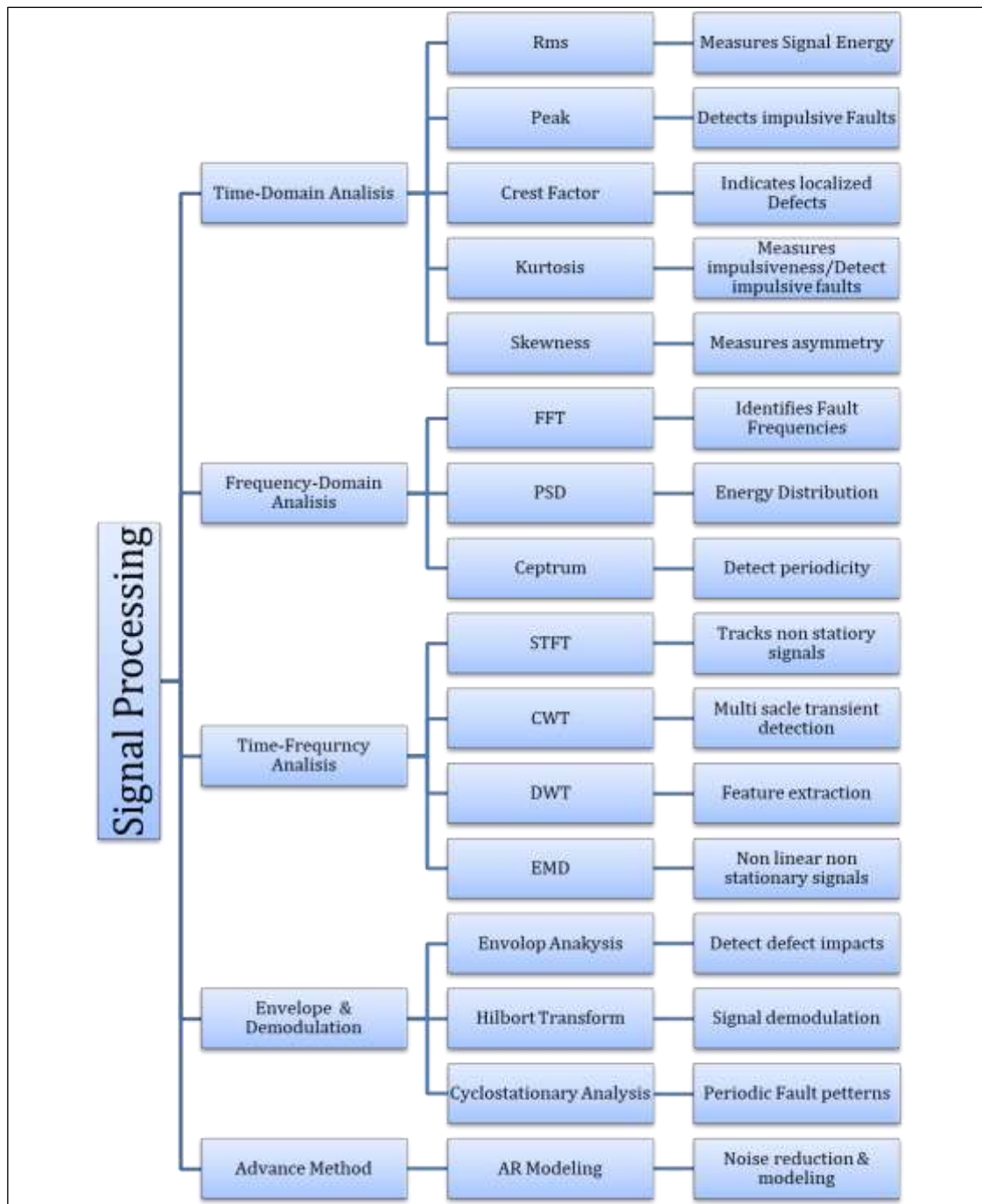


Figure 13: List of signal processing techniques.

Source: Authors, (2026).

Time–frequency techniques describe how frequency content varies with time and are therefore suitable for non-stationary and transient signals. Wavelet techniques offer multi-resolution representations of various frequency bands, whereas the Short-Time Fourier Transform (STFT) uses localized Fourier analysis in short time windows [30],[33],[38]. The Hilbert–Huang Transform (HHT) is commonly used to decompose nonlinear and non-stationary signals into intrinsic mode functions, enabling the isolation of transient faults [5],[28]. Following signal processing, feature extraction converts the processed signals into numerical indicators used for fault detection, classification, and prediction. Common time-domain statistics include RMS and peak-to-peak value, kurtosis, and skewness, but frequency-domain statistics can be used to describe fault-related spectral content and energy distribution [21],[69].

Integrating features from multiple domains provides a more robust representation of bearing condition, especially under variable speed and noisy operating environments. Figure 13 illustrates commonly used signal processing methods, and Table 2 summarizes feature extraction and signal analysis techniques reported in the literature. The representative studies that use such techniques are chosen and discussed below. Recent studies indicate a growing reliance on advanced time–frequency analysis and advanced feature extraction methods in bearing fault diagnosis. According to [23], demonstrate that Short-Time Fourier Transform (STFT) offers powerful representations for detecting localized defects, although its performance depends on window selection and working conditions. According to [27] argue that the explicit extraction of bearing characteristic frequencies and their harmonics that is performed under noisy conditions is worthwhile, and feature engineering, in this case, must be carefully parameter-tuned and domain-informed.

In [18],[25]-26 also explain that time-frequency representations can be combined with dimensionality reduction and machine learning to increase classification accuracy when variables vary in speed and nonstationarity, at the cost of more model complexity and data. There is also interest in nonlinear and adaptive signal decomposition. According to [28] show that nonlinear mode decomposition is vulnerable to the severity of faults, yet its computational complexity can be a limiting factor in real-time implementation. As demonstrated by [31]-32, envelope-based demodulation still can be used to detect early faults, although its effectiveness highly depends on proper band selection and levels of noise. According to [32],[21], hybrid methods that include wavelet-based analysis improve robustness, statistical indicators, and variational mode decomposition improve a more robust analysis, but still, they are provided with a manual-designed feature and dataset-specific tuning. According to [37] reported that lightweight statistical features combined with simple classifiers can be used to perform efficient fault detection, making them appealing for industrial applications; however, their applicability to other machines and operating conditions remains limited. Overall, these studies indicate that although deep learning-based frameworks improve diagnostic accuracy, challenges related to data dependency, parameter sensitivity, interpretability, and generalization to industrial environments remain unresolved.

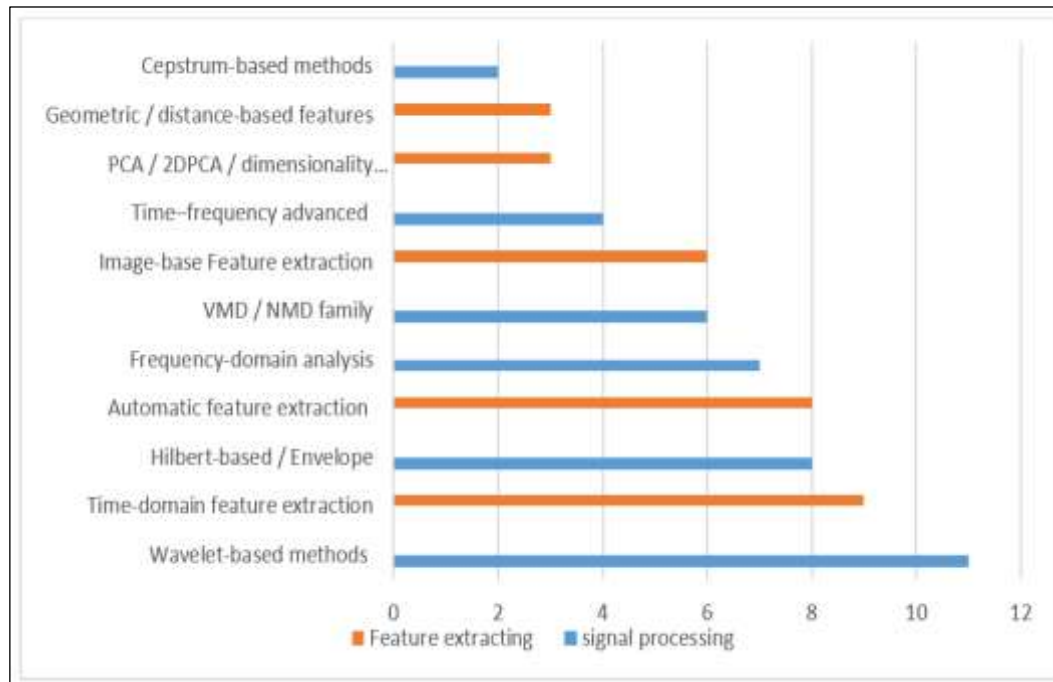


Figure 14: Distribution of signal processing techniques used in reviewed studies.

Source: Authors, (2026).

Figure 14 consolidates the spread of different methods applied in feature extraction and signal processing in the analyzed literature and shows that wavelet-based and time-frequency approaches are still predominant since they have a high localization ability of non-stationary vibration signals. Statistical features of time domain and envelope analysis are also popular due to their simplicity, low computing power as well as physical interpretability. However, during the last few years, the number of applications of deep feature extraction techniques using convolutional neural networks and autoencoders, especially via image-based representations of signals, has grown at a rapid pace, as a response to the move away from handcrafted features and towards data-driven diagnostic models.. Although these deep learning approaches are effective for modeling complex and nonlinear fault patterns, they typically require large labelled datasets and often lack physical interpretability, which limits their acceptance in safety-critical and industrial applications. Once discriminative features are extracted, intelligent classification models are required for accurate fault diagnosis, motivating the application of expert systems discussed in the next section.

IV. EXPERT SYSTEMS FOR FAULT DIAGNOSIS

Expert systems play a crucial role in BFD by enabling automated identification and classification of faults based on extracted signal features. Figure 15 presents the classification of expert systems applied to rolling element bearing fault diagnosis. In this study, expert systems are categorized into knowledge-based, data-driven, and probabilistic approaches according to their reasoning and learning principles. Knowledge-based systems use expert-defined rules and fuzzy logic to infer fault conditions. Data-driven systems extract fault information directly from vibration data and employ machine learning and deep learning techniques such as ANN, SVM, CNN, and RNN. Probabilistic expert systems incorporate uncertainty modeling through methods such as Bayesian networks, hidden Markov models, and Kalman or particle filters. This section reviews the most commonly used expert systems in bearing fault diagnosis and highlights their reported strengths and limitations.

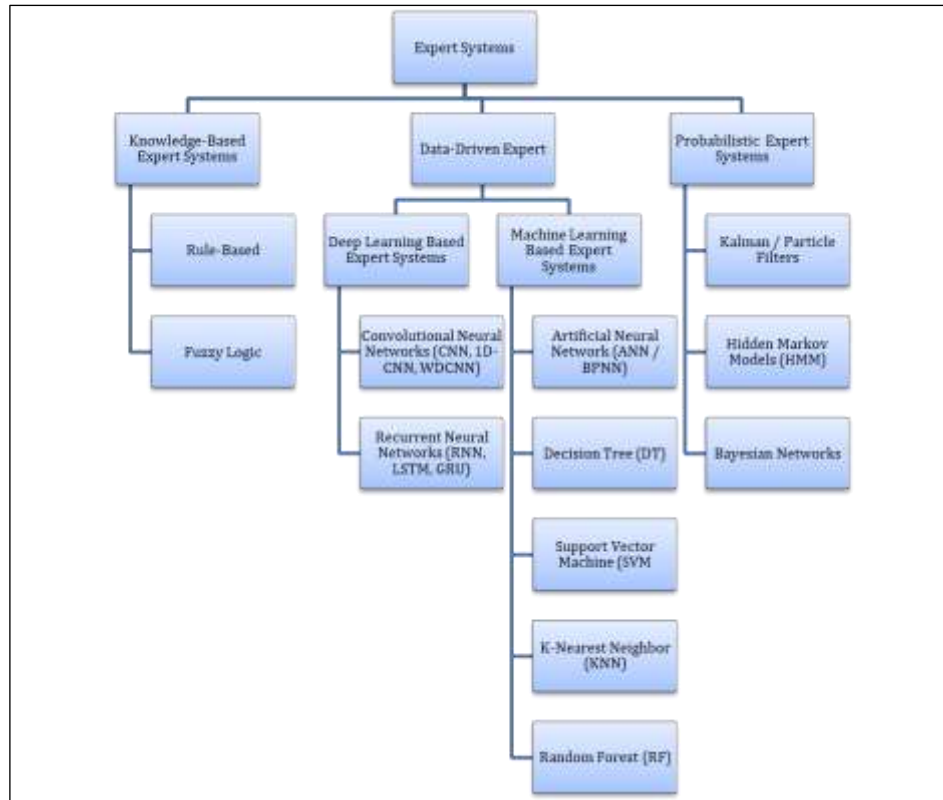


Figure 15: classification of expert for bearing fault diagnosis.
Source: Authors (2026).

IV.1 THE ARTIFICIAL NEURAL NETWORK (ANN)

An artificial neural network (ANN) consists of interconnected processing units arranged in multiple layers that learn patterns from data to solve complex tasks. ANNs are modeled after the way biological brains process information. It generally includes an input layer, several hidden layers, and an output layer. Each neuron receives input, assigns a weight and bias, and then passes the result through an activation function. The input layer accepts initial data and sends it to the hidden levels. Hidden layers manipulate data via mathematical transformations. The output layer then produces the final decision or classification. Figure 16 shows the diagram for ANN. ANNs are suitable for modelling intricate and nonlinear relationships within datasets[19],[65]. Key studies utilizing Artificial Neural Networks (ANNs) for bearing fault diagnosis are summarized to illustrate their application and performance.

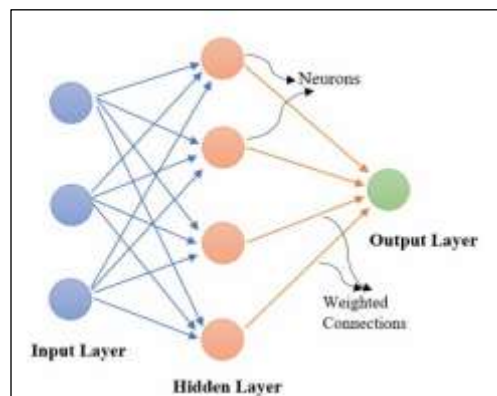


Figure 16: The schematic diagram of neural network.
Source: [68].

A number of studies demonstrate the effectiveness of artificial neural networks (ANNs) to use in BFD in various sensing and working conditions. According to [65], reveal that ANN-based models are capable of not only reflecting how the defect size, load, and speed affect vibration responses but can also be combined with model-based estimation to perform predictive maintenance, but their accuracy still requires proper system modeling to work and the quality of training data. According to [69] contrast ANN with SVM and logistic regression with feature wavelet and indicate that although ANN has high accuracy, its quality is inferior in comparison with SVM, which implies that ANN is not always the best solution, and it is still vulnerable to the choice of features and problem formulations. In [29] demonstrate that ANN models based on statistical features can be highly reliable for fault classification and may outperform traditional methods; however, their adaptability to different machines and operating conditions is limited due to their dependence on handcrafted features.

According to [47] suggests further that ANN is capable of identifying faults of bearing caused by the signature of motor current, which demonstrates the opportunity of an alternative non-vibration-based sensing, but the binary classification framework limits it to scenarios involving more than two faults. Overall, these studies confirm the strong diagnostic capability of ANN-based approaches, while also emphasizing challenges related to feature dependence, scalability to multi-fault conditions, and generalization across operating environments.

IV.2 SUPPORT VECTOR MACHINE (SVM)

SVMs are supervised learning models used for classification and regression tasks. It works by drawing an invisible line, called a hyperplane, that separates different groups of data as clearly as possible. The points closest to this line, called support vectors, play a key role in shaping it. SVM is flexible—it can handle simple straight-line separations or more complex curved boundaries using kernel functions like linear, polynomial, or RBF. It performs effectively with data that has many features and usually avoids overfitting by keeping the margin between groups wide. While it can be slow for very large datasets and needs careful tuning, SVM is a reliable tool for many real-world applications, from image recognition to fault detection. Figure 17 shows the structure of SVM. Notable SVM-based bearing fault diagnosis studies are discussed here.

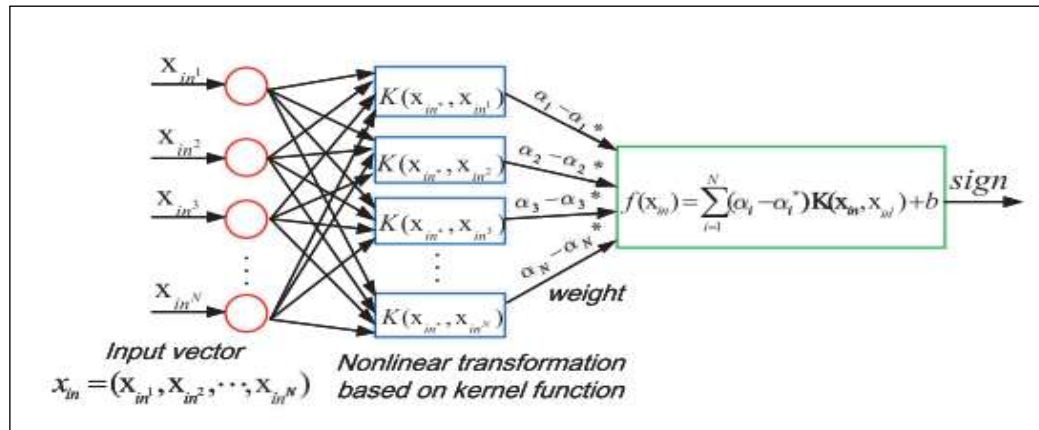


Figure 17: Structure of SVM-based fault diagnosis.

Source: [70].

SVM-based and hybrid learning are still in the limelight in the diagnosis of rolling bearing faults, where the amount of training data is limited and where the number of features is large. According to [51] circumvent these shortcomings of manual feature engineering by suggesting a deep-stacking LS-SVM model that trains discriminative representations on raw signals that get improved classification performance, but the additional depth of the model also comes with higher computational costs, which can limit the scale of such a model to a real-time industrial environment. On this note, [71] show that a combination of attentive feature choice and hyperparameter optimization can contribute to SVM efficiency and accuracy to a large degree and unveil the high sensitivity of SVM performance to feature design and parameter adjustment simultaneously. In order to enhance diagnosis ability, a number of studies combine SVM with other signal processing or learning methods [72] demonstrate that back-propagation neural networks and SVM help to better represent the features before classification and achieve higher performance than the single models but the multi-stage pipeline makes the system more complex and necessitates strict integration.

On the same note, [27] indicate that two-stage SVM-based frameworks have very high accuracy in fault detection and classification, although its proposed extrapolation across different machines without retraining has not been sufficiently validated under a variety of industrial scenarios. In [73] also explain that the artificial fish-swarm algorithm (AFSA) to optimize the SVM hyperparameters is better in convergence speed and accuracy than the traditional PSO-SVM methods. In addition to bearings specific applications, as illustrated by [70] a fault diagnosis approach for photovoltaic arrays using support vector machines, showing that SVM can effectively identify faults in complex engineering systems. Even though their study focused on PV systems, the results suggest that SVM is a reliable classifier and can be applied to fault diagnosis of rotating machinery such as rolling bearings. According to [70] also attest to the fact that SVM is always the best in comparison to unsupervised methods like self-organizing map in fault classification tasks. Overall, these studies indicate that while SVM-based and hybrid approaches offer strong accuracy and robustness, their performance remains highly dependent on feature quality, parameter selection, and dataset characteristics. Consequently, careful validation beyond laboratory benchmarks and under diverse operating conditions is essential for reliable industrial deployment.

IV.3 KNEAREST NEIGHBOR CLASSIFIER (KNN)

The KNN based methods are mainly used in a situation where simplicity, low training cost, and quick deployment are necessary. Pandya et al. (2013) show that KNN with HilbertHuang Transform and intrinsic mode function analysis can be effective to detect early bearing faults and the performance can be enhanced with the help of asymmetric proximity functions; however, the method is still sensitive to the quality of features and noise [5]. Wang, H. et al. (2020) also indicate that KNN can also be effectively used within a real-time online fault diagnosis system, though scalability and computational efficiency could become the barriers to the success of the use of the method with growing dataset size [74]. KNN performance has been suggested to be improved with hybrid frameworks [67-68,46-47].

According to [33], integrating wavelet packet characteristics with IF-LDA enhances the separability of classes and allows KNN to classify with high accuracy, however, multi-stage pipelines with that type of performance demand more complex systems and handcrafted features. The proposed improved k-nearest neighbor (EKNN) architecture by [75] combines sparse filtering to obtain automatic feature removal and a reconstruction-based correlation vector to select the nearest neighbors more adaptively and, thus, enhance the classification performance and stability over classical KNN in rotating machinery fault detection. According to [76], a k-NN-based framework can be used to detect and classify faults in power transmission systems quickly, and the distance-based analysis of the neighbor is an effective approach to identify the type of fault with a high level of accuracy and low computation costs in a power transmission system depending on different system conditions. Overall, these studies indicate that while KNN-based methods offer simplicity and interpretability, their performance is highly dependent on feature representation, dimensionality reduction, and data quality, which constrains their robustness and scalability in complex industrial environments.

IV.4 CONVOLUTIONAL NEURAL NETWORKS (CNN)

CNN is a type of deep learning model that excels at understanding images and visual data. It works by using convolutional layers to automatically identify important features, like edges, shapes, and textures, from raw input. These are often followed by pooling layers, which simplify the information while keeping the essential patterns. CNNs can recognize complex structures by learning step by step, making them very effective for tasks like image classification, object detection, and video analysis. Unlike traditional methods, CNNs do not need manual feature extraction, which saves time and improves accuracy. They are widely used in applications such as medical imaging, facial recognition, and self-driving cars [77],[78].

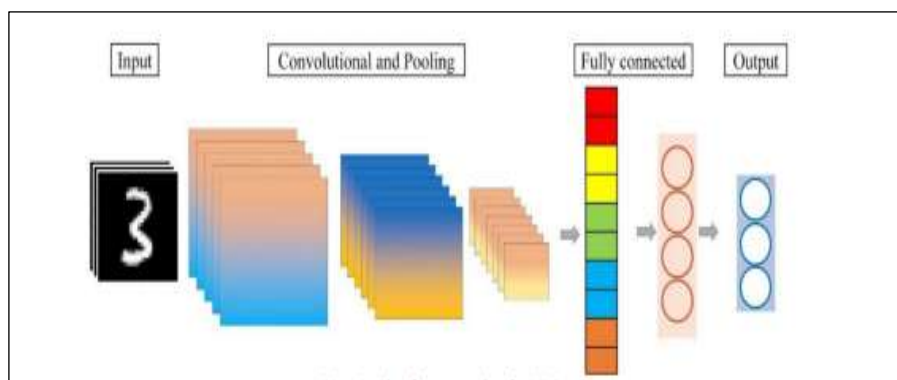


Figure 18: The framework of CNN.
Source: [78].

According to [36] demonstrate that CNN-based diagnostics can be trusted to detect bearing scratches in induction motors at different rotational speeds by reducing the overlap of features and enhancing the separability of the faults, yet these metrics are still dependent on the quality and representativeness of the training data. According to [35] build upon this concept, suggesting a two-channel CNN model that combines both FFT and generalized S-transform representation to handle the imbalance in data and missing spectral information and still benefits with more stable and accurate results, yet again using hand-designed signal transformation. Proposed a deep learning-based method for bearing defect severity assessment using time–frequency images obtained from continuous wavelet transform of vibration signals. A DCNN automatically extracts relevant features from these images, eliminating the need for manual feature design.

The method was tested on defects of varying sizes in different bearing components and achieved high accuracy under constant-speed conditions [40].According to [77] reported that combining CNN-extracted features with predefined frequency-based indicators significantly improves bearing fault diagnosis using motor speed signals, while reducing reliance on expensive vibration sensors and environmental sensitivity. Conversely, by [57]-58 incorporate physical knowledge into a CNN that is grounded on physics in order to enhance interpretability and reduce overfitting. According to [79] fed CNN with bidirectional LSTM to simultaneously learn both spatial and temporal fault properties, with high accuracy on benchmark data, but poor validation in true industrial environments. To optimize the process of selecting hyperparameters and improve the accuracy of fault classification, by [38] combine the wavelet packet transform with a convolutional neural network that is optimized with a simulated annealing algorithm. Their performance on the CWRU dataset shows that they perform better than the SVM, BP neural networks, and non-optimized CNN models.

IV.5 RECURRENT NEURAL NETWORK (RNN)

RNN is an algorithm that processes sequential data (text, speech, or sensor data) in a deep manner. It is characterized by the most important feature, a memory that stores past information, which is used in determining future predictions. The memory enhances activities such as speech recognition, language processing, and time series forecasting. Nevertheless, conventional RNNs have difficulties with sequences of excessive length; advanced versions like LSTM or GRU can overcome this problem by learning temporal features automatically, without separation of features. RNNs are favored when the order and context of data are important. According to [53] suggest a new method of rolling-bearing fault diagnostics, reforming a neural-network architecture based on searching for reinforcement learning. Their model is based on two components: a controller model that is implemented as an RNN and child models that instantiate the design selections that are determined by the controller. It has been demonstrated that the method can automatically produce effective neural-network designs, with enhanced classification accuracy, less expert intervention, and less manual design time.

The article by [80] examines an RNN implemented to classify the failures of the bearing of an induction motor driving a residential water pump. None of the conventional mathematical models can easily address bearing defects; hence, the authors apply an RNN-based solution. They use a Fast Fourier Transform (FFT) to obtain features of the stator current waveform of the IM and serve as inputs to the RNN to identify faults. There are four fault types that are used, including normal (AN), front fault (FF), rear fault (RF), and all fault (AF). The error rate is reduced through training, and the error value has a range of 0.1-0.2 percent as a result of testing, indicating a high accuracy and viability in the real world.

IV.6 DECISION TREE (DT)

The decision tree (DT) is a machine learning algorithm that is applied to classification and regression. It illustrates views of decisions as a tree, in which every internal node represents a test of a feature, every branch is an indication of the test outcome, and every leaf is a final prediction. The tree is constructed by splitting the data recursively by the best features that are able to separate the target, specifying the criteria to be either Gini impurity, entropy, or mean squared error. DTs are simple and easy to visualize, which makes them useful in making data-based choices. Nonetheless, overfitting can be observed in deep trees; thus, methods such as pruning or ensembles (e.g., Random Forest, Gradient Boosting) are more typically used to boost performance [81].

Using data on Qatar University, diagnose and predict bearing failures. Vibration samples of bearings having different faults are tested with three machine-learning frameworks: DT, extreme gradient booster (XGBoost), and random forest (RF). The accuracy of the DT is 82%, and it is rated with the use of the F1 score, precision, and recall.

While decision trees are simple and interpretable, they did not perform as well as XGBoost in this case, particularly with noisy and high-dimensional data. Overall XGBoost achieves 92% accuracy due to its effective handling of data complexity, feature importance analysis, and overfitting mitigation [81]. In their study, in [39] propose a decision-tree-based advanced fuzzy SMO (AFSMO) model as a fault detector in rotary machines in rolling-element bearings that are nonlinear and uncertain. The approach initially controls the system using a fuzzy ARX-Laguerre model, and then the SMO controller of fault error detection (FEDI) is designed. AFSMO limits chattering and enhances accuracy, and a TS fuzzy logic algorithm leads to further finer fault approximation. AFSMO is controlled by a decision tree, which offers high precision in fault detection with regard to crack categories and motor speed. On the CWRU vibration dataset, AFSMO has also been shown to be effective in fault diagnosis of industrial bearings compared to previous ASMO and SMO models and is quite robust even with varying operating conditions, thus making it highly applicable to the industrial bearing fault diagnosis.

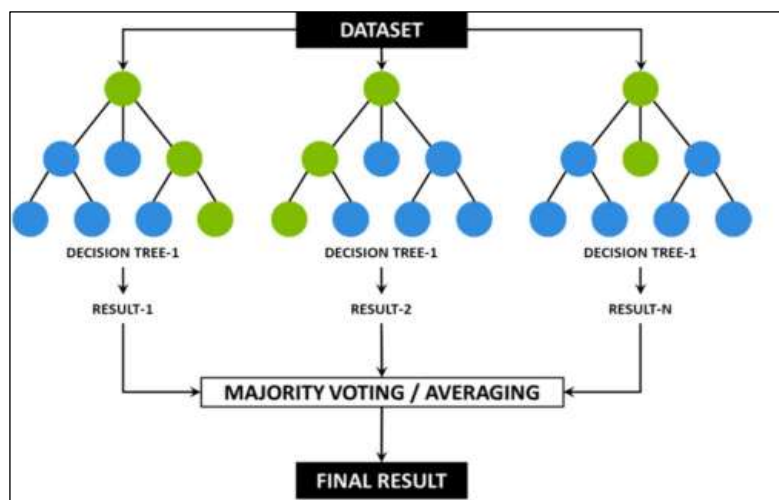


Figure 19: Random Forest algorithm based on DT.

Source: [81].

The decision tree is regarded as a fundamental element of the random forest at [82] to detect rolling-bearing problems. The tree divides the feature set recursively according to certain criteria, creating a decision path to diagnosis. Training is initiated by using a single tree, and its performance is evaluated using held-out samples. The experiment indicates that adding more trees, e.g., 50 trees, increases the classification accuracy, and the random forest gives 94.4% recognition compared to 88.8% when using one tree. This proves that a large number of decision trees are used to enhance the success of the random forest considerably. According to [83] examined the use of decision-tree-based machine learning models for fault diagnosis in industrial systems. The authors compared several tree-based classifiers, including the Extra Trees ensemble method combined with feature selection techniques. The experimental results showed that tree-based ensemble models achieved very high classification accuracy, indicating their strong capability for fault identification. Overall, the study confirmed that decision-tree-based classifiers are efficient, interpretable, and suitable for generalized fault diagnosis applications.

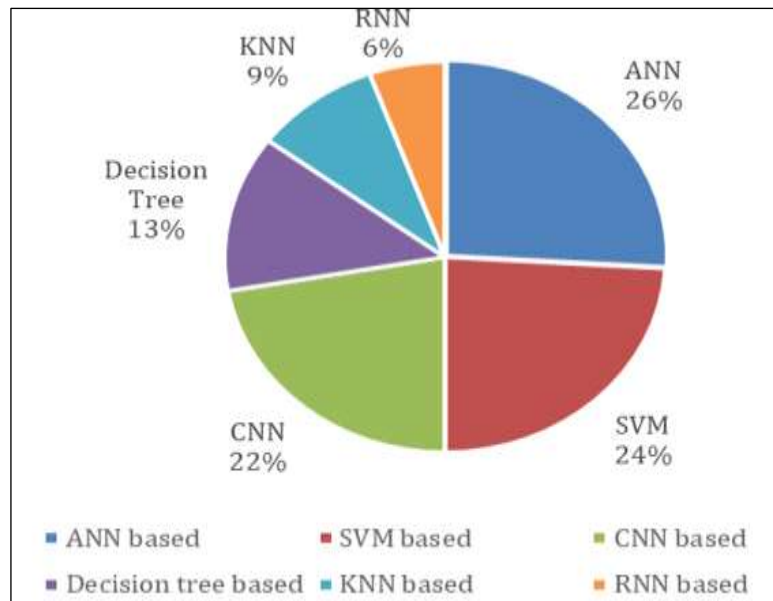


Figure 20: Distribution of expert systems used in bearing fault diagnosis studies.
Source: Authors, (2026).

Figure 20 shows the distribution of expert systems used in bearing fault diagnosis studies. The largest share is attributed to the artificial neural network (ANN)-based methods, which gives them an implication of their still being relevant because of their simplicity and the ability to model nonlinear phenomena. Methods based on SVM and convolutional neural network (CNN) models take up a significant share as well, which demonstrates the great popularity of both standard machine learning classifiers and deep learning models. Moderate in their usage are decision tree based techniques, such as ensemble extensions, and k-nearest neighbor (KNN) classifiers, due to their interpretability and simple implementation.

In contrast, recurrent neural network (RNN)-based approaches exhibit comparatively limited usage, suggesting that sequential modeling remains less explored in bearing fault diagnosis. From a methodological perspective, ANN- and SVM-based approaches remain popular due to their balance between accuracy and computational efficiency, particularly for feature-based classification problems. The CNN-based models are predominant in the high-dimensional inputs like time-frequency images, but they need large labeled datasets and are not easily interpretable, which is still an issue in industrial applications. KNN and tree-based classifiers are transparent, simple, but frequently do not work with noisy and high dimensional signals. RNN-based models are also appropriate in the context of temporal modeling but are not used extensively. This is generally a trade-off in the performance of diagnostic performance, interpretability, and data dependency of various expert systems. Here is a comparison Table 3 summarizing the machine learning techniques discussed for bearing fault diagnosis. This Table provides a quick comparison of the methods based on key advantages, challenges, and typical applications in bearing fault diagnosis.

Table 3: Expert Systems Comparison.

Method	Advantages	Limitations	Suitable for
ANN	High classification accuracy; models complex nonlinear relationships	Requires large datasets; prone to overfitting	Complex fault patterns; large labeled datasets
SVM	High accuracy; effective with small datasets and high-dimensional features	Sensitive to kernel and parameter selection; slow for large datasets	Binary and multi-class fault classification
KNN	Simple and intuitive; effective for nonlinear decision boundaries	Computationally expensive during inference; sensitive to distance metric	Small datasets; instance-based learning
CNN	Automatic feature extraction; excellent for high-dimensional inputs	Computationally intensive; large labeled datasets required; limited interpretability	Time-frequency representations (spectrograms, scalograms)
RNN	Captures temporal dependencies in sequential data	High training complexity; limited interpretability	Time-series data; dynamic and evolving faults
DT	Simple, fast, and interpretable	Prone to overfitting; sensitive to noise	Small datasets; interpretable diagnostic models

Source: Authors, (2026).

V. RESEARCH GAPS AND CHALLENGES

Although significant progress in rolling element bearing fault diagnosis, several research gaps and challenges continue to limit the practical deployment and generalization of existing methods. A major limitation is the over-reliance on a small number of benchmark datasets. Although these datasets facilitate comparative evaluation, their controlled laboratory conditions and artificially seeded faults do not adequately reflect the complexity, noise, and variability of real industrial environments. Consequently, models that are trained using this type of data tend not to be generalized to the real industrial conditions.

Lack of cross-dataset and cross-domain validation is also another critical challenge. Most of their models are supported by one dataset or a test rig and it is difficult to establish how robust they are when implementing on other machines, sensors, and conditions. This restricts the credibility of reported performance measures and industry trust and acceptance. Furthermore, numerous works consider fault diagnosis and prognostics to be two different issues, paying attention either to the categorization of faults or to the estimation of the left useful life. Nonetheless, viable condition-based monitoring systems necessitate combined diagnostic-prognostic models to avert efficient maintenance decision-making.

This lack of such unified structures is a research gap. Model interpretability is another issue of importance. Deep learning models are very accurate but they are usually black box models and the engineer can hardly comprehend or trust the diagnostic decision. This non-transparency is a significant impediment in safety critical systems like power plants, aerospace systems and heavy industrial equipment. Lastly, no standard evaluation procedures, benchmarking standards, and performance indicators exist in inter-study comparisons, making it relatively difficult to provide a fair comparison and hindering scientific advancement. The future research must hence focus more on building more realistic and diverse datasets, domain adaptation and transfer learning methods to cross-machine generalization, physics-informed and interpretable machine learning frameworks, standardized benchmarking protocols, and integrated diagnostic-prognostic systems that are robust, explainable, and can be used in real-industrial settings.

VI. CONCLUSION

This review examined recent research on bearing fault diagnosis with an emphasis on experimental datasets, signal processing techniques, and expert-system-based diagnostic methods. The dataset usage analysis indicates that the CWRU dataset remains the most extensively used benchmark due to its public availability, standardized fault conditions, and ease of comparative evaluation. However, the increasing use of datasets such as IMS, PRONOSTIA, Paderborn, and XJTU-SY reflects a growing interest in run-to-failure data and more realistic operating conditions. Wavelet-based approaches (DWT/WPT) remain the most widely used signal processing techniques because of their effectiveness in analyzing non-stationary vibration signals, while time-domain feature extraction and Hilbert-based or envelope analysis continue to be favored for their simplicity and effectiveness in early fault detection. Among expert systems, artificial neural networks and SVM are the most frequently employed classifiers due to their strong performance in feature-based fault classification.

The increasing adoption of convolutional neural networks indicates a shift toward deep learning frameworks with automatic feature learning capabilities. Overall, the findings highlight the need for integrated diagnostic frameworks that combine robust signal processing, diverse and realistic datasets, and intelligent yet interpretable expert systems. Bridging the gap between laboratory research and industrial deployment remains the central challenge, and future advances must focus on robustness, interpretability, and scalability rather than accuracy alone. These findings have important implications for the deployment of condition monitoring systems in smart manufacturing and Industry 4.0 environments.

VII. AUTHOR'S CONTRIBUTION

Conceptualization: Hitesh K Patel

Methodology: Hitesh K Patel

Investigation: Hitesh K Patel

Discussion of results: Hitesh K Patel, Divyang H Pandya.

Writing – Original Draft: Hitesh K Patel.

Writing – Review and Editing: Hitesh K Patel, Divyang H Pandya.

Resources: Hitesh K Patel, Divyang H Pandya, Ankit Darji.

Supervision: Divyang H Pandya, Ankit Darji.

Approval of the final text: Divyang H Pandya, Hitesh K Patel., Ankit Darji.

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