

A REVIEW OF BEARING FAULT DETECTION, DIAGNOSIS AND PROGNOSTICS

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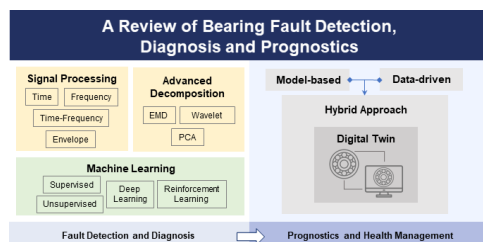
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Graphical abstract



Abstract

This review explores advancements in bearing fault detection, diagnosis, and prognostics, highlighting the transition from traditional to AI-driven approaches. Time-domain, frequency-domain, and time-frequency domain methods are discussed alongside advanced signal decomposition like empirical mode decomposition and wavelet transform. The role of machine learning and deep learning in improving diagnostic accuracy, robustness, and adaptability is also discussed, supported by evaluations on public datasets for benchmarking. Additionally, it emphasizes prognostics and health management for remaining useful life estimation, linking it to degradation modelling and predictive analytics. The potential of digital twin technology for real-time monitoring, adaptive maintenance, and fault simulation is evaluated in bridging the gap between simulated and empirical data. Future research should focus on federated learning, edge AI, and digital twin to enhance predictive accuracy and industrial applicability.

Keywords: Bearing fault diagnosis, signal processing, machine learning, prognostics, digital twin

Abstrak

Kajian ini mengupas kemajuan terkini dalam pengesanan, diagnosis dan prognostik kerosakan galas, dengan menonjolkan peralihan daripada kaedah tradisional kepada pendekatan berasaskan kecerdasan buatan (AI). Perbincangan merangkumi kaedah domain masa, frekuensi dan masa-frekuensi serta teknik penguraian isyarat lanjutan seperti penguraian mod empirik dan transformasi gelombang kecil. Peranan pembelajaran mesin dan pembelajaran mendalam dalam meningkatkan ketepatan diagnostik, ketahanan serta kebolehsuaian turut dibincangkan, disokong oleh penilaian set data awam sebagai penanda aras. Selain itu, ia menekankan aspek prognostik dan pengurusan kesihatan bagi anggaran baki hayat berguna yang berkait dengan pemodelan degradasi dan analitik ramalan. Potensi teknologi kembar digital bagi pemantauan masa nyata, penyelenggaraan adaptif serta simulasi kerosakan turut dinilai sebagai usaha mendapatkan jurang antara data simulasi dan empirikal. Penyelidikan masa hadapan harus ditumpukan kepada pembelajaran teragih, AI pinggir dan kembar digital bagi meningkatkan ketepatan ramalan dan kebolehgunaan industri.

Kata kunci: Diagnosis kerosakan galas, pemrosesan isyarat, pembelajaran mesin, prognostik, kembar digital

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1.0 INTRODUCTION

Bearings are essential mechanical components widely used in rotating machinery. They minimise friction between moving parts while supporting radial and axial loads, ensuring smooth and efficient operation [1, 2]. Bearing classifications are determined by load direction, comprising radial and thrust types, with designs such as deep-groove ball bearings and tapered roller bearings capable of supporting complex load combinations. Conventional rolling bearings consist of an inner ring, outer ring, rolling elements, and a cage [2], as shown in Figure 1.

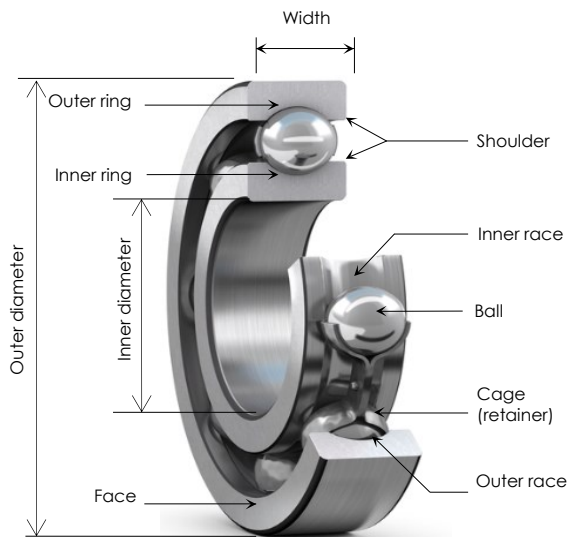


Figure 1 Structural configuration of the ball bearing

Despite their robust design, bearings are susceptible to failure caused by improper assembly, inadequate maintenance, and operational stresses.

Figure 2 presents typical bearing failure modes, consisting of deformation, fracture, corrosion, and wear [2]. Fatigue, a subset of fracture mode, includes mechanical and corrosion fatigue, which occurs due to repeated stress cycles, misalignment and contamination. Understanding these failure mechanisms is crucial for engineering reliability and maintenance planning.

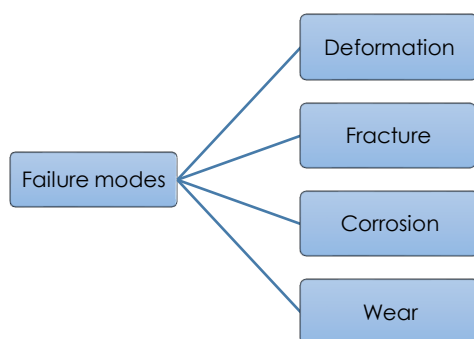


Figure 2 Major failure modes in bearing systems

Studies indicate that bearing failures account for nearly 45–50% of rotating machinery failures [3, 4], leading to unplanned downtime and costly repairs. These failures may cause catastrophic consequences, such as equipment damage, production losses, and safety hazards [5]. Therefore, prompt fault detection, accurate diagnosis, and effective bearing health management are critical [6].

Traditional maintenance strategies were mainly reactive, focusing on fixing failures after they occurred, or preventive, relying on fixed schedules without real-time monitoring [7]. Nowadays, predictive maintenance (PdM) has gained prominence with condition-based maintenance (CBM) or condition monitoring as a key approach that continuously tracks equipment parameters to predict faults early, minimise downtime, and reduce maintenance costs [8].

Numerous studies have thoroughly examined bearing fault diagnosis, with a strong emphasis on advanced condition monitoring techniques, reflecting the extensive number of review papers on this topic. Patel and Patel [9], along with Anwarsha and Babu [10], provided a detailed analysis of signal processing methods, emphasising vibration-based fault detection and recent innovations. Similarly, Pandiyan and Babu conducted a comprehensive survey on fault diagnosis, covering signal processing, machine learning (ML), deep learning, and reinforcement learning (RL) techniques [3]. Mushtaq *et al.* examined data-driven fault diagnosis frameworks, comparing traditional signal processing, classical ML, and deep learning approaches [11]. They also highlighted widely used public datasets, which are critical for benchmarking in bearing fault research. Additionally, Hakim *et al.* reviewed deep learning and transfer learning methods for bearing fault diagnosis, summarising their applications and challenges [12]. Lou *et al.* extended this by exploring deep learning-based fault detection and diagnosis (FDD) frameworks, discussing theoretical foundations, industrial implementations, and dataset availability [13]. Expanding on this, Polverino *et al.* systematically reviewed ML techniques in Prognostics and Health Management (PHM) [14]. Their analysis focused on diagnostic and prognostic approaches, validation procedures, and predominance of synthetic data.

This review synthesises recent advancements in bearing fault detection, diagnosis and prognostics, emphasising comparative benchmarking across signal processing, machine learning, and digital twin frameworks, while outlining their respective strengths and limitations. The paper is organised as follows: Section 2 examines traditional and advanced signal processing, including machine learning approaches; Section 3 discusses prognostics and health management techniques, with emphasis on digital twin technology; Section 4 reviews benchmarking studies using public datasets across these methodologies; and Section 5 summarises key insights, identifies research gaps, and outlines future directions.

2.0 BEARING FAULT DETECTION AND DIAGNOSIS (FDD)

Fault detection is a critical step in PdM, enabling early identification of operational anomalies and reducing unplanned downtime. By distinguishing between normal and abnormal conditions, fault detection enhances system reliability and longevity [15]. Over the past century, condition monitoring techniques have advanced significantly, incorporating vibration analysis [16-19], acoustic emission (AE) monitoring [20-22], infrared thermography [23], and wear-debris analysis [24]. Among these, vibration-based monitoring remains the most extensively researched, particularly for rotating machinery [24, 25]. This method involves strategically placing accelerometers on machinery to capture vibrations indicative of potential bearing defects [17].

2.1 Signal Processing Techniques

Signal processing plays an indispensable role in FDD, particularly in the context of bearings [26]. The process involves transforming raw sensor data into actionable information that can accurately reflect the health of the system and its components [27]. In modern industrial applications, sensors such as accelerometers, microphones, and temperature sensors are routinely employed to capture signals from rotating machinery [28]. These signals contain valuable information that can be analysed to detect and diagnose faults before catastrophic failures occur [29]. The increasing complexity of industrial systems has driven advancements in signal processing methodologies, each tailored to specific challenges in bearing fault detection [30]. These techniques are classified into four main categories: time-domain analysis, frequency-domain analysis, time–frequency analysis, and envelope analysis. The following sections provide a detailed discussion of these techniques.

2.1.1 Time-Domain Analysis

Time-domain analysis is a fundamental approach to bearing fault detection, involving the direct examination of raw vibration signals without transforming them into other domains [31]. It is widely used due to its simplicity and efficiency, offering an intuitive means of assessing signal behaviour [20]. Features such as root mean square (RMS), skewness, kurtosis, and peak-to-peak values are commonly calculated to assess signal behaviour [32]. The RMS value is widely used in vibration analysis to measure signal energy, aiding the detection of misalignments and imbalances in rotating machinery [33]. Similarly, skewness and kurtosis help identify asymmetric and impulsive signals, which indicate specific bearing faults [34]. The mathematical formulations for RMS, skewness, kurtosis (K), and peak-to-peak (P–P) are shown in the following Equations (1) to (4), respectively.

$$\text{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2} \quad (1)$$

$$\text{Skewness} = \frac{\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^3}{\left(\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2\right)^{3/2}} \quad (2)$$

$$K = \frac{\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^4}{\left(\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2\right)^2} \quad (3)$$

$$\text{P-P} = \max(x) - \min(x) \quad (4)$$

where \bar{x} is the mean of the signal; x_i is the value of the signal at sample i ; N is the number of samples; $\max(x)$ is the maximum value of the signal; and $\min(x)$ is the minimum value of the signal.

Geetha and Gethanjali [35] explored time-domain features from both conventional methods, such as mean absolute value and RMS, and non-conventional ones, such as simple sign integral and waveform length, in a study aimed at determining the most optimal and robust time-domain feature ensemble for precise fault diagnosis. In another study, Du et al. [36] compared bearing fault classification accuracy using various time-domain feature combinations, including dimensional features (mean, peak, RMS, square root amplitude) and dimensionless features (peak index, kurtosis, waveform, impulsion, tolerance) features.

Despite its computational efficiency, time-domain analysis has limitations. It may fail to detect low-amplitude faults, such as micro-pitting or surface degradation [31], and is often ineffective for high-frequency or non-stationary fault signatures [37]. These challenges emphasise the need for advanced signal processing techniques for complex machinery.

2.1.2 Frequency-Domain Analysis

Frequency-domain analysis is a widely used method for bearing fault detection, transforming time-domain signals into the frequency spectrum to facilitate fault identification. This process is primarily achieved using the Fast Fourier Transform (FFT), which decomposes signals into their constituent frequency components [38]. Characteristic bearing fault frequencies (BFFs) are directly linked to the geometry of bearings and their rolling elements. These frequencies often appear as distinct spectral peaks, corresponding to inner race faults, outer race faults, rolling element defects, or cage faults [39]. For example, BFFs, as explained in Table 1 and related to the geometry of the bearing and the rolling elements, can be clearly identified in the frequency spectrum [40]. These fault-related frequencies often manifest as spectral peaks, which can be attributed to specific defects, such as inner race or outer race faults, ball defects, or cage faults.

Table 1 Bearing fault frequencies

Bearing Fault Frequency	Characteristic Frequency	Fault Location	Eq. No
Ball Pass Frequency of the Outer Race (BPFO)	$f_r \frac{N_r}{2} \left(1 - \frac{D_b \cos \varphi}{D_p}\right)$	Outer race	(5)
Ball Pass Frequency of the Inner Race (BPFi)	$f_r \frac{N_r}{2} \left(1 + \frac{D_b \cos \varphi}{D_p}\right)$	Inner race	(6)
Ball Spin Frequency (BSF)	$f_r \frac{D_p}{D_b} \left(1 - \frac{D_b^2 \cos^2 \varphi}{D_p^2}\right)$	Rolling element	(7)
Fundamental Train Frequency (FTF)	$f_r \frac{1}{2} \left(1 - \frac{D_b \cos \varphi}{D_p}\right)$	Cage	(8)

where:

- f_r – Rotational speed of the shaft (Hz)
- D_b – Rolling element diameter
- D_p – Pitch diameter
- N_r – Number of the rolling elements (in single row)
- φ – Load angle (contact angle from radial)

In recent literature, Jawad and Jaber [41] applied the FFT to the vibration signal to analyse the fault frequencies and compared them with theoretical values from equations, demonstrating the method's effectiveness in fault detection. Arun et al. [42] analysed bearing faults using the Kruskal–Wallis ANOVA to assess the effectiveness of frequency-domain features, including spectral roll-off, median frequency, spectral centroid, dominant frequency, and spectral flux. Al Mamun et al. [43] proposed a method integrating acoustics and vibration signals with varying sampling rates and limited data, utilising FFT for signal transformation and applying multilinear principal component analysis (PCA) to extract frequency-domain features for neural-network-based fault diagnosis.

While FFT-based frequency analysis is highly effective for detecting periodic vibrations, it has limitations in handling non-stationary or transient faults [44]. Additionally, FFT resolution depends on signal length, making it less effective for detecting localised or weak fault signatures [45]. In high-speed machinery, fault frequencies may overlap with harmonics and external noise, complicating fault isolation [46]. Despite these challenges, frequency-domain analysis remains a cornerstone of bearing fault detection, especially when combined with ML techniques for enhanced accuracy [47, 48].

2.1.3 Time-Frequency Analysis

Time-frequency analysis integrates the strengths of time- and frequency-domain methods, offering a dynamic representation of how a signal's frequency content evolves over time. This makes it particularly effective for analysing non-stationary signals, which

are prevalent in industrial machinery [49]. One of the most widely used methods in time-frequency analysis is the wavelet transform [50], which decomposes a signal into wavelet coefficients, allowing the detection of both high- and low-frequency components with high temporal resolution [51]. Unlike FFT, which provides a global frequency representation, the wavelet transform enables a multi-resolution analysis, meaning that it can zoom in on local features in both time and frequency domains simultaneously [52]. Other time-frequency analysis methods include the Short-Time Fourier Transform (STFT), which offers time-frequency representation with fixed resolution; the Wigner-Ville distribution, providing high resolution but suffering from cross-term interference; and the Hilbert-Huang Transform (HHT) with Empirical Mode Decomposition (EMD), ideal for non-linear and non-stationary signals.

Zhang et al. [53] demonstrated the effectiveness of the STFT in diagnosing high-speed bearing faults, facilitating real-time condition monitoring. Similarly, Alvarez-Gonzalez et al. [54] employed the HHT for fault detection in synchronous machines, validating its accuracy in both simulated and real-time environments. Further, Gundewar and Kane [55] explored seven time-frequency representations, including the Continuous Wavelet Transform (CWT) and Fourier transform, using them as Convolutional Neural Network (CNN) input features for automated fault classification.

The primary advantage of time-frequency analysis lies in its ability to detect transient signals, which are often early indicators of impact-related faults [56, 57]. Additionally, time-frequency analysis enhances fault feature extraction by revealing both temporal and spectral complexities, improving diagnostic accuracy under non-stationary conditions [58]. However, high computational complexity remains a key limitation, posing challenges for real-time industrial applications [59, 60].

2.1.4 Envelope Analysis

Envelope analysis is a widely used technique for bearing fault detection, particularly in identifying fault-induced amplitude modulation in vibration signals [61]. When rolling elements pass over defects on raceways, they generate modulated signals, which can be extracted to highlight fault-related frequencies [62]. This enhances fault identification while reducing noise interference [63].

Alonso-González et al. [64] integrated envelope analysis with frequency-domain techniques, improving fault detection but noting its reduced effectiveness for ball defects. Toumi et al. [65] used envelope analysis for bearing fault classification, achieving high accuracy with a multi-layer perceptron (MLP)-based classifier trained on peak amplitudes from vibration signals. Areias et al. [66] demonstrated its capability in continuous fault tracking through envelope spectrum monitoring.

A key advantage of envelope analysis is its ability to detect early-stage bearing faults, even in noisy environments [61]. It is especially effective for inner race and rolling-element faults, where modulated signals reveal performance degradation [67]. However, it has limitations in detecting non-modulated fault patterns [29]. Accurate filter selection and demodulation techniques are essential for optimising fault feature extraction [68]. Additionally, environmental noise and sensor placement can affect its reliability in real-world applications [69].

2.2 Advanced Decomposition Methods

Advanced decomposition techniques are critical for fault detection, particularly in analysing complex, non-stationary vibration signals in rotating machinery [70]. These methods decompose noisy signals into simpler components, enhancing fault feature extraction and enabling earlier fault detection [71].

2.2.1 Empirical Mode Decomposition (EMD)

EMD is an adaptive signal decomposition technique widely used in bearing fault diagnosis, particularly for non-linear and non-stationary vibration signals [72]. It decomposes signals into intrinsic mode functions (IMFs), which preserve time-varying fault characteristics [72]. Unlike Fourier-based methods, EMD is fully data-driven, eliminating the need for predefined basis functions [73].

Several studies have demonstrated the EMD's effectiveness in bearing fault detection. Ninawe and Deshmukh [17] developed an EMD-based real-time fault diagnosis system, utilising iterative loops and dual clock frequencies for efficient data processing. Their study confirmed that EMD improves fault detection accuracy and enhances machine reliability.

One of the key strengths of EMD is its ability to adaptively decompose a signal without the need for predefined basis functions [72]. This makes it highly effective for analysing signals that are both time-varying and non-stationary, characteristics commonly encountered in machinery fault diagnosis. Additionally, EMD does not rely on predefined decisions or assumptions, and the decomposition process is fully adaptive and unsupervised, without requiring the assumption of linearity in the data, making it more versatile than traditional methods such as Fourier analysis [74].

Despite its advantages, EMD suffers from mode mixing, where closely spaced frequencies merge within a single IMF, reducing decomposition accuracy [75]. To address this, post-processing techniques have been employed to refine signal separation, improving fault classification performance [74].

2.2.2 Wavelet Transform (WT)

The WT is a powerful signal decomposition technique used in bearing fault detection, particularly for

non-stationary and transient signals [76]. Unlike Fourier-based methods, which provide only global frequency information, WT enables multi-resolution analysis, allowing simultaneous time-frequency decomposition [77]. This capability makes WT particularly effective for detecting faults that manifest as short-duration impacts or sudden vibration variations [78].

Recent studies highlight the effectiveness of WT-based fault diagnosis. Qin *et al.* [79] employed the CWT for time-frequency mapping and integrated it with a lightweight CNN for real-time fault classification, achieving 100% accuracy. Similarly, Sharma *et al.* [80] used Empirical Wavelet Transform (EWT) to extract fault-sensitive sub-bands, which were validated through correlation, kurtosis, and permutation entropy. Jalayer *et al.* [81] combined the CWT, FFT, and statistical features in a deep learning model, demonstrating superior accuracy compared to conventional fault detection techniques. Meanwhile, Kaji *et al.* [82] transformed CWT-based vibration signals into 2D images to construct a health indicator (HI) for Remaining Useful Life (RUL) estimation, validating its effectiveness on a benchmark dataset.

The main advantage of WT is its ability to capture both high- and low-frequency fault signatures, which is essential for accurate bearing fault diagnosis [83]. This technique is particularly effective for detecting crack initiation, rolling-element defects, and transient impact signals, which traditional FFT-based techniques may overlook [80, 84].

However, the WT faces several challenges. The selection of an optimal wavelet function significantly affects fault detection accuracy, as different wavelets provide varying levels of resolution and sensitivity [57, 85, 86]. Additionally, high computational costs make real-time implementation challenging, particularly for long-duration signals [83].

2.2.3 Principal Component Analysis (PCA)

PCA is a widely used dimensionality-reduction technique in bearing fault diagnosis, enabling the extraction of essential fault features while minimising data complexity [87]. By transforming raw data into a set of uncorrelated principal components, PCA captures the most significant variance within the dataset, preserving key fault-related information [88]. This makes PCA particularly valuable in machinery health monitoring, as it reduces data complexity while preserving essential fault-related information [89]. PCA has also been used to identify fault-relevant vibration signals, as demonstrated by Elsamanty *et al.* [90]. Additionally, PCA is widely used for feature extraction [91], where the principal components serve as inputs for ML models such as Support Vector Machines (SVM) [92], backpropagation neural networks (BPNN) [90], and neuro-fuzzy classifiers [88]. PCA-based feature extraction and dimensional reduction have also demonstrated strong performance in real-time bearing fault diagnosis, as proposed by Al Mamun *et al.* [93]. Validated on a Machine Fault Simulator, this

approach outperforms CNN-based methods, ensuring efficient fault detection with limited training data.

Despite its advantages, PCA has limitations. It assumes that data follow a linear distribution, which may not always be the case in complex, non-linear systems [94]. To overcome this, non-linear extensions such as Kernel PCA (KPCA) have been developed, which have gained attention in industrial fault detection applications, as noted by Pani [95], Hu *et al.* [96], and Wang *et al.* [97]. Furthermore, PCA does not provide explicit frequency-domain insights, making it less effective for fault detection tasks that rely on frequency-specific features [87].

2.3 Integration of Machine Learning in Fault Diagnosis

The adoption of ML techniques has revolutionised bearing fault diagnosis, offering enhanced accuracy, automation, and real-time analysis. Traditional fault detection methods relied on manual inspection and signal processing, which required expert knowledge and were computationally demanding [98]. In contrast, ML enables automated fault detection, facilitates large-scale data analysis, and enhances real-time PdM [4]. Additionally, ML can autonomously detect faults with high accuracy and is able to handle large, non-linear, and complex datasets [34]. ML techniques for fault diagnosis can be broadly categorized based on how they learn from data, as shown in Figure 3. The following sections explain all approaches in detail.

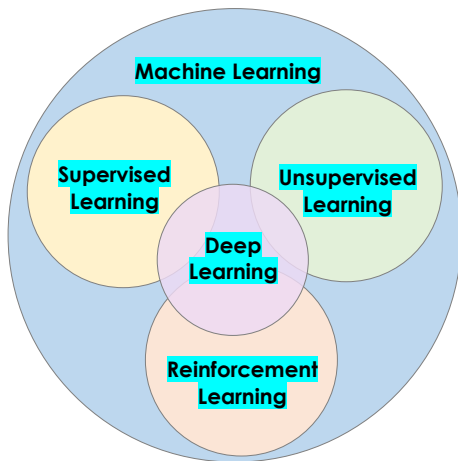


Figure 3 Categorisation of Machine Learning Methods [99]

2.3.1 Supervised Learning

Supervised learning is one of the most widely used ML techniques in fault diagnosis. This category of algorithms involves training models on labelled datasets, where the input features are mapped to known outputs. Supervised learning models such as SVM [100], k-nearest neighbour (kNN) [101], Random

Forests (RF) [102], and Artificial Neural Networks (ANNs) [103] have been extensively applied to fault classification and prediction tasks in industrial settings. These algorithms learn from historical data containing vibration signals, spectral features, or other sensor data, allowing them to classify the presence and type of faults based on learned patterns.

The strength of supervised learning lies in its ability to classify faults accurately, provided that sufficient labelled training data are available. Models like SVM are particularly known for their ability to work effectively with small datasets and high-dimensional data, making them useful in fault classification problems where data are sparse [104]. RF, on the other hand, excels in handling incomplete data and provides interpretable results, making it a robust choice for fault diagnosis in complex systems [105]. Similarly, ANNs have demonstrated excellent performance in complex pattern recognition tasks with high self-learning capability [106].

Despite their strengths, supervised learning methods face significant challenges. One of the primary limitations is the need for labelled data, which can be difficult and expensive to obtain, especially for fault detection tasks that require domain-specific expertise [107, 108]. Furthermore, supervised learning models can struggle to generalise when faced with new or unseen fault conditions, making them less adaptable to novel faults or changes in machinery behaviour. This challenge is particularly pertinent in industrial environments where machinery conditions can vary over time and new failure modes may emerge. Therefore, unsupervised learning methods have been implemented to identify fault patterns without requiring predefined labels.

2.3.2 Unsupervised Learning

Unsupervised learning, which involves training models on unlabelled data, offers a promising alternative for fault detection, especially in cases where labelled fault data are unavailable or difficult to obtain. Techniques such as clustering algorithms (e.g., k-means clustering [109-111]) and autoencoders (AEs) [112] are commonly used for anomaly detection, where the goal is to identify unusual or outlier patterns that may indicate a potential fault. These models rely on the assumption that normal operation patterns are more frequent in the data and that anomalies represent potential faults.

Unsupervised learning models are particularly useful for early fault detection, as they can identify emerging fault conditions that have not been explicitly labelled. For instance, AE, a form of neural network architecture, can learn to represent normal system behaviour and then flag deviations from this behaviour as potential anomalies [113]. Such methods are highly valuable in real-world industrial applications, where labelled datasets for faults are often scarce. Additionally, unsupervised methods do not require prior fault-specific knowledge, making

them suitable for continuous monitoring and detection of new, previously unseen failure modes.

However, the effectiveness of unsupervised learning methods depends on the quality of the normal data and the chosen model parameters. For example, in clustering-based methods like k-means, the number of clusters must be specified a priori, and inappropriate clustering can lead to poor fault detection performance. Furthermore, AEs, though effective, often demand large datasets to learn normal patterns accurately and may struggle to differentiate similar fault types. Traditional AEs typically require pre-training for weight initialization, but early-layer errors can cause the network to reconstruct averaged data [105]. Moreover, their interpretability remains limited. Despite these challenges, unsupervised learning methods continue to be an important area of research for fault

detection, particularly in scenarios where labelled data is unavailable.

2.3.3 Deep Learning

Deep learning has transformed bearing fault diagnosis, providing automated feature extraction and high-accuracy classification without manual intervention [114]. Unlike traditional ML approaches, deep learning models learn directly from raw vibration signals, enabling precise fault detection and PdM. The differences between traditional ML and deep learning are illustrated in Figure 4, where traditional ML involves multiple stages of feature engineering, while deep learning integrates feature learning and classification in an end-to-end pipeline.

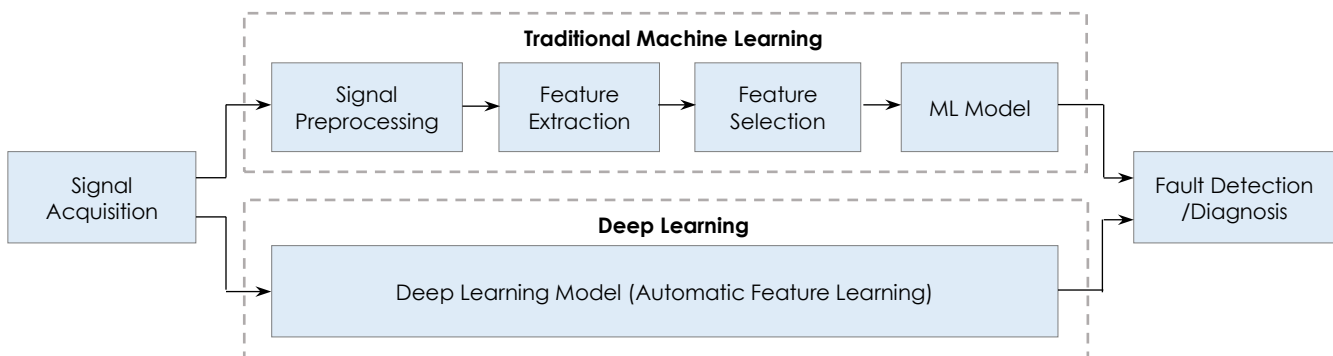


Figure 4 Comparison of Traditional Machine Learning and Deep Learning Pipelines for Bearing Fault Analysis

Two key architectures dominate deep learning-based fault diagnosis. CNNs are widely used for image-based diagnostics, where spectrograms and time-frequency representations of vibration signals are analysed for fault classification [115]. On the other hand, Long Short-Term Memory (LSTM) networks, a form of Recurrent Neural Network (RNN), specialize in time-series analysis, capturing temporal dependencies in vibration data for fault progression monitoring [116].

The strength of deep learning models lies in their ability to learn directly from raw data, obviating the need for hand-crafted features. For instance, CNNs can automatically detect patterns in frequency-domain data, while LSTMs can capture temporal dependencies in time-series data, allowing for highly accurate fault diagnosis. Deep learning models are particularly well-suited to handle large, high-dimensional datasets that are typical in industrial machinery health monitoring systems.

Despite their strengths, deep learning models pose several challenges. Their reliance on large labelled datasets makes implementation costly, and their computational intensity can hinder real-time industrial applications [35, 117, 118]. Overfitting remains a concern, particularly in variable operating conditions, where models may fail to generalise to new fault types [119]. Additionally, the black-box nature of deep

learning techniques limits interpretability, posing challenges for decision-making in industrial environments [35]. Furthermore, the black-box nature of deep learning models limits their interpretability, raising concerns in industrial applications where explainability is crucial [105].

2.3.4 Reinforcement Learning (RL)

Reinforcement learning (RL) represents a more advanced approach to fault diagnosis and PdM, focusing on the development of adaptive maintenance strategies. Unlike traditional ML methods, which typically involve supervised or unsupervised learning, RL algorithms learn optimal decision-making policies by interacting with the environment, receiving feedback, and adjusting actions accordingly [120, 121]. In the context of fault diagnosis, RL models can be used to develop strategies for PdM by continuously learning from operational data and adjusting maintenance schedules to maximize machinery uptime and minimize failure risks [122].

Wen et al. [123] presented an innovative approach utilizing reinforcement learning for the automatic adjustment of learning rates in CNNs for fault classification. The proposed RL-CNN model incorporates a reinforcement learning agent to

dynamically modify the learning rate during the CNN training process, thus eliminating the necessity for manual tuning. The model was rigorously evaluated using data from the Case Western Reserve University (CWRU) dataset and the self-priming centrifugal pump dataset, showcasing superior fault classification performance compared to traditional methods.

Kang *et al.* [124] utilised deep reinforcement learning (DRL) to diagnose rolling bearing faults by treating unbalanced data classification as a sequential decision-making problem. The proposed model employs a dual-experience pool to store samples from majority and minority classes separately, and trains a parallel double residual network to extract deep features, improving diagnostic accuracy for unbalanced data. The datasets used for evaluation include the CWRU dataset and the rolling bearing fault test dataset from Nanjing University of Aeronautics and Astronautics.

RL offers significant advantages in fault diagnosis, as it can dynamically adapt to changing conditions and noisy data, improving the decision-making process [3]. By training an agent to work with vibration data, RL models enhance the accuracy and efficiency of maintenance decisions, leading to better fault detection and prevention. However, RL models require a well-defined environment and a clear reward structure, which can be challenging to define in complex, real-world industrial settings [125]. Additionally, RL does not demonstrate distinct advantages when applied to an already superior feature set, as other methods can achieve comparable results [125]. Despite these challenges, RL offers a promising direction for advancing PdM and fault diagnosis, with more ongoing studies utilizing RL algorithms to enhance efficiency and adaptability in industrial settings.

3.0 PROGNOSTICS AND HEALTH MANAGEMENT (PHM)

PHM is a key strategy in industrial maintenance, designed to predict failures and optimize maintenance decisions. By integrating condition monitoring, diagnostics, and prognostics, PHM estimates the RUL of machinery, reducing downtime and improving operational efficiency [126]. PHM also enables cost-effective maintenance by delivering early failure warnings, preventing collateral damage, and improving system availability and reliability [127]. The concept of PHM is built on the integration of advanced sensors, data analytics, ML models, and decision-support systems, creating a holistic approach to asset health management [128]. While fault detection identifies existing issues, PHM goes further by predicting when a failure is likely to occur, allowing proactive maintenance. This transition from reactive to predictive strategies significantly enhances machine reliability and operational efficiency.

PHM encompasses condition monitoring, diagnostics, prognostics, and decision-making,

focusing on HI identification, and RUL estimation to support data-driven maintenance decisions [129, 130]. PHM involves HI identification, which includes feature extraction, learning, fusion, and selection [129]. Traditional feature extraction methods are manual, whereas deep learning enables automated feature learning. Feature fusion minimizes dimensional complexity, and feature selection isolates key fault indicators. Additionally, prognostics estimates the RUL by analysing the current state and historical health data [127]. This enables enhancements in health management processes, including maintenance planning, logistics strategies, and performance regulations [130]. In a PHM framework, prognostics can be applied through three approaches: physical model-based, sensor data-driven techniques, and a hybrid approach that integrates both [127, 130, 131].

3.1 Model-Based Prognostics

Model-based prognostics utilise mathematical and physical principles to describe failure mechanisms, with a strong emphasis on specific degradation modes such as creep, fatigue, cracking, and wear [131]. These models simulate the behaviour of a system under different conditions, allowing engineers to predict when certain thresholds are likely to be crossed, thus leading to failure. In a recent article, Lin *et al.* proposed a novel model-based approach using the Finite Element Method (FEM) for real-time unbalance monitoring and prognostics in rotor-bearing systems, utilising a two-phase parameter identification method to estimate initial unbalances and track their progression over time [132]. The approach was validated using 16 months of operational data from a turbine-bearing system, demonstrating its robustness through five optimisation algorithms and successful implementation in an industrial CBM system.

A key advantage of model-based prognostics is its ability to simulate the entire physical degradation process, providing a highly accurate approximation of system behaviour [131]. These models predict failures by capturing degradation mechanisms such as fatigue, wear, and creep. While they offer precise failure estimation, their accuracy relies on well-defined system parameters, making implementation challenging for complex machinery. Additionally, model-based approaches require extensive domain expertise and significant computational resources. When physical modelling is impractical, data-driven methods offer a more scalable alternative, as discussed in the next section.

3.2 Data-Driven Prognostics

Unlike model-based approaches, data-driven prognostics use historical and real-time sensor data to predict failures. ML models such as regression, neural networks, and deep learning extract patterns from vibration signals to estimate RUL. These techniques can analyse sensor data from equipment, such as

vibration, temperature, and pressure readings, to detect degradation trends and predict when failure is likely to occur. Regression models, such as support vector regression (SVR) [133] and random forests [134], are commonly used for RUL estimation. Neural networks, particularly deep learning models, have also been successfully applied in data-driven prognostics due to their ability to automatically extract complex features from large datasets without the need for manual feature engineering. RNNs and LSTM networks, in particular, are well-suited for time-series data, as they can capture temporal dependencies in the sensor signals and make predictions based on past observations [135]. Rathore and Harsha [136] presented a data-driven prognostics approach to predict the remaining operational life of high-speed cylindrical roller bearings, utilizing Weibull failure rate function and kNN classification. Additionally, Afridi *et al.* [137] developed an LSTM-based data-driven prognostic approach for condition monitoring and fault prognostics of rolling element bearings, leveraging raw vibrational data to minimize the need for feature engineering and enhance model generalisation. In another study, Saufi and Hassan [138] introduced a data-driven approach called Integrated Laplacian LSTM, combining the Laplacian score, random search optimization, and LSTM for improved RUL analysis. This method tackled challenges in deep learning hyperparameter selection and complex prediction indicators, achieving an 18% accuracy boost on IEEE PHM 2012 and IMS bearing datasets.

However, data-driven methods require large, high-quality datasets for training. Without sufficient data, these models may struggle with generalisation, leading to inaccurate failure predictions. Furthermore, these methods require high computational power and may be prone to overfitting, especially when dealing with small datasets or noisy data. To mitigate these issues, techniques such as feature selection, data pre-processing, and model regularisation are employed to improve the robustness and generalization of the models.

3.3 Hybrid Prognostics Approach

Hybrid prognostics combine model-based and data-driven techniques to enhance failure prediction accuracy. For example, physics-based models can provide initial degradation estimates, which are then refined using ML models trained on real-world data. These approaches seek to leverage the strengths of both techniques to overcome their individual limitations. One popular hybrid approach is the fusion of ML models with physics-based models, where the ML model is used to update or correct the predictions made by the physics-based model. Another example of hybrid prognostics is the combination of signal processing techniques, such as wavelet analysis, with ML models to improve fault detection and prediction in noisy environments. For example, Li and Deng [139] proposed a hybrid prognostic approach by

transforming one-dimensional vibration signals into time-frequency domain feature maps via CWT, improving degradation trend visibility. Next, the feature maps are fed into a CNN, which converts them into one-dimensional feature vectors, enabling the extraction of more refined fault information. Finally, a Bayesian-optimized LSTM model predicts the bearing's RUL.

Hybrid methods are particularly useful in complex systems where both physical knowledge and large amounts of data are available. Despite their advantages, hybrid methods can be computationally expensive and require complex integration between physical models and data-driven algorithms [140]. Among various hybrid prognostic approaches, digital twin stands out as a transformative solution. The next section explores how it enhances prognostics through real-time monitoring, simulation, and PdM.

3.3.1 Digital Twin Technology

Digital twin technology has emerged as a transformative solution for bearing fault diagnosis, enabling real-time simulation, monitoring, and PdM. A digital twin is a virtual replica of a physical system, integrating sensor data, predictive models, and simulations to provide continuous performance insights [141]. By simulating failure scenarios, digital twins offer real-time system health assessment, optimizing maintenance schedules and reducing unexpected failures [142]. In PHM, digital twins serve as hybrid models, combining physical degradation models with data-driven techniques to enable multi-physics PdM [131]. The integration of artificial intelligence (AI) and ML further enhances fault detection and prognosis, creating a closed-loop system where predictions continuously evolve with real-time sensor data [143-146].

Recent studies highlight the efficacy of digital twins in bearing fault diagnostics. Yuan and Fan [147] developed a real-time digital twin monitoring system for motorized spindles, utilizing MATLAB, ANSYS, and LabVIEW to analyse thermal behaviour. Similarly, Wu *et al.* [148] proposed a rolling bearing fault simulation model using Modelica, generating synthetic vibration signals for CNN-based fault classification. However, their approach lacked real-time sensor feedback, limiting its adaptability in dynamic industrial environments.

The primary advantages of digital twins include virtual fault simulation, allowing engineers to test failure scenarios without physical damage, reducing downtime and maintenance costs [149]. Additionally, digital twins enhance failure prediction accuracy, modelling bearing degradation under diverse operating conditions [150]. By offering data-driven insights, digital twins support optimized maintenance decision-making, enabling organizations to balance costs, system uptime, and asset performance [142].

Despite their potential, digital twins face implementation challenges. Developing high-fidelity virtual replicas requires extensive sensor data,

historical failure records, and domain expertise, which can be resource-intensive and time-consuming [151]. Furthermore, integrating digital twins with CBM systems demands high computational resources and advanced analytics [152].

Table 2 provides an overview of recent studies on bearing simulation and digital twin approaches,

covering signal types, fault types, fault sizes, applied algorithms, and key limitations. Notable issues include the absence of real-world validation, incomplete fault severity analysis, limited assessment of fault sizes, and discrepancies between simulated and actual faults.

Table 2 Comparison of various bearing simulation and digital twin approaches from recent literature

Ref.	Year	Application	Signal	Digital Model	Fault Type	Fault Size	Algorithm	Data Source	Limitation
[140]	2023	Ball bearing	Temperature Vibration Load	Physic-based	Outer race	N/A	LSTM PSO	Experimental & simulation	Algorithmic and computational complexity.
[141]	2024	Active magnetic bearing	Vibration	Numerical	Imbalance & misalignment	N/A	CNN	Experimental & simulation	Fault size and severity were not analysed.
[142]	2024	Ball bearing	Vibration	Physic-based	Inner race & outer race	N/A	Modified CNN	Experimental & simulation	Fault size and severity were not analysed.
[143]	2021	Ball bearing	Vibration	Numerical	Inner race, outer race & ball	0.18mm, 0.36mm, 0.53mm	SVM	Simulation & public dataset (CWRU)	No real-world physical twin
[144]	2024	CNC support bearing	Vibration	Numerical	Inner ring & outer ring	N/A	Modified CNN	Simulation & experimental	Fault size and severity were not analysed.
[145]	2023	Ball bearing	Vibration	Numerical	Inner race, outer race & ball	N/A	CNN	Simulation & experimental	Fault size and severity were not analysed.
[146]	2022	Roller bearing	AE	Numerical	Inner race, outer race, ball & mixed	3mm, 6mm	SVM	Simulation & experimental	Limited crack size range
[147]	2024	CNC motorized spindle bearing	Temperature	Physic-based & numerical	N/A	N/A	Polynomial Exponential Fourier Gaussian	Simulation & experimental	Only monitoring, no specific fault
[148]	2024	Ball bearing	Vibration	Physics-based & numerical	Outer ring & inner ring	0.1mm	CNN	Simulation & public datasets (XJTU & CWRU)	No real-world physical twin
[149]	2025	Ball bearing	Vibration	Numerical	Inner race, outer race & ball	1mm, 2mm	PACycleGAN CNN	Simulation, experimental & public datasets (CWRU)	Simulated data may not accurately represent real fault characteristics.
[153]	2025	Ball bearing	Vibration	Numerical	Outer ring crack propagation	0.5mm, 1.0mm (initial)	BPNN	Simulation & public datasets (XJTU)	Crack growth variability adds uncertainty.
[154]	2025	Aircraft bearing	Vibration	Numerical	Inner race, outer race & ball	N/A	CNN	Simulation & experimental	Fault size and severity were not analysed.
[155]	2025	EV PMSM rotor and bearing	Acoustic	Edge-based & cloud digital twins	Inner ring, outer ring, ball & cage	0.5mm	STFT, shallow CNN, DeiT	Experimental	No simulation, only data-driven models
[156]	2023	Roller bearing	Vibration	Numerical	Inner race, outer race & roller	1mm (width) × 0.5mm (depth)	Transformer	Simulation & experimental	Accuracy lower than 85%
[157]	2024	Wind turbine bearing	Vibration	N/A	Inner race, outer race & ball	0.18mm, 0.36mm, 0.53mm	HHT-CNN	Public dataset (CWRU)	No digital or physical twin

4.0 BENCHMARKING BEARING FAULT DETECTION, DIAGNOSIS AND PROGNOSIS

4.1 Public Benchmark Datasets

Public benchmark datasets are indispensable for bearing fault research, providing a foundation for reproducible experiments, objective performance benchmarking, and cross-method comparisons. Among the most influential are the Case Western Reserve University (CWRU), Paderborn University, IMS (University of Cincinnati), and XJTU-SY datasets. Each dataset embodies distinct operational conditions, fault types, and severities, shaping algorithmic choices and result interpretation for both diagnostic and prognostic investigations.

The CWRU dataset is the most extensively cited, featuring vibration signals from seeded inner race, outer race, and rolling element faults. It provides fault sizes ranging from 0.007 to 0.021 inches (0.1778 to 0.5334 mm) and offers sampling rates of 12 kHz and 48

kHz. Its structured classes and low noise levels have made it the de facto benchmark for deep learning-based diagnosis.

The Paderborn dataset contains both artificially induced and naturally degraded faults under multiple speed-load combinations, with vibration and current signals. This dataset is widely utilized for domain adaptation and cross-condition generalization studies.

The IMS dataset captures long-term degradation of bearings until failure under constant conditions, making it pivotal in Remaining Useful Life (RUL) prediction and prognostic modelling.

The XJTU-SY dataset offers high-resolution vibration signals across varied fault types and severities, recorded under diverse operating conditions. Its comprehensiveness and real-world alignment have made it suitable for deep learning architectures and digital twin frameworks.

A concise comparison of these datasets is presented in Table 3, highlighting key attributes for benchmarking and performance evaluation.

Table 3 Overview of Public Benchmark Datasets for Bearing Fault Studies

Ref.	Year	Dataset	Fault Types	Fault Sizes	Sampling Rate	Typical Applications	Limitation
[158]	2003	CWRU	Inner race, outer race, ball faults	0.1778mm 0.3556mm 0.5334mm	12 kHz, 48 kHz	Classifying fault type and size; algorithm benchmarking	Clean laboratory data; lacks noise & cross-condition variation
[159]	2007	IMS (NASA)	Degradation to failure	Naturally evolving	20 kHz	Prognostics and RUL modelling	Only one operating condition; limited fault diversity
[160]	2012	PRONOSTIA (FEMTO)	Inner race and outer race faults	Progressive degradation	25.6 kHz	Transfer learning, RUL estimation techniques	Limited runs per condition; proprietary test bed
[161]	2013	MFPT	Outer race, inner race (plus 3 real-world faults)	Fixed fault (unspecified)	48.8 kHz, 97.7 kHz	Envelope analysis; ML detection benchmarking	Small, controlled dataset; no failure progression; limited generalizability
[162]	2016	Paderborn	Artificial and natural faults	Seeded and natural variations	64 kHz	Cross-condition diagnosis; domain adaptation	Lab-based; narrow load/speed regimes; limited transfer realism
[163]	2020	XJTU-SY	Inner race, outer race, ball faults	Progressive stages	25.6 kHz	Hybrid digital twin validation; fault pattern diagnosis	Focus on seeded faults; lacks run to failure data; limited operating variability
[164]	2020	MaFaulDa	Inner, outer, ball faults; misalignment; imbalance	Bearing faults size unspecified	50 kHz	Multi-class diagnosis; fault severity estimation	Mixed fault types; not exclusively bearings; lab-only; limited transferability
[165]	2022	Mehran (Triaxial)	Inner race and outer race faults	0.7 mm–1.7 mm (0.2 mm increment)	10 kHz	Fault size regression & classification	Motor–bearing setup, not isolated; limited replicates per class
[166]	2023	German Aerospace Centre (DLR)	Outer race, inner race	1.0 – 4.0 mm	25.6 kHz	Fault size quantification; severity modelling	Only artificially seeded spalls; controlled conditions only; limited real industrial relevance
[167]	2023	Hanoi University (HUST)	Inner race, outer race, ball cracks; combinations	0.2 mm	51.2 kHz	Fault-type classification; transfer learning performance	Only one fault size; limited loads, no degradation timeline; transfer limited across machines

4.2 Performance Evaluation Metrics

Performance evaluation for diagnostic tasks typically uses classification metrics, while prognostic tasks rely on regression metrics. Table 4 below summarizes commonly used metrics.

Table 4 Metrics for Diagnostic and Prognostic Tasks

Metric	Formula	Purpose	Eq. No
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$	Diagnostic	(9)
Sensitivity (Recall)	$\frac{TP}{TP + FN}$	Diagnostic	(10)
Specificity	$\frac{TN}{TN + FP}$	Diagnostic	(11)
Precision	$\frac{TP}{TP + FP}$	Diagnostic	(12)
F1-score	$2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$	Diagnostic	(13)
Root Mean Squared Error (RMSE)	$\sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$	Prognostic	(14)
Mean Absolute Error (MAE)	$\frac{1}{n} \sum_{i=1}^n y_i - \hat{y}_i $	Prognostic	(15)
Coefficient of Determination (R ² Score)	$1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$	Prognostic	(16)

where TP is True Positive, FP is False Positive, TN is True Negative, and FN is False Negative; y_i denotes the actual value, \hat{y}_i the predicted value, and \bar{y} the mean of actual values.

4.3 Quantitative Evaluation of FDD and Prognostic Approaches

Benchmarking the quantitative performance of fault detection, diagnosis, and prognostic methods is critical for assessing how different analytical paradigms address the challenges of bearing health monitoring. In contrast to the preceding section, which discussed conceptual frameworks such as digital twin modelling and simulation-driven strategies, this section consolidates empirical findings as reported in Table 5. The studies listed in this comparison were already cited in the preceding subsections and this section now focuses on summarizing their quantitative performance and practical implications. The comparison highlights several key dimensions, including the analytical domains, which follow the detailed categorization already discussed in the earlier sections of this review, the nature of the datasets, whether public benchmarks, laboratory test rigs, or real industrial environments, and the specific tasks targeted, such as fault detection, type classification, severity estimation, or remaining useful life (RUL) prediction.

The table also reports a variety of performance indicators, including accuracy, precision, recall, F1-score, mean absolute error (MAE), and root mean square error (RMSE), alongside explicit descriptions of methodological constraints. Collectively, these results demonstrate a clear performance gradient.

Table 5 Quantitative Performance Benchmarking of Bearing Fault Analysis Methods

Ref.	Year	Method	Domain	Data Source	Application	Performance Metrics	Limitation
[5]	2024	IRLS-VPMCD with variational mode decomposition (VMD) using speed and current measurement	Frequency, Advanced Decomposition	Experimental data	Diagnosis (Classification)	Accuracy: up to 98.44%	Model sensitive to feature correlation
[16]	2024	Convolutional autoencoder (AE), Linear discriminant analysis (LDA)	Time-Frequency, Envelope, Deep Learning	CWRU, Jiangnan University (JNU)	Diagnosis (Classification)	Accuracy: up to 99.73% (CWRU) F1 Score: 0.94+ for most fault types	AE parameters must be manually tuned
[18]	2024	Time-domain feature selection + ML classifiers (kNN, SVM, NB)	Time, Supervised Learning	CWRU	Diagnosis (Classification)	Accuracy: 97% F1 Score: 96% Precision: 96% Recall: 95.7%	Limited to CWRU dataset, Use only time-domain features
[19]	2024	Variational autoencoder (VAE)	Deep Learning	Real data (hydro-generators), IMS dataset	Diagnosis (Classification)	Accuracy: 97% (Real data), 95% (IMS)	Needs polar coordinate-based domain expertise
[22]	2023	AE sensors + Envelope Demodulation	Frequency, Envelope	Experimental data	Diagnosis (Identification)	Multi-harmonic fault frequency identification	Sensitive to temperature variation
[23]	2024	Vibration + Temperature + DWT + ANN	Wavelet Transform, Supervised Learning	Experimental data	Diagnosis (Classification)	Accuracy: 98%	Sensor placement sensitivity

Ref.	Year	Method	Domain	Data Source	Application	Performance Metrics	Limitation
[35]	2024	PSO-based selection of optimal time-domain features (MAV, SSI, WL) + kNN	Time, Envelope, Supervised Learning	Experimental, IMS dataset	Diagnosis (Classification)	Accuracy: > 95% (Experimental), 98.25% (IMS)	Performance drops during individual phase
[37]	2024	Graph Neural Network built using Granger causality test	Deep Learning	CWRU, Paderborn dataset	Diagnosis (Classification)	Accuracy: > 98% (CWRU), 96.51% (Paderborn)	High time and space complexity due to causality graph construction
[41]	2023	FFT-based fault frequency matching	Frequency, Envelope	Experimental data	Diagnosis (Identification)	Amplitude increases with load and speed	Limited to FFT-based analysis
[43]	2023	Frequency-Domain Multilinear PCA + NN classifier	Frequency, PCA, Supervised Learning	Experimental data	Diagnosis (Classification)	Accuracy: 99%, Precision: ≥ 0.97 , Recall: ≥ 0.97	Requires frequency alignment across channels
[45]	2024	FPGA-based vibration monitoring + FFT	Time, Frequency, Time-Frequency	Experimental data	Detection (Identification)	Accuracy: 100% (4 types)	Manual threshold tuning required
[48]	2023	Bitask-based time & frequency feature learning + CNN classifier	Time, Frequency, Deep Learning	Paderborn (bearing)	Diagnosis (Classification)	Accuracy: 99.37%	Performance slightly degraded under strong noise;
[50]	2024	Graph Neural Network with Dilated kNN and Adversarial Discriminative Domain Adaptation	Time-Frequency, Deep Learning	Paderborn, HUST, Ling Gang (LG) dataset	Diagnosis (Classification)	Accuracy on cross-domain tasks (up to ~99%)	Limited exploration of transferability across different bearing sizes
[53]	2023	Multi-Scale CNN + Multi-Head Attention	Time-Frequency, Deep Learning, Model-Based Prognostic	Simulation data	Prognosis (RUL)	MAE: 1.296; RMSE: 0.985;	Assumes idealized bearing models
[56]	2024	Transfer Learning using Variable-Scale Attention Mechanism (Inception + LSTM + MK-MMD)	Time-Frequency, Deep Learning	Experimental, Real factory data	Diagnosis (Classification)	Accuracy: 99.65% (roller), 99.20% (through shaft)	Noisy background affects signal quality
[57]	2023	Variable Convolution Kernel Design guided by Time-Frequency Resolution	Time-Frequency, Wavelet Transform, Deep Learning	Experimental data	Diagnosis (Classification)	Accuracy: 99.85%	Relies on fixed image sizing (128×128)
[58]	2023	Composite Multi-scale TF Reverse Dispersion Entropy + Optimized SVM	Time-Frequency, Supervised Learning	Experimental data, CWRU	Diagnosis (Classification)	Accuracy: 100% (Experimental, CWRU)	Parameter tuning for entropy and classifier is non-trivial
[59]	2024	Multi-Scale TransFusion Network (MSTF) with TFSDP + MFEL + Transformer	Time-Frequency, Deep Learning	Experimental data, CWRU	Diagnosis (Classification)	Accuracy: 99.27% (CWRU), 94.87% (Experimental)	Required time-frequency symmetric dot pattern (TFSDP) preprocessing
[61]	2023	Physics-Informed Sparse Degradation Modelling + Entropy-Based Indicators	Frequency, Model-Based Prognostic	XJTU-SY, IMS dataset	Prognosis (Detection)	Clear degradation trends	Entropy and model parameters require careful tuning
[62]	2023	Variable Spectral Segmentation Harmogram + Harmonic Spectral Kurtosis	Time-Frequency, Envelope	CWRU	Detection (Identification)	Accurate extraction of fault characteristic frequencies	Single-signal processing only; Requires prior bearing parameters
[64]	2023	Envelope Analysis + Fast Kurtogram + Hilbert Transform + Classical ML (kNN, Naive Bayes, SVM, Decision Tree)	Frequency, Envelope, Supervised Learning	CWRU	Diagnosis (Classification)	Accuracy: 100% (Fine kNN, Fine Tree); 94.4% (Kernel Naive Bayes)	Ball defects poorly detected via envelope spectrum

Ref.	Year	Method	Domain	Data Source	Application	Performance Metrics	Limitation
[72]	2023	Empirical Mode Decomposition (EMD) + Genetic Algorithm (GA) + BP Neural Network	Time, EMD, Supervised Learning	CWRU	Diagnosis (Classification)	Accuracy: > 99%	Requires manual IMF selection
[74]	2023	Fast and Adaptive EMD (FAEMD) using Order Statistics Filter (OSF) + Envelope Spectrum Analysis	Time-Frequency, Envelope, EMD	CWRU	Diagnosis (Identification)	Fault frequencies clearly identified in envelope spectrum	No classifier used (pure signal processing)
[77]	2023	Wavelet Packet Transform (WPT) + Mother Wavelet Selection + Medium Gaussian SVM	Time-Frequency, Wavelet Transform, Supervised Learning	Experimental data	Diagnosis (Identification)	Success Rate: 97% (inner race), 77% (outer race), 80% (combined)	Incipient faults not tested
[79]	2023	Triboelectric Linear Bearing Sensor (TLBS) + Continuous Wavelet Transform (CWT) + Lightweight CNN	Time-Frequency, Wavelet Transform, Deep Learning	Experimental data	Diagnosis (Classification)	Accuracy: 100% (3 fault types)	Sensitive to humidity and lubricant type<
[93]	2023	Frequency-Domain Multilinear PCA (FDMPCA) + FFT + Neural Network	Frequency, PCA, Supervised Learning	Experimental data	Diagnosis (Classification)	Accuracy: 99.00% Dimensionality reduction: 99.62% (FD tensor)	Requires full sensor availability
[106]	2023	Complementary ensemble EMD + Artificial Bee Colony (ABC)+ ANN	EMD, Supervised Learning	Experimental data	Diagnosis (Classification)	Accuracy: 95.95% Precision: 94.96% Recall: 94.78% F1-Score: 94.87%	May overfit with excessive hidden neurons
[112]	2024	Autoencoder + Feedforward Neural Network (AE-FFNN)	Deep Learning	CWRU	Diagnosis (Classification)	Accuracy: 98.56% Precision: 97.68% Recall: 97.55% F1-Score: 97.60%	Focuses on improving detection for one misclassified fault type
[114]	2024	Cross-Modal Fusion CNN (CMFCNN) + Online Soft-Label Training (OSLT)	Deep Learning	Experimental data	Diagnosis (Classification)	Accuracy: 99.94% F1-Score: 99.94%	Computational complexity due to fusion modules
[115]	2024	Time-Series-to-Image Conversion + Improved LeNet CNN	Time, Frequency, Deep Learning	Experimental (pump), CWRU	Diagnosis (Classification)	Accuracy: 100% F1-Score: 100%	Requires image transformation tuning per scenario
[117]	2024	Parallel Spatial CNN-LSTM with Physics-Informed Merge Layer	Time-Frequency, Deep Learning	Experimental (gearbox), CWRU	Diagnosis (Classification)	Accuracy: 100% (gearbox), 99.95% (CWRU)	Requires dual input preprocessing (raw + scalogram)
[118]	2024	Constant-Q Nonstationary Gabor Transform (CQ-NSGT) + Enhanced Inception ResNet-V2	Time-Frequency Analysis, Deep Learning	Experimental data	Diagnosis (Classification)	Accuracy: 99.84%; Precision, Recall, F1-Score: 100%	Requires image transformation (CQ-NSGT)
[122]	2024	Multiscale Deep Attention Q Network (MDAQN)	Deep Reinforcement Learning	Experimental data	Diagnosis (Imbalanced Classification)	Accuracy: > 99% across 3 datasets	Requires extensive training steps
[124]	2023	Dual-Experience Pool Deep Reinforcement Learning (DEPDRL)	Deep Reinforcement Learning	Experimental (aeroengine rotor), CWRU	Diagnosis (Imbalanced Classification)	Accuracy: 99.68% (CWRU), 98.86% (aeroengine)	Requires dual residual networks and balanced cross-sampling
[125]	2023	RL-Optimized Support Vector Machine (RL-SVM)	Time, Frequency, Time-frequency, Supervised Learning Reinforcement Learning	XJTU-SY, Experimental	Diagnosis (Classification)	Accuracy: 100%	Requires multi-domain feature extraction and supervised fusion

Ref.	Year	Method	Domain	Data Source	Application	Performance Metrics	Limitation
[132]	2023	Physics-Based Modelling + FEM	Model-Based Prognostic	Real data (turbine–bearing)	Prognosis (Detection)	Forecasting accuracy: consistent with overhaul findings	Prognosis limited to unbalance (not generalized faults)
[135]	2024	Time Transformers + Convolutional long short-term memory (TT–ConvLSTM)	Data-Driven Prognostic	XJTU-SY, PRONOSTIA	Prognosis (RUL)	RMSE: 0.093 (PRONOSTIA), 0.072 (XJTU-SY); MAE: 0.074 (PRONOSTIA), 0.052 (XJTU-SY)	Requires multi-path feature extraction and fusion; Computational complexity due to dual-path architecture
[137]	2023	LSTM (stacked, trained on raw vibration data)	Data-Driven Prognostic	IMS, Real data (hydro & wind turbines)	Prognosis (RUL)	RMSE: 0.01 (IMS), 0.11 (hydro), 0.12 (wind)	Performance depends on quality of raw sensor data
[139]	2023	CNN + Bayesian-optimized LSTM	Deep Learning, Hybrid Prognostic	PRONOSTIA	Prognosis (RUL)	Accuracy: 99.5%; RMSE: 0.0182; MAE: 319.4;	Requires sufficient lifecycle data for effective prediction

The quantitative synthesis of recent studies reveals a clear evolution in bearing fault analysis methodologies. Traditional signal processing and classical machine learning approaches, including techniques such as EMD, FFT, and time-domain feature extraction combined with SVM or kNN, often demonstrate competitive accuracy in controlled environments. However, their performance tends to degrade in noisy industrial settings, under varying load conditions, or when transferred across domains. These limitations are consistent with findings in Table 5, where models restricted to single-domain features or fixed preprocessing pipelines exhibited reduced generalisation and sensitivity to sensor placement, temperature variation, or feature correlation.

Recent deep learning methods, particularly convolutional architectures, graph neural networks, and cross-modal fusion frameworks, consistently achieve state-of-the-art results. Reported accuracies frequently exceed 99% across benchmark datasets such as CWRU, Paderborn, and IMS, with multi-task and attention-based models demonstrating strong adaptability to imbalanced classifications and prognostic tasks. Nonetheless, these methods demand extensive annotated datasets, significant computational resources, and careful parameter tuning. They also remain challenged by interpretability, domain transferability, and robustness under real-time constraints.

Emerging paradigms such as multi-sensor fusion, continual learning, federated learning, and edge AI deployment represent promising strategies for bridging these gaps. Integrating physics-based priors into deep learning pipelines further enhances interpretability and aligns with industry needs for trustworthy, explainable prognostics. The consolidated findings therefore emphasise not only the ongoing methodological shift but also the necessity for standardised evaluation protocols,

enabling fair cross-study comparisons and supporting practical industrial deployment.

5.0 CONCLUSION

This review consolidated recent progress in bearing fault detection, diagnosis, and prognostics, encompassing signal processing, machine learning, and deep learning approaches. It emphasised the shift from handcrafted features to end-to-end deep architectures and highlighted the emerging role of digital twin frameworks in predictive maintenance. Public benchmark datasets, including CWRU, Paderborn, and IMS, have become central to reproducible evaluation; however, inconsistent reporting of metrics such as accuracy, F1-score, and RMSE continues to hinder cross-study comparison.

Comparative analysis of recent studies reveals ongoing challenges. Many models remain highly sensitive to sensor placement, feature correlation, and environmental noise; others demand extensive parameter optimisation or exhibit poor generalisation across bearing types and operating conditions. Real-time deployment is further limited by computational overhead and data imbalance. Addressing these issues requires robust benchmarking protocols, cross-domain transfer learning, and continual learning methods that adapt to evolving machine conditions.

Future research is moving toward combining physics-informed models with deep learning, leveraging multi-sensor data, and adopting federated or edge AI for distributed fault monitoring. A key challenge lies in accurately estimating fault size progression using simulated or digital twin data, as discrepancies with real-world fault evolution can undermine remaining useful life predictions. Addressing this issue will be crucial for developing

interpretable, scalable prognostic systems that bridge laboratory development and industrial application, enabling more reliable and cost-effective predictive maintenance and advancing from fault detection to accurate remaining useful life estimation in real-world rotating machinery.

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Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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