# A Comprehensive Review of Bearing Fault Identification Techniques Using the CWRU Dataset

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***Abstract*—Rolling element bearing faults are one of the major issues that occur in any industrial machine. Hence, predicting fault identification accurately is not only essential for the reliable operation but also for its predictive maintenance. The Case Western Reserve University (CWRU) bearing dataset is one of the most widely used benchmarking datasets for developing and evaluating bearing fault diagnosis techniques. This paper presents a comprehensive overview of bearing fault identification methods based on the CWRU dataset, covering signal processing, machine learning, and deep learning approaches. Traditional techniques such as time-domain, frequency-domain, and time-frequency domain analyses are examined alongside machine learning algorithms like Support Vector Machines, Decision Trees, and Random Forests. Recent advances in deep learning, particularly Convolutional Neural Networks and Long Short-Term Memory networks, are also discussed. The review highlights the strengths and limitations of existing methods, identifies key research gaps related to model generalisation and its real-world deployment, and outlines future directions for intelligent and robust bearing condition monitoring systems.**

***Index Terms*—Bearing Fault Diagnosis, CWRU Dataset, Condition Monitoring, Deep Learning, Machine Learning, Predictive Maintenance, Rotating Machinery, Vibration Analysis.**

## I. INTRODUCTION

Manufacturing, power generation, transportation, aerospace, mining, and petrochemical industries all heavily rely on rotating machinery, which serves as the foundation of modern industries. Maintaining productivity, operational efficiency, and safety depends on the performance of parts, including electric motors, turbines, pumps, compressors, bearings, and gearboxes. Unexpected malfunctions in these devices can lead to expensive downtime, lower-quality products, higher maintenance costs, and possible safety risks. As a result, predictive maintenance and condition monitoring are becoming essential in the industry. [1], [2], [3], [4]

Rolling element bearings play a vital role in rotating machines as it is used to support rotating shafts and reduce friction between moving parts. Bearing is subjected to continuous mechanical loads, vibrations, high-speed rotations, and varying operating conditions, making it prone to wear and degradation over time [5], [6]. Studies have reported that bearing-related failures account for a significant proportion of faults in rotating machinery, highlighting the necessity for effective bearing health monitoring systems [7], [8].

Bearing failures usually occur in the inner race, outer race, rolling elements, or cage due to factors such as material fatigue, inadequate lubrication, contamination, corrosion, high stress, and shaft misalignment. These defects sometimes begin as minor cracks or localised damage and eventually grow into major problems that could cause catastrophic machine malfunctions if not discovered in time [9], [10]. Hence, developing a reliable fault detection method has become an important field of research in the field of condition monitoring of the machine [11].

Vibration analysis has become one of the most popular techniques among acoustic, vibration, and lubrication data techniques for monitoring bearing conditions because vibration signals offer crucial information about the state of bearings and other rotating components. Traditional signal processing methods, such as time-domain, frequency-domain, and time-frequency-domain analyses, have been extensively employed to extract features related to fault from vibration signals [12], [13], [14]. Advanced techniques such as envelope analysis, wavelet transformations, and empirical mode decomposition have improved the diagnosis of early bearing issues under difficult operating conditions [15], [16], [17].

The rapid advancement of artificial intelligence and data-driven technologies has significantly changed the field of bearing defect identification. Traditional machine learning methods such as Support Vector Machines, Decision Trees, Random Forests, and Artificial Neural Networks have demonstrated promising capabilities for automatic fault classification using extracted signal features [18], [19], [20]. Deep learning systems have gathered a lot of attention in recent years because they can automatically train discriminative defect features directly from raw sensor data, eliminating the need for manual feature engineering [21], [22]. Techniques such as Convolutional Neural Networks (CNNs), Autoencoders, and Long Short-Term Memory (LSTM) networks have shown remarkable diagnostic performance in a range of bearing fault diagnostics [23], [24].

The development of intelligent diagnostic systems has been greatly facilitated by the availability of publicly accessible benchmark datasets. The Case Western Reserve University (CWRU) bearing dataset is the most widely used benchmark for evaluating algorithms related to bearing fault diagnosis. The dataset provides vibration measurements under both healthy and faulty bearing conditions with different fault locations, fault severities, and operating loads, allowing researchers to compare diagnostic procedures within a standardised experimental framework [25].

Despite the high diagnostic accuracy reported in the literature, there are still some problems with model robustness, domain adaptation, noise resistance, explainability, and generalisation to real industrial settings. Because of this, there is a growing need to evaluate existing methods critically and identify possible research directions that can bridge the gap between laboratory research and practical industrial applications. This review offers a comprehensive analysis of bearing fault identification techniques developed using the CWRU dataset, with a focus on signal processing techniques, machine learning algorithms, deep learning architectures, hybrid diagnostic frameworks, current challenges, and future research opportunities.

## II. BEARING FAULT IDENTIFICATION USING THE CWRU DATASET: METHODS AND DEVELOPMENTS

The Case Western Reserve University (CWRU) bearing dataset is one of the most popular benchmark datasets for the development, validation, and comparison of bearing defect detection techniques. Since its release, the dataset has been utilised as a common platform for testing signal processing, machine learning, and deep learning algorithms in controlled lab environments. The primary factors that make the CWRU dataset appealing are its accessibility, well-documented experimental design, and availability of vibration data encompassing a range of fault types and severities [13], [26].

The CWRU test apparatus (Fig. 1) consists of a dynamometer, a torque transducer, and a two-horsepower induction motor. The inner race, outer race, and rolling components (ball) of the bearings were artificially damaged using electro-discharge machining (EDM). Fault sizes of 0.007, 0.014, 0.021, and 0.028 inches were created in order to simulate different levels of bearing degeneration. Vibration signals were recorded under various load conditions, ranging from 0 to 3 horsepower, using accelerometers mounted at the motor's drive and fan ends [13], [26]. The large database of this experimental setup allows researchers to study fault diagnosis methods under consistent operational conditions.

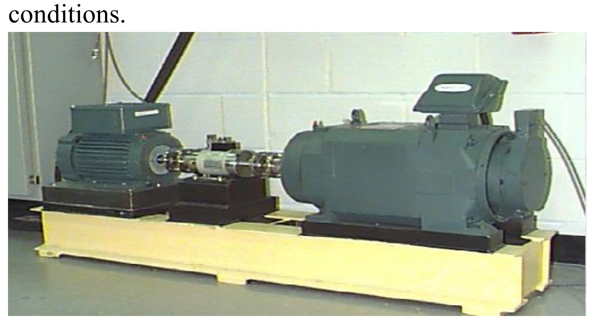

Figure 1: CWRU test apparatus

A. Signal Processing-Based Fault Identification

Signal processing techniques are the oldest and most fundamental ways for diagnosing bearing defects. Because vibration signals from damaged bearings are inherently non-stationary and nonlinear, it is still challenging to extract meaningful fault-related information from raw data [5]. Traditional time-domain methods use statistical indicators like variance, entropy, skewness, kurtosis, root mean square (RMS), and crest factor to characterise bearing conditions [8]. These features may not always be able to distinguish between different fault types under diverse operating conditions, even if they provide crucial information on the severity and progression of bearing issues.

Frequency-domain analysis has been utilised extensively to identify typical failure frequencies associated with bearing defects. Techniques based on the Fast Fourier Transform (FFT), which transforms vibration signals from the time domain into the frequency domain, enable the detection of spectral peaks corresponding to inner race, outer race, and ball defects [5], [7]. However, frequency-domain approaches often have issues when evaluating transient or non-stationary signals since they do not maintain temporal information.

To get around these challenges, researchers are increasingly employing time-frequency analysis methods that can simultaneously capture the spectral and temporal characteristics of vibration signals. Wavelet Transform (WT) and Wavelet Packet Transform (WPT) have become more popular because of their capacity to do multi-resolution analysis and capture localised fault information [7], [27], [28], [29]. These methods facilitate the identification and assessment of fault-induced components by dissecting vibration signals into many frequency bands.

Empirical Mode Decomposition (EMD) and its derivatives, including Ensemble Empirical Mode Decomposition (EEMD), have also been widely applied to CWRU vibration signals. These methods reduce complex signals to Intrinsic Mode Functions (IMFs), which represent different oscillatory modes observed in the data [6]. Similar to this, Variational Mode Decomposition (VMD) has garnered a lot of attention because of its improved decomposition accuracy and resilience to mode mixing problems. Researchers have demonstrated improved fault feature extraction performance when VMD is applied with machine learning classifiers [30].

Envelope analysis is another important technique for identifying bearing problems. Because bearing failures often result in periodic impulsive signals that are modified by resonance frequencies, envelope analysis effectively eliminates fault indications that could be hidden within broadband vibration data [31]. Several studies employing the CWRU dataset have demonstrated that envelope spectrum analysis significantly improves fault identification sensitivity, particularly for early-stage defects [5].

In addition to vibration-based strategies, sensor fusion techniques have been studied to increase diagnostic reliability. Researchers have investigated the combination of temperature, vibration, sound emission, and current sensors to collect complementary data about machine health [9]. These multi-sensor frameworks have shown improved fault classification performance and resilience when compared to single-sensor systems.

B. Machine Learning-Based Fault Identification

The shortcomings of traditional threshold-based diagnostic approaches prompted the development of machine learning techniques for automatic bearing defect categorisation. Machine learning methods use extracted characteristics to find patterns associated with different failure scenarios in order to classify unknown operational statuses [2].

Support Vector Machines (SVMs) are one of the most widely used machine learning techniques for identifying bearing problems. Due to their ability to tackle nonlinear classification problems and high-dimensional feature spaces, SVMs have consistently demonstrated excellent classification accuracy on the CWRU dataset [2], [12], [32]. Because of kernel-based learning techniques, SVMs are able to successfully identify fault classes even when feature distributions significantly overlap.

Decision trees and Random Forests have also been employed extensively because of their computing efficiency and interpretability. These algorithms generate hierarchical decision structures that classify flaws based on retrieved signal attributes. Ensemble learning methods such as Random Forests improve diagnostic performance by combining many decision trees and reducing classification variance [12].

Artificial neural networks (ANNs) are another important class of machine learning techniques utilised for bearing diagnostics. ANN-based models have demonstrated strong abilities to capture nonlinear relationships between vibration variables and fault situations [6]. However, classic neural networks may require considerable feature engineering and careful parameter adjustment to obtain good performance.

The effectiveness of machine learning models is significantly influenced by the quality of extracted features. Dimensionality reduction and feature selection techniques are therefore now crucial components of intelligent fault diagnosis systems. Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and mutual information-based feature selection techniques have been applied to reduce feature redundancy and boost classification efficiency [2], [30].

Comparative studies utilising the CWRU dataset demonstrate that machine learning algorithms can achieve classification accuracies greater than 95% provided appropriate feature extraction and selection methods are applied [12]. Their dependence on manually generated features is still a significant disadvantage, though, which is propelling the transition to deep learning methods that are capable of autonomously learning features.

### C. Deep Learning-Based Fault Identification

Bearing defect diagnosis research has changed dramatically as deep learning has eliminated the need for major human feature engineering. By automatically learning hierarchical feature representations from raw vibration data, deep learning architectures reduce human intervention and enhance diagnostic performance [3], [23].

Convolutional Neural Networks (CNNs) are the most widely used deep learning architecture for CWRU-based fault diagnosis. CNNs use convolutional filters to extract local patterns and hierarchical features from vibration data. Researchers have constructed both one-dimensional CNNs using raw vibration signals and two-dimensional CNNs utilising spectrograms, wavelet scalograms, and time-frequency images [12], [33]. Due to CNNs' capacity to autonomously extract features, classification accuracy on benchmark datasets frequently exceeds 99% [33].

Additionally, Deep Neural Networks (DNNs) have shown encouraging diagnostic potential. To capture intricate nonlinear interactions within vibration signals, these structures make use of several hidden layers. Using the CWRU dataset, DNN-based techniques have been effectively used to categorise different bearing defect types and severity levels [3].

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have become more and more popular as they can simulate the temporal dependencies found in vibration data. LSTM networks efficiently capture sequential information and long-term correlations within time-series data, in contrast to CNNs, which mainly concentrate on spatial feature extraction [19]. As a result, LSTM-based models have proven to perform well in dynamic operating conditions.

Autoencoders have been widely used in anomaly detection and unsupervised feature learning. After learning compressed representations of input data, these architectures can identify anomalous operating conditions by analysing reconstruction errors [23]. Autoencoder-based frameworks are particularly useful in situations where labelled fault data is scarce.

Recent studies have presented lightweight deep learning architectures designed for use on edge computing devices and industrial Internet of Things (IIoT) systems. For example, efficient CNN models developed using the CWRU dataset have achieved exceptional diagnostic accuracy with much reduced computational complexity and memory requirements [33]. Applications for real-time fault monitoring in smart industrial settings are made easier by these developments.

### D. Hybrid and Advanced Diagnostic Frameworks

Researchers are becoming more conscious of the benefits of combining signal processing with deep learning techniques in hybrid frameworks, despite the remarkable performance of deep learning models. These systems combine the best features of both methods by employing signal processing techniques for noise reduction and feature enhancement and deep learning models for automatic classification [11].

One of the best hybrid approaches is the Wavelet-CNN framework. These systems generate time-frequency representations of vibration signals using wavelet transformations, which are subsequently input into CNNs [7]. Using this technique, the network can acquire highly discriminative features while retaining fault-related information.

VMD-CNN and EMD-LSTM designs have also been proposed to improve diagnostic robustness under different operating conditions [30]. While fault-sensitive components are separated by signal decomposition techniques, deep learning models employ enhanced feature representations for classification. Several studies have demonstrated superior performance when compared to independent machine learning or deep learning approaches [11].

Transfer learning is a potential solution to issues caused by inadequate training data and inconsistent operational settings. By applying knowledge from one dataset or operational state to another, transfer learning techniques significantly reduce training requirements and improve model generalisation [3], [23]. This capability is particularly important for industrial applications, where acquiring tagged defect data is sometimes expensive and time-consuming.

Recently, researchers have concentrated on Explainable Artificial Intelligence (XAI) in an attempt to make deep learning models more transparent and understandable. Many deep learning frameworks have excellent classification accuracy, but their black-box nature prevents them from being widely used in industry. By providing insights into decision-making processes, explainable diagnostic models increase user confidence and facilitate practical application [34].

### E. Critical Assessment of the CWRU Dataset

Despite its widespread use, the CWRU dataset has certain shortcomings that should be considered when evaluating diagnostic methods. Because the dataset was produced under controlled laboratory conditions using purposely induced faults, it might not accurately represent naturally occurring bearing failures observed in industrial settings [13]. Therefore, models trained solely on the CWRU dataset may exhibit less generalisation capacity when applied in real-world scenarios.

Other problems include data leaks and inappropriate training-testing techniques utilised in some studies. Researchers have demonstrated that certain experimental methods inadvertently allow the same signal segments to appear in both training and testing datasets, leading to overly optimistic performance estimates [13], [26]. Therefore, rigorous benchmarking procedures are required to provide fair and reliable comparisons among diagnostic algorithms.

Furthermore, most CWRU-based research focuses on steady-state operating conditions, despite the fact that industrial machinery routinely confronts shifting loads, speed variations, and environmental disruptions. To solve these problems, dependable, adaptable, and domain-generalizable diagnostic systems that can maintain high performance under realistic operating conditions must be developed [35].

All things considered, the CWRU dataset continues to be an invaluable benchmark for evaluating intelligent diagnostic systems and has been essential to the development of bearing fault diagnostics research. The shift from traditional signal processing methods to machine learning and deep learning approaches has significantly improved defect identification accuracy and automation. However, future research needs to focus on enhancing model interpretability, robustness, transferability, and real-world applicability in order to fully exploit the potential of intelligent bearing health monitoring systems.

## III. CHALLENGES, RESEARCH GAPS, AND FUTURE DIRECTIONS IN BEARING FAULT IDENTIFICATION

The remarkable developments in bearing problem detection using signal processing, machine learning, and deep learning techniques have significantly increased the reliability of rotating equipment condition monitoring. Applying these intelligent diagnostic systems in industrial contexts is still challenging, despite classification accuracy exceeding 99% on benchmark datasets such as the Case Western Reserve University (CWRU) dataset. According to recent studies [36], [37], [38], [39], [40], the primary limitation is not the lack of sophisticated algorithms but rather the inability of existing models to generalise across different operating environments and industrial contexts.

### A. Generalisation Challenges in Industrial Environments

One of the biggest challenges in identifying bearing faults is the discrepancy between data produced in laboratories and real-world industrial conditions.

Most publicly available datasets, like the CWRU dataset, were collected in controlled experimental environments with predefined fault conditions and relatively low amounts of background noise. However, the various speeds, varying loads, changing ambient conditions, and complex noise sources that industrial machinery operates under have a significant impact on vibration characteristics [38], [40].

Several studies have demonstrated that diagnostic models trained on benchmark datasets often experience significant performance loss when applied to data collected from different machines or operating environments [36], [39]. This phenomenon, sometimes referred to as the domain shift problem, arises because the statistical distributions of the training and testing datasets differ significantly. Because of this, models that function well in laboratory settings frequently do not work as well in practical settings.

According to Smith and Randall's benchmarking study [26], many reported classification accuracies on the CWRU dataset might not accurately reflect real-world diagnostic capabilities because training and testing samples are comparable. Similarly, Hendriks et al. demonstrated how incorrect data partitioning methods might result in too optimistic performance estimates, hiding the true challenges of industrial implementation [13].

B. Domain Adaptation and Transfer Learning

To address the issue of domain shift, researchers have been focusing increasingly on transfer learning and domain adaptation strategies. Transmit learning allows a diagnostic model learned in one operational state to transmit acquired knowledge to another condition with minimal extra training data [36], [37]. This function is particularly helpful in industrial contexts when it is expensive and time-consuming to collect a large amount of tagged defect data.

Deep transfer learning is one of the areas of intelligent defect detection research that is growing the fastest, according to recent surveys [37], [41]. Domain adaptation strategies seek to lessen the distribution differences between source and destination domains by learning invariant feature representations. Techniques such as adversarial domain adaptation, maximum mean discrepancy optimisation, and deep feature alignment have been demonstrated to greatly increase cross-domain diagnostic performance [39], [40].

According to a study by Zhang et al. [40], deep domain adaptation techniques can effectively improve fault classification accuracy in a range of operational scenarios. Similarly, Wang et al. [38] provided a comprehensive analysis that showed how domain adaptation methods might improve diagnostic robustness on different machinery platforms. The growing use of transfer learning frameworks suggests a shift away from dataset-specific solutions and toward more general and practical diagnostic methods [42].

There are still certain challenges in spite of these advancements. Most transfer learning research focuses on relatively minor domain transitions, whereas industrial applications sometimes involve large changes in machine setups, sensor placements, and operational conditions. Therefore, more research is required to develop flexible diagnostic models that can handle difficult cross-domain scenarios with minimal supervision.

C. Data Scarcity and Labelling Challenges

Another major obstacle to diagnosing bearing faults is the absence of marked fault data. Because industrial equipment operates under healthy conditions for extended periods of time, there is typically a significant imbalance between healthy and defective samples. Furthermore, it is difficult to detect naturally occurring faults because maintenance procedures are often performed before major damage occurs [19], [43].

Large amounts of labelled data are required for standard supervised learning algorithms to perform well. However, identifying vibration signals sometimes requires extensive inspections, specific knowledge, and considerable operating costs. To address this issue, researchers have begun looking into few-shot learning, semi-supervised learning, and self-supervised learning techniques [43].

Self-supervised learning methods use unlabelled data to create meaningful feature representations prior to solving classification issues. Because industrial environments generate vast amounts of unlabelled sensor data, these techniques have the potential to significantly reduce dependency on manually labelled datasets. In a similar vein, few-shot learning techniques aim to enhance practical applicability by developing models that are able to identify fault states from a small number of labelled cases [36], [43].

Future research should focus on developing intelligent learning frameworks that can use unlabelled and partially labelled datasets in order to maintain high diagnostic accuracy and robustness.

D. Explainable Artificial Intelligence in Fault Diagnosis

The increasing usage of deep learning models has sparked questions regarding their interpretability and openness. It is still difficult to comprehend how deep neural networks make decisions, despite the fact that they consistently do better in classification. This "black-box" nature presents challenges for industry acceptability since maintenance engineers require clear explanations before making maintenance decisions [2], [3].

Explainable Artificial Intelligence (XAI) is one possible solution to this issue. Techniques such as SHapley Additive exPlanations (SHAP), Gradient-weighted Class Activation Mapping (Grad-CAM), and Local Interpretable Model-Agnostic Explanations (LIME) provide information about the traits and signal components influencing diagnostic decisions [2].

Incorporating explainability into bearing problem diagnosis systems has several advantages. First, it boosts user trust by providing a clear explanation for classification results. Second, it facilitates model validation and debugging. Third, it makes regulatory compliance easier in safety-critical applications where decision transparency is essential. Future intelligent diagnostic systems are therefore expected to combine high projected accuracy with explainable decision-making skills [2], [10].

E. Federated Learning and Data Privacy

Data sharing is a major challenge in industrial settings due to concerns about confidentiality, cybersecurity, and intellectual property. Many businesses are reluctant to share operational data because it may reveal private information about equipment performance and manufacturing processes. Several companies can collaborate to train machine learning models without exchanging raw data thanks to a revolutionary technique called federated learning. Instead, local models are trained separately, and only model parameters are shared with a central server for aggregation. Federated learning offers several benefits for bearing defect diagnosis, including improved model generalisation, increased data privacy, and access to larger and more diverse datasets. Recent studies have shown that federated learning can significantly improve diagnostic performance while complying with data protection laws [44]. As Industry 4.0 usage increases, federated learning is expected to become a key technology for cooperative machinery health monitoring.

F. Digital Twins and Intelligent Maintenance

Digital twin technology is one of the most innovative developments in modern predictive maintenance systems. A digital twin is a virtual representation of a physical asset that continuously updates its state based on real-time sensor measurements. Engineers can monitor equipment health, simulate degradation processes, anticipate future failures, and optimise maintenance schedules by combining bearing defect diagnostic algorithms with digital twin frameworks. Unlike traditional condition monitoring systems that concentrate on defect detection, digital twins provide a full platform for lifecycle management and decision support [45].

By combining digital twins with machine learning and deep learning techniques, intelligent maintenance systems with self-evaluation and predictive analytical capabilities can be developed. Future research is expected to focus on integrating real-time fault diagnosis, remaining useful life prediction, and maintenance optimisation in unified digital twin environments.

G. Edge Intelligence and Industrial Internet of Things

Industrial monitoring has changed as a result of the Industrial Internet of Things' (IIoT) ability to continuously gather and transmit sensor data. Modern bearing monitoring systems are increasingly using cloud platforms, wireless sensors, and distributed computing architectures to support predictive maintenance applications [9], [33].

However, transferring enormous volumes of vibration data to centralised cloud servers has problems with latency, bandwidth, and cybersecurity. Edge computing solves these issues by performing diagnostic computations in close proximity to the data source. Lightweight deep learning architectures designed for edge devices can perform real-time defect detection with low connection requirements [33].

Recent developments in edge intelligence reveal the feasibility of deploying deep learning-based defect detection systems on embedded devices with limited computational resources. These characteristics are expected to be crucial for the implementation of smart factories and autonomous maintenance systems.

### H. Future Outlook

In the future, intelligent sensing systems, edge computing, digital twin technologies, and advanced artificial intelligence will all collaborate to detect bearing flaws. Even while benchmark datasets like CWRU have been essential in advancing algorithm development, future research must focus on improving generality, robustness, interpretability, and real-world applicability [13], [26].

Explainable AI, transfer learning, domain adaptation, self-supervised learning, and federated learning are expected to alleviate many of the drawbacks of current diagnostic systems. Concurrently, the integration of digital twins and IIoT technologies will facilitate the transition from condition monitoring to autonomous predictive maintenance frameworks. Ultimately, these advancements will contribute to Industry 4.0 objectives, reduced maintenance expenses, increased operational effectiveness, and improved equipment dependability.

Future research should therefore focus on developing scalable, interpretable, and adaptive diagnostic frameworks that can perform effectively in a range of industrial situations while maintaining high diagnostic accuracy and reliability.

## IV. CONCLUSION

Rolling element bearings are among the most crucial components of rotating machinery, and their reliable operation is essential to the productivity, efficiency, and safety of industrial systems. Bearing failures can lead to unscheduled downtime, increased maintenance costs, lower equipment lifespans, and significant financial losses. Therefore, the development of effective bearing defect detection techniques has become a significant focus of research due to condition monitoring, predictive maintenance, and intelligent manufacturing.

This review gave a comprehensive overview of bearing failure diagnosis methods with an emphasis on research using the Case Western Reserve University (CWRU) bearing dataset. The CWRU dataset has been crucial to the development of bearing defect diagnosis research because it provides a consistent benchmark for evaluating and comparing various diagnostic methods. Its widespread application has significantly accelerated the creation of intelligent diagnostic frameworks and enabled researchers to systematically investigate fault detection and classification methods in controlled experimental settings.

The review focused on how advanced machine learning and deep learning approaches have replaced traditional signal processing methods in bearing fault diagnosis. Conventional methods based on time-domain, frequency-domain, and time-frequency-domain analysis can be used to extract fault-related information from vibration signals. Techniques like the Fast Fourier Transform, Wavelet Transform, Empirical Mode Decomposition, Variational Mode Decomposition, and envelope analysis have made it easy to identify bearing defects and understand fault causes.

The advancement of machine learning greatly enhanced diagnostic capabilities by enabling automated fault categorisation using extracted signal features. Algorithms such as Support Vector Machines, Decision Trees, Random Forests, and Artificial Neural Networks have shown promising results in recognising various failure scenarios. However, because these techniques rely on manually generated feature extraction, they are not very flexible in complex operational scenarios.

By enabling automated fault categorisation using extracted signal properties, the development of machine learning significantly improved diagnostic capabilities. Convolutional neural networks, deep neural networks, recurrent neural networks, long short-term memory networks, and autoencoders have shown remarkable classification accuracy on benchmark datasets like CWRU. Additionally, hybrid frameworks that integrate deep learning architectures with signal processing techniques have demonstrated improved fault identification performance and robustness when compared to standard methods.

Despite these achievements, the investigation revealed several important barriers that continue to impede the widespread application of intelligent bearing problem detection systems. There is a significant gap between laboratory research and real-world industry applications. Most diagnostic models are developed and evaluated on controlled datasets that do not adequately represent the complexity of industrial operational contexts. Domain shift, noise interference, data imbalance, lack of labelled fault data, computational constraints, and limited model interpretability are some of the research challenges.

In an attempt to get beyond these limitations, more recent research has focused on sophisticated strategies including transfer learning, domain adaptation, self-supervised learning, federated learning, explainable artificial intelligence, digital twins, and edge computing. These technologies aim to improve model generalisation, reduce the need for labelled data, boost openness, safeguard data privacy, and enable real-time deployment in industrial contexts. The integration of these state-of-the-art technologies with Industrial Internet of Things (IIoT) platforms is expected to hasten the transition to intelligent and autonomous maintenance systems.

The reviewed literature suggests that rather than focusing solely on obtaining high classification accuracy on benchmark datasets, future research should focus on developing dependable, adaptable, understandable, and scalable diagnostic systems that can operate in a variety of real-world scenarios. The creation of practical industry datasets, improved benchmarking practices, and standardised assessment frameworks will be necessary to close the gap between academic research and industrial implementation.

In conclusion, the diagnosis of bearing defects has evolved into a highly interdisciplinary field of study that integrates artificial intelligence, mechanical engineering, signal processing, and data analytics. Even though the CWRU dataset has advanced significantly, there are still many opportunities to enhance intelligent defect identification systems. Ongoing study in this field will be beneficial for the development of reliable predictive maintenance systems, greater equipment availability, reduced operating costs, and the implementation of next-generation smart manufacturing and Industry 4.0 settings.

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