

Review

State-of-the-Art Detection and Diagnosis Methods for Rolling Bearing Defects: A Comprehensive Review

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Abstract: Rolling bearings are essential transmission and support components in aircraft engines, playing a critical role in ensuring their safe and stable operation. Rolling bearing faults have a significant impact and should not be ignored. The effective diagnosis of bearing faults has always been a critical requirement for ensuring reliable operation. With the increasing demands of modern manufacturing to reduce costs and improve quality, the development of advanced bearing fault detection methods has become indispensable. This paper presents the brief review of recent trends in research on bearing failure modes, bearing fault detection and diagnosis methods, and development trends and prospects. This article provides a comprehensive review of the existing fault diagnosis methods for rolling bearings in four aspects: the integration of advanced sensor technology and advanced data processing technology, multimodal fusion, intelligent detection, and real-time monitoring. It discusses methods based on vibration analysis, acoustic methods, current-based methods, electromagnetic methods, infrared methods, radiographic methods, visual methods, and intelligent detection methods. This study reveals that the application of intelligent detection technology, multimodal fusion detection technology, and real-time online monitoring technology has achieved favorable results. In the future, bearing fault detection will develop in a more intelligent, integrated, and real-time direction.



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Keywords: bearing failure modes; bearing defect; detection and diagnosis methods; multimodal measurement

1. Introduction

As a critical component in rotating machinery, rolling bearings are widely used in aerospace, chemical engineering, manufacturing, and many other fields [1], playing a vital role in the operational stability and lifespan of equipment. However, bearing failures occur frequently. This may lead to serious environmental issues, personal safety concerns, and economic losses, for instance, resource wastage, leakage of harmful substances, or major accidents such as crashes and derailments that endanger people's lives. It is estimated that bearing faults account for approximately 45–55% of mechanical failures [2]. Timely detection of bearing faults is essential to prevent potential safety risks in mechanical equipment. It also plays a crucial role in preventing equipment failures, reducing maintenance costs, and improving production efficiency.

Rolling bearings, as a type of bearing that operates based on rolling friction, generally consist of four parts, the inner ring, outer ring, rolling elements, and cage, as shown in

Figure 1. The inner ring is typically mounted on the shaft neck, serving to fit with the shaft and rotate together with it. The outer ring is installed within the bearing hole of the frame, providing support in conjunction with the bearing seat. When the inner and outer rings rotate relative to each other, the rolling elements roll within the tracks between the inner and outer rings, with their shape, size, and quantity directly affecting the performance and lifespan of the rolling bearing. The cage ensures an even distribution of the rolling elements. Based on the shape of the rolling elements, rolling bearings can be further classified, with commonly used rolling elements including balls, short cylindrical rollers, long cylindrical rollers, spiral rollers, tapered rollers, spherical rollers, and needle rollers. Each type is optimized for specific application scenarios. For instance, deep groove ball bearings are widely used in medium- to high-speed rotating situations due to their ability to withstand radial loads and certain axial loads, while cylindrical roller bearings are suitable for bearing larger radial loads, making them appropriate for heavy machinery.

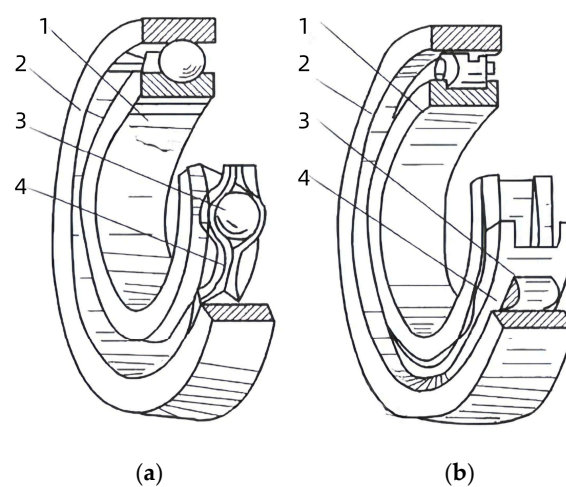


Figure 1. Rolling bearing structure. (a) Deep groove ball bearing. (b) Cylindrical roller bearing. 1—inner ring; 2—outer ring; 3—rolling elements; 4—cage.

The concept of bearing detection can be traced back to the early 20th century. Initially, methods for detecting bearing faults relied on manual inspections, where engineers assessed the operational status of the equipment through visual, auditory, and tactile observations. In the 1920s and 1930s, simple mechanical tools began to be used to assist in detection. By the 1940s, basic vibration measurement instruments were employed to record vibration conditions and conduct preliminary vibration analysis. During the 1950s and 1960s, with the advancement of electronic technology, fundamental sensors were utilized to capture bearing condition data. Signal processing techniques such as Fast Fourier Transform emerged, leading to the application of spectral analysis techniques in bearing fault detection. In the 1970s, with the development of digital signal processing technology, data processing transitioned from qualitative to quantitative. The 1980s saw the emergence of artificial intelligence methods alongside advancements in computer technology. In the 1990s, as multi-sensor fusion technology matured and data processing capabilities improved, detection methods evolved towards multimodal integration. In the early 21st century, machine learning technologies, such as support vector machines, began to be widely applied. From 2010 to the present, deep learning technologies have continued to develop, with intelligent detection that integrates edge computing, big data, and large models becoming prevalent in industrial applications. In the future, with advancements in sensor technology and signal processing techniques, methods for detecting bearing faults will continuously progress towards integration and intelligence.

In 2024, Texas Instruments utilized integrated microcontrollers to achieve real-time system fault detection, primarily for monitoring motor bearing anomalies. The integrated microcontroller operates convolutional neural network models using integrated neural network processing units, aiding in reducing latency and power consumption during fault monitoring. Since convolutional neural network models can autonomously learn the characteristics of different types of signals from raw sensor data, such as motor vibration signals, solar DC currents, or battery voltage and current, they are particularly well suited for sensor data analysis in fault detection and predictive maintenance. Integrating edge AI capabilities into the same integrated microcontroller used for managing real-time control not only optimizes system design but also enhances overall performance: the accuracy of fault detection reaches as high as 99%. This is a reflection of the current state of industrial bearing fault detection, where the integration of sensor technology and artificial intelligence signifies the value of interdisciplinary collaboration. The development of new technologies promotes the intelligent detection of bearing faults. The use of various types of data indicates the application of multimodal fusion; furthermore, the fusion methods can also utilize the output of one method as the input or reference for another method. In addition, the importance of predictive maintenance and real-time monitoring in bearing fault detection is also emphasized. At the same time, the importance of predictive maintenance and real-time monitoring in bearing fault detection is emphasized.

This paper uses the Google Scholar and IEEE Xplore databases to search the literature from 2020 to 2024 to select the latest research related to bearing fault detection techniques, especially studies that include vibration analysis, thermography, AI, or multimodal methods. During the search, the main keywords used were “bearing fault detection” and auxiliary words included “AI-based diagnostics”, “vibration analysis”, “multi-modal technologies”, etc. When conducting research, we selected the literature that was most recently published, highly relevant to the technology, and of good quality, excluding studies that deviated from the topic, were in non-English languages, or had already been discussed in other reviews.

Extant reviews lack a comprehensive perspective of interdisciplinary integration; for instance, they may primarily focus on one aspect while neglecting the synergistic effects between different detection methods. There is a lack of coverage of the latest technologies. Insufficient consideration has been given to practical application scenarios, and the existing reviews lack a comprehensive discussion of factors such as cost and the interpretability of deep learning models in industrial applications. There is inadequate systematic summarization and comparison. This paper conducts a comprehensive analysis from a multidisciplinary perspective, integrating various methods such as vibration, acoustics, current, electromagnetic, infrared, vision, and intelligent detection, systematically exploring their advantages, disadvantages, and potential for integration in practical scenarios. It comprehensively covers the latest research findings from the past 3 years and systematically organizes the development process over nearly 125 years. It focuses on discussing practical application cases in the industrial sector in recent years, showcasing the implementation effects of cutting-edge technologies. It provides an intuitive table that systematically compares the advantages and disadvantages of different technologies through performance parameters. It summarizes applicable scenarios and method selection strategies, offering practical references for engineers and researchers.

This paper summarizes various methods for bearing fault detection, aiming to systematically compare and analyze current research methods and technologies in this field, addressing the shortcomings of existing reviews in terms of comprehensiveness, timeliness, and practicality, thereby providing references and guidance for future studies.

2. Bearing Failure Modes

As early as the 1970s, Widner and Littmann began to focus on the failure modes and diagnostic techniques of bearings [3]. In the first two decades of the 21st century, Gegner studied typical failure modes such as wear and contact fatigue of bearings under extreme working conditions [4]. Cann et al. provided important data on the impact of lubrication state changes on bearing life and performance [5]. Bhadesia studied the performance and failure of bearings from the perspective of material microstructure [6]. In recent years, Xu et al. have further comprehensively summarized the failure modes, mechanisms, and causes of bearing faults [7].

Summarizing common failure modes and analyzing the core causes of these failures is an important step in bearing fault detection. The common failure modes of rolling bearings, as also presented in Figure 2, include the following:

- Fatigue Spalling

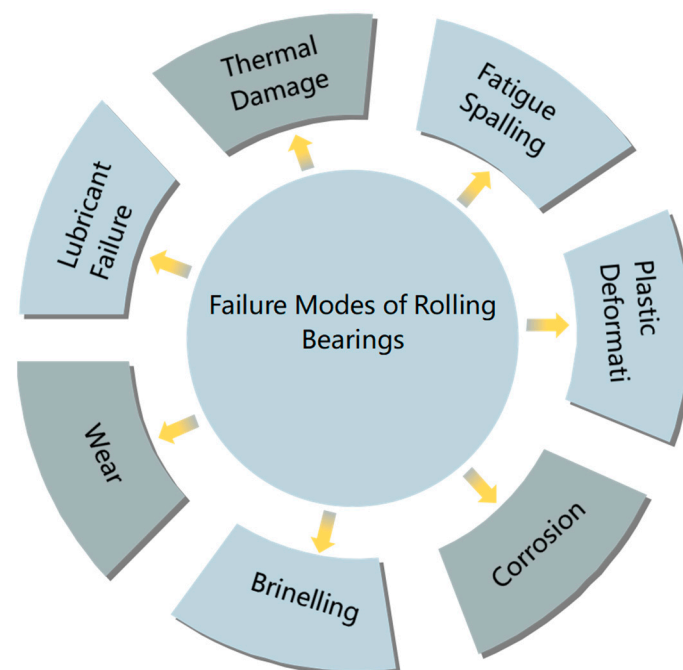


Figure 2. Bearing failure modes.

The microcracks on the rolling elements and raceway surfaces, caused by repeated loads during the operation process, eventually expand into spalling. Fatigue spalling can significantly increase vibration and noise, leading to unstable equipment operation and potentially damaging adjacent components, accelerating the overall failure of the equipment.

- Thermal Damage

It is caused by excessively high temperatures or temperature fluctuations during operation. This can lead to a significant increase in the friction coefficient, and the resulting surface deformation and abnormal gaps can exacerbate bearing vibrations and noise, potentially triggering other failure modes. For instance, high temperatures may result in lubrication failure, accelerate the reaction of corrosive media, or promote the propagation of fatigue cracks.

- Plastic Deformation

When the load exceeds the yield strength of the material, permanent deformation occurs. Plastic deformation can compromise the original precision of the bearing, leading

to a decline in equipment performance. Increased friction can result in energy loss and accelerate other failure modes. Additionally, it is often accompanied by a localized reduction in material hardness and strength, significantly shortening the operational lifespan.

- **Lubricant Failure**

Insufficient, deteriorated, or unevenly distributed lubricants can lead to lubrication failure. The failure of lubricants can cause direct contact between rolling elements and raceways, thereby increasing friction and wear. This not only directly affects the efficiency of bearings but can also lead to heat accumulation and surface damage, triggering a chain reaction.

- **Brinelling**

The formation of dents or permanent deformation on rolling surfaces. Brinell indentations can lead to a decrease in operational accuracy, increased vibration noise, localized stress concentration, increased friction, reduced load capacity, and significantly shorten the service life.

- **Corrosion**

Oxidation or electrochemical reactions in humid or chemically aggressive environments result in surface corrosion or rusting of the bearing metal. Corrosion increases the roughness of the bearing surface, thereby accelerating fatigue spalling and wear. Corrosion products may also mix with the lubricant, further reducing the operational performance of the bearing. To avoid this situation, corrosion-resistant Mg-Li-based alloys can be used [8].

- **Wear**

The contact surfaces between rolling elements and raceways experience wear over prolonged use. Wear reduces the accuracy of the bearings, increases the clearance of the machinery, and affects operational efficiency. As wear intensifies, the accumulation of heat also accelerates the occurrence of other failure modes, causing further damage to the equipment.

3. Bearing Faults Detection Methods

There are various techniques used to detect defects in rolling bearings, which can be classified from different perspectives to meet specific application requirements. These categories include the following:

1. Contact type: can be divided into contact and non-contact techniques;
2. Purpose: can be aimed at fault diagnosis, lifetime prediction, or performance testing;
3. Frequency: may occur in online monitoring or offline inspection;
4. Data dimension: can be a single data type or a combination of multiple data types;
5. Environment: may be performed in controlled laboratory settings or under field conditions;
6. Principle: for example, vibration analysis [9,10], acoustic analysis [11], current analysis, infrared thermography detection [12], electromagnetic detection, radiographic detection, vision detection, and intelligent detection.

The sixth classification method can grasp the technical principles of detection, which can assist in selecting appropriate detection methods in different scenarios.

3.1. Vibration Analysis

Vibration analysis, as the earliest automated bearing fault detection method, detects the fault location and recognizes the failure modes by collecting vibration signals. Usually, collected signals need to be processed and analyzed, and a reasonable signal analysis method is the key to bearing fault detection. Features can be extracted from the original

signal through time domain techniques, frequency domain techniques, time–frequency domain techniques, and techniques combined with intelligent methods [13]. The detection principle of vibration analysis is shown in Figure 3.

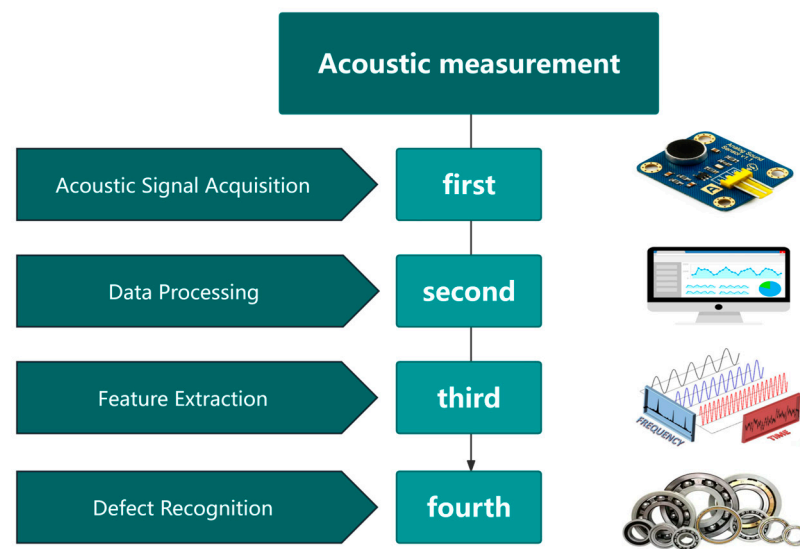


Figure 3. Principle of vibration analysis: The vibration analysis process generally includes steps such as data acquisition, signal preprocessing, feature extraction, and fault diagnosis. First, the bearing’s vibration signals are collected using sensors, followed by filtering and denoising to improve analysis accuracy. Then, key features are extracted using time domain, frequency domain, and time–frequency analysis methods to determine whether faults exist and identify their types.

Time domain analysis is simple and intuitive, focusing on the characteristics of signal changes over time. It can reflect the characteristics of vibration signal changes over a period of time by statistical parameters such as peak value, peak factor, skewness, root mean square, and time domain energy [14]. By observing the statistical parameter values, diagnosis can be achieved.

Frequency domain analysis can clearly identify fault characteristic frequencies. Bearings produce different characteristic frequencies due to different fault locations such as inner and outer rings, rolling elements, and retainers, as well as different failure modes such as wear and cracks. These frequencies are also related to the geometric parameters, rotational speed, contact angle, etc., of the bearing, and can be calculated using existing formulas. When these characteristic frequencies appear in the vibration signal, it indicates that there is a fault in the corresponding part of the bearing [15]. For example, the power spectral density (PSD) function is a model commonly used to describe the spectral characteristics of vibration signals in frequency domain analysis. Fourier transform is a key tool for converting vibration signals from the time domain to the frequency domain.

Combining the advantages of the above two techniques, time–frequency domain analysis not only contains time-varying information, but also characteristic frequencies, so it can handle non-stationary signals [16–28]. Common methods include short-time Fourier transform and wavelet transform.

Traditional vibration analysis methods have been combined with intelligent methods such as machine learning, deep learning, and data-driven approaches [29,30].

The advantages of vibration analysis methods are high sensitivity, strong real-time performance, and non-contact, usually with low cost and easy implementation, suitable for online monitoring and early fault detection. However, in complex environments, signals often contain noise and require complex signal processing methods to improve accuracy.

Also, diagnostic accuracy may be affected by the vibration of other equipment, necessitating dependence on empirical judgment and professional knowledge.

3.2. Acoustic Analysis

Acoustic analysis, as an important supplement to vibration analysis methods [31], utilizes high-frequency acoustic signals to detect small defects and early faults. Similar to vibration analysis, acoustic characteristics such as the frequency and amplitude of the emitted sound waves vary depending on the failure mode and fault location of the bearing [32]. The sound wave signal is also highly susceptible to environmental noise interference, but due to its ability to collect high-frequency signals, it can eliminate low-frequency noise interference. The principle of acoustic analysis is shown in Figure 4.

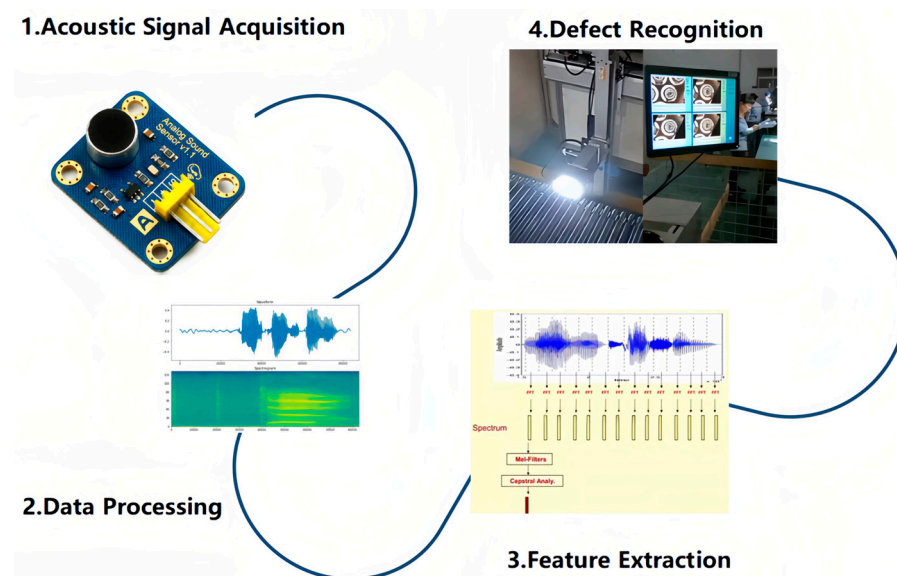


Figure 4. Principle of acoustic signal detection: The detection process generally consists of high-frequency signal acquisition, signal preprocessing, feature extraction, and fault diagnosis. First, high-frequency signals generated during operation are collected using acoustic sensors. After amplifying the signals, specific high-frequency components are extracted, and the acoustic signals are processed to extract feature parameters. These feature signals are typically used to identify specific fault patterns.

Commonly used acoustic detection techniques include ultrasonic testing and acoustic emission technology. The ultrasonic bearing detection method consists of emitting ultrasonic waves to the test object, and when it encounters a defect reflection, it detects its reflection signal to achieve diagnosis [33–36]. Ultrasonic detection has high accuracy, fast speed, and is harmless to the human body and environment, but it is prone to scattering and loss in the air, requiring the use of coupling agents.

Acoustic emission technology refers to when high-frequency signals emitted by materials during the process of bursting and crack propagation under stress and load are analyzed and detected through computer simulation technology [37–44]. It can detect the fatigue state and structural health of materials, but it is characterized as a form of destructive testing with low accuracy.

They are all suitable for detecting small cracks, but according to their characteristics, they are suitable for different detection needs and scenarios.

Compared to vibration analysis, acoustic detection has certain advantages in sensitivity and detection range, particularly in environments with low background noise. However, acoustic signals are susceptible to interference from environmental noise, requiring effective denoising and filtering. Additionally, acoustic detection equipment is often expensive, and

the detection accuracy is dependent on experience, necessitating the use of complementary detection methods to enhance diagnostic precision.

3.3. Current Analysis

Current analysis, as one of the supplementary methods of vibration analysis [45,46], is often used for fault diagnosis of motor bearings [47]. Similar to the previous two methods, the failure mode and fault location of the bearing are different, and the frequency spectrum of the current generated is also different, which can be used for diagnosis. The principle of current analysis is shown in Figure 5.

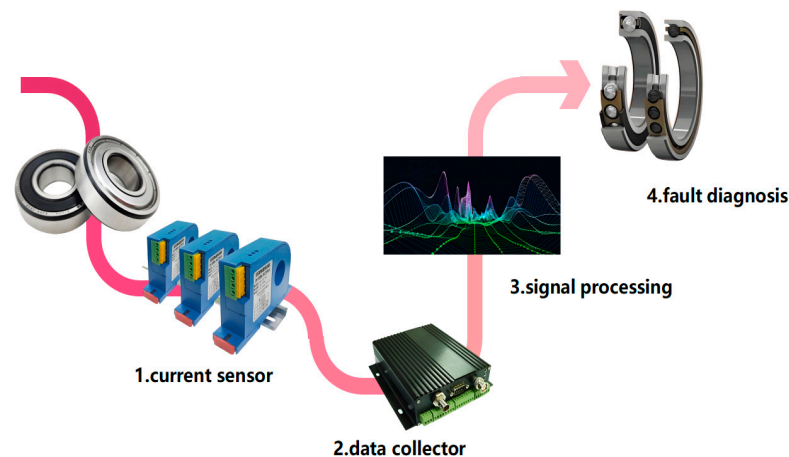


Figure 5. Principle of current signal detection: The detection process generally consists of current signal acquisition, signal preprocessing, feature extraction, and fault diagnosis.

Current analysis is often combined with new technologies such as deep learning, implementing automated detection. For example, Li J et al. used current signals as a key feature for bearing fault diagnosis, combining adaptive kernel functions and semi-supervised learning algorithms to adapt to complex working conditions and different operating states [48]. Research on advanced denoising algorithms, such as Barcelos AS and others, has introduced advanced denoising methods and deep learning algorithms to extract relevant features from noisy current signals [49]. It can also be combined with vibration signals and acoustic signals to achieve multimodal measurement. For example, Wang Z et al. proposed processing signals from multiple phases and using multi-scale feature fusion modules to enhance features, thereby solving the problem of weak fault features in current signals [50].

The advantages of current signal fault detection lie in its non-contact nature, high sensitivity, and real-time monitoring capability. It is less affected by environmental noise and can detect bearing defects at an early stage, preventing excessive mechanical damage. It is suitable for the online monitoring of bearings in industrial equipment such as motors, generators, and pumps, and is widely used in high-demand applications such as wind turbines and aerospace equipment. However, there are still limitations in identifying complex fault patterns, and in some cases, changes in current signals may be affected by external factors such as power supply fluctuations.

3.4. Electromagnetic Detection

Electromagnetic detection, as a non-contact detection method suitable for complex environments, achieves bearing fault detection by inducing the response in the electromagnetic field. A diagram depicting the principle of electromagnetic detection is shown in Figure 6.

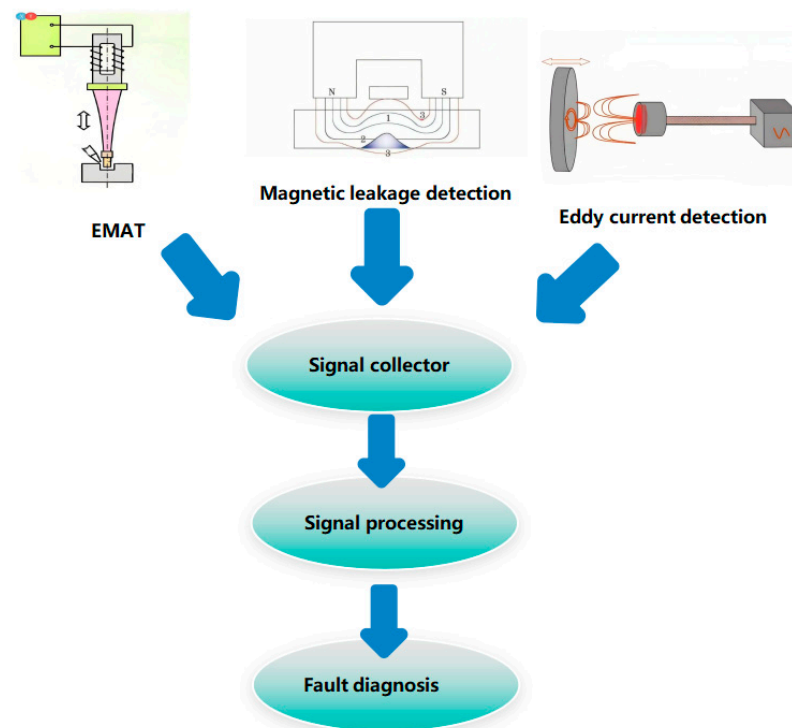


Figure 6. Principle of electromagnetic detection.

Typical electromagnetic-based bearing detection methods include eddy current detection, magnetic flux detection, and electromagnetic acoustic transducers (EMATs), each with unique advantages in different application scenarios.

Eddy current testing is based on Faraday's principle of electromagnetic induction. When a conductive material is excited by an alternating magnetic field, eddy currents are generated inside the material to detect surface or near-surface defects. When bearings experience wear, cracks, or fatigue damage, these defects can cause abnormal distribution of eddy currents, resulting in measurable changes in the detection coil. For example, Kobayashi D et al. developed a method using eddy current detection. Rolling contact fatigue tests were conducted using several types of rolling bearings, and it was found that the eddy current detection measurements of the raceway surface exhibited behavior that was determined as fatigue progressed [51].

Magnetic flux detection identifies fault states by monitoring the changes in magnetic flux generated by bearings during operation. It establishes a connection between the magnetic field changes in bearings and their wear status and captures real-time magnetic flux fluctuations during bearing operation through induction coils or Hall sensors. Insufficient wear and lubrication can cause significant changes in the frequency and amplitude of magnetic flux. Therefore, by analyzing the characteristics of magnetic flux signals, the health status of bearings can be determined. For example, Li E et al. proposed a micromagnetic bridge method for high-sensitivity magnetic leakage detection to detect microcracks and developed a new type of micromagnetic bridge probe (MMBP) with higher spatial resolution, which improves the magnetic leakage detection capability to the micrometer level and can be widely used to detect grinding microcracks in bearing rings [52].

The electromagnetic acoustic transducer (EMAT) is a non-contact detection technology that generates sound waves through the interaction between electromagnetic fields and material surfaces. It can detect defects on metal surfaces and sub surfaces without physical contact and is widely used for fault detection of bearings and other mechanical components. Compared with traditional ultrasonic testing, EMAT has stronger adaptability to surface

contamination and complex shapes, especially suitable for high-temperature environments and hard-to-reach places. Guo Y designed a new type of electromagnetic–acoustic transducer and pulsed eddy current composite sensor. The amplitude of the bottom echo recorded by EMAT is used to identify tiny bottom cracks, as well as the amplitude of the pulsed eddy current signal picked up by the integrated symmetry coil. The signal fusion method can accurately correct the amplitude of the defective signal with a relative error of less than $\pm 8\%$ [53].

Electromagnetic-based detection methods have the advantages of being non-contact, highly sensitive, and suitable for online monitoring. They can quickly detect structural defects caused by wear, cracks, etc., are insensitive to temperature changes, and are especially suitable for detection in complex environments. Additionally, electromagnetic detection has low requirements for the bearing surface and is not affected by oil or dust, making it ideal for harsh environments. However, its detection ability for non-magnetic materials is weak, the equipment cost is high, and it may impact the properties of the bearing itself.

3.5. Infrared Thermography Detection

Infrared thermography, as a non-contact detection technology that does not damage the properties of bearings, is a fault diagnosis technology that determines the health status of bearings by monitoring the temperature field distribution and thermal changes of bearings [54]. The principle is shown in Figure 7.

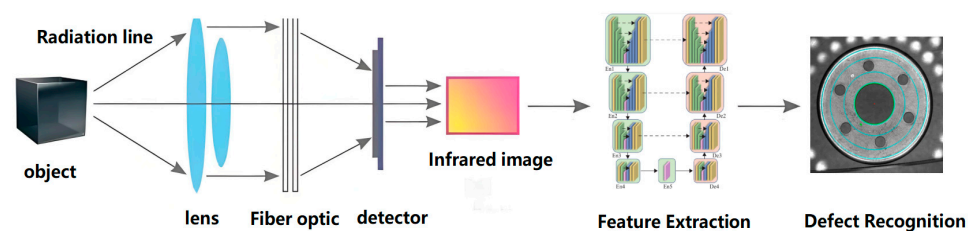


Figure 7. Principle of infrared thermography.

When bearings experience faults such as increased friction, insufficient lubrication, or structural damage during operation, the temperature often rises abnormally [55]. In addition, heating excitation can also be applied to bearings to affect the temperature distribution around defects such as cracks and thermal damage. In thermal imaging detection, a thermal imager is used to capture the temperature distribution map of the bearing surface [56]. By processing these temperature distribution maps, it is possible to determine whether there is abnormal temperature in the bearing and thus determine the potential fault location and type.

Sensors and data processing units are integrated together for detection. For example, Alvarado Hernandez A I et al. proposed using infrared thermal imaging technology as an intelligent sensor, combined with algorithm units, to detect bearing faults in induction motors [57]. To overcome the problems of low machine learning fault diagnosis rate and long consumption time of deep learning in rolling bearing fault diagnosis, an RFR-GA-BLS model is proposed. The model is validated by infrared images of rolling bearings to find the most representative features, the most suitable parameters, and the best diagnostic rate. A fault diagnosis rate of 98.8889% was achieved [58]. Guo L et al. designed an unsupervised learning framework named Feature-Preserving Cycle Consistent Generative Adversarial Network (FP-CycleGAN) for defect detection in imbalanced rolling bearing infrared thermal imaging samples [59].

The main advantage of this method is that the detection process is non-contact and can be carried out during equipment operation without affecting the normal operation of the bearings. Meanwhile, thermal imaging detection can quickly and extensively scan

the entire equipment, making it suitable for regular inspections and online monitoring of large mechanical equipment. It has high sensitivity and can respond to slight temperature changes, which is especially suitable for detecting initial faults.

However, thermal imaging detection also has certain limitations: it can only detect temperature changes at the faulty location and has low sensitivity to minor early damage or faults that have not caused temperature anomalies. Meanwhile, thermal imagers are relatively expensive and may experience temperature interference in high ambient temperatures or densely populated environments, which can affect detection accuracy. Therefore, thermal imaging detection is often combined with vibration analysis, acoustic analysis, and other methods to provide more comprehensive fault diagnosis results.

3.6. Radiographic Detection

Radiographic detection, as a high-precision detection technology, relies on high-energy radiation penetrating materials and imaging to achieve bearing diagnosis. The principle of radiation detection is shown in Figure 8.

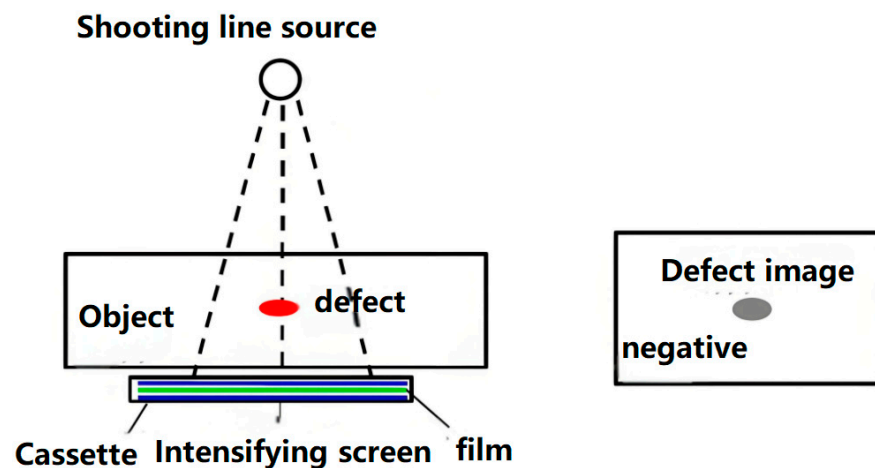


Figure 8. Principle of radiographic detection: When the radiation passes through the object being inspected, the absorption capacity of defective and non-defective parts is different.

Typical ray-based bearing detection methods include X-ray detection, computed tomography (CT), gamma ray detection, and infrared synchrotron radiation technology, each with unique advantages in different application scenarios.

X-ray inspection is the use of X-ray penetration capability to scan the interior of bearings and discover cracks, pores, and other hidden defects on rolling elements or raceways through image analysis. Its advantages are high resolution and intuitive imaging, especially suitable for detecting internal problems that cannot be exposed on the surface. The limitation lies in its limited penetration ability, making it unsuitable for materials that are too thick or high-density.

Computer tomography (CT) combined with X-ray multi-angle imaging can reconstruct three-dimensional images of the interior of bearings and provide comprehensive defect information [60–64]. The advantage lies in the ability to accurately detect bearing components with complex geometric shapes, but high-resolution CT equipment is expensive and not suitable for online detection.

Gamma ray detection has high energy and strong penetrability and is suitable for detecting deep defects in thick-walled or large bearings [65]. Although it has a wider range of applications, it requires higher operational complexity and security.

Infrared synchrotron radiation technology combines synchrotron radiation X-rays and infrared spectroscopy to analyze the microstructure and stress distribution of bearing materials, which is helpful for fault analysis and material research.

Ray-based methods have high sensitivity and can detect defects at the micrometer level, making them a powerful supplement to other non-destructive testing methods. However, these methods require professional operational skills and high-cost equipment and are accompanied by radiation safety risks, so they are often used in practical applications for the detection of high-value and critical components. In addition, they are also used for material fatigue research and predicting the service life of bearings.

With the improvement of radiographic imaging equipment and algorithms, radiation-based detection technology is developing towards higher efficiency and lower cost. At the same time, combining artificial intelligence for image processing will further improve the accuracy and automation level of detection.

3.7. Vision Detection

Visual inspection, as a highly automated detection method, utilizes machine vision technology to detect the appearance and surface defects of bearings [66]. The principle of visual inspection is shown in Figure 9.

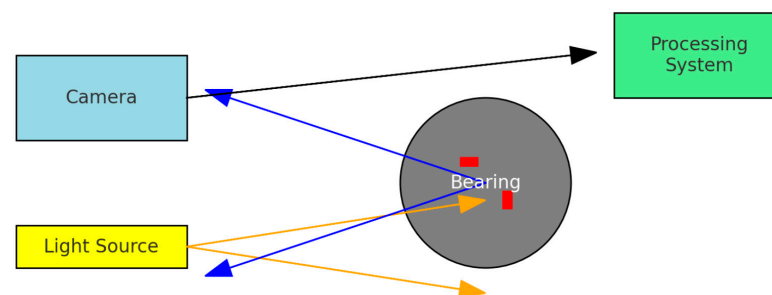


Figure 9. Principle of vision detection: Uses high-definition cameras or industrial cameras to capture images of bearing surfaces, and then identify cracks, wear, scratches, contaminants, or other surface defects through image processing and algorithm analysis.

Image acquisition: When the bearing is in operation or stopped, the system uses high-resolution cameras to capture key parts of the bearing, such as the inner and outer rings and rolling element surfaces. When shooting, parameters such as light source and camera angle can be adjusted to ensure clear image quality, especially highlighting areas where defects may occur for subsequent processing.

Image preprocessing: The preprocessing steps include denoising, contrast enhancement, binarization, etc., with the aim of highlighting defect features and eliminating interference caused by the environment or lighting. For example, binary processing can distinguish defective areas from normal areas, improving the accuracy of subsequent detection.

Image feature extraction: Edge detection, contour extraction, texture analysis, and other techniques are used to identify the shape, size, and location of surface defects on bearings [67].

Image pattern matching: Matching techniques include template matching and deep learning matching. Template matching is the process of comparing the detected image with a standard template to identify differences that are suitable for detecting specific defect patterns. For example, cracks may appear as elongated edge features, while worn areas typically exhibit irregular texture features. The machine vision system will compare these features with standard samples or preset parameters and analyze them through algorithms to determine if there are any abnormalities. Lu M et al. proposed a method for detecting and classifying surface defects of bearings using machine vision technology [68]. To detect

surface defects in subway vehicle rolling bearings, on-site images of black magnetic particle testing defects in subway vehicle rolling bearings were collected. Ge D and others utilized image processing technology to extract all binary images of surface defects and established a dataset that includes both the original images of surface defects and the binary images. It was pointed out that there are significant difficulties and limitations in using traditional machine vision technology to identify defects in subway bearings. Therefore, convolutional neural networks were chosen to identify bearing defects in order to achieve deep feature fusion. Through comparisons with several models, it was concluded that there is a certain improvement in the effectiveness and accuracy of surface defect recognition [69].

The advantage of vision inspection is that it can accurately identify small surface defects, and the detection process is non-contact, suitable for detection under complex working conditions such as high temperature and high speed. Its high degree of automation is suitable for real-time quality monitoring of production lines, which can improve production efficiency and reduce manual errors. However, visual inspection often relies on complex hardware and algorithm support and has low sensitivity to deep-seated internal defects or small cracks that are not directly exposed. It usually requires the combination of other detection methods, such as ultrasonic or eddy current testing, to achieve comprehensive diagnosis.

3.8. Intelligent Detection

Intelligent detection, as a popular research direction, utilizes machine learning, deep learning, and data mining technologies to achieve automatic feature extraction of massive quantities of data and assist in bearing detection. The principle of intelligent detection is shown in Figure 10.

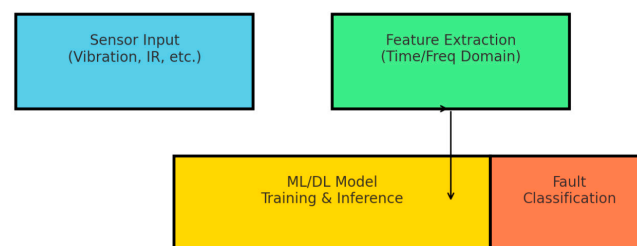


Figure 10. Principle of intelligent detection.

Traditional machine learning relies on manual feature extraction, such as frequency domain and time domain features, and then uses classification algorithms such as support vector machines (SVMs) and random forests to identify faults [70–73]. Deep learning methods improve detection efficiency by automatically extracting data features [74–91]. For example, convolutional neural networks (CNNs) are suitable for extracting spatiotemporal features of vibration signals, long short-term memory (LSTM) networks excel at capturing temporal features in time series, and autoencoders are used for unsupervised anomaly detection. Further combination models, such as CNN-LSTM, combine the advantages of spatiotemporal feature extraction and temporal analysis. In addition, multimodal data fusion provides support for more accurate detection by combining data sources such as vibration, temperature, current, images, and sound signals [92,93]. The continuous development of these intelligent detection technologies has driven the development of bearing fault detection towards automation and intelligence.

Although bearing fault detection methods based on machine learning and deep learning have advantages in automation, accuracy, and unsupervised anomaly detection, they also face challenges in practical applications. The main issues include the demand for a large quantity of high-quality annotated data, high computational resource consump-

tion, insufficient interpretability of the model, poor robustness under variable operating conditions, as well as overfitting and high maintenance costs. These limitations make it difficult for intelligent bearing detection technology to be widely promoted in industrial environments, promoting further research on transfer learning, semi-supervised learning, and interpretable models to improve its applicability.

4. Evaluation

The evaluation of bearing fault detection technology requires consistent benchmarks. The ASTM standards ensure that every aspect of the manufacturing process, from material selection to final bearing testing, complies with internationally recognized standards. Some of the ASTM bearing standards followed in this document are listed in Table 1.

Table 1. Some of the ASTM bearing standards.

Number	Name
ANSI/ABMA B3.1-1992 (S2020)	Rolling Element Bearings—Aircraft Engine, Engine Gearbox, and Accessory Applications—Eddy Current Inspection
ANSI/ABMA B3.2-1992 (S2020)	Rolling Element Bearings—Aircraft Engine, Engine Gearbox, and Accessory Applications—Surface Visual Inspection
ANSI/ABMA B3.3-1992 (S2020)	Rolling Element Bearings—Aircraft Engine, Engine Gearbox, and Accessory Applications—Surface Temper Etch
ANSI/ABMA 9-2015 (R2020)	Load Ratings and Fatigue Life for Ball Bearings
ONORM M 8128: 2017	Tribotechnique—Test machines for rolling bearing grease R0F and R0F+—Evaluation of grease service life
ANSI/ABMA/ISO 15243-2017	Rolling Bearings—Damage And Failures—Terms, Characteristics, and Causes
ANSI/ABMA/ISO 13411-1997 (S2010)	Aerospace—Airframe Needle Roller Cylindrical Roller and Track Roller Bearings—Technical Specification

The evaluation of bearing fault detection is usually based on multiple performance indicators and the actual effectiveness of detection methods [94].

Some key evaluation indicators and commonly used evaluation methods for bearing fault detection methods include the following:

- Accuracy;
- Robustness;
- Timeliness;
- Interpretability;
- Economy;
- Early stage of diagnosis.

Accuracy is the most basic requirement in fault detection, reflecting the detection system's ability to identify different types of faults.

Robustness refers to the stability of a detection system under different working conditions such as noise and load changes.

Timeliness refers to whether the fault detection system can provide detection results within a short period of time when a fault occurs. For high-speed rotating bearing equipment, the processing speed directly affects the real-time performance of fault detection. When deep learning and machine learning methods are applied to fault detection, the inference speed and computational resource requirements of the model become key limiting factors for real-time performance.

Interpretability is the basis and explanation for detecting whether a system can provide fault diagnosis, helping maintenance personnel understand the mechanism of fault occurrence. For complex deep learning models, model interpretability is a challenge, but it is crucial for determining fault types and analyzing fault causes.

The economy of fault detection systems is also an important aspect of evaluation, including equipment costs, detection sensor costs, operating costs, data costs, etc.

Early stage of diagnosis refers to whether the detection method can identify anomalies in the early stages of the fault, thereby achieving predictive maintenance. These evaluation dimensions provide specific guidance for the design and selection of fault detection systems.

According to the literature, this article presents a quantitative comparison of certain performance data against the latest detection methods, as shown Table 2.

Table 2. Quantitative comparison of certain performance data against the latest detection methods.

Techniques	Accuracy	Literature
Vibration Analysis	98.91%	Rolling bearing fault diagnosis method using time-frequency information integration and multi-scale TransFusion network
Acoustic Emission	93%	Acoustic emission monitoring of naturally developed damage in large-scale low-speed roller bearings
Current Analysis	97%	Motor Bearing Fault Diagnosis Bas
Electromagnetic Detection	Less than $\pm 8\%$	Bottom Crack Detection with Real-Time Signal Amplitude Correction Using EMAT-PEC Composite Sensor
Infrared Thermography	94.30%	Unsupervised Feature-Preserving CycleGAN for Fault Diagnosis of Rolling Bearings Using Unbalanced Infrared Thermal Imaging Sample
Vision Detection	99.5%	Detection and Classification of Bearing Surface Defects Based on Machine Vision
Intelligent Detection	Outperformed the baseline by 6.03% and 8.76% in terms of mean average precision (mAP) and mean average recall (mAR)	A hierarchical attention detector for bearing surface defect detection

5. Analysis

Due to different measurement principles, the advantages, shortcomings, and application scenarios of various measurement techniques are also different, as shown in Table 3.

Multimodal data fusion, as a method for the joint detection of multiple signals, can leverage strengths and avoid weaknesses, helping to improve detection accuracy. It is very common in bearing detection technology [95–101]. In comprehensive applications, vibration, analysis, and thermal imaging are the most commonly used combinations for detecting internal and surface faults. Electromagnetic and acoustic detection have high sensitivity and are suitable for early fault identification, while visual detection is suitable for

surface defects and is easy to integrate with automation systems. The choice of appropriate detection method depends on specific detection requirements and fault types.

Table 3. Comparison and application scenarios of different techniques.

Techniques	Advantages	Shortcomings	Application Scenarios
Vibration Analysis	Sensitive to common faults, with high detection accuracy, supporting online monitoring, and usually low cost	Sensitive to environmental noise	Sensor installation requires high-speed rotating equipment, long-term operation equipment status detection, and predictive maintenance
Acoustic Emission	Early fault sensitivity, suitable for high-frequency signal analysis	Destructive detection, affected by environmental noise, signal analysis is complex, and acoustic detection equipment is usually expensive	Lubrication monitoring, microcrack and early fault monitoring
Ultrasonic	Early fault sensitivity, non-contact detection, suitable for high-frequency signal analysis	Affected by environmental noise, signal analysis is complex, and acoustic detection equipment is usually expensive	Microcrack and early fault monitoring
Current Analysis	Non-contact, low cost, suitable for remote monitoring, sensitive to load changes	Weak defect pattern recognition and localization capabilities	Motor driven equipment, batch monitoring in industrial Internet of Things
Electromagnetic Detection	Non-contact, accurate detection of shallow defects, suitable for online monitoring, insensitive to temperature changes, with low requirements for bearing surfaces	Not sensitive to deep defects, with high equipment and technical requirements, which can affect the properties of the bearing itself.	Especially suitable for detection in complex environments
Infrared Thermography	Non-contact, capable of quickly and extensively scanning the entire device, suitable for high temperature environments	Early failures are not sensitive, equipment costs are high, and high-temperature equipment online monitoring is affected by environmental temperature	Combined use with other detection techniques
Radiographic Detection	Highly sensitive, capable of detecting defects at the micrometer level	High requirements for professional operation skills, high equipment costs, large volume, and radiation safety risks	High precision equipment, aerospace and other key mission bearing testing

Table 3. Cont.

Techniques	Advantages	Shortcomings	Application Scenarios
Vision Detection	Surface defect detection is intuitive, non-contact, suitable for detection in complex environments such as high temperature and high speed, with a high degree of automation and rapid progress with technological development	Relying on image quality and algorithms, limited to visible surfaces, usually requiring the combination of other detection methods	Production line quality control, surface defect detection
Intelligent Detection	Automatic feature extraction, processing multiple data types, high fault classification accuracy	Relying on a large amount of data and annotations, high computational complexity, insufficient interpretability of the model, poor robustness under variable operating conditions, and high maintenance costs	Intelligent monitoring, real-time online monitoring combined with the Internet of Things

6. Development Trends and Prospects

The current popular research directions include data-driven intelligent detection, multi-sensor fusion methods, real-time online monitoring, etc., indicating that the research on bearing fault detection methods is developing in a more intelligent, integrated, and real-time direction. In order to improve practicality, it is also important to study early fault prediction, enhance the interpretability of deep learning models, and reduce costs, as shown in Figure 11.

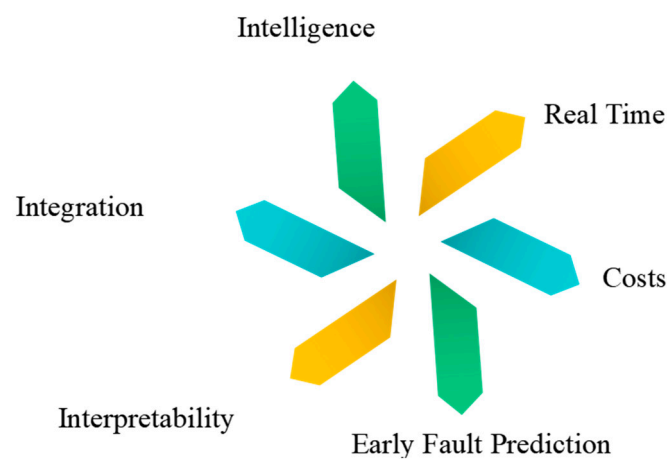


Figure 11. Development trends and prospects.

6.1. Intelligence

Intelligence refers to the application of new technologies such as artificial intelligence. With improvements in big data and computing power, the application of machine learning and deep learning in fault detection is becoming increasingly widespread. Deep learning models such as convolutional neural networks and long short-term memory networks can automatically extract features from bearing signals, freeing them from the limitations of manual feature engineering. Especially in dealing with nonlinear and non-stationary signals, deep learning methods perform well. Meanwhile, the application of new technologies such as transfer learning, semi-supervised learning, and reinforcement learning is driving detection algorithms to become more adaptable and versatile.

In 2021, Schaeffler collaborated with Siemens' Large Drive Applications Division to jointly advance the development of industrial digitalization. Through this partnership, both parties combine Schaeffler's decades of experience and expertise in bearing design, manufacturing, and maintenance with Siemens' digital platform for drive systems and solutions, Sidrive IQ. The Sidrive IQ platform integrates numerous functions into a single solution and further enhances the performance of drive systems through AI-based analytics and digital content. This solution will assist customers in making better decisions regarding the operation, maintenance, and repair measures of drive systems. The integration of Schaeffler's automatic bearing diagnostic analysis service into the Sidrive IQ platform significantly improves the accuracy and precision of bearing condition diagnostics. This collaboration marks the first instance of algorithm-based bearing diagnostics in the field of industrial IoT and serves as a successful case of traditional large technology companies collaborating in new domains.

6.2. Integration

Integration refers to the fusion of multi-source data and multimodal detection. Traditional single detection methods may be limited in certain operating conditions and have difficulty providing comprehensive fault information. With the advancement of data fusion technology, more and more research focuses on combining multi-source data such as vibration signals, thermal imaging, electromagnetic signals, and acoustic signals for multimodal detection. For example, by combining vibration data with thermal imaging images, researchers can more comprehensively identify fault features. This trend enhances the robustness of detection and is suitable for complex industrial scenarios.

To understand how multimodal technology is transforming bearing fault detection, the development of bearing fault detection can be divided into three stages.

The first stage of the single-modal method may fail under dynamic conditions due to environmental changes.

In the second stage, with the advancement of sensor technology and signal processing techniques, the limitations of a single sensor can be overcome by integrating data from multiple sensors, leveraging the advantages of various modes, or ensuring the reliability of diagnostics through cross-modal redundant data. For instance, by combining infrared imaging and acoustic emission signals, it is possible to stably monitor the temperature rise in bearings and structural microcracks in high-speed operating equipment under harsh conditions.

In the third stage, with the gradual maturity of multimodal data processing methods based on artificial intelligence and machine learning, deep correlations in multi-source data can be efficiently explored. Convolutional neural networks, for example, are used to integrate vibration, image, and thermal signals to form an end-to-end diagnostic framework.

Recently, Peng C and others proposed a method for constructing a multimodal knowledge graph based on multimodal data, designing a rolling bearing fault diagnosis method that utilizes a multimodal knowledge graph completion model based on relational cascade graph attention networks to capture the relationships between various faults. The multimodal data include time series vibration signals, spectra, and dataset description texts. Experimental results on the multimodal knowledge graph constructed from seven bearing datasets demonstrate the robustness of the proposed method [102].

6.3. Real Time

Real time refers to intelligent edge computing and real-time monitoring. With the development of Internet of Things technology, fault detection is gradually developing to edge computing and real-time monitoring. Intelligent sensors and edge devices can

directly collect and process data on-site, achieving real-time fault detection and prediction. This trend reduces the latency and cost of data transmission, supporting the immediate application of fault detection in industrial production. For example, deploying lightweight models using low-power edge devices can enable real-time monitoring of bearing status and early warning of faults on the production line.

The Siemens SIPLUS CMS status monitoring system, combined with the cloud-based open IoT operating system MindSphere, can be used to analyze large quantities of data and monitor machines and equipment located around the world in real time.

6.4. Early Fault Prediction

Traditional fault detection methods focus on diagnosing faults after they occur, while fault prediction predicts the occurrence of faults through historical data and real-time monitoring information, achieving predictive maintenance, reducing unplanned downtime, and lowering maintenance costs. This trend has driven the evolution of fault detection from diagnosis to prediction, providing support for the lifecycle management of production equipment.

The early predictive detection of bearings in aircraft engines is of significant importance. Pratt and Whitney specifically developed the Data Collection and Transmission System to obtain high-quality data. They have been upgrading its data ecosystem, data transmission technologies, and analytical tools, accumulating a large number of physics-based predictive algorithms, while continuously iterating on artificial intelligence and machine learning solutions.

6.5. Interpretability

The “black box” nature of deep learning models has always been a barrier to industrial applications. In recent years, the demand for interpretability of models has been on the rise. Researchers are exploring more transparent detection models that enable the generation process of detection results to be understood and interpreted, which is crucial for user trust and fault localization. Researchers are gradually improving the transparency of intelligent fault detection by using attention mechanisms, interpretable feature maps, and other methods.

6.6. Cost

With the development of sensors, edge computing, and low-power technology, fault detection equipment is developing towards being more portable and low-cost. Lightweight detection equipment is not only suitable for installation on production sites but also for remote monitoring and harsh environments. The development of portable devices is expected to make it easier for small- and medium-sized enterprises to adopt intelligent fault detection and further promote the application of technology.

7. Conclusions

Bearing fault detection is one of the important issues in the industrial field. In order to improve the reliability of the equipment, it is necessary to detect the status of the bearings in a timely manner. It is very important to choose the appropriate bearing detection technology for different scenarios. Vibration analysis, acoustic detection, thermal imaging, electromagnetic induction, and methods based on vision, machine learning, and depth can be used to detect bearing faults. These methods have their own characteristics and perform differently in terms of detection efficiency, cost, accuracy, real-time performance, and robustness. In summarizing these methods, it can be seen that research on rolling bearings is progressing towards intelligent detection, integration of advanced sensor technology and data processing technology, multimodal fusion, and real-time detection. In the future, new

technologies such as quantum sensors, edge computing, Internet of Things technologies, multimodal large models, quantum computing, and cloud computing can also be explored.

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