ACTA TECHNICA CORVINIENSIS – Bulletin of Engineering | e–ISSN: 2067 – 3809
Tome XIX [2026] | Fascicule 1 [January – March]

[1.]Frieda FILLEMON, [1.]Idehai O. OHIJEAGBON, [1.]Surendra K. SAINI

RECENT ADVANCES IN ARTIFICIAL INTELLIGENCE FOR CONDITION MONITORING OF ROTATING MACHINERY

[1.] Department of Mechanical and Metallurgical Engineering, University of Namibia, Ongwediva, NAMIBIA

Abstract: Condition monitoring of rotating machinery is crucial for ensuring safe, reliable, and cost-effective industrial operations. Traditional diagnostic methods often struggle with large, complex, and noisy datasets. This paper presents a systematic review of recent applications of artificial intelligence (AI) in monitoring rotating components such as bearings, gears, and rotors. Using the PRISMA protocol, 128 peer-reviewed studies published between 2014 and 2024 were analyzed. The review highlights advances in machine learning and deep learning techniques, including convolutional neural networks, long short-term memory networks, support vector machines, auto encoders, and hybrid models, applied to fault detection, fault isolation, fault prognosis, and multi-sensor data fusion. Findings show that AI enhances feature extraction, classification accuracy, and predictive maintenance; however, challenges remain in data scarcity, model generalization, interpretability, and online deployment. Future research should focus on physics-informed learning, explainable AI, domain adaptation, and digital twin integration to develop robust and transparent diagnostic systems. This review provides a reference framework for researchers and practitioners designing AI-enabled condition monitoring solutions for rotating machinery.

Keywords: rotating machinery; condition monitoring; fault diagnosis; artificial intelligence; predictive maintenance

INTRODUCTION

Rotating machinery is indispensable in industries such as manufacturing, energy, transportation, and aerospace, where uninterrupted operation is vital for safety, efficiency, and cost control. Failures in critical components such as bearings, gears, and rotors can result in costly downtime, equipment damage, and safety hazards. To mitigate such risks, condition monitoring (CM) has become an essential strategy, enabling the early detection of mechanical faults and the implementation of predictive maintenance practices [1].

Traditional CM methods, including vibration analysis, acoustic emission monitoring, and thermography, rely heavily on manual feature extraction and domain expertise. While effective in certain contexts, these methods face limitations when handling the vast and complex datasets generated by modern industrial systems, especially under varying operational and environmental conditions [2]. This challenge has driven growing interest in artificial intelligence (AI) techniques, particularly machine learning (ML) and deep learning (DL) that can learn directly from raw data, adapt to evolving conditions, and improve diagnostic accuracy through automated analysis [3].

Recent advances in AI have led to the development of intelligent fault diagnosis and prognosis (IFDP) systems that integrate multiple data sources, employ hybrid learning strategies, and provide real-time health assessments. Algorithms such as Convolutional Neural Networks (CNNs) excel at extracting spatial and spectral features from vibration signals, while Long Short-Term Memory (LSTM) networks capture temporal dependencies for predicting fault progression. Hybrid approaches and ensemble models further enhance performance by combining the strengths of multiple AI techniques [4].

Despite these advancements, challenges remain in data availability, model generalization, interpretability, and real-time deployment. Many AI models are trained on limited datasets from specific machines, reducing their transferability to other operational contexts. Additionally, the "black box" nature of deep learning models raises concerns regarding transparency and trust in safety-critical applications [5].

This review aims to systematically evaluate the role of AI in condition monitoring of rotating machinery by:

1. Identifying and classifying recent AI techniques applied to fault diagnosis and prognosis.
2. Assessing their performance across various machinery components and fault types.
3. Highlighting strengths, limitations, and practical considerations for industrial deployment.
4. Identifying key research gaps and proposing future directions for robust, interpretable, and scalable AI-based CM systems.

To achieve these aims, the review addresses the following research questions (RQs):

- RQ1: Which AI techniques are most widely adopted for condition monitoring of rotating machinery, and how have their applications evolved over the past decade?
- RQ2: In what ways do AI-based models (e.g., Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), Support Vector Machines (SVMs), Auto-Encoders, and hybrid methods) process and analyze vibration and multi-sensor data to enable fault detection, isolation, and prognosis?
- RQ3: What are the strengths and limitations of these AI models when deployed in industrial environments, particularly under noisy, imbalanced, or limited datasets?
- RQ4: How do hybrid and ensemble AI approaches enhance the robustness, interpretability, and scalability of Intelligent Fault Diagnosis and Prognosis (IFDP)?
- RQ5: What unresolved challenges-such as data scarcity, generalization, interpretability, and adaptability-remain in advancing AI-driven condition monitoring?

METHODOLOGY

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram is presented in Figure 1 to illustrate the process of study identification, screening, eligibility assessment, and inclusion. The initial search in the Web of Science (WOS) and Scopus databases yielded 1,987 and 1,056 records, respectively. These databases were selected because of their comprehensive coverage and reliability as leading sources of peer-reviewed scientific literature.

To ensure relevance and capture recent advances, the search was restricted to publications from 2014 to 2025. After filtering out conference papers, notes, editorials, meeting abstracts, and retracted documents, the records were screened for language, with non-English papers excluded. This step resulted in 567 records from WOS and 345 from Scopus. Subsequent duplicate removal reduced the dataset to 256 papers. These were further screened for eligibility based on relevance to the review objectives and availability of sufficient methodological detail, yielding 230 records. Following a full-text assessment, 128 studies were considered suitable and were included in the final review.

In parallel with this selection process, publication trends over the same period were examined to contextualize the scope of research activity in the field (Figure 2). The analysis revealed a clear and sustained growth trajectory, with the number of publications increasing more than tenfold, from fewer than 200 in 2014 to nearly 2,000 in 2024, representing approximately a 900% increase. Particularly after 2019, the pace of research output accelerated significantly, reflecting the growing recognition of artificial intelligence as a transformative tool for condition monitoring of rotating machinery. As of 2025, 1,510 publications have already been recorded, indicating that the upward momentum is continuing and may surpass previous peaks by year-end.

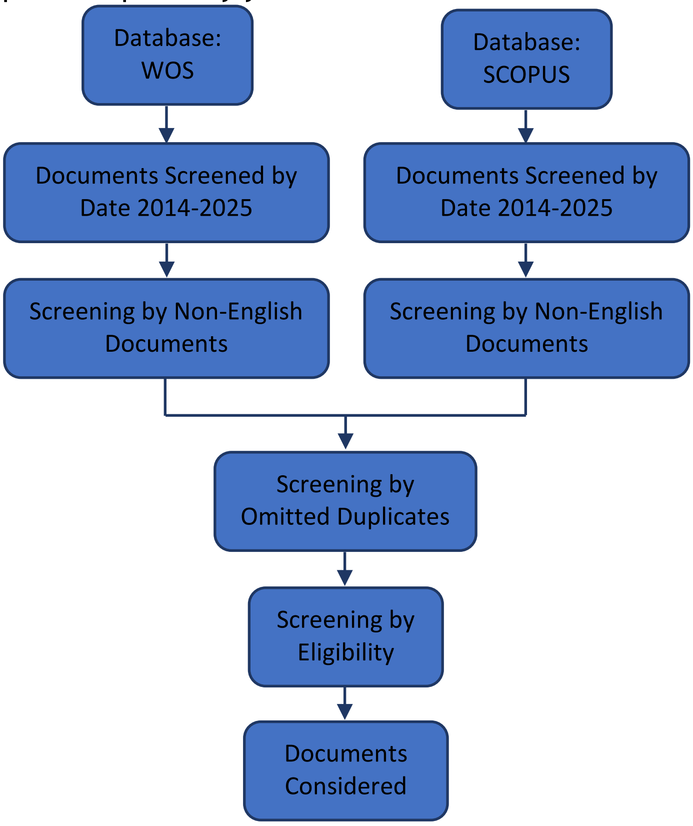

Figure 1. Study inclusion and exclusion process following the PRISMA framework

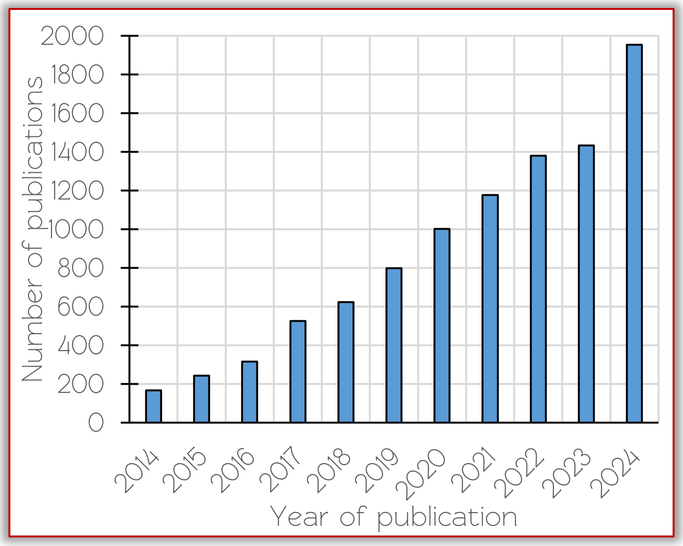

Figure 2. Temporal trends in research output for the study area (2014–2024)

A closer look at the thematic evolution of this body of literature further illustrates the shifting priorities within the field. Early studies (2014-2017) largely concentrated on traditional machine learning approaches for fault detection, signal processing, and feature extraction [6]. From 2018 onward, there has been a steady transition toward deep learning frameworks, including convolutional and recurrent neural networks, as well as hybrid AI models, which enable higher accuracy and automation in fault diagnosis [7]. More recent publications (2021–2024) highlight the integration of digital twins, edge computing, and big data platforms, reflecting the influence of Industry 4.0 paradigms [8], [9]. This thematic progression not only demonstrates the maturation of research methodologies but also underscores the expanding industrial relevance of AI-enabled condition monitoring systems. By consolidating and critically reviewing these developments, the present study aims to provide a comprehensive overview of both the historical trajectory and emerging frontiers of the field.

COMMON ROTATING MACHINERY FAULTS

Gear Faults

Gears are among the most vital components in rotating machinery, as they facilitate the transmission of power and motion between rotating parts. Their shape and size vary based on specific operational requirements. Gear faults can arise due to several factors, including excessive loads, improper installation, inadequate or poor lubrication, fatigue, corrosion, or contamination by dust, dirt, or other harmful materials. Common gear faults include tooth wear, cracked or broken teeth, chipped teeth, gear misalignment, and eccentricity. Like bearing faults, gear faults manifest distinctively in the frequency spectrum, as depicted in Figure 3, which shows the frequency spectrum for normal and faulty gear [10].

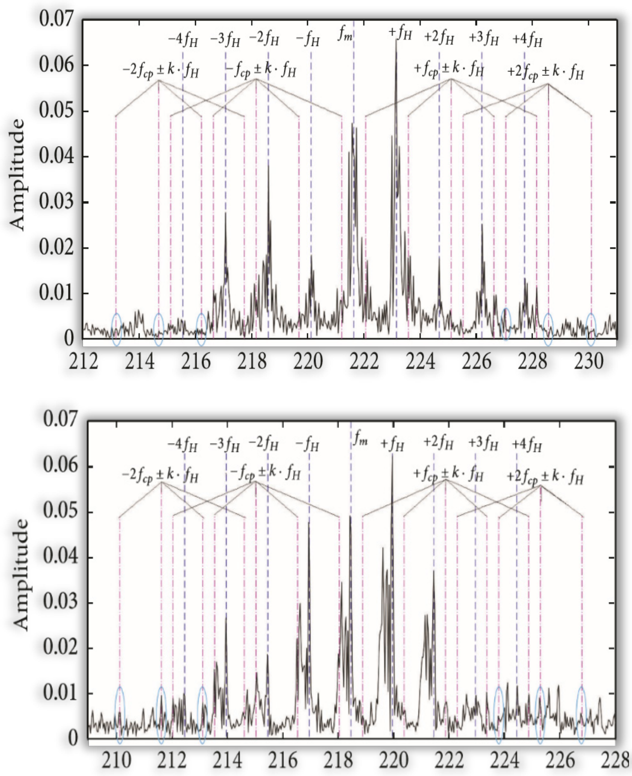

Figure 3. Frequency spectrum for normal and faulty gear [10]

The detection (FD) and prognosis (FP) of gear faults have been widely researched. Within the framework of Intelligent Fault Diagnosis and Prognosis (IFDP), various methods have been developed to address different gear faults. Fewer studies explore fault detection extension (FDE), fault isolation (FI), or fault prognosis (FP), with only about 17% specifically focusing on classification-based FP methods.

Notable studies in IFDP for gear faults include Chen et al. [2] who used a deep learning-based approach for FD and FP in gearboxes with multiple gear and bearing faults. Their analysis covered gear faults such as face wear (FW), chafing (CH), broken teeth (BT), pitting (PT), and chipped teeth (CT). The model achieved 96.8% overall accuracy, with fault-specific accuracy between 91.4% and 98.9%. Precision and recall metrics, though not explicitly provided, can be inferred from the confusion matrix.

Similarly, Chemseddine et al. [11] applied a neural network approach for diagnosing gearbox faults like cracked root (CRC), chipped teeth (CT), misalignment (MT), and worn teeth (WT).

Rotor Faults

The rotor is essential for generating rotational motion that powers or is powered by a machine, interacting dynamically with the stator, which supplies the electric current necessary for rotation. Rotor faults stem from factors such as manufacturing defects, improper maintenance, environmental conditions, excessive loads, faulty installations, and aging. Specific operating conditions also contribute to fault development.

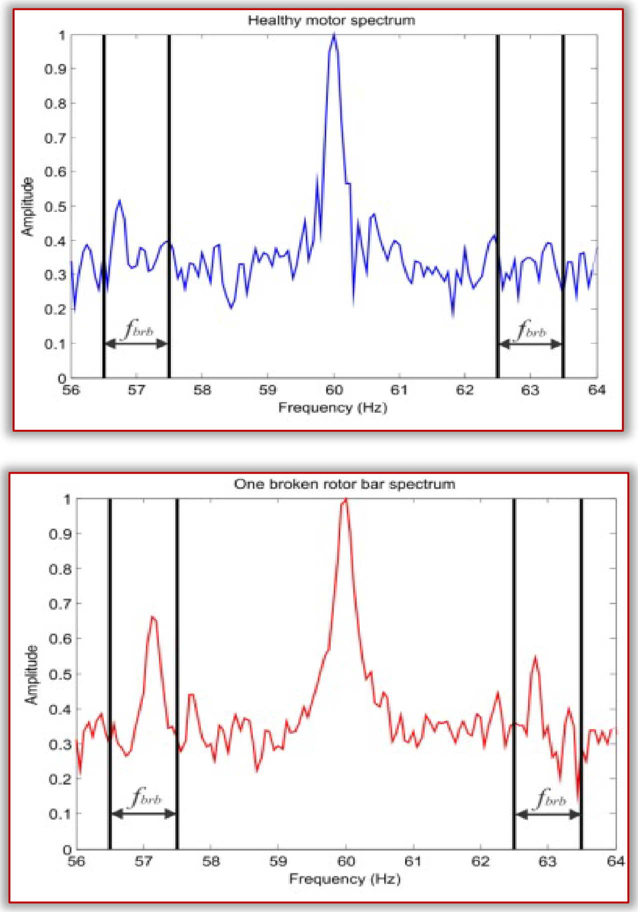

Figure 4. Characteristic shifts or harmonics in the frequency spectrum [12]

Common rotor faults like broken rotor bars, imbalance, misalignment, rub-impact, corrosion, and electrical faults each introduce distinct signatures in machine data (vibration, temperature, pressure, and current). These faults can manifest as characteristic shifts or harmonics in the frequency spectrum, as depicted in Figure 4 [12]. Their identification is critical for advanced condition monitoring and predictive maintenance strategies.

Bearing Faults

Bearings are critical components in rotating machines, guiding and supporting moving parts while reducing friction and enabling smooth operation. Bearing faults can occur due to excessive load, improper selection, faulty installation, poor maintenance, and excessive vibration. Common faults involve the inner race, rolling elements, cage, and outer race, with assembly and lubrication issues leading to wear, increased vibration, and oil leakage [13].

These faults produce specific frequency patterns: outer race faults are indicated by the ball pass frequency outer (BPFO), while inner race faults correspond to the ball pass frequency inner (BPFI). Rolling element faults are associated with the ball spin frequency (BSF), and cage faults relate to the fundamental train frequency (FTF). If not addressed, the appearance of these characteristic frequencies may lead to the disappearance of BPFO, BPFI, BSF, and FTF frequencies, resulting in random vibrations at frequencies above 30 kHz.

Recent studies have extensively explored the intelligent fault diagnosis and prognosis (IFDP) of bearing faults. Many studies utilized benchmark datasets for ball, inner race, and outer race faults under different loads, along with some derived from experimental setups or industry data [14] [15] [16] [17] [18] [19] [20].

Examples of intelligent bearing fault diagnosis studies include Li et al. [21], who applied a support vector classification method to identify IR, OR, RF, and House Eccentricity (HC) faults in gearbox setups. While their method focused on FD, fault-specific performance was not fully evaluated, reporting only overall model accuracy. Sohaib et al. [22] used a deep learning approach for bearing FD and FP, achieving a classification-based FP accuracy above 96.5% for various fault severities, yet emphasized the need for fault-specific metrics.

Zhang et al. [23] employed a Naive Bayes approach for FD and FI of RF, IR, and OR faults, assessing performance with accuracy and confusion matrices. Sanchez et al. [24] utilized five datasets for bearing FD, predicting RF, IR, OR, and HC faults with a best model accuracy of 83.0%. Guo et al. [25] achieved accuracies of 96.04% for FD and 99.93% for FI using deep learning. Choudhary et al. [19] reported an overall accuracy of 99.80% for a deep learning-based FD method targeting RF, IR, OR, CAF, and lack of lubrication (LB) faults, providing both overall and fault-specific metrics.

Despite the breadth of studies, regression-based FP strategies remain underrepresented, and critical evaluation metrics like precision, recall, and confusion matrices are often neglected in intelligent FD research. As illustrated in Figure 5, most studies concentrate on four primary bearing fault types, while others, including house eccentricity, aging, journal bearing faults, and oil issues, receive limited attention [12] [17] [26] [27] [28] [29]. Additionally, compound faults, crucial for FD and FP in rotating machines, are infrequently studied [30] [31] [32] [33] [30].

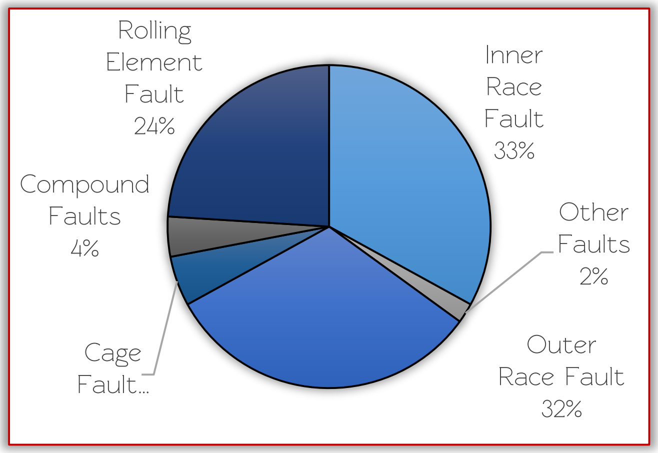

Figure 5. Percentile distribution of the considered bearing fault types

Other Faults

Rotating machines are susceptible to various faults beyond bearings, gears, or rotors, including belt-pulley issues, fan or turbine malfunctions, looseness, and shaft-related problems. Notably, few studies examine looseness faults, which can occur in various machine parts [31] [34] [13]. Similar to research on bearing, gear, and rotor faults, there is a limited number of studies employing detailed evaluation metrics like confusion matrices, precision, and recall for FD in rotating machines. Most research evaluates intelligent models primarily based on overall accuracy for fault detection and identification [35] [2] [36] [37]. The majority of studies focus on single faults, with few addressing the complexities of compound faults. Given that compound faults pose significant challenges in real-world applications, more comprehensive research in this area is warranted [31] [38].

EXISTING DATASETS

This section provides a detailed overview of the various publicly accessible datasets that are commonly used for fault diagnosis through vibration signal analysis. It highlights several key datasets that are widely recognized in the academic and industrial research communities. Among these are the Case Western Reserve University (CWRU) bearing dataset, the University of Paderborn (UPB) bearing dataset, and the Southeast University (SEU) gearbox dataset, as well as a selection of other relevant datasets. The subsequent sections delve deeper into each of these datasets, offering specific information on their composition, data characteristics, and their applications in fault diagnosis research.

(i) The Paderborn University (PU) bearing dataset, as described by Lessmeier et al. [39] is an extensive experimental dataset designed for condition monitoring and diagnostics, utilizing both motor current and vibration signals. This dataset is particularly valuable due to its large volume of data and the wide range of bearing testing scenarios it encompasses. The dataset includes two primary test rigs: a large mining space test rig specifically for bearing condition monitoring and an accelerated lifetime test rig. The bearing condition monitoring test rig is a modular system comprising several components, including a load motor, a flywheel, a bearing test module, a torque measurement shaft, and a driving motor. To accurately collect the necessary data, it is crucial to simulate relevant bearing faults within this setup. One of the key measured variables in this dataset is the vibration signal, captured as acceleration at the bearing housing in the test stand. This vibration data, along with other collected signals, provides critical insights into the condition of the bearings under various testing conditions, making it an essential resource for researchers and practitioners in the field of condition monitoring.

(ii) The Case Western Reserve University (CWRU) bearing dataset, as detailed by Loparo [40] is a widely recognized benchmark in fault diagnosis research. Available through CWRU's public bearing data center, this dataset is highly regarded for its comprehensive data on bearing faults. The test rig used for data collection consists of a two-horsepower induction motor, a torque transducer or encoder, and a dynamometer. An accelerometer positioned near the motor-driven end captures vibration signals at a high sampling frequency of 12 kHz, ensuring detailed data acquisition. To simulate real-world bearing faults, Electric Discharge Machining (EDM) is employed to create single-point defects on the test bearings. These defects are introduced with varying severity levels, resulting in flaw diameters of 0.007, 0.014, and 0.021 inches, respectively. The dataset categorizes bearing faults into three distinct types based on their location: inner-race fault, outer-race fault, and ball fault. Additionally, the dataset includes data for bearings under normal conditions, providing a baseline for comparison. This dataset encompasses a total of ten different bearing defect patterns, each tested under four distinct motor load conditions: 0, 1, 2, and 3 horsepower. The variety of fault types and load conditions makes the CWRU dataset an invaluable resource for researchers and engineers seeking to develop and validate fault diagnosis techniques.

(iii) The XJTU-SY Bearing Dataset, as described by Wang et al. [41], is an extensive collection of data designed for the analysis and diagnosis of bearing faults. The test bed used for this dataset includes an alternating current (AC) induction motor, a motor speed controller, a support shaft, two heavy-duty roller bearings, and a hydraulic loading system. This setup is specifically engineered to accelerate the degradation of rolling element bearings under various operating conditions, providing a robust environment for testing and analysis. The dataset covers three distinct operating conditions, with each condition tested using five different bearings. To capture the necessary vibration data, two accelerometers are strategically mounted on the bearing housing—one on the horizontal axis and the other on the vertical axis, placed at a 90-degree angle from each other. This dual-axis measurement setup ensures a comprehensive collection of vibration signals, which is crucial for accurate fault diagnosis. The data is sampled at a high frequency of 25.6 kHz, allowing for detailed signal analysis. Each sample consists of 32,768 data points, corresponding to a duration of 1.28 seconds. The sampling time for each test is set to 1 minute, providing a substantial amount of data for each bearing under test. This dataset is valuable for researchers aiming to develop and validate fault diagnosis techniques, offering a rich source of information under controlled, accelerated aging conditions.

(iv) The University of Connecticut Dataset, as detailed by Cao et al. [42], involves a comprehensive approach to capturing vibration signals from a two-stage gearbox equipped with adjustable gears. The gearbox test rig is controlled by a motor, which regulates the gear speed, while a magnetic brake provides adjustable torque through modifiable input voltage. The gearbox includes a first stage with a 32-tooth pinion and an 80-tooth gear, and a second stage with a 48-tooth pinion and a 64-tooth gear. The input shaft speed is measured using a tachometer, and the vibration signals from the gears are recorded by an accelerometer. These signals are sampled at a rate of 20 kHz using a dSPACE system. The dataset encompasses nine distinct gear conditions, including healthy gears, as well as gears with issues such as missing teeth, root fractures, spalling, and chipped tips. To facilitate the analysis, the raw vibration signals are converted into images without preprocessing. This conversion process aims to highlight the 2D features of the vibration data, with the final representation being a grayscale image sized 227×227 pixels. For each gear condition, 104 vibration signals were recorded, yielding a total of 3,600 angle-encoded samples per signal. This dataset provides a detailed and varied set of conditions useful for developing and testing gear fault diagnosis techniques.

(v) The ABLT-1A Bearing Dataset 6205, detailed by Ding et al. [43], features a comprehensive collection of data capturing seven distinct bearing health states under zero-load conditions. These health states include: normal operation, outer ring fault, a combination of inner and outer ring faults, inner ring fault, a weaker combination of inner and outer ring faults, and weak faults in both the inner and outer rings. The data for each health state were collected at a sampling rate of 17.5 Hz, with a sampling frequency of 12,800 Hz. The dataset uses a sample group interception technique, where each sample group consists of 1,024 signal points. In total, 2,000 sample groups were collected, resulting in 14,000 sample points across the seven health states. This dataset is designed to provide a broad range of fault conditions for in-depth analysis and diagnosis.

(vi) The ABLT-1A Bearing Dataset 6308, as described by Ding et al. [43], consists of data collected under zero-load conditions to represent five distinct bearing health states. These states are: normal operation, inner ring fault, outer ring fault, a combination of inner and outer ring faults, and a weaker combination of inner and outer ring faults. Data collection for each health state occurred at a rate of 17.5 Hz, with a sampling frequency of 12,800 Hz. The dataset employs a sample group interception method, where each group contains 1,024 signal points. A total of 2,000 sample groups were captured, resulting in 10,000 sample points overall. This dataset provides valuable insights into various fault conditions for bearing analysis and diagnostic purposes.

SYSTEMATIC APPRAISAL

Key Findings

Machine learning algorithms like neural networks, support vector machines (SVMs), and random forests have found increasing application in vibration analysis for fault diagnosis in rotating machinery. Neural networks are particularly adept at handling nonlinear fault classifications, while SVMs offer resilience in detecting faults amidst noisy environments [44]. The integration of these algorithms enables early fault detection and isolation, a crucial factor in industrial reliability.

In the field of Intelligent Fault Diagnosis and Prognosis (IFDP), there have been advancements in utilizing hybrid AI models that combine rule-based systems with deep learning techniques. These models improve the precision of fault characterization by analyzing complex historical vibration patterns, enhancing the effectiveness of real-time monitoring and predictive maintenance [45]. This real-time aspect significantly reduces both downtime and operational costs, making it a critical development for the industrial sector.

Deep learning techniques like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have also shown remarkable capabilities in vibration analysis. CNNs excel in processing high-dimensional data, such as time-frequency representations of vibration signals, while LSTMs capture temporal dependencies, offering valuable predictions about machinery wear and performance over time [43]. These models are increasingly vital for accurate health predictions in complex mechanical systems.

The efficacy of AI-driven diagnostics is supported by various case studies on rotating machinery, including turbines and compressors. These studies demonstrate that AI-based systems achieve higher accuracy in fault detection than traditional approaches. For instance, in centrifugal compressors, AI techniques have significantly reduced the rate of false positives in vibration-based diagnostics, highlighting the superior reliability of these methods in practical applications [42].

Limitations of Studies

Developing and implementing Intelligent Fault Diagnosis and Prognosis (IFDP) models for rotating machinery presents several challenges across data management, algorithm selection, model evaluation, and real-time application. One major challenge is data collection, as relevant and accurate fault data is essential for effective machine learning (ML) methods. Rotating machines generate a wide range of operational data, including vibration, speed, temperature, and voltage, which are crucial for fault analysis. However, deep learning methods require large datasets, which are hard to obtain, especially for faulty conditions, as machines usually operate in healthy states. This data scarcity is a significant issue, particularly for data-intensive ML methods.

Big data management is another challenge, as the increasing volume and complexity of fault-related data from smart manufacturing and IoT systems make analysis difficult. IFDP methods often struggle to capture the underlying physical relationships between cause and effect, necessitating advanced techniques like dimensionality reduction, specialized algorithms, and high storage and computational resources. Additionally, real-world industrial data is often imbalanced, with fewer instances of machine failure compared to normal operations. This imbalance can lead to misleading results, as models may incorrectly classify most data as healthy, despite high overall accuracy. Addressing this imbalance is critical for reliable fault diagnosis.

Data pre-processing is also crucial, as the impact of each data type on model performance varies. Identifying representative features, selecting appropriate processing methods, and tuning parameters are complex tasks requiring significant expertise. Techniques like Fast Fourier Transform or Wavelet Transform can influence outcomes based on parameter settings, making pre-processing a challenge.

Dynamic system adaptability is another hurdle. IFDP models must adapt to changing operational conditions in the Industry 4.0 environment, but most models are designed for specific conditions, and their performance may degrade in different environments. Real-time adaptability is also challenging, as machines in real-world settings operate differently from controlled environments. This necessitates models that are resilient to environmental changes like temperature, humidity, and noise.

Algorithm selection is equally challenging, as each fault analysis problem is unique, and the choice of an ML algorithm depends heavily on the data. Supervised learning techniques may work well for labeled data but can be less effective when data is diverse, making fault detection rather than identification a better focus in some cases. Additionally, optimal parameter selection is crucial for algorithm effectiveness, but finding the right parameters is time-consuming and computationally expensive, requiring extensive experimentation.

Model evaluation poses another significant challenge. It's essential to avoid under-fitting or over-fitting by providing balanced training data and testing with unseen, real-world data, which can be time-consuming and costly. Unbalanced data further complicates evaluation, as high accuracy may mask poor fault detection. Metrics like precision, recall, and confusion matrices are vital for accurate performance assessment.

Interdisciplinary collaboration is essential for implementing ML models for rotating machinery, requiring expertise from mechanical engineering, computer science, and other fields. Collaboration across these disciplines is often needed for successful model development.

Domain adaptation is another challenge, as IFDP methods are typically trained on a single dataset. However, models may perform poorly when tested on data from different machines. Developing models that generalize across different machines within the same domain is crucial for reliable fault diagnosis.

Finally, addressing fault types and compound faults is vital. IFDP models must consider all possible faults, including those that may trigger additional faults in other components, as these can affect performance. A comprehensive approach to account for compound faults is necessary when designing IFDP systems for rotating machinery.

FUTURE DIRECTIONS

This study reviews the application of Deep Learning (DL) algorithms for fault diagnosis using vibration signals. Despite the significant advances in DL, several challenges and limitations persist. For instance, noise in data from real-world industrial environments poses a challenge in determining whether current DL algorithms can effectively handle such noisy conditions. Another issue is the imbalance in datasets, as most machine health data represents normal conditions, which can adversely affect the training of fault diagnosis models.

The interpretability of DL algorithms for fault diagnosis using vibration signals remains underexplored. The internal workings of DL models are often opaque, making it difficult to explain how they arrive at their decisions. To address this, methods like feature visualization [46], and class activation maps (CAMs) [47] [48] have been proposed. These techniques help identify key areas in the data that contribute to the model's predictions, which is particularly useful for detecting faults without relying on vibration sensors. For example, CAMs have been used to detect defects in a laboratory-scale water pump.

In addition, some studies have employed approaches like SincNet to improve interpretability from a frequency domain perspective [49]. SincNet uses parameterized Sinc functions to create more meaningful filters in the first layer [50]. Other research has introduced interpretable Convolutional Neural Networks (CNNs) for gearbox fault diagnosis by using layer-wise relevance propagation (LRP) [51] [52]. Moreover, the WaveletKernelNet (WKN) uses a continuous wavelet convolution (CWConv) layer to extract significant fault information from vibration signals, making the convolution kernels more interpretable [53].

While DL algorithms are data-driven and suitable for observations, their predictions can be inconsistent or unreasonable due to data biases, leading to poor generalization. Therefore, there is a growing need to incorporate fundamental physical principles and domain knowledge into DL algorithms. This approach, known as physics-informed learning, helps to govern physical norms and reduce observational biases, thereby improving the performance of DL models [52]. Physics-informed neural networks (PINNs) are a recent development in this area, integrating partial differential equations (PDEs) into the loss function to incorporate domain knowledge [54].

Another promising direction is the use of the self-attention mechanism, particularly in the Transformer model [55]. Although the Transformer has excelled in tasks like natural language processing and image analysis, its application in fault diagnosis is still emerging. The Transformer Convolution Network (TCN) has been introduced for fault diagnosis in rotating machinery, demonstrating robustness and resilience against noise [56]. However, further modifications are needed to optimize TCN for analyzing vibration signals, particularly in real-world industrial settings with limited fault data.

Most studies focus on diagnosing bearing faults, which are common in industrial systems. However, future research should also address other types of faults in rotating machinery, such as coupling faults, rolling element defects, and ball screw issues, given the complex interactions between various components [40] [57] [47] [58] [31] [59] [60].

CONCLUSION

Machine Learning (ML) and Deep Learning (DL) are subsets of artificial intelligence that enable systems to learn patterns and make decisions based on data. ML involves algorithms that improve performance on a task over time with experience, focusing on tasks like classification, regression, and clustering. DL, a more advanced subset of ML, utilizes neural networks with multiple layers (deep networks) to model complex patterns and achieve higher accuracy in tasks like image recognition, natural language processing, and predictive analytics (RQ1).

The primary fault analysis strategies for rotating machinery include condition-based monitoring (CBM), which relies on continuous data collection to detect anomalies, and predictive maintenance (PdM), which forecasts potential failures based on historical data. These strategies are supported by techniques such as vibration analysis, acoustic monitoring, and thermography. Traditional maintenance approaches include reactive maintenance, where repairs are made post-failure, and preventive maintenance, which schedules regular inspections regardless of machine condition (RQ2).

In the context of intelligent fault diagnosis and prognosis (IFDP) using ML, the most frequently targeted rotating machine components are bearings, gears, rotors, and motors. These components are critical to the operation of rotating machinery, and their failure can lead to significant operational disruptions. ML models are extensively applied to monitor and predict faults in these components, leveraging data such as vibration signals, temperature, and acoustic emissions (RQ3).

ML techniques are employed to detect, localize, identify, and predict a variety of faults in rotating machinery. Common faults include bearing defects, gear tooth damage, rotor imbalances, and shaft misalignments. ML models analyze data from sensors to detect these faults early, localize the specific area of the fault, identify the fault type, and predict its progression, allowing for timely maintenance interventions (RQ4).

Deep Learning (DL) techniques that have seen significant development in the field of IFDP include Convolutional Neural Networks (CNNs), which are effective in image and signal processing tasks; Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, which excel in time-series data analysis; and Auto-Encoders, used for anomaly detection and unsupervised learning tasks. These techniques have been widely adopted for their ability to model complex, non-linear relationships in large datasets (RQ5).

AUTHOR CONTRIBUTION STATEMENT AND DECLARATION

The authors affirm that they have no financial conflicts of interest or personal relationships that might have impacted the research or findings detailed in this paper. They emphasize that their work has been conducted with full impartiality and without any external influences that could have affected the outcomes.

References

[1] X. Zhu, "Rotor fault diagnosis using a convolutional neural network with symmetrized dot pattern images," Measurement, vol. 138, p. 526–535, 2019.

[2] J. Chen, D. Zhou, C. Lyu and C. Lu, "An integrated method based on CEEMD-SampEn and the correlation analysis algorithm for the fault diagnosis of a gearbox under different working conditions," Mechanical Systems and Signal Processing, vol. 113, p. 102–111, 2018.

[3] D. Cabrera, "Fault diagnosis of spur gearbox based on random forest and wavelet packet decomposition," Frontiers in Mechanical Engineering, vol. 10, p. 277–286, 2015.

[4] T. Ince, "Real-time broken rotor bar fault detection and classification by shallow 1D convolutional neural networks," Electrical Engineering, vol. 101, p. 599–608, 2019.

[5] J. Fan and Z. Wang, "Fault early recognition and health monitoring on aeroengine rotor system," Journal of Aerospace Engineering, vol. 28, p. 04014065, 2015.

[6] O. AlShorman , M. Irfan, N. Saad, D. Zhen , N. Haider , A. Glowacz , M. AlShorman, "A review of artificial intelligence methods for condition monitoring and fault diagnosis of rolling element bearings for induction motor," Shock and Vibration, vol. 2020, no. 8843759, pp. 1-20, 2020.

[7] P. Gangsar, A. R. Bajpei, R. Porwal, " A review on deep learning based condition monitoring and fault diagnosis of rotating machinery," Noise & Vibration Worldwide, vol. 53, no. 11, pp. 550-578, 2022.

[8] M. Xia, H. Shao, D. Williams, S. Lu, L. Shu, C. W. de Silva, "Intelligent fault diagnosis of machinery using digital twin-assisted deep transfer learning, Reliability Engineering & System Safety," Reliability Engineering & System Safety, vol. 215, no. 107938, pp. 1-9, 2021.

[9] V. Inturi, B. Ghosh, S. G. Rajasekharan, and V. Pakrashi, "A review of digital twinning for rotating machinery," Sensors, vol. 24, no. 15, p. 5002, 2024 .

[10] Q. Zhou and Q. Miao, "Planetary gearbox vibration signal characteristics analysis and fault diagnosis," 2020.

[11] R. Chemseddine, "Gear fault feature extraction and classification of singular value decomposition based on Hilbert empirical wavelet transform," Journal of Vibroengineering, vol. 20, p. 1603–1618, 2018.

[12] A. G. Garcia-Ramirez, "Smart sensor for online detection of multiple-combined faults in VSD-fed induction motors," 2012.

[13] F. K. Geitner and H. P. Bloch, "Machinery Failure Analysis and Troubleshooting," Vibration Analysis, p. 391–478, 2012.

[14] G. Razik and C. Soualhi, "Detection and diagnosis of faults in induction motor using an improved artificial ant clustering technique," IEEE Transactions on

Industrial Electronics, vol. 60, p. 4053–4062, 2013.

[15] Z. Zhang, Y. Wang and K. Wang, "Intelligent fault diagnosis and prognosis approach for rotating machinery integrating wavelet transform, principal component analysis, and artificial neural networks," International Journal of Advanced Design and Manufacturing, vol. 68, pp. 763–773,, 2013.

[16] S. Saufi, "Machinery fault diagnosis based on a modified hybrid deep sparse autoencoder using a raw vibration time-series signal," Ambient Intelligence and Humanized Computing, 2022.

[17] J. Lee, "Fault diagnosis of induction motor using convolutional neural network," Applied Sciences, vol. 9, p. 2950, 2019.

[18] Kim, M. M. M. Islam and J. -M, "Automated bearing fault diagnosis scheme using 2D representation of wavelet packet transform and deep convolutional neural network," Computers in Industry, vol. 106, p. 142–153, 2019.

[19] T. Choudhary, S. Mian and Fatima, "Convolutional neural network based bearing fault diagnosis of rotating machine using thermal images," Measurement, vol. 176, p. 109196, 2021.

[20] S. Liu, "Multi-feature fusion for fault diagnosis of rotating machinery based on convolutional neural network," Computers and Communications, vol. 173, p. 160–169, 2021.

[21] Li, C.; Sanchez, R.; Zurita, G.; Cerrada, M.; Cabrera, D.; Vásquez, R. E., "Gearbox fault diagnosis based on deep random forest fusion of acoustic and vibratory signals," Mechanical Systems and Signal Processing, vol. 76–77, p. 283–293, 2016.

[22] M. Sohaib, "A hybrid feature model and deep-learning-based bearing fault diagnosis," Sensors, vol. 17, 2017.

[23] N. Zhang, "Naive Bayes bearing fault diagnosis based on enhanced independence of data," Sensors, vol. 18, p. 46, 2018.

[24] ". R. -V. Sánchez, "Feature ranking for multi-fault diagnosis of rotating machinery by using random forest and KNN," Journal of Intelligent & Fuzzy Systems, vol. 34, p. 3463–3473, 2018.

[25] S. Guo, "Multitask convolutional neural network with information fusion for bearing fault diagnosis and localization," IEEE Transactions on Industrial Electronics, vol. 67, p. 8005–8015, 2020.

[26] X. Wu, "A hybrid classification autoencoder for semi-supervised fault diagnosis in rotating machinery," Mechanical Systems and Signal Processing, vol. 149, p. 107327, 2021.

[27] J. Xiong, "A diagnosis method for rotation machinery faults based on dimensionless indexes combined with K-nearest neighbor algorithm," Mathematical Problems in Engineering, 2015.

[28] A. Yin, "Fault diagnosis of wind turbine gearbox based on the optimized LSTM neural network with cosine loss," Sensors, vol. 20, p. 2339, 2020.

[29] J. Li, "The hybrid KICA-GDA-LSSVM method research on rolling bearing fault feature extraction and classification," Shock and Vibration, 2015.

[30] K. N. Ravikumar, "Gearbox fault diagnosis based on multi-scale deep residual learning and stacked LSTM model," Measurement, vol. 186, p. 110099, 2021.

[31] X.-B. Wang, "Novel paralleled extreme learning machine networks for fault diagnosis of wind turbine drivetrain," Memetic Computing, vol. 11, p. 127–142, 2019.

[32] K. Vernekar and H. Kumar, "Engine gearbox fault diagnosis using machine learning approach," Journal of Quality in Maintenance Engineering, vol. 24, p. 345–357, 2018.

[33] K. Yu, "A multi-stage semi-supervised learning approach for intelligent fault diagnosis of rolling bearing using data augmentation and metric learning," Mechanical Systems and Signal Processing, vol. 146, p. 107043, 2021.

[34] A. G. Nath, "An early classification approach for improving structural rotor fault diagnosis," IEEE Transactions on Instrumentation and Measurement, vol. 70, p. 1–13, 2021.

[35] A. Krishnakumari, "Fault diagnostics of spur gear using decision tree and fuzzy classifier," International Journal of Advanced Design and Manufacturing Technology, vol. 89, p. 3487–3494, 2016.

[36] M. Seera, "Application of the fuzzy min-max neural network to fault detection and diagnosis of induction motors," Neural Computing and Applications, vol. 23, p. 191–200, 2013.

[37] X. Wu, "Rub-impact fault diagnosis of rotating machinery based on 1-D convolutional neural networks," IEEE Sensors Journal, 2019.

[38] M. Hassan, "Wavelet-based multiresolution bispectral analysis for detection and classification of helicopter drive-shaft problems," Journal of Dynamic Systems, Measurement, and Control, vol. 140, 2017.

[39] C. Lessmeier, O. Enge-Rosenblatt, C. Bayer and & Zimmer, "Data Acquisition and Signal Analysis from Measured Motor Currents for Defect Detection in Electromechanical Drive Systems.," in Second European Conference of the Prognostics and Health Management Society, , Nantes, 2014.

[40] K. Loparo, "Case western reserve university bearing data center. Bearings vibration data sets," Case Western Reserve University, p. 22–28, 2012.

[41] Z. Wang and H. Huang, "Fault diagnosis of planetary gearbox using multi-criteria feature selection and heterogeneous ensemble learning classification," Measurement, vol. 173, 2021.

[42] P. Cao, S. Zhang and J. Tang, "Preprocessing-free gear fault diagnosis using small datasets with deep convolutional neural network-based transfer learning," IEEE Access, vol. 6, p. 26241–26253, 2018.

[43] Y. Ding, M. Jia, Q. Miao and Y. Cao, "A novel time-frequency transformer based on self-attention mechanism and its application in fault diagnosis of rolling bearings," Mech. Syst. Signal Process, vol. 168, p. 108616, 2022.

[44] W. Deng, "Fault diagnosis of rotating machinery based on convolutional neural networks," Journal of Vibration and Control, vol. 25, no. 6, p. 910–924, 2019.

[45] C. Li, "Vibration signal analysis using deep learning for fault detection in rotating machines," IEEE Access, vol. 7, p. 123, 2019.

[46] D. Fergus and R. Matthew, "Visualizing and understanding convolutional neural networks," in Proc. 13th Eur. Conf. Comput. Vis. Pattern Recognit, Switzerland, Zurich, 2014, p. 6–12.

[47] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh and D. Batra, "Grad-cam: visual explanations from deep networks via gradient-based localization," Proc. IEEE Int. Conf. Comput. Vis, p. 618–626, 2017.

[48] F. Jia, Y. Lei, J. Lin, X. Zhou and N. Lu, "Deep neural networks: a promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data," Mechanical Systems and Signal Processing, vol. 72, p. 303–315, 2016.

[49] F. B. Abid, M. Sallem and A. Braham, "Robust interpretable deep learning for intelligent fault diagnosis of induction motors," IEEE Trans. Instrum. Meas, vol. 69, no. 6, p. 3506–3515, 2020.

[50] M. Bengio and Y. Ravanelli, "Speech and speaker recognition from raw waveform with sincnet," 2018. [Online]. Available: https://arxiv.org/abs/1812.05920..

[51] J. Grezmak, P. Wang, C. Sun and R. X. Gao, "Explainable convolutional neural network for gearbox fault diagnosis," Procedia CIRP, vol. 80, p. 476–481, 2019.

[52] G. E. Karniadakis, I. G. Kevrekidis, L. Lu, P. Perdikaris, S. Wang and L. Yang, "Physics-informed machine learning," Nat. Rev. Phys, vol. 3, no. 6, p. 422–440, 2021.

[53] X. Li, "Deep representation clustering-based fault diagnosis method with unsupervised data applied to rotating machinery," Mechanical Systems and Signal Processing, vol. 143, p. 106825, 2020.

[54] M. Raissi, P. Perdikaris and G. Karniadakis, "Physics-informed neural networks: a deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations," J. Comput. Phys, vol. 378, p. 686–707, 2019.

[55] Vaswani, Shazeer, P. Uszkoreit, Jones, Gomez, Kaiser and I. Polosukhin, "Attention is all you need," Advances in Neural Information Processing Systems, vol. 30, 2017.

[56] X. Pei, X. Zheng and J. Wu, "Rotating machinery fault diagnosis through a transformer convolution network subjected to transfer learning," IEEE Trans. Instrum. Meas, vol. 70, p. 1–11, 2021.

[57] M. Pradhan and P. Gupta, "Fault detection analysis in rolling element bearing: a review," Mater. Today: Proc, vol. 2, no. 4, p. 2085–2094, 2017.

[58] K. Vos, "Vibration-based anomaly detection using LSTM/SVM approaches," Mechanical Systems and Signal Processing, vol. 169, 2022.

[59] X. Xu, D. Cao, Y. Zhou and J. Gao, "Application of neural network algorithm in fault diagnosis of mechanical intelligence," Mechanical Systems and Signal Processing, vol. 141, pp. 106-625, 2020.

[60] L. Jing, "A convolutional neural network based feature learning and fault diagnosis method for the condition monitoring of gearbox," Measuremen, vol. 111, p. 1–10, 2017.

ISSN: 2067–3809