JOURNAL OF PRODUCTION ENGINEERING VOL. 29, NO. 1 (2026)
DOI: 10.24867/JPE-2026-01-001

Review article

Journal of
Production Engineering

https://jpe.ftn.uns.ac.rs/index.php/jpe
ISSN: 1821-4932 (print), ISSN: 2956-2252 (online)

Artificial intelligence for vibration-based fault diagnosis in rotating machinery

Idehai O. Ohijeagbon* 0000-0003-2202-6431, ***Frieda Fillemon*** 0009-0004-0873-1614, ***Surendra K. Saini*** 0000-0002-8780-695X

School of Engineering and the Built Environment, Mechanical and Metallurgical Engineering Department, University of Namibia, Ongwediva, Namibia

ABSTRACT

Rotating machinery underpins numerous industrial systems, where reliable fault diagnosis is essential for ensuring safety, operational efficiency, and cost reduction. Conventional vibration-based diagnostic methods often struggle with non-stationary, noisy, and high-dimensional data. Recent advances in artificial intelligence (AI), particularly deep learning techniques such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have introduced robust and effective solutions for condition monitoring and fault diagnosis. This systematic review synthesizes recent progress in AI-driven vibration analysis, focusing on feature extraction, fault classification, temporal modeling, and multi-sensor data fusion. Key challenges, including model generalization, interpretability, and data scarcity, are critically examined in the context of industrial deployment. Furthermore, emerging research directions such as explainable AI, domain adaptation, edge computing, and digital twin integration are discussed. By consolidating current knowledge and identifying open research challenges, this review provides a comprehensive reference for the development of intelligent, scalable, and practical fault diagnosis systems for rotating machinery.

ARTICLE INFO

Received: 01 November 2025
Revised: 12 February 2026
Accepted: 18 March 2026

KEYWORDS:
Rotating machinery;
Fault diagnosis;
Condition monitoring;
Artificial intelligence;
Deep learning;
Digital twin.

**Corresponding author's.e-mail:*
iohijeagbon@unam.na

1. INTRODUCTION

Rotating machinery represents a fundamental component of modern industrial systems and plays a vital role in sectors such as manufacturing, energy production, transportation, aerospace, and process industries [1]. The reliability, efficiency, and safety of these systems directly influence production continuity, operational costs, and overall industrial productivity. Consequently, the early detection of faults and continuous monitoring of machine health have become essential requirements for ensuring stable and sustainable industrial operations.

Among various condition monitoring techniques, vibration analysis has established itself as one of the most effective and widely adopted approaches for detecting mechanical defects, including imbalance, misalignment, bearing degradation, gear damage, and shaft-related failures. Vibration signals contain valuable information about machine operating conditions and can reveal early signs of deterioration before severe failures occur. However, traditional vibration-based diagnostic methods face several challenges, particularly when dealing with complex industrial environments characterized by non-stationary signals, high levels of noise, varying operating conditions, and large volumes of data. In addition, conventional approaches often rely heavily on manual feature extraction and expert knowledge, which may limit their scalability and general applicability [2].

In recent years, the rapid development of artificial intelligence (AI) has significantly transformed the field of machinery fault diagnosis. Advances in computational power, data availability, and machine learning algorithms have enabled the development of intelligent diagnostic systems capable of automatically learning hidden patterns from vibration data. AI-based methods have demonstrated considerable potential in improving diagnostic accuracy,

Published by the University of Novi Sad, Faculty of Technical Sciences, Novi Sad, Serbia.

reducing human intervention, and enabling predictive maintenance strategies that support the transition toward smart manufacturing and Industry 4.0 environments [3].

Deep learning techniques, in particular, have attracted substantial attention due to their ability to automatically extract meaningful features directly from raw vibration signals. Architectures such as Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Deep Belief Networks (DBNs), Graph Neural Networks (GNNs), Capsule Networks (CapsNets), and autoencoder-based models have shown promising results in fault detection, fault classification, and remaining useful life prediction. Furthermore, hybrid and ensemble frameworks have emerged as powerful solutions that integrate signal preprocessing, feature extraction, and classification into unified diagnostic systems.

Despite the growing number of studies in this field, several challenges remain. Existing review papers often focus on a limited subset of AI techniques, emphasize only specific machine components, or provide insufficient discussion regarding industrial deployment, model robustness, computational complexity, interpretability, and generalization across different operating conditions. Moreover, the rapid emergence of advanced deep learning architectures and hybrid approaches has created a need for a comprehensive and up-to-date synthesis of current developments.

Therefore, this review aims to provide an integrated overview of AI-driven approaches for vibration-based fault diagnosis in rotating machinery. Unlike previous studies, this work simultaneously analyzes conventional and advanced deep learning architectures, hybrid frameworks, multi-sensor data fusion strategies, and the practical challenges associated with real-world industrial implementation. Particular attention is given to sequential learning methods such as Long Short-Term Memory (LSTM) networks, graph-based techniques for representing complex relationships within vibration signals, and autoencoder-based models for unsupervised feature learning.

Through a comprehensive comparative analysis, this review identifies current research trends, evaluates the strengths and limitations of different AI models, highlights emerging technologies, and outlines future research directions toward more robust, explainable, and transferable intelligent diagnostic systems.

The primary objective of this systematic review is to analyze and synthesize current research trends, methodologies, and applications of artificial intelligence in vibration-based fault diagnosis of rotating machinery. Specifically, this review aims to:

1. Provide a structured classification of AI models employed in vibration analysis, including Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Deep Belief Networks (DBNs), Graph Neural Networks (GNNs), Capsule Networks (CapsNets), and autoencoder-based architectures.
2. Evaluate the effectiveness, advantages, and limitations of various AI-based diagnostic frameworks.
3. Investigate the role of hybrid approaches, multi-sensor data fusion, and advanced feature learning techniques in improving diagnostic performance.
4. Identify existing research gaps and propose future directions for the development of intelligent condition monitoring systems.
5. Provide a practical reference for researchers, engineers, and practitioners involved in the development and implementation of AI-driven fault diagnosis systems

To achieve these objectives, the following research questions (RQs) are addressed:

RQ1. What are the major AI techniques currently applied in vibration-based fault diagnosis of rotating machinery?

RQ2. How do these AI techniques process vibration signals to achieve accurate fault classification and health prediction?

RQ3. What are the strengths and limitations of individual AI models (e.g., CNNs, RNNs, and GNNs) in real-world industrial applications?

RQ4. How do hybrid and ensemble approaches contribute to improving diagnostic accuracy, robustness, and reliability?

RQ5. What challenges remain in deploying AI-based vibration analysis systems, and which research directions hold the greatest potential for future advancements?

2. CONCEPTUAL FRAMEWORK

2.1 Machine Learning for Vibration-Based Fault Diagnosis

Computational Machine learning (ML) is a branch of artificial intelligence that enables computer systems to learn from data and improve their performance without being explicitly programmed for specific tasks. In the field of rotating machinery diagnostics, ML has become an essential tool due to its ability to process and analyze large volumes of vibration data acquired from condition monitoring systems.

Modern industrial equipment continuously generates vast amounts of sensor data, particularly from accelerometers used to monitor machine health. These datasets are often complex, high-dimensional, and affected by varying operating conditions and noise. Traditional diagnostic approaches largely depend on manual feature extraction and expert knowledge, which can be time-consuming and difficult to generalize across different applications. Machine learning addresses these limitations by automatically identifying hidden patterns, correlations, and relationships within the data.

Various ML algorithms have been successfully applied to vibration-based fault diagnosis and condition monitoring of rotating machinery. Support Vector Machines (SVMs) are widely used because of their strong performance in classification tasks, particularly for distinguishing between healthy and faulty operating conditions. Decision Trees (DTs) and k-Nearest Neighbors (k-NN) provide relatively simple and interpretable models capable of identifying different fault categories based on vibration signal characteristics. Ensemble methods, such as Random Forests (RFs) and boosting algorithms, further improve diagnostic performance by combining multiple weak learners into a robust predictive framework.

The application of ML techniques enables the development of intelligent maintenance systems that can not only detect faults at an early stage but also predict potential failures before they occur. This capability supports predictive maintenance strategies, reduces unplanned downtime, and improves operational reliability in industries such as manufacturing, energy production, transportation, and aerospace [4], [5].

2.2 Deep Learning for Vibration-Based Fault Diagnosis

Deep Learning (DL), a specialized subfield of machine learning, has emerged as one of the most influential technologies for intelligent fault diagnosis. The rapid development of deep neural networks (DNNs) since the early 2010s has significantly expanded the capabilities of artificial intelligence (AI) in solving complex industrial problems [6]. Figure 1 illustrates the hierarchical relationship between AI, ML, and DL, as well as their historical evolution.

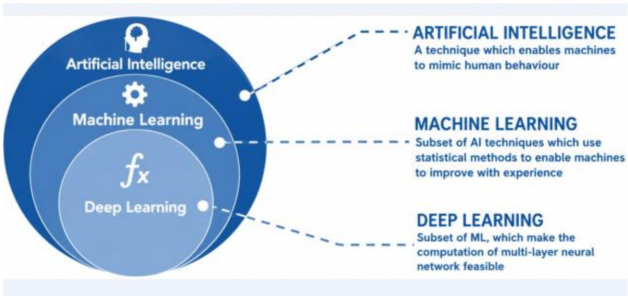

Fig. 1 The relationship and a time frame between AI, ML, and DL [7].

A machine learning (ML) algorithm typically learns the features of input data X through a feature extractor. The features extracted by this process are then used to train a classifier $F_\theta(.)$ which generates predictions Y. In contrast, a deep learning (DL) algorithm does not rely on handcrafted feature representations. Instead, the input data X is transformed using a transformation function T_θ, which consists of several learnable parameters. This transformation creates a new representation $T_\theta(.)$. Which is then utilized for classification by $F_\theta(.)$ to produce the final output Y.

DL techniques have become particularly prominent in the fault diagnosis of rotating machinery. These techniques can be trained in various ways, including supervised and unsupervised learning, as well as other learning paradigms like reinforcement learning [10]. For a comprehensive understanding of DL, readers are encouraged to consult the extensive literature available on the subject [11] [12]. Several widely recognized DL architectures include convolutional neural networks (CNNs), deep belief networks (DBNs), recurrent neural networks (RNNs), generative neural networks, and graph neural networks (GNNs). A brief discussion of these architectures follows in the next section. Figure 2 presents a comparison between conventional ML and DL approaches.

Several DL architectures have demonstrated excellent performance in machinery fault diagnosis, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Deep Belief Networks (DBNs), Graph Neural Networks (GNNs), generative models, and other advanced architectures. These models will be discussed in greater detail in the following sections.

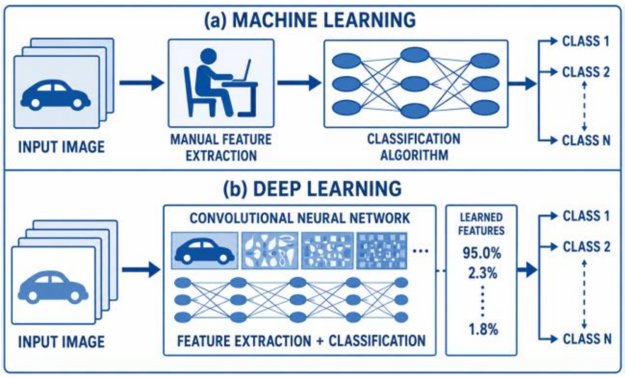

Fig. 2 Comparison between Machine Learning (ML) and Deep Learning (DL) [9].

3. METHODOLOGICAL APPROACHES FOR AI-BASED VIBRATION ANALYSIS

3.1 Feature Extraction and Feature Selection

Feature extraction and feature selection constitute fundamental steps in AI-based vibration analysis, as they transform raw vibration signals into meaningful representations that can be effectively utilized for fault diagnosis. Vibration signals generated by rotating machinery are inherently complex and often contain a combination of high- and low-frequency components associated with different operating conditions and fault mechanisms. Therefore, extracting relevant information while reducing data dimensionality is essential for building reliable diagnostic models.

Traditional feature extraction methods can be broadly categorized into time-domain, frequency-domain, and time-frequency domain approaches. Time-domain analysis utilizes statistical indicators such as root mean square (RMS), skewness, kurtosis, crest factor, and peak-to-peak amplitude to characterize signal behavior [5]. Although these indicators are computationally efficient, they may not fully capture the complexity of machinery faults.

Frequency-domain methods, particularly the Fast Fourier Transform (FFT), analyze the spectral content of vibration signals and are highly effective for identifying periodic components and harmonics associated with specific defects. However, because rotating machinery often operates under varying conditions, vibration signals are frequently non-stationary. To address this limitation, time-frequency analysis techniques, including Wavelet Transform (WT) and Empirical Mode Decomposition (EMD), have been extensively adopted. These methods simultaneously capture temporal and spectral information, providing a more comprehensive representation of machine behavior [13].

Once features have been extracted, feature selection techniques are employed to identify the most informative subset of variables. This process reduces computational complexity, eliminates redundant information, and improves model generalization. Commonly used techniques include Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Genetic Algorithms (GAs). Effective feature selection also helps mitigate overfitting and enhances the robustness of AI models when applied to unseen operating conditions [14].
Overall, the performance of AI-based fault diagnosis systems strongly depends on the quality of the extracted features, as inadequate feature representation can significantly compromise diagnostic accuracy.

3.2 Data-Driven Modeling

Data-driven modeling represents another important methodological approach in AI-based vibration analysis. Unlike conventional physics-based models, which rely on mathematical formulations derived from first principles, data-driven approaches learn system behavior directly from measured data.
Data-driven approaches are commonly implemented using supervised learning techniques, where models are trained on labeled datasets corresponding to various fault conditions. Algorithms such as Decision Trees (DTs), Support Vector Machines (SVMs), and Artificial Neural Networks (ANNs) learn the relationship between vibration signal features and machine health states. Once trained, these models can provide real-time fault classification and support predictive maintenance strategies [15].
In practical applications, obtaining sufficiently labeled datasets is often challenging. Consequently, unsupervised learning methods have gained considerable attention. Techniques such as clustering and anomaly detection can identify abnormal operating conditions without requiring predefined fault labels. These approaches are particularly valuable for early fault detection because they can reveal subtle deviations from normal machine behavior before severe failures occur [16].
By continuously learning from operational data, data-driven models enable adaptive condition monitoring systems that improve maintenance planning, reduce unexpected downtime, and enhance overall equipment reliability.

3.3 Deep Learning architectures for vibration analysis

Deep learning has revolutionized vibration-based fault diagnosis by enabling the automatic extraction of hierarchical features directly from raw sensor data. Unlike traditional machine learning approaches that depend on handcrafted features, deep learning architectures can simultaneously perform feature extraction and classification within a unified framework.
Convolutional Neural Networks (CNNs) are among the most widely used architectures for rotating machinery diagnostics. Their ability to learn spatial representations makes them highly effective for identifying localized fault signatures within vibration signals. CNNs can automatically detect changes in amplitude, frequency, and phase characteristics associated with various fault conditions [2]. Furthermore, combining CNNs with spectrograms, Wavelet Transforms, or other time-frequency representations often leads to improved diagnostic performance.
Recurrent Neural Networks (RNNs) are specifically designed for sequential data analysis and are therefore well suited for processing time-series vibration signals. Among them, Long Short-Term Memory (LSTM) networks have demonstrated excellent performance in capturing long-term temporal dependencies and modeling fault evolution over time. This capability is particularly important for prognostics and remaining useful life (RUL) estimation, where understanding fault progression is essential for implementing condition-based maintenance strategies [17].
Recent research has also expanded toward more advanced architectures, including Deep Belief Networks (DBNs), Graph Neural Networks (GNNs), autoencoder-based models, and hybrid deep learning frameworks. These approaches further enhance the ability of intelligent diagnostic systems to operate under varying industrial conditions while improving robustness, adaptability, and predictive performance.
Overall, deep learning has become one of the most promising technologies for intelligent fault diagnosis, providing a foundation for the development of next-generation condition monitoring systems within Industry 4.0 environments.

4. ANALYSIS OF VIBRATION SIGNALS IN ROTATING MACHINERY

As illustrated in Fig. 3, the fault diagnosis process for rotating machinery follows a systematic workflow that includes data acquisition, data preparation, model development, evaluation, prediction, result visualization, and decision-making. Each stage plays an essential role in transforming raw sensor measurements into actionable information that supports maintenance planning and operational reliability.
The data acquisition stage is strongly influenced by the type of machinery, the monitored components, the selected sensors, and the data transmission infrastructure. Fault diagnosis systems primarily focus on critical rotating elements such as bearings, gears, shafts, belt-pulley systems, and induction motors, particularly their rotor and stator components. Sensor selection is performed according to potential failure mechanisms and their corresponding early warning indicators. Commonly monitored parameters include vibration, acoustic emissions, temperature, and pressure, while visual monitoring systems may also be employed to provide additional information about machine condition.
After acquisition, sensor data are transmitted to centralized storage systems through communication technologies such as Wi-Fi, Bluetooth, or industrial Internet of Things (IIoT) platforms. The collected data are typically stored in cloud-based databases as time-indexed records that continuously describe machine operating conditions.
However, raw sensor data alone do not provide sufficient information for reliable fault diagnosis. Consequently,

signal processing and data preparation are essential steps that transform raw measurements into a format suitable for analysis. Data pre-processing commonly includes normalization, filtering, aggregation, linearization, missing data handling, feature extraction, and feature selection. These procedures improve data quality and facilitate the development of robust AI models.

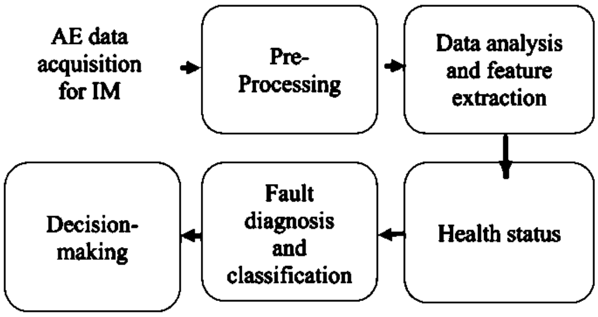

Fig. 3 Fault analysis process [14].

During the learning stage, various artificial intelligence techniques, including machine learning, ensemble learning, and deep learning algorithms, are employed to build predictive models capable of identifying different fault conditions. Once trained, these models are evaluated using standard performance metrics such as accuracy, precision, recall, F1-score, confusion matrices, and the area under the receiver operating characteristic curve (ROC-AUC). These indicators provide quantitative measures of diagnostic performance and model reliability.

After validation, the developed model enters the prediction phase, where it analyzes previously unseen data to detect potential machinery faults and estimate machine health conditions in real time. The diagnostic results are subsequently presented to end users through web-based dashboards, mobile applications, or industrial monitoring platforms, allowing operators and maintenance engineers to quickly interpret machine status.

In the final decision-making stage, the generated insights are used to support fault detection, fault isolation, prognostics, and corrective maintenance actions. By enabling timely interventions, AI-based vibration analysis contributes to reducing unplanned downtime, improving equipment availability, and enhancing the overall reliability and efficiency of industrial systems [18].

5. AI MODELS FOR VIBRATION-BASED FAULT DIAGNOSIS

Artificial intelligence has become one of the key enabling technologies for vibration-based fault diagnosis in rotating machinery. Different AI models have been developed to address specific challenges associated with machinery monitoring, including high-dimensional data, nonlinear behavior, varying operating conditions, and the presence of noise. Each architecture offers unique capabilities for feature extraction, pattern recognition, temporal analysis, and decision-making. This section provides an overview of the most widely used AI models and discusses their principles, advantages, limitations, and applications in rotating machinery diagnostics.

5.1 Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are among the earliest AI techniques applied to fault diagnosis and condition monitoring of rotating machinery. Inspired by the structure of biological neural systems, ANNs consist of interconnected processing units (neurons) organized into input, hidden, and output layers [19]. A standard feed-forward neural network, particularly one with a single hidden layer, is illustrated in Fig. 4.

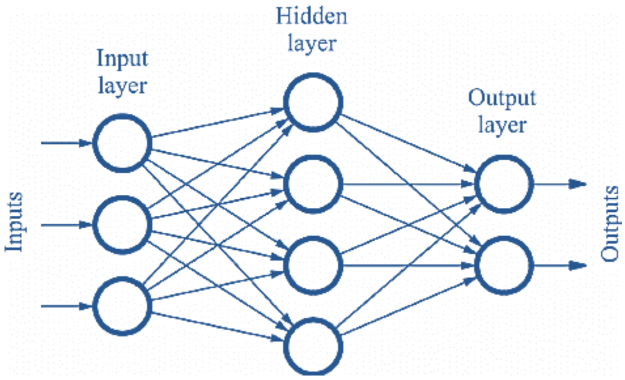

Fig. 4 Feed-forward neural network [19].

ANNs have demonstrated excellent capabilities in modeling nonlinear relationships between vibration signal features and machine operating conditions. Their ability to learn directly from historical data makes them suitable for a wide range of industrial applications, including fault classification, machine health assessment, vibration-based pressure reconstruction, image processing, and pattern recognition.

Among the various ANN training methods, feed-forward neural networks combined with the backpropagation algorithm have become particularly popular in machinery diagnostics. These models can effectively handle noisy environments and provide reliable fault identification even under varying operating conditions.

Despite their advantages, traditional ANNs depend heavily on manually extracted features and may experience reduced performance when dealing with high-dimensional datasets. Furthermore, their shallow architecture limits their ability to learn complex hierarchical representations compared with more advanced deep learning models.

Nevertheless, ANNs remain valuable due to their relatively simple implementation, low computational requirements, and strong baseline performance in many industrial fault diagnosis applications.

Advantages:

- Simple architecture and easy implementation.
- Effective for nonlinear pattern recognition.
- Robust against moderate levels of noise.
- Suitable for various industrial applications.

Limitations:

- Dependence on handcrafted features.
- Limited capability for hierarchical feature learning.
- Reduced scalability for very large datasets.

5.2 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) have become one of the most widely used deep learning architectures for vibration-based fault diagnosis. Originally introduced through the LeNet-5 architecture [20], CNNs were developed to automatically extract meaningful features from structured data.

Unlike conventional machine learning algorithms, CNNs integrate feature extraction and classification into a single end-to-end learning framework. This significantly reduces the need for manual feature engineering.

CNNs are commonly divided into one-dimensional (1D) and two-dimensional (2D) architectures. While 2D CNNs are primarily applied to image-based representations such as spectrograms, 1D CNNs directly process raw vibration signals and offer lower computational complexity [21].

A typical CNN consists of convolutional layers, pooling layers, and fully connected layers [20]. Convolutional layers automatically identify local fault signatures, while pooling layers reduce dimensionality and improve computational efficiency. Finally, fully connected layers perform the classification task.

CNNs have demonstrated excellent performance in detecting bearing defects, gear failures, shaft misalignment, and other rotating machinery faults. Furthermore, combining CNNs with time-frequency analysis techniques, such as spectrograms and wavelet transforms, further improves diagnostic accuracy [22], [23]. A typical CNN architecture is illustrated in Fig. 5.

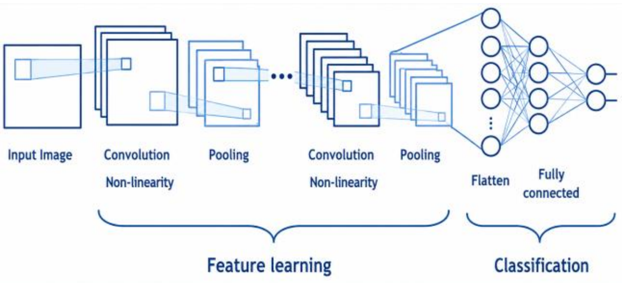

Fig. 5 A typical CNN architecture [22].

The computational complexity of 1D and 2D convolutions in neural networks varies significantly, especially when comparing their efficiency. For instance, convolving a 2D image of dimensions M × M with a kernel of size T × T results in a computational cost of O (M^2T^2). In contrast, a 1D convolution applied to data of similar dimensions M and T incurs a much lower computational cost of O (MT). This clearly demonstrates that under similar design conditions, network structures, and hyper parameters, 1D CNNs are computationally less demanding than their 2D counterparts.

Moreover, unlike standard neural networks, CNNs consist of multiple types of layers: convolutional layers, pooling (subsampling) layers, and fully connected layers, typically at the final stages of the network [20]. Each of these layers serves a distinct function and has its own set of parameters that can be adjusted to process input data in different ways. The convolutional layer, the core component of a CNN, is responsible for most of the computational workload. In this layer, a dot product is computed between two matrices: a set of learnable parameters known as the kernel and a localized region of the input image, known as the receptive field. The kernel, which is smaller than the input image, slides across the height and width of the image during the forward pass, generating an activation or feature map that captures the response of the kernel at each spatial location in the image. The resulting feature map is a 2D representation, with the stride SSS determining the size of the kernel's movement and the padding P controlling the output dimensions.

The size of the feature map is typically smaller than the input image (see **Error! Reference source not found.**). Formally, the output of a convolutional layer is given by a set of t feature maps of size $(m-q+2P)/S)+1\times(n-r+2P)/S)+1$.

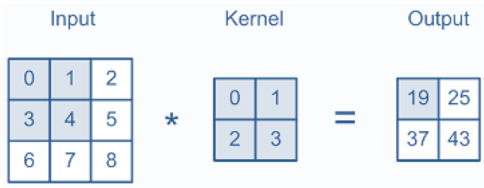

Fig. 6 Convolutional process in a CNN's convolution layer [23].

The values in the convolutional layer are computed by assigning a weight w_{ir}^{s} to each pixel of the input image, summing these weighted values, and extracting the relevant features. After adding a bias term to these sums, the result is passed through a nonlinear activation function, such as φ or sigmoid. The output y_r^s of the activation function for a specific feature map r in layer s is defined by the equation:

$$y_r^s = \varphi\left[\epsilon_r^s + \sum_{i\in M_r^s} y_i^{s-1} \otimes w_{ir}^s\right] \quad (1)$$

Where φ represents the nonlinear activation function, ϵ_r^s is the bias for the s-th layer, M_r^s denotes the selected feature map i in the previous layer, and $\otimes$ is the convolution operator.

Following the convolutional layers, the pooling layer comes into play. Pooling layers are similar to convolutional layers but perform specific functions, such as max pooling, which selects the highest value in a filter region, or average pooling, which computes the average value within the filter region. These pooling layers are typically employed to reduce the dimensionality of the network. The activation map f_h^s after reducing the feature map r nto a feature map h in layer $s$is calculated by the equation:

$$f_h^s = \delta(g_r^s, N^s) \quad (2)$$

Where δ is the reduction-sampling function by a factor of N^s and g_r^s is the convoluted feature map to be reduced.

At the final layer, the network is characterized by a classification layer. The output o of this layer is computed as:

$$o = \xi(b_o + W_z) \quad (3)$$

where b_o represents the bias of the output layer W, is the weight matrix connecting the penultimate layer to the output layer, and z is the concatenated feature maps from the penultimate layer.

The limitations of traditional Convolutional Neural Networks (CNNs) have paved the way for the development of a new architecture known as Capsule Networks (Caps Net). Caps Net, introduced by [24] is designed to address some of the shortcomings of conventional CNNs. The architecture of Caps Net consists of an encoder and a decoder, each comprising three distinct layers. The encoder is built with a convolutional layer, a Primary Caps layer, and a Digit Caps layer, while the decoder is made up of three fully connected layers (see Fig. 7).

Although Capsule Networks and CNNs share similarities in their operations, key differences set them apart. Traditional CNNs rely on max-pooling and scalar-output feature detectors to identify important features within data. In contrast, Caps Net replaces max-pooling with a process known as routing by agreement and substitutes CNNs' scalar-output feature detectors with vector-output capsules. These capsules produce outputs in the form of vectors, which carry directional information. This vectorized output allows Caps Net to preserve detailed information about an object's location and orientation throughout the network, a property known as equivariance.

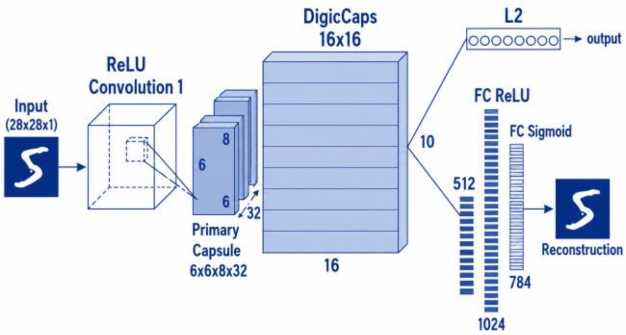

Fig. 7 The architecture of Caps Net [14].

Sabour et al. [24] highlight a key feature of Capsule Networks (Caps Net) in contrast to traditional Convolutional Neural Networks (CNNs). In Caps Net, higher-level capsules capture larger image regions, similar to CNN layers. However, unlike CNNs, which use max-pooling and lose positional information, Caps Net retains precise spatial details of objects. This retention is crucial for tasks requiring accurate location and posture information, giving Caps Net an advantage over CNNs.

The first key operation in Caps Net is matrix multiplication of input vectors with weight matrices, converting the image into vector values. These vectors, multiplied by weight matrices representing spatial relationships, guide how capsules move to the next layer, supporting the dynamic routing algorithm.

This dynamic routing is essential, allowing capsules in lower layers, like the Primary Caps, to communicate with higher layers, such as the Digit Caps. Only relevant information is passed to capsules that "agree" with the input, enhancing Caps Net's ability to capture hierarchical relationships.

Caps Net also uses a non-linear squashing function to compress output vectors between 0 and 1, unlike the ReLU function in CNNs. Longer vectors, indicating a higher probability of an object, are compressed just under one, while shorter vectors are nearly zeroed out. This method reflects the likelihood of an object's presence. While promising, CapsNet is still new, and ongoing research is needed to optimize its performance for broader applications.

Despite their success, CNNs require large datasets and significant computational resources for training. Their performance may also degrade when operating conditions differ substantially from training conditions.

Advantages

- Automatic feature extraction.
- High diagnostic accuracy.
- Excellent performance with large datasets.
- Suitable for raw vibration signals.

Limitations

- High computational requirements.
- Dependence on large training datasets.
- Limited interpretability.

5.3 Deep belief network (DBN)

A Deep Belief Network (DBN) is a hybrid probabilistic generative model that combines several Restricted Boltzmann Machines (RBMs) to form its structure [25] [26]. As illustrated in **Error! Reference source not found.**, the DBN architecture consists of a feed forward network with three hidden layers. Consider a training dataset $((x^1, y^1), (x^2, y^2)... (x^n, y^n))$ containing N instances.

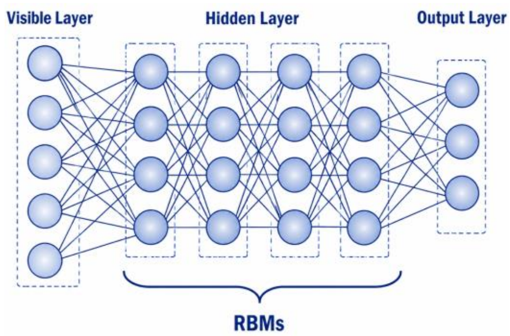

Fig. 8 Deep Belief Network architecture [15].

An input vector $\vec{\boldsymbol{x}}$ asses through the network's nodes, with the DBN assigning initial weights $\vec{\boldsymbol{w}}$.

The goal of training a DBN is to minimize a cost function C defined as:

$$C(\vec{\boldsymbol{w}}, \vec{\boldsymbol{x}}, y) = \tfrac{1}{2}\|h_w(\vec{\boldsymbol{x}}) - y\|^2 \tag{4}$$

Where $h_w(\vec{\boldsymbol{x}})$ is the hypothesis function that predicts the output. The total cost across all instances is calculated as:

$$C(\vec{\boldsymbol{w}}) = \frac{1}{N}\sum_{n} C(\vec{\boldsymbol{w}}, \vec{\boldsymbol{x}}^n, y^n) + \frac{\lambda}{2}\sum_{k}^{K}\sum_{i}^{L_m}\sum_{j}^{L_{m+1}} \left(w_{ij}^k\right)^2 \tag{5}$$

In this equation, K represents the network's depth, L_m is the number of nodes in the M-th layer, and w_{ij}^{k} in $\vec{\boldsymbol{w}}$ denotes the weight of the edge connecting node i in layer $k-1$ to node j in layer k. The parameter set $\vec{\boldsymbol{w}}^{\star}$ is determined by minimizing the overall cost function:

$$\vec{\boldsymbol{w}}^{\star} = \underset{w}{argmin}\, C(\vec{\boldsymbol{w}}) \qquad (6)$$

To optimize the weights $\vec{\boldsymbol{w}}$, a backpropagation algorithm is typically employed. This algorithm iteratively updates the weight vectors from the top layer to the bottom layer by solving the following equation:

$$w_{ij}^{k} = w_{ij}^{k-1} + \xi \frac{\partial}{\partial w_{ij}^{k}} C(\vec{w}) \qquad (7)$$

Where ξ is the learning rate, which controls the extent of the weight adjustments during the training process.
Nevertheless, DBNs often require considerable training time and may be sensitive to hyperparameter selection.
Advantages

- Hierarchical feature learning.
- Effective unsupervised pretraining.
- Good performance for complex datasets.

Limitations

- Slow training process.
- Sensitive hyperparameter tuning.
- High computational requirements.

5.4 Recurrent neural network (RNN)

Recurrent Neural Networks (RNNs) are a prominent deep learning algorithm, widely utilized in tasks such as natural language processing and speech recognition [27]. The strength of RNNs lies in their ability to capture sequential information, allowing them to extract valuable insights from patterns embedded within a sequence of data. A more advanced variant of the RNN is the Long Short-Term Memory (LSTM) network, designed to address some of the limitations of traditional RNNs. An example of a typical LSTM network is shown in **Error! Reference source not found.**, where the LSTM modules are represented by blue circles. The key principle of LSTMs is forward propagation. In a standard LSTM, at any given time step t, the network processes an input vector $\mathbf{x}_t$ a hidden state $\mathbf{h}_t$ and an output vector $\mathbf{h}_t$. The hidden state at time t is derived from a function f, which takes the input at time t and the hidden state from the previous time step $t-1$ as inputs:

$$\boldsymbol{h}_t = f(\boldsymbol{h}_{t-1}, \boldsymbol{x}_t) \qquad (8)$$

A separate function g is responsible for mapping the hidden states to output probabilities, and the output at time t is determined by:

$$\boldsymbol{y}_t = g(\boldsymbol{h}_t) \qquad (9)$$

In more detail, let W_{xh} represent the $p \times d$ input-to-hidden matrix, W_{hh} the $p \times p$ hidden-to-hidden matrix, and W_{hy} the $d \times p$ hidden-to-output matrix. Using these matrices, the hidden state and output at time t can be expressed as:

$$\begin{aligned} \boldsymbol{h}_t &= tanh(W_{xh}\boldsymbol{x}_t + W_{hh}\boldsymbol{h}_{t-1}) \\ \boldsymbol{y}_t &= W_{hy}\boldsymbol{h}_t \end{aligned} \qquad (10)$$

This structure allows LSTMs to effectively model long-range dependencies in sequences, overcoming challenges faced by traditional RNNs, such as vanishing gradients.

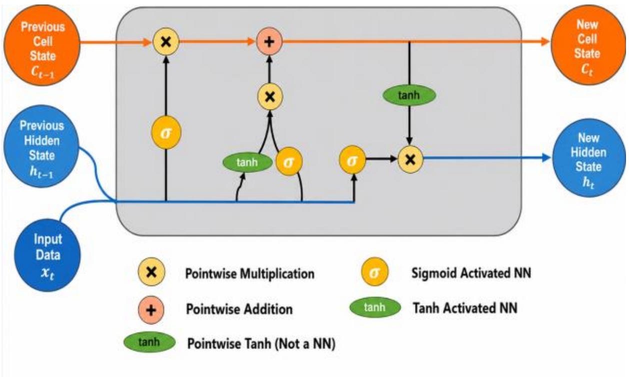

Fig. 9 The Long Short-Term Memory (LSTM) network [28].

Liu et al. [29] introduced a novel approach for fault diagnosis of rolling bearings using a recurrent neural network (RNN) structured as an auto encoder. This method predicts future vibration data based on previous periods with a gated recurrent unit (GRU)-based denoising auto encoder, effectively capturing temporal patterns for fault diagnosis. Zhang et al. [30] developed a long short-term memory (LSTM) network to assess bearing performance degradation, accurately identifying degradation states and predicting remaining useful life (RUL).
Rao et al. [31] proposed a many-to-many-to-one bidirectional LSTM (MMO-BLSTM) model for automatic extraction of rotational speed from vibration signals, validated across different mechanical systems. Xu et al. [32] combined a deep residual network (DRN) with LSTM to process features from multisensory condition monitoring data, showing robust performance in fault detection and system monitoring.

5.6 Graph Neural Networks (GNNs)

Researchers have increasingly focused on Graph Neural Networks (GNNs), an algorithm within graph signal processing [32]. GNNs extract and infer relationships by aggregating information from neighboring nodes, making them ideal for complex data structures. Li et al. [33] introduced a bearing fault diagnosis model using a horizontal visibility graph (HVG) combined with a GNN. The HVG transforms time series data into a graph with condition-specific topology, adding structural information for classification. Li et al. [33] showed that this GNN-based model significantly outperforms recurrent neural networks (RNNs) in diagnosing bearing faults.
Graph convolutional networks (GCNs), a variant of GNNs, enhance performance by building associations through an association graph, speeding up training [34]. Zhou et al. [35] applied a GCN-based method to integrate multi-sensor data for more accurate fault detection in rotating

machinery. For wind turbine gearbox faults, Yu et al. [36] introduced a fast deep GCN (FDGCN), which categorizes fault types by efficiently extracting features from the input graph.

Zhang et al. [37] employed a deep GCN (DGCN) for acoustic-based fault diagnosis in roller bearings, achieving superior classification accuracy. However, unbalanced datasets remain a challenge. Liu et al. [35] introduced an auto encoder-based Super Graph learning method to address this, but Yang et al. [3] noted that over-connected signals in the Super Graph led to high computational costs. Li et al. [1] improved upon traditional GCNs by developing a multireceptive field GCN (MRF-GCN), which outperforms other algorithms on unbalanced datasets. Chen et al. [5] used structural analysis (SA) for pre-diagnosing faults, introducing a weight coefficient to enhance diagnosis accuracy.

For unsupervised fault diagnosis, Li et al. [38] proposed a domain adversarial GCN (DAGCN) to manage data discrepancies in unsupervised domain adaptation (UDA) for machinery fault diagnosis. DAGCN outperformed six other methods in extracting domain-invariant features. Zhao et al. [39] developed the multiple-order graphical deep extreme learning machine (MGDELM) to extract both local and global structural information from raw data. Additionally, they introduced a semi-supervised deep convolutional belief network (SSD-CDBN) for motor-bearing fault diagnosis, utilizing both labeled and unlabeled data to boost performance.

Although GNNs are highly promising, graph construction remains computationally challenging.

Advantages

- Models structural relationships.
- Integrates multi-sensor data.
- Robust under complex operating conditions.

Limitations

- Complex graph construction.
- High computational cost.
- Difficult implementation.

5.6 Stacked Auto-Encoders

Jia et al. [40] trained deep neural networks (DNNs) using two steps: pre-training with an auto encoder and fine-tuning via a back propagation algorithm for classification. Similarly, Sun et al. [41] employed a sparse auto encoder (SAE) to enhance feature robustness, which was then used to train a neural network classifier. Chen et al. [42] demonstrated that stacking multiple SAEs followed by a classifier can effectively identify the severity of rolling bearing faults.

Shao et al. [43] highlighted that combining denoising and contractive auto encoders significantly improves feature learning, further enhanced by using a locality-preserving projection to fuse deep features. Likewise, Qi et al. [30] applied a stacked SAE for machine fault diagnosis, using ensemble empirical mode decomposition and autoregressive models to preprocess non-stationary and transient signals. Shao et al. [43] also proposed a deep auto encoder-based approach using maximum correntropy to create a loss function that boosts feature learning from vibration signals.

Lu et al. [44] suggested a reliable method for identifying machinery health conditions through a stacked denoising auto encoder, which performed well in recognizing specific health states from noisy data with varying working conditions. Jia et al. [45] introduced a Local Connection Network (LCN) combined with a normalized sparse auto encoder (NSAE) to create the LCN-NSAE for intelligent fault diagnosis, integrating feature extraction and detection into a unified learning process. Ahmed et al. [46] developed a deep neural network (DNN) with an unsupervised feature learning algorithm based on a sparse auto encoder, improving classification performance on highly compressed bearing vibration data.

Each AI architecture offers distinct advantages depending on the application requirements. ANNs provide simple and reliable baseline solutions, whereas CNNs excel at automatic feature extraction. CapsNet improves spatial representation, DBNs facilitate hierarchical learning, LSTMs effectively model temporal dependencies, GNNs capture structural relationships, and SAEs provide robust unsupervised feature extraction.

However, no single model universally outperforms all others. The selection of an appropriate architecture depends on several factors, including data availability, computational resources, machine complexity, and industrial deployment requirements. Recent research trends increasingly favor hybrid and ensemble approaches that combine multiple architectures to improve diagnostic accuracy, robustness, and generalization capabilities.

Future developments are expected to focus on explainable AI, transfer learning, lightweight models, federated learning, and digital twin integration to enable more intelligent and scalable condition monitoring systems for Industry 4.0 and smart manufacturing environments.

6. FUTURE DIRECTIONS

Despite the considerable advancements in AI-driven vibration analysis for rotating machinery, several key challenges persist-each offering valuable directions for future research. One of the most pressing issues is the generalization and transferability of AI models. Many models are trained on narrow datasets tailored to specific machines or operating conditions, limiting their ability to perform accurately across varied environments or fault types. Addressing this limitation calls for the integration of techniques such as domain adaptation, transfer learning, and federated learning to enhance model robustness and adaptability in diverse industrial settings [47].

Another critical challenge lies in the explainability and trust of AI systems. Most deep learning models function as "black boxes," offering limited interpretability of their decision-making processes. To foster confidence and enable broader adoption, especially in safety-critical industries, researchers should incorporate explainable AI (XAI) frameworks that clarify model outputs and enhance transparency for end-users and regulators alike [37].

Furthermore, the data efficiency and label scarcity problem continues to hinder progress. Deep learning models typically require large volumes of labeled vibration data, which are often costly or impractical to obtain in real-world scenarios. Future efforts should focus on developing semi-supervised, self-supervised, and unsupervised learning methods that reduce reliance on labeled datasets while maintaining high diagnostic accuracy. As industrial systems increasingly transition to decentralized architectures, edge and real-time deployment of AI models becomes essential. There is a growing need for lightweight, efficient models capable of performing fault diagnosis directly on embedded or resource-constrained devices to ensure timely detection and minimal latency.

Lastly, the integration of AI with digital twin technology presents a promising frontier. Digital twins, virtual replicas of physical systems, can be combined with AI-based diagnostic models to create intelligent, closed-loop systems for real-time simulation, predictive maintenance, and operational optimization. This fusion of technologies has the potential to revolutionize condition monitoring by enabling continuous learning, fault forecasting, and adaptive control [13].

In addition, foundation models and large language models (LLMs) are emerging as promising tools for supporting intelligent maintenance systems, automated report generation, and decision support in industrial environments.

7. CONCLUSION

This review has comprehensively explored the application of artificial intelligence (AI) techniques in vibration-based fault diagnosis of rotating machinery. The discussed approaches ranging from classical Artificial Neural Networks (ANNs) to advanced models like Capsule Networks (CapsNet), Graph Neural Networks (GNNs), and Stacked Auto-Encoders (SAEs) demonstrate the significant progress made in automating feature extraction, improving diagnostic accuracy, and enabling real-time monitoring. Deep learning methods, particularly CNNs, RNNs, and LSTMs, have shown strong capabilities in handling complex vibration signals and temporal dependencies, while hybrid and graph-based models offer new perspectives on structural representation and multi-sensor data integration. Collectively, these AI-based methods offer promising solutions to overcome the limitations of traditional diagnostic techniques [22].

REFERENCES

[1] Krishnakumari, A. (2016). Fault diagnostics of spur gear using decision tree and fuzzy classifier. *International Journal of Advanced Design and Manufacturing Technology*, 89: 3487–3494.

[2] Deng, W. (2019). Fault diagnosis of rotating machinery based on convolutional neural networks. *Journal of Vibration and Control*, 25(6): 910–924.

[3] Yang, M. Y. M. (2022). Bearing vibration signal fault diagnosis based on LSTM-cascade CatBoost. *Journal of Internet Technology*, 23: 1155–1161.

[4] Zhang, S. (2018). Deep learning-based fault diagnosis in rotating machinery: A review. *Mechanical Systems and Signal Processing*, 98: 162–183.

[5] Wang, J., Gao, R. X., & Yan, R. (2014). Multi-scale enveloping order spectrogram for rotating machine health diagnosis. *Mechanical Systems and Signal Processing*, 46: 28–44.

[6] Simon, H. A. (1969). *The Sciences of the Artificial*. Cambridge, MA: MIT Press.

[7] Li, C. (2019). Vibration signal analysis using deep learning for fault detection in rotating machines. *IEEE Access*, 7: 123.

[8] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553): 436–444.

[9] Lee, M. H. (2020). AI-based diagnostics in centrifugal compressors: A comparative study of vibration analysis techniques. *Journal of Vibration and Control*, 26(6): 978–988.

[10] Salimans, T., & Kingma, D. P. (2016). Weight normalization: A simple reparameterization to accelerate training of deep neural networks. *Advances in Neural Information Processing Systems*, 901–909.

[11] Pouyanfar, S. (2018). A survey on deep learning: Algorithms, techniques, and applications. *ACM Computing Surveys (CSUR)*, 51(5): 1–36.

[12] Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural Networks*, 61: 85–117.

[13] Amudha, S. C. T. (2022). Categorization of breast masses based on deep belief network parameters optimized using chaotic krill herd optimization algorithm for frequent diagnosis of breast abnormalities. *International Journal of Imaging Systems and Technology*, 32(13).

[14] Olah, S. (2018). LSTM Networks: A detailed explanation. Retrieved October 3, 2024, from https://towardsdatascience.com/lstm-networks-a-detailed-explanation-8fae6aefc7f9

[15] Liu, H. (2016). Intelligent fault diagnosis of rotating machinery using unsupervised deep feature learning. *Journal of Mechanical Science and Technology*, 30(1): 117–129.

[16] Lei, F. (2020). An intelligent fault diagnosis method using unsupervised feature learning towards mechanical big data. *Future Generation Computer Systems*, 108: 632–641.

[17] Kannapiran, P., & Subbaraj, B. (2014). Fault detection and diagnosis of pneumatic valve using adaptive neurofuzzy inference system approach. *Applied Soft Computing*, 19: 362–371.

[18] Basic CNN Architecture Explained. Retrieved October 2, 2024, from https://www.upgrad.com/blog/basic-cnn-architecture

[19] LeCun, Y., Bengio, Y., & LeCun, Y. (1995). Convolutional networks for images, speech, and time series. *Handbook of Brain Theory and Neural Networks*, 3361–3370.

[20] Kiranyaz, S., Avci, O., Abdeljaber, O., Ince, M., Gabbouj, J., & Inman, D. (2021). 1D convolutional neural networks and applications: A survey. *Mechanical Systems and Signal Processing*.

[21] Datta, G. (2024). Convolutional neural networks. Retrieved October 2, 2024, from https://medium.datadriveninvestor.com/convolutional-neural-networks-3b241a5da51e

[22] Salihu, B., & Tafa, Z. (2020). On computational performances of the actual image classification methods in C# and Python. In *Proceedings of the 9th Mediterranean Conference on Embedded Computing (MECO)*. Budva, Montenegro.

[23] Sabour, S., Frosst, N., & Hinton, G. E. D. (2017). Dynamic routing between capsules. In *Advances in Neural Information Processing Systems*.

[24] Hinton, G. E. (2009). Deep belief networks. *Scholarpedia*, 4(5): 5947.

[25] Hinton, G. E., Osindero, S., & Teh, Y. W. (2006). A fast learning algorithm for deep belief nets. *Neural Computation*, 18(7): 1527–1554.

[26] Cho, K., van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., & Bengio, Y. (2014). Learning phrase representations using RNN encoder-decoder for statistical machine translation.

[27] Izuchukwu, F., & Olorunniwo, A. (1991). Scheduling imperfect preventive and overhaul maintenance. *International Journal of Quality & Reliability Management*, 8.

[28] Xia, M. (2017). Fault diagnosis for rotating machinery using multiple sensors and convolutional neural networks. *IEEE/ASME Transactions on Mechatronics*, 23: 101–110.

[29] Cao, L. (2019). Fault diagnosis of wind turbine gearbox based on deep bi-directional long short-term memory under time-varying non-stationary operating conditions. *IEEE Access*, 7: 155219–155228.

[30] Dziedziech, K., Jablonski, A., & Dworakowski, Z. (2018). A novel method for speed recovery from vibration signal under highly non-stationary conditions. *Measurement*, 128: 13–22.

[31] Cardona-Morales, O., Avendaño, L., & Castellanos-Dominguez, G. (2014). Nonlinear model for condition monitoring of non-stationary vibration signals in ship driveline application. *Mechanical Systems and Signal Processing*, 44(1–2): 134–148.

[32] Li, X. (2020). Deep representation clustering-based fault diagnosis method with unsupervised data applied to rotating machinery. *Mechanical Systems and Signal Processing*, 143: 106825.

[33] Kateris, D., Moshou, D., Pantazi, X. E., Gravalos, I., Sawalhi, N., & Loutridis, S. (2014). A machine learning approach for the condition monitoring of rotating machinery. *Journal of Mechanical Science and Technology*, 28(1): 61–71.

[34] Xiang, C. (2021). Data-driven fault diagnosis for rolling bearing based on DIT-FFT and XGBoost. *Complexity*.

[35] Li, Y. (2020). Rotating machinery fault diagnosis based on convolutional neural network and infrared thermal imaging. *Chinese Journal of Aeronautics*, 33: 427–438.

[36] Martin-Diaz, D. (2018). Hybrid algorithmic approach oriented to incipient rotor fault diagnosis on induction motors. *ISA Transactions*, 80: 427–438.

[37] Wan, L. (2021). An efficient rolling bearing fault diagnosis method based on spark and improved random forest algorithm. *IEEE Access*, 9: 37866–37882.

[38] Marins, M. A. (2018). Improved similarity-based modeling for the classification of rotating-machine failures. *Journal of the Franklin Institute*, 355: 1913–1930.

[39] Lei, Y. (2016). *Intelligent Fault Diagnosis and Remaining Useful Life Prediction of Rotating Machinery*. Oxford, UK: Butterworth-Heinemann.

[40] Sun, W. (2016). A sparse auto-encoder-based deep neural network approach for induction motor faults classification. *Measurement*, 89: 171–178.

[41] Li, Z., & Chen, W. (2017). Multisensor feature fusion for bearing fault diagnosis using sparse autoencoder and deep belief network. *IEEE Transactions on Instrumentation and Measurement*, 66: 1693–1702.

[42] Shao, L. M., Wang, Y., & Y.-M. (2018). Crack fault classification for planetary gearbox based on feature selection technique and K-means clustering method. *Chinese Journal of Mechanical Engineering*, 31.

[43] Lu, N., Xiao, Z., & Malik, O. P. (2015). Feature extraction using adaptive multiwavelets and synthetic detection index for rotor fault diagnosis of rotating machinery. *Mechanical Systems and Signal Processing*, 52–53: 393–415.

[44] Jia, F., Lei, Y., Lin, J., Zhou, X., & Lu, N. (2016). Deep neural networks: A promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data. *Mechanical Systems and Signal Processing*, 72: 303–315.

[45] Ahmed, H. O. A., Wong, M. D., & Nandi, A. K. (2018). Intelligent condition monitoring method for bearing faults from highly compressed measurements using sparse over-complete features. *Mechanical Systems and Signal Processing*, 459–477.

[46] Randall, R. B. (2011). *Vibration-based Condition Monitoring: Industrial, Aerospace and Automotive Applications*. Hoboken, NJ, USA: Wiley.