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Recent advances in journal bearings: wear fault diagnostics, condition monitoring and fault diagnosis methodologies

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HIGHLIGHTS

- Journal bearings have a resurgence in usage across compressors, motors, turbines, and pumps.
- Advanced diagnostics integrate vibration analysis, machine learning, and simulations.
- Ensemble models, like CNNEPDNN, enhance diagnostic metrics by 15-20%.
- Convolutional autoencoders achieve 91% accuracy in wear estimation.
- Challenges include uniform evaluation criteria and comprehensive diagnostic models.

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ABSTRACT

This review comprehensively encompasses a range of recent studies on journal bearings, emphasizing wear fault diagnostics, condition monitoring, and fault diagnosis methodologies. A significant finding reveals a shift back to the utilization of journal bearings in various rotating machinery such as compressors, motors, turbines, and pumps. Various methodologies employed in these recent studies include vibration analysis, machine learning, deep learning, and both numerical and experimental simulations. Key findings indicate that ensemble models, such as the CNN and deep neural network (CNNEPDNN) model, significantly improve convergence speed, test accuracy, and F-Score in bearing fault diagnosis by 15-20% compared to individual models. Additionally, convolutional autoencoders have demonstrated impressive performance, achieving an average Pearson coefficient of 91% in wear estimation, underscoring the critical importance of predictive maintenance. Despite these remarkable advancements, challenges persist due to the lack of uniform evaluation criteria and the focus on specific error types under particular operating conditions. Collaborative efforts among researchers are essential for developing robust and broadly applicable diagnostic models. Addressing these ongoing issues will further enhance condition monitoring and defect detection, leading to more reliable and academically rigorous diagnostic methods applicable in diverse real-world scenarios.

1. Introduction

Journal bearing fault diagnostics is crucial in numerous sectors where journal bearings are extensively used to support and guide rotating shafts in machinery such as compressors, motors, turbines, and pumps. The primary goal of fault investigation in journal bearings is to extend their operational life and prevent unexpected failures. Such failures can lead to decreased machine performance, shortened service life, and potential safety hazards. A range of observing techniques, including airborne sound, surface vibration, and acoustic emission measures, have been used to identify journal-bearing faults at an early stage. As seen in Figure 1, several observing techniques include the use of an accelerometer to measure the vibration signal, a microphone to measure the near-field acoustic signal, and an AE sensor for every bearing [1]. Furthermore, utilizing simulated vibration signals, sophisticated condition monitoring methods such as deep learning algorithms are suggested for categorizing wear defects in journal bearings. 80% of the datasets are used for training, and 20% are used for testing. The model used is a CNN with three convolutional layers, activation and pooling, and then three fully connected layers. Overfitting can be avoided with the use of drop-out layers, as depicted in Figure 2. The data of the test is provided in the trained CNN model for determining the probability of every class. Then, the prediction of fault is founded upon the class having the uppermost likelihood. The effective fault diagnosis in the journal bearings needs the use of diagnostic tools as well as specifying the crucial fault parameters.

Despite the considerable advancements in fault diagnostics and condition monitoring techniques, several significant gaps remain in the literature.

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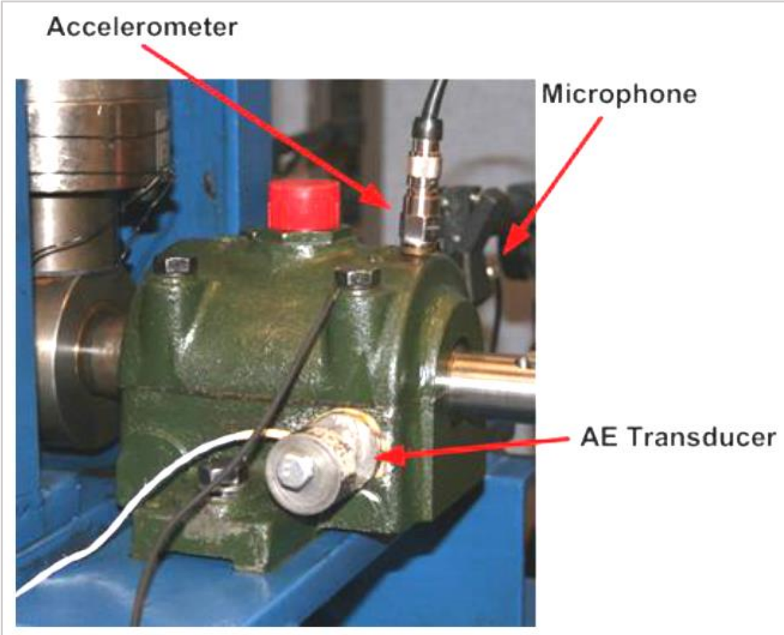

Figure 1: Accelerometer, microphone and AE sensor installations [1]

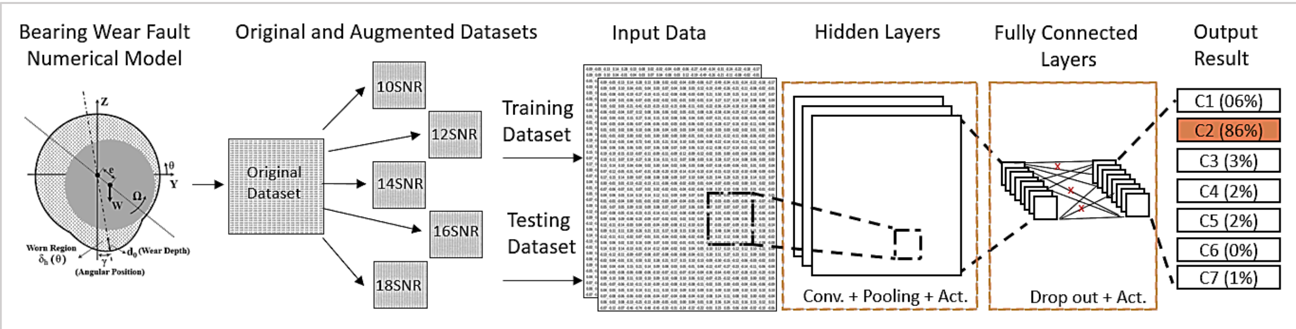

Figure 2: The diagnostics framework of wear fault with convolutional neural network [2]

Firstly, there is a lack of uniform evaluation criteria, which complicates the comparison and validation of different diagnostic methods [2,3]. Secondly, many studies have concentrated on specific error types under narrowly defined operating conditions, thereby failing to address the broader spectrum of factors influencing journal-bearing performance [3,4]. These limitations highlight the necessity for developing robust and universally applicable diagnostic models that can effectively function across diverse and real-world scenarios. Artificial intelligence (AI) and the analysis of vibration take part in observing the state and diagnosing the faults in the revolving machinery in the industries**.** Vibrations in machinery signals provide visions into the equipment's functionality and condition. Conventional approaches, such as Fast Fourier Transform (FFT), encounter defies in extracting the data of fault from such signals owing to their stationary and nonlinear nature. To overcome these limitations researchers have evolved data of signal processing, like the empirical mode decomposition, wavelet transformation and empirical mode decomposition. In addition, Artificial Intelligence (AI) motivated methods, such as Convolutional Neural Networks (CNNs) and networks (RNNs) Stacked Autoencoders (SAEs) have been employed for the fault diagnosis throughout the analysis of vibration. These AI methods enhance identification accuracy by handling non-stationary and nonlinear vibration signals. By combining vibration analysis with AI algorithms, early detection of issues in revolving machinery can be improved, leading to maintenance schedules and reduced downtime. Integration of vibration analysis with AI has the potential to enhance maintenance strategies and facilitate fault detection.

The data analysis techniques are categorized into methods of feature extraction and artificial intelligence, as illustrated in Table1 [4]. Difficulty in handling changes between training and testing sample distributions impacts model accuracy. Additionally, class imbalance, where fault samples are limited, affects the precision of derived models. Furthermore, the scarcity of labelled data increases the challenges in the training process, necessitating more advanced techniques and diverse data to ensure effective diagnostics. There is also a lack of samples in varied conditions, resulting in insufficient experimental data under diverse operating scenarios. This limitation hinders the ability to train models effectively for different conditions. Additionally, there is a significant requirement to build a large and diverse dataset for training deep learning models. Analyzing non-stationary signals poses a significant challenge due to high noise levels in the data. Effective techniques such as wavelet transform, and Hilbert-Huang transform are needed to handle these types of signals efficiently. Additionally, there is a gap in the comprehensive comparison and evaluation of various sensor tools (e.g., accelerometers, velocity sensors, optical sensors) across diverse operational environments and conditions. Understanding when and how to use each sensor type is crucial for improving diagnostic accuracy.

Table 1: Advantages and disadvantages of the described data analysis method **[4]**

Method	Advantages	Disadvantages
Statistical method	Simple and intuitive, and does not rely on empirical knowledge	Only obtain the surface information, easy to be disturbed by noise
Feature extraction	It can get deep information and has good robustness	Relies on empirical knowledge
artificial ntelligence	realizes end-to-end intelligent diagnosis	lacks reliability, model optimization still relies on empirical knowledge

There is a lack of automation in the current systems, highlighting the need to develop an automatic diagnostic system that covers all stages, from signal acquisition to result output. Additionally, traditional methods are often time-consuming and require performance improvements to be viable for real-time implementation [5-8]. There is also a need to improve diagnostic accuracy in the presence of signal interference from other mechanical components. Verifying the effectiveness of the method under varied and complex operating conditions is crucial to ensure reliability and robustness in real-world applications. Verification in real-world conditions is essential, as there is a need to validate the method in realistic and complex operating scenarios. Enhancing model transferability across different environments is crucial for accurate predictive maintenance. Identifying suitable quantitative indicators for diagnostics in various systems is also necessary to improve diagnostic accuracy and reliability. Furthermore, there is a need to develop accurate diagnostic methods for complex and coupled faults. Improving machine learning models to handle diversity in operating conditions and provide accurate results is essential for effective fault diagnosis [9-11]. Significant advancements have been made in diagnosing journal-bearing defects, but several gaps and challenges remain. There is a lack of uniform evaluation criteria, making it difficult to compare and validate different diagnostic methods fairly. Many studies focus narrowly on specific fault types under defined operating conditions, neglecting other influencing factors. Models often fail to handle changes between training and testing data distributions and are affected by class imbalance due to limited fault samples. The scarcity of varied data and operating conditions further hinders model efficacy. Analyzing non-stationary signals is challenging due to high noise levels, and there is a lack of comprehensive evaluation of different sensor tools in diverse environments. Improving model accuracy in the presence of mechanical signal interference and verifying their effectiveness under realistic conditions is essential.

2. Vibration analysis in fault diagnosis

Analyzing vibrations is essential for diagnosing issues in revolving machinery. It offers insights into equipment health. It's commonly utilized for proactive maintenance purposes. Numerous methods have been created to examine vibration signals, for identifying faults. These include time-frequency analysis approaches, deep learning methods, sophisticated denoising algorithms, and signal decomposition techniques. For instance, Tama et al. address the use of vibration signals and deep learning (DL) for problem diagnostics. They go over (DL) and data-driven approaches to vibration-based state observing. Furthermore, time-frequency analysis has been investigated by researchers as a means of obtaining defect characteristics from vibration data. For example, provide a time-frequency transformer model for defect identification based on the Transformer model. Generally, the analysis of vibration gives valuable devices for the defect diagnostics of the rotating equipment if combined with cutting-edge approaches [12,13].

2.1 Basics of vibration analysis

The analysis of vibration is a necessary method to monitor the spinning machinery, and it includes seeking the mistakes or variations in the status of machines via analyzing the vibration signals' features. In the analysis of the time domain, statistical parameters comprising Root-Mean-Square (RMS), kurtosis, crest factor, and peak, are utilized for characterizing the signals of vibration. Such characteristics give explanations for the amplitude, spreading, and form of the signal of vibration, which may reveal topics or variations in the performance of the machine. The analysis of time-frequency is one more method to display the features of vibration signals that vary over time. Such a technique permits specifying the frequency constituents and their time-varying features via converting the signal of vibration from the time domain into the time-frequency domain.Via incorporating numerous analytical techniques, engineers or maintenance people may analyze the real-time frequency of the analysis of machine vibration as well as achieve diagnostic evaluations of the machine's dynamic condition.For the rotating equipment, there're (3) rudimentary kinds of the analysis of vibration: The analysis of time-domain, frequency-domain, and time-frequency. The analysis of the time domain includes tracking the vibration signal waveform over time to identify the characteristics, like the frequency constituents of the shaft, transients, constituents of higher frequency, and modulation of amplitude. Statistical indicators, such as the Root-Mean-Square (RMS), kurtosis, crest factor, and peak, may be employed for analyzing the signal in the temporal-domain. The frequency-domain analysis is concerned with the frequency content of the vibration signal; specific frequency components and their magnitudes are identified using techniques such as the Fourier transform. Combining the time and frequency domains yields time-varying aspects of the signal and the instantaneous frequency composition of each frequency component in time-frequency analysis [13-15]. The papers serve as instruments for state observing and fault detection, which helps in finding journals with faults. Such methods aim to detect and address the problems of journal bearing, which can cause catastrophic damage, safety dangers, and financial loss. Among the recommended methods in the research are logical combinatorial pattern recognition, analysis of power spectral density joined with the Support Vector Machines and K-Nearest Neighbor, analysis of wavelet, and approaches for deep learning. Such methods utilize the signals of vibration as well as statistical features for extracting the characteristics and classifying the flaws. The researches highlight how significant it is to rapidly forecast as well as diagnose the topics of journal bearing for lowering the expenditures and enhancing the outcomes of maintenance. Also, the researches encourage the identification of automated bearing damage via the utilization of different techniques [16,17].

2.2 Utilized approaches to the analysis of vibration

Among the methods of the analysis of vibration utilized in observing and diagnosis of misalignment in a rotor-bearing regime are observing the analysis of vibrations, observing the noise, Thermography, Artificial Neural Networks (ANNs), and Motor Current Signature Analysis (MCSA). Further methods covered in the literature comprise sparse decomposition, Wavelet Transformations (WT), Ensemble Empirical Mode Decomposition (EEMD), Empirical Wavelet Transform (EWT), Local Mean Decomposition (LMD), Variational Mode Decomposition (VMD), and Wavelet Transformation (WT). Also, the analysis of the time domain utilizes statistical metrics comprising Root-Mean-Square (RMS), kurtosis, crest factor, and peak. Such approaches aim to extract information about fault from the signals of vibration signals via accentuating the attributes of attention for the identification and diagnosis of fault [18-20].

2.2.1 Time-domain analysis

The analysis of the time domain is the technique for testing the data in terms of time. And, it includes observing the time series signal determined from the apparatus for finding the problems. The statistical factors are utilized for generating the features of the time-domain from the fresh data of vibration that may appropriately define the variations in the vibration signals of bearing through the failures. The attributes of the time domain comprise the Root Mean Square (RMS), kurtosis, skewness, peak-to-peak, crest factor, shape factor, impulse factor, and Margin Factor. Also, the benefits of the analysis of the time-domain are its short calculating period and the easiness of application. These attributes are represented by Equations 1 through 8.

$$\text{RMS} = \left(\frac{1}{N}\sum_{i=1}^{N} x_i^2\right)^{1/2} \tag{1}$$

$$\text{Kurtosis} = \frac{1}{N}\sum_{i=1}^{N} \frac{(x_i-\bar{x})^4}{\sigma^4}, \tag{2}$$

$$\text{Skewness} = \frac{1}{N}\sum_{i=1}^{N} \frac{(x_i-\bar{x})^3}{\sigma^3}, \tag{3}$$

$$\text{Peak to Peak} = x_{\max} - x_{\min}, \tag{4}$$

$$\text{Crest Factor} = \frac{\max|x_i|}{\text{RMS}}, \tag{5}$$

$$\text{Shape Factor} = \frac{\text{RMS}}{\frac{1}{N}\sum_{i=1}^{N} |x_i|}, \tag{6}$$

$$\text{Impulse Factor} = \frac{\max|x_i|}{\frac{1}{N}\sum_{i=1}^{N} |x_i|}, \tag{7}$$

$$\text{Margin Factor} = \frac{\max|x_i|}{\left(\frac{1}{N}\sum_{i=1}^{N} |x_i|^{1/2}\right)^2}, \tag{8}$$

2.2.2 Frequency-domain analysis

The analysis of frequency-domain is a usually utilized method in the machinery condition observing for analyzing the data of vibration and discovering the mechanical fingerprints of the machine depending upon the features of frequency. It includes converting the signals of the vibration of the time domain into the frequency domain via employing methods from the Fourier analysis, like discrete Fourier transform, Fourier series, and continuous Fourier transform, as well as supposing that the signal's frequency constituents stay fixed during the time, such technique is appropriate for still signals caused via the revolving machinery. On the other hand, non-stationary signals might be caused by other variables or changes in the speed of spinning machinery. Order tracking and other advanced approaches have been developed to disclose frequency components in time-varying environments better. The generalized demodulation as well as the cyclic spectrum relationship theory are (2) instances of such approaches.

2.2.3 Time-frequency analysis

The analysis of time-frequency is a technique to determine the features of the signals of vibration that vary over time. The signal of vibration requires to be transformed from the time-domain into the time-frequency domain to be stated utilizing a density function of 2D time-frequency. Also, this ascertains the features of time-varying of every constituent of frequency as well as the immediate signal frequency. Numerous approaches were evolved for the analysis of time-frequency, comprising the chirplet transform-based approaches, short-time Fourier transform, Hilbert-Huang transform, and wavelet transform. Such approaches were utilized for the defect's diagnosis in the rotating machinery, surrounding the bearing malfunctions identification. And, they were utilized in deep learning-based fault identification approaches, feature extraction, and network structure optimization [19,20].

3. Artificial intelligence in fault diagnosis

AI is acquiring attention from engineering specialists, especially in the field of diagnosing and expecting topics with rotating equipment. And, it has been revealed that the fault diagnostics' achievement and flexibility may be augmented via the combination of AI methods, comprising SVMs, ANNs, evolutionary algorithms, and fuzzy logic regimes. Such methods of AI scrutinize numerous data types, comprising acoustic emission signals, for identifying and diagnosing the topics in intricate manufacturing equipment. Moreover, artificial intelligence-based fault scrutiny frameworks have been made to increase the efficiency of rotating apparatus fault detection as well as prognosis models. Employing AI in engineering has the prospective for continuing the growing and enhancement owing to the progress in the intelligent info, capabilities of the sensor, and else fields [21-23].

AI methods have extensive utilization in the diagnosis of defects. Such methods, which comprise ANN, genetic GA and (SVMs), have displayed encouraging outcomes in the faults diagnosis and machine state observing. Many methods of AI, comprising naive Bayes, k-nearest neighbour, and deep learning, have been employed for the spinning apparatus for detecting the flaws.The AI implementation for problematic diagnostics is crucial for the dependability as well as the safety of manufacturing regimes. Nevertheless, there are difficulties and restrictions, like signals of noise and circumstances of practical functioning. In spite of such defies, AI algorithms have been fruitfully employed for identifying the fault in a variety of manufacturing uses, providing benefits, comprising the elevated obtainability of apparatus and inexpensive care. The upcoming investigation in such field area will focus on obtaining solutions for the topics connected with optimization, the collection of data, and the choice of method [23,24].

3.1 Theoretical and mathematical foundations of AI

AI algorithms for fault diagnosis of rotating machinery have gained popularity due to their robustness and adaptability. These algorithms do not necessitate comprehensive prior physical knowledge, which can be challenging to acquire in practical scenarios. Among the various AI algorithms, Support Vector Machines (SVM), Neural Networks (NN), k-nearest Neighbour (k-NN), and Naive Bayes classifiers are most commonly applied in fault diagnosis. Additionally, deep learning methods have shown significant potential in this field, offering advanced capabilities in learning complex patterns and hierarchies from data, thereby enhancing the accuracy and efficiency of fault diagnosis systems.

3.1.1 Support vector machines (SVM)

Support Vector Machines (SVM) is a computational learning technique designed for classifying small sample sizes. Algorithmically, SVM constructs an optimal separating hyperplane $f(x) = 0$ between datasets by solving a constrained quadratic optimization problem grounded in structural risk minimization (SRM). As indicated by Equation 9:

$$y = f(x) = W^T x + b = \sum_{i=1}^{N} W_i x_i + b \quad (9)$$

W is an N-dimensional vector and b is a scalar. The optimal separating hyperplane is defined as the plane that maximizes the distance between itself and the nearest data points, referred to as the maximum margin. By transforming the optimization problem using the Kuhn-Tucker conditions into the corresponding Lagrangian dual quadratic optimization problem, the classifier based on support vectors can be derived.

3.1.2 Neural Networks (NNs)

Neural Networks (NNs) are among the most widely used algorithms in machine learning. They primarily consist of three layers: the input layer, the hidden layer, and the output layer. The hidden layer contains units called hidden units whose values are not directly observed. An NN operates on interconnected nodes or neurons, where each neuron receives inputs x_1, x_2, x_3 and an intercept term, producing an output y. The output is calculated in Equation 10:

$$y = f(W^T x) = f(\sum_{i=1}^{3} W_i x_i + b) \quad (10)$$

Here, f is the activation function, often the sigmoid function, W represents the weights, and b is the bias term. NNs learn by iteratively adjusting the weights based on known input-output patterns, mimicking neurological functions such as learning from experience and generalizing from similar situations.The number of hidden layers can be approximated by the formula in Equation 11:

$$N_h = \frac{N_s}{(\alpha \times (N_i + N_0))} \quad (11)$$

α typically ranges from 2 to 10, N_0 is the number of output neurons, N_i is the number of input neurons and N_s is the number of training samples. Empirical formulas to determine the number of neurons in the hidden layer as indicated by Equation 12:

$$\begin{aligned} h &= \sqrt{i + o} + \alpha \\ h &= \log_2 i \\ h &= \sqrt{io} \end{aligned} \quad (12)$$

where i, o and h are the numbers of input, output, and hidden neurons, respectively, and α is an adjustment constant ranging from 1 to 10.

3.1.3 k-Nearest neighbour

k-NN is an instance-based learning algorithm based on the principle that the instances within a dataset will generally exist in close proximity to other instances with similar properties. For a given training set of classified instances $T = \{(x_1, y_1), (x_2, y_2) \dots, (x_N, y_N)\}$, where x_i is the feature vector of the unlabeled instance, y_i is the label and $y_i = c_1, c_2, \dots, c_K, i = 1,2, \dots N$. For a training sample (x, y), the k-NN algorithm searches for the k nearest instances to x based on a given distance metric. The neighbourhood containing these k instances is represented by $N_k(x)$. Then, the label of test sample x can be calculated based on decision rules In line with Equation 13:

$$y = \arg\max_{c_g} \sum_{x_i \in N_i(x)} I(y_i = c_j),\ i = 1,2, \dots, N;\ j = 1,2, \dots K \tag{13}$$

where I is the indicator function. If the instances are tagged with a classification label, then the label of an unclassified instance can be determined by observing the class of its nearest neighbours. There are three basic elements in the k-NN algorithm: the number of measured instances k, the distance metric and the decision rule for classification. Compared with other AI algorithms, k-NN shows an advantage of simple implementation.

3.1.4 Naive Bayes classifier

The Naive Bayes approach is a classification technique founded on Bayes' Theorem and the assumption of conditional independence. For a given training set $T = \{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$ with label $y, y_i = c_1, c_2, \dots, c_K, i = 1,2, \dots . N$, assume there are S_l possible values for $x^I, l = 1,2, \dots, n$; and there are K possible values for Y. Naive Bayes primarily learns the joint probability distribution $P(X, Y)$ of the input and output by the conditional probability distribution based on the conditional independence assumption according to Equation 14:

$$\begin{aligned} P(X = x \mid Y = c_j) &= P(X^{(l)} = x^{(l)}, \dots, X^{(n)} = x^{(n)} \mid Y = c_j) \\ &= \Pi_{l=1}^{n} P(X^{(l)} = x^{(l)})\ j = 1,2, \dots, K \end{aligned} \tag{14}$$

Then, based on the learnt model, the output label y with the biggest posterior probability for the given input x can be calculated via Bayes' Theorem as can be seen in Equations 15 and 16:

$$P(Y = c_j \mid X = x) = \frac{P(X=x|Y=c_j)P(Y=c_j)}{\sum_j P(X=x|Y=c_j)P(Y=c_j)} \tag{15}$$

and

$$y = \arg\max_{c_j} P(Y = c_j) \Pi_l P(X^{(l)} = x^{(l)} \mid Y = c_j) \tag{16}$$

The Naive Bayes classifier is widely used for classification due to its simplicity and high efficiency.

3.1.5 Deep learning

Deep learning involves learning feature hierarchies through deep architectures with multiple layers of nonlinear operations, enabling complex mappings from inputs to outputs. In models like autoencoders, the objective is to learn a function $h_{w,b} \approx x$, finding low-dimensional data representations. For Restricted Boltzmann Machines (RBM), the energy function illustrates in Equations 17,18 and 19:

$$E(v, h) = -b'v - c'h - h'Wv \tag{17}$$

With W weights between hidden and visible units and b and c as biases. The free energy is:

$$F(v) = -b'v - \sum_i \log \sum_{h_i} e^{h_i(c_i + w_i v)} \tag{18}$$

RBMs assume conditional independence:

$$\begin{aligned} p(h \mid v) &= \prod_i p(h_i \mid v) \\ p(v \mid h) &= \prod_j p(v_j \mid h) \end{aligned} \tag{19}$$

Deep Boltzmann Machines (DBM) and Deep Belief Networks (DBN) extend RBMs with more hidden layers, enhancing their ability to model complex relationships. Deep learning performance improves significantly with large datasets and strong computational resources [15-24].

3.2 Machine learning (ML) algorithms

They're broadly utilized in numerous areas, comprising sensing as well as state observing. Such algorithms enhance the data processing's attributes and efficacy, assisting large sensory data scrutiny and clarification. The methods of supervised ML, like SVM and ANNs are broadly employed for the categorization as well as regression uses. The approaches of unsupervised

ML, especially clustering algorithms, are applied for categorizing the data in the pre-established classes' nonexistence. The (2) approaches of deep learning, Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) have depicted abundant encouragement in treating intricate sensory input as well as extracting the elevated-level characteristics. And, in the actual-period state observing and sensing uses, such algorithms have been utilized for delivering perceptive scrutiny and forecasts. Also, the whole regarded things, the sensing and state observing field have been updated via ML algorithms, assisting further accurate and effective scrutiny of data scrutiny [13-21].

3.2.1 Support Vector Machines (SVMs)

SVMs are a famous method of ML for identifying the topic and apparatus state observing. An instance of an ultimate margin is illustrated in Figure 3. The support vector machines (SVMS) have been confirmed to be active in amending the data over--fitting as well as performing elevated accurateness in investigation upon the revolving apparatus problems' diagnosis. Investigators have adapted SVMs in numerous methods to fit their specific investigation goals better. And, for example, evolved a 2-phase kernel regime employing kernel PCA and ICA beyond evolving a Wavelet Support Vector Machine (W-SVM) with sturdy generalization capability.Moreover, multiclass approaches, like One-Against-One (OAO) and One-Against-All (OAA), have been employed for SVM-based categorization. It's crucial to keep in mind that the SVMs might require processing power and a big memory, as well as that choosing the correct kernel possesses an influence on how efficiently they serve. SVMs are able to manage the difficulties with the data of the sensor and are valuable to diagnose the faults in the rotating equipment with fewer datasets; nevertheless, they mightn't be suitable for large manufacturing datasets [19-23].

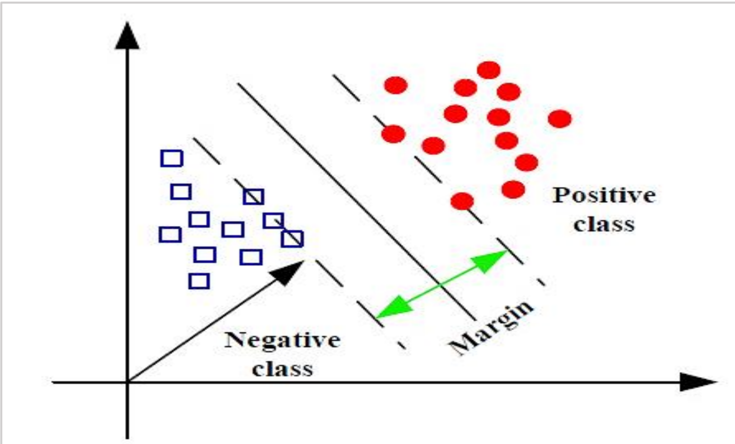

Figure 3: The optimal hyperplane for a binary classification by SVM [19]

3.2.2 Neural networks

Neural networks find extensive applications in a variety of fields, such as pattern recognition and machine fault detection. They provide advantages like fault tolerance, adaptive parallel processing, distributed information storage, and nonlinear mapping capabilities. Figure 4 depicts the fundamental architecture of an artificial neural network [11].

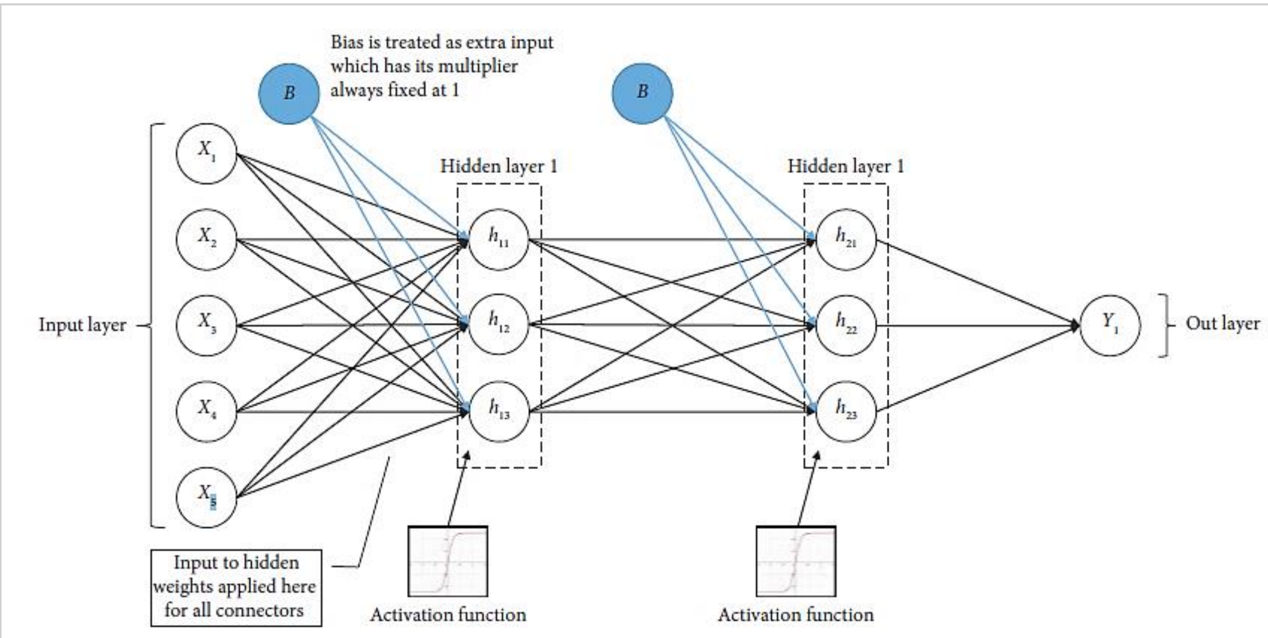

Figure 4: Basic structure of artificial neural network [11]

Additionally, MATLAB was used for modelling and simulation, as seen in Figure 5. Neural networks' hidden layers essentially function as information processors, taking in inputs from layers above and sending processed outputs to layers below. There is no direct communication between these layers and the outside world. As shown in Figure 6, nodes in the network use nonlinear activation functions to handle the nonlinear relationships between inputs and outputs. Neural networks can be utilized as classifiers in fault diagnosis to distinguish between various defects in rotating machinery. In order to provide quick and precise defect detection in gearboxes and bearings, researchers have developed enhanced neural network techniques that can accept raw signals as input without requiring preprocessing. Neural networks have also been used for tasks like blood pressure calculation, picture categorization, fall detection, and filtering and prediction. They have also been used in domains such as RNA sequence analysis, 3D object detection, and solar irradiance prediction. Neural networks have shown to be reliable and successful instruments across a range of fields, providing excellent performance and accuracy in jobs involving data processing and prediction [25-27].

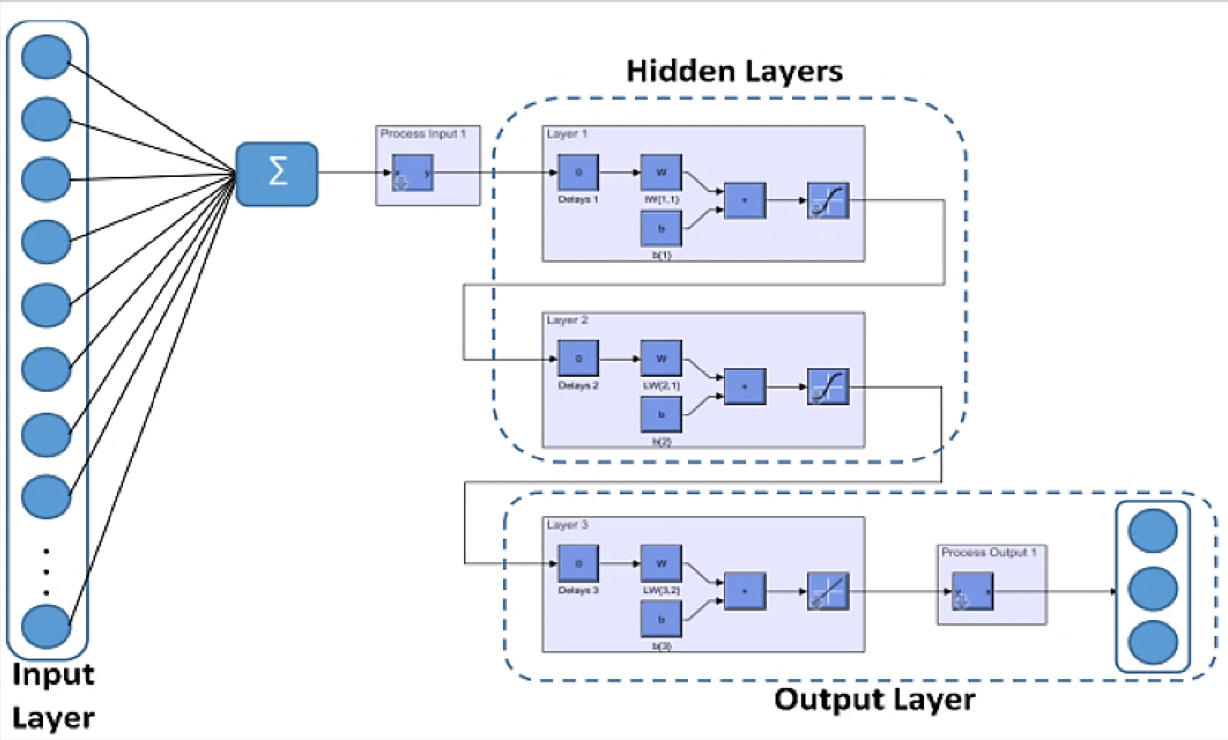

Figure 5: Architecture of artificial neural network [25]

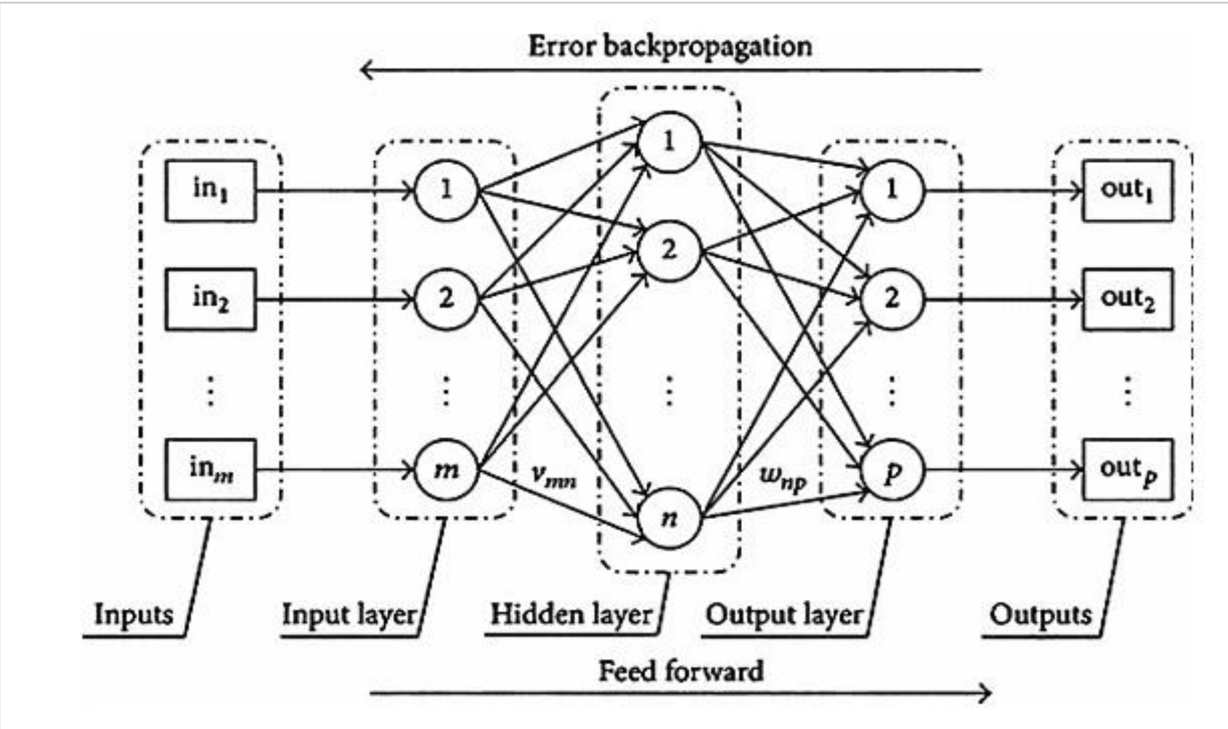

Figure 6: Typical three layers ANN [26]

3.2.3 Decision trees

Models called decision trees employ a sequence of if/else queries to forecast the value of a target variable. With the intention of producing precise and timely predictions, these questions divided the data into smaller groups. One of the algorithm's termination criteria is the user's choice of how many questions to ask. A node is any group that the questions form, and a node's size can be used as a criterion for termination. Every data feature is used in the training procedure [28].

3.3 Deep learning (DL) techniques

Deep learning (DL) methods have garnered significant interest recently, particularly in diagnosing problems in rotating equipment. DL, a subset of machine learning, utilizes large-scale deep neural networks to automatically detect features from raw data without the need for manual feature engineering. This approach offers several advantages over traditional machine learning techniques, notably its ability to extract abstract and high-level features from diverse data sources such as audio, video, and sensor data. Convolutional neural networks (CNNs), a type of DL model, have been successfully applied in various domains, including image classification, speech recognition, and defect diagnostics. These models are well-suited for real-time status monitoring and intelligent systems because they can learn complex functions and establish strong correlations between multiple input signals [12-27].

3.3.1 Convolutional neural networks (CNN)

Applications for image processing and pattern identification make extensive use of Convolutional Neural Networks or CNNs. Convolutional, pooling and fully linked layers make up their composition. CNNs are used in equipment failure detection and are very good at extracting features. Better CNNs have looked toward expanding their capabilities to include scenarios with changing speeds throughout time. These include residual learning techniques, multi-scale kernel algorithms, nuisance attribute projection, Pythagorean spatial pyramid pooling, cascade CNNs with progressive optimization, and the integration of intraclass and interclass restrictions with adaptive activation functions. For intelligent failure detection and Remaining Useful Life (RUL) prediction, CNNs have also been integrated with other deep learning architectures, such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks. The structure is separated into two parts: the first extracts features made up of Max pooling, ReLU, and convolutional layers. As depicted in Figure 7, the data classification segment is comprised of a completely connected network [12-30].

3.3.2 Recurrent Neural Networks (RNN)

One kind of DL architecture called recurrent neural networks (RNNs) uses feedback connections from hidden or output layers to analyze dynamic input. RNNs are useful for tasks like time series analysis and natural language processing because they can detect temporal connections in sequential data. The Long Short-Term Memory (LSTM) network is one particular kind of RNN that solves the issue of vanishing and exploding gradients that can arise in conventional RNNs. With the memory cell included in LSTMs, long-term dependencies can be preserved more effectively because it keeps the state intact when the network is not in use. Applications such as gear defect diagnostics, bearing problem detection, and remaining useful life prediction have drawn interest in RNNs, particularly LSTMs. as shown in Figure 8 [15-30].

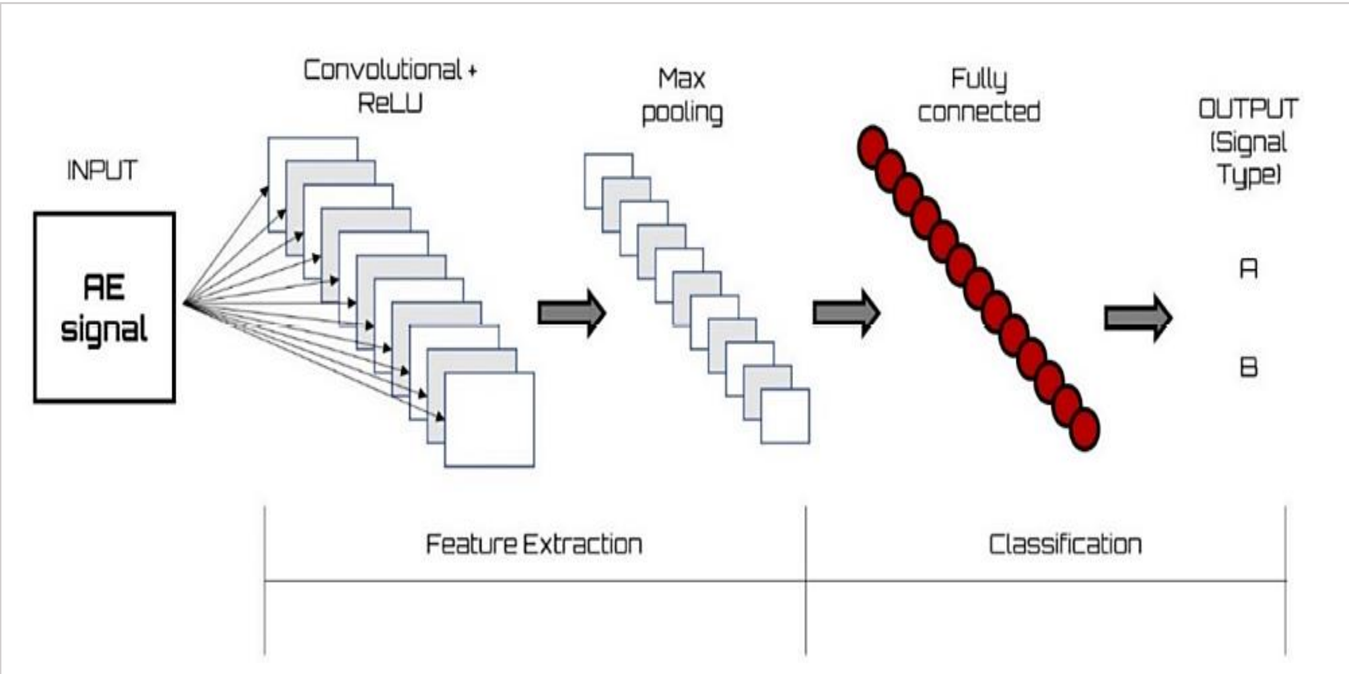

Figure 7: Typical CNN architecture

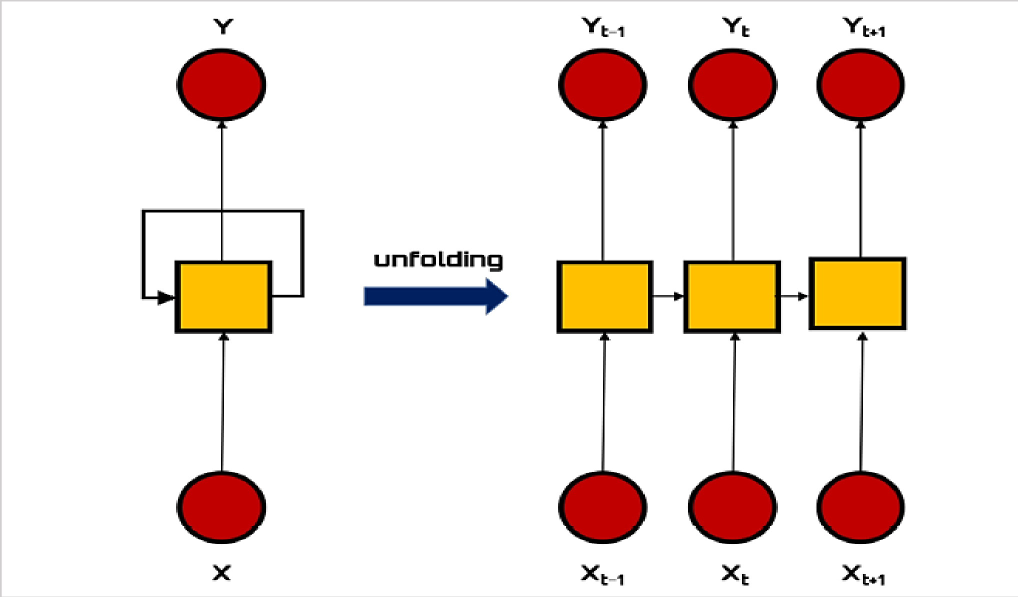

Figure 8: RNN architecture unfolded: feedforward version of networkof arbitrary length depending on a sequence of inputs

3.4 Hybrid AI models

Systems that integrate several artificial intelligence techniques to enhance machine learning performance are referred to as hybrid AI models. Neural networks, evolutionary computing, fuzzy logic, support vector machines (SVMs), Bayesian networks, and statistical learning are among the methods that these models frequently make use of. Hybrid AI systems aim to improve on the strengths of different approaches. For instance, it has been demonstrated that hybrid neural network regression models that incorporate fuzzy clustering techniques perform better than standalone techniques like K-means and Fuzzy C-means in some scenarios. An additional instance is a hybrid regime that joins the SVM algorithms, ANNs, naive Bayes, and fuzzy logic for obtaining more than (99%) rate of recognition as well as detection for the species recognition and illness diagnosis. Such hybrid models join the numerous AI methods' advantages for increasing the performance in a diversity of uses [27-31].

4. Integration of vibration analysis and artificial intelligence

The analysis of vibration and the AI incorporation have harvested care in the rotating apparatus topic diagnosis field. Investigators have studied numerous methods of AI, comprising ANNs, fuzzy logic regimes, and Deep learning (DL), in a trial for improving vibration-based topic identification. ANNs have been broadly employed in such manufacturing; an investigation has concentrated on optimizing the network topology as well as integrating the time-frequency mapping of the signals of vibration. Via increasing the deep learning designs with the methods of period-synchronized re-sampling for including the analysis of vibration as a restriction, greater diagnostic accurateness has been reached. In addition, the improved ANN models have evolved, like the dynamic fuzzy NN and the multi-scale residual generative adversarial network, for handling the difficulties, comprising the lost specimens and the unbalanced data of fault. The progressions in practices of AI have manifested the ability to augment the accurateness as well as the efficacy of vibration scrutiny-based topic detection.

AI and analysis of vibration join efficiently for enhancing the spinning apparatus failure diagnosis. Employing AI-based approaches, like ANNs, for characteristic extracting and detecting the defect from the signals of vibration can enhance the fault diagnosis accurateness. Additionally, the analysis of time-frequency pictures may be utilized with the approaches of AI for finding concealed features and producing exceptionally dependable and widely implementable diagnostic models. The methods of AI adaptive decomposition can effectively denote the signals transiently via automatically decomposing the signals and stressing the resident characteristics reasoned via the faults. Moreover, the data of vibration may be assessed, and the fault info can be taken out employing the algorithms of AI, which can overwhelm the non-fixed signals as well as numerous simultaneous failures. Collected, the analysis of vibration and the AI assist further precise and effective defect diagnosis in the spinning equipment [12-22].

Combining techniques in machine learning models has several advantages. Combining data or pertinent information from several sources improves the resilience and accuracy of the models. Overall performance is improved by combining the predictions of many classifiers using ensemble approaches like boosting and bagging. By integrating the benefits of many techniques, ensemble approaches may effectively manage extremely nonlinear and non-stationary data. The disadvantages of individual techniques, such as complexity, interpretability, power and time consumption, can also be helped by combining methodologies. In general, combining techniques in machine learning models can result in predictions that are more predictable and accurate, which makes them valuable tools in a range of applications, including defect diagnostics and prognostication.

Some of the challenges and limitations in this subject are the focus on diagnostic rather than prognostic techniques, the complexity of implementing real-time predictive maintenance in different application areas, and the effect of unknown components and sources on prediction outcomes. For academics, accurately and correctly estimating the lifespan of a machine or piece of equipment is a challenging issue. However, this technique might be used in the future to spot anomalies instantly and prevent more damage to machinery or processes [21-30].

5. Case studies and applications

The topics of journal bearing have been fruitfully diagnosed employing the analysis of vibration and AI. The analysis of vibration is a famous method to locate the concealed signs of failure in the rotating equipment like the journal bearings. For identifying the irregularities and the flaws' initial warning signals, comprising the misalignment, wear, and fractures, the analysis of vibration signs has to be tested. AI-based approaches like ML algorithms, such as SVM and K-Nearest Neighbors (KNN), founded upon the data of vibration, have been employed for classifying the fault conditions of journal bearing. Such methods depend upon training classifiers utilizing categorized data and deriving characteristics from the Power Spectral Density (PSD) of the signals of vibration.

The analysis of vibration, joined with the algorithms of AI can offer a precise detection of fault for the journal bearings. This creates the foretelling upkeep of the spinning equipment likely as well as improves the state observing [16-20]. The following tables provide a comprehensive overview of recent studies on journal bearings, categorized based on their specific focus areas and methodologies. These tables offer detailed insights into various aspects of wear fault diagnostics, fault diagnosis in bearings, advanced machine learning techniques, simulation and experimental studies, and case studies and applications. Table 2 summarizes studies focusing on the detection and monitoring of wear faults in journal bearings. Table 3 this table highlights research on fault diagnosis methodologies for bearings, including integrated wear debris analysis, vibration data, and temperature analysis, as well as the application of deep learning algorithms. Table 4 presents studies that leverage advanced machine learning techniques for condition monitoring and fault diagnosis in journal bearings, emphasizing the use of convolutional neural networks, autoencoders, and other AI models.

Table 5 outlines simulation and experimental research on journal bearings, focusing on the impact of micro-grooves, misalignment, and lubrication performance and providing guidelines for optimal bearing design. Table 6 lists case studies and practical applications of journal bearings research. It details simulation methodologies, wear model evaluations, and the effects of bearing design parameters on system performance.

Table 2: Wear fault diagnostics in journal bearings

Focus	Methodology	Key Findings	Ref.
Wear fault diagnostics in journal bearings	Simulation-driven deep learning with CNN	Simulated data used for real-world wear severity prediction	[32]
Wear monitoring of journal bearings	Acoustic emission for qualitative wear estimation	Challenges in quantitative wear volume estimation highlighted	[33]
Monitoring lubrication conditions in bearings	Contact potential-based method for diesel engine bearings	The relationship established between contact potential and asperity contact; novel method for accurate wear monitoring	[34]
Monitoring tribe-dynamic interaction in journal bearings	Vibration analysis to assess induced friction and tribological performance	Importance of monitoring tribological performance and lubrication regimes in journal bearings under heavy load and high rotational speeds	[35]
Particle contamination detection in bearings	Acoustic emission (AE) and vibration monitoring	Quantitative evaluation of particle sizes and concentrations effective condition monitoring using AE and vibration	[36]

Table 3: Fault diagnosis in bearings

Focus	Methodology	Key Findings	Ref.
Bearing fault diagnosis	Ensemble CNN and deep neural network (CNNEPDNN) model	Improved convergence speed, test accuracy, and F-Score in bearing fault diagnosis compared to individual models	[37]
Fault diagnosis in hydropower plant bearings	Integrated wear debris analysis, vibration data, and temperature analysis	Abnormal temperature and vibrational energy increase identified fault; successful rectification through bearing block replacement	[38]
Vibration characteristics in hydrodynamic journal bearings	Investigation of Tribofilm-Asperity Interaction (TAI) for early wear monitoring	Analytical expressions for microscopic pressure fluctuations derived; SPSD used for analyzing microscopic pressure fluctuations providing effective techniques for early wear monitoring of journal bearings	[39]
Fault detection in floating bush bearings	Time and frequency domain vibration analysis	Various parameters including waveform, form factor, and kurtosis are effective for identifying external and internal defects in floating bush bearings	[40]
Influence of journal bearings on gearbox dynamics of a wind turbine drivetrain	Multibody simulation (MBS) model comparison for journal bearings versus roller bearings	The investigation aims to clarify the advantages or disadvantages of using journal bearings in wind turbine gearboxes.	[41]
Fault diagnosis in journal bearings	Deep learning and vibration analysis	Enhanced fault detection accuracy using deep learning algorithms on vibration data	[42]

Table 4: Advanced machine learning techniques

Focus	Methodology	Key Findings	Ref.
Identifying ovalization faults in bearings	Deep convolutional neural network (CNN) using simulated data	CNN algorithm demonstrated efficacy in identifying ovalization faults; statistical evaluations supported its effectiveness for training with simulated data	[43]
Stochastic analysis of lubrication in misaligned journal bearings	Polynomial chaos expansion (PCE) to analyze stochastic Reynolds equation	Misalignment in hydrodynamic journal bearings introduces stochasticity affecting lubrication performance; significant effects of misalignment and stochastic parameters identified	[44]
Vibration-based wear condition estimation of journal bearings	Convolutional autoencoders for feature extraction	Convolutional autoencoders achieved impressive performance (91% average Pearson coefficient) in wear estimation, highlighting the importance of predictive maintenance	[45]
Bearing fault diagnosis based on deep learning and health state division	Deep learning and health state division with Xi'an Jiaotong University (XJTU-SY) dataset	Improved network model demonstrated effective fault diagnosis and noise immunity under complex working conditions, achieving high diagnostic accuracy and efficiency	[46]
Condition monitoring of hydrodynamic journal bearings	Machine learning and signal processing	Implementation of advanced signal processing techniques combined with machine learning for improved condition monitoring	[47]

Table 5: Simulation and Experimental Studies

Focus	Methodology	Key Findings	Ref.
Transient lubrication behaviour of loaded journal bearings with micro-groove	Numerical investigation with a mixed lubrication model	Micro-grooves impact bearing performance; study offers guidelines for optimum design of dynamically loaded micro-groove bearings	[48]
Minimizing misalignment effects in finite-length journal bearings	Finite difference method-based numerical solution with a three-dimensional misalignment model	The edge modification approach improves lubricant layer thickness, reduces pressure spikes, and decreases friction coefficient under misalignment	[49]
Mixed lubrication performance of journal bearings with misalignment and thermal effects	Experimental and numerical study introducing a misaligned journal mixed lubrication model	Visible wear phenomena observed on the bush and shaft contributed to the understanding of mixed lubrication mechanisms in misaligned journal bearings	[50]
Continuation analysis of rotor-bearing systems	Direct solution of the Reynolds equation for sliding contact bearings	Practical approach for examining the dynamics of a rigid rotor bearing system without relying on approximations	[51]
Experiment and simulation analysis of vibration response in rotor-bearing systems	Investigation of unbalanced mass effects on vibration response	Insights into amplitude variations and trends under different conditions are valuable for fault diagnosis and dynamic characteristics analysis	[52]

Table 6: Case studies and applications

Focus	Methodology	Key Findings	Ref.
Simulation methodology for identifying critical conditions of planetary journal bearings	Simulation tool chain coupling multibody simulation (MBS) and elastohydrodynamic (EHD) model	Methodology aids in identifying critical operating conditions of planetary journal bearings early in the design phase, supporting reliable bearing design for wind turbines	[53]
Wear models for journal bearings in planetary gears	Evaluation of wear models under wind turbine-like conditions	Insights into where model selection for calculating wear in planetary gear journal bearings addressing challenges in wind turbine drive systems	[54]
Effects of bearing design parameters on rotor-bearing systems with 3D misalignment	Investigation of dynamic response with linear and parabolic bearing profiles	Both profiles enhanced system performance, reducing the adverse effects of misalignment on lubricant layer thickness and pressure distribution	[55]
Statistical features-based approach for bearing fault diagnosis	Statistical features of vibration signals in time and frequency domains	The proposed method using statistical features achieved over 95% reduction in features and demonstrated high accuracy in roller bearings' fault classification	[56]
Intelligent fault diagnosis of rotating machinery	Deep learning applications	A comprehensive review of deep learning techniques in fault diagnosis, highlighting recent advancements and practical applications	[57]

6. Comparative analysis

6.1 A comparison between AI-based and conventional approaches

Conventional and artificial intelligent-based practices have been compared in the diagnostics as well as the fault prognostics domains. Techniques utilizing deep learning have the potential to attain greater recognition rates compared to conventional methods that rely on specialized expertise. An illustration of a conventional method is artificial feature extraction. Even though these traditional methods are simple to use and efficient in terms of processing, they struggle to distinguish features from non-stationary signals when speeds change over time. But AI-based methods, such as those that make use of deep learning, could be able to directly extract characteristics from signals, doing away with the requirement for labor-intensive human work and specialized knowledge. However, further study is required to identify faults under time-varying speeds, and deep learning-enabled approaches' accuracy needs to be improved for industrial use. Various data sources, including vibration/kinematic, acoustic, and visual data, are employed in the field of rotating machinery for fault prognostics and diagnostics. Neural networks and support vector machines, two AI-based techniques, have been effectively used in these fields. When compared to traditional methods, AI-based solutions generally show promise in improving fault diagnosis and prognostics; nonetheless, further study and advancements are required [12-30].

6.2 Effectiveness and efficiency

The efficacy and efficiency of several intelligent techniques for diagnosing faults in rotating machinery are demonstrated through comparative analysis. While computationally efficient and easy to use, artificial feature extraction-enabled techniques may not be able to extract deep distinguishing characteristics from non-stationary data and necessitate previous information. However, deep learning-enabled techniques are more straightforward to use, and by fusing deep learning models with signal processing techniques, they are able to discover more intricate characteristics. The paper highlights that automated diagnosis should not just rely on data-driven AI techniques but also make use of defect characteristics and prior knowledge. It also emphasizes the necessity of thorough reference points and fault-wise analysis for rotor problems, including fault simulation in test beds. By retrieving characteristics from hidden layers, deep neural networks like autoencoders can increase the accuracy of fault categorization [12-58].

7. Future trends and directions

Numerous future trends and directions in the field of intelligent fault analysis of rotating machinery can be researched. First of all, real-world datasets that consider operational and environmental factors are needed, as the majority of datasets currently in use were developed in lab conditions [14]. This will make it possible to create IFDP models that are adaptable to variations in these parameters. Second, instead of making generalizable models, it could be advantageous to construct the constituent- and fault-particular models to decrease the problem's intricacy. And, it's likely to evolve further active methods of IFDP via concentrating upon specific constituents as well as adapting factors based upon the fault type. Finally, it's crucial to assess the efficiency of the methods of IFDP in manipulating compound failures, which are the failures occurring in numerous discrete or alike constituents. It's essential to perform more investigation upon such a topic, which hasn't acquired abundant care in literature.

7.1 Emerging technologies

The diagnosis, as well as the prognosis of the defect for the revolving apparatus, is an issue shedding light upon the prospective upcoming tendencies and technical directions. The joining (AI) with the methods of ML, like the DL, has come to be further famous for the identification of faults. Since such algorithms can efficiently use the historical data's enormous volumes and increase the accurateness of recognition, they're appropriate for utilization in clever industrial uses. Also, Cyber-physical systems (CPS), in addition to the integration of sensors, have assisted the practices of Prognostics and Health Management (PHM), which are necessary for the industry (4.0). The progress in the collection of data, the approaches of data fusion, and also the choice of algorithm have resulted in the Intelligent Failure Detection and Prognosis (IFDP) models formation for revolving equipment. The general upcoming tendency of developing techniques is the employment of PHM, CPS, DL, ML, and AI to the identification as well as prediction of fault for the revolving apparatus [12- 59]

7.2 The prospective progress in AI and the analysis of vibration for the detection of fault

The following tendency, as well as directions in the analysis of vibration and artificial intelligence (AI) for the diagnosis of defect, is the progress of DL approaches motivated via the simulation for the journal-bearing state observing. Such approaches using the dynamic models for estimating the vibration reactions of journal bearing at different scenarios of failure can be more reasonable than collecting more training data throughout the area field of observations or the physical experimentations. Furthermore, there is growing interest in the application of intelligent fault diagnosis and prognosis (IFDP) models and artificial intelligence-based fault analysis for rotating machinery. Model evaluation, applicability to real-world scenarios, development of fault-specific models, existence of compound faults, data source, data collecting, and method selection are among the difficulties in this field. For IFDP of rotating machinery components, including bearings, gears, rotors, stators, and shafts, to be effective, these issues must be resolved. These developments in AI and vibration analysis could lead to better fault diagnosis and detection in rotating machinery, improving industrial system reliability and safety [21- 60].

8. Conclusion

This comprehensive review highlights the significant progress that has been made in fault diagnosis and condition monitoring in journal bearing. Progress has been made by incorporating machine and deep learning techniques, especially ensemble models such as CNN and CNNEPDN, which have shown improvements of 15 to 20 per cent in Test accuracy and convergence speed in detecting errors compared to individual models performance, achieving an average Pearson correlation factor of 91% in fatigue estimation.

1) The need to use a variety of data sets is necessary because it is empirical and realistic.
2) Future research should include different types of defects and different operating conditions to improve the representativeness of the data set.
3) One essential is common evaluation criteria to improve program reprogramming and enable consistent comparisons between studies.
4) Comprehensive models covering a wide range of operating conditions and malfunction scenarios must be developed in order to improve diagnostic accuracy.
5) Physical computing and advanced data integration techniques to develop intelligent models for defect diagnosis and prediction. Key extraction processes: Constant and nonlinear.

Future developments will benefit from the integration of deep learning, physical computer systems, and advanced data integration techniques to develop intelligent models for defect diagnosis and prediction. By addressing these areas, future research can significantly enhance the reliability and effectiveness of control conditions and fault diagnosis in magazine holders, leading to improved maintenance strategies and reduced downtime in various industrial applications. By addressing these areas, future research can significantly enhance the reliability and effectiveness of control conditions and fault diagnosis in magazine holders, leading to improved maintenance strategies and reduced downtime in various industrial applications.

Author contributions

Conceptualization, **N. Jebur**. and **W. Soud**.; investigation, **N. Jebur**. and **W. Soud**.; project administration, **W. Soud**., resources, **N. Jebur**. and **W. Soud**.; supervision, **W. Soud**.; writing—original draft preparation, **N. Jebur**.; writing—review and editing, **N. Jebur**. and **W. Soud**. All authors have read and agreed to the published version of the manuscript.

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author.

Conflicts of interest

The authors declare that there is no conflict of interest.

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