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Review Article

A Review of Artificial Intelligence Methods for Condition Monitoring and Fault Diagnosis of Rolling Element Bearings for Induction Motor

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The fault detection and diagnosis (FDD) along with condition monitoring (CM) and of rotating machinery (RM) have critical importance for early diagnosis to prevent severe damage of infrastructure in industrial environments. Importantly, valuable industrial equipment needs continuous monitoring to enhance the safety, reliability, and availability and to decrease the cost of maintenance of modern industrial systems and applications. However, induction motor (IM) has been extensively used in several industrial processes because it is cheap, reliable, and robust. Rolling bearings are considered to be the main component of IM. Undoubtedly, any failure of this basic component can lead to a serious breakdown of IM and for whole industrial system. Thus, many current methods based on different techniques are employed as a fault prognosis and diagnosis of rolling elements bearing of IM. Moreover, these techniques include signal/image processing, intelligent diagnostics, data fusion, data mining, and expert systems for time and frequency as well as time-frequency domains. Artificial intelligence (AI) techniques have proven their significance in every field of digital technology. Industrial machines, automation, and processes are the net frontiers of AI adaptation. There are quite developed literatures that have been approaching the issues using signals and data processing techniques. However, the key contribution of this work is to present an extensive review of CM and FDD of the IM, especially for rolling elements bearings, based on artificial intelligent (AI) methods. This study highlights the advantages and performance limitations of each method. Finally, challenges and future trends are also highlighted.

1. Introduction

Many industries have adopted several measures in their drive to optimize the reliability, availability, and safety to reduce the maintenance cost of modern industrial systems and applications, which are vital to process [1, 2]. Thus, condition-based maintenance (CBM) has gained a significant role in an industrial world [3, 4]. However, CBM is applied in order to achieve early maintenance decisions through CM collected data [5]. Moreover, condition monitoring (CM) and fault detection and diagnosis (FDD) of rotating machinery (RM) [6, 7] have recently gained huge attention [8, 9]. Therefore, CM and FDD become the most important and critical aspects of industrial life (i.e., system design and maintenance) [10]. The main aim of CM and FDD is to follow up the machinery health and the remaining useful life (RUL) in modern industrial machinery [11, 12]. However, predictive health monitoring (PHM) methods are important to guarantee the required health state of the machinery [13, 14]. Thus, CM and FDD help to ensure the health state of the machinery [15, 16]. Figure 1 shows the main components of a typical CBM [17]. CM methods are categorized into two groups, invasive and noninvasive methods. On the one hand, invasive CM is considered to be simple and basic technique. On the other hand, it is hard to implement. To overcome this challenge, noninvasive CM methods are highly used nowadays [18].

As key components of industrial systems and applications [19–21], rotating machinery, such as motor, gearbox, wind turbines, generator, and engine, is vital equipment in modern industrial applications [22]. These important machines have to run efficiently, accurately, and safely [23]. Due to the criticality and importance of this issue, several analysis and studies were published during the past years where many different approaches have been investigated to improve the CM and FDD for rotating machinery [24, 25]. Conventionally, the traditional CM and FDD methods (such as model and signal as well as data-based methods) [26–29] need to extract the diagnosable information manually from the raw data [30]. Following that, pattern recognition models were developed using the features vector in the classification process [31]. This scenario requires much experience knowledge and complex feature extraction methods [32, 33]. To address this issue, artificial intelligent (AI) methods and techniques for CM and FDD of RM [34–39] are widely employed and applied nowadays [40, 41].

Induction motor (IM) [42–49] is vital in industrial processes and applications [50, 51]. Moreover, IM is extensively used, for example, in mining machines, automotive applications, pumps, blowers, fans, chemical machines, lifts, compressors, vacuums, conveyors cranes, and engines [52–59]. Figure 2 summarizes applications of the IM.

All parts of IM (stator, bearing, bar, and rotor) are affected by stress, aging, vibration, long operating time, continuously monitoring, and electrodynamic forces [60–62]. Thus, any failure of any part of IM may cause a serious breakdown of the machine, which increases the maintenance cost and leads to heavy losses [63, 64]. Figure 3 shows IM faults and their percentage.

Rolling bearings [66] were considered to be the main component of rotating machinery [67]. However, bearings are used in several mechanical and electrical applications, including IM, turbines, medical devices, cars and trucks, engines, automobile industry, and aerospace [68]. Importantly, any failure of this basic component can lead to a serious breakdown of rotating machines [69]. Rolling bearing faults could be categorized by two main factors, location of the fault and nature of the fault. For location category, five main faults occurred including, imbalance shaft faults, ball faults, inner race faults, outer race faults, and cage faults. For nature category, two main faults are considered, including cyclic faults and noncyclic faults [70, 71].

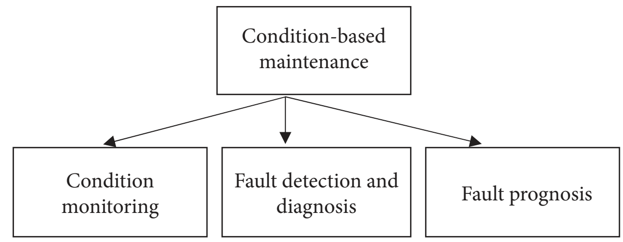

Figure 1: The main components of CBM.

CM and FDD of bearing element bearings of RM are widely used to follow up the operation condition of the machine [72–74]. However, the main task of CM and FDD is to diagnose faults and failures [75, 76]. As a result, any failure may cause a serious breakdown, which increases the maintenance cost and leads to heavy losses [77]. Recently, various methodologies of CM and FDD of IM have been discussed. Moreover, several data and model-based techniques have been introduced including signal processing-based techniques [78, 79], image processing based techniques [80–83], intelligent techniques [84, 85], data fusion techniques [86–90], data mining techniques [91–96], and expert system techniques [97–99]. All those techniques have used specific analyses to develop the FDD methodology to arrive at efficient and accurate results [100, 101]. As shown in Figure 4, the analyses used in those studies include chemical analysis, electrical analysis, and mechanical analysis, in more details, temperature analysis [102–107], vibration analysis [108–112], noise analysis [113, 114], radio-frequency (RF) analysis [115–118], infrared analysis [119–124], current and voltage analysis [125, 126], electromagnetic field analysis [127–129], oil analysis [110, 130–132], pressure analysis [133–137], ultrasound analysis [138–140], and sound and acoustic emission analysis [141, 142]. Figure 5 shows a general block diagram of a noninvasive FDD for rotating machinery. As an example, preprocessing stage includes data denoising and filtering. However, most electrical and mechanical signals are nonlinear and nonstationary signals. Thus, denoising techniques have been extensively studied nowadays. However, wavelet transform (WT), continuous wavelet transform (CWT), discrete wavelet transform (DWT), Kalman filtering, Wiener filtering, Empirical mode decomposition (EMD), variational mode decomposition (VMD), and singular value decomposition (SVD) are some common denoising techniques [143]. Table 1 shows a comparison between various CM analysis techniques.

The main objective of this work is to review the CM and FDD of the IM, especially for rolling elements bearings, based on artificial intelligent (AI) methods. The study also points out the advantages and drawbacks of each method. Finally, research challenges and possible future trends directions in this field are also presented in this article.

The rest of the paper has been organized as follows. Firstly, background and general introduction are discussed in Section 2. Secondly, AI for CM and FDD for

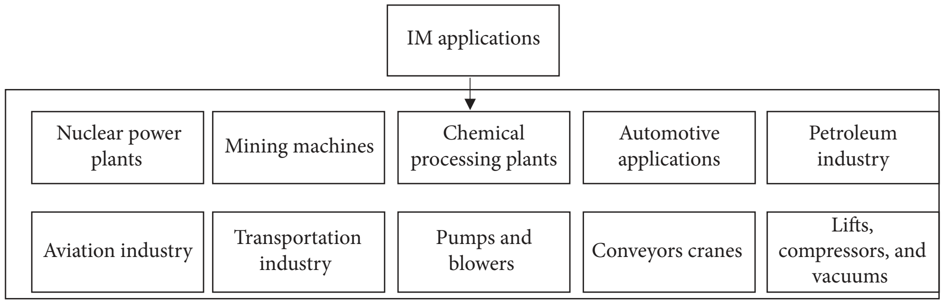

Figure 2: Applications of the IM.

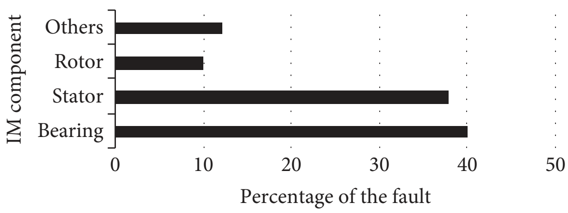

Figure 3: IM faults [65].

rolling bearings are presented in Section 3. Finally, challenges and future trends are discussed in Section 4.

2. Background and General Introduction

Nowadays, the need for earlier detection of faults for IM is crucial. However, in order to increase the reliability of IM, AI has been used to measure the accuracy at the incipient stage of CM and FDD for IM [144]. Figure 6 shows all most AI methods used in CM and FDD. A variety of AI studies of CM and FDD for IM have been recently reported. In [145], an intelligent FDD of RM (i.e., automotive engine) framework is introduced. Therefore, in the feature extraction stage, ensemble empirical mode decomposition (EEMD) is implemented followed by intrinsic mode functions (IMF) decomposition. The correlation coefficient (CC) along with singular value decomposition (SVD) is employed to eliminate the redundant IMF and to obtain fault features. To add a new layer of improvement, five single classifiers based on the probabilistic committee machine (PCM) and Bayesian learning machine are trained and used in the classification stage.

Furthermore, (1) the single probabilistic classifiers, (2) the single probabilistic and Bayesian machines, (3) pairwise-coupled, and (4) two classifiers without pairwise-coupling strategy are used for further comparison of classification. As a result, the proposed probabilistic committee machine method showed the superiority of diagnosing faults. In [146], an online feature condition monitoring approach based on unsupervised feature learning (dictionary learning) under different operational conditions using vibration and acoustic emission signals is introduced. This work also presents dictionary distance and signal fidelity driven methods and techniques for anomaly detection are also described. Moreover, time-propagated characteristics are used along with sparse approximation of signals received from vibration and acoustic emissions. Importantly, the results of three case studies, i.e., the approximation accuracy, overall computational overhead, and the adaptation rate, are presented. As a result, under normal variation condition, the learned features change slowly in comparison with high-speed variation when a fault appears. In [147], an FDD system of IM designed on multiscale entropy and support vector machine (SVM) in combination with mutual information algorithm is proposed. The aim is to retrieve the required entropy feature; techniques like vibration signals, sample entropy, and multiscale entropy are applied. Importantly, a support vector machine classifier is used for the entropy feature vector. Furthermore, classification results showed that these SVM based entropy techniques could effectively diagnose various motor faults (i.e., bearing faults, stator faults, and rotor faults). In [148], a multiclass FDD approach of IM using wavelet and Hilbert transforms is introduced. Moreover, for a feature extraction stage, Hilbert transform (HT) and continuous wavelet transform (CWT) are applied as advance signal processing techniques to retrieve features and characteristics from radial vibration signals and to detect rotor, bearing, and stator faults. Importantly, three classifiers are employed in this research: the neural network (multilayer perceptron), neural network (radial basis function), and support vector machines. As a result, in this study, the performance of SVM is found to be the best compared with NN classifiers, i.e., MLP and RBF classifiers. In [149], a compound FDD approach for IM at variable operating conditions using the SVM classifier is introduced. Moreover, radial vibration and stator currents are used. Four motor conditions are extracted and classified, including healthy induction motor, misalignment, unbalanced rotor, and bearing fault. Kernel-nonlinear SVM along with Gaussian radial basis function is employed. As a result, SVM bootstrap based technique with features data fusion has an ability of classifying multiple and single faults for different operating conditions of the IM with good accuracy (84.8–100%). In [150], vibration and current monitoring based approach for both electrical and mechanical faults' prediction under various operating conditions for IM is proposed. Moreover, nine mechanical and electrical faults are detected and classified using a multiclass SVM algorithm. In the feature extraction stage, time domain of vibration and current signals is used to seek statistical features. Importantly, MSVM is trained using the radial basis function (RBF) kernel. As a result, for the vibration signal and

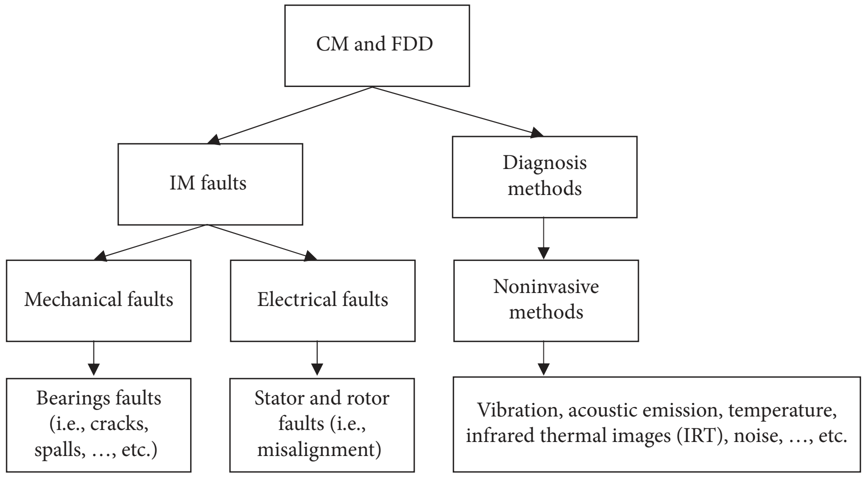

Figure 4: CM and FDD techniques of IM.

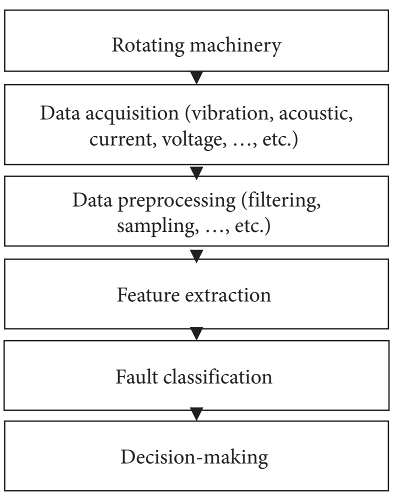

Figure 5: General block diagram of FDD using machine learning.

mechanical faults, the MSVM showed an ability of predicting all faults, but it could not predict current signals based on electrical faults. However, the SVM is better than MSVM for electrical faults diagnosis.

Recently, deep learning [151–153] is extensively used in CM and FDD for IM. In [154], an automatic FDD approach of IM uses deep learning techniques to combine the feature extraction process with the classification process. Moreover, deep belief networks (DBN) are modelled for vibration signals to retrieve key features. Moreover, the restricted Boltzmann machine (RBM) is used to build and train the DBN using a layer-by-layer pretraining algorithm. Importantly, the proposed approach could detect the fault directly from frequency distribution without needing traditional feature extraction methods. Furthermore, to elevate the classification accuracy and reduce training error, the proposed approach could learn multiple layers of representation and model high-dimensional data. In [155], an unsupervised feature learning sparse autoencoder-based deep neural network approach for induction motor faults classification is proposed. Moreover, the proposed approach detected and classified multiple faults, three-rotor faults (bowed, unbalanced, and rotor bars), defective bearing, and stator winding fault. Features obtained from a sparse autoencoder are used to train a neural network classifier. Importantly, the method called "dropout" is used to prevent the training process from overfitting. As a result, SAE-based DNN approach showed good results in terms of feature learning capability and classification accuracy of FDD for IM. To avoid complex sensor data problems, deep learning technique is recently used. In [156], deep learning for infrared thermal (IRT) images is introduced to detect various machine conditions. Moreover, convolutional neural networks (NNs) are employed. The accuracy of this method is at least 6.67% better compared with normal approaches. Importantly, it can be used for online FDD and CM when the access is very difficult such as in offshore wind turbines. Table 2 summarizes AI studies of CM and FDD for IM.

The bearing is a critical component in IM. Thus, robust and intelligent CM and FDD methods are highly needed to enhance detection, diagnosis, monitoring, and prognosis capabilities.

3. AI in CM and FDD of Rolling Element Bearings for IM

Bearing faults are considered to be a majority of faults in IM [164–166]. In [167], four classification methods for intelligent CM and FDD of rolling bearings are proposed. Moreover, accuracy, time consumption, intelligibility, and maintaining ability of intelligent methods like SVM based particle swarm optimization (PSO-SVM), *K*-Nearest Neighbor algorithm (KNN), a rule-based method (RBM) based on the MLEM2 algorithm and probabilistic neural network (PNN) are discussed. As a result, PSO-SVM ranked the first in terms of accuracy followed by the RBM, but PSO-SVM and RBM required more programming efforts. Furthermore, the RBM showed the best in terms of interpretation and reduction. In [168], an adaptive method for the health monitoring of rotating bearings using the vibration signal is introduced. The proposed

Table 1: Comparison between various CM analysis techniques for bearings of IM.

The technique	Advantages	Drawbacks	Fault
Temperature and infrared analysis	(i) Basic method (ii) Noninvasive	(i) Expensive sensor is required (ii) It cannot be used as early FDD	(i) Mechanical and electrical faults
Vibration and noise analysis	(i) Reliable and standard method (ii) It can be used as early FDD	(i) Sensitive to the noise (ii) Expensive sensor is required (iii) Intrusive	(i) Mechanical faults
Chemical and oil analysis	(i) Fault estimation and location capabilities (ii) High performance for bearing FDD	(i) Expensive (ii) Applicable for big size machines	(i) Mechanical faults
Sound and acoustic emission analysis	(i) It could be used as reliable and remote CM (ii) It is easily implemented (iii) Fault estimation and location capabilities (iv) Signal to noise ratio is high (v) It deals with high frequency range	(i) Sensitive to the noise (ii) Expensive sensor is required (iii) Intrusive	(i) Mechanical faults
Current, voltage, and electromagnetic field analysis	(i) Inexpensive (ii) Nonintrusive	(i) Sensitive to the noise (ii) It cannot be used as early FDD	(i) Mechanical and electrical faults
Ultrasound analysis	(i) Effective in low speed bearings (ii) It deals with low and middle frequency ranges (iii) High signal to noise ratio	(i) Expensive sensor is required (ii) Intrusive	(i) Mechanical and electrical faults

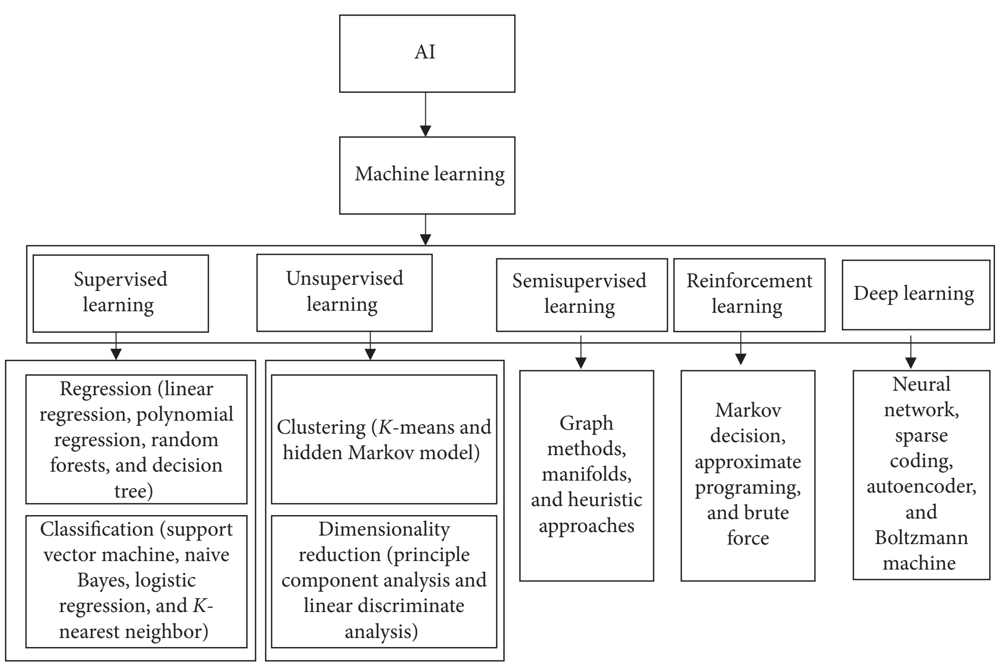

Figure 6: AI methods used in CM and FDD for rotating machinery.

method applies the empirical mode decomposition–self-organizing map (EMD–SOM) to find a confidence value (CV) and to find the degradation of the fault. As a result, SOM based technique showed a high ability for online condition monitoring, especially for limited computing resources cases.

3.1. Bayesian Network. Bayesian network [169, 170] is a probabilistic statistical model, which uses a directed acyclic graph (DAG) to seek conditional dependencies. This model shows a direct representation of causal relations between variables. Currently, the Bayesian network is extensively used [171] in several applications, such as feature extraction

Table 2: AI studies of CM and FDD for IM.

Reference	Analysis type	Feature extraction	Classification	Highlights
[145]	Vibration	Ensemble empirical mode decomposition (EEMD) and correlation coefficient (CC) along with singular value decomposition (SVD)	(1) The single probabilistic classifiers (2) The single probabilistic and Bayesian machines (3) Pairwise-coupled (4) Two classifiers without pairwise-coupling	(i) It diagnoses multiple and single faults (ii) There is simultaneous fault diagnosis (iii) The accuracy for a single fault is 92.62% and for simultaneous faults is 85.73%
[146]	Vibration and acoustic emission	Unsupervised feature	Dictionary learning	(i) There is online monitoring (ii) There are different operational conditions (iii) There are good computational costs
[147]	Vibration	Multiscale entropy	SVM	(i) It diagnoses multiple faults (ii) The average accuracy is 96.25%
[148]	Vibration	Hilbert transform (HT) and continuous wavelet transform (CWT)	Neural network (multilayer perceptron), neural network (radial basis function), and support vector machines	(i) There is multiclass FDD (ii) SVM is found to be the best (with SVM 99.71%) compared to NN classifiers
[149]	Vibration and current	SVM bootstrap based technique with features data fusion	Kernel-nonlinear SVM along with Gaussian radial basis function	(i) SVM multiclassification scheme is presented (ii) It diagnoses multiple faults (iii) There are different operational conditions (iv) The average accuracy is 99.4%
[150]	Vibration and current	Statistical features analysis	SVM and multiclass SVM	(i) It diagnoses multiple faults (ii) There is electrical and mechanical faults' prediction (iii) There are different operational conditions (iv) MSVM showed an ability of predicting all mechanical faults (v) SVM is better than MSVM for electrical faults diagnosis (vi) The average accuracy is 93.28%
[154]	Vibration	Deep learning	Deep belief networks (DBN)	(i) There is automatic FDD (ii) The proposed approach could detect the fault directly from frequency distribution without needing traditional feature extraction methods (iii) It learns multiple layers of representation and models high-dimensional data (iii) The average accuracy is 99.00%
[155]	Vibration	Deep learning	Sparse autoencoder	(i) It diagnoses multiple faults (ii) It prevents training process overfitting (iii) The average accuracy is 97.61%
[156]	Infrared thermal (IRT) images	Deep learning	Convolutional neural networks	(i) There is online monitoring (ii) There are different operational conditions (iii) The average accuracy is 95%
[157]	Stator current	Deep learning	Deep neural network	(i) IM bearings monitoring tool based on deep learning is proposed (ii) Different load conditions 25%, 50%, 75%, and 100% are tested (iii) Deep neural network showed better classification accuracy than shallow neural network (SNN) and principle component analysis (PCA)

Table 2: Continued.

Reference	Analysis type	Feature extraction	Classification	Highlights
[158]	Vibration	Kurtogram and deep learning	Recurrent NN, long-/short-term memory, and gated recurrent unit	(i) FDD method based on kurtogram and deep learning is proposed (ii) Computational time, computing resources and number of layers, is small (iii) Misclassification occurred (iv) The average accuracy is 98%
[159]	Vibration	Neural networks	Transfer learning	(i) Bearing FDD approach based on transfer learning with neural networks is proposed (ii) Different working conditions are analysed (iii) Training time comparing with NN is reduced (iii) It deals with massive data (iv) Transfer learning improved the classification accuracies (v) The total classification accuracy is improved by 10.4 %
[160]	Acoustic emission	Transfer learning-based convolutional neural network	Transfer learning	(i) Bearing FDD acoustic spectral imaging and transfer learning under variable speed conditions and different rotational speeds is proposed (ii) Two-dimensional acoustic frequency spectral imaging with a transfer learning is discussed (iii) The proposed method achieved an average accuracy of 94.67%
[161]	Vibration	Long-/short-term memory recurrent neural network and feature-transfer learning (joint distribution adaptation)	Grey wolf optimization algorithm	(i) Bearing FDD based on adaptive deep transfer learning is proposed (ii) Massive labeled fault data is collected and analysed (iii) The proposed method achieved an average accuracy of 99.4 %
[162]	Vibration	Multiscale deep intraclass adaptation network	Multiple scale feature learner	(i) Bearing FDD is based on multiscale deep intraclass transfer learning (ii) Different working conditions are analysed (iii) The proposed method achieved an average accuracy of 99 %
[163]	Vibration	Hybrid deep signal processing approach	Autoencoder	(i) Deep learning with time synchronous resampling mechanism is proposed (ii) The proposed method dealt with shift variant properties, periodic inputs, and misclassification challenges (iii) The proposed method achieved an average accuracy of 99 %

and classification machine learning algorithms, data mining and data processing, speech processing, bioinformatics, error-control codes, medical applications, industrial diagnosis, and wireless sensor networks [172–174]. As a ML algorithm for FDD of IM fault, the Bayesian network is applied. In [175], different operating conditions of bearing FDD approach based on acoustic signal are proposed. Decision tree (dimensionality reduction) is applied to extract descriptive statistical features vector in the feature extraction stage. Next, Bayes classifier is used in the classification stage. In [170], the diagnosis approach of bearing faults in rotary machinery based on the nonnative Bayesian approach using vibration signals is introduced. In detail, EMD is utilized to split up vibration signals into IMFs, and then the correlation coefficient is used to pick the appropriate IMFs. Shannon energy entropy of IMFs is used to seek useful statistical properties and features. Finally, a nonnative Bayesian classifier (NNBC) is employed to find independence among features. Furthermore, in order to compare classification results, backpropagation neural networks, normal naive

Bayesian classifiers, and kernel naive Bayesian classifiers are employed. Importantly, in this research study, the NNB classifier showed superiority compared with the other classifiers, including neural network and normal NB.

3.2. Support Vector Machine. The support vector machine (SVM) [176, 177] uses supervised machine learning models along with statistical and predictive methods for classification and regression analysis. SVM is being used to solve big data and multidomain classification problems in the modern industrial environment [178]. SVM is also used as CM and FDD method for IM. Subsequently, in [179], a bearing fault detection scheme using vibration signals of IM is proposed. SVM and continuous wavelet transform (CWT) are used together. As a result, for using SVM with CWT, the proposed scheme is simple to implement, very fast, and high accurate. Using another ANN based techniques requires the cumbersome process of trial and error to obtain an optimal solution. Nevertheless, using a hybrid CWT-SVM technique gives promising results (fast and efficient). In [180], an FDD approach for bearings of IM based on Stockwell transform and SVM is introduced. Moreover, in the feature extraction stage, Stockwell transform technique is used for stator current signals to retrieve features in time and frequency domains. Then, Fisher score ranking is employed to select high-ranking features. Importantly, in the classification and location of faults stages, SVM is used. Following this, comparing the results with another classifier is also applied. Notably, the efficiency achieved using ANN equalled 77.78% whereas the efficiency achieved using SVM classifier equalled 91.667%. In [181], a multi-FDD method for rolling element bearing employing orthogonal supervised linear local tangent space alignment (OSLLTSA) and least square SVM (LS-SVM) is proposed. Furthermore, vibration signals are analysed and crumbled using EMD. In addition, autoregressive (AR) coefficients and instantaneous amplitude Shannon entropy are applied to seek the statistical features for intrinsic mode functions (IMFs). After that, the OSLLTSA technique is applied for dimension minimization to obtain a low-dimensional fault features vector. Importantly, LS-SVM is employed using features vector as an input. Moreover, the LS-SVM components are selected based on enhanced particle swarm optimization (EPSO). As a result, in this study, LS-SVM based OSLLTSA technique gave good results for small sample size problem. In [182], prediction method for machine condition based on wavelet and SVM using vibration signals is proposed. In order to enhance the modeling process, wavelet transform along with SVM is applied. Moreover, SVM-WT degradation-prediction model is employed to reduce irregular characteristics and the complexity of the vibration signal. Importantly, to compare the results, the neural network (NN) approach is also employed. As a result of this research study, WT-SVM model showed the best results compared with the NN and single SVM models. In [183], an FDD approach for rolling element bearings involving the use of enhanced multiscale fuzzy entropy (IMFE), local mean decomposition (LMD), Laplacian score (LS), and improved SVM based binary tree (ISVM-BT) is proposed. Moreover, the local mean decomposition is applied to decompose the complicated vibration signal into a series of product functions (PFs). Particularly, the improved multiscale fuzzy entropy is used to assess the complexity and similarity of the signal. Importantly, the obtained feature is fed to the ISVM-BT classifier. Interestingly, IMFE-ISVM method showed a stable and high performance for analysis of samples of discrete and small time units in series. In [184], a hierarchical fuzzy entropy and binary tree SVM technique for FDD of rolling bearing are introduced. For instance, a hierarchical fuzzy entropy method is applied as a feature retrieval process. To get the fault feature vector by ordering the scale factors, the Laplacian score (LS) method can also be used. Importantly, the obtained feature vector is fed to an improved SVM based binary tree (ISVM-BT) classifier. The proposed ISVM-BT based on hierarchical fuzzy entropy approach showed a good performance for diagnosis of diverse conditions and severities of rolling element bearings.

3.3. Artificial Neural Network (ANN). Recently, artificial neural networks (ANN) [185, 186] have gained great attention in industrial applications [187, 188]. Moreover, NN is used as data processing and classification. Correspondingly, AI self-adaptive FDD system inspired from genetic algorithm (GA) and nearest neighbor (NN) is presented in [189]. Infrared thermography (IRT) is used to diagnose various conditions of roller element bearings. In feature extraction stage to find approximation coefficients, a 2-dimensional discrete wavelet transform (2D-DWT) along with Shannon entropy is used. Moreover, GA and nearest neighbor are applied to find the histograms of chosen coefficients to be fed as an input to the feature space selection method. Cost-effectiveness, noncontact, and nonintrusiveness are the main advantages of applying this method. Multilayer perceptron (MLP) [190] is a multiple layer fee-forward neural network which uses supervised learning. Authors in [125] present an FDD bearing fault identification approach based on ANN for IM. Moreover, in the proposed pattern identification approach, two current sensors are used. Thus, a multilayer perceptron (MLP) with one and two hidden layers is employed. As a result, two hidden layers of MLP are not suitable for bearing fault identification. Two hidden layers MLP showed comparatively low accuracy and indicate higher computational costs compared with one hidden layer MLP.

In [191], an intelligent online approach employing empirical mode decomposition and ANN based technique for automatic FDD of rolling bearings using vibration signals are proposed. Moreover, the feature retrieval method is based on EMD energy entropy. The most significant intrinsic mode functions (IMFs) are selected by applying a mathematical analysis. Then, the picked features are given an input to the ANN to classify bearings defects. Importantly, the proposed EMD-ANN approach could effectively detect the intensity of the bearing defect and assess the bearing performance degradation. Because of this, the proposed approach could be considered as an expert diagnosis and prognosis system. In [192], a fault discovery for roller bearings and gearboxes neural networks using multiple sensors and convolutional is introduced. The key contribution of this work is to achieve robust diagnosis accuracy by applying data fusion and CNN techniques. Moreover, features are extracted automatically without applying any manual feature extraction/selection processes. As a result, the CNN-data fusion technique showed posing superior diagnosis performance as compared with manual feature extraction techniques.

3.4. Combined ANN and SVM. In order to achieve high diagnostic performance, combined ANN and SVM CM and FDD techniques have been proposed [193]. In more details, according to [194], an FDD approach of rolling element bearings employing statistical feature extraction method using vibration signals is proposed. Here, statistical features are obtained using advanced signal processing tools and central limit theory. Importantly, the output feature vector (statistical feature vector) is fed as an input vector to a classifier which categorizes different types of faults by using ANN and SVM. As a result, in this study, the authors argued that ANN and SVM could not offer an analytical guarantee for the accuracy of FDD classifier. Furthermore, in [195], an FDD method of ball bearings using both ANN and SVM is introduced. Moreover, features of vibration signals are retrieved in time domain using statistical techniques. Following this, ANN and SVM are applied in the classification stage. The key findings of this work are that the accuracy of FDD classifiers based on SVM is comparatively higher than the ANN based classifiers in context of detection and prediction of faults in combined bearing components. In [196], an FDD of ball bearings using the vibration signal is proposed. Correspondingly, multiscale permutation entropy and wavelet based on ANN approach are introduced. Moreover, a multiscale permutation entropy method is applied to seek the best wavelet for a feature selection process. For the classification stage in this approach, two artificial intelligence techniques, ANN and SVM, are employed. As a result of this research study, both ANN and SVM, along with permutation entropy, give identical classification results.

3.5. Neuro-Fuzzy. Neuro-fuzzy is also used as an FDD technique [197]. Yet, in [198], an enhanced real-time FDD scheme for bearing CM based on a neuro-fuzzy (NF) classifier using vibration signals is proposed. Firstly, two signal processing techniques are implemented for the signals from both time and frequency domains, and the time domain includes wavelet-spectrum reference functions and kurtosis ratio reference functions. Secondly, an adaptive NF classifier is developed. Importantly, by considering the future states, the integrated NF based model showed the ability of enhancing diagnostic reliability.

3.6. Deep Neural Network. Recently, deep neural networks [199–203] are highly used in CM and FDD of rotating machinery. Consequently, in [204], a hierarchical diagnosis network (HDN) approach which uses deep learning (DL) technique for FDD of rolling element bearings and uses vibration signals is proposed. Furthermore, HDN is used to obtain deep belief networks (DBN) for the hierarchical layer discovery of the proposed method. Importantly, a two-layer HDN is employed as a two-level diagnosis using the wavelet packet energy feature. The faults are diagnosed at the first layer, while the intensity or severity of the faults is measured at the second layer of HDN. As a comparison process, backpropagation neuron networks (BPNNs) and SVM are both applied to validate the effectiveness of applying HDN-based technique. As a result, HDN shows a very promising result for fault location classification and fault severity identification. In [205], an improved deep fusion method is developed for FDD of IM using vibration data. Moreover, in order to improve and enhance the training of machine learning, a deep autoencoder is built with both contractive autoencoder (CAE) and denoising autoencoder (DAE). Then, locality-preserving projection (LPP) is employed to obtain the deep features vector and to enhance learning capabilities by adding a new layer of learning enhancements. Furthermore, for the training of smart fault detection and diagnosis, the deep fusion features are fed to the neural network-based classifier (softmax). Importantly, as a result of this approach, the proposed method showed more effectiveness and robustness compared with standard CNN. In [206], an innovative DL approach based on deep autoencoder feature learning is introduced as an FDD of rotating machinery using vibration signals. In this study, feature learning is enhanced using the loss function of deep autoencoder based on the maximum correntropy. After that, the artificial fish swarm algorithm is utilized to get the best optimization values of the deep autoencoder signal features. As a result, the authors summarized their conclusions by stating that the proposed method shows effectiveness and robustness compared with other learning methods. In [207], an FDD health state identification approach of rotating machinery components by means of a stacked denoising autoencoder (SDA) using vibration signals is proposed. Furthermore, SDA model is made of training and testing groups. Next, the transmitting rule of greedy training is used to build a deep hierarchical structure via layer-by-layer scenario. In order to obtain a better robustness and high-order characteristics, sparsity representation along with data destruction is employed. As a result, the SDA-based health state identification approach showed promising results, especially for signals with ambient noise and working condition fluctuations. Authors in [208] proposed a deep learning FDD approach using acoustic emission for rolling element bearing which is introduced. Moreover, a short-time Fourier transform (STFT) is used as a preprocessing stage. Then, a simple spectrum matrix is used for optimizing DL networks, large memory storage retrieval (LAMSTAR) neural network specifically. Key advantages of this approach are that it deals with different working conditions, solving the big data and manual feature extraction problems. In [209], a hierarchical adaptive deep convolution neural network approach evolving from an enhanced algorithm for bearing FDD and severity determination using vibration signals is proposed. Moreover, hierarchical learning rate-adaptive deep CNN (ADCNN) is applied to deal with big data and to use as a feature extraction method for diagnosable information from several mass samples. In addition, a two-layer ADCNN is developed; fault patterns are diagnosed from first layer, while second layer evaluates the fault size. The proposed automatic feature extraction model showed very accurate results compared with the benchmark methods used for fault diagnosis, such as traditional DCNNs. In [210], a deep-learning-based hybrid feature model for bearing FDD approach using vibration signals is proposed. Moreover, the proposed approach can deal with several working conditions, multiple faults, and fault severity. In order to achieve an effective and accurate diagnosis, multiple severities faults, a hybrid technique includes sparse stacked autoencoder (SAE) and deep neural networks (DNNs) are applied. The main advantage of applying this hybrid technique is the ability of extracting more diagnosable vibration information with multiple crack sizes. As a result, the proposed approach showed that it can produce better results in diagnosing bearing multiple severities defects than SVM and backpropagation neural networks (BPNNs). In [211], an FDD approach for gearbox and bearing systems based on deep statistical feature learning using vibration signal analysis is introduced. Furthermore, time domain analysis and frequency domain analysis as well as time-frequency domain analysis are applied to obtain features vector from vibration signals. As a deep statistical feature learning tool, Gaussian-Bernoulli and Boltzmann machines (GRBMs) methods are used to build a Gaussian-Bernoulli deep Boltzmann machine (GDBM). The proposed approach showed good classification performances (95.17% for the gearbox and 91.75% for the bearing system). Importantly, compared with SVM classifier, GRBM based on deep learning model showed ability of posing the best fault classification rate. In [212], an intelligent FDD of bearings and gearboxes based on deep neural networks tool with massive vibration data is introduced. Moreover, the proposed method is applied in different health conditions among different operating conditions. To overcome the deficiencies of the traditional shallow smart FDD methods (i.e., ANN), deep neural networks (DNNs) are employed to seek the useful diagnostic data from the vibration signals and to approximate complex nonlinear functions. Importantly, this work also highlights the superiority diagnosis accuracy method and comparative analysis with the traditional approaches. In [213], an FDD for rolling bearings approach based on improved convolutional deep belief network using a vibration signal is proposed. Moreover, to enhance the feature learning ability, convolutional deep belief network (CDBN) model is employed along with Gaussian visible units. Consequently, exponential moving average (EMA) technique is used to further elevate the performance of overall system. Importantly, the proposed CDBN based method is more robust and effective than the normal shallow methods.

In [214], a multimodal deep SVM classification (MDSVC) approach with homologous features FDD using vibration signals is introduced. In this approach, time and frequency, as well as wavelet modalities, are separated first. For each modality, to learn the patterns and different representations for different features, Gaussian-Bernoulli deep Boltzmann machine (GDBM) is used. Finally, an SVM classifier is also employed to combine GDBMs with different sensory system to obtain the improved version of MDSVC method. Importantly, compared with representative deep and traditional shallow learning methods, the suggested data aggregation with a DL-based method achieved the best classification rate. In [215], a feature learning model for CM and FDD of the bearing based on convolutional neural networks using vibration signals is proposed. Moreover, the end-to-end machine learning system is developed. Importantly, compared with a classical approach (i.e., random forest classifier), the overall accuracy is six times better than the classical approaches. In [216], a deep neural network FDD approach which uses vibration signals for analysis is presented for rolling bearing. Moreover, time domain, frequency domain, and time-frequency domain techniques are applied to obtain the feature vector. In this research study, three deep neural network models are employed as a fault condition monitoring of rolling bearing, including deep Boltzmann machines, deep belief networks, and stacked autoencoders. Importantly, the classification accuracy for those techniques is highly reliable (achieved more than 99%). In [217], deep learning enabled FDD approach using time-frequency image analysis of rolling element bearings is proposed. Moreover, deep neural network, image representation, and time-frequency (TF) analysis techniques are used together. The vibration data is mapped into time-frequency domain in order to draw relevant image representations. Short-time Fourier transform, wavelet transform, and Hilbert-Huang transforms are used as feature extraction methods. Importantly, a deep convolutional neural network (CNN) is applied in the classification stage. Furthermore, the proposed CNN architecture based approach showed high fault detection ability for noisy environments and with less learnable parameters. In [218], a new deep residual learning-based fault diagnosis method for the rolling bearing in rotating machinery using vibration signals is proposed. The main contribution of this research study is to improve the information flow throughout the deep neural network. Moreover, CNN is adopted in feature extraction and 1D convolutional layers are employed to obtain the feature vector. In addition, basic neural network, deep neural networks, stacked autoencoders, convolutional neural network, and deep convolutional neural networks are also employed for comparisons. As a result, the proposed approach could be effectively trained with a high classification accuracy. In [219], a new CNN based on the LeNet-5 FDD method is proposed for bearings using vibration signals. In this method, the vibration signal is decomposed into two-dimensional images; thus, the features are extracted from the converted image. As a result, the proposed method showed potentiality in the data-driven fault diagnosis field. However, the prediction accuracy was about 99 %.

Table 3 summarizes AI algorithms used in FDD of IM [193, 220–227].

Table 3: AI algorithms used in CM and FDD of IM.

The method	Highlights
Random forest	(i) The small number of training samples is required (ii) There is low computational cost (iii) There is good performance for high-dimensional data
Bayesian network	(i) There is high classification speed (ii) It is useful if the prior knowledge is reliable (iii) There is low storage need (iv) It is computationally expensive (v) There is prior beliefs' problem
KNN	(i) There is low classification speed (ii) It is simple and easy to apply (iii) There is poor performance for high-dimensional data (iii) It is memory-intensive (iv) It is noise sensitive (v) It is computationally expensive
SVM	(i) There is good performance for high-dimensional data (ii) There are low storage needs (iii) There is high classification speed (iv) It is not efficient for big data (v) It is noise sensitive (vi) It has good accuracy
ANN	(i) There is fault tolerance (ii) There is high classification speed (iii) There is parallelism (iv) There is hidden training problem (v) It is efficient for big data (vi) It is computationally expensive (vii) There is black box behavior problem
Neuro-fuzzy	(i) There is good performance for high-dimensional data (ii) It has good diagnosis accuracy (iii) There is robustness (iv) There is parallelism (v) It is efficient for big data (vi) There is black box behavior problem (vii) It has self-learning capability
DNN	(i) There is good classification speed (ii) There are automatic fault diagnosis and detection (iii) There is good accuracy (iv) There is parallelism (v) It has complex and deep architecture (vi) It is feature extraction free (vii) It is computationally expensive (viii) There are massive parallel computations (ix) It is efficient for big data (x) There is long time training problem (xi) A large number of training samples are required

As a result of this study, it can be showed that both DL and ML algorithms can be used as an intelligent diagnostic method of bearings for IM. Conventional ML algorithms manually extract the features, where DL algorithms learn the feature directly from input data. So, human expertise and prior knowledge are not required [228]. Table 4 shows a comparison between DL and ML algorithms for bearings CM and FDD. Importantly, for small datasets, conventional ML algorithms show better accuracy results than DL algorithms, whereas, for big datasets, DL algorithms show better accuracy results than conventional ML algorithms. According to [144], as a classification accuracy between SVM, KNN, and CNN, the classification accuracy was 81.96, 86.25, and 82.70, respectively, for small dataset, and 83.04, 87.85, and 89.26, respectively, for big dataset.

4. Challenges and Future Trends

Intelligent CM and FDD method is considered to be as a key factor of fault diagnosis development [43, 229]. However, this field still faces many challenges [35, 230, 231]. This section summarizes the challenges and the future trends of AI methods in CM and FDD of rolling element bearings for IM [232–235]:

(i) Dealing with all operating conditions, sensitivity to the noise, and working environment (indoor/outdoor) should be taken in a high consideration when CM and FDD method is built and developed.

(ii) Benefit from all strength points for each AI algorithm is crucial for building a hybrid intelligent, online, low cost, nonintrusive, and large scale CM and FDD for industrial machinery.

(iii) Developing highly accurate sensors with cost-effective, fast, wireless, and energy-efficient characteristics is highly required.

(iv) In order to increase diagnostic performance, knowledge-based intelligent systems should be further investigated.

(v) Automatic, online, continuous, and wireless diagnosis approach with better detection capabilities based on IoT, expert systems, and AI may be employed.

(vi) Compound faults and fault severity detection and diagnosis approaches should be explored.

(vii) CM and FDD of multimotor systems have to be proposed.

(viii) Integrated and comprehensive CM and FDD system to deal with all faults of IM and to determine the damage level and severity should be proposed.

(ix) Industrial Internet of things (IIoT) technologies a long with AI should be used to develop high performance CM and FDD methods.

(x) Big data problem is how to pick useful diagnostic information from big data obtained by different sensors quickly.

(xi) Data from different sensors should be used to develop an effective heterogeneous methodology.

(xii) In order to achieve high availability of IM and to reduce maintenance cost, fault-tolerant FDD and

Table 4: DL vs. ML for bearing CM and FDD.

The point	DL algorithms	Conventional ML algorithms
Feature extraction	Automated	Manual
Classification	Simultaneous feature learning and classification	Feature extraction and classification are separated
Human expertise	Not required	Required
Prior knowledge	Not required	Required
External noise	Better	Sensitive
Frequent change	Better	Sensitive
Diagnostic accuracy	High accuracy	Lesser accuracy
Dataset	Efficient for big data	Efficient for small datasets
Computational training cost	Expensive	Lesser computational training cost is required
Hardware requirements	GPU is required	CPU is efficient

prognostic techniques have to be further investigated.

5. Conclusions

Importantly, enhancing the reliability, availability, and safety to reduce maintenance cost of modern industrial systems and applications is crucial. Thus, following up the health of the machinery such as induction motor (IM) is vital. The bearing is a critical component in IM. Therefore, robust and intelligent condition monitoring (CM) and fault detection and diagnosis (FDD) methods are highly needed to enhance detection, diagnosis, monitoring, and prognosis capabilities. In this paper, a general descriptive review of intelligent diagnostics methods of rolling element bearings for IM is presented. The advantages and limitations of each method are highlighted. Finally, challenges and future trends are also discussed.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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