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

Omar AlShorman,1 Muhammad Irfan,2 Nordin Saad,3 D. Zhen,4 Noman Haider,5 Adam Glowacz,6 and Ahmad AlShorman7

1Faculty of Engineering and AlShrouk Trading Company, Najran University, Najran, Saudi Arabia
2College of Engineering, Electrical Engineering Department, Najran University, Najran, Saudi Arabia
3Department of Electrical and Electronics Engineering, Universiti Teknologi PETRONAS, 32610 Seri Iskandar, Perak, Malaysia
4Hebei University of Technology, Tianjin, China
5College of Engineering and Science, Victoria University, Sydney, Australia
6Department of Automatic Control and Robotics, AGH University of Science and Technology, 30-059 Kraków, Poland
7Mechanical Engineering Department, Jordan University of Science and Technology, Irbid, Jordan

Correspondence should be addressed to Omar AlShorman; omar2007_ahu@yahoo.com

Received 27 July 2020; Revised 13 October 2020; Accepted 22 October 2020; Published 4 November 2020

Academic Editor: Yongfang Zhang

Copyright © 2020 Omar AlShorman et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

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 main 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
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
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
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.

### 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  
(iv) Expensive  
(v) Applicable for big size machines                                     | (i) Mechanical faults                                                      |
| Chemical and oil analysis      | (i) Fault estimation and location capabilities  
(ii) High performance for bearing FDD  
(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 |
| Sound and acoustic emission analysis | (i) Inexpensive  
(ii) Nonintrusive                                                    | (i) Sensitive to the noise  
(ii) Expensive sensor is required  
(iii) Intrusive                                                              | (i) Mechanical faults                                                      |
| Current, voltage, and electromagnetic field analysis | (i) Effective in low speed bearings  
(ii) It deals with low and middle frequency ranges  
(iii) High signal to noise ratio                                              | (i) Sensitive to the noise  
(ii) It cannot be used as early FDD                                         | (i) Mechanical and electrical faults                                    |
| Ultrasound analysis            |                                                                          | (i) Expensive sensor is required  
(ii) Intrusive                                                               | (i) Mechanical and electrical faults                                    |

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
| 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% (i) It diagnoses multiple faults (ii) There is electrical and mechanical faults' prediction (iii) There are different operational conditions |
| [150]     | Vibration and current | Statistical features analysis | SVM and multiclass SVM | (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) It learns multiple layers of representation and models high-dimensional data (ii) 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 prevents training process overfitting (ii) There are different operational conditions (iii) The average accuracy is 97.61% |
| [156]     | Infrared thermal (IRT) images | Deep learning | Convolutional neural networks | (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) |
| [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) |
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

| 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) 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 intracllass adaptation network | Multiple scale feature learner | (i) Bearing FDD is based on multiscale deep intracllass 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% |
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 highly 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 non-intrusiveness 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 convolutional 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 [201], 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 (GRBM) methods are used to build a Gaussian-Bernoulli deep Boltzmann machine (DBM). 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].
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 along 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
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.

References

[1] A. González-Muñiz, I. Díaz, and A. A. Cuadrado, “DCNN for condition monitoring and fault detection in rotating machines and its contribution to the understanding of machine nature,” Heliyon, vol. 6, no. 2, Article ID e03395, 2020.

[2] A. Choudhary, S. Jamwal, D. Goyal, R. K. Dang, and S. Shegal, “Condition monitoring of induction motor using internet of things (IoT),” in Recent Advances in Mechanical Engineering, pp. 353–365, Springer, Berlin, Germany, 2020.

[3] G. Yu, T. Lin, Z. Wang, and Y. Li, “Time-reassigned multisynchrosqueezing transform for bearing fault diagnosis of rotating machinery,” IEEE Transactions on Industrial Electronics, p. 1, 2020.

[4] Y. Chen, G. Peng, Z. Zhu, and S. Li, “A novel deep learning method based on attention mechanism for bearing remaining useful life prediction,” Applied Soft Computing, vol. 86, Article ID 105919, 2020.

[5] X. Chen, S. Wang, B. Qiao, and Q. Chen, “Basic research on machinery fault diagnostics: Past, present, and future trends,” Frontiers of Mechanical Engineering, vol. 13, no. 2, pp. 264–291, 2018.

[6] M. S. Kan, A. C. C. Tan, and J. Mathew, “A review on prognostic techniques for non-stationary and non-linear rotating systems,” Mechanical Systems and Signal Processing, vol. 62–63, pp. 1–20, 2015.

[7] L. Song, H. Wang, and P. Chen, “Intelligent diagnosis method for machinery by sequential auto-reorganization of histogram,” ISA Transactions, vol. 87, pp. 154–162, 2019.

[8] C. Lu, Y. Wang, M. Ragulskis, and Y. Cheng, “Fault diagnosis for rotating machinery: a method based on image processing,” PLoS One, vol. 11, no. 10, Article ID e0164111, 2016.

[9] C. Peeters, J. Antoni, and J. Helsen, “Blind filters based on envelope spectrum sparsity indicators for bearing and gear vibration-based condition monitoring,” Mechanical Systems and Signal Processing, vol. 138, Article ID 106556, 2020.

[10] W. Qian, S. Li, P. Yi, and K. Zhang, “A novel transfer learning method for robust fault diagnosis of rotating machines under variable working conditions,” Measurement, vol. 138, pp. 514–525, 2019.

[11] B. Wang, Y. Lei, T. Yan, N. Li, and L. Guo, “Recurrent convolutional neural network: a new framework for remaining useful life prediction of machinery,” Neurocomputing, vol. 379, pp. 117–129, 2020.

[12] D. Verstraete, E. Droguett, and M. Modarres, “A deep adversarial approach based on multi-sensor fusion for semi-supervised remaining useful life prognostics,” Sensors, vol. 20, no. 1, p. 176, 2020.

[13] E. Luguhofer and M. Sayed-Mouchaweh, “Prologue: Predictive maintenance in dynamic systems,” in Predictive Maintenance in Dynamic Systems, pp. 1–23, Springer, Berlin, Germany, 2019.

[14] Y. Zheng, "Predicting remaining useful life based on Hilbert–Huang entropy with degradation model," Journal of Electrical and Computer Engineering, vol. 2019, pp. 1–11, Article ID 3203959, 2019.

[15] X. Yan, Y. Liu, and M. Jia, “Multiscale cascading deep belief network for fault identification of rotating machinery under various working conditions,” Knowledge-Based Systems, vol. 193, Article ID 105484, 2020.

[16] J. Liu, Z. Xu, L. Zhou, W. Yu, and Y. Shao, “A statistical feature investigation of the spalling propagation assessment for a ball bearing,” Mechanism and Machine Theory, vol. 131, pp. 336–350, 2019.
[17] V. T. Tran and B.-S. Yang, “An intelligent condition-based maintenance platform for rotating machinery,” Expert Systems with Applications, vol. 39, no. 3, pp. 2977–2988, 2012.

[18] M. Irfan, R. I. Nordin Saad, V. S. Asirvadam, A. Alwadie, and M. Aman, “An assessment on the non-invasive methods for condition monitoring of induction motors,” Fault Diagnosis and Detection, p. 87, 2017.

[19] C. Huang, L. D. Xu, H. Cai, G. Li, J. Du, and L. Jiang, “A context-based service matching approach towards functional reliability for industrial systems,” Enterprise Information Systems, vol. 13, no. 2, pp. 196–218, 2019.

[20] I. Mistry, S. Tanwar, S. Tyagi, and N. Kumar, “Blockchain for 5G-enabled IoT for industrial automation: A systematic review, solutions, and challenges,” Mechanical Systems and Signal Processing, vol. 135, Article ID 106382, 2020.

[21] C. P. Gatica and M. Platzner, “Adaptable realization of industrial analytics functions on edge-devices using reconfigurable architectures,” in Machine Learning for Cyber Physical Systems, pp. 73–80, Springer, Berlin, Germany, 2020.

[22] J. L. Contreras-Hernandez, D. L. Almanza-Ojeda, S. Ledesma et al., “Quaternion signal analysis algorithm for induction motor fault detection,” IEEE Transactions on Industrial Electronics, vol. 66, no. 11, pp. 8843–8850, 2019.

[23] G. Lian, J. Zhang, B. Chen, F. Ban, Z. Hou, and H. Li, “Design and experimental study of the wireless online monitoring system of a high-temperature superconducting machine,” IEEE Transactions on Applied Superconductivity, vol. 29, no. 2, pp. 1–5, 2019.

[24] S. Muthanandan and K. A. B. Nor, “Condition monitoring and assessment for rotating machinery,” in Rotating Machines, pp. 1–22, Springer, Berlin, Germany, 2019.

[25] A. Glowacz, “Fault diagnosis of single-phase induction motor based on acoustic signals,” Mechanical Systems and Signal Processing, vol. 117, pp. 65–80, 2019.

[26] M. González, O. Salgado, X. Hernandez, J. Croes, B. Plymers, and W. Desmet, “Model-based condition monitoring of guiding rails in electro-mechanical systems,” Mechanical Systems and Signal Processing, vol. 120, pp. 630–641, 2019.

[27] M. Khazaei, A. Rezaniakolaie, A. Moosavian, and L. Rosendahl, “A novel method for autonomous remote condition monitoring of rotating machines using piezoelectric energy harvesting approach,” Sensors and Actuators A: Physical, vol. 295, pp. 37–50, 2019.

[28] D. Crivelli, S. Hutt, A. Clarke, P. Borghesani, Z. Peng, and R. Randall, “Condition monitoring of rotating machinery with acoustic emission: A British–Australian collaboration,” in Asset Intelligence through Integration and Interoperability and Contemporary Vibration Engineering Technologies, pp. 119–128, Springer, Berlin, Germany, 2019.

[29] T. Wang, G. Li, and P. Yan, “Multi-sensors based condition monitoring of rotary machines: An approach of multidimensional time-series analysis,” Measurement, vol. 134, pp. 326–335, 2019.

[30] V. Atamurodov, K. Medjaher, F. Camci, N. Zerhouni, P. Dersin, and B. Lamoureux, “Machine health indicator construction framework for failure diagnostics and prognostics,” Journal of Signal Processing Systems, vol. 92, no. 6, pp. 591–609, 2020.

[31] Y. Wang, Z. Wei, and J. Yang, “Feature trend extraction and adaptive density peaks search for intelligent fault diagnosis of machines,” IEEE Transactions on Industrial Informatics, vol. 15, no. 1, pp. 105–115, 2019.

[32] B. Luo, H. Wang, H. Liu, B. Li, and F. Peng, “Early fault detection of machine tools based on deep learning and dynamic identification,” IEEE Transactions on Industrial Electronics, vol. 66, no. 1, pp. 509–518, 2019.

[33] G. Jiang, H. He, J. Yan, and P. Xie, “Multiscale convolutional neural networks for fault diagnosis of wind turbine gearbox,” IEEE Transactions on Industrial Electronics, vol. 66, no. 4, pp. 3196–3207, 2019.

[34] H. Wang and P. Chen, “Intelligent diagnosis method for rolling element bearing faults using possibility theory and neural network,” Computers & Industrial Engineering, vol. 60, no. 4, pp. 511–518, 2011.

[35] Y. Liu and A. M. Bazzi, “A review and comparison of fault detection and diagnosis methods for squirrel-cage induction motors: State of the art,” ISA Transactions, vol. 70, pp. 400–409, 2017.

[36] G.-Q. Jiang, P. Xie, X. Wang, M. Chen, and Q. He, “Intelligent fault diagnosis of rotary machinery based on unsupervised multiscale representation learning,” Chinese Journal of Mechanical Engineering, vol. 30, no. 6, pp. 1314–1324, 2017.

[37] Z. Gao, C. Cecati, and S. X. Ding, “A survey of fault diagnosis and fault-tolerant techniques-Part I: fault Diagnosis with model-based and signal-based approaches,” IEEE Transactions on Industrial Electronics, vol. 62, no. 6, pp. 3757–3767, 2015.

[38] Z. Feng, M. Liang, and F. Chu, “Recent advances in time-frequency analysis methods for machinery fault diagnosis: A review with application examples,” Mechanical Systems and Signal Processing, vol. 38, no. 1, pp. 165–205, 2013.

[39] A. Taheri-Garavand, H. Ahmadi, M. Omid et al., “An intelligent approach for cooling radiator fault diagnosis based on infrared thermal image processing technique,” Applied Thermal Engineering, vol. 87, pp. 434–443, 2015.

[40] B. Peng, H. Xia, X. Ma, S. Zhu, Z. Wang, and J. Zhang, “A mixed intelligent condition monitoring method for nuclear power plant,” Annals of Nuclear Energy, vol. 140, Article ID 107307, 2020.

[41] C. Wu, P. Jiang, C. Ding, F. Feng, and T. Chen, “Intelligent fault diagnosis of rotating machinery based on one-dimensional convolutional neural network,” Computers in Industry, vol. 108, pp. 53–61, 2019.

[42] Y. Merzalde, L. Hernández-Callejo, and O. Duque-Perez, “State of the art and trends in the monitoring, detection and diagnosis of failures in electric induction motors,” Energies, vol. 10, no. 7, p. 1565, 2017.

[43] A. Choudhary, D. Goyal, S. L. Shimi, and A. Akula, “Condition monitoring and fault diagnosis of induction motors: A review,” Archives of Computational Methods in Engineering, vol. 26, no. 4, pp. 1221–1238, 2018.

[44] S. Nandi, H. A. Toliyat, and X. Li, “Condition monitoring and fault diagnosis of electrical motors-A review,” IEEE Transactions on Energy Conversion, vol. 20, no. 4, pp. 719–729, 2005.

[45] Y. Trachi, E. Elbouchikhi, V. Choqueuse, and M. E. H. Benbouzid, “Induction machines fault detection based on subspace spectral estimation,” IEEE Transactions on Industrial Electronics, vol. 63, no. 9, pp. 5641–5651, 2016.

[46] M. Seera, C. P. Lim, D. Ishak, and H. Singh, “Application of the fuzzy min-max neural network to fault detection and diagnosis of induction motors,” IEEE Transactions on Industrial Electronics, vol. 60, no. 4, pp. 191–200, 2012.

[47] A. Widodo, B.-S. Yang, D.-S. Gu, and B.-K. Choi, “Intelligent fault diagnosis system of induction motor based on transient
current signal,” *Mechatronics*, vol. 19, no. 5, pp. 680–689, 2009.

[48] B. V. Gopal and E. Shivakumar, “Design and simulation of neuro-fuzzy controller for indirect vector-controlled induction motor drive,” in *Data Analytics and Learning*, pp. 155–167, Springer, Berlin, Germany, 2019.

[49] N. Rajeswaran, M. Lakshmi Swarupa, T. Sanjeeva Rao, and K. Chetasw, “Hybrid artificial intelligence based fault diagnosis of svc pwm voltage source inverters for induction motor,” *Materials Today: Proceedings*, vol. 5, no. 1, pp. 565–571, 2018.

[50] P. Majumdar, P. Mishra, S. Sarkar, and S. Das, “State-space model based induction motor stator winding inter-turn fault detection technique,” in *Advances in Computer, Communication and Control*, pp. 225–236, Springer, Berlin, Germany, 2019.

[51] P. Donolo, C. Pezzani, G. Bossio, C. De Angelo, and M. Donolo, “Derating of induction motors due to power quality issues considering the motor efficiency class,” *IEEE Transactions on Industry Applications*, vol. 56, 2020.

[52] A. Glowacz and Z. Glowacz, “Diagnosis of the three-phase induction motor using thermal imaging,” *Infrared Physics & Technology*, vol. 81, pp. 7–16, 2017.

[53] A. A. Z. Diab, A.-H. M. Al-Sayed, H. H. A. Mohammed, and Y. S. Mohammed, “Literature review of induction motor drives,” in *Development of Adaptive Speed Observers for Induction Machine System Stabilization*, pp. 7–18, Springer, Berlin, Germany, 2020.

[54] M. M. Stopa, M. R. Resende, A.-S. A. Luiz, J. C. G. Justino, G. G. Rodrigues, and B. J. Cardoso Filho, “A simple torque estimator for in-service efficiency determination of inverter fed induction motors,” *IEEE Transactions on Industry Applications*, vol. 56, 2020.

[55] G. Cirrincione, V. Randazzo, R. R. Kumar, M. Cirrincione, and E. Pasero, “Growing Curvilinear Component Analysis (GCCA) for stator fault detection in induction machines,” in *Neural Approaches to Dynamics of Signal Exchanges*, pp. 235–244, Springer, Berlin, Germany, 2020.

[56] M. J. Akhtar and R. K. Behera, “Space vector modulation for distributed inverter fed induction motor drive for electric vehicle application,” *IEEE Journal of Emerging and Selected Topics in Power Electronics*, p. 1, 2020.

[57] M. Stopa, C. Lima, B. Cardoso, L. de Miranda, A.-S. Luiz, and C. Martinez, “Detection of gaseous nuclei in centrifugal motor pumps by analysis of their estimated torque,” *IEEE Transactions on Industry Applications*, 2020.

[58] S. K. Gundewar and P. V. Kane, “Fuzzy FMEA analysis of induction motor and overview of diagnostic techniques to reduce risk of failure,” in *Reliability, Safety and Hazard Assessment for Risk-Based Technologies*, pp. 927–939, Springer, Berlin, Germany, 2020.

[59] S. Perumandla, P. Upadhyay, A. Jayalaxmi, and J. P. Nasam, “Modulated frequency triangular carrier based space vector PWM technique for spreading induction motor acoustic noise spectrum,” in *Proceedings of the Advances in Decision Sciences, Image Processing, Security and Computer Vision*, pp. 470–480, Allahabad, Uttar Pradesh, August 2020.

[60] J. K. Jain, S. Ghosh, and S. Maity, “Concurrent PI controller design for indirect vector controlled induction motor,” *Asian Journal of Control*, vol. 22, no. 1, pp. 130–142, 2020.

[61] W. F. Godoy, I. N. da Silva, T. D. Lopes, A. Goedtel, and R. H. C. Palacios, “Application of intelligent tools to detect and classify broken rotor bars in three-phase induction motors fed by an inverter,” *IET Electric Power Applications*, vol. 10, no. 5, pp. 430–439, 2016.

[62] A. Glowacz, W. Glowacz, J. Kozik et al., “Detection of deterioration of three-phase induction motor using vibration signals,” *Measurement Science Review*, vol. 19, no. 6, pp. 241–249, 2019.

[63] S. B. Jiang, P. K. Wong, R. Guan, Y. Liang, and J. Li, “An efficient fault diagnostic method for three-phase induction motors based on incremental broad learning and non-negative matrix factorization,” *IEEE Access*, vol. 7, pp. 17780–17790, 2019.

[64] M. Al-Badri, P. Pillay, and P. Angers, “A novel in situ efficiency estimation algorithm for three-phase induction motors operating with distorted unbalanced voltages,” *IEEE Transactions on Industry Applications*, vol. 53, no. 6, pp. 5338–5347, 2017.

[65] K. S. Gaeid and H. W. Ping, “Wavelet fault diagnosis and tolerant of induction motor: A review,” *International Journal of the Physical Sciences*, vol. 6, no. 3, pp. 358–376, 2011.

[66] J. Liu, “A dynamic modelling method of a rotor-roller bearing-housing system with a localized fault including the additional excitation zone,” *Journal of Sound and Vibration*, vol. 469, Article ID 115144, 2020.

[67] J. Ma, J. Wu, Y. Fan, and X. Wang, “The rolling bearing fault feature extraction based on the LMD and envelope demodulation,” *Mathematical Problems in Engineering*, vol. 2015, pp. 1–13, Article ID 429185, 2015.

[68] F. Xu, Z. Huang, F. Yang, D. Wang, and K. L. Tsui, “Constructing a health indicator for roller bearings by using a stacked auto-encoder with an exponential function to eliminate concussion,” *Applied Soft Computing*, vol. 89, Article ID 106119, 2020.

[69] Y. Ying, J. Li, Z. Chen, and J. Guo, “Study on rolling bearing on-line reliability analysis based on vibration information processing,” *Computers & Electrical Engineering*, vol. 69, pp. 842–851, 2018.

[70] L. Frossini and E. Bassi, “Stator current and motor efficiency as indicators for different types of bearing faults in induction motors,” *IEEE Transactions on Industrial Electronics*, vol. 57, no. 1, pp. 244–251, 2009.

[71] L. Ciabattoni, F. Ferracuti, A. Freddi, and A. Monteriu, “Statistical spectral analysis for fault diagnosis of rotating machines,” *IEEE Transactions on Industrial Electronics*, vol. 65, no. 5, pp. 4301–4310, 2017.

[72] A. Sharma, M. Amarnath, and P. Kankar, “Feature extraction and fault severity classification in ball bearings,” *Journal of Vibration and Control*, vol. 22, no. 1, pp. 176–192, 2016.

[73] A. K. Choudhary and D. A. Khan, “Introduction to conditioning monitoring of mechanical systems,” in *Soft Computing in Condition Monitoring and Diagnostics of Electrical and Mechanical Systems*, pp. 205–230, Springer, Berlin, Germany, 2020.

[74] M. Cerrada, R.-V. Sánchez, C. Li et al., “A review on data-driven fault severity assessment in rolling bearings,” *Mechanical Systems and Signal Processing*, vol. 99, pp. 169–196, 2018.

[75] Y. Zhang, X. Li, L. Gao, W. Chen, and P. Li, “Intelligent fault diagnosis of rotating machinery using a new ensemble deep auto-encoder method,” *Measurement*, vol. 151, Article ID 107323, 2020.

[76] X. Zhao, M. Jia, and M. Lin, “Deep Laplacian Auto-encoder and its application into imbalanced fault diagnosis of rotating machinery,” *Measurement*, vol. 152, Article ID 107320, 2020.
Shock and Vibration

[77] P. J. Tavner, "Review of condition monitoring of rotating electrical machines," *IET Electric Power Applications*, vol. 2, no. 4, pp. 215–247, 2008.

[78] S. A. McNerny and Y. Dai, "Basic vibration signal processing for bearing fault detection," *IEEE Transactions on Education*, vol. 46, no. 1, pp. 149–156, 2003.

[79] M. E. H. Benbouzid, H. Nejjar, R. Bequenane, and M. Vieira, "Induction motor asymmetrical faults detection using advanced signal processing techniques," *IEEE Transactions on Energy Conversion*, vol. 14, no. 2, pp. 147–152, 1999.

[80] S. Dutta, S. K. Pal, S. Mukhopadhyay, and R. Sen, "Application of digital image processing in tool condition monitoring: A review," *CIRP Journal of Manufacturing Science and Technology*, vol. 6, no. 3, pp. 212–232, 2013.

[81] Y. S. Wong, A. Y. C. Nee, X. Q. Li, and C. Reisdorf, "Tool condition monitoring using laser scatter pattern," *Journal of Materials Processing Technology*, vol. 63, no. 1–3, pp. 205–210, 1997.

[82] M. Castejón, E. Alegre, J. Barreiro, and L. K. Hernández, "On-line tool wear monitoring using geometric descriptors from digital images," *International Journal of Machine Tools and Manufacture*, vol. 47, no. 12-13, pp. 1847–1853, 2007.

[83] A. K. Al-Musawi, F. Anayi, and M. Pachianã, "Three-phase induction motor fault detection based on thermal image segmentation," *Infrared Physics & Technology*, vol. 104, Article ID 103140, 2020.

[84] B.-S. Yang, T. Han, and W.-W. Hwang, "Fault diagnosis of rotating machinery based on multi-class support vector machines," *Journal of Mechanical Science and Technology*, vol. 19, no. 3, pp. 846–859, 2005.

[85] Y. D. Nyanteh, S. K. Srivastava, C. S. Edrington, and D. A. Cartes, "Application of artificial intelligence to stator winding fault diagnosis in permanent magnet synchronous machines," *Electric Power Systems Research*, vol. 103, pp. 201–213, 2013.

[86] L.-I. Jiang, H.-K. Yin, X.-J. Li, and S.-W. Tang, "Fault diagnosis of rotating machinery based on multisensor fusion using SVM and time-domain features," *Shock and Vibration*, vol. 2014, pp. 1–8, Article ID 418178, 2014.

[87] E. Ayaz, A. Öztürk, S. Şeker, and B. R. Upadhyaya, "Fault detection based on continuous wavelet transform and sensor fusion in electric motors," *COMPEL - The International Journal for Computation and Mathematics in Electrical and Electronic Engineering*, vol. 28, no. 2, pp. 454–470, 2009.

[88] X. Liu, L. Ma, and J. Mathew, "Machinery fault diagnosis based on fuzzy measure and fuzzy integral data fusion techniques," *Mechanical Systems and Signal Processing*, vol. 23, no. 3, pp. 690–700, 2009.

[89] G. Niu, T. Han, B.-S. Yang, and A. C. C. Tan, "Multi-agent decision fusion for motor fault diagnosis," *Mechanical Systems and Signal Processing*, vol. 21, no. 3, pp. 1285–1299, 2007.

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

[91] B. Bagheri, H. Ahmadi, and R. Labbafi, "Application of data mining and feature extraction on intelligent fault diagnosis by artificial neural network and k-nearest neighbor," in *Proceedings of the Electrical Machines (ICEM), 2010 XIX International Conference*, pp. 1–7, Rome, Italy, September 2010.

[92] A. Purarjomandlangojirudi, A. H. Ghapanchi, and M. Esmali-falak, "A data mining approach for fault diagnosis: an application of anomaly detection algorithm," *Measurement*, vol. 55, pp. 343–352, 2014.

[93] J. Blair and A. Shirhodaie, "Diagnosis and prognosis of bearings using data mining and numerical visualization techniques in system theory," in *Proceedings of the 33rd Southeastern Symposium*, pp. 395–399, Ohio University, Athens, OH, USA, 2001.

[94] D. He, R. Ruoyu Li, J. Jun-da Zhu, and M. Zade, "Data mining based full ceramic bearing fault diagnostic system using AE sensors," *IEEE Transactions on Neural Networks*, vol. 22, no. 12, pp. 2022–2031, 2011.

[95] D. He, R. Li, and J. Zhu, "Plastic bearing fault diagnosis based on a two-step data mining approach," *IEEE Transactions on Industrial Electronics*, vol. 60, no. 8, pp. 3429–3440, 2013.

[96] A. Verma, Z. Zhang, and A. Kusiak, "Modeling and prediction of gearbox faults with data-mining algorithms," *Journal of Solar Energy Engineering*, vol. 135, no. 3, Article ID 031007, 2013.

[97] B. Yang, D. Lim, and A. Tan, "VIBEX: An expert system for vibration fault diagnosis of rotating machinery using decision tree and decision table," *Expert Systems with Applications*, vol. 28, no. 4, pp. 735–742, 2005.

[98] J.-D. Wu, M. R. Bai, F.-C. Su, and C.-W. Huang, "An expert system for the diagnosis of faults in rotating machinery using adaptive order-tracking algorithm," *Expert Systems with Applications*, vol. 36, no. 3, pp. 5424–5431, 2009.

[99] T. Berredjem and M. Benidir, "Bearing faults diagnosis using fuzzy expert system relying on an Improved Range Overlaps and Similarity method," *Expert Systems with Applications*, vol. 108, pp. 134–142, 2018.

[100] J. Liu and Y. Shao, "Overview of dynamic modelling and analysis of rolling element bearings with localized and distributed faults," *Nonlinear Dynamics*, vol. 93, no. 4, pp. 1765–1798, 2018.

[101] J. Liu and Y. Shao, "Dynamic modeling for rigid rotor bearing systems with a localized defect considering additional deformations at the sharp edges," *Journal of Sound and Vibration*, vol. 398, pp. 84–102, 2017.

[102] D. D. Reigosa, J. M. Guerrero, A. B. Diez, and F. Briz, "Rotor temperature estimation in doubly-fed induction machines using rotating high-frequency signal injection," *IEEE Transactions on Industry Applications*, vol. 53, no. 4, pp. 3652–3662, 2017.

[103] A. Mohammed and S. Djurovic, "Stator winding internal thermal monitoring and analysis using in situ FBG sensing technology," *IEEE Transactions on Energy Conversion*, vol. 33, no. 3, pp. 1508–1518, 2018.

[104] Z. Zhao, F. Ji, Y. Guan, J. Xu, and X. Yuan, "Method and experiment of temperature collaborative monitoring based on characteristic points for tilting pad bearings," *Tribology International*, vol. 114, pp. 77–83, 2017.

[105] L. B. Visnadi and H. F. de Castro, "Influence of bearing clearance and oil temperature uncertainties on the stability threshold of cylindrical journal bearings," *Mechanism and Machine Theory*, vol. 134, pp. 57–73, 2019.

[106] S. Bagavathiappan, B. B. Lahiri, T. Saravanan, J. Philip, and T. Jayakumar, "Infrared thermography for condition monitoring - A review," *Infrared Physics & Technology*, vol. 60, pp. 35–55, 2013.

[107] J. Liu, Y. Shao, and T. C. Lim, "Vibration analysis of ball bearings with a localized defect applying piecewise response
function,” *Mechanism and Machine Theory*, vol. 56, pp. 156–169, 2012.

[108] T. Y. Wu and Y. L. Chung, “Misalignment diagnosis of rotating machinery through vibration analysis via the hybrid EEMD and EMD approach,” *Smart Materials and Structures*, vol. 18, no. 9, Article ID 095004, 2009.

[109] H. Y. Jiang and P. Chen, “Analysis and sensitivity evaluation of AE signals and vibration signals for fault diagnosis of low-speed rotating machinery,” *Applied Mechanics and Materials*, vol. 128–129, pp. 79–84, 2011.

[110] T. H. Loutas, D. Roulias, E. Pauly, and V. Kostopoulos, “The combined use of vibration, acoustic emission and oil debris on-line monitoring towards a more effective condition monitoring of rotating machinery,” *Mechanical Systems and Signal Processing*, vol. 25, no. 4, pp. 1339–1352, 2011.

[111] A. Medoued, M. Mordjaoui, Y. Soufî, and D. Sayad, “Induction machine bearing fault diagnosis based on the axial vibration analytic signal,” *International Journal of Hydrogen Energy*, vol. 41, no. 29, pp. 12688–12695, 2016.

[112] J. K. Sinha and K. Elbhbah, “A future possibility of vibration based condition monitoring of rotating machines,” *Mechanical Systems and Signal Processing*, vol. 34, no. 1-2, pp. 231–240, 2013.

[113] G. K. Chaturved and D. W. Thomas, “Adaptive noise cancelling and condition monitoring,” *Journal of Sound and Vibration*, vol. 76, no. 3, pp. 391–405, 1981.

[114] T. Wang, M. Liang, J. Li, W. Cheng, and C. Li, “Bearing fault diagnosis under unknown variable speed via gear noise cancellation and rotational order sideband identification,” *Mechanical Systems and Signal Processing*, vol. 62-63, pp. 30–53, 2015.

[115] B. Lu and V. C. Gungor, “Online and remote motor energy monitoring and fault diagnostics using wireless sensor networks,” *IEEE Transactions on Industrial Electronics*, vol. 56, no. 11, pp. 4651–4659, 2009.

[116] S. Cheng, K. Tom, L. Thomas, and M. Pecht, “A wireless sensor system for prognostics and health management,” *IEEE Sensors Journal*, vol. 10, no. 4, pp. 856–862, 2010.

[117] J. Timperley, “Incipient fault identification through neutral RF monitoring of large rotating machines,” *IEEE Transactions on Power Apparatus and Systems*, vol. 102, no. 3, pp. 693–698, 1983.

[118] J. Henson and C. Restrepo, “Devices, systems, and methods for adaptive RF sensing in arc fault detection,” Google Patents, 2008.

[119] A. Agoston, C. Schneidhofer, N. Dörre, and B. Jakoby, “A concept of an infrared sensor system for oil condition monitoring,” *e i Elektrotechnik und Informationstechnik*, vol. 125, no. 3, pp. 71–75, 2008.

[120] A. R. Caneca, M. F. Pimentel, R. K. H. Galvão et al., “Assessment of infrared spectroscopy and multivariate techniques for monitoring the service condition of diesel-engine lubricating oils,” *Talanta*, vol. 70, no. 2, pp. 344–352, 2006.

[121] M. S. Jadin and S. Taib, “Recent progress in diagnosing the reliability of electrical equipment by using infrared thermography,” *Infrared Physics & Technology*, vol. 55, no. 4, pp. 236–245, 2012.

[122] S. Bagavathiapan, T. Saravanan, N. P. George, J. Philip, T. Jayakumar, and B. Raj, “Condition monitoring of exhaust system blowers using infrared thermography,” *Insight - Nondestructive Testing and Condition Monitoring*, vol. 50, no. 9, pp. 512–515, 2008.

[123] N. Utami, Y. Tamsir, A. Pharmatsisanti, H. Gumilang, B. Calhyono, and R. Siregar, “Evaluation condition of transformer based on infrared thermography results,” in *Proceedings of the IEEE 9th International Conference*, pp. 1055–1058, China, 2009.

[124] A. S. N. Huda and S. Taib, “Suitable features selection for monitoring thermal condition of electrical equipment using infrared thermography,” *Infrared Physics & Technology*, vol. 61, pp. 184–191, 2013.

[125] T. D. Lopes, A. Goedtel, R. H. C. Palácios, W. F. Godoy, and R. M. de Souza, “Bearing fault identification of three-phase induction motors bases on two current sensor strategy,” *Soft Computing*, vol. 21, no. 22, pp. 6673–6685, 2016.

[126] D. Dhalio, M. E. H. Benbouzid, D. Hamad, and X. Pierre, “Fault detection and diagnosis in an induction machine drive: a pattern recognition approach based on concordia stator mean current vector,” *IEEE Transactions on Energy Conversion*, vol. 20, no. 3, pp. 512–519, 2005.

[127] N. M. Roscoe and M. D. Judd, “Harvesting energy from magnetic fields to power condition monitoring sensors,” *IEEE Sensors Journal*, vol. 13, no. 6, pp. 2263–2270, 2013.

[128] S. Pöyhönen, M. Negrea, P. Jover, A. Arkkio, and H. Hyötyniemi, “Numerical magnetic field analysis and signal processing for fault diagnostics of electrical machines,” *COMPEL - The International Journal for Computation and Mathematics in Electrical and Electronic Engineering*, vol. 22, no. 4, pp. 969–981, 2003.

[129] J. A. Farooq, A. Djerdj, and A. Mirouei, “Analytical modeling approach to detect magnet defects in permanent-magnet brushless motors,” *IEEE Transactions on Magnetics*, vol. 44, no. 12, pp. 4599–4604, 2008.

[130] S. Feng, B. Fan, J. Mao, and Y. Xie, “Prediction on wear of a spur gearbox by on-line wear debris concentration monitoring,” *Wear*, vol. 336-337, pp. 1–8, 2015.

[131] A. Agoston, C. Ötsch, and B. Jakoby, “Viscosity sensors for engine oil condition monitoring: Application and interpretation of results,” *Sensors and Actuators A: Physical*, vol. 121, no. 2, pp. 327–332, 2005.

[132] S. Kumar, P. S. Mukherjee, and N. M. Mishra, “Online condition monitoring of engine oil,” *Industrial Lubrication and Tribology*, vol. 57, no. 6, pp. 260–267, 2005.

[133] S. M. Schultheis, C. A. Lickteig, and R. Parchewsky, “Reciprocating compressor condition monitoring,” in *Proceedings of the 36th Turbomachinery Symposium*, San Antonio, TX, USA, June 2007.

[134] M. Elhaj, M. Almrabet, M. Rgeai, and I. Ehtiwesh, “A combined practical approach to condition monitoring of reciprocating compressors using IAS and dynamic pressure,” *World Academy of Science, Engineering and Technology*, vol. 63, no. 39, pp. 186–192, 2010.

[135] Y. Gao, Q. Zhang, and X. Kong, “Wavelet-based pressure analysis for hydraulic pump health diagnosis,” *Transactions of the ASAE*, vol. 46, no. 4, p. 969, 2003.

[136] H. Sun, R. Xiao, W. Liu, and F. Wang, “Analysis of S characteristics and pressure pulsations in a pump-turbine with misaligned guide vanes,” *Journal of Fluids Engineering*, vol. 135, no. 5, Article ID 051101, 2013.

[137] E. Mucchi, G. Dalpiaz, and A. Fernández del Rincón, “Elastodynamic analysis of a gear pump. part I: pressure distribution and gear eccentricity,” *Mechanical Systems and Signal Processing*, vol. 24, no. 7, pp. 2160–2179, 2010.

[138] E. Y. Kim, A. C. C. Tan, J. Mathew, and B. S. Yang, “Condition monitoring of low speed bearings: a comparative study of the ultrasound technique versus vibration measurements,” *Australian Journal of Mechanical Engineering*, vol. 5, no. 2, pp. 177–189, 2008.
[139] J. Zhang, B. W. Drinkwater, and R. S. Dwyer-Joyce, “Monitoring of lubricant film failure in a ball bearing using ultrasound,” Journal of Tribology, vol. 128, no. 3, pp. 612–618, 2006.

[140] N. H. Abu-Zahra and G. Yu, “Gradual wear monitoring of turning inserts using wavelet analysis of ultrasound waves,” International Journal of Machine Tools and Manufacture, vol. 43, no. 4, pp. 337–343, 2003.

[141] P. A. Delgado-Arredondo, D. Mornigo-Soto, R. A. Osorio-Rios, J. G. Avina-Cervantes, H. Rostro-Gonzalez, and R. D. J. Romero-Troncoso, “Methodology for fault detection in induction motors via sound and vibration signals,” Mechanical Systems and Signal Processing, vol. 83, pp. 568–589, 2017.

[142] B. Van Hecke, J. Yoon, and D. He, “Low speed bearing fault diagnosis using acoustic emission sensors,” Applied Acoustics, vol. 105, pp. 35–44, 2016.

[143] X. Dong, G. Li, Y. Jia, B. Li, and K. He, “Non-iterative denoising algorithm for mechanical vibration signal using spectral graph wavelet transform and detrended fluctuation analysis,” Mechanical Systems and Signal Processing, vol. 149, Article ID 107202.

[144] S. E. Pandarakone, Y. Mizuno, and H. Nakamura, “A comparative study between machine learning algorithm and artificial intelligence neural network in detecting minor bearing fault of induction motors,” Energies, vol. 12, no. 11, p. 2105, 2019.

[145] J.-H. Zhong, P. K. Wong, and Z.-X. Yang, “Fault diagnosis of rotating machinery based on multiple probabilistic classifiers,” Mechanical Systems and Signal Processing, vol. 108, pp. 99–114, 2018.

[146] S. Martin-del-Campo and F. Sandin, “Online feature learning for condition monitoring of rotating machinery,” Engineering Applications of Artificial Intelligence, vol. 64, pp. 187–196, 2017.

[147] S. Pan, T. Han, A. C. C. Tan, and T. R. Lin, “Fault diagnosis system of induction motors based on multiscale entropy and support vector machine with mutual information algorithm,” Shock and Vibration, vol. 2016, pp. 1–12, 2016.

[148] P. Konar and P. Chattopadhyay, “Multi-class fault diagnosis of induction motor using Hilbert and Wavelet Transform,” Applied Soft Computing, vol. 30, pp. 341–352, 2015.

[149] J. D. Martinez-Morales, E. R. Palacios-Hernández, and D. U. Campos-Delgado, “Multiple-fault diagnosis in induction motors through support vector machine classification at variable operating conditions,” Electrical Engineering, vol. 100, no. 1, pp. 59–73, 2016.

[150] P. Gangsar and R. Tiwari, “Comparative investigation of vibration and current monitoring for prediction of mechanical and electrical faults in induction motor based on multiclass-support vector machine algorithms,” Mechanical Systems and Signal Processing, vol. 94, pp. 464–481, 2017.

[151] P. Tamilselvan and P. Wang, “Failure diagnosis using deep belief learning based health state classification,” Reliability Engineering & System Safety, vol. 115, pp. 124–135, 2013.

[152] G. Helbing and M. Ritter, “Deep Learning for fault detection in wind turbines,” Renewable and Sustainable Energy Reviews, vol. 98, pp. 189–198, 2018.

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

[154] S.-Y. Shao, W.-J. Sun, R.-Q. Yan, P. Wang, and R. X. Gao, “A deep learning approach for fault diagnosis of induction motors in manufacturing,” Chinese Journal of Mechanical Engineering, vol. 30, no. 6, pp. 1347–1356, 2017.

[155] W. Sun, S. Shao, R. Zhao, R. Yan, X. Zhang, and X. Chen, “A sparse auto-encoder-based deep neural network approach for induction motor faults classification,” Measurement, vol. 89, pp. 171–178, 2016.

[156] O. Janssens, R. Van de Walle, M. Loccufer, and S. Van Hoecke, “Deep learning for infrared thermal image based machine health monitoring,” IEEE/ASME Transactions on Mechatronics, vol. 23, no. 1, pp. 151–159, 2018.

[157] F. Cipollini, L. Oneto, A. Corradu, and S. Savio, “Unsupervised deep learning for induction motor bearings monitoring,” Data-Enabled Discovery and Applications, vol. 3, no. 1, p. 1, 2019.

[158] S. S. Udmale, S. K. Singh, and S. G. Bhairud, “A bearing data analysis based on kurtogram and deep learning sequence models,” Measurement, vol. 145, pp. 665–677, 2019.

[159] R. Zhang, H. Tao, L. Wu, and Y. Guan, “Transfer learning with neural networks for bearing fault diagnosis in changing working conditions,” IEEE Access, vol. 5, pp. 13437–13457, 2017.

[160] M. J. Hasan, M. M. M. Islam, and J.-M. Kim, “Acoustic spectral imaging and transfer learning for reliable bearing fault diagnosis under variable speed conditions,” Measurement, vol. 138, pp. 620–631, 2019.

[161] Z. Wu, H. Jiang, K. Zhao, and X. Li, “An adaptive deep transfer learning method for bearing fault diagnosis,” Measurement, vol. 151, p. 107227, 2020.

[162] X. Wang, C. Shen, M. Xia, D. Wang, J. Zhu, and Z. Zhu, “Multi-scale deep intra-class transfer learning for bearing fault diagnosis,” Reliability Engineering & System Safety Reliability Engineering & System Safety, vol. 202, Article ID 107050, 2020.

[163] M. He and D. He, “A new hybrid deep signal processing approach for bearing fault diagnosis using vibration signals,” Neurocomputing, vol. 396, pp. 542–555, 2020.

[164] A. Cubillo, S. Perinpanayagam, and M. Esperon-Miguez, “A review of physics-based models in prognostics: application to gears and bearings of rotating machinery,” Advances in Mechanical Engineering, vol. 8, no. 8, Article ID 168781401666466, 2016.

[165] R. B. Randall and J. Antoni, “Rolling element bearing diagnostics-A tutorial,” Mechanical Systems and Signal Processing, vol. 25, no. 2, pp. 485–520, 2011.

[166] D. Abboud, J. Antoni, S. Sieg-Zieba, and M. Eltabach, “Envelope analysis of rotating machine vibrations in variable speed conditions: A comprehensive treatment,” Mechanical Systems and Signal Processing, vol. 84, pp. 200–226, 2017.

[167] D. Dou and S. Zhou, “Comparison of four direct classification methods for intelligent fault diagnosis of rotating machinery,” Applied Soft Computing, vol. 46, pp. 459–468, 2016.

[168] S. Hong, Z. Zhou, E. Zio, and W. Wang, “An adaptive method for health trend prediction of rotating bearings,” Digital Signal Processing, vol. 35, pp. 117–123, 2014.

[169] M. G. Don and F. Khan, “Dynamic process fault detection and diagnosis based on a combined approach of hidden Markov and Bayesian network model,” Chemical Engineering Science, vol. 201, pp. 82–96, 2019.

[170] M. Y. Asr, M. M. Ettefaghi, R. Hassannejad, and S. N. Razavi, “Diagnosis of combined faults in rotary machinery by non-naive bayesian approach,” Mechanical Systems and Signal Processing, vol. 85, pp. 56–70, 2017.
[171] I. Ben-Gal, “Bayesian networks,” *Encyclopedia of Statistics in Quality and Reliability*, vol. 1, 2008.

[172] S. Nie, M. Zheng, and Q. Ji, “The deep regression Bayesian network and its applications: probabilistic deep learning for computer vision,” *IEEE Signal Processing Magazine*, vol. 35, no. 1, pp. 101–111, 2018.

[173] R. Agrahari, “Applications of Bayesian network models in predicting types of hematological malignancies,” *Scientific Reports*, vol. 8, no. 1, p. 6951, 2018.

[174] Z. Wang, Z. Wang, X. Gu, S. He, and Z. Yan, “Feature selection based on Bayesian network for chiller fault diagnosis from the perspective of field applications,” *Applied Thermal Engineering*, vol. 129, pp. 674–683, 2018.

[175] H. Kumar, V. Sugumaran, and M. Amarnath, “Fault diagnosis of bearings through sound signal using statistical features and Bayes classifier,” *Journal of Vibration Engineering & Technologies*, vol. 4, no. 2, pp. 87–96, 2016.

[176] X. Zhang, Y. Liang, J. Zhou, and Y. zang, “A novel bearing fault diagnosis model integrated permutation entropy, ensemble empirical mode decomposition and optimized SVM,” *Measurement*, vol. 69, pp. 164–179, 2015.

[177] F. Chen, B. Tang, T. Song, and L. Li, “Multi-fault diagnosis study on roller bearing based on multi-kernel support vector machine with chaotic particle swarm optimization,” *Measurement*, vol. 47, pp. 576–590, 2014.

[178] S. Suthaharan, “Support vector machine,” in *Machine Learning Models and Algorithms for Big Data Classification*, pp. 207–235, Springer, Berlin, Germany, 2016.

[179] P. Konar and P. Chattopadhyay, “Bearing fault detection of induction motor using wavelet and Support Vector Machines (SVMs),” *Applied Soft Computing*, vol. 11, no. 6, pp. 4203–4211, 2011.

[180] M. Singh and A. G. Shaik, “Faulty bearing detection, classification and location in a three-phase induction motor based on Stockwell transform and support vector machine,” *Measurement*, vol. 131, pp. 524–533, 2019.

[181] Z. Su, B. Tang, Z. Liu, and Y. Qin, “Multi-fault diagnosis for rotating machinery based on orthogonal supervised linear local tangent space alignment and least square support vector machine,” *Neurocomputing*, vol. 157, pp. 208–222, 2015.

[182] S. Liu, Y. Hu, C. Li, H. Lu, and H. Zhang, “Machinery condition prediction based on wavelet and support vector machine,” *Journal of Intelligent Manufacturing*, vol. 28, no. 4, pp. 1045–1055, 2015.

[183] Y. Li, M. Xu, R. Wang, and W. Huang, “A fault diagnosis scheme for rolling bearing based on local mean decomposition and improved multiscale fuzzy entropy,” *Journal of Sound and Vibration*, vol. 360, pp. 277–299, 2016.

[184] Y. Li, M. Xu, H. Zhao, and W. Huang, “Hierarchical fuzzy entropy and improved support vector machine based binary tree approach for rolling bearing fault diagnosis,” *Mechanism and Machine Theory*, vol. 98, pp. 114–132, 2016.

[185] P. A. Schmid, A. Steinecker, J. Sun, and H. F. Knapp, “Neural networks and advanced algorithms for intelligent monitoring in industry,” in *Electronic Components and Systems for Automotive Applications*, pp. 173–183, Springer, Berlin, Germany, 2019.

[186] Z. Zhang, Y. Wang, and K. Wang, “Fault diagnosis and prognosis using wavelet packet decomposition, Fourier transform and artificial neural network,” *Journal of Intelligent Manufacturing*, vol. 24, no. 6, pp. 1213–1227, 2013.

[187] Z. Geng, Y. Zhang, C. Li, Y. Han, Y. Cui, and B. Yu, “Energy optimization and prediction modeling of petrochemical industries: An improved convolutional neural network based on cross-feature,” *Energy*, vol. 194, p. 116851, 2020.

[188] D.-K. Bui, T. N. Nguyen, T. D. Ngo, and H. Nguyen-Xuan, “An artificial neural network (ANN) expert system enhanced with the electromagnetism-based firefly algorithm (EFA) for predicting the energy consumption in buildings,” *Energy*, vol. 190, Article ID 116370, 2020.

[189] Z. Huo, Y. Zhang, R. Sath, and L. Shu, “Self-adaptive fault diagnosis of roller bearings using infrared thermal images,” in *Proceedings of the 43rd Annual Conference of the IEEE Industrial Electronics Society (IECON)*, Beijing, China, 2017.

[190] A. V. Joshi, “Perceptron and neural networks,” in *Machine Learning and Artificial Intelligence*, pp. 43–51, Springer, Berlin, Germany, 2020.

[191] J. Ben Ali, N. Fnaiech, L. Saidi, B. Chebel-Morello, and F. Fnaiech, “Application of empirical mode decomposition and artificial neural network for automatic bearing fault diagnosis based on vibration signals,” *Applied Acoustics*, vol. 89, pp. 16–27, 2015.

[192] M. Xia, T. Li, L. Xu, L. Liu, and C. W. de Silva, “Fault diagnosis for rotating machinery using multiple sensors and convolutional neural networks,” *IEEE/ASME Transactions on Mechatronics*, vol. 23, no. 1, pp. 101–110, 2018.

[193] P. Agrawal and P. Jayaswal, “Diagnosis and classifications of bearing faults using artificial neural network and support vector machine,” *Journal of The Institution of Engineers (India): Series C*, vol. 101, no. 1, pp. 61–72, 2020.

[194] W. Li, Z. Zhu, F. Jiang, G. Zhou, and G. Chen, “Fault diagnosis of rotating machinery with a novel statistical feature extraction and evaluation method,” *Mechanical Systems and Signal Processing*, vol. 50-51, pp. 414–426, 2015.

[195] P. K. Kankar, S. C. Sharma, and S. P. Harsha, “Fault diagnosis of ball bearings using machine learning methods,” *Expert Systems with Applications*, vol. 38, no. 3, pp. 1876–1886, 2011.

[196] V. Vakharia, V. Gupta, and P. Kankar, “A multiscale permutation entropy based approach to select wavelet for fault diagnosis of ball bearings,” *Journal of Vibration and Control*, vol. 21, no. 16, pp. 3123–3131, 2015.

[197] K. Gowthami and L. Kalaivani, “Fault classification of induction motor bearing using adaptive neuro fuzzy inference system,” in *Proceedings of the Fifth International Conference on Electrical Energy Systems (ICEES)*, pp. 1–6, Beijing, China, 2019.

[198] L. Jie, W. Wang, and F. Golnaraghi, “An enhanced diagnostic scheme for bearing condition monitoring,” *IEEE Transactions on Instrumentation and Measurement*, vol. 59, no. 2, pp. 309–321, 2010.

[199] S. Khan and T. Yairi, “A review on the application of deep learning in system health management,” *Mechanical Systems and Signal Processing*, vol. 107, pp. 241–265, 2018.

[200] R. Zhao, R. Yan, Z. Chen, K. Mao, P. Wang, and R. X. Gao, “Deep learning and its applications to machine health monitoring,” *Mechanical Systems and Signal Processing*, vol. 115, pp. 213–237, 2019.

[201] M. Bach-Andersen, B. Rømer-Oggaard, and O. Winther, “Deep learning for automated drivetrain fault detection,” *Wind Energy*, vol. 21, no. 1, pp. 29–41, 2018.

[202] D.-T. Hoang and H.-J. Kang, “A survey on Deep Learning based bearing fault diagnosis,” *Neurocomputing*, vol. 335, pp. 327–335, 2019.

[203] W. Dai, Z. Mo, C. Luo, J. Jiang, H. Zhang, and Q. Miao, “Fault diagnosis of rotating machinery based on deep reinforcement learning and reciprocal of smoothness index,” *IEEE Sensors Journal*, vol. 20, no. 15, pp. 8307–8315, 2020.
[204] M. Gan, C. Wang, and C. Zhu, “Construction of hierarchical diagnosis network based on deep learning and its application in the fault pattern recognition of rolling element bearings,” Mechanical Systems and Signal Processing, vol. 72-73, pp. 92–104, 2016.

[205] H. Shao, H. Jiang, F. Wang, and H. Zhao, “An enhancement deep feature fusion method for rotating machinery fault diagnosis,” Knowledge-Based Systems, vol. 119, pp. 200–220, 2017.

[206] H. Shao, H. Jiang, H. Zhao, and F. Wang, “A novel deep autoencoder feature learning method for rotating machinery fault diagnosis,” Mechanical Systems and Signal Processing, vol. 95, pp. 187–204, 2017.

[207] C. Lu, Z.-Y. Wang, W.-L. Qin, and J. Ma, “Fault diagnosis of rotary machinery components using a stacked denoising autoencoder-based health state identification,” Signal Processing, vol. 130, pp. 377–388, 2017.

[208] M. He and D. He, “Deep learning based approach for bearing fault diagnosis,” IEEE Transactions on Industry Applications, vol. 53, no. 3, pp. 3057–3065, 2017.

[209] X. Guo, L. Chen, and C. Shen, “Hierarchical adaptive deep convolutional neural network and its application to bearing fault diagnosis,” Measurement, vol. 93, pp. 490–502, 2016.

[210] M. Sohaib, C.-H. Kim, and J.-M. Kim, “A hybrid feature model and deep-learning-based bearing fault diagnosis,” Sensors, vol. 17, no. 12, p. 2876, 2017.

[211] C. Li, R.-V. Sánchez, G. Zurita, M. Cerrada, and D. Cabrera, “fault diagnosis for rotating machinery using vibration measurement deep statistical feature learning,” Sensors, vol. 16, no. 6, p. 895, 2016.

[212] F. Jia, Y. Lei, J. Lin, X. Zhou, and N. Lu, “Deep neural networks: a promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data,” Mechanical Systems and Signal Processing, vol. 72-73, pp. 303–315, 2016.

[213] H. Shao, H. Jiang, H. Zhang, W. Duan, T. Liang, and S. Wu, “Rolling bearing fault feature learning using improved convolutional deep belief network with compressed sensing,” Mechanical Systems and Signal Processing, vol. 100, pp. 743–765, 2018.

[214] G. Li, R.-V. Sanchez, G. Zurita, M. Cerrada, D. Cabrera, and R. E. Vásquez, “Multimodal deep support vector classification with homologous features and its application to gearbox fault diagnosis,” Neurocomputing, vol. 168, pp. 119–127, 2015.

[215] O. Janssens, V. Slavkovikj, B. Vervisch et al., “Convolutional neural network based fault detection for rotating machinery,” Journal of Sound and Vibration, vol. 377, pp. 331–345, 2016.

[216] Z. Chen, S. Deng, X. Chen, C. Li, R.-V. Sanchez, and H. Qin, “Deep neural networks-based rolling bearing fault diagnosis,” Microelectronics Reliability, vol. 75, pp. 327–333, 2017.

[217] D. Verstraete, A. Ferrada, E. L. Drogue, V. Meruane, and M. Modarres, “Deep learning enabled fault diagnosis using time-frequency image analysis of rolling element bearings,” Shock and Vibration, vol. 2017, pp. 1–17, Article ID 5067651, 2017.

[218] W. Zhang, X. Li, and Q. Ding, “Deep residual learning-based fault diagnosis method for rotating machinery,” ISA Transactions, vol. 95, p. 295, 2019.

[219] L. Wen, X. Li, L. Gao, and Y. Zhang, “A new convolutional neural network-based data-driven fault diagnosis method,” IEEE Transactions on Industrial Electronics, vol. 65, no. 7, pp. 5990–5998, 2018.

[220] J. Zheng, J. Zhu, G. Chen, Z. Song, and Z. Ge, “Dynamic Bayesian network for robust latent variable modeling and fault classification,” Engineering Applications of Artificial Intelligence, vol. 89, p. 103475, 2020.

[221] C. Duan, V. Makis, and C. Deng, “A two-level Bayesian early fault detection for mechanical equipment subject to dependent failure modes,” Reliability Engineering & System Safety, vol. 193, p. 106676, 2020.

[222] B. Song, S. Tan, H. Shi, and B. Zhao, “Fault detection and diagnosis via standardized k nearest neighbor for multimode process,” Journal of the Taiwan Institute of Chemical Engineers, vol. 106, pp. 1–8, 2020.

[223] S. Jalali, H. Ghandi, and M. Motamedi, “Intelligent condition monitoring of ball bearings faults by combination of genetic algorithm and support vector machines,” Journal of Nondestructive Evaluation, vol. 39, no. 1, pp. 1–12, 2020.

[224] A. Ghosh, G.-N. Wang, and J. Lee, “A novel automata and neural network based fault diagnosis system for PLC controlled manufacturing systems,” Computers & Industrial Engineering, vol. 139, Article ID 106188, 2020.

[225] A. S. Aljuha, D. S. Ramteke, and A. Parey, “Vibration-based fault diagnosis of a bevel and spur gearbox using continuous wavelet transform and adaptive neuro-fuzzy inference system,” in Soft Computing in Condition Monitoring and Diagnostics of Electrical and Mechanical Systems, pp. 473–496, Springer, Berlin, Germany, 2020.

[226] H. A. Saeed, H. Wang, M. Peng, A. Hussain, and A. Nawaz, “Online fault monitoring based on deep neural network & sliding window technique,” Progress in Nuclear Energy, vol. 121, Article ID 103326, 2020.

[227] L. Chen, Z. Zhang, J. Cao, and X. Wang, “A novel method of combining nonlinear frequency spectrum and deep learning for complex system fault diagnosis,” Measurement, vol. 151, Article ID 107190, 2020.

[228] S. Zhang, S. Zhang, B. Wang, and T. G. Habetler, “Deep learning algorithms for bearing fault diagnostics–A comprehensive review,” IEEE Access, vol. 8, pp. 29857–29881, 2020.

[229] R. Liu, B. Yang, E. Zio, and X. Chen, “Artificial intelligence for fault diagnosis of rotating machinery: A review,” Mechanical Systems and Signal Processing, vol. 108, pp. 33–47, 2018.

[230] Y. Lei, N. Li, L. Guo, N. Li, T. Yan, and J. Lin, “Machinery health prognostics: a systematic review from data acquisition to RUL prediction,” Mechanical Systems and Signal Processing, vol. 104, pp. 799–834, 2018.

[231] H. Henao, G.-A. Capolino, M. Fernandez-Cabanas et al., “Trends in fault diagnosis for electrical machines: a review of diagnostic techniques,” IEEE Industrial Electronics Magazine, vol. 8, no. 2, pp. 31–42, 2014.

[232] A. M. Alshorman, O. Alshorman, M. Irfan, A. Glowacz, F. Muhammad, and W. Caesarendra, “Fuzzy-based fault-tolerant control for omnidirectional mobile robot,” Machines, vol. 8, no. 3, p. 55, 2020.

[233] O. Alshorman, B. Alshorman, M. Alkhassaweneh, and F. Alkahtani, “A review of internet of medical things (IoMT) – based remote health monitoring through wearable sensors: A case study for diabetic patients,” Indonesian Journal of Electrical Engineering and Computer Science, vol. 20, no. 1, 2020.

[234] O. Alshorman, B. Alshorman, and F. Alkahtani, “A review of wearable sensors based monitoring with daily physical activity to manage type 2 diabetes,” International Journal of...
[235] O. AlShorman, B. Alshorman, and M. Masadeh, “A review of physical human activity recognition chain using sensors,” Indonesian Journal of Electrical Engineering and Informatics (IJEII), vol. 8, no. 3, 2020.