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ORIGINAL PAPER

Review on Machine Learning Algorithm Based Fault Detection in Induction Motors

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Abstract
Fault detection prior to their occurrence or complete shut-down in induction motor is essential for the industries. The fault detection based on condition monitoring techniques and application of machine learning have tremendous potential. The power of machine learning can be harnessed and optimally used for fault detection. The faults especially in induction motor needs to be addressed at a proper time for avoiding losses. Machine learning algorithm applications in the domain of fault detection provides a reliable and effective solution for preventive maintenance. This paper presents a review of the machine learning algorithm applications in fault detection in induction motors. This paper also presents the future prospects and challenges for an efficient machine learning based fault detection systems.

1 Introduction

Early fault detection in induction motor provides the leverage of minimum downtime and maximum production. The study of maintenance of induction motors and its failure analysis is a vast area of research for the researchers for many years [4]. Traditionally, the fault detection for the IM was dependent on current and vibration [67, 70]. The simple methods which were earlier used were overcurrent, overvoltage and earth-fault. However, with the modernisation and advancement in techniques, the combination of traditional and modern approach provides an efficient technique for the fault detection in the induction motors. The predictive maintenance based on the condition-based monitoring of the induction motor is the dire need of the modern industries for minimal downtime [15, 27, 107]. The preamble of fault detection has four components, namely: (a) Identifying fault location; (b) Determining faulty parts; (c) learning incipient failure and their causes; (d) predicting the pattern of faults. The fault detection can be treated as classification problem and pattern recognition problem too. ML algorithms are powerful tools for classification problems and classification problems [99]. Due to this reason, Artificial Intelligence (AI) based on machine learning algorithm has attracted researchers in the domain of condition monitoring.

The fault detection in IMs is divided into multiple stages like data acquisition, data processing, feature extraction and implementation of ML algorithms for fault recognition [34, 103]. Most AI-based fault detection system requires the features for developing the input vector for the ML algorithms. The data is preprocessed by feature extraction algorithms [103] to develop an input feature vector for ML algorithm for classification of faults. Sometimes, independent component analysis (ICA) is used to convert the high dimensional vector to a low dimensional vector for easier analysis and recognition [10, 48]. The feature vector is used as an input vector for developing AI enabled fault identification system. The techniques like Genetic algorithm, Particle swarm optimization, convex optimization and statistical learning have been used for feature selection and extraction [13, 53, 75, 86]. For developing AI based system, ML algorithms like k-Nearest Neighbor (k-NN) [11], Artificial Neural Network (ANN) [26, 87, 89], Support Vector Machines (SVM) [56, 59], Decision trees [52], Bayesian Classifier [3], random forest [68] and deep learning [33] techniques have been efficiently used. In recent times, deep learning have also been explored by researchers for fault detection [49].

This paper has been divided into different sections. Section 2 enumerates the faults and their causes in the induction motors. Section 3 enlists the machine learning algorithms

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technique for the induction motors. Section 4 includes the machine learning algorithm based condition monitoring and fault diagnosis. Section 5 presents the discussion, limitations and future scopes of machine learning based fault detection algorithms. Finally, Sect. 6 concludes the work.

2 Faults and their Causes

The faults in the IM can be segregated as a mechanical faults and electrical faults [1, 42, 43, 91]. Mechanical faults are categorised as bearing fault, broken rotor bar fault (BRB) and eccentricity. Electrical faults are stator winding faults and rotor winding faults. These fault in the IM have several symptoms which includes: (a) Unbalance magnetic pull; (b) Excessive heating; (c) Increased losses; (d) Efficiency reduction; (e) Decrease in average torque; (f) Enhanced torque pulsation. The causes of faults can vary from the operating conditions and ambient temperature. Some of these causes have been enlisted, namely: (a) Overloading; (b) Overspeed; (c) Manufacturing defect; (d) Dirt, debris and corrosion; (e) Components failure; (f) Overheating in winding and bearing; (g) Excessive dielectric stress; (h) Shock loads.

2.1 Bearing Fault

Bearing is among the basic components of the IM which helps in separating the stationary part with the moving part. IM mostly consist of rolling or ball element bearings. The bearing has two rings, namely outer ring and inner ring. A set of balls or rolling element rotates between the two rings. The bearing fault can occur due to fatigue under balanced condition too. The fault can take place due to wear and tear and due to ageing, shock loads, overheating, imbalances and improper lubrication. Bearing fault has a majority stake (40–50%) of all IM failures [46]. The ball bearing fault is characterised as outer raceway defect, inner raceway defect, ball defect and train defect [79]. Each defect has its own characteristic vibration frequency depending on the construction and mechanical dimension of the bearing and is given as follows [63, 93]:

$$f_{or} = \frac{N_b f_{rot}}{2}\left(1 - \frac{b_d cos\beta}{p_d}\right) \tag{1}$$

$$f_{ir} = \frac{N_b f_{rot}}{2}\left(1 + \frac{b_d cos\beta}{p_d}\right) \tag{2}$$

$$f_{db} = \frac{p_d f_{rot}}{2b_d}\left(1 - \left[\frac{b_d cos\beta}{p_d}\right]^2\right) \tag{3}$$

$$f_{td} = \frac{f_{rot}}{2}\left(1 - \frac{b_d cos\beta}{p_d}\right) \tag{4}$$

where f_{rot} is the rotational frequency, N_b is the number of balls, b_d is the ball diameter, p_d is the pitch diameter, f_{or} is the vibration frequency for outer raceway fault, f_{ir} is the vibration frequency for inner raceway fault, f_{db} is the vibration frequency for the ball defect, f_{td} is the vibration frequency for the train defect and β is the contact angle. Schoen et. al. [81] have revealed that vibration frequency component is noticeable in the current spectrum. Current spectrum has vibration frequency component and is given by:

$$f_{bng} = |f_r \pm m \cdot f_v| \tag{5}$$

where f_{bng} is the vibration component frequencies in the current spectrum, $m = 1, 2, 3, \ldots$.

2.2 Broken Rotor Bar

There has been a lot of changes in the design of the stator core, stator windings and construction. However, rotor bar has been left out and no significant changes have been introduced in it. The rotor failure accounts for 5–10% of total induction motor faults [7, 44, 45, 63]. The BRB related fault is pre-dominant in medium or high rating motor over the small rating motors as the starting torque demand and thermal stress is high. Due to a BRB, it produces an enriched field in the vicinity of the faulty region in IM. It is because of local demagnetising slip frequency and induced current in the damaged rotor slots. Flux density is more in amplitude in the vicinity of faulty area. The result shows that for an IM with 40 rotor bars, damage of one broken bar causes degradation of 2–4% in the steady state torque performance whereas, for three and five broken bars, it is between 10 and 15% [18]. Few possible reasons for damaged broken bar have been enlisted below [63]:

1. Stresses like magnetic stress and thermal stress caused due to electromagnetic forces, unbalanced magnetic pull (UMP), noises, thermal overload, excessive losses, sparking;
2. Dynamic stresses;
3. Mechanical stresses;

If a BRB exists, flow of current in that bar will be obstructed. As a result, a field will be unavailable near the faulty bar in the rotor. Due to this imbalance, UMP is created which rotates at one time the rotational speed. It modulates at a frequency which is equal to multiple of slip frequency and number of poles. This frequency is called as pole pass frequency. This causes increased magnitude in the vibration spectrum and occurs at rotational frequency and its side-bands are given by:

$$f_{brb} = f_{rot} \pm f_p \tag{6}$$

$$f_p = (f_{syn} - f_r) \cdot P \tag{7}$$

where f_p is the pole pass frequency, P is the number of poles and f_{syn} is synchronous speed [21]. These side-bands are predominantly present in higher harmonics of rotational speed ($2f_{rot}$, $3f_{rot}$,...). The broken rotor bar detection using Eqs. 6 and 7 have been used in several literatures and has high practical implementation [60]. The low value of slip or slight loading causes the rotational frequency f_{rot} to be close to the synchronous speed and side-bands is closer to the principle slot harmonics makes it difficult to identify in the vibration signal spectrum. Broken rotor bar (BRB) fault is among the most common fault occurring in the underground mines. Due to BRB fault, side-bands are visible around the principle slot harmonics in the current spectrum and is given by Gyftakis et al. [24].

$$f_{lsb} = f(1 - 2ks)Hz \tag{8}$$

$$f_{rsb} = f(1 + 2ks)Hz \tag{9}$$

where $k = 1$ for principle slot harmonic, f is the supply frequency, f_{lsb} is the left side-band frequency and f_{rsb} is the right side-band frequency.

2.3 Stator Faults

These are primarily associated to winding faults and insulation failure. These faults may be line-to-ground or line to line fault. It accounts for 30–40% of all reported IM failures [45]. Factors leading to stator insulation failures are:

1. electrical discharges;
2. leakage in the cooling system;
3. heating in winding leading to a higher temperature;
4. loose bracing for end winding [63].

2.4 Eccentricity

The non-uniform air-gap distribution between the stator and rotor leads to eccentricity [9, 28, 93]. The eccentricity at an incipient stage doesn't affect much but with large eccentricities, it can lead to non-uniform flux distribution, resulting unbalanced magnetic pull that can cause stator to rotor rub. Furthermore, varying inductances due to eccentricity cause an unbalanced magnetic flux in the air gap. It creates fault frequencies in the line current. Airgap eccentricity is basically of three types i.e. static eccentricity, dynamic eccentricity and mixed eccentricity. In static eccentricity, there is a persistent offset between centreline of stator and rotor. Dynamic eccentricity caused from mutable offset between the centreline of stator and rotor. Eccentricity may be caused due to bearing wear and tear, bent rotor shaft, mechanical resonance etc. An air-gap eccentricity of up to 10% is permissible. Static and dynamic eccentricity generally co-occur.

3 Machine Learning Algorithms Theory

Machine learning algorithm have become renowned in fault detection system due to their reliability, adaptability and robustness. The application of these algorithms have helped in developing an efficient system. These systems do not need prior knowledge for their operation [56]. The algorithms like Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Artificial Neural Network (ANN), Decision trees, Bayesian Classifier, random forest and Convolutional Neural Network (CNN) are commonly used in fault prognosis and diagnostic.

3.1 Support Vector Machine

SVM is a powerful tool for classification problems. Vladimir Vapnik introduced SVM in 1994. SVM algorithm constructs a hyperplane or set of hyperplane in an infinite dimensional space. The hyperplane for which the margin is maximum is the optimal hyperplane. Thus, SVM tries to make a decision boundary in such a way that the separation between the two classes is as wide as possible. For small database cases and machine fault detection, SVM is an effective tool for classifications. SVM is popular in the area of machine fault detection due to its attractive features and good empirical performance. Binary classification is a basic model of SVM [98]. It is basically two class problem and hyperplane is drawn to separate two classes optimally in the space. This hyperplane is used to separate new data once given to the algorithm. The basic idea of SVM is shown in Fig. 1.

There are two classes represented by positive (+) sign and negative (−) sign. It draws a boundary (or hyperplane) to separate two classes. The boundary is done in such a way that the distance is maximised between the boundary and nearest data points of both classes. The margin is kept as bargain between the margin level and error. There can be number of hyperplane drawn for separating two classes (as shown in Fig. 1), however, the hyperplane having the maximum distance from the nearest data point on the either side of classes will be chosen for the best fit and accuracy. Figure 2 shows the hyperplane which segregate the two classes optimally i.e. positive (+) sign and negative sign (−). Finally, SVM classification problem is solved by an

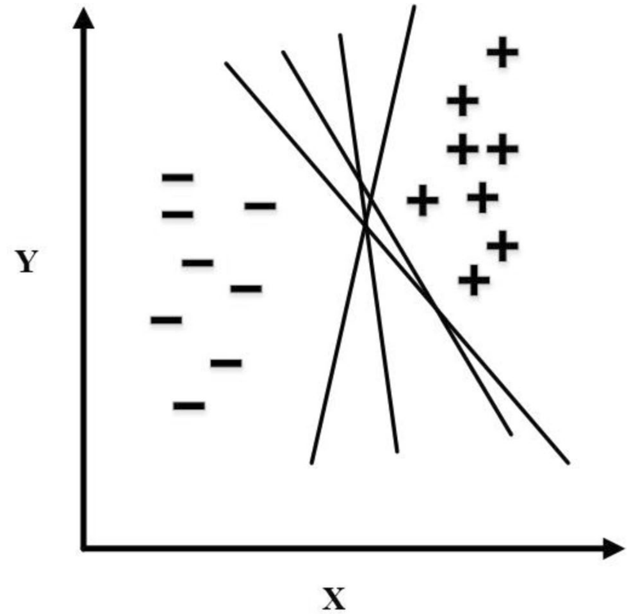

Fig. 1 Positive and negative class

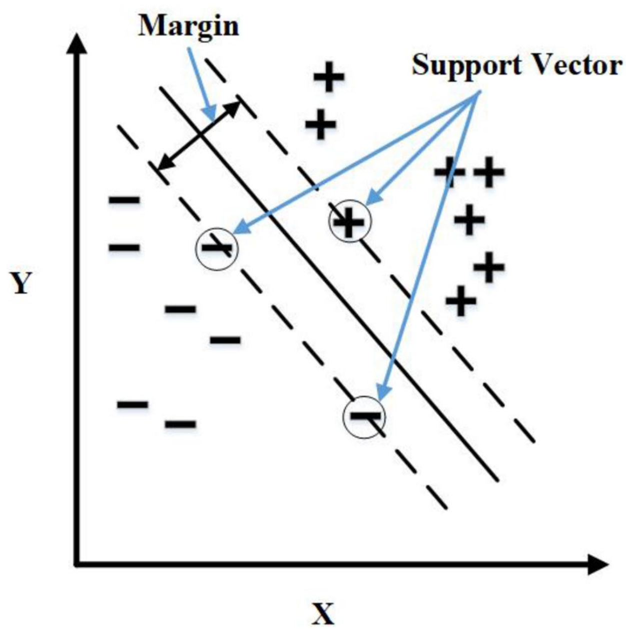

Fig. 2 Optimal separating hyperplane

optimization technique so that margin is kept maximum and error is minimum. Lastly, SVM models is developed which can predict the class of new data. The traditional approach in machine learning is to minimize the error on the training data set and it is called empirical risk minimization. However, support vector machines (SVM) is based on structural risk minimization [40, 92]. SVM can handle large data sets efficiently. The training of SVM is done so that the dimension of classified vector does not influence the performance of SVM and it differentiate it from conventional classifiers. Generally this method provides better generalization capabilities with respect to methods based on empirical risk minimization. This is advantageous in fault classification problem as number of features need not be limited.

Generally, these classifiers have good classification properties as compared to conventional classifiers. The support vector contains the information needed for defining the classifier and when support vectors are properly selected, rest feature is not of much interest. It can be used for solving linear and non-linear classification problems. For non-linear classification, kernel functions like Gaussian, quadratic and cubic are required.

3.2 k-Nearest Neighbors

k-Nearest Neighbors is among the simple machine learning methods used for the classification problems. k-NN is a non parametric and instance based learning in which similar items are placed together. It belongs to the supervised learning category and is significantly used in pattern recognition problem and data mining. In this algorithm, the specimen or samples within the class will be near to the samples with similar features [14]. In this algorithm, all the samples belongs to points in n-dimensional space $\mathfrak{R}^n$. Euclidean distance is used for determining the samples with similarities. Let a random sample x given by the feature vector $a_1(x), a_2(x), \ldots a_n(x)$ shows the distribution of the sample x. The distance between two samples x_i and x_j is defined to be $d(x_i, x_j)$,where

$$d(x_i, x_j) = \sqrt{\sum r = 1n(a_r(x_i) - a_r(x_j))^2} \tag{10}$$

The target function in the k-NN can be real valued or discrete valued. For each training example $(x, f(x))$, it is added to the list of training examples. For a query instance x_q to be classified. Let $x_1, x_2, \ldots x_k$ denotes the k instances from training samples that are nearest to x_q, then

$$\hat{f}(x_q) \leftarrow arg\,max_{v \in V} \sum_{i=1}^{k} \delta(v, f(x_i)) \tag{11}$$

where $\delta(a, b) = 1$ if $a = b$ and where $\delta(a, b) = 0$ otherwise.

3.3 Artificial Neural Network (ANN)

ANN is among the handiest tool for non-linear analysis. ANN is an information paradigm that is motivated by the way the biological nervous system works and processes information with the help of the brain. The most common form of ANN has three layers: input layer, hidden layer and output layer. ANN can be represented by a set of links between input layer and hidden layer connected with the multiple of weight and associated bias. ANN has connected units called artificial neurons which emulates the neurons of the biological brain. The connected units transmit a signals like the synapses in biological neurons. A simple structure of ANN in shown in Fig. 3.

ANN takes an input x_1, x_2, x_3 and output is given as:

$$y = A(W^T x) = A\left(\sum_{i=1} W_i x_i + b\right) \tag{12}$$

where A is an activation function (can be sigmoid, logsig, purelin etc.), W is a weight matrix, b is a bias (scalor). Initially, weights (W) are initialised randomly and then optimized by an iterative training procedure, based on relationship between input-output patterns.

3.4 Decision Trees and Random Decision forest

A decision tree is a type of machine learning algorithm which has a pyramid like structure or we can say an inverse tree like structure. It is used to solve classification and regression problems. It emulates tree like structure. Each non-leaf node represents an input feature. The arcs branching from internal node (non-leaf nodes) are marked with an input feature. These arcs are mapped with possible values of the target or output feature. It might also lead to a subordinate decision node on a different input feature. The top node of a tree is called as root node. Each leaf is marked with a class or a probability distribution over the class. It signifies that dataset has been classified into an unique class or a probability distribution.

Random forest is a combination of multiple decision trees for the decision making. It has multitude of decision trees at a training time. It outputs the the mode of the class of the individual tree. It also resolve the problem of over-fitting of decision trees. It is an ensemble learning method. Each individual tree in the random forest tells about a class prediction. The class with maximum votes are selected as our prediction model. The low correlation between the model is the key. The random forest provides an optimum classification performance because the tree protect each other from their individual errors (as long as they don't constantly all err in the same direction). Decision trees are very sensitive to changes to the data they are trained on. Even the small changes to the training set results in different tree structure. So, the performance also varies [29].

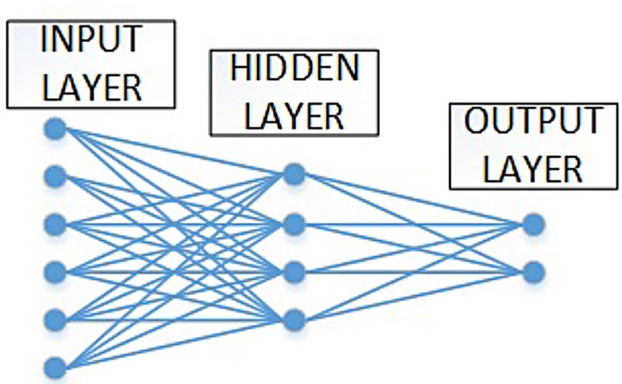

Fig. 3 Structure of simple ANN

3.5 Bayesian Classifier

Bayesian classifier is among the most practical learning methods used in activity recognition and pattern recognition. It belongs to the category of probabilistic classifiers. These classifiers are based on the Baye's theorem and their working lies in basic assumption that features are independent of each other. Consider a training set $S = (I_1, O_1), (I_2, O_2), \dots, (I_N, O_N)$ with label o, $o_h = m_1, m_2, \dots, m_G, h = 1, 2, \dots N$,, assuming Z_t possible values for i^t, $t = 1, 2, \dots, n$; and G possible vales of O. These classifiers learns the probability distribution between input and output with the help of conditional probability distribution based on assumption of conditional independency:

$$P(I = i|O = o_d) = P(I^{(1)} = i^{(1)}, \dots, I^{(n)} = i^{(n)}|O = m_d) \tag{13}$$

$$P(I = i|O = o_d) = \prod_{t=1}^{n} P(I^{(t} = i^{(t)}) \quad d = 1, 2, \dots, G \tag{14}$$

Based on the learning model, the output value o with the highest probability for given input i can be calculated by Baye's Theorem:

$$P(O = m_d|I = i) = \frac{P(I = i|O = m_d)P(O = m_d}{\sum dP(I = i|O = m_d)P(O = m_d)} \tag{15}$$

and

$$O = arg\,max_{c_j} P(O = m_d) \prod_t P(I^{(t)} = i^{(t)}|O = m_d) \tag{16}$$

3.6 Deep Learning

Deep learning (DL) belongs to the family of machine learning and is based on ANN. DL has deep architectures for solving the complex problems. There are many deep learning architectures namely, deep neural networks (DNN), convolutional neural networks (CNN), deep belief networks and recurrent neural networks (RNN). DL also falls under the subclass of machine learning. DL uses deep architectures and multiple layers to extract features from the raw input signals [5].

Deep learning refers to the deep and multiple layers for handling the complex structures. DL has substantial credit assignment path (CAP) which is basically about finding weight that makes the network to exhibit desired behaviour. CAP is the sequence of transformation from input to output. In a feed-forward NN, depth of CAP's is equal to the network and hidden layers plus one for output as it is parametrised. In the network where signals might propagate multiple times through a layer, potentially CAP depth is incalculable. Deep learning models have $CAP > 2$ for efficient extraction of features and better performance than shallow structures. The multiple layers in DL based networks helps in learning features eloquently [80].

4 Machine Learning Algorithm Based Condition Monitoring of IMs

4.1 Pre-processing of Data

The application of machine learning algorithm for condition monitoring of IMs require signal processing of raw data. The implementation of AI technique in real world requires the feature extraction and feature vector as an input vector [55]. Analysis like frequency-domain analysis, time-domain analysis, time frequency analysis has been done for developing the pattern for fault recognition. Statistical features like mean, standard deviation, kurtosis and skewness is estimated for generating the feature vector. Frequency domain analysis like Fast Fourier Transform (FFT) and bi-spectrum analysis are used for analysis of the signals. Time-frequency analysis like wavelet analysis [101], short-time fourier transform [2], wavelet packet transformation [41], Hilert–Huang tranform [66] and sparse decomposition [102] are used for feature extraction. The availability of highly efficient computational machines have contributed a lot in applying machine learning algorithms in fault detection. The concepts like internet of things, remote diagnostics, wireless monitoring have changed the way in which fault detection is done. Due to this development, there is a large amount of data accumulation for developing more accurate fault detection system [49]. The availability of humongous amount of data is also posing a challenge to data pre-processing task. The data fusion and dimensionality reduction has become an integral part of fault detection system. In [8], authors have used principal component analysis for dimensionality reduction of data obtained from fast fourier transform. In [82], preprocessing of vibration signal has been done using principal component analysis for reducing the dimension of feature vector without compromising the performance of system. Authors have used poly-coherent composition spectrum (p-CCS) along with data fusion technique for fault diagnosis [105].

4.2 Support Vector Machine Based Fault Detection

SVM is among the powerful tool for the classification of faults in IMs. The selection of kernel functions directly affects the performance of SVM classifiers. For developing an efficient fault detection system, several structures of SVM has been developed in recent times. The particle swarm optimization algorithm and least square-SVM has been proposed to diagnose the faults of the motor bearing [16]. Authors have used higher order statistics technique along with the SVM for condition monitoring and fault diagnosis in the rotating machines [73]. Acceleration signal based full spectrum are being used as a feature input vector for SVM for analysing rotor faults [20]. A hybrid intelligent technique based on wavelet transform, principal component analysis and twin SVM has been presented for classifying multiple faults in rotating machines [58]. An empirical mode decomposition (EMD) along with the weighted least square SVM has been used for improving the performance of fault detection system [57]. High-frequency intermittent components and non-Gaussian noises have been suppressed with the help of weighted least square SVM. The c-SVC and mu-SVC model of SVM is presented with four kernel functions for faults classification using statistical features calculated from vibration signal under healthy and faulty condition [74]. A methodology based on pseudo Wigner–Ville Distribution (PWVD) and SVM in combination has been demonstrated for time-domain feature extraction and fault identification with acoustic emission signals [51].

The practical application and need of industries motivated the researchers for improved and more efficient SVM for fault prognosis and diagnosis. Authors have used multiclass SVM and features were extracted for SVM based on binary particle swarm optimization algorithm from the vibration data [110]. An empirical mode decomposition and multi-class transductive SVM are used in combination to diagnose the faults in gear reducer [85]. Feature extraction based on statistical parameters from a wavelet packet transform (WPT) has been used along with distance evaluation technique (DET) and a support vector regression (SVR)-based generic multi-class solver for fault detection [84]. SVM based on modified shuffled frog-leaping algorithm (MSFLA) has been presented for an efficient fault classification [104]. Features for modified SVM were extracted from wavelet energy time spectrum and power spectrum of maximum wavelet energy level. A comparison is done based on different machine learning algorithms to SVM for developing efficient system [25]. A comparative study based on ANN and SVM for detecting bearing faults based on statistical features [37].

4.3 k-Nearest Neighbors based fault detection

k-NN is an instance based learning and has worked well in fault classification problems. Authors have presented a bearing health monitoring based on feature extraction from spectral kurtosis and cross relation along with principal component analysis and k-NN [90]. An advanced k-NN based fault severity detection model has been developed using redundant statistical features estimated from wavelet packet transform [94]. k-NN algorithm based on feature extraction from vibration signal has been presented for unbalanced fault detection [61]. Authors investigated multiscale energy analysis of discrete wavelet transformation to generate low dimensional feature vector for k-NN based classifiers for machine fault diagnosis [36]. A condition monitoring system based on k-NN classifiers has been developed using load and acceleration indices as feature from vibration signal along with principal component analysis for dimensionality reduction [72]. A bearing fault diagnosis system has been demonstrated using low dimensional feature extracted by Hilbert Huang Transform (HHT) as an input vector to the k-NN classifier [65]. A multi-fault detection system based on feature extraction from acoustic signal and using it as an input to Nearest Neighbour [23]. Lein and Zuo presented a weighted k-NN for identifying the severity of gear crack based on feature extraction by two-stage feature selection and weighting technique (TFSWT) via Euclidean distance evaluation technique (EDET) [50]. A k-NN based fault detection is presented by developing isolation index by decomposing the k-NN distance [109]. The selection of k is an important parameter in an efficient k-NN algorithm implementation and it should be wisely selected.

4.4 Artificial Neural Network (ANN) Based Fault Detection

ANN is a powerful tool for pattern recognition in several applications. It is among the most commonly used classifiers in developing an intelligent fault detection systems. A fault detection system based on ANN and radial basis function (RBF) classifier is presented by feature extraction from multiresolution analysis of vibration signals for automatic detection of cracks in rotors [12]. Multi-layer perceptron is a kind of ANN consists of only forward connections to units in subsequent layers [31]. A feature vector from vibration signal is developed by calculating standard deviation of wavelet packet coefficients which is used an input vector for ANN classifiers [69]. An artificial neural networks based robust fault detection system is developed using outer bounding ellipsoid algorithm for estimating model uncertainty [62]. A multilayer perceptron neural network has been developed using as statistical features derived from wavelet transform as input to the network [77]. Authors have presented a method for online rotor bar detection using feature representation as an input vector to ANN network [71]. A feature extraction based on WPD and EMD has been used as an input to backpropagation neural network for early fault detection in rotating machinery [6]. Authors have analysed the performance of ANN and SVM in faulty rotor bearing systems [38]. It also showed that ANN performance was better than SVM classifier. A RBF-NN based electrical and mechanical fault detection has been proposed for induction machine fault diagnosis [100]. Feature extraction was done from power spectra of vibration signal. A high-dimensional hybrid model for machine fault diagnosis based on multiple feature selection and RBF neural network is presented [106]. Authors have presented an intelligent fault diagnosis method for bearing faults based on probabilistic theory and a fuzzy neural networks using frequency features as an input vector [95]. The online fault detection in induction motors is developed by combining the discrete wavelet transform (DWT), feature extraction, genetic algorithm (GA), and neural network (ANN) techniques [26]. Samanta et. al. [76] have used feature extraction from vibration signal with selection of optimal feature by genetic algorithm as an input to ANN, MLP and RBF network for bearing fault detection. The performance of three networks has been compared too. A recurrent neural network has been used for bearing fault diagnosis in the form of an autoencoder [54]. A fault detection for rotating machinery has been developed with the help of multi-sensor data fusion and bottleneck layer optimized CNN [96].

4.5 Decision Trees and Random Decision Forest Based Fault Detection

Sun et. al. [88] proposed the fault diagnosis system based on decision trees using principal component analysis as way to reduce features after feature extraction. It has been shown that decision tree and PCA based system has good accuracy and reduced training time than backpropagation neural network systems. Decision tree algorithm is used for faults classification and feature extraction has been done from wavelet transformations [78]. In most of the cases, decision trees are used along with other classifiers for an efficient fault detection system. Standalone use of decision trees are less in fault detection systems.

4.6 Naive Bayes Classifier Based Fault Detection

This method is suitable only for independent feature vector i.e. mostly the statistical features. Authors have proposed a model to extract the frequency based features from wavelet packet transform [19]. This feature is used as an input to Naive Bayes classifier for bearing fault detection in induction motors. A Naive Bayes classifier is used along with frequency spectrum estimation for optimising the shaft voltage condition monitoring [17]. Authors have presented a broken rotor bar detection based analysis and results were compared from Naive Bayes classifier [68]. Authors have proposed a combinational method for fault detection in transformers based on Bayesian network and AdaboostMI algorithm [108]. Authors have compared fault detection system based on feedforward ANN and Naive Bayes for induction motors. The features for classifiers were extracted by the dual tree complex wavelet transform [82].

The comparison has been made in several papers in between Naive Bayes classifier and other classifiers. Authors [64] have discussed a pattern classification methods for fault detection based on Naive Bayes classifiers, k-NN, SVM and ANN using time domain features as input vector. A fault diagnosis based on automated segmentation method of thermographic images has been developed using Naive Bayes classifiers and C-45 decision trees [39].

4.7 Deep Learning Based Fault Detection

Deep learning methods learns the features automatically at multiple levels of abstraction in the network. The abstraction at multiple level allows the automatic learning of the complex function directly from the raw data. ANN is often used to develop a deep neural networks. Deep Neural Networks (DNNs) have overcome the disadvantage of ANN by using deep architectures instead of shallow one as in case of ANN. DNN allows the processing of raw data without much processing and can handle complex non-linear functions [35]. A deep belief network (DBN) based diagnostic network has proved to be more reliable for fault classification than SVM and back propagation neuron networks (BPNN) and it also overcomes the problem of disturbances and noises [22]. A deep belief network for bearing fault detection has been developed by using combination of Stochastic gradient descent, restricted Boltzmann machines and particle swarm optimization [83].

Convolutional neural network (CNN) is a class of deep neural networks which has been used for fault detection in recent times. A 1-D convolutional neural network having self feature extraction and classification properties has been designed [32]. CNN provides a functionality of feature extraction form raw data and enable fault detection in motor bearings [97]. CNN has been used for bearing fault detection without feature extraction based on conversion of 1-dimensional vibration signal to 2-dimensional vibration image [30]. Deep learning is comparatively new and fault detection system based on it has been developed recently. Deep learning has great potential owing to its deep architectures and its use will help in developing a better and reliable fault diagnostic systems.

5 Discussion, Limitations and Future Scopes

The machine learning algorithm based fault detection system has more reliability and adaptability. It is being used widely in fault detection. Moreover, a decision of choosing the right algorithm depending on the data is foremost important. The pros and cons of algorithms are mentioned in Table 1.

SVM works really well for small datasets with an excellent generalization properties. SVM can also classify non-linear datas with the help of kernel functions. SVM provides high accuracy in fault detection and diagnosis. k-NN is an instance based learning and is often called lazy learner. In k-NN algorithm, k denotes the data points of training set lying in the vicinity of the data points of test data sets. It is faster during training process, however it is slow during classification process. ANN is among the efficient classifiers and

Table 1 Pros and cons of ML algorithms

Algorithms	Pros	Cons
SVM	1. High Accuracy	1. Sluggish for large data
	2. Handles outliers better	2. No physical meaning
k-NN	1. Easy implementation	1. Slow in real time
	2. Robust to noise	2. Sensitivity to Outlier
ANN	1. Parallel processing capability	1. Hardware
	2. High accuracy	2. Overfitting
Decision trees and random forest	1. Easy to understand and interpret	1. Overfitting
		2. Longer Training Period
Naive Bayes	1. Robust to noise	1. Assumption of independent features
	2. Low computation cost	
Deep learning	1. Robustness to variations in data	1. Large data requirement
	2. Self feature extraction	2. Large time for training

has been used significantly in fault detection systems. The structure of ANN can be adjusted for achieving better classification properties. It can be used for an efficient fault detection systems. A decision tree represents a tree-like structure. Decision trees are often used for fault classification properties. A higher version of decision trees, i.e. random forests can be used as it is immune to external noises and easier to interpret. Naive Bayes classifiers depends on the probability of two independent sets. It rather tells about the probability of an instance belonging to a particular class rather then the classification. Deep learning is relatively a new technique in the field of fault detection systems. It overcomes some of the disadvantages of other algorithms. Generally, SVM, ANN and deep learning performs well in multi-dimensional and continuous data and k-NN, decision trees and Naive Bayes works well for discrete data [47].

The future of AI is immense and needs more attention, especially in the field of deep learning. Some of the future scope and possibilities are enlisted below:

1. With the availability of high computational machines, a hybrid deep learning based fault detection system can be developed which will be fail-safe and can improve diagnostic performance.
2. Current system are dependent on feature selection, feature extraction, data collection and so many processes. Deep learning has the potential to develop a complete diagnostic system and needs more attention.
3. Smart-hybrid fault detection system can be developed for a real time applications based on deep learning.

6 Conclusion

This paper has presented a detailed review of machine learning-based algorithm for fault detection. This review is fruitful for developing an effective fault monitoring system for induction motors. The fault detection based on machine learning has improved the reliability and efficiency. The machine learning algorithms like ANN, k-NN, SVM, decision trees and deep learning have been discussed thoroughly. The machine learning algorithm based fault detection has been given due attention in this paper. Also, latest deep learning algorithms like convolutional neural network and deep belief network have been reviewed for fault detection. Application of deep learning gives an advantage of self-feature extraction and selection which consequently, reducing the risk of human error in feature extraction and their selection. Along with it, future scopes have been proposed too for developing an effective system. The future of AI is immense and needs more attention to developing a complete and self-learning package for unified fault prognosis and diagnosis.

Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

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