AUT Journal of Electrical Engineering

AUT J. Elec. Eng., 56(1) (Special Issue) (2024) 79-94
DOI: 10.22060/eej.2023.22675.5558

Recent Advances in Fault Diagnosis Methods for Electrical Motors- A Comprehensive Review with Emphasis on Deep Learning

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ABSTRACT: This paper provides a review of deep learning-based methods for fault diagnosis of electrical motors. Electrical motors are crucial components in various industrial applications, and their efficient operation is essential for maintaining productivity and minimizing downtime. Traditional fault diagnosis methods have limitations in accurately detecting and classifying motor faults. Deep learning, a subset of machine learning, has emerged as a promising approach for improving fault diagnosis accuracy. This review discusses various deep learning methods, such as convolutional neural networks, recurrent neural networks, autoencoders, transfer learning, and transformers that have been utilized for motor fault diagnosis. Additionally, it examines different datasets and features used in these methods, highlighting their advantages and limitations. The paper also discusses challenges and future research directions in this field, such as data augmentation, transfer learning, and interpretability of deep learning models. Based on the findings, it is concluded that deep learning-based technologies are replacing manual expert involvement as the new norms in this field. Besides, methods are getting more standard, and official benchmarks are being created. A summarized table is provided at the end of the paper and numerous methods have been reported.

Review History:

Received: Oct, 07, 2023
Revised: Nov. 09, 2023
Accepted: Nov. 14, 2023
Available Online: Feb. 01, 2024

Keywords:

Fault diagnosis
deep learning
inter-turn fault diagnosis
bearing fault diagnosis
convolutional neural network
Transfer learning

1- Introduction

Electrical motors play a pivotal role in various industrial applications, ranging from manufacturing and transportation to energy production and robotics. These motors are crucial components that drive the machinery and systems, ensuring smooth operations and productivity. However, over time, electrical motors are susceptible to various faults and failures, which can lead to significant downtime, costly repairs, and potential safety hazards. Effective fault diagnosis and early detection of these issues are paramount to maintaining the efficiency and reliability of motor-driven systems. While fault detection is the process of detecting the presence of a fault, fault diagnosis is more comprehensive than fault detection and it aims to identify the nature and source of the fault. Both are vital for motor reliability and safety, particularly in sensitive applications such as aerospace and automotive operations.

Deep learning (DL) has had a significant impact on almost every industry. One of the fields that has been significantly impacted by it is control engineering. DL is now regarded as one of the most advanced branches of artificial intelligence. In contrast to traditional machine learning algorithms, which require the feature to be extracted manually, this task can be performed automatically. As an example, convolutional neural networks (CNNs) begin with a convolution layer that serves as a feature extraction tool [1]. Because of this powerful mechanism, 1D CNN can handle noisy signals, because it only captures the necessary information and thus omits the unwanted data.

Utilizing deep learning methods in fault diagnosis and fault severity monitoring is one of the latest available trends. Fault diagnosis methods can be divided into three main categories: model-based, signal-based [2], knowledge-based, and hybrid fault diagnosis methods [3]. Among these methods, knowledge-based methods are the ones that utilize AI-based algorithms [4]. It should be mentioned that knowledge-based methods are also referred to as data-driven methods. The fundamental goal of this paper is to examine the most recent knowledge-based studies, particularly those that used deep learning. Other studies that use model-based and signal-based paradigms are reviewed for comparison reasons.

Artificial intelligence and machine learning methods do not have many of the difficulties and problems of conventional analytical methods. In deep learning methodology, the equations and system parameters do not affect the performance of the algorithm. The most crucial part is the data i.e., inputs and outputs of the system. For example, in fault detection, the inputs can be in the range of different motor current frequencies, and the output can only be labeled as a fault occurring. What is important in the machine learning process is that the need for analysis is significantly reduced. If the network is properly trained, the feature extraction process is done in successive layers in a completely automated manner.

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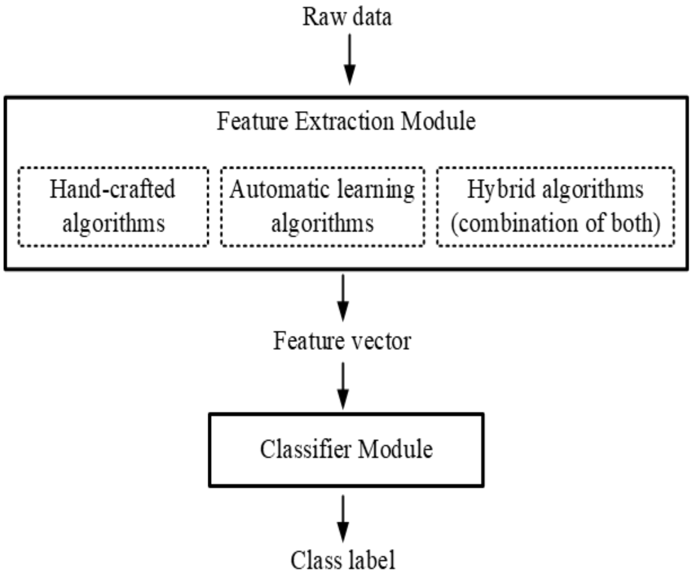

Fig. 1. Feature extraction methodologies in classification problems

Particularly, in the current frequency example, the network learns which frequencies change when a fault occurs. If the process is done manually by a field expert, it will be very complex and time-consuming.

Deep learning networks have a substantially higher computational cost than other analytical methods due to their inherent complexity. A trained network consumes a large amount of memory space, which in many cases exceeds the entire microcontroller memory, making most methods practically impossible to implement. On the other hand, the method's comprehensiveness is important. Almost all classical fault diagnosis methods were designed for a certain state or type of fault. Linear or nonlinear load, motor power range, and simultaneous fault diagnosis are all conditions that are only partially supported by any conventional method. DL, on the other hand, has the capacity to consider all of them. It replaces the if/else structure found in traditional methods. Instead of addressing all of the different modes analytically in the method, a fault diagnosis model that contains all of the specific states can be constructed by gathering data containing the above states and training the network with them.

Numerous direct and indirect fault detection methods based on machine learning have been proposed thus far. AI-based fault diagnosis methods are not limited to only electrical machines. There are various papers reporting fault diagnosis of different components of power systems, as seen in [5], where fault diagnosis of high voltage circuit breakers is investigated. However, here we only limit the scope of the paper to fault diagnosis of electrical machines. First, a brief introduction to deep learning is provided. Then a comprehensive review of the most recent works on electrical machine fault diagnosis is presented, covering a wide range of fault types. This review concludes that deep learning is the dominant trend in the scientific literature. Similar to the computer vision and natural language processing fields, official datasets and benchmarks are established. The well-known motor bearing dataset from Case Western Reserve University (CWRU) [6] is an example.

2- Deep Learning Introduction

Traditionally, machine learning algorithms largely depend on the features of the input dataset. In other words, the ability of the field expert in feature extraction is one of the key factors in the performance of the classifier, not the algorithm itself. This procedure is not only prone to human errors but also needs its preprocessing procedure for every different problem. According to [7], this procedure has been illustrated in Fig. 1. It can be seen that the feature extraction module can be implemented in the following three ways: Hand-crafted, automatic learning, and hybrid. However, this procedure was revolutionized by the advent of deep learning methods. Deep learning, at its core, tries to replace hand-crafted feature extraction algorithms with automatic ones.

Deep learning networks were developed initially as a response to this demand for automatic feature extraction. The majority of the architectures in fault diagnosis fall under the category of convolutional neural networks (CNN). Whether the raw signals are used or 1D to 2D preprocessing is used, the CNNs can be either 1D or 2D. A simple 1D CNN with two input channels is demonstrated in Fig. 2. Consecutive windows of a signal are extracted and undergo convolution operation with a specific filter size. Note that although only one convolution layer is shown

in Fig. 2, usually several back-to-back convolution layers are utilized in the networks. After the convolution layers, pooling layers are used to reduce the size of feature maps. Then the resultant vectors are fed into a fully connected artificial neural network for the classification part.

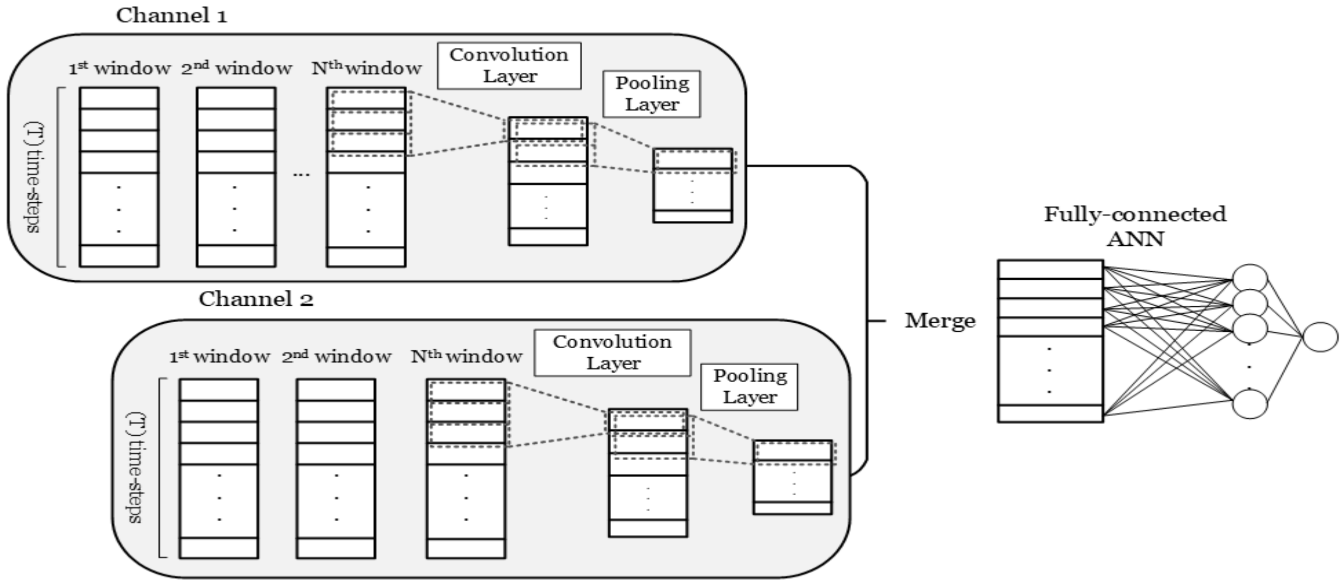

Fig. 2. Structure of a 2-channel, 1D convolutional neural network (1D-CNN)

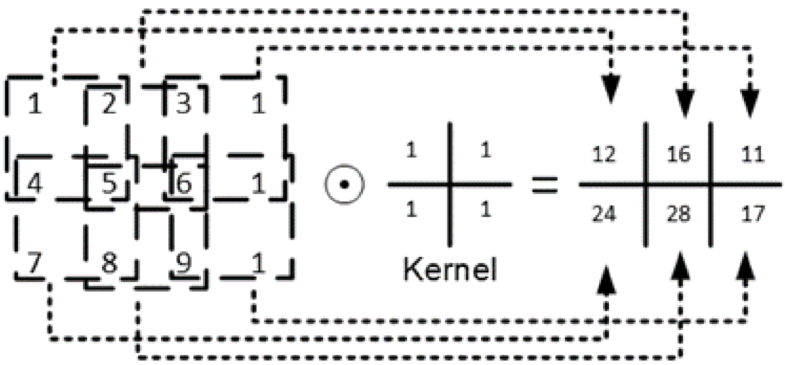

Fig. 3. 2D Convolution operation in discrete format [8].

Convolution can be best explained through a discrete 2D example. A Simple 2D convolution has been explained in [8] and shown in Fig. 3. In this simple example, a 2x2 Kernel moves over an image. The result for each position of the Kernel is the sum of products of numbers that are placed in the same location. In the above-mentioned example, convolution results have been depicted for the 6 different positions of the Kernel.

Most of the time, signals are augmented with noise to make the model more robust and prevent overfitting. In terms of 1D input signals, this noise augmentation is usually reported with a signal-to-signal-to-noise (SNR) ratio. Noise augmentation of two signals with three levels of SNR is shown in Fig. 4. This method not only increases the number of samples, it also teaches the network to denoise the input and extract the relevant features.

3- Faults in Electrical Motors

3- 1- Electrical Faults

3- 1- 1- Stator/rotor winding short circuit

Most following reported faults fall under the category of interturn short circuit fault (ISCF). However, phase- to-ground and phase-to-phase faults can also be observed. In model-based fault diagnosis methods, some performance aspect of the machine is estimated. This estimated value can be a system state or a parameter. Either way, the fault is detected via the difference between the estimated output and the measured output [3]. Mathematical modeling of the system is a requirement in this type of diagnosis. The Kalman filter is utilized in

[9] for ISCF diagnosis of switched reluctance motors. The proposed method belongs to the class of model-based methods. In addition to the state vectors, the Kalman filter

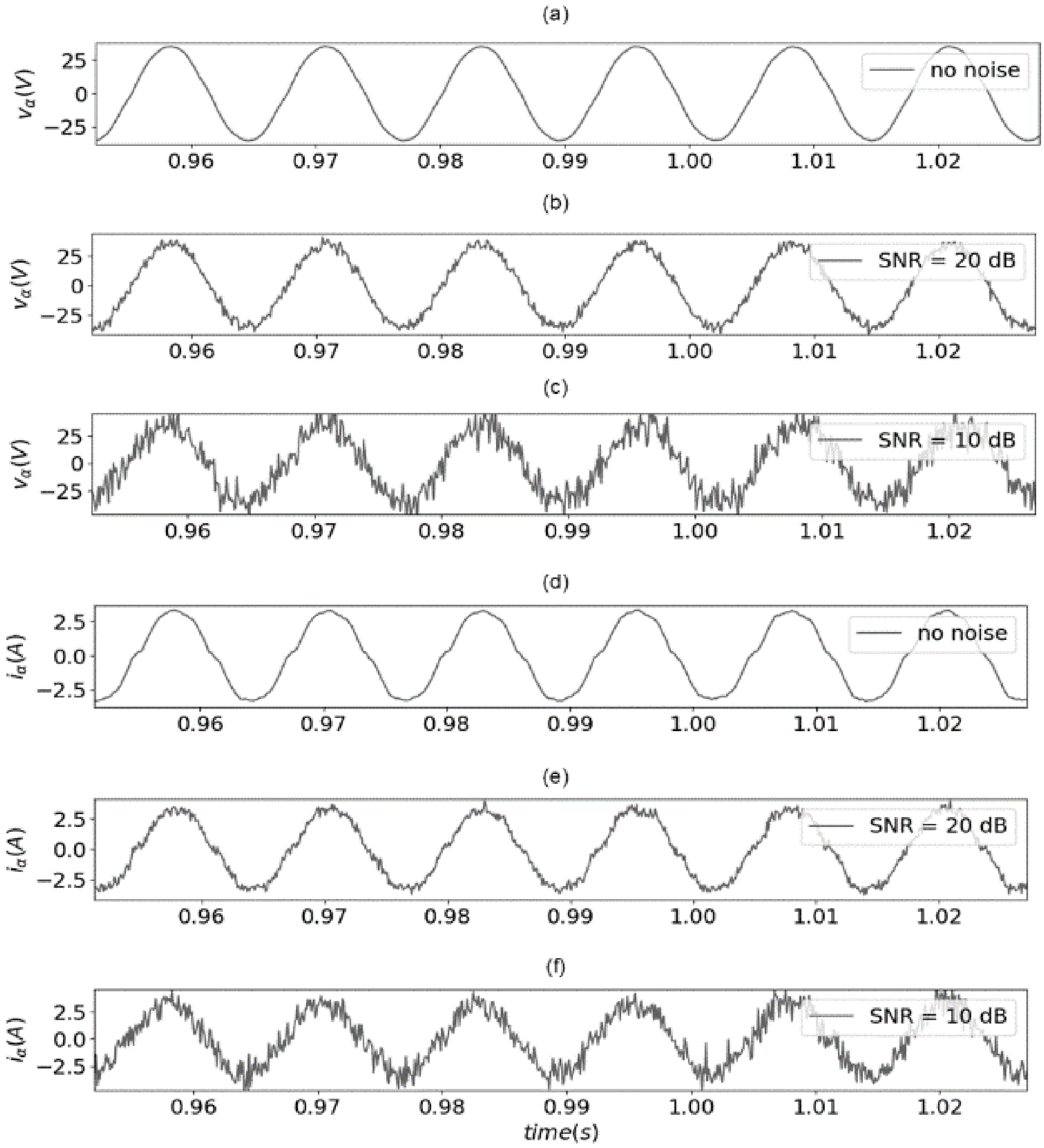

Fig. 4. 1D noise augmentation of two signals with three different SRN levels

estimates phase resistance. The difference between the estimated phase resistance and the phase resistance in normal operating conditions, referred to as the residual signal, is used to diagnose the fault. It has been demonstrated that the increase in the residual signal is considerably greater in ISCF occurrence than the increase in sudden load changes. A time-efficient equivalent circuit for ISCF diagnosis of PMSMs [10], ISCF diagnosis of PMSM using moving horizon observer [11], ISCF diagnosis using zero sequence voltage [12], the weighted linear combination of three-phase currents for ISCF diagnosis of BLDC motors [13], measuring six impedances in a stationary d-q plane of induction motors (IMs) [14], measured torque's DC offset for five-phase interior PMSM [15], and extended Park's vector approach (EPVA) modeling of PMSM [16] are among other model-based methods reported in the literature.

Flux monitoring as a promising fault diagnosis tool with low false alarms is suggested in the literature [17], [18]. Gyftakis et al. have focused on low-severity ISCF of IMs, which is a more challenging task compared to high-severity cases [19]. It has been stated that most classical diagnosis methods are not sensitive enough to detect low-severity scenarios. The method is visualized in Fig. 5, whereas the fault severity increases, the locus of stray flux components becomes more elliptical.

A support vector machine (SVM) classifier is used in [20] to detect ISCFs in inverted-fed induction motors. As input features, the Euclidean norms of the wavelet coefficients of the three-phase currents are selected. It has been reported that when the fault severity grows, the Euclidean norm for the faulty phase rises. The approach has high sensitivity and can identify ISCF faults with as little as 350 mA of fault current.

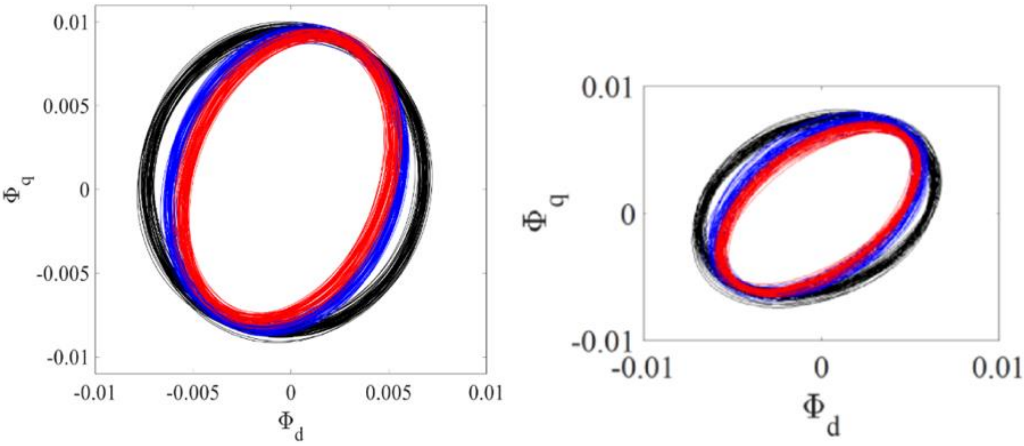

Fig. 5. Full-load (left) and no-load (right) fundamental component of stray flux for healthy motor (black), 0.25 fault index (blue), and 0.5 fault index (red) [22].

One of the less explored topics in the literature is the location of the defective stator winding. Two support vector machine (SVM) models have been proposed in [21], focusing on faulty phase detection in ISCF and phase-to-ground faults. The method primarily relies on stator current signature analysis (SCSA), but the extracted signatures use Stockwell transform decomposition. This indicator has only ever been used to identify faults. Using this indicator, the fault type (ground fault or turn fault) is identified, and the faulty phase is then detected using the SVM model. The three-phase currents' standard deviation for a particular bandwidth serves as one of the SVM classifier's features. Zero sequence current has been employed as the indicator to identify ISCF from phase to ground fault. Other similar methods with manually extracted features are reported in [22]–[25]. SCSA is also used for rotor asymmetry fault detection in wound rotor IMs and has been shown that it can provide higher resolution and lower computational complexity in comparison to Fast Fourier Transform (FFT)-based approaches [26].

An algorithm for ISCF diagnosis of brushless doubly fed induction motor (BDFIM) based on power winding current spectrum has been proposed in [27]. There are two magnetically coupled stator windings in a brushless doubly-fed induction machine BDFIM: power winding (PW) and control winding (CW). By monitoring a specific set of frequency components in the PW current spectrum, ISCF in either PW or CW can be identified. The proposed method is only suitable for the steady-state operation of the motor. Signal-based indicators such as leakage flux-linkage [28] and DC offset of measured torque [15] are among other noticeable studies.

Wang et al. [29] suggested an auto-encoder with a softmax classifier for detecting ISCF. Multiple time steps of three-phase currents are fed into the AE. The classifier's input features are obtained from one of the AE's hidden layers, which contains two neurons. It has been stated that the model requires less data and processing resources than CNNs or Deep Belief Networks (DBN).

An emerging trend in ML is federated learning (FL). In an FL setting, a single model is trained on multiple distributed nodes. Then each node's parameters are sent back to a central server, where a global model is generated using these distributed models. This process is done without accessing the data on each node. The process is shown in Fig. 6. In terms of fault diagnosis, it helps with the problem of unbalanced data. We can deploy a model on multiple fault diagnosis systems and train locally on them. Then we can aggregate these models on a central server. In a way, this model is trained on multiple datasets, so it has a high generalization ability. This approach is investigated in [30], in which a Siamese network is trained on multiple nodes for ISCF fault diagnosis.

3- 1- 2- Drive system faults

Although fault diagnosis of the drive system is not in the scope of this paper, it should be mentioned that learning-based methods are also used in that area. The pattern of incipient fault in the inverter switches of inverter-fed induction motors has been investigated in [31]. The method, just like any other learning-based method, has been tested against parameter variance and different load situations. The method can identify the location of the faulty switch in a three-legged inverter. The mean current vector has been used as the main time-domain feature and the SVM has been selected as the classifier.

3- 1- 3- Hall effect sensor

Fault diagnosis in the hall effect sensor of BLDC motors and reconstructing them has been implemented in [32] the fault tolerant control (FTC. A counter system has been proposed for the fault detection of the sensor. The counter resets every time one of the hall effect signals changes. The counter increments with a sampling rate much higher than the commutation rate. If the counted samples of one state are less or more than a threshold, the fault is identified. Then, the faulty sensor signal is reconstructed, and the motor can continue its operation without any interruption.

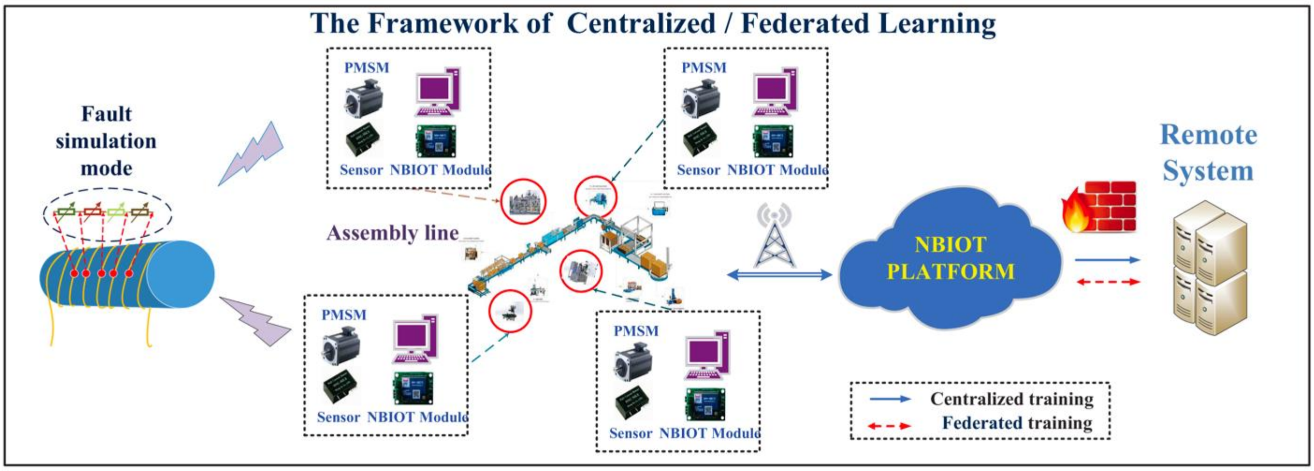

Fig. 6. Overview of ISCF diagnosis under FL framework [32].

3- 2- Magnetic Faults

Local demagnetization fault diagnosis is another less investigated topic. In [33], this topic is investigated in linear PMSMs. B-emf has been selected as the fault indicator signal. The high-level features of the time-frequency representation of the b-emf signal have been extracted with S-Transform. The 14 fault types have been classified with the modified version of the SVM algorithm.

3- 3- Mechanical Faults

Mechanical fault diagnosis is attributed to a wide area of faults. This paper covers the broken rotor bars, gear and bearing faults, and rotor eccentricity faults.

3- 3- 1- Broken Rotor Bars

Induction motor stray flux monitoring has been suggested as a method [34]. This method depends on the placement of Hall-effect sensors on some external coils. Using a frequency spectral subtraction analysis method, the method can identify rotor bar breakage faults in both adjacent and non-adjacent bars. According to [35],the Hall-effect signal's statistical (time-domain) features and FFT features have both been used to diagnose the broken rotor bars fault. This method can function well in low slip ranges and does not rely on slip estimation, in contrast to conventional analytical diagnosis methods like motor current signature analysis (MCSA). Additionally, it has been claimed that the proposed method requires significantly fewer samples than MCSA, which results in lower memory needs and computational constraints.

The MCSA is the standard algorithm used in broken rotor bar fault detection. One of the problems with this approach is that the signature frequency components appear in low frequencies, mostly near the fundamental component. This is the reason that a rather long time window is needed for calculations of these low-frequency components. A more lightweight solution to this problem has been proposed in [36].In the proposed method, first, the complex envelope of the current signal has been calculated using a Taylor-Kalman filter. Then, the signal envelope has been downsampled and fed to another Taylor-Kalman filter, which is responsible for calculating the amplitude and frequency of the fault components. Every stage is only responsible for one frequency component, so it has been stated that this method can perform much faster than the traditional one.

The distinction in the method has been suggested in [37], in which the transient mode of the fault indicator signal has been analyzed, instead of the steady-state mode. It has been claimed that the patterns appearing in the transient mode are unique to the fault phenomena, and do not appear in non-faulty scenarios. As a result, false detections can be prevented. Measurements of three coil sensors have been used for the fault indication.

Multivariate relevance vector machine (MRVM) has been proposed in [38]a multivariate relevance vector machine with multiple Gaussian kernels (MKMRVM as the BRB fault classifier. The supported fault states are healthy, 1 broken rotor bar to 4 broken rotor bars and the fault indicator signal is stator current. Similar to the SVM, Kernel parameters are crucial in the performance of the classifier, so an intelligent optimization method called the Levy fight mechanism is used for Kernel parameter optimization. Since each dimension of the features vector has its own Kernel parameter, the proposed method shows competent accuracy.

3- 3- 2- Gear faults

A CNN-based gear fault diagnosis method has been presented in [39]. Unlike other deep learning-based methods, a shallow neural network (one convolution layer and one fully connected layer) has been selected. Vibration, torque, acoustic pressure, stator voltage, and stator current are the signals that have been considered as the fault detection features. The reason behind the selection of a shallow network is explained using the class manifolds. In other words, it has been shown with only three types of gear faults, the geometry of data is

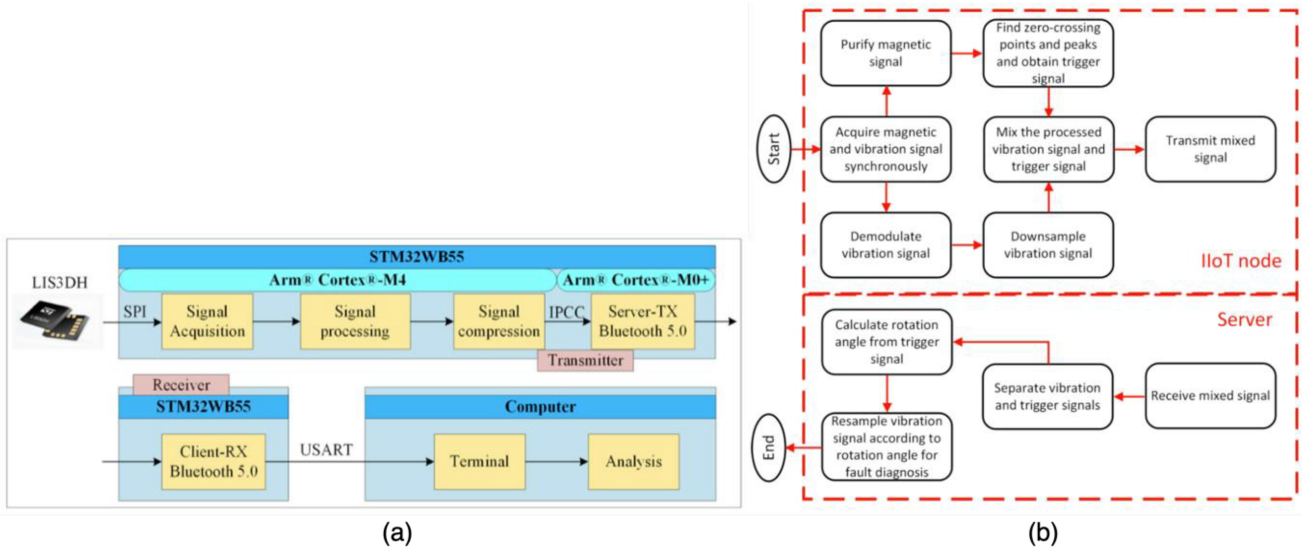

Fig. 7. Schematics of the IoT-based fault diagnosis methods proposed in [55] using Bluetooth (a) and [54] using LoRa (b).

already well separated and no deep representation is needed for classification.

3- 3- 3- Bearing faults

The most naive methods in this section start with [40], where every time sample of the vibration signal is used as the input nodes of a deep stacking network. The labels are encoded into binary values to make them sparser and avoid overfitting.

More sophisticated studies use preprocessing methods such as Kernel local characteristic-scale decomposition (KLCD) to stationary wavelet packet transform (SWPT) in their framework. In [41], the raw vibration signal has been fed to the Kernel local characteristic-scale decomposition (KLCD) method, which decomposes the signal into multiple intrinsic scale components (ISC). The envelope spectrum of these components has been fed to the extreme learning machine (ELM) classifier. In [42], optimized SWPT (Op-SWPT) is applied on the stator current because of the low required sampling frequency. Artificial immune system (AIS) nested within support vector machines (SVM) was chosen as the classifier.

Principal component analysis (PCA) is a very popular feature extraction methodology in this type of fault [43]–[45]. In [43], the fault is diagnosed by applying PCA on multiple signals such as vibration, temperature, and shaft speed. The proposed method not only detects the fault by screening the PCA-extracted features but also identifies the signal responsible. In [44] and [45], PCA is applied to the spectral kurtosis and space-mapped versions of the vibration signals to reduce the dimensionality. Manifold learning is another methodology that is used by Zhao et al. [46] to learn a low representation manifold of different fault patterns and reduce dimensionality.

In [47] and [48] raw vibration signals are converted to images using the short-time Fourier transform (STFT). STFT is a non-stationary, time-frequency analysis method suitable for transient regimes [49]. Then the inputs are classified using a transformer neural network. The proposed methods need a 1D to 2D image transformation. It should be noted while 2D transformation has its benefits in transfer learning and using pre-trained image networks, it will complicate the method and add more computational complexity to the model. 1D models are extremely beneficial in terms of both the training and the inference time. So, they can also be used in real-time fault diagnosis. In [50], and [51] raw vibration and current signals have been used respectively, and no 1D to 2D transformation is used. The former proposes bearing fault diagnosis while the latter is focused on ISCF diagnosis. Hoseintabar Marzebali et al. [52] proposed using both LSTM and 1D CNN as back-bone models for feature extraction of raw current signals. The resultant feature vector and a softmax classifier show an accuracy of 95.8% for bearing fault diagnosis.

Lu et al. [53] proposed the use of a well-known AlexNet network in bearing fault diagnosis. With the help of transfer learning, the parameters of the first few layers of AlexNet are kept constant, while the last nine layers of the network are trained specifically for this task. 1D to 2D transformation of vibration signals have been with Non-Uniform Fast Fourier Transform (NFFT) with Hamming window. As a result, spectrograms (RGB images) have been generated from vibration signals.

As deep learning models used in fault diagnosis continue to increase in complexity, processing predictions on edge devices becomes impractical. This is precisely where IoT-based methods come to play. Two IoT-based fault diagnosis methods have been presented in [54], and [55]. In multi-source methods such as[54], leakage flux and vibration have been down-sampled and mixed, while in [55] only the vibration signal is compressed before transmitting. Then, the received signal can be separated and processed to detect bearing faults. Bluetooth and LoRa are the preferred communication technologies selected by the authors. An overview of these methods is illustrated in Fig. 7.

Transfer learning is one of the active topics in the fault literature. The motivation behind this is the large size of data required in the deep learning models. A transfer learning approach for the bearing fault diagnosis has been proposed in [56]. The network has been transferred from the well-known ResNet network. In addition, a modified distance metric has been introduced so that the Kernel parameter robustness and learning efficiency can be achieved. A similar approach with ResNet-50 as the model and continuous wavelet transform as the preprocessing step is proposed in [57].

Auto-encoders have been used for the task of deep transfer learning of bearing fault diagnosis in [58]. Three layers of autoencoders have been trained separately using the source dataset. Then, the classifier has been trained with the source dataset. After that, the whole network has been fine-tuned using both the source dataset and the target domain dataset. This fine-tuning has been utilized by adding the MMD metric to the loss function. The present paper uses the famous bearing fault dataset of Case Western Reserve University.

Karnavas et al. [59]have encoded the vibration signal's global and local content into a single feature vector. The convolution and attention mechanisms are used to extract the local features, while two consecutive dense layers are used to extract the global features. The global features are extracted in parallel with the former network using two consecutive dense layers. Two resulting feature vectors are concatenated and fed to the classification network. Validation results on two famous bearing datasets of Paderborn University and CWRU show more than 99% accuracy for both of the datasets.

3- 3- 4- Eccentricity

Almost all of the recent studies are either model or signal-based. Static eccentricity fault detection of BDFIMs is investigated in [60] in which by monitoring a specific set of harmonics in the power winding, the static eccentricity fault has been detected. Also, the severity of the fault is also evident in the magnitude of the proposed frequencies. Masoumi et al. [61] proposed two faulty and healthy dq models for synchronous generators and used estimated eigenvalues as the fault indicators.

3- 4- Multiple types of faults

The application of machine learning in fault diagnosis has enabled the development of systems capable of detecting various fault types originating from different sources, including electrical, mechanical, and magnetic origins. For instance, in induction motors, three common fault types—broken rotor bars, unbalanced shaft rotation, and bearing faults—have been investigated in [62]. These studies have leveraged methods such as harmonic spectra analysis, analysis of variance (ANOVA), and p-value tests to select fault indicators, as well as surface fitting for calculating fault signatures of untested scenarios. Additionally, the use of CNNs has demonstrated superior accuracy when employing time-frequency images of vibration signals as input compared to traditional time series or Fourier transform approaches [63]. This CNN-based method also offers interpretability through Layer-wise Relevance Propagation.

For mechanical faults, vibration signals have been transformed into images using wavelet transformation, coupled with a deep CNN architecture that utilizes low-level features extracted from the VGG-16 network [64]. The efficiency impact of rotor bar failures and bearing faults on induction motors has been quantified in [65], highlighting the significance of adjacent rotor bar faults. Further investigations have extended to other fault types, such as eccentricity, local demagnetization, and load unbalance in PMSMs [66].The use of analog signals from hall effect sensors has been proposed for distinguishing these fault types accurately.

Some approaches, like the one presented in [67], have focused solely on the time-domain representation of vibration signals for fault detection, demonstrating improved performance and lower dimensionality by employing RNN-based autoencoders. Another study emphasizes the use of Sinc convolution, a non-traditional approach, in the first layer of a 1D CNN for bearing fault and broken rotor bar fault detection, leading to more interpretable feature maps by extracting certain frequency components [68].

For signals with varying frequency content over time, like non-stationary signals, novel methods like Rational-Dilation Wavelet Transform (RADWT) have been introduced to provide better frequency resolution and improved fault detection in various scenarios, including single-phase open-circuit, bearing, and broken rotor bar faults [69]. The research has demonstrated that different fault types can be diagnosed by estimating the torque value based on changes in the acoustic signal produced by the machine's output.

In petrochemical units, the transformation of 1D vibration time-series signals into 2D images using the Gram matrix has been explored for fault detection [70], as shown in Fig. 8. Additionally, the combination of winding currents and vibration signals has been employed in a broad learning algorithm [71]. This approach allows for retraining until satisfactory accuracy is achieved. A similar broad learning method with acoustic and current signals as the input has been proposed to facilitate the retraining process [72].

The application of CNNs for BLDC motor fault diagnosis has been addressed in various studies, such as [73].

For BLDC motors, fault diagnosis has also been achieved through a combination of current and vibration signals [74]. These studies emphasize feature selection, employing methods such as Complete Ensemble Empirical Mode Decomposition (CEEMD) to enhance accuracy. Real-time diagnosis of demagnetization and bearing faults has been proposed, utilizing stator current analysis and comparing the performance of wavelet packet transform (WPT) with 1D CNNs [75]. Diagnosis of bearing faults and demagnetization faults with no additional sensor has been proposed in [76]. The bearing fault has been detected via the DWT of motor speed and the demagnetization fault has been diagnosed via the kurtosis index of the output of the Hall Effect sensor.

In the context of an oil pump, deep belief networks have been used for feature extraction and fault classification based solely on current signals [77]. These networks require fewer labels and shorter training times compared to traditional back-propagation-based networks.

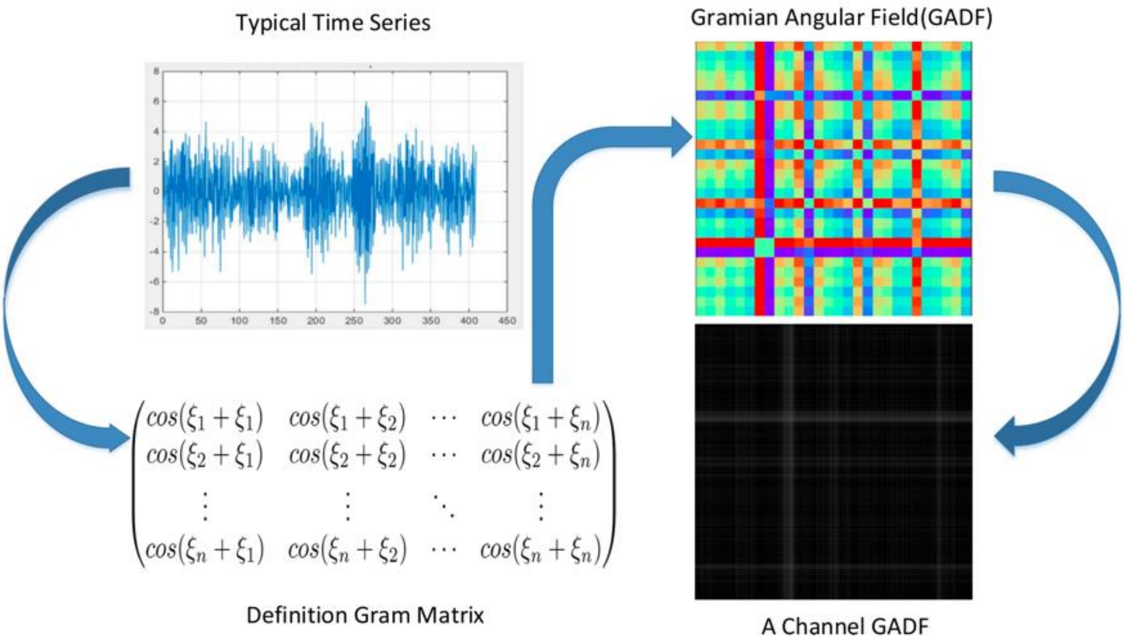

Fig. 8. Time-series 1D to 2D transformation using Gram matrix [69].

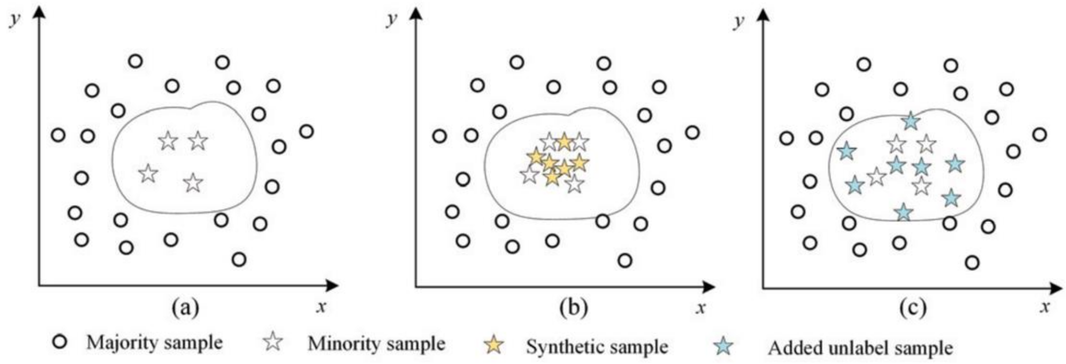

Fig. 9. A simplified illustration of imbalanced data (a) along with the two solutions: synthetic data generation (b) and labeling unlabeled data using weakly-supervised learning [80].

Model-based strategies have been introduced for fault diagnosis, addressing various sensor faults, including speed-sensor, voltage-sensor, current-sensor, open-phase, and open-switch faults [78]. The method leverages harmonic content analysis of current signals and other methods such as estimation of speed and voltage model-based observers.

To address the issue of dataset distribution differences between source and target domains, a regularization term has been proposed to align high-level features in CNNs, enhancing the fault detection accuracy of transferred models [79].

A comparison of different machine learning algorithms for induction motor fault diagnosis has been presented, highlighting the significance of feature extraction methods like discrete wavelet transform and matching pursuit [80]. For imbalanced classification scenarios, weakly supervised learning has been introduced as an alternative to synthetic samples [81], promoting better generalization by incorporating unlabeled data [82]. Fig. 9 compares the two approaches.

Some more popular criteria have been listed in [83. According to that, signature frequencies in different fault indicator signals can be summarized in Table 1. Where is the supply frequency, is a positive integer, is the number of stator slots, is the number of pole pairs, is the rotor frequency, is the inner raceway

fault frequency, f_{ORF} is the outer raceway fault frequency, f_{BF} is the ball fault frequency, f_{CF} is the cage fault frequency, D_B is the ball diameter, D_P is the pitch diameter, N_B is a number of rolling elements and θ is the ball contact angle. Also, a summary of the latest methods/technologies used in the literature has been reported in Table 2.

Table 1. Signature frequencies of different types of faults in electric motors

Motor	Fault type	Fault indicator	Frequency component
PMSM	Inter-turn	Current	$f_{itsc} = f_s\left(1 \pm k\frac{z}{p}\right)$
	Eccentricity	Current	$f_{eccentricity} = f_s\left(1 \pm \frac{2k-1}{p}\right)$
	Demagnetization	Current	$f_{dmg} = f_s\left(1 \pm \frac{k}{p}\right)$
Any	Inter-turn, 3∅ asymmetry	Vibration	$2f_s, 4f_s, 8f_s$
	Bearing	Vibration	$f_{IRF} = \frac{N_B}{2} f_R\left(1 + \frac{D_B\cos\theta}{D_P}\right)$ $f_{ORF} = \frac{N_B}{2} f_R\left(1 - \frac{D_B\cos\theta}{D_P}\right)$ $f_{BF} = \frac{D_P}{2D_B} f_R\left(1 - \frac{{D_B}^2\cos^2\theta}{{D_P}^2}\right)$
IM	Rotor cage	Vibration	$f_{CF} = \frac{1}{2} f_R\left(1 - \frac{D_B\cos\theta}{D_P}\right)$

Table 2. A summary of methods used in fault diagnosis of electrical machines

Ref.	Signal	Motor	Method	Studied Faults						
				ISCF	PI	DMG	ECC	RC	Gear	Bearing
[3]	Current	PMSM	Model-Based (Kalman Filter)	✓						
[9]	Current	SRM	Model-Based (Kalman Filter)	✓						
[10]	Unknown	PMSM	Model-Based	✓						
[11]	Unknown	PMSM	Model-Based (Moving Horizon Observer)	✓						
[12]	Voltage	Unknown	Model-Based (Zero Sequence Voltage)	✓						
[13]	Current	BLDC	Model-Based (Weighted Linear Combination)	✓						
[14]	Impedances	IM	Model-Based (Stationary d-q Plane)	✓						
[15]	Torque	5-Phase Interior PMSM	Model-Based	✓						
[16]	Unknown	PMSM	Model-Based (EPVA)	✓						
[18]	Airgap and stray Flux	IM	Signal-based, STFT					✓		
[19]	Flux	IM	Flux Monitoring	✓						
[20]	Current	Inverted-Fed IM	SVM	✓						

Ref.	Signal	Motor	Method	Studied Faults						
				ISCF	PI	DMG	ECC	RC	Gear	Bearing
[21]	Current	Unknown	MCSA and SVM	✓	✓					
[22]	Current	IM	MI, DT, MLP	✓						
[23]	Flux linkage	Sync. Gen.	RBF, ANN	✓						
[24]	Current	LSPMSM	CNN	✓						
[25]	Current	LSPMSM	ANN	✓						
[26]	Current	Wound Rotor IM	MCSA					✓		
[27]	Current	BLDFIM	Current Spectrum Analysis	✓						
[29]	Current	Unknown	Auto-encoder with Softmax Classifier	✓						
[30]	Current	Unknown	Siamese Network (Federated Learning)	✓						
[32]	Unknown	BLDC	Counter System							
[33]	B-emf	Linear PMSMs	S-Transform			✓				
[34]	Hall-effect	Induction Motor	External Coils with Frequency Spectral Subtraction					✓		
[35]	Hall-effect	Induction Motor	Statistical and FFT Features					✓		
[36]	Current	Unknown	Taylor-Kalman Filter (Amplitude and Frequency Calculation)					✓		
[37]	Current	Unknown	Transient Mode Analysis							
[38]	Current	Unknown	MRVM (Multivariate Relevance Vector Machine)					✓		
[39]	Vibration	Torque	Acoustic Pressure						✓	
[40]	Vibration	Unknown	Deep Stacking Network							✓
[41]	Vibration	Unknown	KLCD and ELM							✓
[42]	Current	IM	Op-SWPT, AIS, SVM							✓
[43]	Temperatur e Speed Vibration	IM	DIPCA, RBC, CNN				✓			✓
[44]	Vibration	IM	SK, PCA, GMM							✓
[45]	Vibration	IM	PCA, DCN							✓
[46]	Vibration	DC	Manifold Learning, Semi-supervised, MDELM				✓			✓
[47]	Vibration	IM	STFT, TNN							✓
[48]	Vibration	IM	STFT, ViT							✓
[50]	Vibration	IM	TNN							✓

Ref.	Signal	Motor	Method	Studied Faults						
				ISCF	PI	DMG	ECC	RC	Gear	Bearing
[51]	Current	PMSM	TNN	✓						
[52]	Current	IM	LSTM, 1D CNN							✓
[53]	Vibration	IM	AlexNet, TL, NFFT							✓
[54]	Vibration, Leakage flux	PMSM	SEC, IoT							✓
[55]	Vibration	BLDC	SEC, IoT							✓
[56]	Vibration	IM	Regularized TL, ResNet-50							✓
[57]	Vibration	IM	CWT, fine-tuned ResNet-50							✓
[58]	Vibration	IM	AE, TL							✓
[62]	Various	IM	Harmonic Spectra Analysis				✓	✓		✓
[63]	Vibration	IM	CNN with Time-Frequency Images				✓			
[64]	Vibration	IM	DWT, fine-tuned VGG-16				✓	✓		✓
[67]	Vibration	BLDC	RNN-AE				✓			
[68]	Vibration	IM	Sinc Convolution, 1D CNN					✓		✓
[69]	Acoustic	IM	RADWT					✓		✓
[70]	Vibration	IM	2D Transform, Gram Matrix							✓
[71]	Acoustic, Current	IM	Broad Learning Algorithm	✓	✓		✓	✓		✓
[72]	Acoustic, Current	IM	Broad Learning Algorithm	✓	✓		✓	✓		✓
[73]	Vibration	BLDC	B2LS, 2D CNN				✓			✓
[74	Current, Vibration	BLDC	CEEMD, ANN	✓				✓		
[75]	Current	PMSM	WPT, 1D CNN			✓				✓
[76]	Speed	BLDC	DWT, Kurtosis Index			✓				✓
[77]	Current	Oil Pump	Deep Belief Networks							
[78]	Current	PMSM	Voltage observer		✓					
[79]	Vibration	IM	MMD regularized CNN				✓	✓		✓
[80]	Current, Vibration	IM	Matching Pursuit, DWT, SVM, KNN					✓		✓
[82]	Vibration	CNC machine	Incorporating Unlabeled Data, SVM, BGRU							

Abbreviations: PI, phase imbalance, DMG, demagnetization, ECC, eccentricity, RC, rotor cage, SEC, signal enhancement and compression, IoT, internet of things, NFFT, non-uniform fast Fourier transform, STFT, short-time Fourier transform, ViT, Vision Transformer, MDELM, multi-manifold deep extreme learning machine, DCN, deformable convolution networks, GMM, gaussian mixture model, DIPCA, dynamic incremental principal component analysis, MI, mutual information, DT, decision tree, MLP, multi-layer perceptron.

4- Conclusion

This paper provided a review of machine learning-based fault diagnosis methods of electrical machines. Recent trends in all types of faults (electrical, mechanical, and magnetic) have been reviewed. However, attention to some specific categories of faults such as stator ISCF or bearing faults is much higher than other types. First, a high-level introduction to deep learning and the related methods is provided. Then the advantages of each method have been stated individually, but also an overall analysis is provided as a guide for future studies. The following conclusions can be drawn from the reviewed literature:

Challenges:

1.Real-time and low-latency prediction: There is a significant need for real-time and low-latency prediction. Obtaining fast replies in fault diagnosis remains a significant problem, particularly in applications such as aerospace and automotive, where rapid decision-making is required.

2.Online Learning Capabilities: There is a clear need for online learning capabilities. Adapting models, in real-time, to dynamic, evolving scenarios is critical for maintaining accuracy and relevance in fault diagnosis systems.

3.High-Quality Labeled Data: Obtaining high-quality labeled data remains a challenge. Obtaining sufficiently annotated datasets that effectively represent the complexities of electrical machine faults is a constraint in the advancement of machine learning models.

4.Demanding Computational Infrastructure: The resource-intensive nature of deep learning models requires extensive computational infrastructure. Overcoming this obstacle is critical to enable wider use of these advanced fault diagnostic systems.

Future research directions:

1.End-to-end methodologies popularity: We anticipate a paradigm shift away from manual feature extraction and toward methods that require minimal expert interaction, automating preprocessing, and eliminating the requirement for intermediary signal estimate in future investigations.

2.Integration of Multiple Fault Sources: It is worth noting the expanding trend of studies focused on fault diagnosis from multiple sources (electrical, magnetic, and mechanical). Deep learning methods demonstrate the ability to identify numerous fault types through current or vibration data, paving the way for full fault diagnosis systems.

3.Transfer Learning Advancements: The direction toward transfer learning to improve performance and reduce computing burden suggests a viable option. Transfer learning is a potential solution to increased accuracy on target datasets, from using early layers of known vision networks in simple approaches to including regularization terms in fine-tuning for advanced studies.

4.Synthetic Dataset Generation: There is a significant gap in the development of synthetic datasets for fault diagnosis. With the emergence of generative AI, there is the potential for massive amounts of high-quality data to be generated, providing a significant resource for training and testing machine learning models across a wide range of fault types.

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HOW TO CITE THIS ARTICLE

J. Faiz, F. Parvin, Recent Advances in Fault Diagnosis Methods for Electrical Motors- A Comprehensive Review with Emphasis on Deep Learning, AUT J. Elec. Eng., 56(1) (Special Issue) (2024) 79-94.

DOI: 10.22060/eej.2023.22675.5558