

Fault diagnosis of bearing of induction motor using CNN: A Review

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Abstract- Bearings are among the most failure-prone components in induction motors, and their degradation often leads to unplanned downtimes and considerable financial losses. Early and accurate fault diagnosis of motor bearings is thus a critical concern in industrial practice. While classical approaches such as vibration analysis and motor current signature analysis (MCSA) have long served this purpose, the emergence of convolutional neural networks (CNNs) has transformed the diagnosis process through automated feature extraction and superior multi-class discrimination. This paper presents a detailed and comprehensive review of recent advances in CNN-based bearing fault diagnosis for induction motors. Detailed types of bearing faults are discussed, alongside a critical comparison of traditional and CNN-based methodologies, the operational flow of CNNs, specific model architectures, and the standing of CNNs in relation to other leading diagnostic approaches.

Keywords: Induction motor, signal processing, bearing faults, vibration analysis, motor current signature analysis, convolutional neural networks.

I. INTRODUCTION

The landscape of bearing fault diagnosis in induction motors has witnessed a paradigm shift with the increasing adoption of deep learning methodologies, particularly CNNs. Early investigations predominantly relied on analyzing stator current or vibration signals using signal processing techniques such as FFT and MCSA to extract features indicative of bearing faults. For instance, classical MCSA-based studies focused on extracting sideband frequencies associated with characteristic defect frequencies to detect both bearing and other faults, sometimes augmented by pre-processing techniques like Wiener filtering and wavelet denoising to counteract noise and enhance sensitivity to early faults[1][2].

Traditional diagnosis techniques were frequently supplemented by classical machine learning, including support vector machines (SVMs) and artificial neural networks (ANNs), which achieved high accuracy through the use of expert-curated feature sets derived from current harmonics or vibration metrics[3][4][5][6]. SVMs, due to their robustness in handling non-linear feature spaces, became particularly prominent, with studies demonstrating their ability to achieve fault classification accuracies above 97% using

parameters such as total harmonic distortion, stator current spectral features, and vibration signal statistics[3][6].

However, the dependency on hand-crafted features limits scalability and adaptability, particularly in cases involving compound faults or varying operational conditions. The limitations of this two-stage approach manual feature extraction/crafting followed by classification precipitated the turn towards CNN-based solutions.

Pioneering work by Ince et al. introduced a 1-D CNN capable of ingesting raw current or vibration signals, fusing feature extraction and classification into a unified learning system. This approach eliminated the need for laborious feature engineering, achieving not only higher classification accuracy but also real-time applicability suitable for deployment on embedded hardware[7]. Similarly, Hoang and Kang demonstrated that fusing information from multiple phase currents and processing them through parallel CNNs, with a subsequent decision-level information fusion, significantly enhanced the discriminative power for bearing faults, even those arising in external or inaccessible bearing configurations[8]. Yang et al. further addressed dataset scarcity by combining conditional generative adversarial networks (CGANs) with 2D-CNN models.

CGANs generate additional synthetic training samples, enabling robust training of deep models in small-sample scenarios. Their methodology, which transformed 1D signals into grayscale images for use as 2D-CNN inputs, surpassed SVMs, LSTM, and even 1D-CNNs in accuracy when diagnosing bearing faults[9].

Additional research explored hybrid deep learning models, such as flat diagnosis structures fusing 2D-CNNs with recurrent units (LSTM/GRU), enabling simultaneous early-stage detection and fault severity assessment, applicable under variable frequency and load regimes[10]. Sun et al. provided a theoretical foundation for convolutional discriminative feature learning, combining backpropagation-trained local filters with a feed forward convolutional pooling architecture to capture robust fault representations from raw sensory data[11].

Other studies validated the advantages of CNNs in terms of generalizability, scalability, and the ability to handle multi-fault conditions, often outperforming expert systems, classical machine learning, and wavelet-transformed feature approaches in both laboratory and industrial experimental platforms[5][8][11].

II. TYPES OF BEARING FAULT IN INDUCTION MOTOR

Bearing faults in induction motors can be classified into the following principal categories:

- Outer Race Faults

These faults are associated with localized defects on the static outer ring, often caused by poor alignment or contamination. They excite the characteristic outer race fault frequency:

$$f_{ORF} = n/2(1 - d/D \cos \theta) f_r$$

where n is the number of rolling elements, d is the ball diameter, D is the pitch diameter, θ the contact angle, and f_r the shaft rotational frequency.

Inner Race Faults

Defects on the rotating inner ring generally arise from wear or misalignment, producing the inner race fault frequency:

$$f_{IRF} = n/2(1 + d/D \cos \theta) f_r$$

Ball Faults

These reflect imperfections on the rolling elements (balls) themselves. They are typically due to fatigue, indentations, or spall formations.

Cage (Retainer) Faults

Damage or deformation of the cage impairs the regular motion and spacing of the rolling elements, leading to erratic vibration and sporadic current anomalies.

Generalized Roughness and Lubricant Degradation

Diffuse wear often from lubrication deficiencies or contaminants can result in non-localized random roughness, which degrades both vibration and current signal quality.

Each of these faults produces distinct spectral signatures and sidebands, yet their frequencies may overlap, especially as degradation progresses or in the presence of co-existing faults[8][9].

III. COMPARISON BETWEEN TRADITIONAL AND CONVOLUTIONAL NEURAL NETWORK APPROACHES

Traditional Approaches:

- **Signal-Based Methods:** These include MCSA, FFT, envelope and demodulation analysis, and time-frequency transformations (e.g., wavelet transform) to extract diagnostic features from current or vibration signatures relevant to bearing defects[1][2][12].
- **Manual Feature Engineering:** Experts select and extract features based on known fault frequencies, sideband patterns, or other statistical descriptors. The effectiveness of these steps is highly dependent on prior domain knowledge and can be suboptimal when dealing

with non-stationary, compound, or incipient faults[2][13].

- **Classical ML Models:** SVMs and ANNs are often trained on these hand-crafted features for classification[3][4][5][6].

Convolutional Neural Networks:

- **End-to-End Learning:** CNNs obviate the need for manual feature extraction by learning feature hierarchies directly from raw signals[7][9][11].
- **Scalability & Generalization:** CNNs effectively recognize overlapping, subtle, or evolving patterns, supporting robust multi-fault classification across diverse operating conditions[8].
- **Performance:** Empirical studies consistently report higher accuracy, particularly for early-stage, masked, or incipient bearing faults; CNNs perform exceptionally well in comparison with SVMs, ANNs, and even other advanced hybrid models[5][9][11].

- **Input Layer:** Receives 1D time-series (current, vibration) or 2D representations (spectrogram, grayscale images of signal slices)[7][9][11].
- **Convolution Layers:** Learn spatial (or temporal) filters, automatically extracting local patterns, such as periodic artifacts linked to specific fault frequencies. Deep stacks allow capture of higher-level motifs relevant for distinguishing compound or incipient faults[7][11].
- **Activation and Pooling:** Usually ReLU for non-linearity. Pooling layers (max or average) reduce spatial dimensionality, highlighting the most salient features and providing some translational invariance[7][11].
- **Flattening and Dense Layers:** The output feature maps are flattened and processed through one or more fully-connected layers for higher-level feature integration.
- **Output Layer:** Often a softmax function, producing class probabilities corresponding to healthy state, outer/inner race fault, ball fault, cage fault, or even multi-fault conditions.

IV. CONVOLUTIONAL NEURAL NETWORK FOR FAULT DETECTION

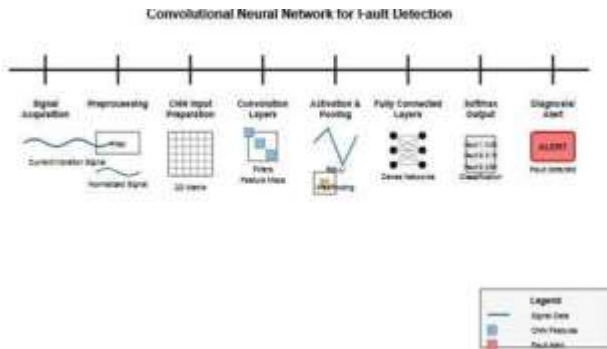


Figure 4. Convolutional Neural Network for Fault Detection

Model Innovations

- **1D CNN:** Ingests raw time-series, optimal for real-time hardware implementations and embedded diagnostic systems[7].
- **2D CNN:** Processes 2D data (e.g., spectrogram, image-like signal transforms), capturing richer contextual correlations[9].
- **Ensemble/Fusion CNN:** Multiple CNNs process segmental or phase-specific inputs, with results fused via decision-level aggregation for improved accuracy and robustness[8].
- **Hybrid Deep Models:** Combining CNNs with LSTM/GRU enables simultaneous diagnosis and severity assessment, accommodating both spatial and long-term temporal features[10].

V. CONVOLUTIONAL NEURAL NETWORK AND ITS MODELS ARCHITECTURE OVERVIEW

VI. COMPARISON BETWEEN CONVOLUTIONAL NEURAL NETWORK AND OTHER TECHNIQUES

Table.6 Comparison Between Convolutional Neural Network and Other Techniques

Method	Multi-Fault Capability	Incipient Fault Sensitivity	Feature Engineering	Diagnostic Accuracy	Real-Time Applicability	Interpretability	Reference

MCSA/FFT	Moderate	Weak–Moderate	Manual	Moderate	High	High	[1][12][13]
Wavelet/Adaptive	Moderate–Strong	Strong	Manual	High	Moderate	Moderate	[1][2]
SVM/ANN	Strong	Strong	Manual features	High	Moderate–High	Moderate	[3][4][5][6]
Hybrid FMM–CART	Strong	Strong	Manual features	High	Moderate	High	[4]
CNN	Excellent	Excellent	None (Automated)	Very High	High	Moderate /Low	[5][7][8][9][11]
Ensemble/Fusion CNN	Excellent	Excellent	None	Very High	High	Low	[8][9]
Hybrid CNN-LSTM/GRU	Excellent	Excellent	None	Very High	Moderate	Low	[10]

CNNs and their hybrids routinely provide the highest accuracy and robustness, especially in multi-class and incipient fault scenarios, compared to both classical machine learning and traditional signal-based approaches. The trade-offs are a need for more training data and reduced native interpretability though research into explainable AI and decision-level fusion continues to bridge this gap[8][9].

VII. CONCLUSION

Recent advances confirm that convolutional neural networks represent the cutting edge in the diagnosis of bearing faults in induction motors. By superseding manual feature design and leveraging hierarchical feature learning directly from raw or minimally processed signals, CNNs deliver decisive improvements in diagnostic accuracy, sensitivity to early and compound faults, and online applicability. Ensemble and hybrid CNN models further enhance performance, particularly under challenging conditions such as limited sensor access, variable loading, or data scarcity.

While challenges of interpretability and data requirements remain, ongoing research such as the integration of generative data augmentation (CGANs) and information fusion continues to enhance both practicality and reliability. In sum,

CNN-based systems are establishing themselves as essential tools for the predictive maintenance and health management of modern induction motors.

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