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Comparative Study of SVM, MLP, and CNN for Induction Motor Fault Diagnosis with Limited Data

Porównanie zastosowania SVM oraz perceptronu wielowarstwowego z CNN do diagnostyki uszkodzeń silników indukcyjnych przy ograniczonym zbiorze danych

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Abstract: This paper presents a novel fault diagnosis method for squirrel-cage induction motors, specifically targeting rotor bar breakage detection during the transient operating state of motor startup. The analysis was conducted using the Transient Motor Current Signature Analysis (TMCSA) method. The approach is based on a unique dataset comprising startup current signals from several distinct motor units, offering an unprecedented variety of test objects in the literature. Continuous Wavelet Transform (CWT) was applied to generate time-frequency representations, which were synthetically augmented using spectrogram augmentation. These images were used to train a lightweight Convolutional Neural Network (CNN). The proposed method was compared with traditional artificial intelligence techniques: Support Vector Machine (SVM) and Multilayer Perceptron (MLP). A new application of the Histogram of Oriented Gradients (HOG) technique was introduced for SVM-based image classification. The methodology relies on low-resolution images, enabling implementation on portable platforms. Results show that the proposed approach performs comparably to or better than classical AI methods, even with limited data.

Keywords: SVM, MLP, CNN, induction motor, limited data

Streszczenie: W artykule przedstawiono nową metodę diagnostyki uszkodzeń silników indukcyjnych klatkowych, ze szczególnym uwzględnieniem wykrywania pęknięć prętów klatki wirnika w przejściowym stanie pracy, jakim jest rozruch. Analiza została przeprowadzona z wykorzystaniem metody TMCSA (ang. Transient Motor Current Signature Analysis). Opracowana metoda opiera się na unikalnym zbiorze danych zawierającym sygnały prądów rozruchowych pochodzące z kilkunastu różnych silników, co stanowi niespotykaną dotąd skalę różnorodności obiektów badawczych w literaturze. Do uzyskanych sygnałów zastosowano ciągłą transformację falkową (CWT), a następnie ich transformaty zostały rozszerzone syntetycznie z wykorzystaniem techniki spectrogram augmentation. Na tak przygotowanych obrazach nauczono lekką sieć neuronową typu CNN. Zaproponowaną metodę porównano z klasycznymi technikami sztucznej inteligencji: maszyną wektorów nośnych (SVM) – z użyciem metody HOG (ang. Histogram of Oriented Gradients) – oraz perceptronem wielowarstwowym (MLP). Metodologia oparta na obrazach niskiej rozdzielczości umożliwia implementację na platformach przenośnych. Wyniki wskazują, że proponowana metoda głębokiego uczenia może osiągać skuteczność porównywalną lub lepszą od klasycznych metod nawet przy ograniczonym zbiorze danych.

Słowa kluczowe: SVM, wielowarstwowy perceptron, CNN, silnik indukcyjny, ograniczony zbiór danych

Introduction

This paper presents a novel approach to the diagnosis of faults in squirrel-cage induction motors, with a particular focus on detecting rotor bar breakages. The methodology is based on a unique dataset comprising several dozen startup current signals acquired from distinct and independent motor units. To the best of the authors' knowledge, such diversity of measurement objects has not been reported on this scale in the existing literature.

The acquired signals were transformed using the Continuous Wavelet Transform (CWT), and spectrogram augmentation techniques were applied to generate synthetic time-frequency representations. These images were then used to train a Convolutional Neural Network (CNN) for automatic fault classification. The fault under investigation–broken rotor bars in squirrel-cage induction motors–was identified using the Transient Motor Current Signature Analysis (TMCSA) method. This approach exploits the transient startup phase of the motor, allowing the recognition of a characteristic time-frequency pattern associated with rotor bar breakage, as revealed on the CWT scalogram. The proposed deep learning method is benchmarked against two traditional artificial intelligence techniques: Support Vector Machine (SVM) and Multilayer Perceptron (MLP).

In the case of SVM, a novel application of the Histogram of Oriented Gradients (HOG) method–originally developed for image feature extraction–is introduced to process the time-frequency representations. The entire diagnostic framework is designed to operate on low-resolution input images, making it computationally lightweight and well-suited for implementation on portable embedded platforms.

The authors postulate that the proposed deep learning solution tailored to small datasets can achieve performance comparable to–or even exceeding–that of classical AI methods, while offering enhanced generalizability to new, previously unseen machines.

Literature Review

In order to determine the current state of the art in the use of deep learning techniques for induction motor diagnostics, a review of recent publications from reputable sources was conducted at the time of writing. This section focuses on machine learning methods applied to motor fault diagnosis prior to the widespread adoption of deep learning approaches.

Several works explored classical machine learning for identifying faults in induction motors. In [1], a diagnostic technique using thermal imaging and feature extraction methods (DAMOM, DAM20HP, DAMMH, IB) combined with Nearest Neighbor and LSTM classifiers achieved up to 100% accuracy. The study [2] applied time- and frequency-domain feature extraction with ANOVA-based selection, training five classifiers–including SVM and neural networks–on vibration data, achieving accuracies from 78.3% to 98.8%. Article [3] emphasized preprocessing and identified ensemble classifiers as highly efficient and cost-effective.

The authors of [4] used vibration analysis and random forest to detect stator faults with 99.86% accuracy and applied Explainable AI for interpretability. Work [5] combined PCA with Decision Forest to diagnose faults in electric vehicle motors. In [6], machine learning methods were reviewed for fault detection in centrifugal pumps, including MCSA and various AI models. The study [7] utilized a NARX neural network to improve liquid flow identification in industrial pumps using electrical input signals.

Cloud-based predictive maintenance was explored in [8], combining wavelet-transformed features with Random Forest on Google Cloud Platform.

These studies collectively highlight the growing relevance of machine learning in motor diagnostics, particularly in scenarios with limited or noisy data.

Among machine learning techniques applied to induction motor diagnostics, Support Vector Machine (SVM) and Multilayer Perceptron (MLP) have shown promising results.

The study [9] proposed a machine learning framework for monitoring and predicting power quality (PQ) disturbances affecting induction motors. Using the Hilbert-Huang Transform for time-frequency analysis and an SVM classifier, the authors achieved a high classification accuracy of 97.2% in detecting PQ anomalies such as voltage sags, surges, harmonics, and transients.

In terms of MLP-based approaches, article [10] described the use of a neural network with one hidden layer (40 neurons) trained using a conjugate gradient algorithm to classify motor bearing faults based on vibration signals. The model reached an accuracy of 78.5% across three fault categories. Meanwhile, [11] addressed inter-turn stator faults (SITF) by analyzing three-phase current signals and applying PCA for time-domain feature reduction. A narrow neural network model achieved a classification accuracy of 98.23%, supporting the development of more reliable condition monitoring strategies.

These works highlight the effectiveness of both SVM and MLP in fault detection and classification tasks for induction motors, particularly when paired with appropriate signal processing and feature extraction techniques.

Recent research has increasingly focused on comparing traditional machine learning (ML) algorithms with deep learning (DL) models in the context of induction motor fault diagnosis. These comparative studies highlight the growing advantages of DL techniques, especially in processing raw signals and achieving high accuracy with minimal manual feature engineering.

The study [12] evaluated the influence of hyperparameters in low-data scenarios using raw stator current signals, demonstrating that 1D CNNs outperformed Random Forest (RF) and Decision Trees (DT) due to automatic feature extraction. In [13], an optimized CNN-based method achieved superior fault detection accuracy on the CWRU dataset, surpassing shallow classifiers such as SVM, MLP, and LVQ in both precision and computational efficiency.

Work [14] confirmed the effectiveness of both CNN and SVM for bearing fault classification based on FFT features.

The hybrid model proposed in [15], combining CNN, LSTM, and handcrafted features, exceeded SVM and XGBoost performance in detecting distributed bearing faults using multi-sensor data. In [16], a method combining SIFT, pretrained CNNs, and SVM reached 100% accuracy in thermal image-based fault detection, demonstrating the strength of integrating DL feature extraction with classical ML classifiers.

Articles [17] and [18] showed that LSTM networks analyzing raw vibration data outperformed LR, SVM, MLP, and RNN, eliminating the need for manual feature engineering. Similarly, [19] revealed that LSTM models not only matched Random Forest in fault classification but also provided superior RUL (Remaining Useful Life) prediction capabilities.

These studies consistently demonstrate that deep learning–particularly CNN and LSTM architectures–offers significant improvements in diagnostic performance, robustness to raw data variability, and potential for real-time industrial implementation, outperforming traditional machine learning approaches in most evaluated scenarios.

The recent studies have increasingly addressed the challenge of diagnosing induction motor faults under transient or nonstationary operating conditions using deep learning techniques. These methods leverage the ability of neural networks to process complex, variable data without manual feature engineering.

In [20], transfer learning was applied in a CNN-based system that processes raw phase current signals, enabling precise fault detection in both steady-state and transient conditions within 0.07 seconds. Article [21] introduced thermal imaging combined with gravitational enhancement and CNN analysis, offering an alternative to traditional signal-based diagnostics under variable speed conditions. Study [22] presented an adaptive diagnostic method using time-frequency analysis and a CNN trained with symmetric pattern perception, improving accuracy in rapidly changing speeds.

The work [23] proposed a physically grounded 1D CNN using envelope power spectrum features, achieving 94.2% cross-domain accuracy. In [24], a lightweight multiscale CNN (CVPN) incorporating hierarchical perception and attention modules was shown to outperform prior multiscale models under noisy, variable-speed conditions. Article [25] combined bispectrum analysis with CNNs using AdaMax optimization, demonstrating superior performance in identifying bearing faults under variable speeds and compound failures.

Further advancements include the GC-ResCNN architecture in [26], which utilizes global context modules and multiscale fusion layers to maintain robustness under fluctuating signal patterns. Finally, [27] reviewed the recent developments in predictive maintenance using deep learning and multi-agent systems, emphasizing their role in smart manufacturing and CPS integration.

Collectively, these works confirm that deep learning models–particularly CNN variants–are highly effective in handling the diagnostic complexity of induction motors operating in nonstationary and transient regimes.

The conducted literature review encompassed a broad spectrum of studies applying machine learning and deep learning techniques to the diagnosis of induction motor faults, both in steady-state and transient conditions. Traditional machine learning methods such as SVM and MLP have demonstrated good performance, especially when combined with appropriate feature extraction techniques. However, the recent comparative studies consistently indicate the superiority of deep learning models–particularly CNN and LSTM architectures–in terms of accuracy, adaptability to raw signals, and suitability for nonstationary conditions.

Despite the growing body of research, only two articles–[12] and [20]–specifically address the challenge of induction motor fault diagnosis under limited data conditions. Moreover, neither of these studies achieves the diversity of real-world test objects nor the scale of experimental uniqueness presented in the current work. This indicates a clear research gap and justifies the necessity of further investigation in this area.

The present study aims to fill this gap by proposing a deep learning-based method tailored to small datasets, using data from multiple unique motors and transient-state current signals–a combination not thoroughly explored in prior literature.

Measurement Objects

The study involved the acquisition of startup current signals from three-phase induction motors in two technical conditions: healthy and with rotor cage faults in the form of one or more broken bars. The aim was to obtain real diagnostic data for further analysis and validation of artificial intelligence methods in fault detection.

The measurements were carried out on both laboratory and industrial motors. Laboratory tests were conducted at the Cracow University of Technology and AGH University of Science and Technology. Industrial motors were measured under real operating conditions; however, due to their decommissioning status, complete technical documentation and nameplate data were unavailable.

In total, 29 startup current recordings were collected, including 18 from faulty motors and 11 from healthy ones. All signals were recorded under uniform sampling and acquisition conditions. The dataset reflects a diversity of motor designs and startup conditions, ensuring representativeness. Selected images and specifications of laboratory motors are included to illustrate the types of measurement objects used.

The test object at the Cracow University of Technology was the Sg112M-4 induction motor, whose nameplate data and photograph are presented in Fig.1.

Rotor bar defects were manufactured at the factory as a set of interchangeable rotors.

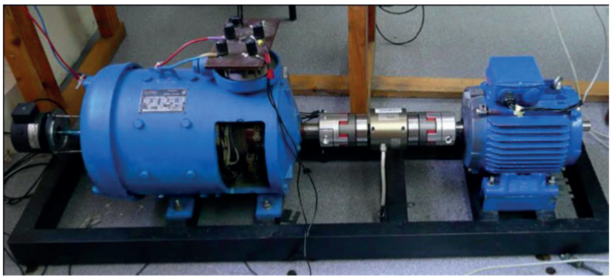

Fig. 1. Sg112M-4 induction motor

One of the test objects at the AGH University of Science and Technology was the Sg100L-4A induction motor, whose nameplate data and photograph are presented below.

Rotor bar faults were introduced by drilling through a bar with a bit of diameter comparable to the bar width, effectively interrupting its continuity.

Fig. 2. Sg100L-M4 induction motor

Figure below presents the schematic of the measurement system used for recording the motor startup current waveforms.

Table 1. Nameplate data of the Sg112M-4 motor

Parameter	Value
Rated power PN [kW]	4.0
Rated voltage UN [V]	380
Rated current [A]	2.9
Power factor cosφN	0.84
Rated speed [rpm]	1445
No-load speed [rpm]	1492
Stator winding connection	Y
Number of pole pairs *p*	2
Supply frequency [Hz]	50
Number of rotor bars	28
Moment of inertia [kg·m^2]	0.0197

Table 2. Nameplate data of the Sg100L-4A motor

Parameter	Value
Rated power PN [kW]	2.2
Rated voltage UN [V]	400
Rated current [A]	4.8
Power factor cosφN	0.80
Rated speed [rpm]	1425
Stator winding connection	Y
Number of pole pairs *p*	2
Supply frequency [Hz]	50

The current of a single motor phase was considered as the diagnostic signal.

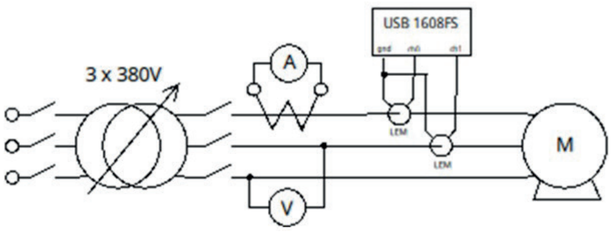

Fig. 3. Schematic diagram of the test setup

Startup current waveforms were recorded using LEM current transducers and a data acquisition card, as shown in the test setup diagram.

The sampling frequency of the current waveform for the object at Cracow University of Technology was 5 kHz, while for the other objects it was 2 kHz.

Notably, the available scientific literature rarely includes diagnostic datasets containing such a large number of real startup current measurements from diverse sources–both laboratory and industrial. Most studies rely on data from a single motor or simulated conditions. Therefore, the collected dataset provides valuable material for testing artificial intelligence methods under limited sample conditions and signal variability.

TMCSA for Diagnosing Rotor Bar Faults in Induction Motors

The use of time-frequency analysis in fault diagnostics of induction motors has been explored in numerous studies, including [28], [29], [30], [31], and [32]. Initial concepts of analyzing startup current signals for diagnostic purposes date back to the 1980s and 1990s, when pioneers such as Elder and Qiu Arui proposed using transient current waveforms to detect rotor asymmetries. Early work focused on identifying the characteristic left-side slip harmonic generated during motor startup due to broken rotor bars.

TMCSA (Transient Motor Current Signature Analysis) extends classical MCSA methods to nonstationary startup conditions by enabling dynamic tracking of fault-related frequency components. Unlike traditional Fourier-based approaches–which assume stationarity–TMCSA uses time-frequency tools such as Short-Time Fourier Transform (STFT), wavelet transforms, and in some cases Wigner-Ville distributions [29], [30], [33]. These methods allow the analysis of evolving harmonic trajectories, taking into account changes in slip and load during startup [34], [33].

The recent works emphasize that broken rotor bar faults often manifest more distinctly in transient conditions, with higher amplitude components and richer diagnostic information than in steady-state signals [29], [28]. TMCSA provides the additional benefit of revealing the temporal evolution of fault-related harmonics, improving detection reliability [34]. However, this approach typically requires more advanced signal processing and acquisition systems.

The limitations of FFT-based MCSA–such as low resolution under dynamic load, signal smearing, and assumptions of fixed slip–are effectively addressed by TMCSA. Consequently, this method has gained interest for predictive maintenance and early fault detection in industrial settings [37], [36].

The methodology presented in [32] builds upon this foundation by applying TMCSA with advanced time-frequency representations to identify rotor bar breakages in diverse real-world motors.

In summary, TMCSA offers a robust framework for detecting rotor faults under transient operating conditions by incorporating time-frequency domain analysis and tracking of harmonic components. Despite its computational complexity, advances in signal processing make it increasingly feasible for real-time diagnostics, representing a valuable evolution of classical MCSA techniques [34], [33].

Three-phase induction motors are widely used in industrial applications due to their simple design and high reliability. Despite continuous advancements in stator winding materials and insulation techniques, the rotor cage–particularly the bars–has seen limited structural evolution, making it more susceptible to mechanical fatigue and damage. Recent studies report an increasing incidence of rotor bar faults, such as cracked or broken bars [36].

The analysis of higher-order harmonics has been shown to be useful in complex fault conditions, especially in large machines where inter-bar leakage currents may suppress low-frequency fault components, or in systems with oscillating loads [35]. However, in this study, the diagnostic approach focuses on low-frequency harmonics, specifically the left-side slip harmonic, which typically exhibits higher amplitudes and serves as a reliable indicator of rotor bar faults.

Rotor asymmetry diagnosis has been extensively investigated in literature [33], [34], [35], [36], [37], [29], [28], [38], [39], [30], [40], [31], with the Motor Current Signature Analysis (MCSA) method gaining significant industrial traction due to its non-invasive nature and ease of implementation. Since stator current can be measured using standard industrial current sensors, MCSA eliminates the need for additional hardware or machine disassembly [38].

Among the most established techniques is the detection of slip harmonics near the supply frequency [36]. A rotor bar break causes a local disruption in current flow, producing electromagnetic disturbances that interact with the main air-gap field. This results in additional current components at characteristic frequencies within the stator windings. The amplitude of these harmonics depends on several factors, including machine construction, load conditions, and system inertia [29].

In this study, rotor fault detection in the transient startup phase is performed using TMCSA, focusing on the most widely accepted indicator–the left-side slip harmonic.

The left-side slip harmonic (LSH), which serves as a key indicator of rotor asymmetry caused by broken bars, is defined by the following expression [37], [38]:

$$f_{\mathrm{LSH}} = f_s\,(1-2s) \tag{1}$$

where:
f_{LSH} is the frequency of the left-side slip harmonic,
f_s is the supply frequency,
s is the slip of the induction motor.

This component typically appears in the stator current spectrum due to the modulation effect caused by the asymmetrical rotor field interacting with the main stator field. Its presence and amplitude are directly related to the severity and nature of the rotor fault.

The left-side slip harmonic (LSH) is a key diagnostic component for identifying rotor bar faults in induction motors. Its frequency depends on motor slip and is described by equation (1).

While higher-order harmonics may be theoretically informative, their amplitudes are typically lower and often undetectable due to winding factors and spectral noise [29]. Consequently, fault detection most often focuses on the LSH, which usually exhibits higher amplitudes than its right-side counterpart [29].

In classical MCSA methods applied under steady-state conditions, LSH detection presents challenges due to its proximity to the supply frequency and sensitivity to slip fluctuations. These issues often result in spectral smearing, particularly under lightly loaded or unloaded conditions. Literature recommends applying at least 30% rated load to improve detection accuracy [37].

To overcome these limitations, TMCSA exploits the transient startup phase, where LSH shows clear dynamic behavior with increased amplitude, independent of the mechanical load. This approach improves detectability and does not require long acceleration times or high inertia [38].

The theoretical trajectory of the instantaneous frequency (IF) of the LSH during motor startup follows a characteristic, repeatable pattern. As shown in Figure 4, the IF starts at f_s when slip s = 1, decreases to 0 at s = 0.5, and then increases again as the motor approaches steady state. When plotted as a function of slip, the IF trajectory forms two linear segments with a slope of $\pm 2f_s$, providing a universal diagnostic signature independent of machine design or initial conditions [34].

CWT

Prior to time-frequency analysis, the startup current signals were preprocessed using a low-pass filter to suppress the 50 Hz supply frequency component. This dominant component, if not removed, would obscure the visibility of lower-amplitude diagnostic features associated with rotor faults.

To extract the nonstationary characteristics of the transient signals, the Continuous Wavelet Transform (CWT) was employed. Unlike the Fourier Transform, which assumes signal stationarity, CWT provides both time and frequency localization, making it highly suitable for analyzing dynamic signals such as motor startup currents.

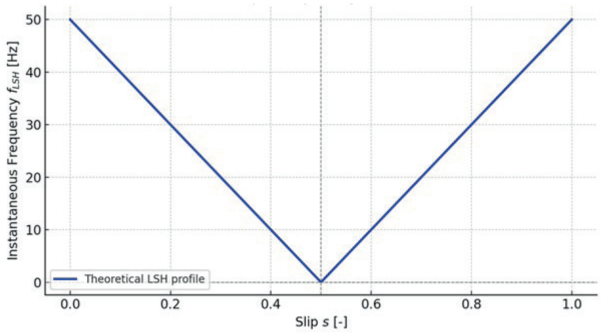

Fig. 4. Slip–frequency representation of the instantaneous frequency of the left-side slip harmonic during startup of a motor with broken rotor bars

Mathematically, the CWT of a signal x(t) is defined as [42]:

$$W(a,b) = \int_{-\infty}^{+\infty} x(t) \cdot \frac{1}{\sqrt{|a|}} \psi^*\left(\frac{t-b}{a}\right) dt \tag{2}$$

where:
a is the scale parameter (related to frequency),
b is the translation parameter (related to time),
$\psi(t)$ is the mother wavelet,
$\psi^*(t)$ is its complex conjugate.

In this study, the Morlet wavelet was selected as the mother function due to its favourable time-frequency resolution and suitability for harmonic content detection. The Morlet wavelet, being a complex sinusoid modulated by a Gaussian envelope, is particularly effective in identifying oscillatory components associated with rotor asymmetries.

The resulting current scalograms are shown in the figures below and serve as input representations for subsequent fault classification using deep learning techniques.

SVM and HOG

In this study, Support Vector Machine (SVM) was employed as a representative classical machine learning technique for the diagnosis of induction motor faults. To enable the use of CWT-based scalograms–obtained through TMCSA–as input features for the SVM classifier, a novel approach was introduced by incorporating the Histogram of Oriented Gradients (HOG) method. This allowed effective transformation of time-frequency representations into compact and informative feature vectors suitable for image-based classification.

SVM is a supervised learning algorithm that aims to find an optimal hyperplane which maximally separates data points belonging to different classes. In the context of image classification, each image is first convert-

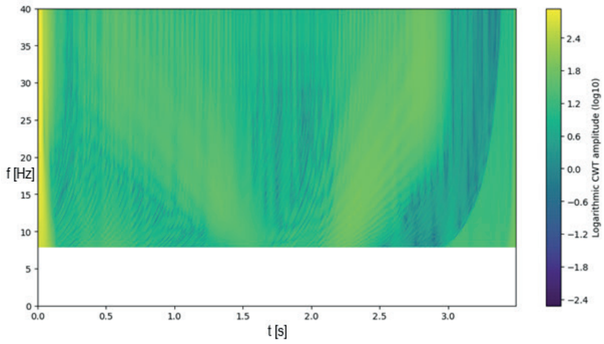

Fig. 5. Scalogram of a large industrial induction motor with a single broken rotor bar

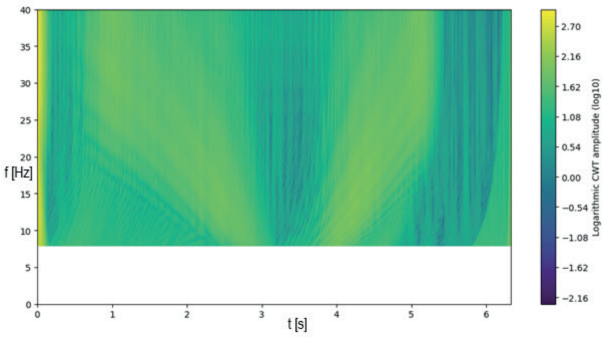

Fig. 6. Scalogram of a large industrial induction motor with two broken rotor bars

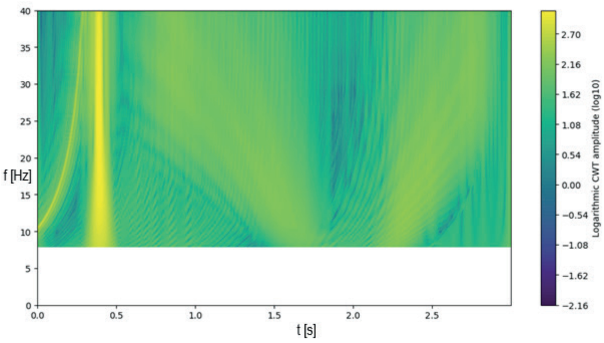

Fig. 7. Scalogram of a large industrial induction motor with three broken rotor bars

ed into a fixed-length feature vector. The SVM then attempts to identify a boundary in this high-dimensional feature space that distinguishes between fault categories–such as healthy and faulty motors [43].

To extract meaningful features from scalogram images, the HOG descriptor was applied. HOG is a well-established technique in computer vision, particularly in object detection tasks. It works by dividing an image into small spatial regions (cells), computing the gradient orientation histogram within each cell, and normalizing the results across larger blocks to ensure invariance to illumination and contrast. The resulting feature vector captures local edge patterns and structural information, making it highly suitable for texture-like images such as time-frequency scalograms.

By combining HOG feature extraction with SVM classification, the proposed method enables robust and computationally efficient fault diagnosis based on visual patterns in CWT scalograms. This hybrid approach bridges the gap between traditional signal processing and modern image-based machine learning techniques in the context of motor diagnostics.

In this study, the Support Vector Machine (SVM) algorithm was used as a representative classical machine learning method for the fault diagnosis of induction motors. To enable the classification of CWT scalograms obtained via the TMCSA method, a novel approach was introduced by applying the Histogram of Oriented Gradients (HOG) descriptor. This technique, commonly used in computer vision, allows for effective conversion of time-frequency images into compact feature vectors suitable for image-based classification.

The HOG algorithm extracts structural features by calculating gradient orientations in small spatial regions (cells) of the image and compiling histograms of these orientations. These histograms are then normalized over larger blocks to improve invariance to local changes in illumination and contrast. The resulting feature vectors capture edge and texture information that is highly relevant for distinguishing between healthy and faulty signal patterns in motor diagnostics.

The extracted HOG features were then used to train a linear SVM classifier. To reliably assess the generalization ability of the model and avoid overfitting, cross-validation was applied. In this procedure, the dataset is systematically split into training and testing subsets multiple times, ensuring that each sample is evaluated as part of the test set. The final classification performance is reported as the average accuracy obtained across all validation rounds.

This approach provides a robust and repeatable evaluation framework, combining the simplicity and interpretability of classical machine learning with the expressiveness of time-frequency image features.

The proposed method, combining HOG feature extraction with SVM classification, achieved an overall accuracy of 85.42%, demonstrating its suitability for fault detection based on time-frequency representations of transient current signals.

MLP

In this study, a Multilayer Perceptron (MLP) neural network was used as a classical model for the classification of motor condition based on CWT scalograms. To reduce the input dimensionality and avoid excessive computational cost, the scalograms were downscaled to smaller sizes before being flattened and passed to the neural network. This approach significantly limits the number of learnable parameters and improves generalization when working with relatively small datasets, as recommended in [41].

MLP is a type of feedforward artificial neural network composed of an input layer, one or more hidden layers, and an output layer. Each neuron in a layer is fully connected to the neurons in the subsequent layer. The network learns to map input vectors to output classes through supervised learning, using a backpropagation algorithm to minimize the loss function, typically the cross-entropy for classification tasks [43].

The architecture dimensions were selected empirically.

In this application, each CWT scalogram–after normalization and resizing–is flattened into a one-dimensional feature vector, which serves as the input to the MLP. The network processes this input through nonlinear activation functions (such as ReLU or sigmoid) across hidden layers, enabling it to capture complex patterns associated with healthy or faulty motor conditions.

The advantage of using an MLP in this context lies in its computational simplicity and interpretability, especially when the input dimensionality is controlled. Although MLPs lack the spatial feature extraction capabilities of convolutional networks, their performance remains competitive when provided with preprocessed and structured input, such as downsampled scalograms.

To classify the technical condition of induction motors based on transformed scalograms, a classical Multilayer Perceptron (MLP) neural network was employed. The scalograms obtained from the Continuous Wavelet Transform (CWT) were first converted to a logarithmic scale and then resized to matrices of 10×10 dimensions. This preprocessing step helped reduce the number of input features and minimize the risk of overfitting. Each matrix was flattened into a 100-element feature vector and normalized using Min-Max scaling.

The model was implemented using the scikit-learn library. The MLP architecture consisted of two hidden layers: the first with 100 neurons and the second with 50 neurons. The ReLU (Rectified Linear Unit) activation function was used, and the Adam optimizer was chosen for training. The training process was limited to a maximum of 500 iterations.

Model performance was evaluated using 4-fold cross-validation, where the data were divided into four subsets: in each iteration, 75% of the data were used for training and 25% for testing. The final classification accuracy obtained with the MLP model reached 91.67%, demonstrating the effectiveness of this approach in analyzing CWT-based image representations of motor startup currents.

CNN and Spectrogram Augmentation

In this study, a data augmentation method known as spectrogram augmentation was applied to enhance the performance of a convolutional neural network (CNN) in classifying the condition of induction motors. This technique addresses the challenge of limited data availability, which is especially problematic in industrial diagnostics involving real measurements.

Spectrogram augmentation consists of generating synthetic spectrograms based on real data by applying various transformations such as:

- Time-shifting (slight delays in the signal),
- Scaling (amplitude modifications),
- Noise injection (simulating measurement variability),
- Frequency masking or time masking (hiding random parts of the spectrogram to simulate occlusion or signal loss),
- or using algorithms like SMOTE, WGAN, or mixup applied to spectrogram images.

These artificially generated spectrograms retain the key features of the original signals while introducing variability that enables the model to generalize better and reduces overfitting. The augmented dataset was used to train a convolutional neural network (CNN).

To address the challenge of limited data availability, the spectrogram augmentation technique was employed. Using this method, a total of **1000 synthetic samples** were generated for each class: **healthy motor** and **faulty motor**. This augmentation process involved transforming and perturbing the original spectrograms in a controlled manner, such as through random scaling, shifting, or noise injection, while preserving their diagnostic features. The enriched dataset allowed for effective training of deep learning models, such as CNNs, even in scenarios with a limited number of real-world measurements.

The synthetic sample set was divided into training, validation, and test sets.

A convolutional neural network is a class of deep neural networks designed to process and classify data with a grid-like structure, such as images or spectrograms. Unlike traditional multilayer perceptrons (MLPs), CNNs use a hierarchical structure where convolutional layers automatically extract local features from input data [43].

The main components of a CNN include:

- Convolutional layers, which apply multiple trainable filters (kernels) to the input data. Each filter slides over the input and captures patterns such as edges, shapes, or textures in the case of images or frequency patterns in spectrograms.

- Activation functions (typically ReLU) introduce non-linearity, allowing the network to learn complex representations.
- Pooling layers, such as max pooling, reduce the spatial dimensions of the feature maps, helping to lower computational cost and improve translation invariance.
- Fully connected layers, placed near the output, interpret the extracted features and perform classification.
- The final softmax layer outputs probabilities associated with each class (e.g., healthy or faulty motor).

The CNN architecture was selected empirically, aiming for the minimal possible network size with future implementation on embedded systems in mind.

The model is trained using an optimization algorithm such as Adam to minimize a loss function (commonly categorical cross-entropy). During training, the network adjusts the weights of its filters and neurons to improve classification performance on the training data.

In this study, the CNN was trained on synthetically augmented spectrograms generated using the spectrogram augmentation method, while the evaluation (testing) was performed on real spectrograms of motor startup currents.

In this study, the convolutional neural network (CNN) was implemented using the PyTorch framework. The model architecture and training procedure included the following hyperparameters and structural choices:

- Input size: 1 × 10 × 10 (spectrograms resized and normalized)
- Convolutional layers:
  - Conv1: 1 → 32 filters, kernel size 3 × 3, padding = 1, activation: ReLU
  - Conv2: 32 → 64 filters, kernel size 3 × 3, padding = 1, activation: ReLU
  - Conv3: 64 → 128 filters, kernel size 3 × 3, padding = 1, activation: ReLU
  - Conv4: 128 → 256 filters, kernel size 3 × 3, padding = 1, activation: ReLU
- Pooling layers:
  - MaxPooling (2 × 2) after Conv2 and Conv4
- Fully connected layers:
  - FC1: dynamically initialized to match the flattened output of convolutional blocks → 128 neurons, activation: ReLU
  - FC2: 128 → 1 neuron, activation: Sigmoid (binary classification)
- Loss function: Binary Cross Entropy Loss (BCELoss)
- Optimizer: Adam
- Learning rate: 0.001
- Batch size: 128
- Epochs: Up to 100
- Validation split: 20% of the training set
- Early stopping: applied with a patience of 10 epochs (training was stopped if no validation improvement occurred over 10 consecutive epochs)
- Model checkpointing: the model with the best validation loss was saved and used for final evaluation on the real test set.

This configuration, combined with the spectrogram augmentation technique for training data generation, aimed to enhance generalization despite the limited availability of real measurement samples.

The classification accuracy achieved using this method reached 90%, confirming the effectiveness of convolutional neural networks trained on synthetically augmented spectrograms and validated on real-world test data.

Figure below presents the confusion matrix corresponding to the classification results obtained using the CNN model.

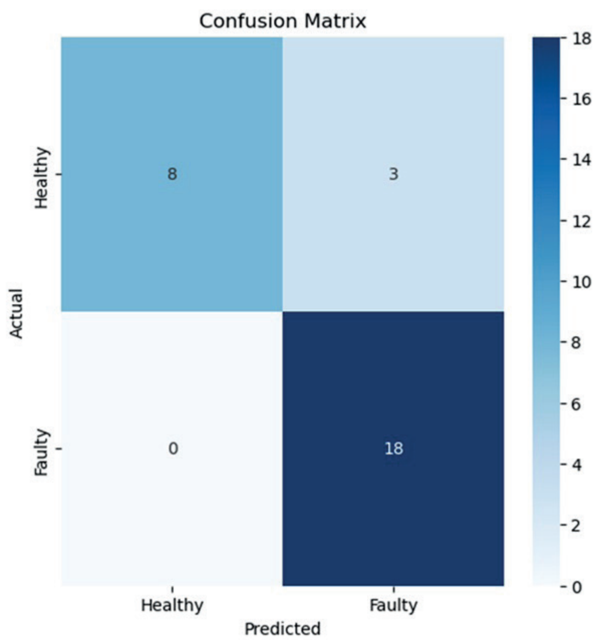

Fig. 8. Confusion Matrix.

It is worth noting that in this case, the CNN misclassified a few healthy motors as faulty, which is a safer outcome from a diagnostic perspective. Such false positives only result in additional verification or preventive diagnostics. On the other hand, misclassifying faulty motors as healthy could lead to unexpected failures and potential damage. Therefore, the obtained classification pattern is acceptable and even desirable in practical applications.

Conclusion

The conducted experiments confirmed the effectiveness of various artificial intelligence methods for diagnosing rotor bar faults in induction motors, even when using a limited dataset. Table 3 summarizes the classification accuracy obtained for each method tested in this work.

Table 3. Comparison of classification accuracy across different methods.

Method	Accuracy [%]
SVM and HOG	85.42
MLP	91.67
CNN and Spectrogram Augmentation	90.0

The results demonstrate that the proposed convolutional neural network trained exclusively on synthetically augmented spectrograms (using the spectrogram augmentation technique) achieved comparable or superior accuracy relative to classical machine learning models, such as support vector machines and shallow MLPs.

The observed difference in accuracy between the MLP and CNN models is minor and could be attributed, among other factors, to the methodology used for calculating accuracy: cross-validation for the MLP and the confusion matrix for the CNN.

Importantly, traditional AI models typically perform better with small datasets and carefully extracted features. However, the use of spectrogram augmentation enabled the CNN to generalize well despite the limited number of real-world samples. This suggests that synthetic data generation can be a viable approach in practical scenarios where acquiring large diagnostic datasets is challenging.

Furthermore, the CNN architecture showed robustness, with high classification performance and a favourable confusion matrix, where faulty motors were reliably detected, and only a few healthy cases were misclassified as faulty – which is a safer diagnostic outcome in the industrial applications.

The applied CNN architecture was deliberately simplified and adapted for potential use in embedded systems. The input size was reduced to 10×10, and the number of layers was kept small to enable implementation on platforms with limited computational resources. The number of filters was increased in subsequent layers, in accordance with standard CNN design practices. Despite the simplified architecture, the model achieved high classification accuracy (90%), which confirms the validity of the proposed approach.

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