DEEP LEARNING APPLICATION FOR MULTIPLE FAULT DETECTION IN THREE-PHASE INDUCTION MOTORS

H. Selcuk NOGAY

Bursa Uludağ University, Vocational School of Technical Sciences, Department of Electricity and Energy, Bursa / Türkiye

Abstract: This study presents a deep learning application designed to detect and classify multiple fault conditions in three-phase induction motors using thermal imaging. Leveraging the capabilities of convolutional neural networks (CNNs), the model aims to predict ten specific types of fault conditions and one healthy operating condition. The CNN model was trained on a diverse dataset of thermal images capturing these fault conditions, achieving an impressive accuracy rate of 98.7%. The high accuracy underscores the model's effectiveness in identifying and classifying various fault states, which is critical for timely maintenance and prevention of motor failures.

Keywords: Deep Learning, CNN, Fault Detection, Three-Phase Induction Motors, Thermal Imaging

INTRODUCTION AND THEORETICAL FRAMEWORK

The efficient and reliable operation of three-phase induction motors is critical to the performance and productivity of various industrial processes. These motors are widely used in numerous applications due to their robustness, efficiency, and cost-effectiveness. However, their continuous operation is often threatened by different types of faults, which can lead to significant downtime, costly repairs, and even catastrophic failures. Accurate and timely detection of these faults is essential to maintain operational efficiency and ensure safety (Sheikh et al., 2022; Bird et al., 2021).

Traditional fault detection methods for induction motors primarily rely on manual inspections and signal processing techniques. These methods, while effective to some extent, are often limited by their inability to provide real-time, accurate, and comprehensive diagnostics. The complexity and variety of potential faults, coupled with the need for precise fault classification, necessitate the development of more advanced and automated diagnostic tools (Adouni and Cardoso, 2020; Jiang et al., 2019).

Recent advancements in machine learning, particularly deep learning, have opened new avenues for enhancing fault detection and classification processes. Convolutional Neural Networks (CNNs), a class of deep learning models known for their proficiency in image recognition tasks, have shown great potential in various diagnostic applications, including fault detection in electrical machines. CNNs can automatically learn and extract relevant features from raw data, making them ideal for analyzing complex patterns in thermal images of induction motors (Badr et al., 2023; Hsueh et al., 2019; Nazemi et al., 2023).

This study leverages the capabilities of CNNs to develop an automated fault detection system for three-phase induction motors. By using a pre-trained ResNet18 model and applying transfer learning techniques, we aim to classify ten different types of fault conditions and one healthy operating condition based on thermal images. The proposed approach not only enhances the accuracy of fault detection but also provides a scalable and efficient solution for real-time monitoring.

PURPOSE

The primary purpose of this study is to develop a deep learning-based method for the automated detection and classification of various fault conditions in three-phase induction motors using thermal images. By achieving high classification accuracy, the study aims to provide a robust and reliable solution for real-time monitoring and predictive maintenance in industrial settings.

SCOPE

The scope of this study includes the development, training, and evaluation of a CNN model for classifying thermal images of induction motors. The classification includes ten different fault conditions and one healthy operating condition. The study uses the ResNet18 architecture, fine-tuned via transfer learning, to achieve high accuracy and reliability. The performance of the model is evaluated based on accuracy, loss curves, and confusion matrices.

METHODOLOGY

The methodology employed in this study involves several key steps, outlined below:

Dataset Acquisition and Preparation

The dataset used in this study consists of thermal images of induction motors under various operating conditions. The data set used in the study was obtained from an international and public database, and those who are interested can access the data set from the web address "https://data.mendeley.com/datasets/m4sbt8hbvk/3". Table 1 shows the number of thermal images in each category (Najafi et al., 2020).

For the induction motor, 8 different situations such as short circuit failure in the stator windings, stuck rotor failure and cooling fan failure are taken into account. Thermal image acquisition was carried out in an Electrical Machinery Laboratory at 23° ambient temperature with a Dali-tech T4/T8 infrared thermal image camera. Table 2 shows the characteristics of the asynchronous motor used in the experiment (Najafi et al 2020).

Figure 1 presents sample thermal images of each category. 75% of the entire data set was used for training and 25% for testing, and the test data was randomly selected. Images were pre-processed by resizing to ensure compatibility with the ResNet18 model.

Table 1. Faults and Image Data Counts for Each Category

Fault situations	Num. of thermal images	Abbreviation
50% two-phase short circuit fault	38	A&B50
10% three-phase short circuit fault	31	A&C&B10
30% three-phase short circuit fault	42	A&C&B30
10% two-phase short circuit fault	31	A&C10
30% two-phase short circuit fault	38	A&C30
10% one-phase short circuit fault	34	A10
30% one-phase short circuit fault	37	A30
50% one-phase short circuit fault	35	A50
Cooler failure	28	Fan
Rotor failure	30	Rotor
No fault condition	25	Healthy
TOTAL	369	

Table 2. Technical Specifications of the Induction Motor

Phase	**Y-3**
Power	1.1 KW
Voltage	220/380 V
Input Current	5 A
Speed	2000 RPM
Frequency	50 Hz

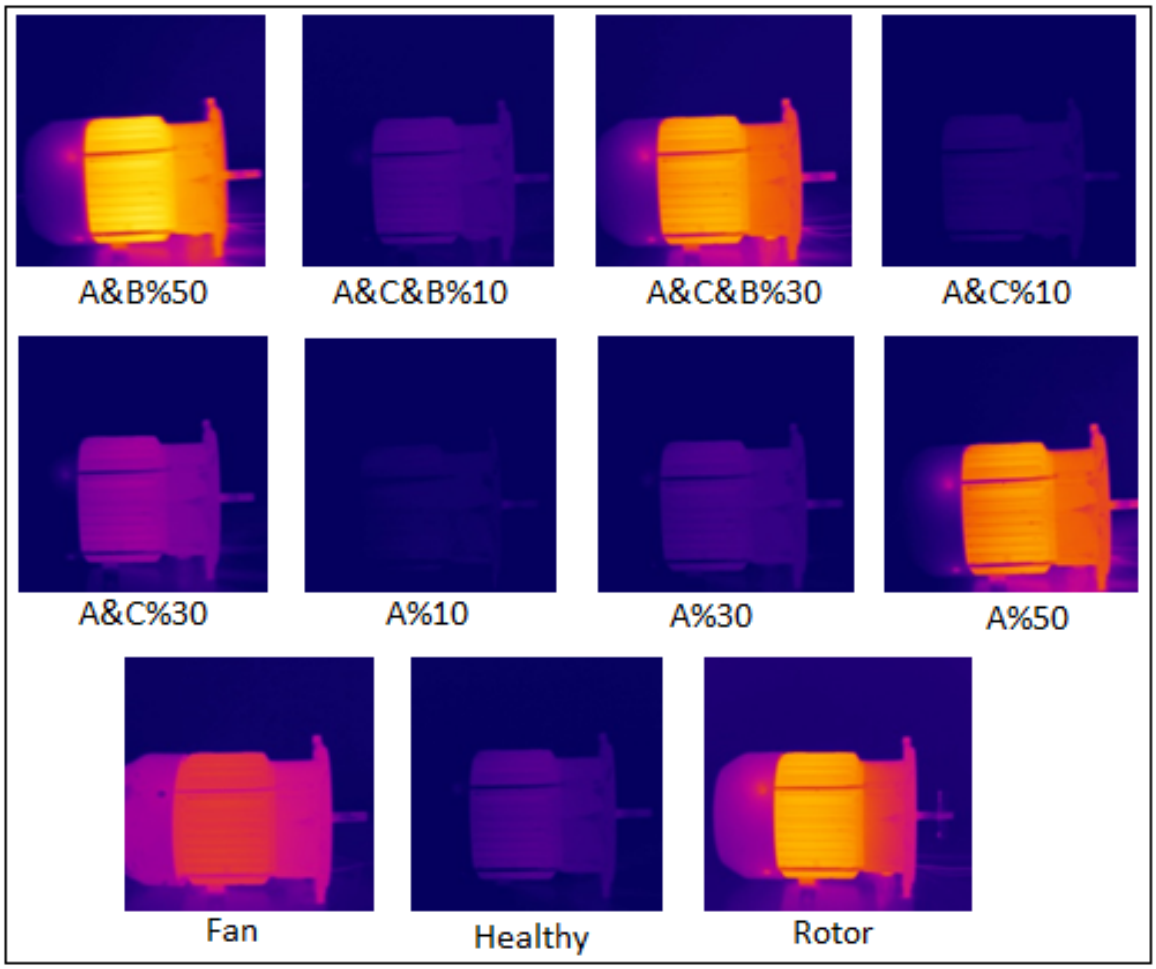

Figure 1. Sample Images of Each Category

Model Architecture Selection

The ResNet18 model, pre-trained on the ImageNet dataset, was selected for its robustness and ability to learn complex features through residual learning. The final layers of the ResNet18 model were modified to adapt to the specific task of fault classification using transfer learning techniques (He et al 2016). Table 3 shows the internal structure of the Resnet18 pre-trained CNN model used in the study and the layers rearranged with the transfer learning technique.

Table 3. Structural Information of the Proposed Model

Input Image	224x224x3
Number of Convolution Layer	20
Number of Pooling	2
Number of Fully Connected	1
Number of Dropouts	-
Number of Normalization	20
Number of Activation Function (ReLu)	17
Total number of all layers	72
Rearranged layers via transfer learning	Classification, Softmax and Last Fully Connected

Model Training and Testing

The training process involved fine-tuning the pre-trained ResNet18 model on the thermal image dataset. The model parameters were adjusted to minimize the cross-entropy loss function, utilizing techniques such as grid search and cross-validation for hyperparameter optimization. The training continued until the loss value reached its minimum. The testing process involved evaluating the model on 25% of the dataset randomly selected and reserved for testing, with performance measured by accuracy rates and confusion matrices. The CNN model trains until the loss value is minimized. The loss function is illustrated in Equation (1). In the loss function, N denotes the sample size, while K signifies the number of classes. Here, t_{ij} corresponds to the ith sample in class j, and y_{ij} denotes the output for sample j in class i (Bishop 2006). Table 4 shows the limitations of the training and testing process.

$$Loss = -\sum_{i=1}^{N}\sum_{j=1}^{K} t_{ij} \ln y_{ij} \quad (1)$$

Table 4. Limitations for the Training and Testing Process

Maximum epoch	30
Maximum iteration	180
Iteration per epoch	6
Validation Frequency	10 Iteration
Initial learning rate	0.001
Mini batch size	42
Learning rate schedule	Constant

Transfer learning is a technique where a pre-trained model, initially developed for a specific task, is adapted for a different but related task. By leveraging the knowledge acquired from the initial training on a large dataset (such as ImageNet), the model can be

fine-tuned on a smaller, task-specific dataset with fewer resources and time. This approach is particularly effective in scenarios where labeled data is limited (Zhu et al., 2020; Tuncer et al., 2020; Yu and Wang, 2019).

FINDINGS

The experimental results demonstrate the efficacy of the proposed CNN-based approach in the automated detection of faults in three-phase induction motors. The trained ResNet18 model achieved an accuracy rate of 98.7% in distinguishing between the eleven categories. The accuracy-loss curves and confusion matrix, as shown in Figures 2 and 3 and Table 5, respectively, indicate the model's high performance and reliability.

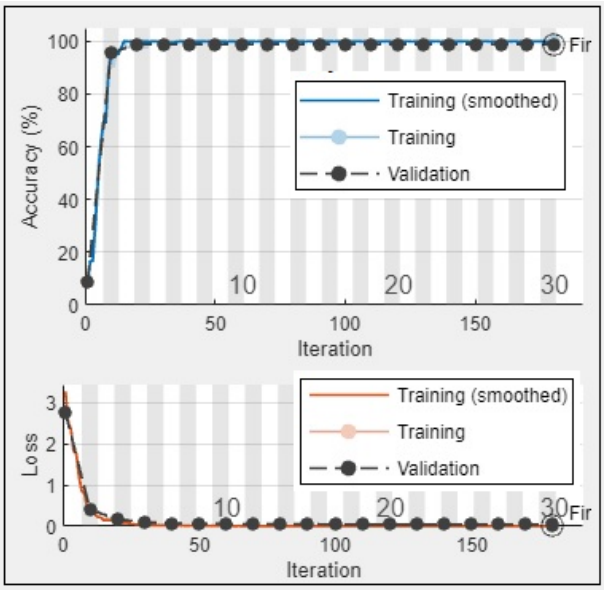

Figure 2. Loss and Accuracy Curves of the Proposed CNN Model

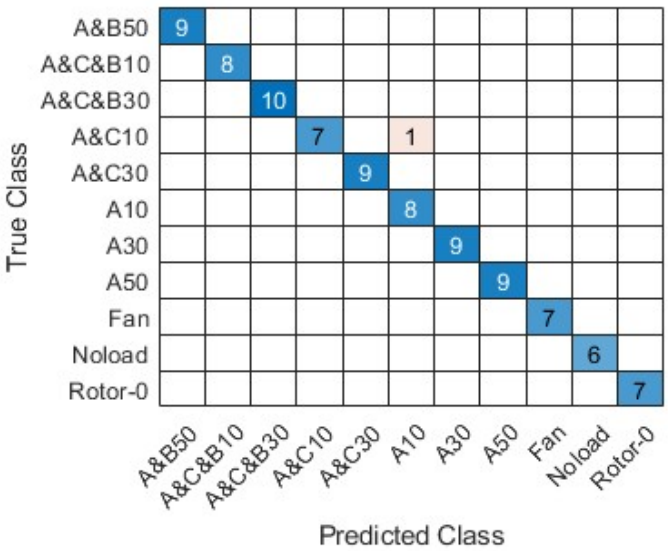

Figure 3. Confusion Matrix Obtained for Testing

Table 5. The Results of Proposed CNN Model

Training Accuracy (%)	Testing Accuracy (%)	Training Loss	Testing Loss	Epoch	Iteration
100	98.89	0.0033	0.0414	30	180

CONCLUSION

This study presents an approach for the automated detection of multiple fault conditions in three-phase induction motors using pre-trained convolutional neural networks (CNNs) and transfer learning techniques. By employing the ResNet18 architecture, we developed a classifier capable of accurately identifying various fault conditions and a healthy operating state from thermal images. The high accuracy rate of 98.7% achieved by the model underscores its potential for real-world applications. The proposed method offers a cost-effective and efficient solution for real-time monitoring and maintenance systems in industrial settings, contributing to the advancement of predictive maintenance technologies. Future research may explore the scalability of this approach to larger datasets and its integration into real-time monitoring systems for enhanced industrial automation and sustainability.

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