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Fault Detection in Induction Motors Using Texture-Based Features and Artificial Intelligence

Detección de fallas en motores de inducción mediante características basadas en texturas e inteligencia artificial

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Abstract

Induction motors are fundamental components in the industry, but their continuous operation makes them susceptible to internal faults that can lead to unscheduled downtime and high repair costs. Timely fault detection is crucial for preventive maintenance. This paper proposes the development of an automated fault classification system by analyzing texture features extracted from thermal images. Unlike proposals that rely on deep neural networks, this project utilizes classic machine learning models, allowing for an implementation with lower computational cost, making it suitable for embedded systems. A K-Nearest Neighbors (KNN) model achieved the highest accuracy at 84.1%, demonstrating that this approach is a fast, non-invasive, and precise solution for a preventive diagnosis of motor failures. The results position this method as an effective and computationally efficient alternative to more complex models.

Key words: Induction motor; Fault diagnosis; Machine-learning; Image analysis.

Introduction

Currently, induction motors are widely used in various industries, such as manufacturing, automotive, textile, and food processing, due to their efficiency, low operating cost, and robustness. However, one of the main challenges is the timely detection of internal faults, since these machines operate continuously and without direct supervision, which can lead to unscheduled downtime and high repair costs. This project proposes the development of a fault classification system through the analysis of texture features extracted from thermal images. Subsequently, an intelligent system is implemented to classify these faults. The aim of this proposal is to provide a non-invasive, fast, and accurate solution for preventive diagnostics in motors. Unlike other approaches that rely on deep neural networks, this project employs classical machine learning models, which enables implementation with lower computational cost and facilitates adaptation to embedded systems.

Proposed Methodology

The proposed framework was designed in Python to automate the feature extraction and classification process from thermal images. The workflow consists of four main stages: (1) Thermal Image Collection, (2) Intensity Profile Generation, (3) Feature Extraction, and (4) Model Training and Validation.

The dataset consists of thermal images (.bmp format) of an induction motor operating under 11 distinct conditions. These include a healthy state and various induced faults, such as:

- Short circuits of 10%, 30%, and 50% in the stator across one, two, or three phases.
- Rotor faults.
- Ventilation (cooling) failures.

The figure 1 were captured with a Dali-Tech T4/T8 thermal camera with a measurement range of -20°C to +650°C.

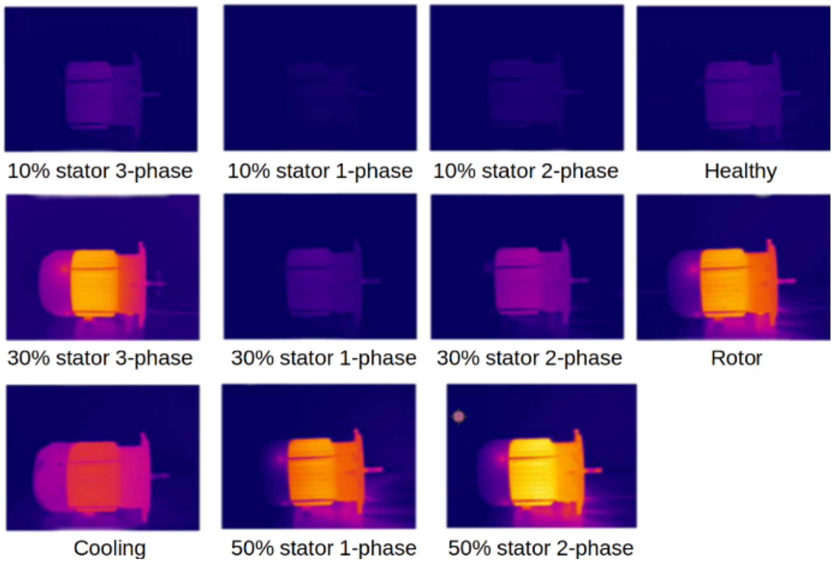

10% stator 3-phase
10% stator 1-phase
10% stator 2-phase
Healthy
30% stator 3-phase
30% stator 1-phase
30% stator 2-phase
Rotor
Cooling
50% stator 1-phase
50% stator 2-phase

Figure 1. Thermal images of an induction motor operating under 11 distinct conditions.

First, an intensity profile was generated for each thermal image. This profile is calculated as the average pixel value of each column in the grayscale image, effectively summarizing the thermal distribution across the motor's surface. The equation 1 describes the process to obtain the intensity profile:

$$I_f = \frac{1}{n}\sum_{j=1}^{n} I(i,j) \; (1)$$

Where $I(i,j)$ represents the image to analyze. Next, two key texture features were extracted from each intensity profile:

Kurtosis: This metric measures the "tailedness" of the intensity distribution. A high kurtosis indicates that the thermal data has more extreme values (hotspots), which can be indicative of a fault. The equation 2 describes the process to measure the kurtosis feature:

$$Kurtosis = \frac{1}{n}\sum_{i=1}^{n} \frac{(x_i - \mu)^4}{\sigma} \; (2)$$

Where x_i represents the signal to be analyze, μ is the mean of the signal, and σ represents the standard deviation.

Entropy: This quantifies the randomness or disorder in the thermal image. Higher entropy can suggest thermal complexity related to an internal failure. The Shannon Entropy is described in the equation 3:

$$H(x) = \sum_{i=1}^{n} p(xi) \log_2 p(x_i) \; (3)$$

Where $p(x_i)$ represents the probability of occurrence to each value in the signal.

Finally, the extracted features were used to train and evaluate several supervised machine learning models: K-Nearest Neighbors (KNN), Decision Tree, Naive Bayes, Logistic Regression, and Support Vector Machine (SVM). The dataset was split into training and testing sets, with proximally 8 samples per class reserved for testing.

Results

In the first stage of the analysis, two main features were extracted from the images: kurtosis and entropy. These metrics enabled the visualization of class distribution through a scatter plot, where clear groupings among different labels were observed.

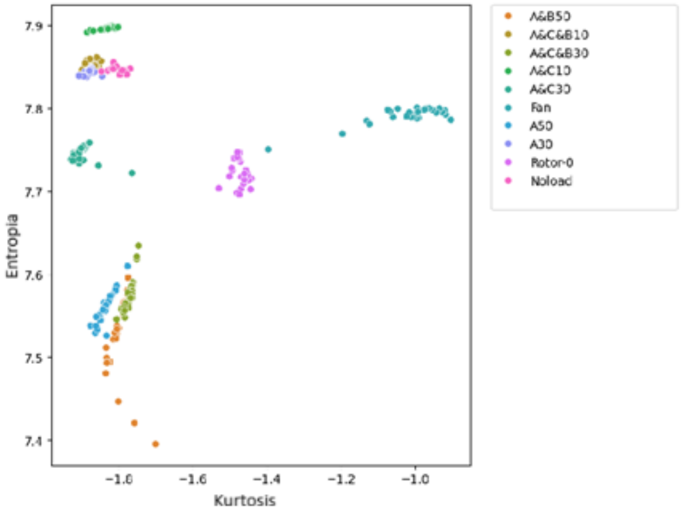


Figure 2. Kurtosis and entropy results for each fault.

Subsequently, several classification models were trained using these two features. The dataset was divided into training and testing subsets, ensuring a balanced number of samples per fault category, such as A50, Fan, A30 and others.

Table 1. Results obtained from the proposed models.

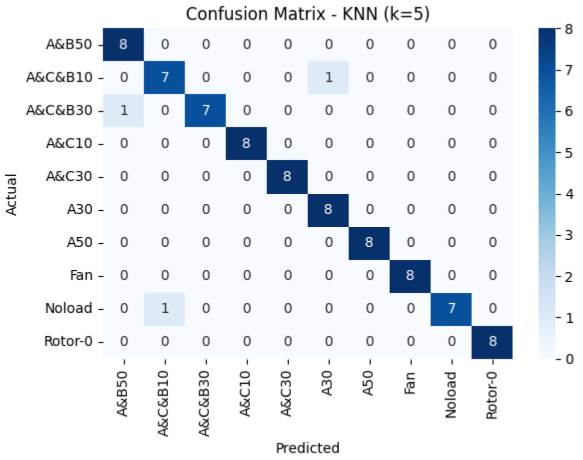
Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
KNN (K = 5)	0.840909	0.799495	0.840909	0.813097
DECISION TREE	0.829545	0.769107	0.829545	0.795387
NAIVE BAYES	0.818182	0.755517	0.818182	0.780261
KNN (K = 3)	0.806818	0.805051	0.806818	0.793642
LOGISTIC REGRESSION	0.386364	0.299642	0.386364	0.282275
SVM (C = 1)	0.090909	0.008264	0.090909	0.015152
SVM (C = 0.2)	0.090909	0.008264	0.090909	0.015152

Source: Own authorship.

In addition to numerical metrics, confusion matrices were generated for each model in order to visually evaluate their performance in classifying the different labels. Confusion Matrix 1 shows the results of the KNN model with k = 5. The high values along the diagonal indicate that the model correctly classified the samples of those classes. This model achieved an accuracy of 84% and correctly classified the following classes:

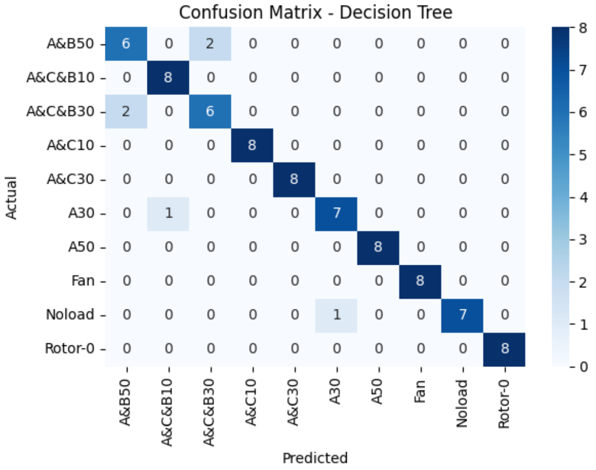
- A&B50: 8 correct
- A&C&B10: 7 correct
- A30: 8 correct
- Fan: 8 correct
- A50: 8 correct

The two matrices (figure 3 and figure 4) present the results obtained using the Decision Tree and Naive Bayes models. These matrices illustrate how frequently each class was correctly predicted and which confusions occurred. It can be observed that models with higher accuracy (such as KNN and Decision Tree) tend to classify most samples correctly, with minimal confusion among similar classes.


Confusion Matrix - KNN (k=5)

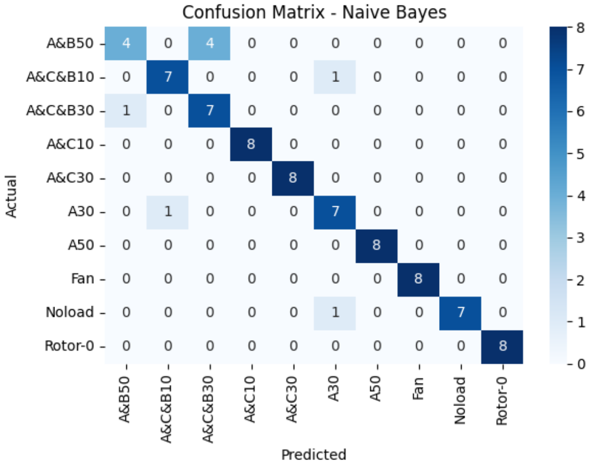
	A&B50	A&C&B10	A&C&B30	A&C10	A&C30	A30	A50	Fan	Noload	Rotor-0
A&B50	8	0	0	0	0	0	0	0	0	0
A&C&B10	0	7	0	0	0	1	0	0	0	0
A&C&B30	1	0	7	0	0	0	0	0	0	0
A&C10	0	0	0	8	0	0	0	0	0	0
A&C30	0	0	0	0	8	0	0	0	0	0
A30	0	0	0	0	0	8	0	0	0	0
A50	0	0	0	0	0	0	8	0	0	0
Fan	0	0	0	0	0	0	0	8	0	0
Noload	0	1	0	0	0	0	0	0	7	0
Rotor-0	0	0	0	0	0	0	0	0	0	8

Figure 3. Confusion matrix – KNN.


Confusion Matrix - Decision Tree

	A&B50	A&C&B10	A&C&B30	A&C10	A&C30	A30	A50	Fan	Noload	Rotor-0
A&B50	6	0	2	0	0	0	0	0	0	0
A&C&B10	0	8	0	0	0	0	0	0	0	0
A&C&B30	2	0	6	0	0	0	0	0	0	0
A&C10	0	0	0	8	0	0	0	0	0	0
A&C30	0	0	0	0	8	0	0	0	0	0
A30	0	1	0	0	0	7	0	0	0	0
A50	0	0	0	0	0	0	8	0	0	0
Fan	0	0	0	0	0	0	0	8	0	0
Noload	0	0	0	0	0	1	0	0	7	0
Rotor-0	0	0	0	0	0	0	0	0	0	8

Figure 4: Confusion matrix - Decision tree.


Confusion Matrix - Naive Bayes

	A&B50	A&C&B10	A&C&B30	A&C10	A&C30	A30	A50	Fan	Noload	Rotor-0
A&B50	4	0	4	0	0	0	0	0	0	0
A&C&B10	0	7	0	0	0	1	0	0	0	0
A&C&B30	1	0	7	0	0	0	0	0	0	0
A&C10	0	0	0	8	0	0	0	0	0	0
A&C30	0	0	0	0	8	0	0	0	0	0
A30	0	1	0	0	0	7	0	0	0	0
A50	0	0	0	0	0	0	8	0	0	0
Fan	0	0	0	0	0	0	0	8	0	0
Noload	0	0	0	0	0	1	0	0	7	0
Rotor-0	0	0	0	0	0	0	0	0	0	8

Figure 5. Confusion matrix - Naive Bayes.

Finally, table 2 shows a comparison of the results obtained against the results of previous research.

Table 2. Comparison between studies presents in the state of the art.

Reference	**Main model**	**Data source**	**Accuracy (%)**	**Comments**
Shao *et al.* (2017)	CNN (Deep Learning)	Motor current signals	81.2%	Used a deep CNN architecture for motor fault diagnosis, affected by class imbalance.
Sobhi *et al.* (2023)	LSTM (Deep Learning)	Small induction motors	78.5%	Deep neural network applied to normal vs. fault states.
Gundewar *et al.* (2021)	MLP (Machine Learning)	Vibration signals	82.3%	Classified multiple faults; overfitting issues were observed.

Conclusions

This study validates the viability of using thermal images combined with classic machine learning algorithms for the early detection of faults in induction motors. Among the evaluated models, KNN with k=5 demonstrated the best performance, achieving 84% accuracy, which makes it a reliable and efficient option. Future works are focusing in bettering the different validation metrics.

References

Chang, H., Wang, Y., Shih, Y., & Kuo, C. (2022). Fault Diagnosis of Induction Motors with Imbalanced Data Using Deep Convolutional Generative Adversarial Network. *Applied Sciences,* 12(8), 4080. https://doi.org/10.3390/app12084080

Gundewar, S. K., & Kane, P. V. (2021). Condition monitoring and fault diagnosis of induction motor. *Journal of Vibration Engineering & Technologies*, *9*, 519–532. https://doi.org/10.1007/S42417-020-00253-Y

Javed, M. R., Shabbir, Z., Asghar, F., Amjad, W., Mahmood, F., Khan, M. O., Virk, U. S., Waleed, A., & Haider, Z. M. (2022). An Efficient Fault Detection Method for Induction Motors Using Thermal Imaging and Machine Vision. *Sustainability,* 14(15), 9060. https://doi.org/10.3390/su14159060

Reyes-Malanche, J. A., Villalobos-Pina, F. J., Ramırez-Velasco, E., Cabal-Yepez, E., Hernandez-Gomez, G., & Lopez-Ramirez, M. (2023). Short-Circuit Fault Diagnosis on Induction Motors through Electric Current Phasor Analysis and Fuzzy Logic. *Energies,* 16(1), 516. https://doi.org/10.3390/en16010516

Shao, S. Y., Sun, W. J., Yan, R. Q., & Wang, P. (2017). A deep learning approach for fault diagnosis of induction motors in manufacturing. *Chinese Journal of Mechanical Engineering*, *30*, 1341–1350. https://doi.org/10.1007/s10033-017-0189-y

Sobhi, S., Reshadi, M. H., Zarft, N., Terheide, A., & Dick, S. (2023). Condition monitoring and fault detection in small induction motors using machine learning algorithms. *Information*, *14*(6), 329. https://www.mdpi.com/2078-2489/14/6/329

Toma, R. N., Prosvirin, A. E., & Kim, J. (2020). Bearing Fault Diagnosis of Induction Motors Using a Genetic Algorithm and Machine Learning Classifiers. *Sensors,* 20(7), 1884.