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Artificial Intelligence-Based Recommendation System for Detecting and Diagnosing Broken Bars in Induction Motors under Transient Operation

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AGENDA

Introduction | Framework | Results | Conclusion

Introduction

- Motivation
- Problem Statement
- Research Aim

Framework

- Data pre-processing
- Feature extraction
- Feature selection
- Machine Learning Models
- Performance evaluation based on multicriteria method

Results

- Two classification approaches
- Analysis of selected features
- Robustness analysis

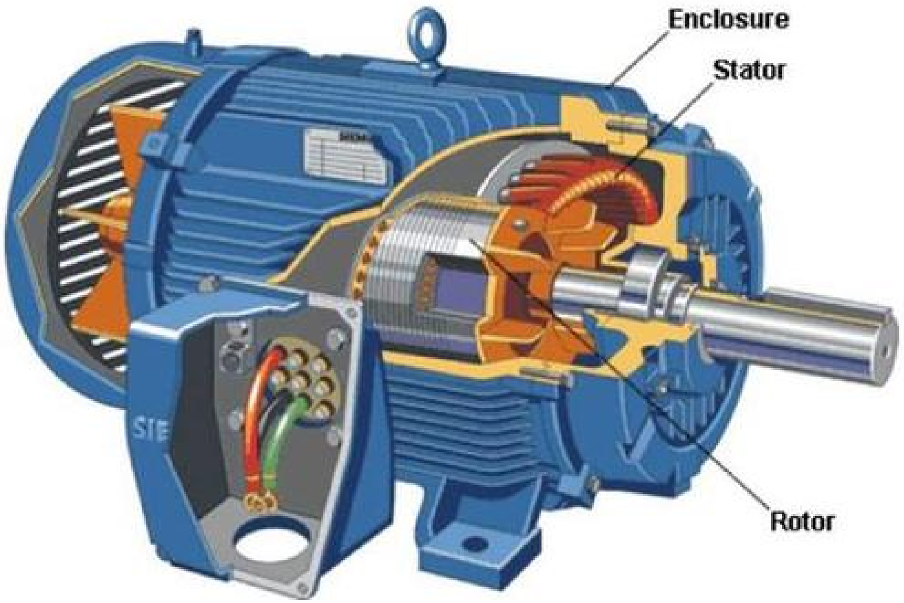
Conclusion

- Recommendations
- Future works

MOTIVATION

- Three-phase induction motors are crucial for converting electrical energy into mechanical energy in several industries:
  - Low cost.
  - Robustness.

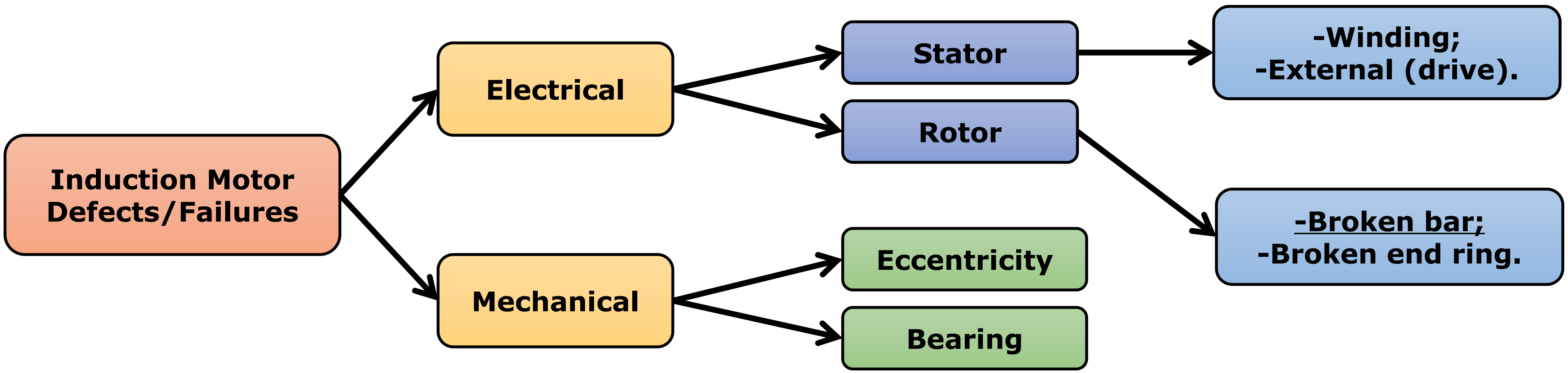
- Systems to identify defects:
  - Preventive and predictive maintenance.
  - Machine cost vs. Machine stop cost.
  - Maintenance costs.
  - Unplanned disconnections of the production line.



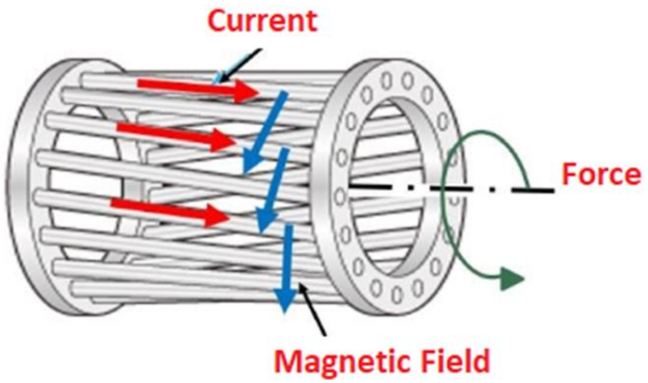
MOTIVATION

Type of defects and failures in induction motors:

- Its internal or external condition can influence the appearance of failures of an induction motor.
- The failures can be classified as mechanical or electrical, according to their origin.

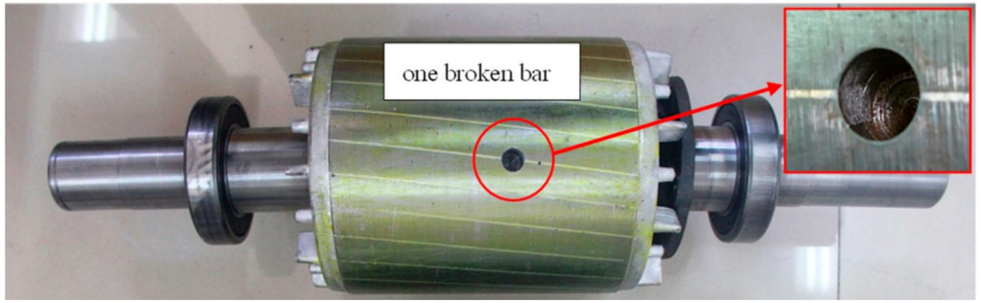


STATEMENT PROBLEM



<u>Broken rotor bar:</u>

- Symptoms:
  - Unbalanced line currents.
  - Increased torque ripple.
  - Decreased average torque.
  - Reduced efficiency.
  - Excessive heating.



- Interruption of a rotor bar results in the absence of current and, consequently, magnetic flow around the bar.
- This disruption leads to asymmetry in the rotor's magnetic field, causing a backward rotation field and induction of harmonic failure components in the stator current.

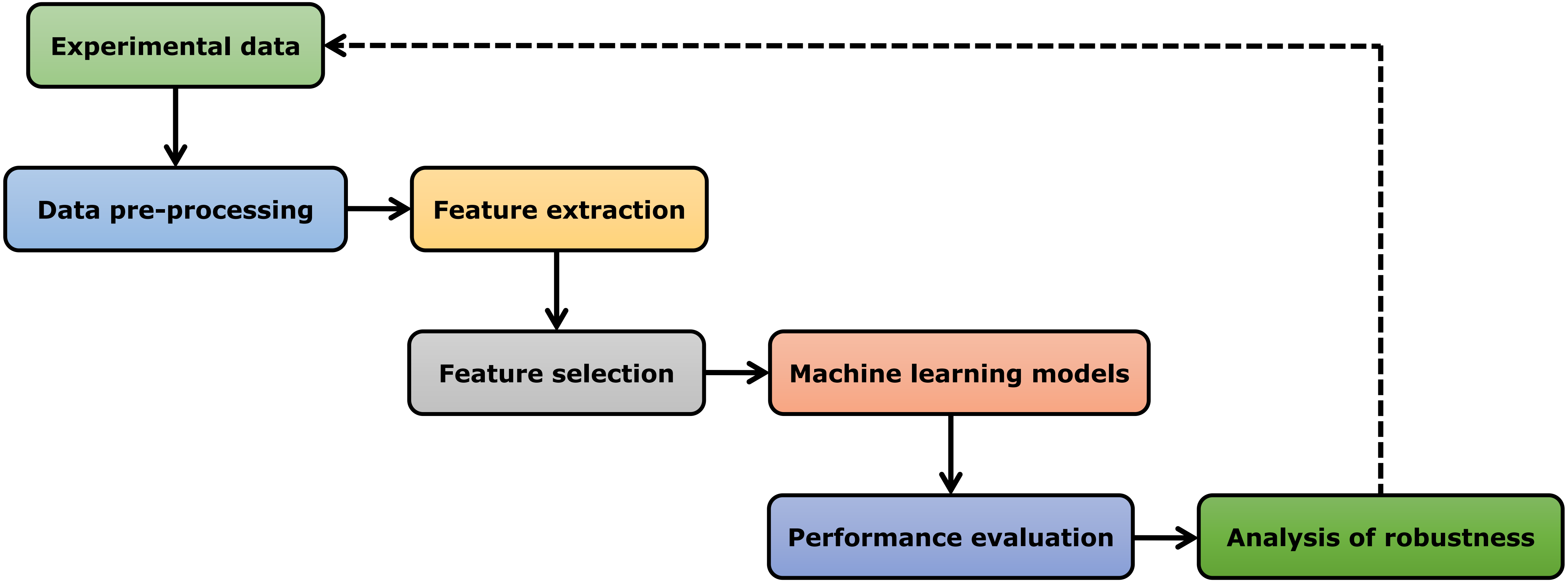
STATEMENT PROBLEM

Importance of transient operation:

- Traditional methods focus on steady-state signals for detecting and diagnosing defects in broken rotor bars.
- Applications involve intermittent starts, load and speed variations, real-time analysis, and initial commissioning tests across different industries.
- Detection and diagnosis of defects in the transient operating regime face challenges due to random factors like excessive noise and transient effects on system frequencies.
- Techniques used must be robust to noise, generalist, and aim to reduce error rates and false alarms to ensure accurate diagnosis and detection.

RESEARCH AIM

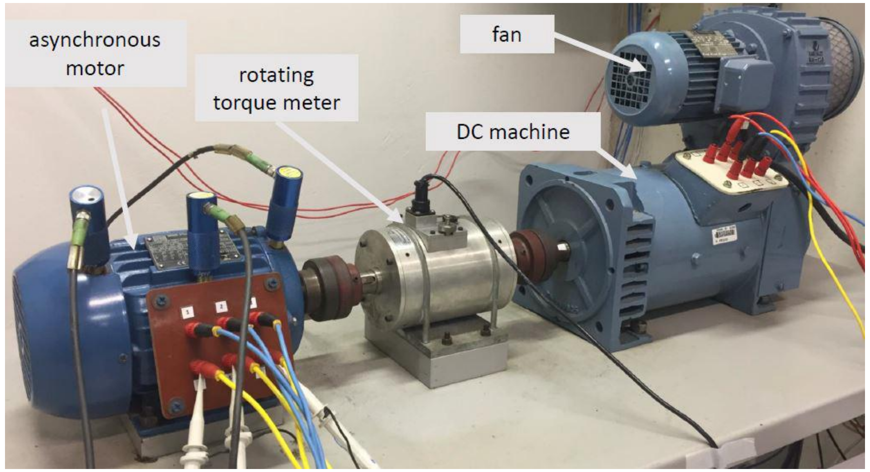
To develop a framework for recommending techniques for detecting and diagnosing broken bar defects in three-phase induction motors in the transient regime according to the imposed conditions.


Experimental data
Data pre-processing
Feature extraction
Feature selection
Machine learning models
Performance evaluation
Analysis of robustness

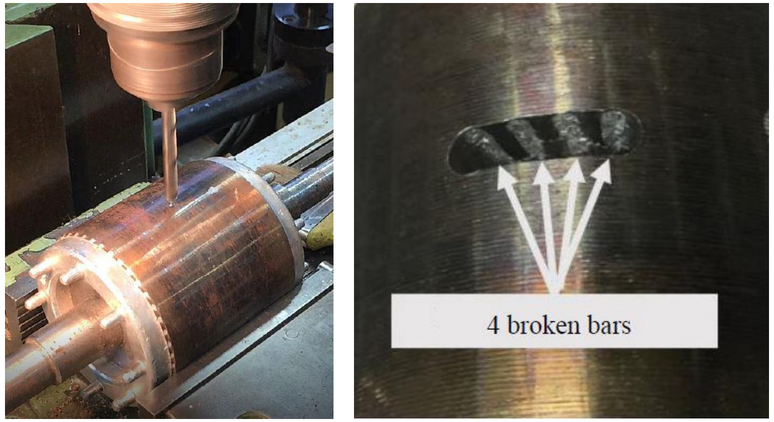
Experimental data:

- Currents in phases A, B and C.
- Voltages in phases A, B and C.
- Mechanical vibration speed:
    - Tangential in the housing.
    - Tangential at the base.
    - Axial on the driven side.
    - Radial na the driven side.
    - Radial on the non-driven side.
- Loading conditions:
    - 0.5 Nm to a nominal torque of 4.0 Nm, with a 0.5 Nm increment.
- Rotor configurations:
    - A rotor without defects.
    - A rotor with one broken bar.
    - A rotor with two adjacent broken bars.
    - A rotor with three adjacent broken bars.
    - A rotor with four adjacent broken bars.

Experimental setup



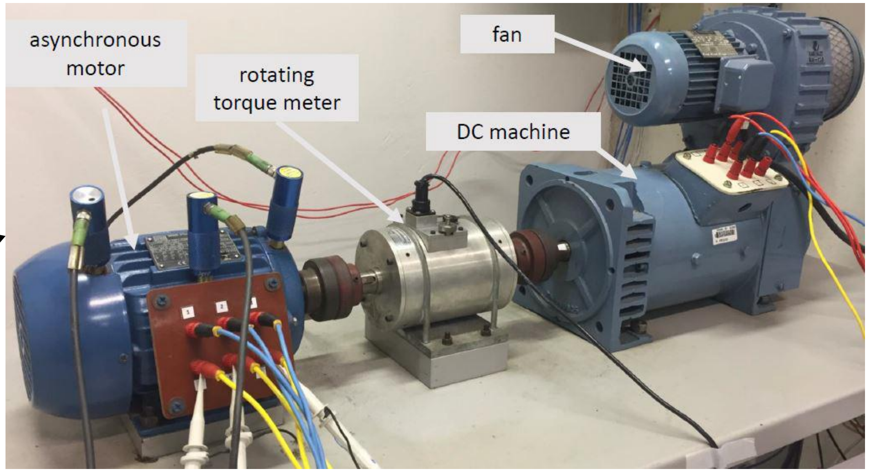
Procedure for rotor defect insertion: (a) positioning the drill bit in the center of the rotor, (b) detail of the rotor with four adjacent broken bars.



Experimental data:

- Three-phase induction motor.
- Squirrel cage type, with 34 bars.
- 1cv, 4 poles.
- Operates at a frequency of 60Hz.
- Voltage specifications of 220/380V.
- Current ratings of 3.02/1.75A.
- Nominal torque of 4.1Nm.
- Nominal speed of 1715rpm.
- Direct drive.

Experimental setup



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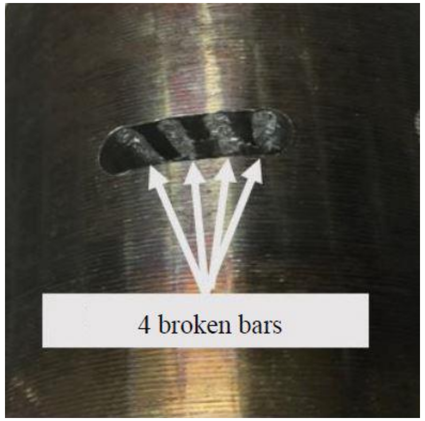


Data pre-processing:

- Data normalization depending on the load on the motor shaft.
- Identification of the transient regime.

Feature extraction:

CATEGORIES AND MEASURES EXTRACTED AS DESCRIPTORS OF DATASETS

Category of measures	Features
Statistical	Average, standard deviation, variance, median, extreme values, quartiles, kurtosis, asymmetry, covariance, sum, mode
Information-based	Entropy, signal energy, signal contrast, homogeneity of the signal, moment of 3rd order of the signal, signal strength, noise ratio, total harmonic distortion, noise and signal distortion rate, 3rd order intersection point of the signal, signal free dynamic range
Based on complexity	Fractal dimension
Based on systems analysis	Root mean square, trace of the symmetric matrix of the signal, 1st order eigenvalue of the signal

Feature selection:

- Consistency-based Filter (CBF).
- Correlation-based Feature Selection (CFS).
- InfoGain.
- ReliefF.

Machine learning models:

- Naïve Bayes (NB).
- Decision tree C4.5 (C4.5).
- Random Forest (RD).
- Multilayer Perceptron (MLP).
- Support Vector Machine (SVM).

Performance evaluation based on multicriteria hexagon:

- The smaller internal area of the multicriteria hexagon.
- The vertices represent:

I - false positive or false alarm or type I error.

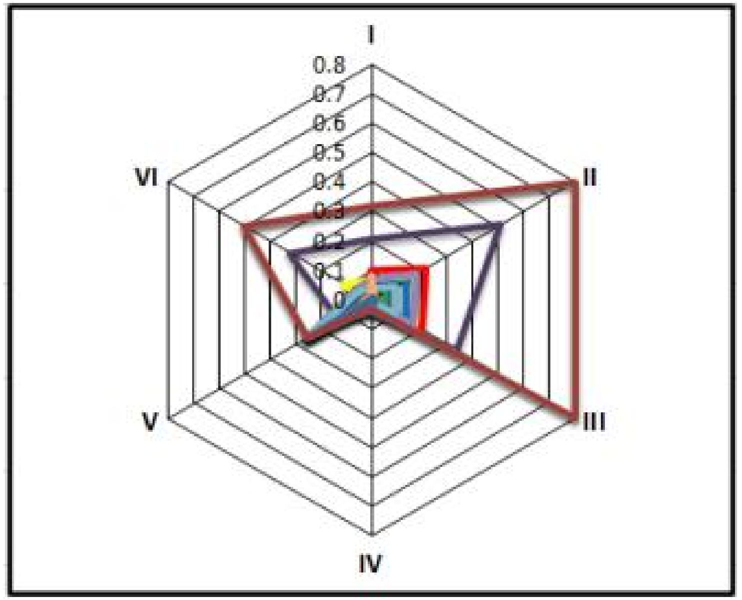
II - false negative or type II error.

III - accuracy complement.

IV - learning time based on the computational complexity of the feature selection and machine learning algorithms.

V - percentage of selected features.

VI - complement area under Receiver Operating Characteristics (ROC) curve.



Robustness Analysis

1. Corruption of the input signals: white noise was introduced to all samples in the dataset, with an intensity proportional to the signal's energy. The intensity ranged from 0 to 100%, with a step size of 5%.

2. Features extraction and selection: a subset containing the most important features was chosen from the original dataset using the feature selection techniques and algorithms described earlier.

3. Modeling of intelligent systems: the previously mentioned machine learning models received, as inputs, the new corrupted dataset during the test phase.

4. Robustness of the inference system: by considering the machine learning model's response.

Two classification approaches

- Binary case: detection/defect or non-defect.
- Multiclass case: diagnosis the defect/healthy in 1, 2, 3 or 4 broken bars.

Analysis of selected features

- Binary case:
  - Exclusively, features from the statistical and information-based categories were selected;
  - Measures based on complexity and based on systems analysis were not selected or redundant.
- Multiclass case:
  - Correlation-based Feature Selection (CFS) – The biggest subset of features selected, 8.15% of the total features.
  - CBF and CFS – Preference for statistical measures.

ANALYSIS OF NORMAL DISTRIBUTION BY FEATURES EXTRACTED BY EACH CATEGORY

Category of measures	Total number of features	Gaussian features
Statistical	154	31
Information- based	121	25
Based on complexity	11	0
Based on systems analysis	33	0

Comparison of induced models:

- Binary case:

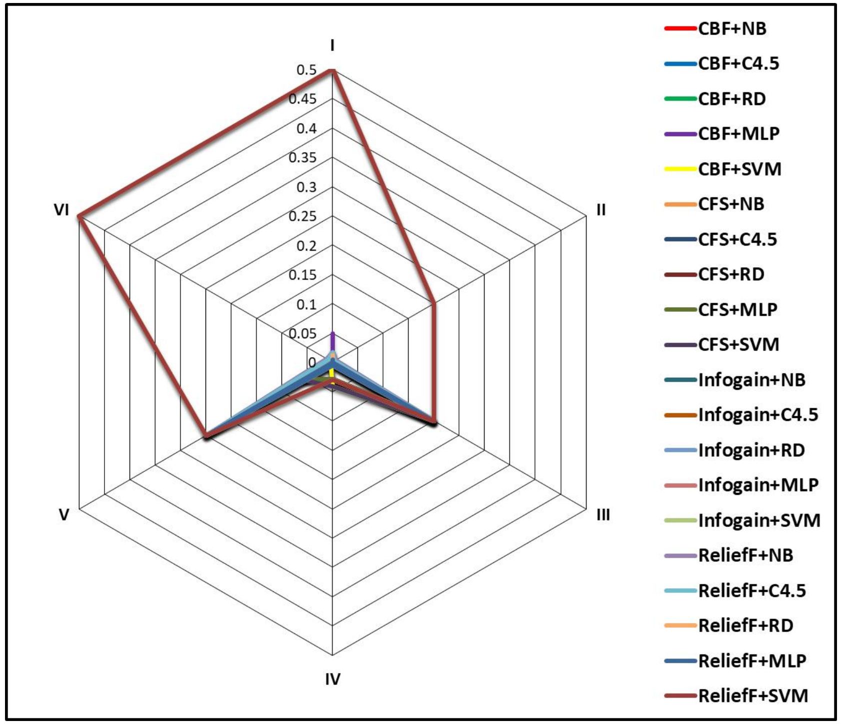


Illustration of the multicriteria measure for evaluating the performance of classifiers in a usual way for binary classification.

RANKING FOR THE SELECTION OF DETECTION SYSTEMS FOR THE BINARY CLASSIFICATION SCENARIO.

Ranking	Detection system	Multicriteria hexagon area
1st	CBF+SVM	0.0167
2nd	CBF+RD	0.0175
3rd	CBF+NB	0.0175
4th	CBF+C4.5	0.0179
5th	CFS+SVM	0.0182
6th	CBF+MLP	0.0187
7th	CFS+RD	0.0193
8th	CFS+MLP	0.0194
9th	CFS+C4.5	0.0195
10th	CFS+NB	0.0195
11th	Infogain+NB	0.0506
12th	Infogain+C4.5	0.0507
13th	ReliefF+NB	0.0507
14th	ReliefF+C4.5	0.0508
15th	Infogain+MLP	0.0513
16th	Infogain+RD	0.0513
17th	ReliefF+MLP	0.0514
18th	ReliefF+RD	0.0514
19th	ReliefF+SVM	0.1265
20th	Infogain+SVM	0.1266

Comparison of induced models:

- Multiclass case:

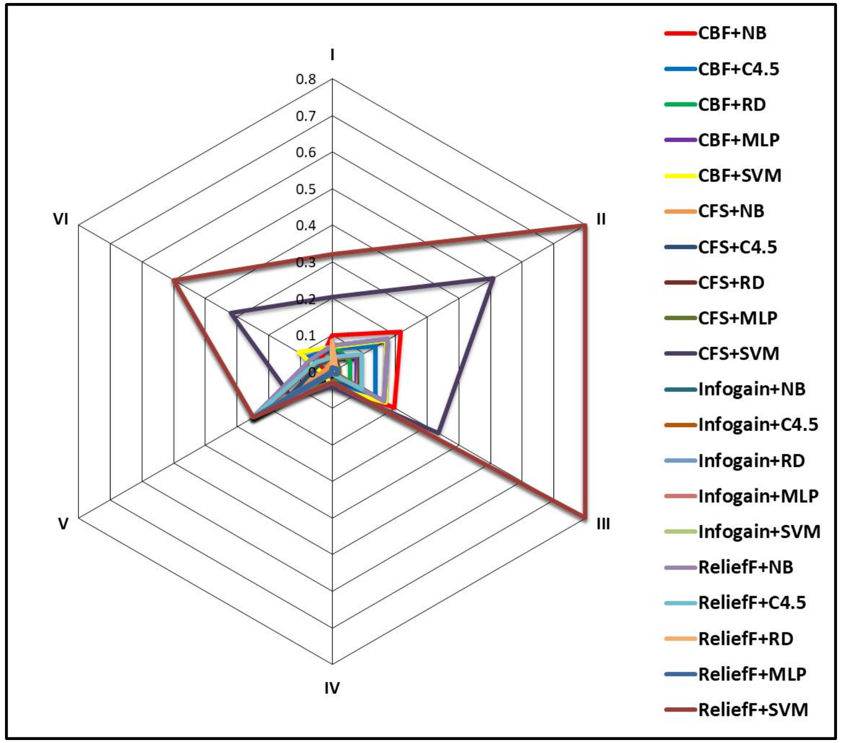


Illustration of the multicriteria measure for evaluating the performance of classifiers in a usual way for multiclass classification.

RANKING FOR SELECTING DIAGNOSTIC SYSTEMS FOR THE MULTICLASS CLASSIFICATION SCENARIO.

Ranking	Diagnostic system	Multicriteria hexagon area
1st	CBF+RD	0.0021
2nd	CBF+MLP	0.0030
3rd	CFS+MLP	0.0102
4th	CFS+C4.5	0.0109
5th	CBF+C4.5	0.0111
6th	CFS+RD	0.0117
7th	CFS+NB	0.0126
8th	CBF+SVM	0.0177
9th	CBF+NB	0.0260
10th	Infogain+C4.5	0.0305
11th	ReliefF+C4.5	0.0310
12th	Infogain+MLP	0.0315
13th	ReliefF+MLP	0.0320
14th	Infogain+RD	0.0345
15th	ReliefF+RD	0.0349
16th	Infogain+NB	0.0413
17th	ReliefF+NB	0.0415
18th	CFS+SVM	0.1576
19th	ReliefF+SVM	0.4643
20th	Infogain+SVM	0.4644

Robustness analysis

- The limit of a given inference system's robustness is the amount of white noise the system supports until there is a statistically significant difference in its evaluation measures, such as the multicriteria measure.

- Shapiro-Wilk normality test, with a significance level of 5%.

- Binary case:
  - The robustness limit for all systems induced was 60%;
  - Except for the CFS+SVM, Infogain+SVM, ReliefF+SVM, and ReliefF +RD, that did not show statistically significant similarities in the value of the multicriteria hexagon area.

- Multiclass case:
  - The robustness limit for the inference systems was 80%;
  - Except for CBF+SVM, CBF+NB, CFS+SVM, Infogain+SVM, and ReliefF+SVM. These exceptions showed statistically significant differences before 80% of white noise.

RECOMMENDATIONS

Binary case – Defect detection:

1. **Types of features:** Features of the statistical category, more specifically the second quartile of the mechanical axial vibration speed signal;
2. **Experimental Performance:** Configuration of the CBF (Correlation-based Feature Selection) with the SVM (Support Vector Machine);
3. **Robustness analysis:** The configuration of CBF with RD (Random Forest) was the most robust for the specific application of defect detection in induction motors, with a robustness limit of 60% of admitted white noise.

Multiclass case – Defect diagnosis:

1. **Types of features:** features mostly from the statistical category, such as the standard deviation of voltage signals in phase A and current in phase B, median axial vibration signal, third quartile of radial vibration signals on the driven side, and voltage in phase B. Voltage signal noise ratio feature in phase A, belonging to the information-based category, and the fractal dimension of the radial vibration signal on the driven side, belonging to the complexity-based category.
2. **Experimental performance:** configuration of the CBF with the RD.
3. **Robustness analysis:** The configuration of CFS with MLP was the most robust for the specific application of defect diagnosis, with a robustness limit of 80% of admitted white noise.

CONCLUSIONS

- The framework offers recommendations for intelligent systems to detect and diagnose defects in induction motors effectively.
- Features that follow a Gauss distribution had greater predictive power.
- A robustness analysis assessed the degree of generalization of the models.
- More generic models have greater application capabilities in new conditions.
- The multicriteria hexagon is presented as a performance measure suitable for the recommendation context, as it evaluates both the feature selector and the learning models. The quantification of computational complexity was a differentiator in enabling online applications.
- Future research could explore different types of defects and new intelligent system paradigms for multiple applications.

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Thank You

Questions

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