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Non-invasive diagnosis of broken rotor bars in induction motors using deep learning and GASF representations

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INTRODUCTION & OBJECTIVES

Three-phase induction motors are widely used in industry for their reliability and low maintenance. However, faults such as broken rotor bars (**BRBs**) can disrupt performance and increase costs. Early detection is therefore necessary. This work presents a non-invasive method that combines phase current signals with deep learning to detect and classify BRB faults in squirrel-cage induction motors.

METHOD

Signals were generated through **FEMM** simulations for rotors with 22, 24, 26, and 28 bars-typical configurations in industrial motors. Zero to six broken bars were considered, and the resulting phase current signals were transformed into two-dimensional images using Gramian Angular Summation Fields (**GASFs**) to highlight fault-related patterns. Two datasets were used: dataset A (**79,086 GASF images**, **11,298** per class) for training, and dataset B (**22,488 time signals**, with class sizes from **2,459** to **3,212**) for testing (see **Figure 1**). Several convolutional neural networks with residual connections (**ResNet18** to **ResNet152**) were evaluated. **ResNet152** was selected for its superior performance, achieving **95.13%** accuracy and **96.77%** sensitivity on dataset A.

RESULTS & DISCUSSION

To evaluate the model's final behavior under real conditions, the full evaluation **dataset B** was used, consisting of **22,488** phase current signals processed into images using **GASF**, this set includes data from multiple motors configurations.

The model performance is good across all classes. Notably, in the classes **1_BRB**, **2_BRB**, and **NO_FAULT**, which have a low number of samples, it achieves a Sensitivity of **100%**. It is important to highlight that the model is very strong at distinguishing between **faulty** and **non-faulty** motors; however, confusion arises when classifying faults involving a higher number of broken bars, particularly from **4_BRB** to **6_BRB**, due to the high similarity in their current signals.

Metrics	Value
Sensitivity	0.95
Weighted Sensitivity	0.92
Macro F1-score	0.87
Matthews Correlation Coefficient (MCC)	0.82
Jaccard Index	0.78

Table 1: Summary of global metrics of the classification system based on the ResNet152 architecture.

Given the class imbalance in **dataset B**, metrics that are suited for imbalanced multiclass classification were used. The model achieved a sensitivity of **0.95**, macro F1-score of **0.87**, Matthews correlation coefficient of **0.82**, and Jaccard index of **0.78**, showing good generalization (see **Table 1**).

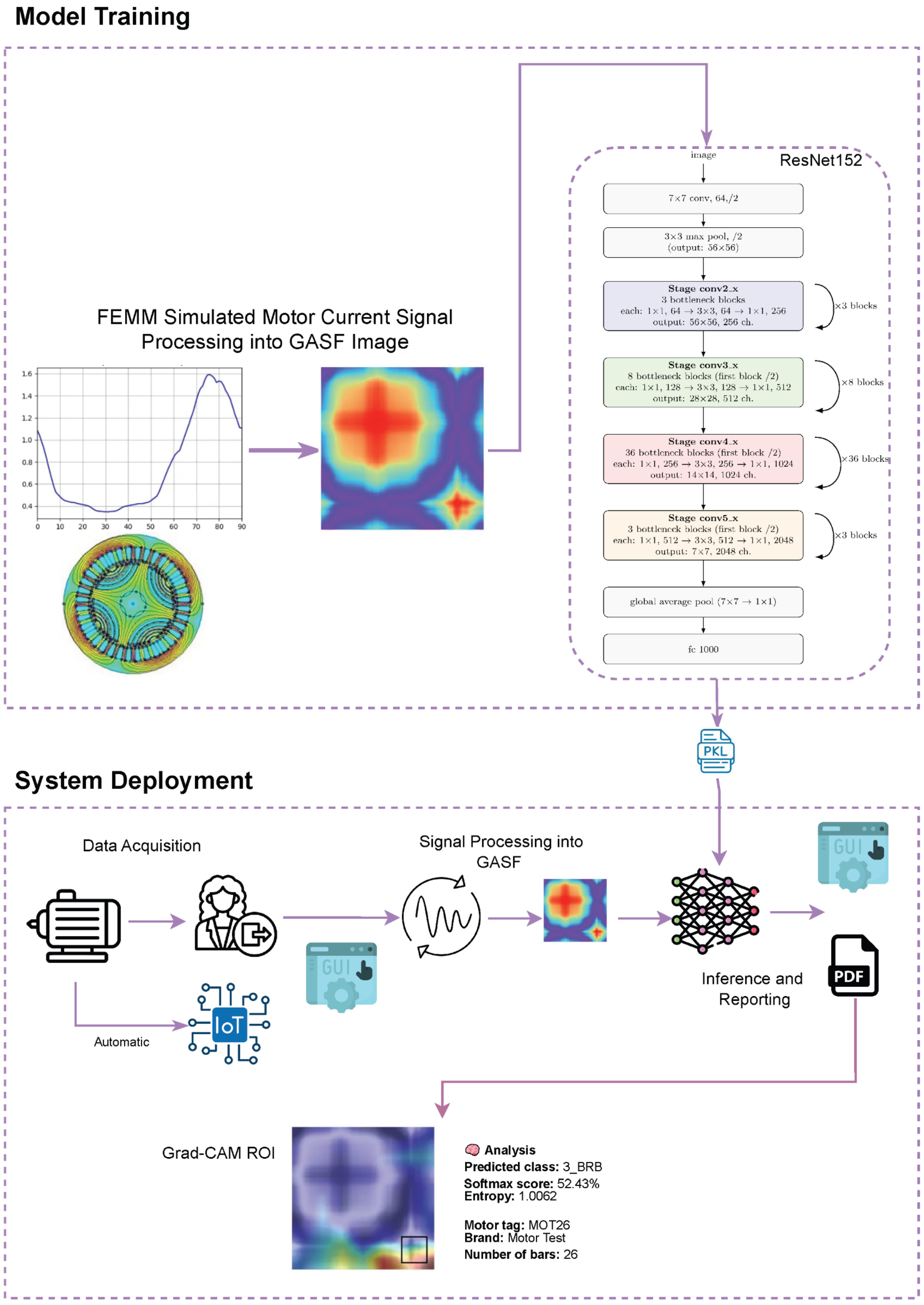

Figure 1: Training workflow for the classification model and system deployment.

CONCLUSION

The proposed system offers a non-invasive, data-driven approach to **BRB fault diagnosis**, which is capable of operating under real conditions without interrupting the motor. Its industrial applicability is reinforced by a graphical interface, allowing users to upload raw signals and obtain reliable predictions easily, supporting predictive maintenance strategies.