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Inter-turn short circuit fault detection in induction motor using XGBoost, KNN and Random Forest

***Abstract**. In this research endeavor, the focus was directed towards investigating a specific fault occurrence within an induction motor, namely an inter-turn short circuit (ITSC), intentionally induced within phase A of the motor. The employed dataset encompassed both correct operational states and instances afflicted with the aforementioned fault, with parameters such as current flows and torque outputs meticulously recorded and analyzed. When employing a methodology rooted in machine learning, a suite of algorithms was applied to discern and identify the presence of the fault. From among the array of algorithms utilized, the notable contenders included Random Forest (RF), k-nearest neighbors (KNN), and Extreme Gradient Boosting (XGBoost), each meticulously trained and tested on the dataset to gauge their efficacy in fault detection. The outcomes obtained in the mentioned study unequivocally demonstrate the superiority of the Random Forest algorithm in terms of accuracy assessment, boasting a remarkable accuracy rate of 99.7%. In the stark contrast, both KNN and XGBoost algorithms exhibited comparatively lower accuracy rates, standing at 96.6% and 96.5%, respectively.*

***Streszczenie.** W tym przedsięwzięciu badawczym skupiono się na badaniu konkretnego wystąpienia usterki w silniku indukcyjnym, a mianowicie zwarcia międzyzwojowego (ITSC), celowo indukowanego w fazie A silnika. Zastosowany zbiór danych obejmował zarówno prawidłowe stany operacyjne, jak i przypadki dotknięte wyżej wymienionymi usterkami, przy czym parametry takie jak przepływy prądu i wyjściowy moment obrotowy były skrupulatnie rejestrowane i analizowane. Stosując metodologię opartą na uczeniu maszynowym, zastosowano zestaw algorytmów w celu rozpoznania i zidentyfikowania obecności usterki. Wśród szeregu wykorzystywanych algorytmów godnymi uwagi konkurentami byli Random Forest (RF), k-najbliższi sąsiedzi (KNN) i Extreme Gradient Boosting (XGBoost), każdy skrupulatnie przeszkolony i przetestowany na zbiorze danych w celu oceny ich skuteczności w wykrywaniu usterek. Wyniki uzyskane w tym badaniu jednoznacznie wskazują na wyższość algorytmu Random Forest pod względem oceny dokładności, który może pochwalić się niezwykłym współczynnikiem dokładności wynoszącym 99,7%. Dla kontrastu, zarówno algorytmy KNN, jak i XGBoost wykazywały stosunkowo niższe wskaźniki dokładności, wynoszące odpowiednio 96,6% i 96,5%. (**Wykrywanie zwarć międzyzwojowych w silniku indukcyjnym przy użyciu XGBoost, KNN i Random Forest**)*

Keywords: Fault detection, machine learning, accuracy, ITSC fault.
Słowa kluczowe: Wykrywanie błędów, uczenie maszynowe, dokładność, błąd ITSC.

Introduction

Induction motors are the workhorses of modern industrial applications, powering everything from conveyor belts to pumps, Electric Vehicle and fans [1,2]. However, like all electromechanical systems, they are susceptible to faults that can compromise their performance and reliability. Among the various faults encountered, inter-turn short circuit (ITSC) faults are particularly concerning due to their potential to escalate into catastrophic failures [3,4]. The detection and diagnosis of ITSC faults in induction motors are critical for ensuring the safety and efficiency of industrial processes. Traditional methods of fault detection, relying on manual inspection and periodic maintenance, are often insufficient for identifying incipient faults in a timely manner [5, 6].

In recent years, there has been a growing interest in leveraging advanced data-driven techniques, particularly machine learning, to enhance the reliability and effectiveness of fault detection systems. Machine learning algorithms offer the promise of automating the process of fault detection by analyzing vast amounts of data collected from sensors embedded within the motor. By identifying patterns and anomalies indicative of impending faults, these algorithms can enable proactive maintenance strategies that minimize downtime and reduce the risk of costly failures [7-9].

The ITSC (Insulation Testing and Evaluation) fault in the induction motor is a significant issue in the industry and has been the focus of research in this field. Various methods have been proposed in the literature for detecting and diagnosing ITSC faults. For instance, in one study, an ITSC fault was investigated using a robust and adaptive parameter [10]. This study provided valuable insights into the insulation condition of the motor and emerged as a reliable diagnostic method in industrial applications. Additionally, a VI locus-based technique was relied upon to diagnose a fault in the stator [11]. This technique provided an effective approach to assess the condition of stator windings.

In another research effort, a method based on the spectrogram of induction motor currents was proposed for detecting ITSC faults[12]. This method improved the fault detection process by analyzing specific patterns that emerge in the frequency spectrum. Furthermore, Park's difference vector method was considered for fault diagnosis [13]. This method offers an effective approach to capture the dynamic behavior of the induction motor.With the rapid advancement of contemporary technologies, machine learning and deep learning techniques have played a significant role in detecting induction motor faults[14].

Particularly, using data extracted from studied cases, machine learning and deep learning methods have been employed for the detection and diagnosis of induction motor faults. Among these techniques, algorithms such as Support Vector Machines (SVM) and XGBoost have emerged as prominent ones due to their effectiveness in rapid fault recognition. In the field of deep learning, technologies such as Convolutional Neural Networks (CNNs) have been used for the detection and classification of induction motor faults [15,16] .These techniques contribute to more accurate and faster diagnosis of induction motor faults through the advancements they provide in data analytics and pattern recognition.

In this study, we explore the application of three machine learning algorithms: XGBoost, KNN, and Random Forest for the detection of ITSC faults in induction motors. Drawing upon a diverse dataset encompassing both healthy and faulty motor operation data, we aim to evaluate the performance of these algorithms in terms of accuracy, sensitivity, and computational efficiency. Our findings have implications for the development of robust fault detection systems that can enhance the reliability and safety of industrial processes.

Material and Method

The operation of an induction motor is governed by several equations, with one of the fundamental ones being the torque equation. The torque developed by an induction motor can be expressed as [17, 18]:

$$\left[v_s\right]=\left[R_s\right].\left[i_s\right]+\frac{d\left[\varphi_s\right]}{dt}$$

$$\left[0\right]=\left[R_r\right].\left[i_r\right]+\frac{d\left[\varphi_r\right]}{dt}$$

$$\left[\varphi_s\right]=\left[L_s\right].\left[i_s\right]+\left[L_m\right].\left[i_r\right]$$

$$\left[\varphi_r\right]=\left[L_r\right].\left[i_r\right]+\left[L_m\right].\left[i_s\right]$$

$$T=\tfrac{3}{2}P(\varphi_s * i_s)$$

Now, when an inter-turn short circuit (ITSC) fault occurs in an induction motor, it introduces a new impedance path between the turns of the winding. This fault alters the motor's electrical characteristics and can lead to changes in current distribution and torque production. The presence of an ITSC fault typically results in an increase in winding resistance and a distortion of the magnetic field within the motor.

Mathematically, the effects of an ITSC fault can be incorporated into the motor equations by modifying the parameters related to winding resistance and reactance. Additionally, the fault may introduce asymmetries in the motor's behavior, which can be detected through variations in current signatures or vibration patterns [19,20], as show in Fig. 1.

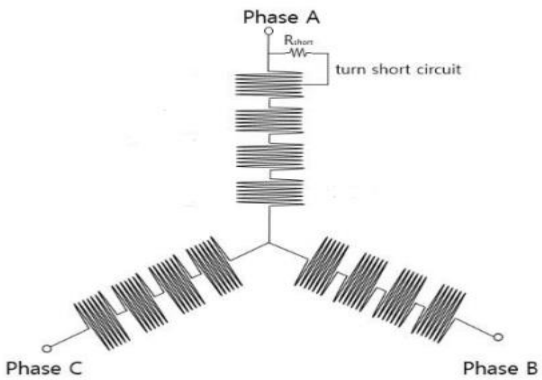

Fig. 1. ITSC fault

XGBoost

Short for "Extreme Gradient Boosting," is a highly effective machine learning algorithm, particularly suited for regression and classification problems. It is a variant of the gradient boosting method and allows the aggregation of weak predictors (typically decision trees) to learn complex relationships. XGBoost is faster and more high-performing compared to other gradient boosting methods, enabling effective operation on large datasets.

The fundamental principle behind XGBoost is to construct a powerful predictor by assembling a series of weak predictors. Initially, a baseline prediction is made on the dataset. Subsequently, in each iteration, a new predictor is trained to correct the errors of the previous predictions using the gradient descent algorithm, minimizing the error between the predicted and actual values of the target variable. Finally, the new predictor contributes to the ensemble by combining with the previous predictors [21-23].

The process of regression with XGBoost involves the following steps:

- **Initial Prediction:** A simple prediction, such as the mean value of the target variable, is used as the initial estimate. This serves as the starting point for the model.
- **Error Calculation:** The errors between the initial prediction and the actual values are calculated. These errors will be minimized in subsequent iterations.
- **Decision Tree Construction:** A new decision tree is constructed to minimize the errors. The decision tree is trained on the dataset to capture the complex relationships between features and the target variable.
- **Learning Rate Adjustment:** In each iteration, a learning rate is determined to control the contribution of the new predictor and prevent overfitting.
- **Combination of Predictions:** The predictions from each iteration are combined to create a stronger predictor by summing up the predictions from all previous predictors.
- **Termination Condition:** The training of the model stops when a termination criterion is met, such as reaching a certain number of iterations or a threshold error.

XGBoost repeats these steps to assemble a series of weak predictors into a strong regression model, effectively learning complex relationships and providing accurate predictions for new data points. It is known for its high performance, scalability, and ability to handle large datasets, making it a popular choice for regression tasks[24]. Fig. 2 shows the XGBoost flowchart.

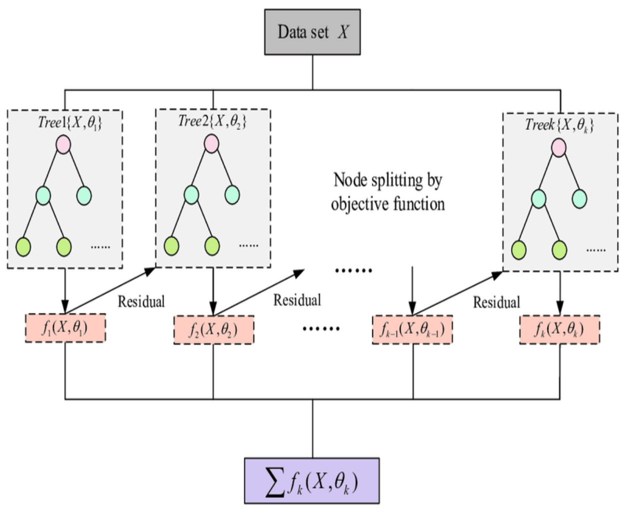

Fig. 2. XGBoost flowchart

k-Nearest Neighbors

The KNN algorithm is a popular machine learning technique used for both classification and regression tasks. It's a simple yet effective algorithm that makes predictions based on the similarity of data point [25-27].

Here's how the KNN algorithm works:

- **Training**: During the training phase, the algorithm simply memorizes the features and labels of the training dataset.
- **Prediction**: When making a prediction for a new data point, the algorithm calculates the distance between that point and all other points in the training dataset.
- **Nearest Neighbors**: It then selects the k nearest data points (neighbors) to the new data point based on the calculated distances. The value of k is a hyperparameter that needs to be specified before training the model.
- **Majority Vote (Classification) or Average (Regression)**: For classification tasks, KNN predicts the class label of the new data point based on the majority class among its k nearest neighbors. For regression tasks, it predicts the average value of the target variable among its k nearest neighbors.
- **Decision**: Finally, the algorithm assigns the predicted class label or regression value to the new data point.

Key considerations for using the KNN algorithm include choosing the appropriate value of k and selecting a suitable distance metric (such as Euclidean distance or Manhattan distance) based on the nature of the data. Additionally, KNN is computationally expensive, especially for large datasets, as it requires calculating distances for each new data point against all training data points. However, it is non-parametric and doesn't make any assumptions about the underlying data distribution, making it robust in various scenarios Fig. 3.

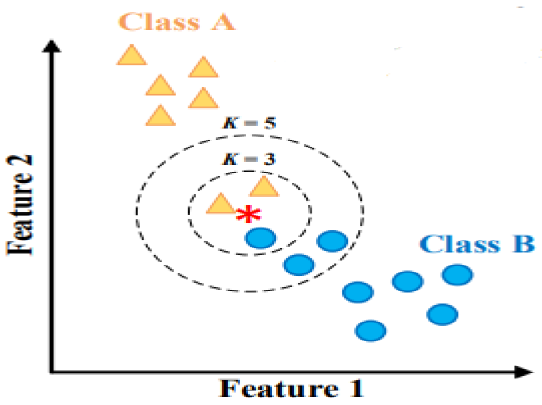

Fig. 3. KNN

Random Forest

RF is a versatile and powerful ensemble learning algorithm widely used for both classification and regression tasks in machine learning. It operates by constructing a multitude of decision trees during training and outputs the mode (for classification) or mean prediction (for regression) of the individual trees [28-30].

Here's how the Random Forest algorithm works:

- **Bootstrapped Sampling:** Random Forest begins by creating multiple decision trees, each trained on a different subset of the training data. This process involves randomly sampling the training data with replacement, a technique known as bootstrapping.
- **Random Feature Selection:** At each node of the decision tree, a random subset of features is considered for splitting. This helps to decorrelate the individual trees and improve the overall model's performance.
- **Decision Tree Construction:** Each decision tree is constructed recursively by selecting the best feature to split on at each node. The splitting criterion, typically based on measures like Gini impurity for classification or mean squared error for regression, aims to maximize the homogeneity of the target variable within each node.
- **Ensemble Learning:** Once all decision trees are built, predictions are made by aggregating the predictions of each individual tree. For classification tasks, the mode (most frequent class) among the predictions of all trees is selected as the final prediction. For regression tasks, the mean prediction of all trees is taken Fig. 4.

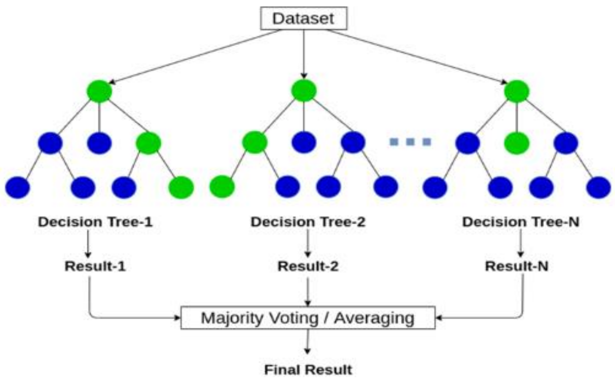

Fig. 4. Random Forest

Results and Discussion

A comprehensive simulation of an induction motor was meticulously conducted using MATLAB, a versatile computational tool widely employed in engineering applications. The primary objective of this simulation was to closely examine the dynamic response of the motor under varying operational conditions, particularly focusing on the effects of induced faults. The simulation setup involved supplying the induction motor with three-phase voltage inputs, simulating real-world operating conditions. By manipulating the voltage inputs across the motor's phases, a controlled environment was created to observe the resulting currents and torques, which are fundamental parameters indicative of the motor's performance. In this experimental setup, a deliberate error was introduced in phase A of the induction motor, simulating a fault scenario commonly encountered in practical applications. This fault injection allowed for the observation and analysis of the motor's response to abnormal operating conditions, providing valuable insights into fault detection and diagnosis strategies.

Fig. 5 serves as a visual representation of the simulation process, depicting the motor's behavior and response dynamics over time. This graphical representation enables a clear visualization of the changes occurring within the motor under different operating conditions, facilitating a deeper understanding of its behavior. Table 1 complements the simulation results by presenting a comprehensive overview of the machine variables involved in the study. These variables include crucial parameters such as voltage levels, currents, and torque values, providing essential insights into the motor's operational characteristics. Analyzing the simulation results, Fig. 6 illustrates the currents extracted from the induction motor during normal operation. Each phase exhibits a steady current magnitude of 14 A, indicative of stable and balanced operation under healthy conditions. A comparative analysis between the healthy and faulty states of current in phase A is presented in Fig. 7. The graphical representation clearly delineates the differences in current profiles between the two scenarios, highlighting the impact of the induced fault on the motor's electrical behavior.

Fig. 8 provides further insights into the torque values obtained from the simulation. Notably, a discernible decrease in torque values is observed in the presence of the fault, signifying a deviation from expected performance levels. This observation underscores the importance of torque analysis in fault detection and diagnosis methodologies for induction motors. In summary, the comprehensive simulation conducted using MATLAB offers invaluable insights into the dynamic behavior of induction motors under varying operating conditions. By simulating fault scenarios and analyzing the resulting changes in motor behavior, this study contributes to the development of robust fault detection and diagnosis strategies, ultimately enhancing the reliability and performance of induction motor systems in practical applications.

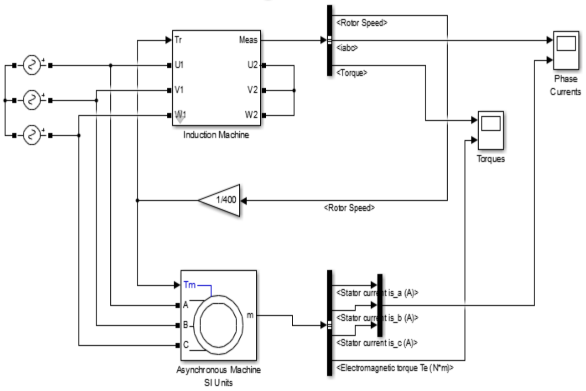

Fig. 5. Induction motor simulation.

Table 1.

Parameter	Value
stator resistance	2.3 ohm
stator inductance	0.005 H
rotor resistance	3.1 ohm
rotor inductance	0.001 H
mutual inductance	0.09 H
inertia	0.005 Kg.m^2
pole pairs	1
friction factor	1 $*10^{-7}$ N.m. s

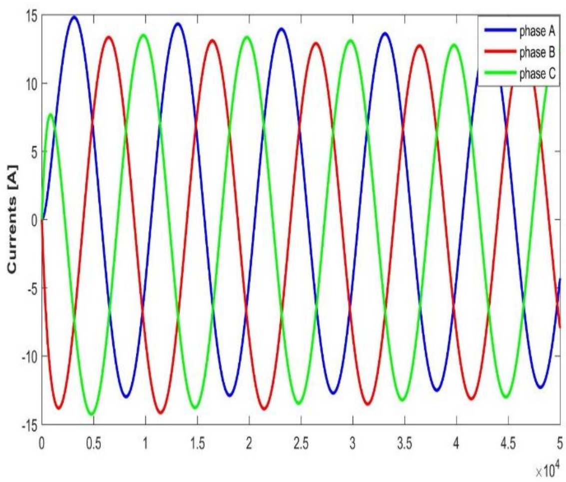

Fig. 6.Three phase currents

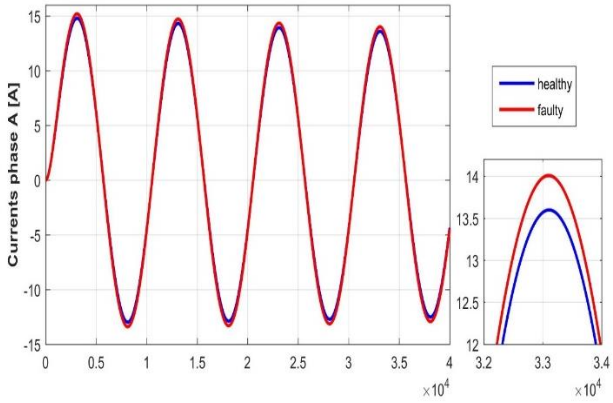

Fig. 7. The difference in current in phase A between the healthy and faulty states

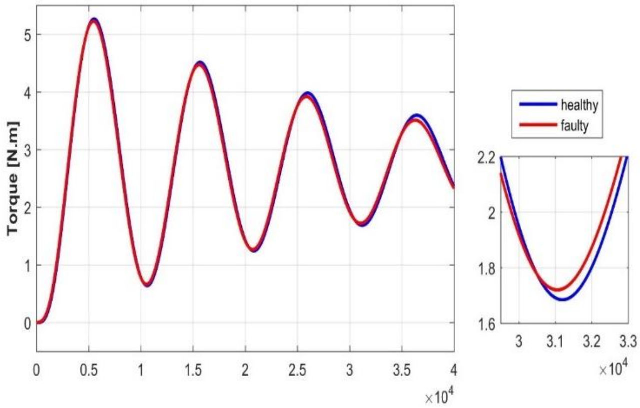

Fig. 8. Torque

In the investigation of the induction motor's behavior, data extraction was initially carried out under healthy operational conditions. Subsequently, to discern the variations induced by faults, data corresponding to faulty states was meticulously identified and isolated. Leveraging the machine learning algorithms proposed in this study, an endeavor was made to classify the state of the motor based on the extracted data, as depicted in Fig. 9.

Upon the identification of test data, a rigorous evaluation of the algorithms was conducted. Notably, it was observed that the RF algorithm exhibited a remarkable convergence with the expected test data, as illustrated in Fig. 10. This convergence underscores the efficacy of the RF algorithm in accurately discerning between healthy and faulty states of the motor. Furthermore, in order to assess the robustness of each algorithm, the error associated with each was meticulously determined and visualized in Fig. 11. Remarkably, it was evident that the error associated with the RF algorithm approached zero, indicating a high degree of precision and reliability in its predictions. To provide a quantitative measure of the performance of each algorithm, the accuracy was determined using the Root Mean Square Error (RMSE), as outlined in Table 2. It is noteworthy that a high accuracy score in the RF algorithm corresponds to a significantly low value in RMSE, reaffirming the superior performance and predictive capability of the RF algorithm in discerning the state of the induction motor.

In the summary, the meticulous analysis and evaluation of machine learning algorithms, particularly the RF algorithm, have yielded promising results in accurately detecting and classifying the state of the induction motor. These findings underscore the potential of machine learning techniques in enhancing fault detection and diagnosis methodologies, ultimately contributing to the advancement of industrial automation and operational efficiency.

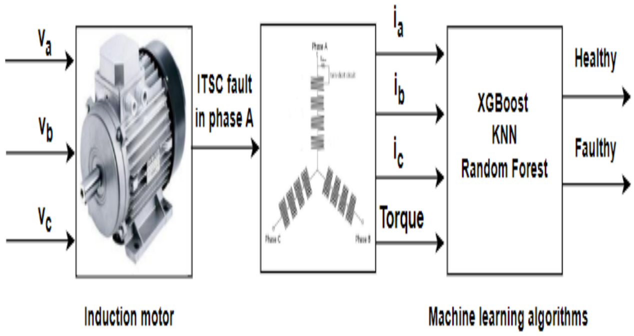

Fig. 9. Structuring fault identification using machine learning in an induction motor

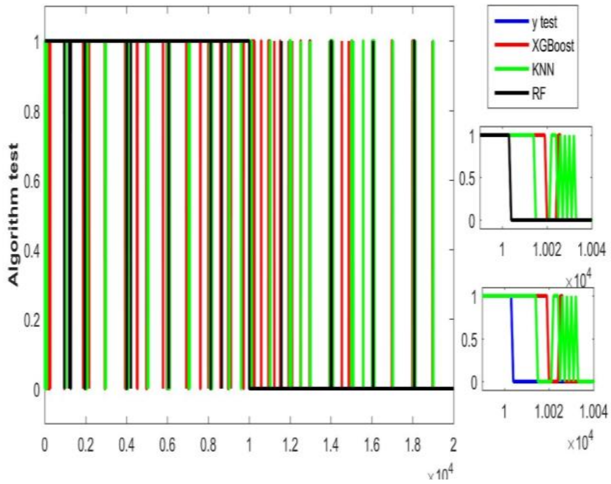

Fig. 10.Compare test algorithms with real test values

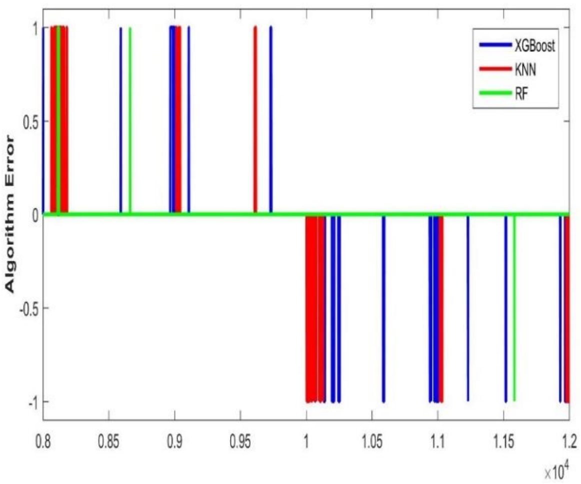

Fig. 11.the error of each algorithm accuracy

Table 2.

algorithms	RMSE	Accuracy (%)
Random Forest	0.0543	99.7
KNN	0.1823	96.6
XGBoost	0.1871	96.5

Conclusion

In this study, we conducted a comprehensive analysis of machine learning algorithms for fault detection in induction motors. Our investigation focused on the performance of RF, KNN, and XGBoost algorithms in distinguishing between healthy and faulty states of the motor based on extracted data. The results of our analysis reveal that the RF algorithm outperforms both KNN and XGBoost in terms of accuracy and robustness. With the lowest RMSE value and the highest accuracy rate, RF demonstrates its efficacy in accurately identifying fault conditions with minimal errors. While KNN and XGBoost algorithms show potential as alternatives for fault detection, particularly in cases where computational efficiency is a priority, they do not achieve the same level of accuracy and reliability as RF. Overall, the findings of this study underscore the effectiveness of machine learning algorithms, particularly Random Forest, in enhancing fault detection methodologies for induction motors. These insights have significant implications for the development of proactive maintenance strategies and the optimization of industrial processes, ultimately contributing to improved reliability, safety, and efficiency in industrial applications. Further research may explore the integration of additional features and optimization techniques to enhance the performance of machine learning algorithms in fault detection for induction motors.

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