ML-Driven Smart Manufacturing for Accurate Mechanical Fault Detection and Classification

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Abstract

Mechanical faults in industrial machinery can lead to significant operational disruptions, increased maintenance costs, and safety hazards. In 2023, the global market for predictive maintenance technologies was valued at over $10 billion, reflecting the growing emphasis on early fault detection and prevention. Accurate classification of mechanical faults is critical for maintaining equipment reliability and minimizing downtime. Traditional methods for fault diagnosis often involve manual inspection and heuristic analysis, which can be labor-intensive and prone to errors, particularly when dealing with complex machinery or large-scale operations. Manual fault detection methods typically rely on visual inspections, vibration analysis, and other diagnostic techniques that require substantial expertise and are often reactive rather than proactive. These approaches can struggle to detect early signs of failure or subtle anomalies, leading to delayed maintenance actions and potential system failures. The limitations of manual methods highlight the need for more effective and automated solutions to improve fault detection and classification. Machine learning provides a robust solution for classifying mechanical faults by analyzing sensor data and identifying patterns indicative of various fault types. Techniques such as classification algorithms, anomaly detection, and deep learning models can be trained on historical fault data to recognize and predict faults. By leveraging features extracted from sensors monitoring vibrations, temperature, and other operational parameters, machine learning models can offer high accuracy in fault classification and early warning of potential issues. This approach enhances the reliability of predictive maintenance systems, reduces downtime, and optimizes maintenance strategies, ultimately contributing to more efficient and cost-effective industrial operations.

Keywords: accuracy, anomaly detection, deep learning, fault classification, machine learning, predictive maintenance, reliability

1. Introduction

Permanent Magnet Synchronous Machines (PMSMs) have a rich history dating back to the late 19th century when electrical machinery began to revolutionize industrial processes. The concept of using permanent magnets to generate motion in synchronous machines emerged as a promising alternative to traditional electromagnets. In the early 20th century, significant advancements in magnet materials and manufacturing techniques facilitated the widespread adoption of PMSMs in various applications, including power generation, transportation, and industrial automation.

The development of PMSMs gained momentum during the mid-20th century with the advent of modern power electronics and control systems. The integration of solid-state devices such as transistors and thyristors enabled more precise control over motor operation, leading to improved efficiency and performance. As industries increasingly sought energy-efficient solutions, PMSMs emerged as a preferred choice due to their high efficiency and superior controllability.

In recent decades, advancements in materials science, motor design, and computational modeling have further propelled the evolution of PMSM technology. The integration of rare-earth magnets, such as neodymium and samarium-cobalt, has significantly enhanced motor performance while reducing size and weight. Moreover, advancements in sensor technology and data analytics have enabled the development of sophisticated monitoring and diagnostic systems for PMSMs, enhancing reliability and maintenance efficiency.

Despite their long history and widespread adoption, PMSMs continue to evolve, driven by ongoing research and technological innovation. Emerging trends such as Industry 4.0 and the Internet of Things (IoT) are shaping the future of PMSM technology, ushering in an era of smart, interconnected machines with enhanced monitoring, diagnostics, and predictive maintenance capabilities.

2. Literature Survey

Electric vehicles (EVs) are attracting more and more attention in transportation due to enhanced performance, safety, and reduced environmental impacts. In particular, permanent magnet synchronous motors (PMSM) are applied widely as traction motors in EVs because of their high efficiency and power density. The healthy operation of the traction motor is crucial for the proper functioning of an EV. Since EV motors run in a harsh environment and complicated operating conditions, the stator winding insulation exhibits a higher failure rate [1]. This fault can lead to a catastrophic accident; therefore, timely identification and diagnosis of insulation faults for traction PMSMs are extremely important to ensure the safe operation of EVs.

It is reported that inter-turn short faults (ITSF) account for 21% of all motor faults [**2**], which can lead to reduced motor efficiency and power output and even catastrophic failure. The majority of ITSFs originate in winding faults, which are caused by insulation malfunctions [3], but rapidly evolve into more severe failures that substantially impact motors. On the one hand, short-circuit paths in the motor can lead to a decline in its performance. These paths allow currents to bypass the normal winding segments [**4**], leading to reduced output power and efficiency. For PMSMs, this type of fault can generate a magnetic field with a higher intensity than the coercivity of the magnets, leading to permanent demagnetization and machine damage. On the other hand, ITSFs cause excessive temperature rises in the motor. Excessive heat can accelerate the aging and embrittlement of insulation materials, potentially leading to burnouts and exacerbating the short-circuit phenomenon [5]. Furthermore, ITSFs increase motor noise and vibration. The presence of short-circuit paths introduces additional electromagnetic forces and vibrational forces in the motor, resulting in abnormal sounds and vibrations [6]. This not only adds to the noise pollution in the working environment but also risks loosening and damaging other components, further exacerbating the development of faults.

The impacts and losses caused by stator winding short circuits in electric motors are extremely severe [**7**]. Therefore, timely diagnosis and repair of these faults are crucial to ensure the safe operation and prolongation of the motor's lifespan.

The health model of the Kalman filter is used to estimate the residual voltage drop of the rotor reference DQ axis under an ITSF [10]. This observer avoids the use of voltage sensors but does not reduce the diagnostic accuracy of the ITSF. Ali performed KF observations on the current and voltage signals respectively [11], using the residual signal as the fault detection index; this method was robust against different fault resistances. However, linear KF cannot be used for systems with significant nonlinearity. Since most systems are nonlinear, suboptimal state estimation techniques can be employed. The extended Kalman filter (EKF) is one of these suboptimal techniques [12], where the measurement and system model equations are linearized, enabling the application of the linear Kalman filter algorithm. Nonetheless, the linearization in EKF may introduce instability to the method, particularly when dealing with extremely nonlinear systems. To overcome the limitations of EKF, the unscented Kalman filter (UKF) was proposed in [13]. The UKF employs a set of sigma points to estimate the propagation of the mean and covariance matrix [14]. EKF and UKF were used to detect the percentage and location of faults [15]. Another difference in the method is that the ratio of short-circuit turns is used as the state estimator.

The ITSF diagnosis method based on the Luenberger state observer and current second-order harmonics was established in [16].

3. Proposed System

This project focuses on the development and evaluation of stator fault detection strategies in Permanent Magnet Synchronous Machines (PMSMs) using machine learning techniques as shown in Figure 1. Let's break down the key components and functionalities of the code.

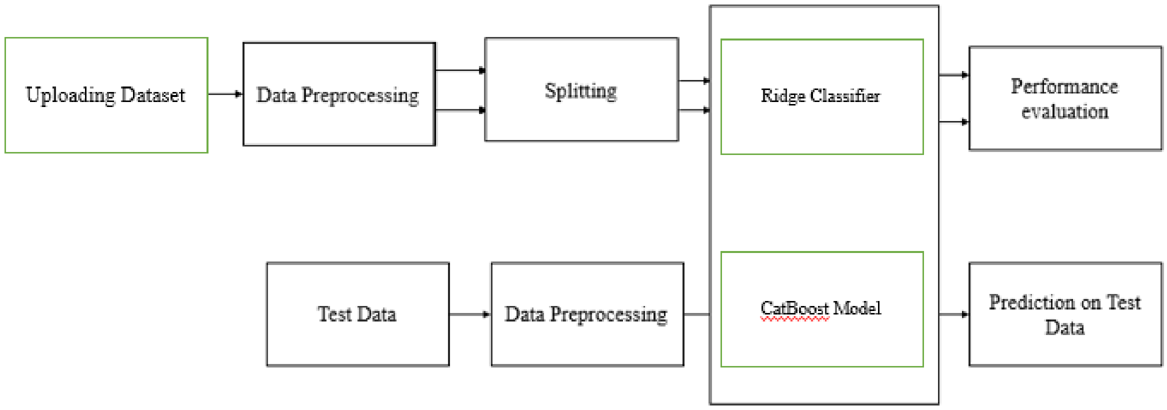

Figure 1: Block Diagram of Proposed System.

- **Importing Libraries and Modules:** By importing necessary libraries and modules such as NumPy, Pandas, Matplotlib, Seaborn, scikit-learn, and CatBoost. These libraries provide functionalities for data manipulation, visualization, model building, and evaluation.
- **Importing Dataset:** The dataset containing various electrical parameters of PMSMs is imported using Pandas' **read_csv** function. This dataset serves as the foundation for training and testing machine learning models for stator fault detection.
- **Data Analysis and Visualization:** Exploratory data analysis (EDA) techniques are employed to gain insights into the dataset's characteristics. Descriptive statistics, correlation analysis, and visualization using Seaborn are utilized to understand the distribution of data and identify patterns relevant to stator fault detection.
- **Data Preprocessing:** Data preprocessing steps such as handling missing values, encoding categorical variables, and splitting the dataset into independent variables (features) and the target variable (stator fault) are performed. Additionally, the dataset is divided into training and testing sets using scikit-learn's **train_test_split** function.
- **Model Building:** Two classification algorithms, namely Ridge Classifier and CatBoost Classifier, are chosen for stator fault detection. Ridge Classifier is a linear classification algorithm, while CatBoost Classifier is a gradient boosting algorithm specifically designed to handle categorical features efficiently. Both models are trained using the training data.

— **Performance Evaluation:** The performance of each classifier is evaluated using various evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix. The se metrics provide insights into the models' ability to accurately classify instances into their respective classes, including the detection of stator faults.

3.1 CatBoost Classifier:

CatBoost Classifier is a gradient boosting algorithm designed for classification tasks, particularly when dealing with categorical features as shown in Figure 2. It belongs to the family of ensemble learning methods and is known for its robustness, efficiency, and ability to handle categorical variables without the need for extensive preprocessing. Below is a detailed explanation of the principle, working, and process of the CatBoost Classifier, along with its disadvantages.

Principle: The principle behind the CatBoost Classifier lies in its gradient boosting framework, which combines multiple weak learners (decision trees) to create a strong predictive model. CatBoost stands for "Categorical Boosting," indicating its capability to handle categorical features effectively. It employs a variant of gradient boosting that incorporates techniques to handle categorical variables and mitigate overfitting.

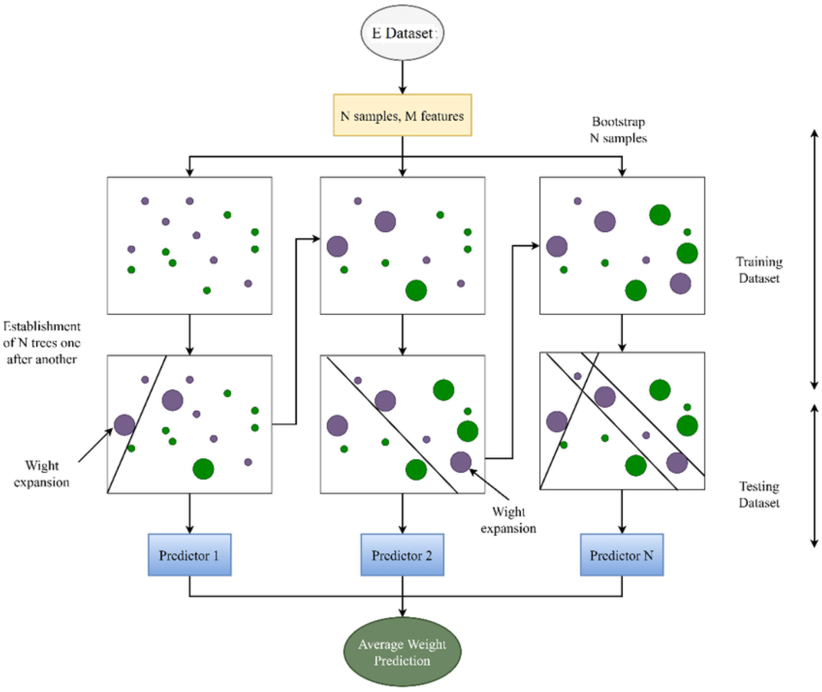

Figure 2: Cat Boost Classifier Model Diagram.

4. Results Description

The figure 3 confusion matrix of the Ridge Classifier model visually represents the performance of the model in classifying different categories of mouth diseases. It provides a clear overview of the true positive, true negative, false positive, and false negative predictions made by the model for each class. The figure 4 classification report of the CatBoost Classifier model presents a detailed summary of the model's performance in terms of precision, recall, F1-score, and support for each class. It offers insights into the model's ability to correctly classify instances of each disease category. The figure 6 confusion matrix of the CatBoost Classifier model illustrates the model's performance but specifically for this classifier. It provides a visual representation of how well the model predicts the actual classes of Fitness activities, aiding in understanding its activities.

```
RidgeClassifier Accuracy    : 97.15062179864495
RidgeClassifier Precision   : 96.0178765535225
RidgeClassifier Recall      : 97.01541100247837
RidgeClassifier FSCORE      : 96.49916603845975

 RidgeClassifier classification report
              precision    recall  f1-score   support

    No Fault       0.97      0.99      0.98    283716
       Fault       0.97      0.93      0.95    115529

    accuracy                           0.97    399245
   macro avg       0.97      0.96      0.96    399245
weighted avg       0.97      0.97      0.97    399245
```

Fig 3: Shows a classification report of a Ridge Classifier model.

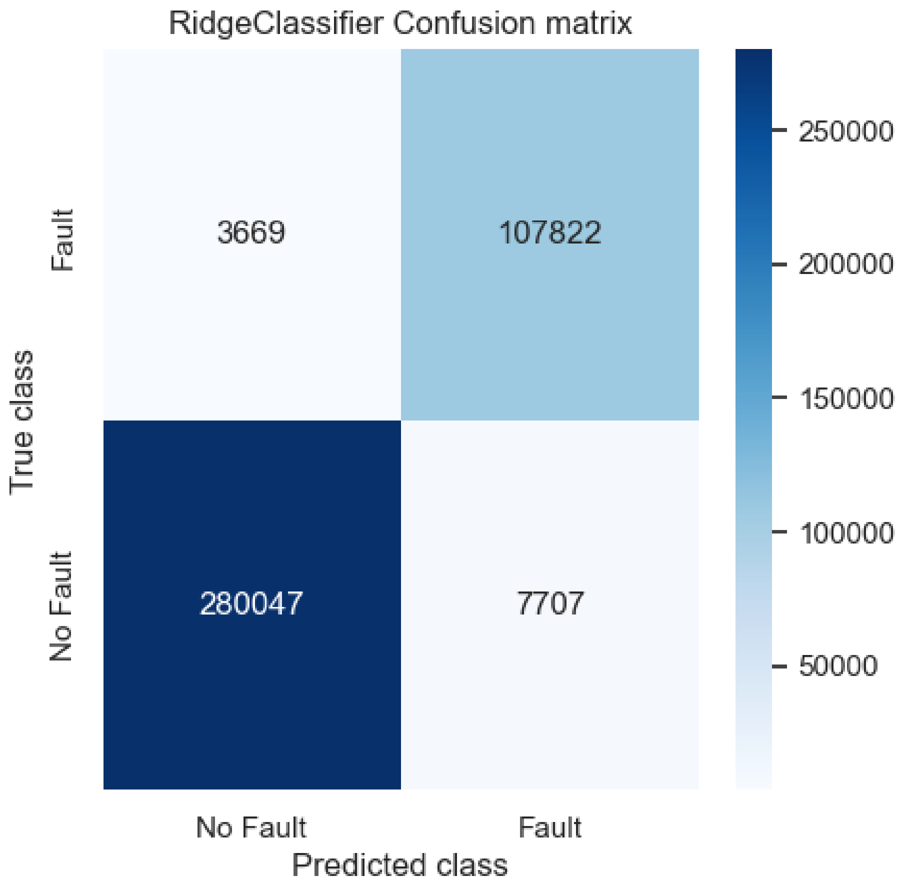

Fig 4: Confusion matrix of Ridge Classifier model.

The figure 5 comparison table of performance metrics presents a comprehensive overview of the performance of different classifiers, such as Ridge Classifier and CatBoost Classifier. It allows for a direct comparison of metrics such as accuracy, precision, recall, and F1-score, enabling stakeholders to make informed decisions about model selection. The figure 6 proposed CatBoost Classifier model's prediction of fault on a test data demonstrates the practical application of the model.

```
CatBoost Classifier Accuracy    : 99.92460769702815
CatBoost Classifier Precision   : 99.92597017575699
CatBoost Classifier Recall      : 99.88671339136582
CatBoost Classifier FSCORE      : 99.90631813733455

 CatBoost Classifier classification report
              precision    recall  f1-score   support

    No Fault       1.00      1.00      1.00    287897
       Fault       1.00      1.00      1.00    111348

    accuracy                           1.00    399245
   macro avg       1.00      1.00      1.00    399245
weighted avg       1.00      1.00      1.00    399245
```

Fig 5: Shows a classification report of a CatBoost Classifier model.

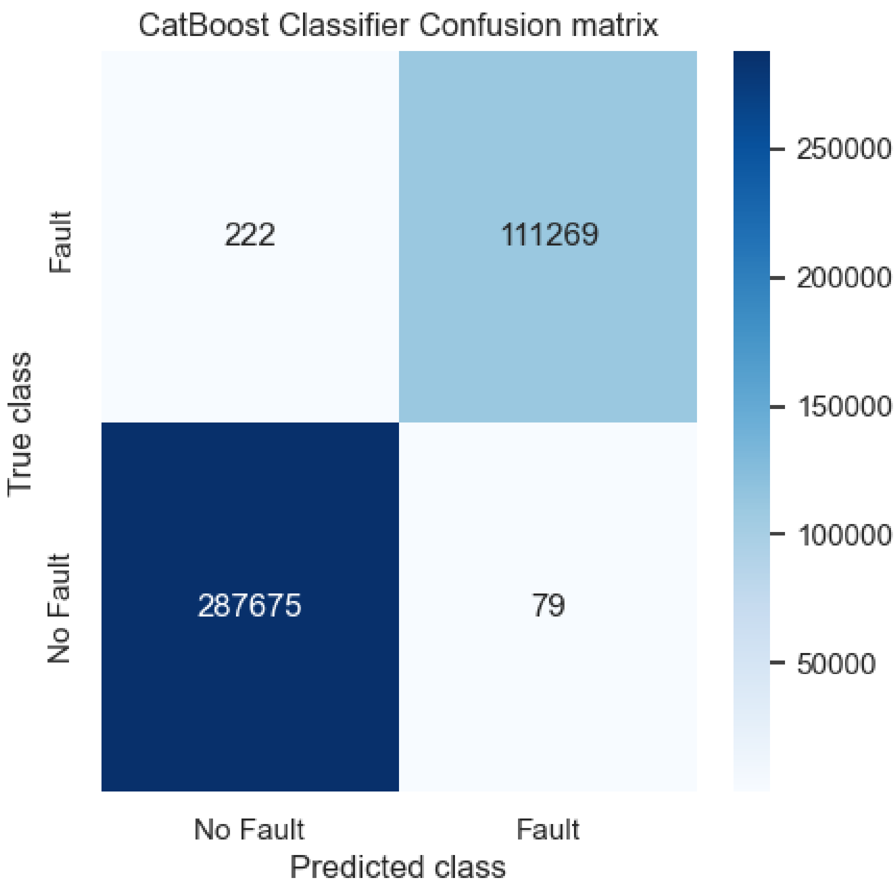

Fig 6: Confusion matrix of CatBoost Classifier model.

5. Conclusion

The development of advanced stator fault detection strategies for PMSMs is essential for ensuring reliable and uninterrupted operation in industrial applications. By leveraging cutting-edge technologies such as machine learning and sensor fusion, researchers aim to overcome the limitations of traditional maintenance methods and develop proactive fault detection systems capable of accurately identifying stator faults in real-time. Looking ahead, future research in this field may focus on further improving the accuracy, robustness, and scalability of fault detection algorithms, as well as exploring novel sensor technologies and data analytics techniques. Additionally, integrating fault detection systems with predictive maintenance and condition monitoring platforms can enable more proactive and data-driven maintenance strategies, further enhancing the reliability and efficiency of PMSMs in industrial environments.

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