MACHINE LEARNING APPROACHES FOR FAILURE PREDICTION IN MECHANICAL COMPONENTS

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ABSTRACT

Permanent Magnet Synchronous Machines (PMSMs) are widely used in industrial applications due to their high efficiency and precise control capabilities; however, stator faults remain a critical threat to their operational reliability. Traditional detection methods, such as periodic inspections and basic electrical monitoring, often fall short in providing early, accurate fault detection and can result in either false alarms or overlooked issues. These limitations contribute to unplanned downtime, increased maintenance costs, and potential equipment damage. To address this challenge, the proposed system integrates advanced machine learning algorithms with sensor fusion techniques to improve the accuracy and reliability of stator fault detection in PMSMs. By leveraging data from multiple sensors—such as voltage, current, temperature, and vibration—the system offers a holistic view of machine health. Trained on historical datasets, the machine learning models identify patterns linked to stator faults, while built-in false alarm suppression algorithms ensure only genuine alerts prompt maintenance action. This approach enables proactive maintenance, reduces downtime, enhances safety, and lowers operational costs.

Keywords: PMSM, Stator Fault Detection, Machine Learning, Sensor Fusion, Predictive Maintenance

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]. The advantage of this method is the ability to assess the severity of failures, as well as the efficiency with which failures can be detected at an early stage and under various operating conditions. A high-order sliding mode observer was used to estimate the rotor flux and three-phase stator current in the fault state [17]. By comparing the measured and estimated values of stator three-phase currents, a fault detection method was designed. This comparison produces a set of residuals that are sensitive to failure. The analysis of these residual signals can be used to detect the damage of the stator windings. An equivalent model of the single-phase interturn fault motor served as the observer [18], where the error between the measured current and the estimated current were corrected as the core of the fault severity estimator. A sufficiently accurate model is established to determine the variation of different variables in the motor under this fault condition, and then the residual generated by the sliding mode observer is used to detect the ITSF. In another study, a PMSM model of single-phase short-circuit fault is established, and a sliding mode observer is developed to extract voltage disturbance information from the derived equivalent control signal to detect interturn faults [19]. However, the Luenberger observer is sensitive to changes in motor parameters.

3. PROPOSED SYSTEM

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

- **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.

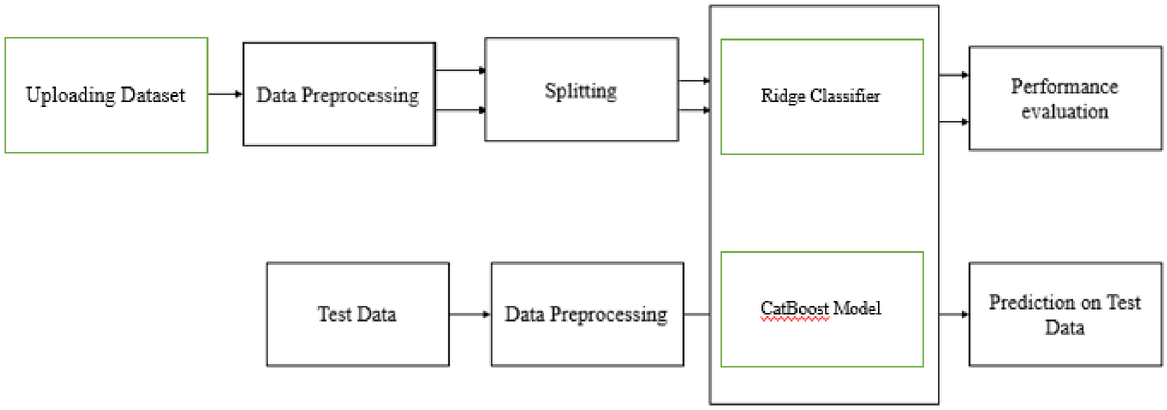

Figure 1: Block Diagram of Proposed System.

3.1 CatBoost Classifier:

CatBoost Classifier is a gradient boosting algorithm designed for classification tasks, particularly when dealing with categorical features. 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.

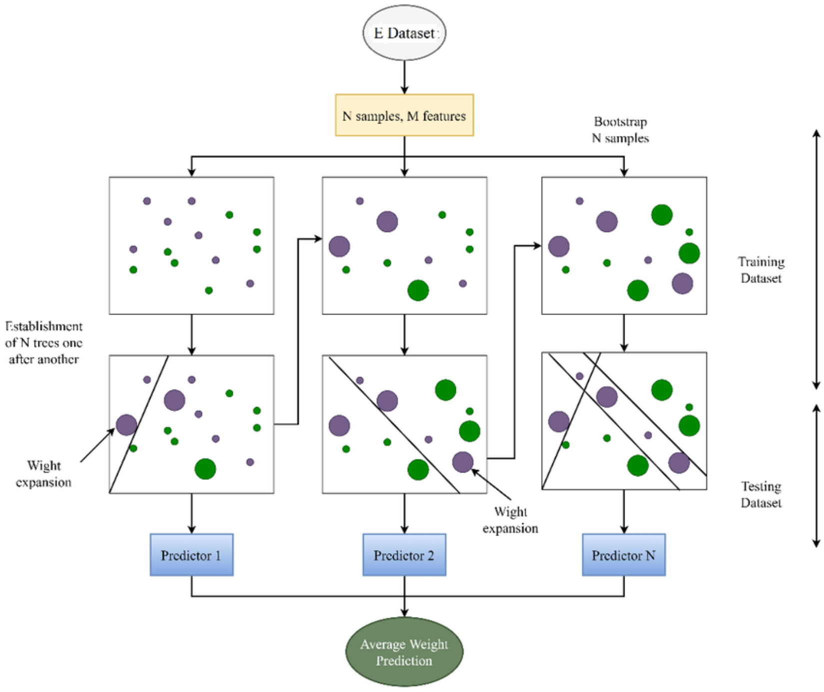

Figure 2: Cat Boost Classifier Model Diagram.

Working:

1. Gradient Boosting Objective Function: The objective function of gradient boosting aims to minimize the loss between the predicted values and the true labels. In CatBoost, the objective function typically involves a differentiable loss function such as log-loss for binary classification or multinomial logistic loss for multiclass classification. Mathematically, the objective function can be expressed as:

$$J(\theta)=\sum i=1NL(yi,F(xi))J(\theta)=\sum i=1NL(yi,F(xi))$$

Where:

- $J(\theta)J(\theta)$ represents the total loss function.
- NN is the total number of samples.
- $yiyi$ is the true label of sample ii.
- $F(xi)F(xi)$ is the predicted value for sample ii.
- $L(yi,F(xi))L(yi,F(xi))$ is the loss function that measures the discrepancy between the true label and the predicted value for sample ii.

2. Regularization Techniques: CatBoost incorporates various regularization techniques to prevent overfitting and improve model generalization. One such technique is depth regularization, which penalizes deeper trees to control model complexity. Mathematically, the depth regularization term can be expressed as:

$$Rdepth=\lambda\sum t=1T\gamma t2Rdepth=\lambda\sum t=1T\gamma t2$$

Where:

- $RdepthRdepth$ represents the depth regularization term.
- $\lambda\lambda$ is the regularization parameter controlling the strength of regularization.
- TT is the total number of trees in the ensemble.
- $\gamma t\gamma t$ is the depth of tree tt.

3. Learning Rate Adaptation: CatBoost introduces an adaptive learning rate strategy that adjusts the learning rate dynamically based on the current tree structure and feature importance. The adaptive learning rate $\eta\eta$ for each tree can be computed as:

$$\eta = \frac{1}{1+\text{num\_trees}\cdot\text{leaf\_estimation\_iterations}}$$

Where:

- $\eta\eta$ is the adaptive learning rate.
- num_treesnum_trees is the current number of trees in the ensemble.
- leaf_estimation_iterationsleaf_estimation_iterations is the number of iterations used for leaf value estimation.

4. Categorical Feature Handling: CatBoost employs an efficient algorithm to handle categorical features during tree construction. It assigns numerical values to categorical variables based on their frequency and the target variable's response, preserving their semantic meaning. The categorical feature handling process is integral to CatBoost's performance and efficiency.

5. Parallel and GPU Training: CatBoost implements efficient parallelization techniques and supports GPU acceleration, allowing for fast training on large datasets. By leveraging parallel processing and GPU resources, CatBoost achieves significant speedups compared to traditional gradient boosting implementations.

Disadvantages:

- **Slow Training Time:** Despite its efficiency improvements, CatBoost training can still be slower compared to simpler algorithms like logistic regression or decision trees. The algorithm's complexity and the need for extensive tree building iterations contribute to longer training times, especially on large datasets.
- **High Memory Consumption:** CatBoost requires significant memory resources, particularly when dealing with high-dimensional datasets or datasets with a large number of categorical features. The algorithm's internal data structures and the need to store intermediate results during training contribute to high memory consumption.
- **Sensitivity to Hyperparameters:** CatBoost performance is sensitive to hyperparameter tuning, including parameters related to tree depth, learning rate, regularization, and feature combinations. Finding the optimal set of hyperparameters can be challenging and may require extensive experimentation.
- **Potential Overfitting:** Despite its regularization techniques, CatBoost is susceptible to overfitting, especially when training on noisy or small datasets. Careful hyperparameter tuning and regularization strategies are necessary to prevent overfitting and ensure good generalization performance.
- **Limited Interpretability:** Like other ensemble learning methods, CatBoost models are inherently complex, making them less interpretable compared to simpler models like logistic regression or decision trees. Understanding the individual contributions of features or the decision-making process of the model can be challenging.
- **Difficulty in Handling Imbalanced Data:** CatBoost may struggle to effectively handle imbalanced datasets, where one class is significantly more prevalent than the others. While it provides options for class weighting and sampling techniques, finding the right balance between different strategies can be challenging.
- **Dependency on Data Quality:** The performance of CatBoost heavily depends on the quality and representativeness of the training data. Noisy or biased data can lead to suboptimal model performance and may require preprocessing steps such as data cleaning or feature engineering.

4.RESULTS AND DESCRIPTION

Here's a description of the features present in the dataset:

- **u_q**: This represents the quadrature-axis voltage component in the motor's control system. It is an important parameter in field-oriented control (FOC) of electric motors, impacting torque production.
- **coolant**: This feature measures the temperature or flow rate of the coolant used to maintain the motor's temperature. Effective cooling is crucial to prevent overheating and ensure optimal motor performance.

- **stator_winding**: This represents the temperature of the stator winding. Stator winding temperature is critical for diagnosing insulation issues and preventing damage due to excessive heat.
- **u_d**: Similar to u_q, this represents the direct-axis voltage component. Together, u_d and u_q are used to control the motor's magnetic field and torque production.
- **stator_tooth**: This measures the temperature of the stator tooth. The stator tooth temperature can indicate overheating or hot spots that may lead to motor failure.
- **motor_speed**: This feature records the rotational speed of the motor, typically measured in revolutions per minute (RPM). Motor speed is a fundamental operational parameter affecting performance and efficiency.
- **i_d**: This represents the direct-axis current component. In FOC, i_d is used to control the magnetizing current of the motor, impacting the efficiency and stability of the motor operation.
- **i_q**: This represents the quadrature-axis current component, which directly affects the torque produced by the motor.
- **pm**: stands for permanent magnet temperature. This is crucial in motors with permanent magnets, as excessive heat can demagnetize the magnets, reducing efficiency and torque.
- **stator_yoke**: This measures the temperature of the stator yoke. The stator yoke temperature helps in monitoring the overall thermal state of the motor.
- **ambient**: This feature records the ambient temperature around the motor. Ambient temperature affects the motor's cooling efficiency and overall thermal management.
- **torque**: This measures the torque produced by the motor, an essential performance metric indicating the motor's ability to perform work.
- **profile_id**: This is an identifier for different operational profiles or test conditions. Each profile ID might correspond to a specific test scenario or configuration.
- **target**: This is the target variable for the machine learning model, indicating whether a fault is present (binary classification). Typically, a value of 0 might indicate 'No Fault' and a value of 1 might indicate 'Fault'.

u_q	coolant	stator_winding	u_d	stator_tooth	motor_speed	i_d	i_q	pm	stator_yoke	ambient	torque	profile_id	target
-0.450682	18.805172	19.086670	-0.350055	18.293219	0.002866	0.004419	0.000328	24.554214	18.316547	19.850691	1.871008e-01	17	1
-0.325737	18.818571	19.092390	-0.305803	18.294807	0.000257	0.000606	-0.000785	24.538078	18.314955	19.850672	2.454175e-01	17	1
-0.440864	18.828770	19.089380	-0.372503	18.294094	0.002355	0.001290	0.000386	24.544693	18.326307	19.850657	1.766153e-01	17	1
-0.327026	18.835567	19.083031	-0.316199	18.292542	0.006105	0.000026	0.002046	24.554018	18.330833	19.850647	2.383027e-01	17	1
-0.471150	18.857033	19.082525	-0.332272	18.291428	0.003133	-0.064317	0.037184	24.565397	18.326662	19.850639	2.081967e-01	17	1

Figure 3: Presents the Sample dataset of the Stator false dataset.

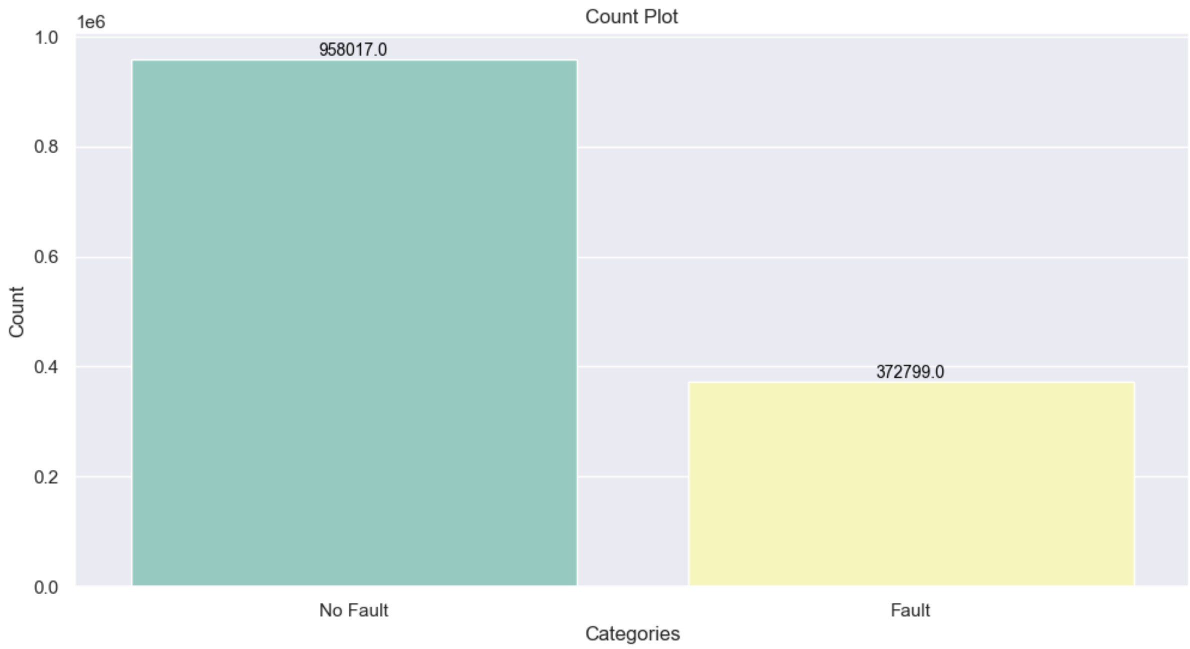

Figure 4: Presents the count plot of Stator false dataset.

```
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
```

Figure 5: Shows a classification report of a Ridge Classifier model.

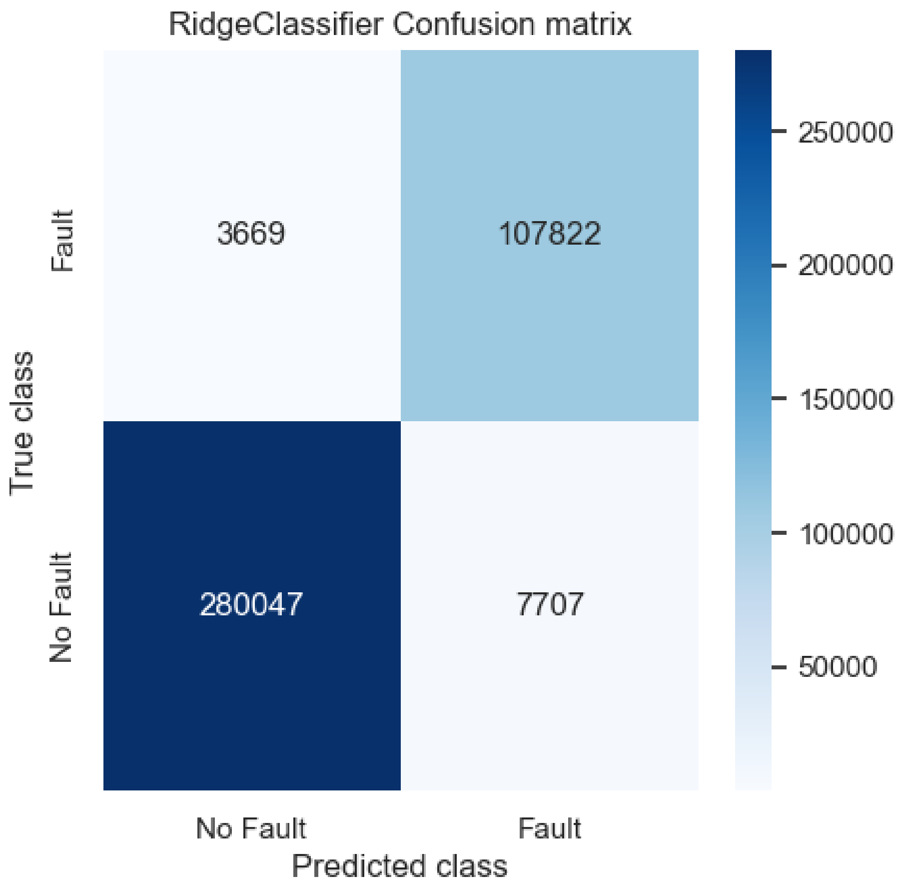

Figure 6: Confusion matrix of Ridge Classifier model.

```
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
```

Figure 7: Shows a classification report of a CatBoost Classifier model.

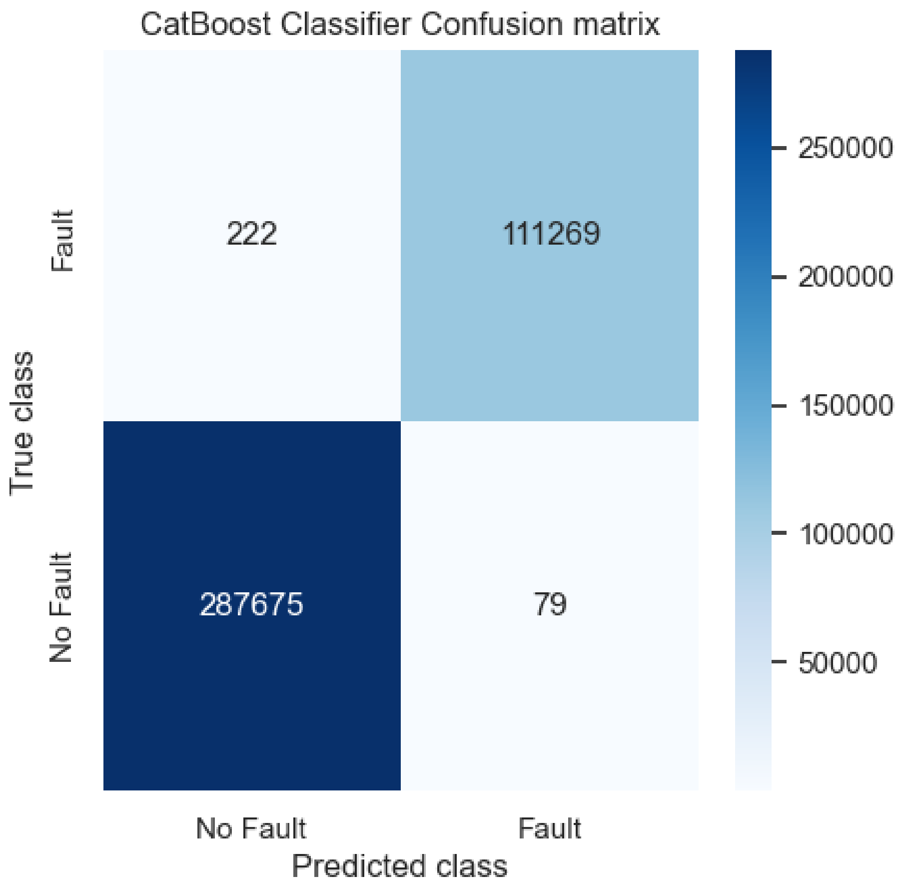

Figure 8: Confusion matrix of CatBoost Classifier model.

The figure 6 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 8 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 68confusion 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.

```
u_q                 90.015923
coolant             19.162436
stator_winding      50.011501
u_d                -93.275330
stator_tooth        39.070023
motor_speed       4999.953125
i_d               -141.171906
i_q                 52.995888
pm                  36.276936
stator_yoke         28.822945
ambient             20.624588
torque              48.584831
Name: 4, dtype: float64
Model Predicted of Row 4 Test Data is---> Fault
u_q                 90.142769
coolant             19.086964
stator_winding      50.134396
u_d                -93.113174
stator_tooth        39.168396
motor_speed       4999.951660
i_d               -141.444672
i_q                 52.985378
pm                  36.441761
stator_yoke         28.892696
ambient             20.303011
torque              48.648247
Name: 5, dtype: float64
Model Predicted of Row 5 Test Data is---> No Fault
```

Figure 9: Proposed CatBoost Classifier model Prediction on test data.

The figure 9 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.

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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