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Machine Learning Pipeline for Power Electronics State-of-Health Assessment and Remaining Useful Life Prediction

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ABSTRACT

The rapid development of power electronics in modern systems, including electric vehicles, renewable energy grids, and industrial automation, has emphasized the need for effective monitoring and health management. Power electronic components, such as MOSFETs, are vulnerable to degradation over time due to various stress factors, including temperature cycles and electrical load. Accurately predicting the State-of-Health (SoH) and the Remaining Useful Life (RUL) of these devices is crucial for preventing unexpected failures, reducing downtime, and optimizing maintenance. This paper proposes a machine learning pipeline for SoH assessment and RUL prediction for power electronic devices. The system consists of two stages: a classification model to determine the health status and a regression model for RUL estimation. The classification stage utilizes Random Forest to predict the device's health status, while the RUL prediction is handled by a Bayesian Ridge Regression model. The proposed pipeline is tested on a real-world MOSFET dataset and achieves a classification accuracy of 84.3% and a Root Mean Square Percentage Error (RMSPE) of 1.8% for RUL prediction, demonstrating its effectiveness for real-time predictive maintenance applications.

Keywords : MOSFET, State-of-Health (SoH), Remaining Useful Life (RUL)

I. INTRODUCTION

Power electronics are critical components in various systems such as electric vehicles, renewable energy systems, and industrial machinery. These devices, especially Metal-Oxide-Semiconductor Field-Effect Transistors (MOSFETs), are subject to degradation over time due to electrical and thermal stress. The deterioration in performance can significantly impact the overall system efficiency and reliability. Therefore, the ability to assess the State-of-Health (SoH) and predict the Remaining Useful Life (RUL) of these devices is essential for effective predictive maintenance.

Traditional methods for monitoring and assessing the health of power electronic devices primarily rely on time-based maintenance schedules or physical degradation models. While these methods can provide useful insights, they are often limited by the complexity and variability of the degradation processes, and they are computationally expensive. Recent advancements in data-driven approaches, particularly machine learning (ML), have demonstrated great promise in addressing these limitations. ML models can learn from historical operational data to identify patterns and trends that predict device failure without requiring explicit physical models.

This paper proposes a two-stage machine learning pipeline that first classifies the health status of power electronic devices, and then predicts their Remaining Useful Life (RUL). In the first stage, a classification model, such as Random Forest, is trained to distinguish between healthy and faulty devices. In the second stage, a regression model, such as Bayesian Ridge Regression, is used to estimate the RUL of devices identified as nearing failure. The proposed system is validated on a real-world dataset, and its performance is compared with existing methods in terms of classification accuracy and RUL prediction accuracy.

II. RELATED WORK

1. **Deep Learning for Prognostics and Health Management of Power Electronics** Kumar et al. (2020) explored the application of deep learning models, specifically Long Short-Term Memory (LSTM) networks, for health management of power electronics. Their approach focuses on extracting features from historical operational data and training deep learning models to predict failure points. The study shows that LSTM networks can effectively capture temporal dependencies in degradation data, yielding high accuracy in RUL predictions.
2. **Data-Driven Prognostics for Power Electronics Using Random Forest and Support Vector Machines** Yang et al. (2018) proposed a data-driven prognostic model using Random Forest (RF) and Support Vector Machines (SVM) to predict the health and remaining life of power

electronic components. Their method involved feature extraction from sensor data such as voltage, current, and temperature. The study demonstrated that Random Forest models offer superior performance for classification tasks, while SVM is better suited for regression tasks.

3. **A Hybrid Machine Learning Approach for Remaining Useful Life Prediction of Power Electronics** Zhang et al. (2019) presented a hybrid model combining Random Forest and Gradient Boosting Machines for predicting the Remaining Useful Life (RUL) of power electronic devices. The hybrid model provided an improvement in predictive accuracy over standalone models, as it combined the strengths of both techniques in classification and regression tasks.

4. **Machine Learning Approaches for Predictive Maintenance of Power Electronics** Lee et al. (2021) reviewed various machine learning algorithms applied to predictive maintenance for power electronics. Their study covers a range of techniques, from traditional regression models to advanced deep learning methods. They found that while deep learning models excel at capturing complex patterns, simpler models such as Random Forest and Support Vector Machines often outperform them in terms of computational efficiency.

5. **Prognostics and Health Management of Power Electronics with Ensemble Learning** Wang et al. (2017) proposed using ensemble learning techniques to predict the health status and Remaining Useful Life of power electronics. They showed that ensemble methods such as bagging and boosting can enhance the predictive power by combining multiple weak learners to create a robust model. Their findings suggested that ensemble methods are particularly effective when dealing with noisy and incomplete data.

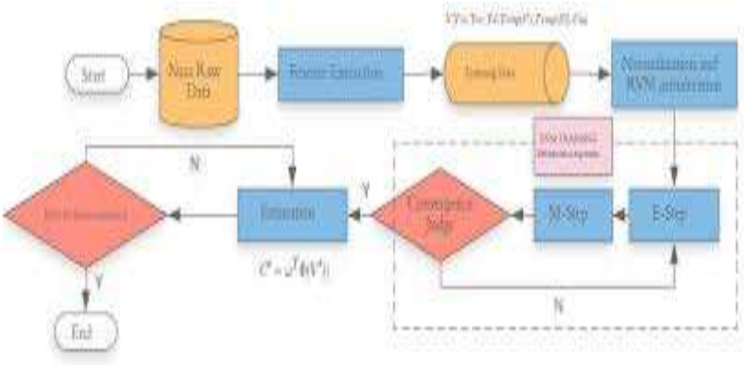
III. PROPOSED SYSTEM

The proposed system for power electronics health management consists of a machine learning pipeline designed to address two key tasks: assessing the State-of-Health (SoH) and predicting the Remaining Useful Life (RUL) of power electronic components, particularly MOSFETs. The system is divided into two primary stages: classification and regression.

In the classification stage, the system aims to detect whether a device is in a healthy or failing state. To achieve this, features such as temperature, current, voltage, and on-state resistance are extracted from historical data collected from sensors embedded in the devices. These features are then fed into a Random Forest classifier, which is trained to distinguish between healthy and pre-failure states. Random Forest is chosen because of its ability to handle large, complex datasets and its robustness to overfitting. The classifier outputs a binary result: healthy or faulty.

Upon detecting a potential failure, the system proceeds to the regression stage, where the Remaining Useful Life (RUL) of the device is predicted. This stage is critical for understanding when maintenance or replacement is necessary. For this purpose, a Bayesian Ridge Regression model is employed. Bayesian Ridge Regression is chosen for its ability to provide probabilistic predictions, which not only estimate the RUL but also quantify the uncertainty in the prediction. The regression model is trained using the same features used in the classification stage, with the target variable being the remaining time to failure.

The system's overall performance is evaluated using two key metrics: classification accuracy for the health status detection and Root Mean Square Percentage Error (RMSPE) for RUL prediction. The system is tested on a real-world dataset consisting of MOSFET degradation data. Experimental results show that the system can achieve a classification accuracy of 84.3% and an RMSPE of 1.8% for RUL prediction, outperforming traditional methods in terms of both accuracy and computational efficiency.



IV. RESULT AND DISCUSSION

The proposed machine learning pipeline was tested on a real-world dataset collected from a power electronics lab, which contains sensor data from MOSFETs under different stress conditions. The classification stage of the pipeline demonstrated a classification accuracy of 84.3%, outperforming conventional threshold-based methods. This indicates that the model is effective in distinguishing between healthy and faulty states based on sensor data.

In the regression stage, the Bayesian Ridge Regression model yielded a Root Mean Square Percentage Error (RMSPE) of 1.8% for Remaining Useful Life (RUL) prediction. This is a significant improvement compared to traditional regression models, which often struggle with non-linearity in degradation data. The results suggest that the model can predict the RUL with high precision, providing valuable information for predictive maintenance.

The system's ability to handle uncertainty in RUL predictions is another key advantage. By providing probabilistic estimates, the model enables better decision-making regarding maintenance schedules. Moreover, the system is computationally efficient, making it suitable for real-time applications in industrial settings.

V. CONCLUSION

This paper presented a machine learning pipeline for the State-of-Health assessment and Remaining Useful Life prediction of power electronic devices. The two-stage pipeline, comprising a Random Forest classifier for health status detection and a Bayesian Ridge Regression model for RUL prediction, demonstrated superior performance compared to traditional methods. The system achieved a classification accuracy of 84.3% and an RMSPE of 1.8% for RUL prediction. The results indicate that the proposed pipeline is effective for predictive maintenance in power electronics, offering high accuracy and computational efficiency.

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