Aircraft Maintenance and Predictive System

Abstract

Predictive maintenance has emerged as a transformative approach in industrial settings, significantly reducing unexpected equipment failures and associated costs. By leveraging machine learning, businesses can anticipate failures in advance, ensuring timely interventions and minimizing operational disruptions. Among various machine learning models, the Random Forest classifier demonstrated superior performance, achieving a 94% accuracy rate and an F1-score of 0.90, making it a reliable choice for predictive maintenance applications. The system was deployed using Streamlit, an interactive and user-friendly interface that allows real-time monitoring and decision-making. Additionally, MLflow was integrated to track model performance, enabling continuous improvement and adaptation to evolving industrial conditions. These tools collectively ensure that the predictive maintenance system remains efficient and easy to use, facilitating its adoption across different industrial sectors.

Despite its advantages, implementing predictive maintenance presents challenges such as data imbalance and real-time processing complexities. Industrial datasets often contain significantly fewer failure cases than normal operating data, making it difficult for the model to learn from limited failure instances. Addressing this requires advanced techniques such as synthetic data generation, resampling methods, and anomaly detection to enhance the model's predictive capability. Additionally, real-time processing demands robust computational infrastructure to handle large-scale data streams and provide timely predictions. By overcoming these challenges, machine learning-powered predictive maintenance systems can enhance operational efficiency, reduce downtime, and optimize resource allocation, ultimately leading to more cost-effective and sustainable industrial practices.

Keywords: Predictive Maintenance, Machine Learning, Random Forest, MLflow, Decision-making, streamlit, F1-Score.