

Prediction and Assessment of Aircraft Engine Damage and Remaining Useful Life

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Abstract: Predictive maintenance is crucial in aviation, ensuring safe and efficient operations. This report presents an analysis of various machine learning models applied to predict the Remaining Useful Life (RUL) of aircraft engines, aiding in maintenance decisions. The models considered include Random Forest, XGBoost, and Long Short-Term Memory (LSTM) networks. The dataset used is from the C-MAPSS dataset, containing sensor data and RUL labels for aircraft engines.

Introduction: Aircraft engines require effective maintenance to prevent unexpected failures and ensure safety. Predictive maintenance aims to forecast engine failures, optimizing maintenance schedules. This report explores the performance of different machine learning models in predicting the RUL of aircraft engines.

Data Preprocessing: The C-MAPSS dataset is loaded and preprocessed. Irrelevant columns are dropped, and the data is normalized using MinMax scaling. The dataset is divided into training and testing sets.

Model Training and Evaluation: Three models are trained and evaluated: Random Forest, XGBoost, and LSTM.

1. **Random Forest:** A Random Forest Regressor is trained using the training data. The model is evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R2) score.
2. **XGBoost:** An XGBoost Regressor is trained and evaluated similarly to the Random Forest model, using the same metrics.
3. **LSTM (Long Short-Term Memory):** An LSTM network is designed and trained for sequence prediction using the sensor data. The network

architecture consists of LSTM layers followed by dropout layers. The model is trained using sequences of sensor data and corresponding RUL values. Training progress is monitored using R2 score, MAE, and loss values.

Model Comparison: The performance of the three models is compared based on various metrics. Individual scores for each model are presented for better understanding. Graphs illustrate the models' MAE, R2, and loss during training.

Predictive Maintenance Strategies: Several predictive maintenance strategies are investigated, including individual predictions, single training, and multi-prediction averaging. These strategies are applied to Random Forest and XGBoost models to improve prediction accuracy.

Classification for Maintenance Decision: A classifier is introduced to determine whether an engine's remaining resource is less than a predefined threshold (e.g., 10 cycles). Random Forest and XGBoost classifiers are trained using attributes from the dataset.

Conclusion: This report demonstrates the effectiveness of Random Forest, XGBoost, and LSTM models in predicting aircraft engine RUL. Comparison of individual model performance and training strategies highlights their strengths and limitations. The classification model further enhances maintenance decision-making by categorizing engines into resource-exhausted and non-exhausted categories. Predictive maintenance using machine learning models can significantly improve aircraft safety and operational efficiency.