Predictive Maintenance of Jet Engines Using Random Forest and XGBoost

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Abstract

Predictive maintenance (PdM) is a pivotal strategy to reduce unexpected equipment failures and maintenance costs. In this paper, we present a PdM framework applied to the NASA CMAPSS dataset, focusing on predicting the Remaining Useful Life (RUL) of jet engines. Two ensemble learning methods, Random Forest and XGBoost, are employed to capture degradation patterns in the sensor data. Our experiments reveal that both models achieve a Root Mean Squared Error (RMSE) of approximately **41**, indicating reliable predictive capabilities. However, XGBoost exhibits slightly better residual balance and more distributed feature importance. These findings underscore the value of advanced machine learning techniques in improving predictive maintenance for aerospace applications.

1 Introduction

Maintenance strategies in the aviation sector are critical for ensuring safety, reliability, and cost-effectiveness. Traditional maintenance approaches, such as scheduled or reactive maintenance, often lead to increased downtime or risk of catastrophic failures. Predictive maintenance (PdM) aims to mitigate these risks by forecasting when an engine or component is likely to fail, enabling proactive interventions.

Recent advancements in machine learning (ML) have made it possible to analyze large volumes of sensor data and predict the Remaining Useful Life (RUL) of complex systems. In this study, we leverage the NASA **Commercial Modular Aero-Propulsion System Simulation (CMAPSS)** dataset to train two ensemble models—**Random Forest** and **XGBoost**—to estimate jet engine RUL.

2 Literature Review

Predictive maintenance has gained significant traction across industries like manufacturing, automotive, and aerospace. Traditional approaches to RUL estimation often involved **linear regression** or **survival analysis**. However, these methods struggle to capture nonlinearities in sensor data. Recent research demonstrates the efficacy of **ensemble learning** (Random Forest, Gradient Boosting) and **deep learning** (LSTMs, CNNs) in handling complex, high-dimensional sensor data.

- **Random Forest**: Proposed by **Breiman [2]**, Random Forest uses multiple decision trees to improve prediction stability.
- **XGBoost**: A scalable tree boosting framework introduced by **Chen and Guestrin [3]**, known for its speed and performance.

Research on the **NASA CMAPSS** dataset highlights ensemble methods' superior performance in capturing engine degradation patterns compared to simpler models [1].

3 Methodology

3.1 Dataset Description

The **CMAPSS dataset** simulates run-to-failure conditions for multiple jet engines. Each engine has:

- **Unit Number**: Unique identifier for each engine.

- **Time in Cycles**: Operational cycles elapsed.
- **Operational Settings**: Varying flight/engine conditions.
- **Sensor Readings (21 total)**: Temperature, pressure, vibration, and other key parameters.

3.2 Data Preprocessing

- **Data Cleaning**: Removed empty columns and handled missing values.
- **RUL Calculation**: RUL = max(time_in_cycles) − time_in_cycles.
- **Normalization**: Applied MinMaxScaler to scale features between [0, 1].

3.3 Model Setup

- **Random Forest**: Tuned with $n\_estimators = 200$, $max\_depth = 10$.
- **XGBoost**: Tuned with $n\_estimators = 100$, $max\_depth = 5$, $learning\_rate = 0.05$, $subsample = 0.8$, using GPU acceleration.

3.4 Evaluation Metrics

We use **Root Mean Squared Error (RMSE)**:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{1}$$

Lower RMSE indicates more accurate RUL predictions.

4 Results and Discussion

4.1 Data Exploration

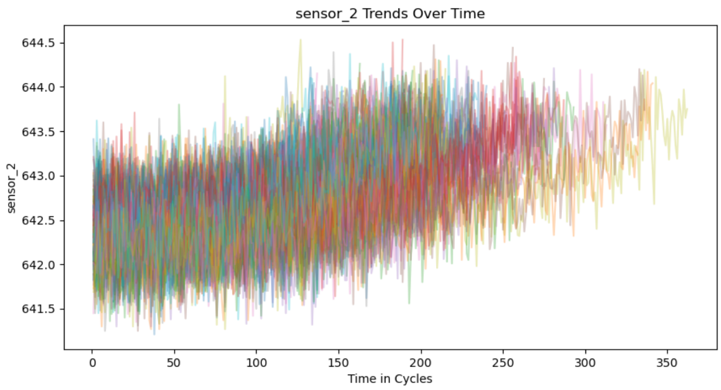

Figure 1: Sensor Trends Over Time

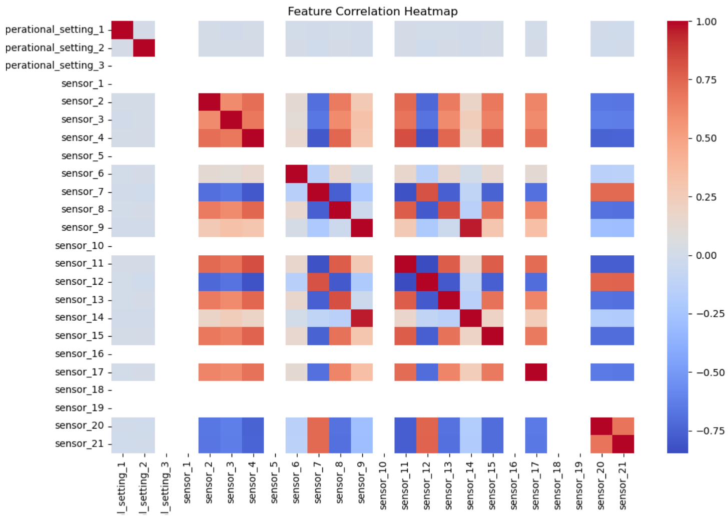

Figure 2: Feature Correlation Heatmap

4.2 Model Performance

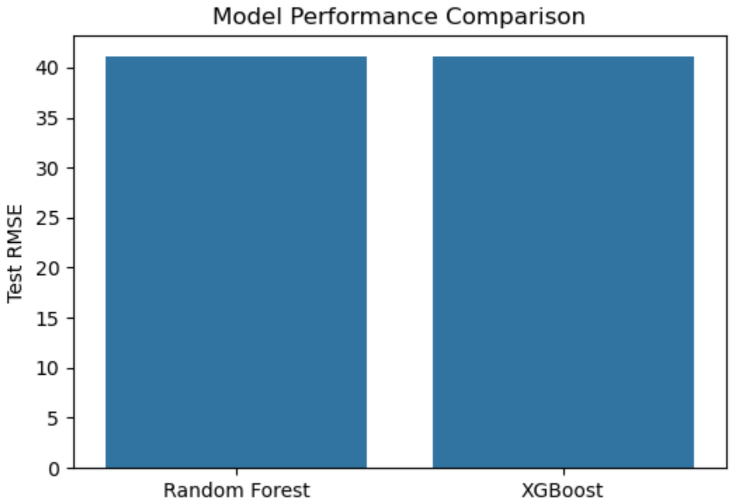

Figure 3: Model Performance Comparison

4.3 Predicted vs. Actual RUL

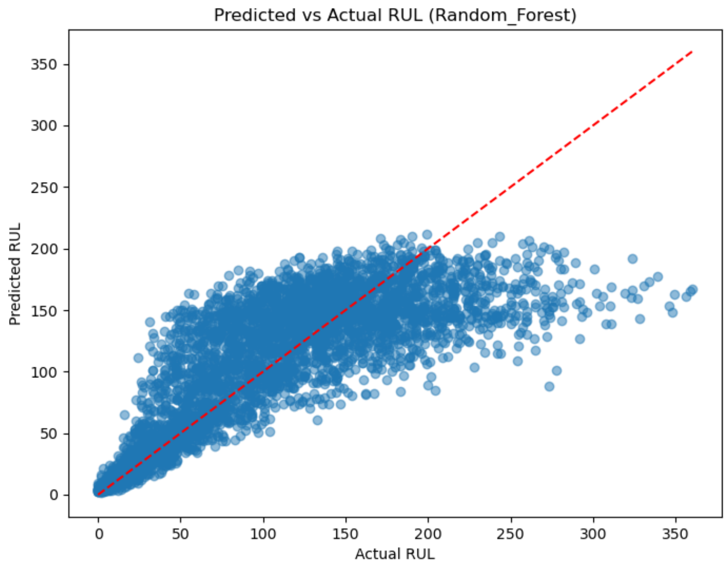

Figure 4: RF Predicted vs. Actual RUL

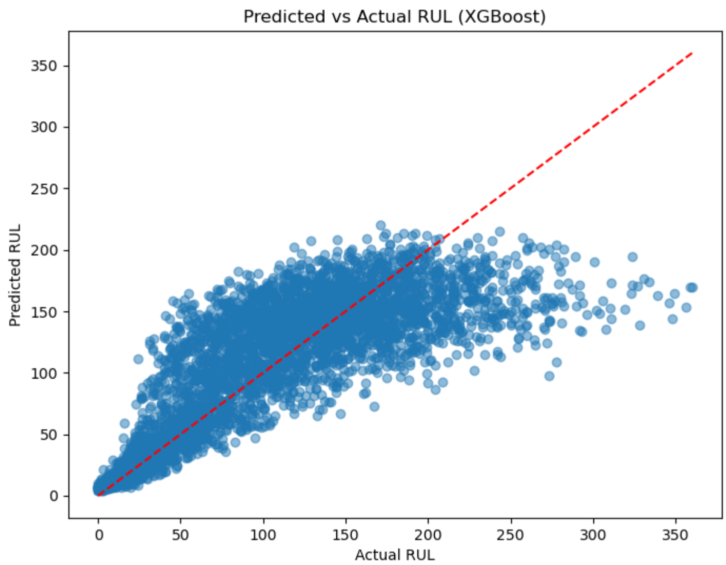

Figure 5: XGBoost Predicted vs. Actual RUL

4.4 Residual Analysis

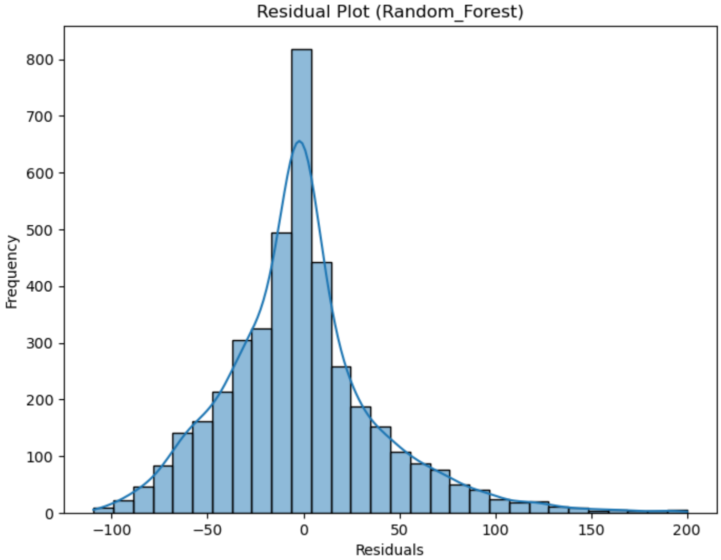

Figure 6: RF Residual Plot

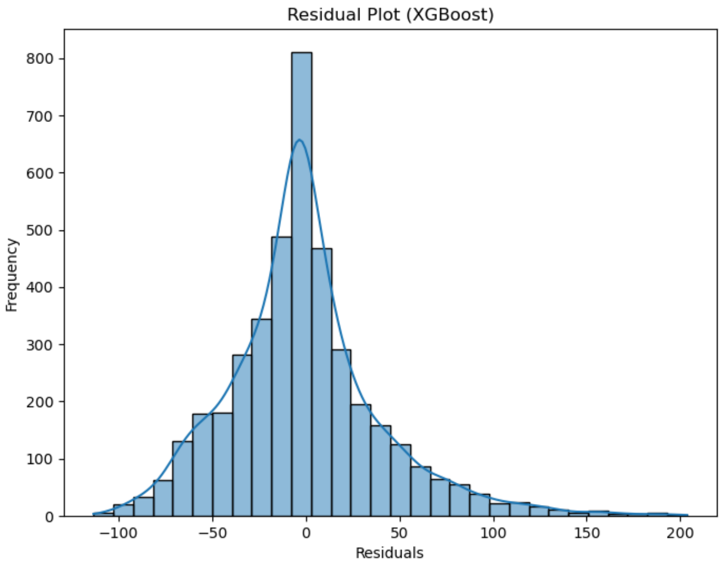

Figure 7: XGBoost Residual Plot

4.5 Feature Importance

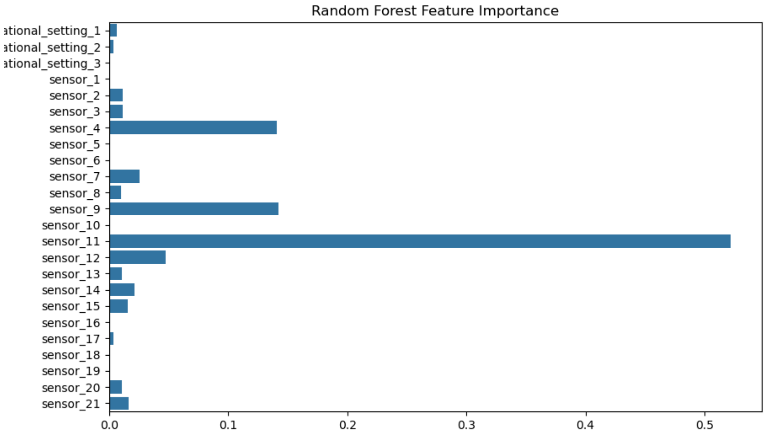

Figure 8: RF Feature Importance

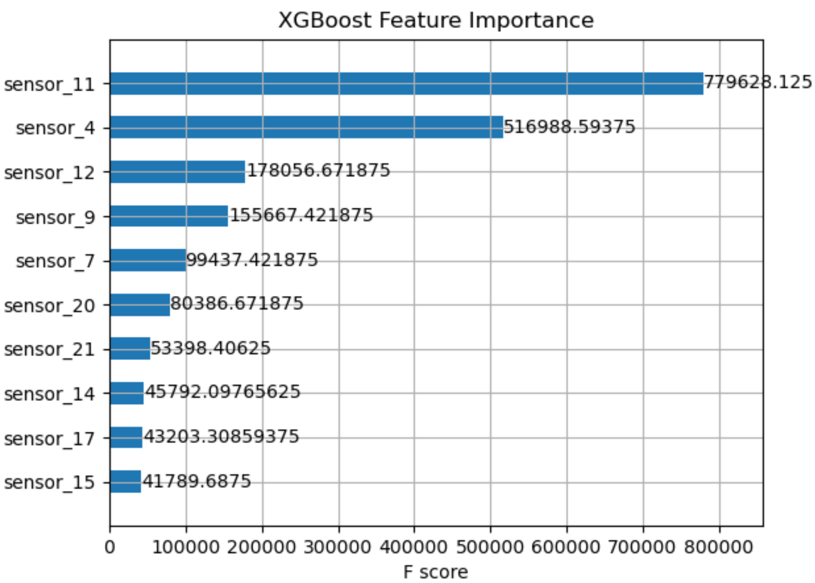

Figure 9: XGBoost Feature Importance

5 Conclusion

This study confirms the efficacy of **ensemble learning** for predictive maintenance on jet engines. Both **Random Forest** and **XGBoost** successfully model degradation trends in the CMAPSS dataset, achieving an RMSE of 41. However, deeper analysis of residuals and feature importance highlights **XGBoost** as the more reliable option due to its balanced feature use and tighter residual distribution.

Future Work

- Incorporating LSTMs for time-series data.
- Combining physical degradation models with ML for interpretability.
- Implementing real-time RUL prediction.

References

[1] NASA CMAPSS Dataset, *Prognostics Data Repository*, Available: https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/

[2] L. Breiman, "Random Forests," *Machine Learning*, vol. 45, no. 1, pp. 5-32, 2001.

[3] T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," in *Proceedings of the 22nd ACM SIGKDD*, 2016.

[4] J. Brownlee, "Ensemble Learning Algorithms," *Machine Learning Mastery*, 2016.