Predictive Maintenance on Turbofan Engines

Prof. Hamidreza Heidari

Group members :
Kishan cheeramath
Dalmy John
Tomson Roy
Adithye Mathew

Index

01

Introduction

Understanding predictive maintenance and the NASA CMAPSS dataset

02

Objective

Defining our RUL prediction goals and fault detection strategy

03

Methodology

Tools and technologies powering our analysis

04

Project Milestones

Key phases and deliverables

05

Expected Outcomes

Anticipated results and business impact

06

MVP s References

Minimum viable product scope and supporting research

07

Introduction

Predictive maintenance leveraging real-time sensor data and machine learning algorithms to forecast equipment failure before it occurs, enabling proactive intervention.

Enables proactive maintenance scheduling, minimizes unplanned downtime, enhances operational safety, and significantly reduces maintenance costs across fleet operations.

The NASA Turbofan Engine Degradation Simulation Dataset provides multivariate time-series sensor data from simulated aircraft engines, capturing complete operational cycles from healthy state through degradation to failure.

Objective

Our primary goal is to develop a robust predictive maintenance model that accurately estimates the Remaining Useful Life (RUL) of turbofan engines using multivariate sensor data analysis.

RUL Prediction

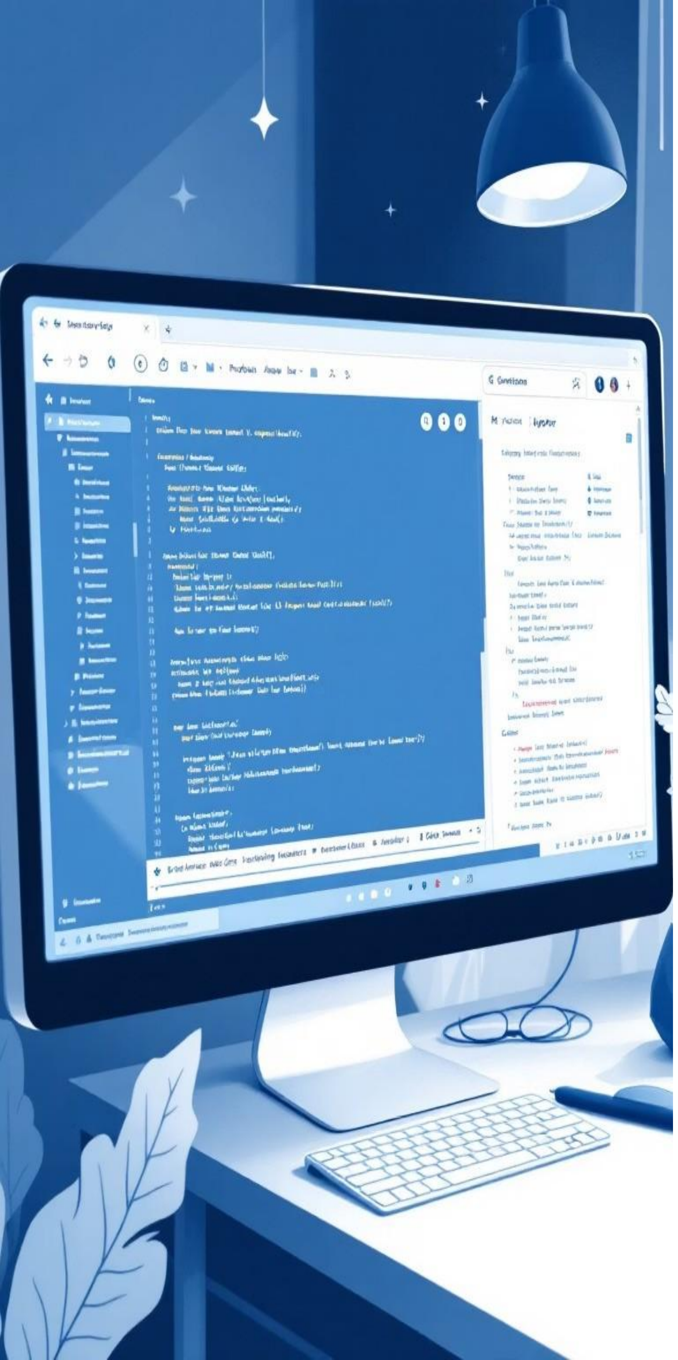
Build and train an LSTM-based deep learning model to estimate the number of operational cycles remaining before engine failure, providing actionable maintenance windows.

Pattern Recognition

Identify subtle patterns and anomalies in multivariate sensor data that correlate with engine wear and degradation trajectories, enabling early fault detection.

Maintenance Optimization

Enable data-driven proactive maintenance scheduling that optimizes resource allocation, reduces emergency repairs, and extends overall fleet operational efficiency.



Methodology - Technical Stack

Development Environment

Python 3.9 Core programming language for ML pipeline development

Jupyter Notebook / Google Colab: Interactive development and experimentation platform

GitHub: Version control and collaborative development

Data Science Libraries

NumPy & Pandas: Efficient data manipulation and time-series processing

Matplotlib & Seaborn: Statistical visualization and exploratory data analysis

TensorFlow/Keras: LSTM model architecture and training (implied)

Project Milestones

1

Phase 1: Data Acquisition & EDA

Load NASA CMAPSS dataset, perform exploratory data analysis, identify key sensor features, and understand degradation patterns across operational cycles.

2

Phase 2: Feature Engineering

Engineer temporal features, create rolling statistics, normalize sensor readings, and construct RUL labels for supervised learning.

3

Phase 3: Model Development

Design LSTM architecture, implement sequence windowing, configure hyperparameters, and establish training/validation splits.

4

Phase 4: Training & Validation

Train model on historical degradation cycles, validate on holdout engines, tune hyperparameters, and optimize loss functions for RUL prediction accuracy.

5

Phase 5: Evaluation & Deployment

Assess model performance using RMSE and scoring functions, conduct error analysis, and prepare model for production deployment.

Expected Outcomes

Trained LSTM Model

Production-ready deep learning model capable of accurately estimating RUL for turbofan engines across varied operational profiles and environmental conditions.

Operational Benefits

Significant reduction in unexpected breakdowns, optimized maintenance scheduling, lower total cost of ownership, and improved fleet availability through data-driven prognostics.

Minimum Viable Product

- A functional Long Short-Term Memory (LSTM) deep learning model estimating the **Remaining Useful Life (RUL)** for turbofan engines
- Achieved Performance Metric: Demonstration that the model has achieved a specified level of accuracy, measured by an error metric such as the Mean Absolute Error (MAE) and Coefficient of Determination (R2)
- Visualizations for the Model Evaluation and Validation Report

References

1. A. Saxena and K. Goebel (2008). "Turbofan Engine Degradation Simulation Data Set", NASA Ames Prognostics Data Repository (https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/#turbofan), NASA Ames Research Center, Moffett Field, CA
http://boschsoftwaretechnologies.com/media/documents/downloads/2023/remaining_useful_life_with_industry4-0_a_bosch_pov.pdf

2. **De Vita, F., & Bruneo, D. (2019).**
On the Use of LSTM Networks for Predictive Maintenance in Smart Industries.
IEEE International Conference on Smart Computing (SMARTCOMP)
https://ieeexplore.ieee.org/document/8784003