***FINAL PROJECT REPORT***

**for**

***DEEP LEARNING 1***

**on**

***PREDICTIVE MAINTENANCE OF NASA TURBOFAN JET ENGINES***

**by**

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**1. INTRODUCTION**

Prognostics and health management is an important topic in the aviation industry for predicting the state of assets to avoid downtime and failure. Each engine starts with different degrees of initial wear and manufacturing variation which is unknown to the user. This wear and variation are considered normal, i.e., it is not considered a faulty condition. There are three operational settings that have a substantial effect on engine performance: compressor pressure ratio, turbine inlet temperature and specific thrust and fuel consumption.

The engine is operating normally at the start of each time series and develops a fault at some point during the series. In the training set, the fault grows in magnitude until system failure. In the test set, the time series ends some time prior to system failure.

**OBJECTIVE:**

To develop a machine learning framework to predict the number of remaining operational cycles before failure in the test set, i.e., the number of operational cycles after the last cycle that the engine will continue to operate. Also to provide a vector of true Remaining Useful Life (RUL) values for the test data based on historical performance data.

This enables proactive maintenance strategies, ensuring optimal aircraft reliability and performance by making sure that none of the aircraft need to put up with malfunctioning or faulty components causing delays in expected project deadlines.

Additionally, we have included a new classification called engine health, which helps improve the accuracy of predictions by assessing the overall condition of the engine and identifying patterns that may indicate impending failures.

**2. DATASET OVERVIEW**

Data Acquisition: Utilizing NASA’s C-MAPSS dataset, which provides comprehensive information on aircraft engine performance.

* + Dataset: Batch FD001- 13,000 rows
  + Train Trajectories: 100
  + Test Trajectories: 100
  + Conditions: One (Sea Level)
  + Fault Modes: One (HPC Degradation)
  + The Dataset Contains a Total of 26 Columns with readings for these Values
  + A variable called "RUL" is created as the target variable which will be tested against the following predictors:

|  |  |
| --- | --- |
| **Values** | **Values** |
| **'Unit',** | **SM\_9- "(Physical core speed) (rpm)",** |
| **'cycle',** | **SM\_10- "(Engine pressure ratio(P50/P2)",** |
| **'Op\_setting\_1',** | **SM\_11- "(HPC outlet Static pressure) (psia)",** |
| **'Op\_setting\_2',** | **SM\_12- "(Ratio of fuel flow to Ps30) (pps/psia)",** |
| **'Op\_setting\_3** | **SM\_13- "(Corrected fan speed) (rpm)",** |
| **SM\_1- "(Fan inlet temperature) (◦R)",** | **SM\_14- "(Corrected core speed) (rpm)",** |
| **SM\_2- "(LPC outlet temperature) (◦R)",** | **SM\_15- "(Bypass Ratio) ",** |
| **SM\_3- "(HPC outlet temperature) (◦R)",** | **SM\_16- "(Burner fuel-air ratio)",** |
| **SM\_4- "(LPT outlet temperature) (◦R)",** | **SM\_17- "(Bleed Enthalpy)",** |
| **SM\_5- "(Fan inlet Pressure) (psia)",** | **SM\_18- "(Required fan speed)","** |
| **SM\_6- "(bypass-duct pressure) (psia)"** | **SM\_19- "(Required fan conversion speed)",** |
| **SM\_7- "(HPC outlet pressure) (psia)"** | **SM\_20- "(High-pressure turbines Cool air flow)",** |
| **SM\_8- "(Physical fan speed) (rpm)",** | **SM\_21- "(Low-pressure turbines Cool air flow)** |

**3. CODING PROCESS MODEL**

**Feature Engineering:** Extract relevant features from raw data, including sensor readings, operating conditions, and maintenance history.

**Model Selection and Training:** There were 2 Main Approaches adopted For This Model

* Static Data Model: where we Experiment with various regression and classification models (e.g., Linear Regression, Decision Tree, Random Forest, SVM, XGBoost) to identify the most effective approach for predicting RUL and we assumed that the dataset will not change over time.
* Dynamic Data model: where we made dynamic RLU predictions to predict RUL at each time step , looking for degradation pattern , capture long term dependency , anomaly detection , continuous monitoring where we considered the whole data frame (historical data) that is updated in a timely manner and treated it as time series problem and solve with RNN , LSTM , GRU models.

**Model Evaluation:** Assess model performance using metrics like accuracy and Mean Absolute Error to select the best-performing model.

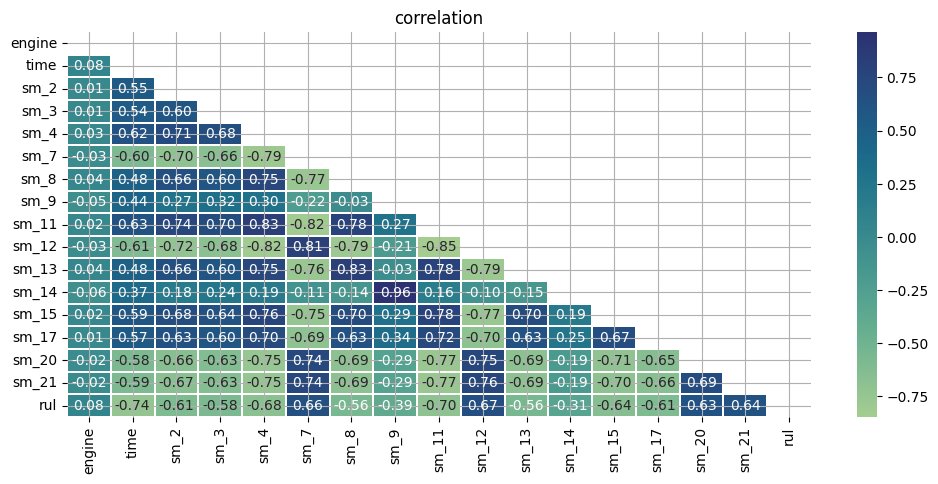
**4. POSSIBLE PROBLEMS TO SOLVE:**

* Accurate RUL Predictions: Enhance the precision of RUL predictions to improve maintenance scheduling.
* Proactive Maintenance: Enable timely interventions to prevent unexpected failures.
* Optimized Performance: Ensure continuous and optimal performance of aircraft engines.
* Cost Reduction: Minimize maintenance costs by avoiding unnecessary repairs and downtime.
* Check and Classify the Status of health of the Engine based on RUL

**5.GRAPHICAL INSIGHTS**

**5.1 CORRELATION HEATMAP**

The correlation heatmap is used to visualize the relationships between various sensor measurements and the Remaining Useful Life (RUL) of aircraft engines. Understanding these correlations is essential for predictive maintenance and for optimizing model training in predicting the RUL accurately.

**Key Insights from the Heatmap:**

* RUL Correlation: The Remaining Useful Life (RUL) shows notable correlations with specific sensor measurements. These correlations provide valuable insight into which features (sensor measurements) are most influential in predicting the RUL of the engines.
* Top Negative Correlations: Time and sm\_11 have the strongest negative correlation with RUL. This indicates that as the engine runs longer (in terms of cycles) and the HPC outlet static pressure (sensor measurement sm\_11) changes, the RUL decreases, meaning these features are highly predictive of the engine nearing failure.
* Top Positive Correlations: sm\_7 and sm\_12 exhibit the strongest positive correlation with RUL. These features are associated with the HPC outlet pressure (sm\_7) and the ratio of fuel flow to Ps30 (sm\_12). The positive correlation suggests that higher readings for these sensors correspond to a longer remaining operational life for the engine.

**Methodology:**

1. **Data Collection:** Sensor data from NASA’s C-MAPSS dataset was utilized, where each sensor (e.g., sm\_11, sm\_7, etc.) corresponds to a specific engine characteristic. The dataset records multiple operational cycles, which enables training a machine learning model to predict RUL based on these sensor readings.
2. **Correlation Calculation:** Correlation measures the linear relationship between two variables. In this case, the Pearson correlation coefficient was likely used to measure how each sensor reading is related to the RUL. The values range between -1 (strong negative correlation) to 1 (strong positive correlation). A value close to 0 indicates little to no linear relationship.
3. **Heatmap Visualization:** A correlation matrix was computed, and the relationships between different sensors were visualized as a heatmap. The shading and numerical values in the heatmap help identify which sensors have the most influence on predicting the RUL.
4. **Interpretation:**
   1. Negative correlation implies that as the sensor reading increases, the RUL decreases.
   2. Positive correlation implies that as the sensor reading increases, the RUL also increases.

By focusing on the top positively and negatively correlated features, predictive models can be better trained to forecast engine failures accurately, thereby improving maintenance scheduling and reducing unexpected downtimes.

Application: These insights are crucial for developing predictive models. Knowing which features are most correlated with RUL allows for better feature selection and model tuning. By emphasizing sensors such as sm\_11, sm\_7, and sm\_12, predictive models (e.g., regression models or time-series models like LSTM) can better capture the engine’s health and forecast when maintenance is required.

**5.2 AVERAGE RUL FOR THE ENGINES**

This chart displays the distribution of the Remaining Useful Life (RUL) for the engines. The goal is to identify when the engines are likely to fail and how the RUL is distributed across different instances.

A graph with blue lines

Description automatically generated

**Key Insights from the Chart:**

* Failure Trend: The histogram shows that most engines tend to fail when their RUL is around 200 cycles. The y-axis represents the count of engines that share the same RUL range, while the x-axis represents the RUL, indicating how many cycles are left before the engine failure.
* Peak of Failures: The highest count (peak) occurs when the RUL is approximately 200. This indicates that a significant number of engines fail around this point, as seen from the maximum bar height reaching above 20 on the y-axis.
* Long Tail: There is a noticeable long tail on the right side of the distribution, showing that some engines can still operate up to 350 RUL cycles, but these are fewer in number.
* Distribution Shape: The overall distribution appears somewhat skewed to the right, with most engines failing at a lower RUL range (around 150 to 200), but some engines survive longer.

**Methodology:**

1. Data Collection: The RUL values are derived from NASA’s C-MAPSS dataset, where the performance of various engines was monitored, and their failure points were recorded based on historical data.
2. Visualization: The histogram is used to visualize the distribution of engine failures across different RUL values. The blue bars represent the frequency of engines within a particular RUL range, and a line is overlaid to illustrate the overall trend and distribution.
3. Interpretation:
   1. Higher Failure Probability Near 200 RUL: The concentration of failures near the 200 RUL mark suggests that engines are most prone to failure at this point, which could be an important trigger for maintenance interventions.
   2. Fewer Long-Lived Engines: Engines that surpass 250-300 RUL cycles are fewer, as shown by the significantly lower counts on the right side of the distribution.

**Application:** This insight is vital for planning proactive maintenance strategies. Knowing that most engines tend to fail around the 200 RUL mark allows maintenance teams to schedule repairs or part replacements before failure occurs, ensuring optimal engine performance and reducing the risk of unexpected downtimes. Additionally, it can guide the predictive maintenance models to focus on engines approaching this critical RUL range.

**6. HYPERPARAMETER SELECTION –MODEL TRAINING**

After hyperparameter tuning, each model's performance was evaluated to determine how well it handled the complexity of the data. The various models that we used are:

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| --- | --- |
| **Model** | **Hyperparameters** |
| Linear Regression | No Parameters  Best MSE: 2015.093287639543 |
| Decision Tree | Best parameters: {'max\_depth': 10, 'min\_samples\_leaf': 4, 'min\_samples\_split': 10}  Best MSE: 2122.4716964872887 |
| Random Forest | Best parameters: {'max\_depth': 10, 'min\_samples\_split': 2, 'n\_estimators': 200}  Best MSE: 1744.0371925293598 |
| SVM | Best parameters: {'C': 10, 'gamma': 'scale', 'kernel': 'rbf'}  Best MSE: 1786.8689297746616 |
| XGBoost | Best parameters: {'learning\_rate': 0.1, 'max\_depth': 5, 'n\_estimators': 50}  Best MSE: 1747.8226387737236 |

Random Forest and XGBoost are the top-performing models, capturing complex relationships in the data with optimal hyperparameter tuning. SVM performed well for handling non-linear patterns, while Decision Tree was effective but simpler. Linear Regression, being the simplest model, was outperformed by the others, especially on more complex patterns in the data.

**7.  MODEL ESTIMATIONS**

In this project, we tested different machine learning models to predict how long an aircraft engine will keep working before it fails (Remaining Useful Life - RUL). We used various error measures, such as MAE (Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error), and R², to see which model made the most accurate predictions.

**7.1 STATIC MODELS**

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| --- | --- | --- | --- | --- |
|  | **MAE** | **MSE** | **RMSE** | **R2** |
| Linear Regression | 34.02 | 1972.23 | 44.41 | 0.57 |
| Random Forest | **30.15** | **1760.18** | **41.95** | **0.62** |
| Decision Tree | 42.03 | 3578.68 | 59.82 | 0.22 |
| XGBoost | 31.27 | 1897.27 | 43.56 | 0.59 |
| SVM | 30.09 | 1817.51 | 42.63 | 0.60 |

Random Forest emerged as the best-performing model, producing the lowest MAE, MSE, and RMSE values, along with the highest R². Linear Regression, XGBoost, and SVM had similar performance, but none were able to outperform Random Forest. Decision Tree showed the weakest results, highlighting the importance of using more complex models for accurate predictions in this dataset.

**7.2 DYNAMIC MODELS**

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|  | **MAE** | **MSE** | **RMSE** | **R2** |
| LSTM | 30.83 | 1782.81 | 42.22 | 0.61 |
| GRU | **30.10** | **1735.03** | **41.65** | **0.62** |

The GRU model is better than LSTM in this case because it has slightly lower MAE, MSE, and RMSE values, indicating better prediction accuracy. Additionally, its R² value is higher, suggesting it explains more variance in the data. GRUs are generally simpler and faster to train, which can contribute to better performance in some scenarios.

**8. ENGINE HEALTH CLASSISFICATION PREDICTION**

The classification system for engine health enhances prediction accuracy by evaluating the engine's overall condition and detecting patterns that could signal potential failures. This proactive assessment helps in identifying issues before they escalate, leading to more reliable performance insights.

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* **CAT Boost** is the best-performing model, achieving the highest accuracy and balanced metrics across classes.
* **Random Forest** performs reasonably well but not as effectively as CAT Boost, particularly in precision and recall for specific classes.
* **Logistic Regression** shows signs of underperformance, especially with certain classes, likely due to convergence issues and class imbalance.

**Best Model Identification**

After evaluating all models, **CAT Boost** is identified as the best model based on accuracy, and Recall with the following performance metrics:

* **Accuracy**: 0.8835
* **Precision**: 0.8828
* **Recall**: 0.8835
* **F1-Score**: 0.8818

**9. DEVELOPMENT IDEAS FOR THE FUTURE OF PROJECT:**

* Make predictions from each of these models to determine the RUL of each of the engine components in real-time so we can reach the set target goals.
* Create time series graphs to show forecasts of the possibilities of the engine parts malfunctioning or failing.
* Fine tune the code through changing hyper parameters for better results and more accurate RUL prediction
* Make it a real time monitoring tool by connecting it to dynamic databases.
* More Precise Ranges could be calculated in real time to predict the Status of the Engine’s Health.

**10. CONCLUSION:**

* The problem was approached in the aspects of static and dynamic models to check the individual estimations such as MSE, MAE etc. to get an idea of the overall performance of the prediction models.
* Further steps of predicting the remaining useful life (RUL) of aircraft components need to be worked further upon to determine the solutions for the issues that are being tackled in this project.