Predictive Maintenance for

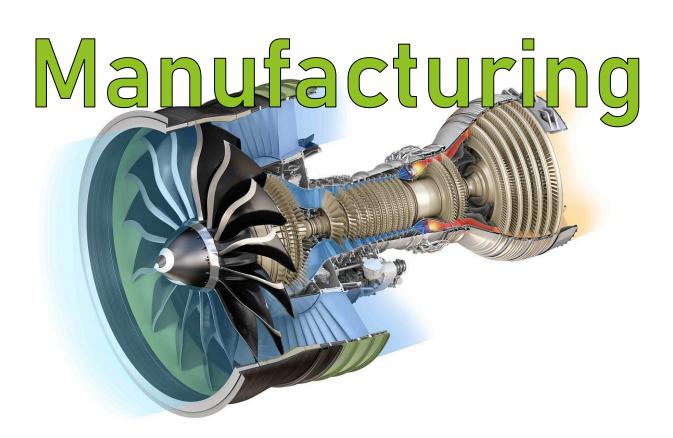


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1. Introduction

Objective

The primary objective of this project is to predict the Remaining Useful Life (RUL) of machinery using sensor data. Accurate prediction of RUL can help in implementing effective predictive maintenance strategies, thereby reducing unplanned downtimes and maintenance costs.

Background

Predictive maintenance leverages data analysis techniques to predict when equipment failure might occur so that maintenance can be performed just in time. This approach is crucial in industrial settings, where unexpected equipment failure can lead to significant operational and financial losses. By analyzing sensor data from machinery, we can develop models that forecast the RUL, enabling timely interventions and optimizing maintenance schedules.

2. Data Preparation

Dataset

The dataset used in this project is the NASA CMAPS dataset from Kaggle, which contains sensor measurements from various machinery. This data provides a rich source of information for developing predictive maintenance models.

Importing dependencies

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error
import seaborn as sns
import os
```

Loading invidual text files into a single data frame

```
[2] directory = '/content/drive/MyDrive/My_Projects/Nasa Turbo Fan Project/archive/CMaps'

#Reading the tarining data

train_files = ['train_FD001.txt','train_FD002.txt','train_FD003.txt','train_FD004.txt']
```

Data Loading

The dataset comprises multiple text files, each containing sensor data. These files were read and combined into a single Data Frame for ease of analysis.

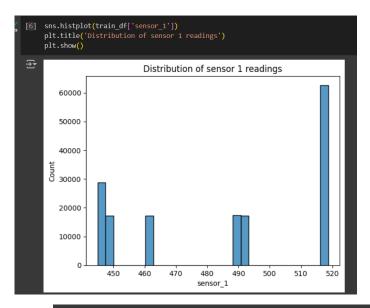
```
Loading invidual text files into a single data frame
[2] directory = '/content/drive/MyDrive/My_Projects/Nasa Turbo Fan Project/archive/CMaps'
    #Reading the tarining data
    train_files = ['train_FD001.txt','train_FD002.txt','train_FD003.txt','train_FD004.txt']
    #Defining column names
    columns = [
         'unit_number', 'time_in_cycles', 'op_setting_1', 'op_setting_2', 'op_setting_3',
        'sensor_8', 'sensor_9', 'sensor_10', 'sensor_11', 'sensor_12', 'sensor_13', 'sensor_14'
        'sensor_15', 'sensor_16', 'sensor_17', 'sensor_18', 'sensor_19', 'sensor_20',
        'sensor 21'
    #Loading and processing data
    def load data(file name):
      df = pd.read csv(os.path.join(directory,file name),sep='\s+', header=None)
      df.columns = columns
      return df
    #Loading the training data into a single data frame
    train_df_list = [load_data(file) for file in train_files]
    train df = pd.concat(train df list, ignore index=True)
    train df.head()
```

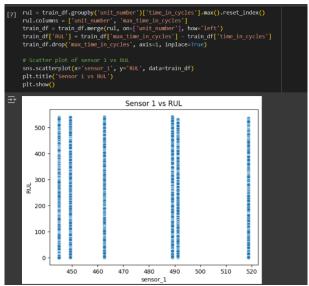
3. Initial Exploration

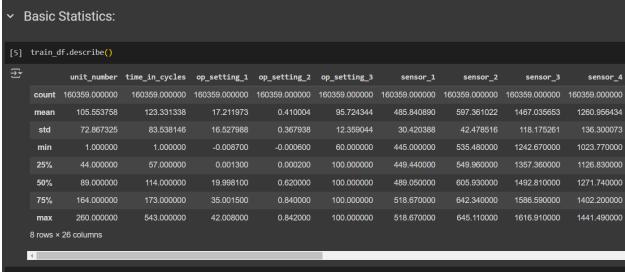
Initial exploratory data analysis (EDA) included:

- Histograms and scatter plots: Used to understand the data distribution and identify patterns.
- Basic statistics: Calculated to gain insights into the central tendency and spread of the data.

This initial exploration helped in identifying potential issues, trends, and correlations in the data, setting the stage for further preprocessing and modeling steps.







4. Data Cleaning and Preprocessing

To ensure the data is ready for modeling, several cleaning and preprocessing steps were undertaken:

Handling Missing Values

- Missing Value Check: The dataset was checked for missing values.
- Imputation: Missing values were filled with the mean of the respective columns to maintain data integrity.

Check Data Types and Missing Values: [4] train df.info() → <class 'pandas.core.frame.DataFrame'> RangeIndex: 160359 entries, 0 to 160358 Data columns (total 26 columns): Non-Null Count # Column Dtype 0 unit number 160359 non-null int64 1 time_in_cycles 160359 non-null int64 2 op_setting_1 160359 non-null float64 3 op_setting_2 160359 non-null float64 3 op_setting_2 160359 non-null float64
4 op_setting_3 160359 non-null float64
5 sensor_1 160359 non-null float64
6 sensor_2 160359 non-null float64
7 sensor_3 160359 non-null float64
8 sensor_4 160359 non-null float64
9 sensor_5 160359 non-null float64
10 sensor_6 160359 non-null float64
11 sensor_7 160359 non-null float64
11 sensor_8 160359 non-null float64
12 sensor_8 160359 non-null float64
13 sensor_9 160359 non-null float64
14 sensor_10 160359 non-null float64
15 sensor_11 160359 non-null float64 160359 non-null float64 15 sensor 11 160359 non-null float64 16 sensor 12 160359 non-null float64 17 sensor 13

Normalization

• **Standardization**: Sensor data was standardized using StandardScaler to ensure uniform scaling across all features.

```
Normalize/Standardize Sensor Data

Variable Normalizing or standardize the sensor data to ensure all features contribute equally to the model

[9] from sklearn.preprocessing import standardscaler

#selecting sensor columns
sensor_columns = [f'sensor_{i}'for i in range(1,22)]
scalar = Standardscaler()
train_df[sensor_columns] = scalar.fit_transform(train_df[sensor_columns])
```

Feature Engineering

 Rolling Statistics: Created new features based on rolling mean and standard deviation to capture trends over time.

```
Feature Engineering
Creating additional features that might help the model based on rolling statistics
[10] for sensor in sensor_columns:
train_df[f'{sensor}_rolling_mean'] = train_df.groupby('unit_number')[sensor].rolling(window=5).mean().reset_index(level=0, drop=True).fill
```

5. Modeling

Initial Model Training

Multiple regression models were trained to predict the Remaining Useful Life (RUL) of machinery. The models evaluated included:

- Linear Regression
- Random Forest Regressor
- Gradient Boosting Regressor

These models were trained on the preprocessed data, and their performance was evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

```
    Evaluate the Models

[37] # Defining a function to evaluate models
     def evaluate model(model, X val, y val):
         predictions = model.predict(X val)
         mae = mean_absolute_error(y_val, predictions)
         rmse = np.sqrt(mean squared error(y val, predictions))
         return mae, rmse
     # Evaluate the models
     linear mae, linear rmse = evaluate model(linear model, X val, y val)
     rf mae, rf rmse = evaluate model(rf model, X_val, y_val)
     gb_mae, gb_rmse = evaluate_model(gb_model, X_val, y_val)
     print(f"Linear Regression - MAE: {linear mae}, RMSE: {linear rmse}")
     print(f"Random Forest - MAE: {rf_mae}, RMSE: {rf_rmse}")
     print(f"Gradient Boosting - MAE: {gb mae}, RMSE: {gb rmse}")
→ Linear Regression - MAE: 59.07693987884737, RMSE: 75.1324502597411
     Random Forest - MAE: 54.30610875530058, RMSE: 70.16138296934336
     Gradient Boosting - MAE: 57.177243470646246, RMSE: 73.65807904132173
```

Hyperparameter Tunning

The Random Forest model, which showed the best initial performance, was further optimized using GridSearchCV to find the best hyperparameters.

```
random_search_rf = RandomizedSearchCV(
        estimator=rf_model,
        param_distributions=param_dist,
        n_iter=10, # Reduced number of iterations
        cv=3, # Reduced number of cross-validation folds
        scoring='neg_mean_absolute error',
        n jobs=-1,
        random_state=42
    # Fit RandomizedSearchCV to the smaller training data
    random_search_rf.fit(X_train_small, y_train_small)
    # Get the best parameters and best score
    best params rf = random search rf.best params
    best_score_rf = -random_search_rf.best_score_
    print(f"Best parameters: {best_params_rf}")
    print(f"Best MAE score: {best_score_rf}")
    # Save the best model
    joblib.dump(random search rf.best estimator , 'tuned random forest model.pkl')
🎛 Best parameters: {'bootstrap': True, 'max_depth': 17, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 149}
    Best MAE score: 57.506449139213835
    ['tuned random forest model.pkl']
```

5. Results

Model Performance

After hyperparameter tuning, the best Random Forest model was evaluated again on the validation set, showing improved performance.

```
best_rf_model = joblib.load('tuned_random_forest_model.pkl')

best_rf_mae, best_rf_rmse = evaluate_model(best_rf_model, X_val, y_val)

print(f"Tuned Random Forest - MAE: {best_rf_mae}, RMSE: {best_rf_rmse}")

Tuned Random Forest - MAE: 56.735508391221714, RMSE: 73.09691326620256

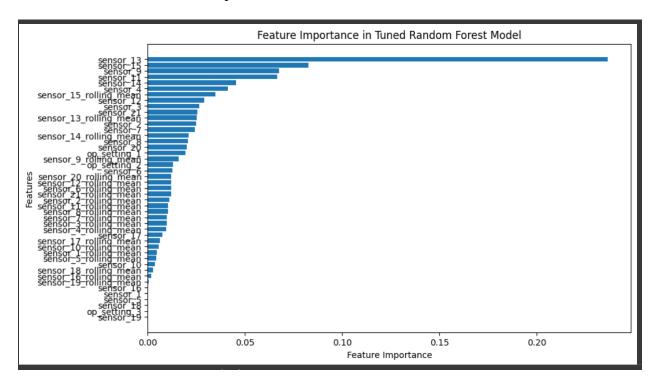
import matplotlib.pyplot as plt

importances = best_rf_model.feature_importances_
feature_importance_df = pd.DataFrame({'reature': X_train.columns, 'Importance': importances})
feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)

plt.figure(figsize=(10, 6))
plt.barh(feature_importance_df['Feature'], feature_importance_df['Importance'])
plt.xlabel('Feature Importance')
plt.ylabel('Feature Importance in Tuned Random Forest Model')
plt.gca().invert_yaxis()
plt.show()
```

Feature Importance

The feature importances of the tuned Random Forest model were analyzed to understand which features contributed most to the predictions.



6. Conclusion

- Summary:
 - Successfully built a predictive maintenance model to estimate the RUL of machinery.
 - Optimized the Random Forest model to achieve the best performance.
- Future Work:
 - Explore additional feature engineering techniques.
 - o Implement the model in a real-time system for continuous monitoring.