Predicting Engine Failure

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Video Demo

https://youtu.be/jBvGLsg9_vc

Motivation

The Problem

- There are around 150-200 engine failure-related accidents per year.
- About 37-50 of those accidents result in fatalities.
- A lot of engine failures in airplanes are preventable.
- It is especially dangerous for non-commercial pilots who might not have as much practice with crash prevention.

What Our Solution Can Do

- In being able to predict engine failures, we can pull at risk airplanes.
- We can also identify patterns that are possibly increasing the risk of engine failure and correct them.
- In creating this solution, we are making it easier for airlines to engage in safer practices.
- Non-commercial pilots might also be also to recognize some of the patterns occurring with their engines and avoid potential crashes.

Background of Data

- The NASA C-MAPSS 2 Turbofan Engine Degradation dataset models aircraft engine run-to-failure trajectories based on realistic flight conditions
- With help from aerospace research institutions (NASA PCoE, ETH Zurich, PARC), flight condition parameters were derived from commercial aviation data across a fleet of aircraft engines
- Measurements of the degradation were taken in a sequential manner, producing a time-series format
- The data set contains multi-variate sensor readings, 45 operational condition variables, a complete run-to-failure trajectories, metadata and documentation

Related Work

I found two projects that use CMAPSS data to predict engine failure using different methods and packages.

One person used engine failure data with a simple neural network using keras with a 90% success rate. But it only tells you whether an engine will fail within the next 30 cycles.
Here is the code base: aircraft-engine-failure-prediction/Aircraft Engine Failure Prediction- A Classification Case Study.ipynb at main · NisargaInfraOps13/aircraft-engine-failure-prediction

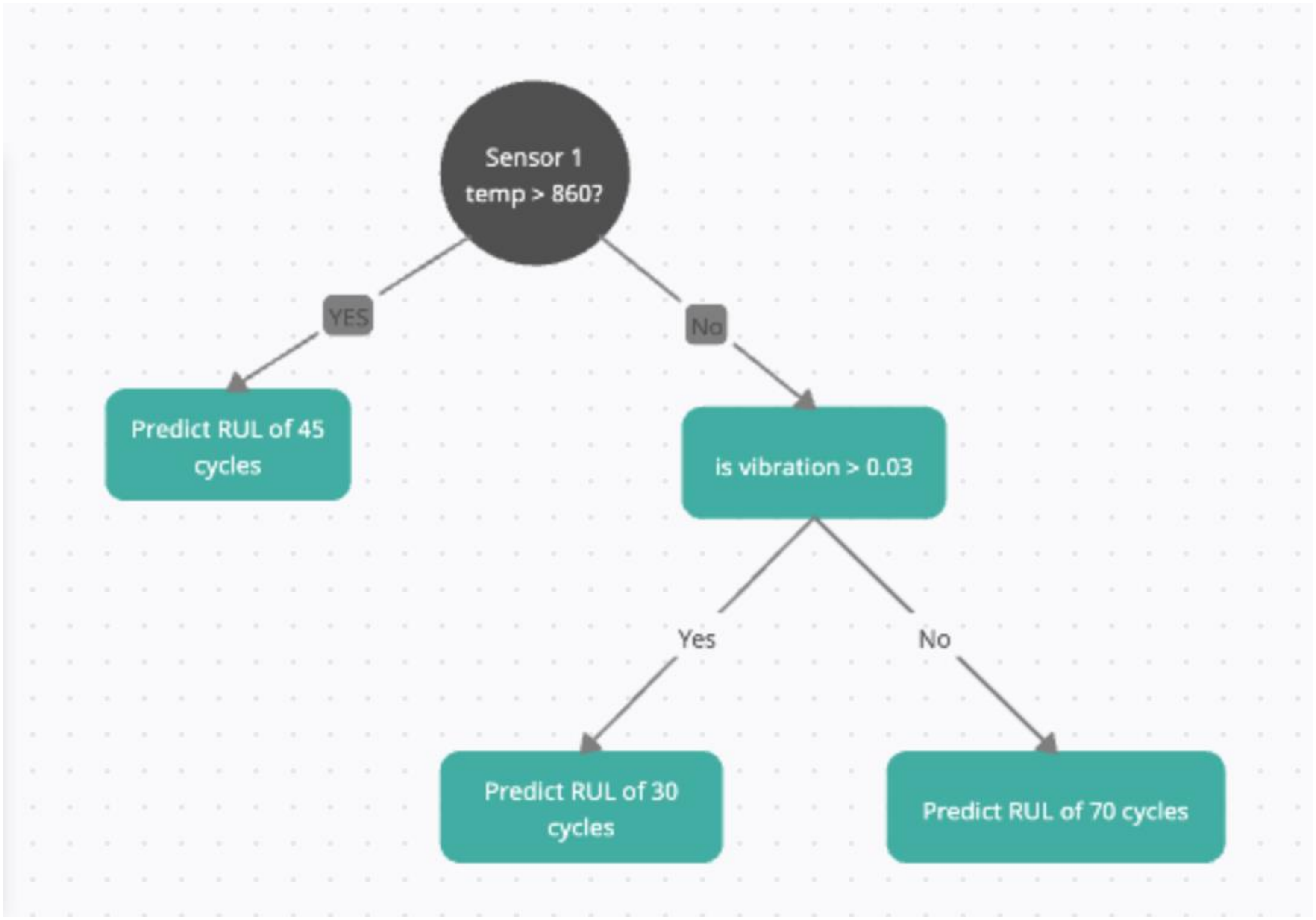
Another does XGBRegression and a simple neural network using pytorch to predict the engine failure. However, the repository does not give us the prediction success rate.
Here is the code base for that code: stevespreiz/engine_failure_prediction: Machine learning based approach to predicting aircraft engine failure using open NASA dataset.

Claim / Target Task

Using a **regression tree classifier** on the **CMAPSS data** from NASA, we will be able to **predict future engine failure**.

- The target variable will be the Remaining Useful Life (RUL) metric <= 5, which indicates how many cycles the engine has before failure
- We aim to predict given prior sensor data, how many predict cycles remain until failure
- We plan on using a regression tree classifier to handle non-linear relationships between sensors and degradation, work with multiple predictive features, and get an average prediction RUL depending on the path through the tree
- Since we are working with time-series data, we'll process data in a sequential manner and employ lags to features, we will also hyper-parameter tune and lightly feature engineer by calculating feature importance

An Intuitive Figure Showing WHY Claim



Proposed Solution

Formulate engine degradation prediction as a Remaining Useful Life (RUL) regression task using the NASA C-MAPSS 2 turbofan dataset.

For each engine cycle, use sensor readings + operating conditions as features and compute the target label as:

RUL = Cycle at Engine Failure – Current Cycle

Primary Models

- **Random Forest Classifier (Primary Model)**
  Chosen to:
  - Capture **non-linear degradation patterns**
  - Remain robust to noisy or correlated sensor channels
  - Provide **feature importance scores** for interpretability
- **Support Vector Classifier (Baseline)**
  Used to:
  - Establish a strong nonlinear baseline
  - Compare performance against an ensemble-based model

Implementation

Data Preparation

- Due to dataset scale (~5M rows), controlled subsampling is applied

Model Training

- All models are implemented using **scikit-learn**.
- Hyperparameters are tuned using **k-fold cross-validation** on the reduced dataset.
- Models are trained on NumPy arrays for memory and speed efficiency.

Evaluation

- Performance is evaluated using **classification accuracy** on held-out test data.
- Results:
  - Random Forest achieves the highest accuracy
  - SVM performs competitively as a baseline
- The small train–test gap suggests good generalization to unseen engine data.

Data Summary

Data Set

- Due to memory constraints, the dataset was subsampled to ~5,000 representative observations

Binary Conversion Rule

- We defined a near-failure threshold at RUL ≤ 5 cycles.
- Labels were assigned as:
  - Target =
    - 0 if RUL ≤ 5 (Bad / Near Failure)
    - 1 if RUL > 5
    - This threshold marks the critical degradation window immediately preceding failure.

Data Cleaning:

- Removed constant features that provide no predictive signal
- Forward filled missing values to maintain continuity within engine trajectories

Experimental Results

SVM Baseline:

{'kernel': 'rbf', 'C': 1, 'degree': 1}, accuracy: 0.996842253175913

RF:

n_estimators: 50, min_sample_splits: 2, max_depth: 2, accuracy: 0.9983552218744834

n_estimators: 50, min_sample_splits: 2, max_depth: 4, accuracy: 0.9988194265371614

n_estimators: 50, min_sample_splits: 3, max_depth: 2, accuracy: 0.9983666827326911

n_estimators: 50, min_sample_splits: 3, max_depth: 4, accuracy: 0.9988194265371614

n_estimators: 100, min_sample_splits: 2, max_depth: 2, accuracy: 0.9981403113231136

n_estimators: 100, min_sample_splits: 2, max_depth: 4, accuracy: 0.9988194265371614

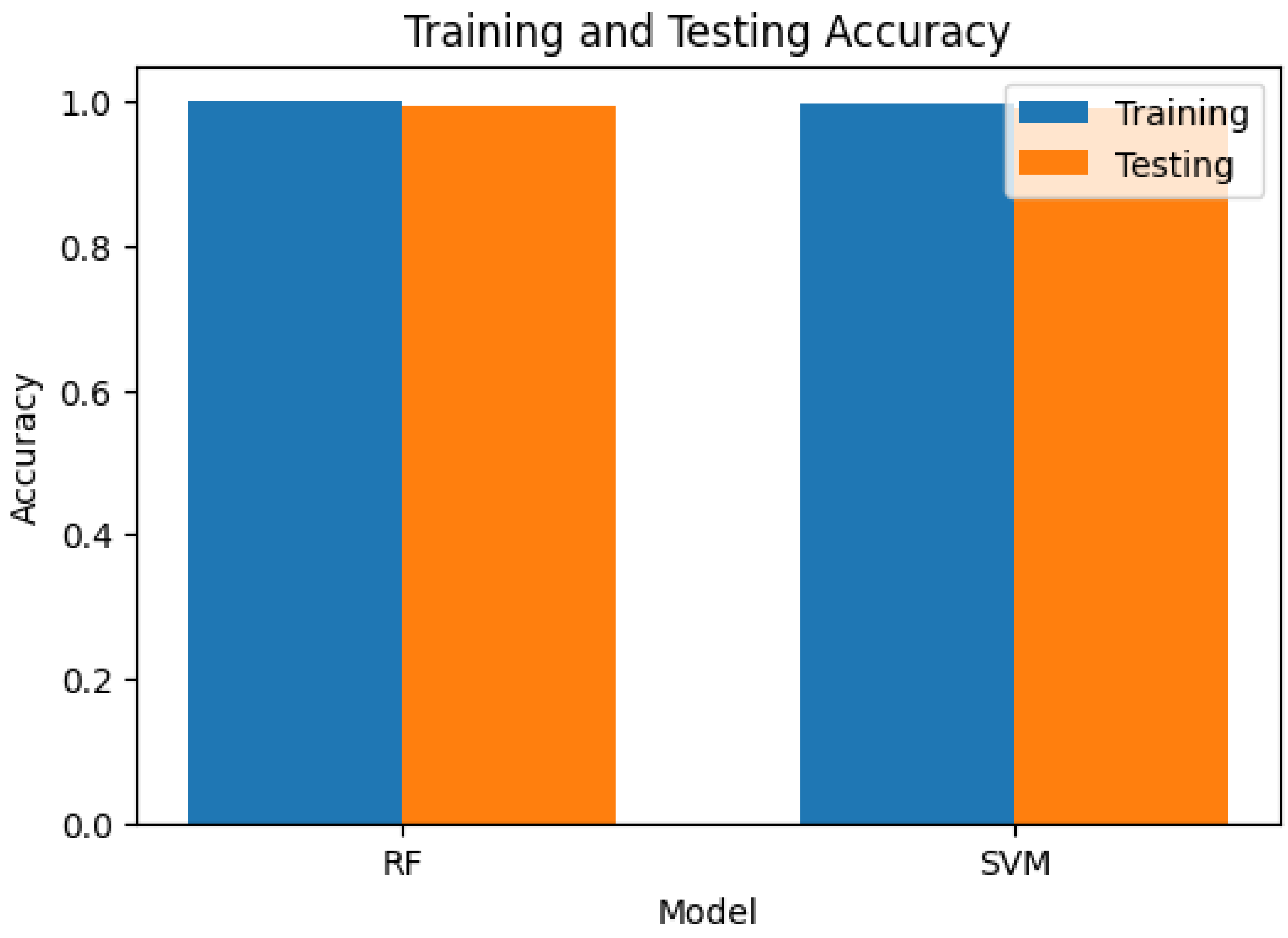
n_estimators: 100, min_sample_splits: 3, max_depth: 2, accuracy: 0.9982463343610157

n_estimators: 100, min_sample_splits: 3, max_depth: 4, accuracy: 0.9988194265371614

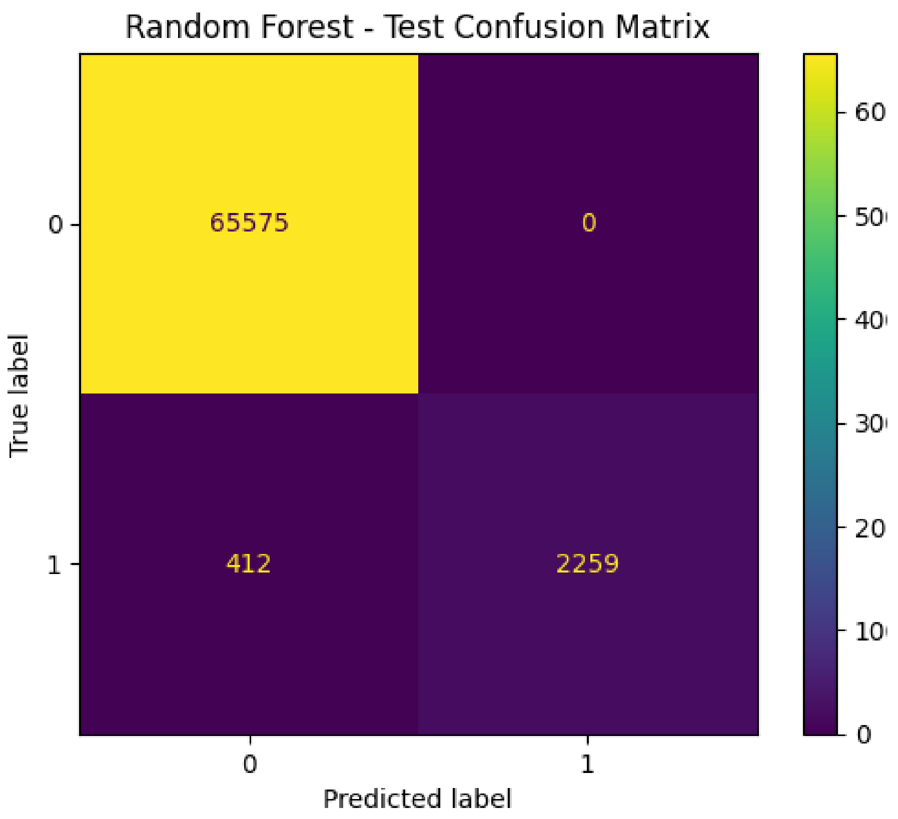
SVM accuracy on Test Data : 0.991105705828913

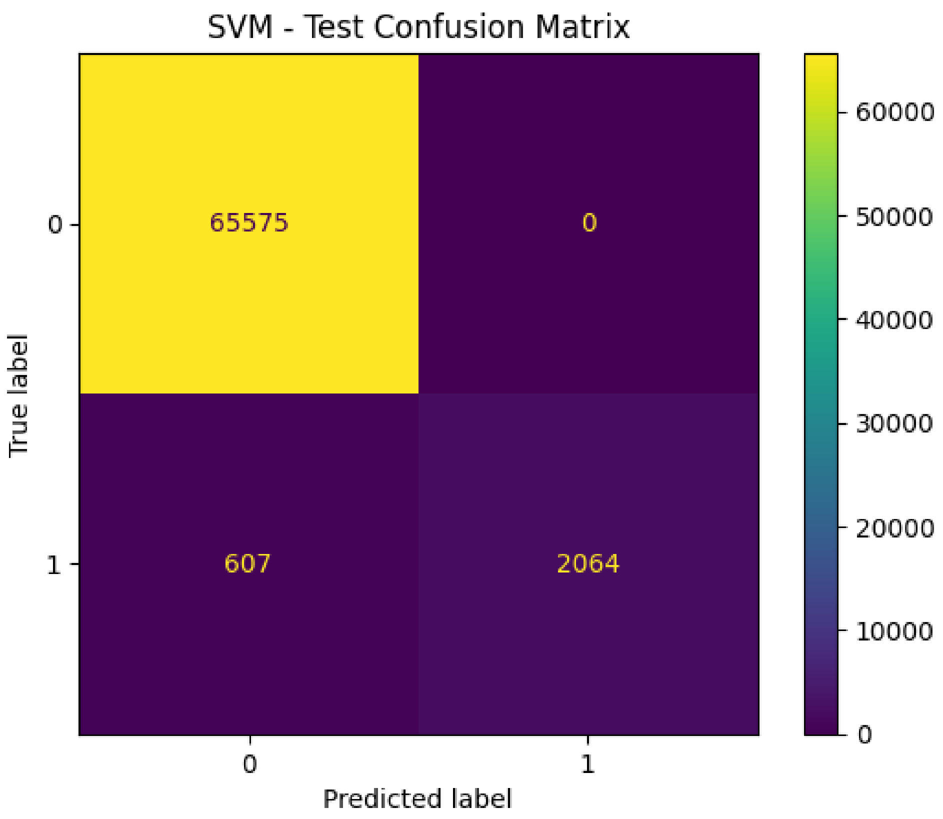
RF accuracy on Test Data: 0.993963016147466 5

Test Results



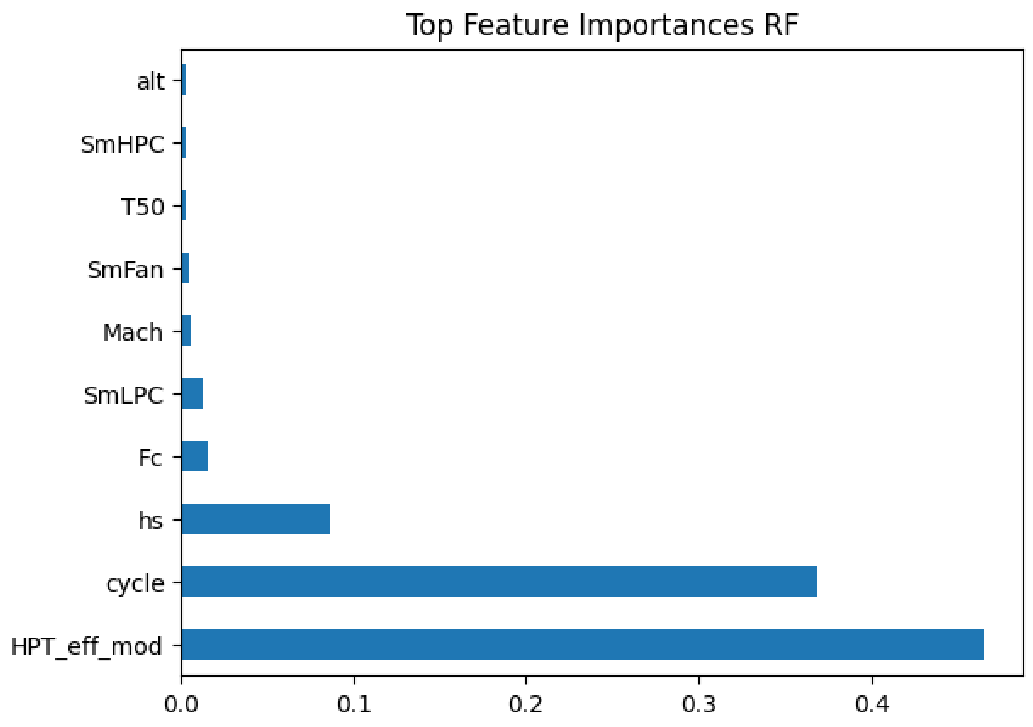
Test Results





Note that there are only false positives and no false negatives, so the model predicts engine failures when they occur

Experimental Analysis



Random Forest did about 0.03% better than SVM overall which likely means that they are equally accurate metrics. But Random Forest ran in a fraction of the time

Conclusion and Future Work

Conclusion:

- Only a few, easily identifiable features affect engine failure which is beneficial for noncommercial fliers.
- We required less estimators than we originally predicted.
- Since the random forest method had 99% accuracy, our method is an improvement from neural net solutions.

Future Work

- Penalize false positives.
- Apply similar models to other kinds of engines.
- Try a temporal method, like a temporal fusion transformer.

What We Did

Eve

- Wrote the code for cross-validation, SVM, Random Forest, and some helper methods.
- Played around with temporal fusion transformers, however we did not end up using this
- I also helped with the slides.

Yechan

- Wrote the code for importing that data and turning it into a pandas dataframe and a numpy. Tested data format and cleaned dataset to be usable
- I also helped with the slides.

Marin

- Wrote hyperparameter tuning methods.
- Split data by model, set targets, forward filled data, down-sampled data, reduced features by feature importance and produced a visual, wrote code for confusion matrices and accuracy plots
- I also helped with the slides.