Predictive Maintenance

A Deep Learning Approach

Samuel Ghalayini

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Introduction

Motivation

Predicting equipment degradation is vital for every physical system. "Every physical system" covers a huge array of systems: aircraft, medical, robotics, manufacturing, agricultural, etc.

These modern sensors can gather sequential data that leads up to a system failure so we can then use that data to try and predict when another failure will happen.

Scope

The task we are specifically given in this notebook is to predict the Remaining Useful Life (RUL) of the engine. Another way to say this is to predict the lifetime of the engine. We can do this because in our training data we have a label of how much RUL each engine has.

Our task is specifically a classification of if our engine has RUL or not. The goal of this is project is to assess different deep learning models so that engineers that work with physical systems in the field can be warned ahead of time of a system failure.

Physical Systems

Examples of physical systems that use predictive maintenance.

NASA Engine Degradation Dataset

- Dataset contained hundreds of engines with sensor data that ran-till-failure.
- 17 sensors were predictive
- 3 sensors were operational
- 20631 training data entries
- 13096 testing data entries

Sensor Name	Description
T2	Total temperature at fan inlet (°R)
T24	Total temperature at LPC outlet (°R)
T30	Total temperature at HPC outlet (°R)
T50	Total temperature at LPT outlet (°R)
P2	Pressure at fan inlet (psia)
P15	Total pressure in bypass duct (psia)
P30	Total pressure at HPC outlet (psia)
Nf	Physical fan speed (rpm)
Nc	Physical core speed (rpm)
epr	Engine pressure ratio (P50/P2) (–)
Ps30	Static pressure at HPC outlet (psia)
phi	Fuel-flow to Ps30 ratio (pps/psi)
NRf	Corrected fan speed (rpm)
NRc	Corrected core speed (rpm)
BPR	Bypass ratio (–)
farB	Burner fuel-air ratio (–)
htBleed	Bleed-air enthalpy (–)

Exploratory Data Analysis and Demo of Notebook

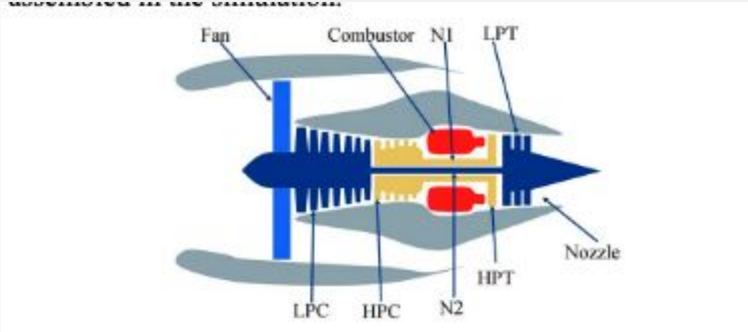

Figure 1. Simplified diagram of engine simulated in C-MAPSS [11].

1. https://c3.ndc.nasa.gov/dashlink/static/media/publication/2008_IEEEPHM_CMAPPSDamagePropagation.pdf

Models

Key Architectural Features

ANN: Dense Layers, Sigmoid, ReLU

CNN: 1D Convolution Filters, Pooling

LSTM: LSTM layer

Transformer: Attention Layer, Embedding, Normalization, Dropout, Pooling

Results

Model	Accuracy	Precision	Recall	F1-score	False Positives	False Negatives	Time
ANN	0.875	0.653	0.610	0.631	201	242	33.06
CNN	0.992	0.971	0.985	0.978	18	9	135.91
LSTM	0.991	0.962	0.987	0.975	24	8	120.78
Transformer	0.979	0.946	0.935	0.941	33	40	195.02

Discussion and Conclusion

- Importance of feature engineering
- CNN on non-image datasets
- Transformer model

Improvements:

- General model
- Across different domains

References

1. https://c3.ndc.nasa.gov/dashlink/static/media/publication/2008_IEEEPHM_CMAPPSDamagePropagation.pdf
2. https://data.nasa.gov/dataset/cmapss-jet-engine-simulated-data#:~:text=The%20engine%20is%20operating%20normally,values%20for%20the%20test%20data
3. https://www.tensorflow.org/api_docs/python/tfm/nlp/layers/Transformer
4. https://www.tensorflow.org/api_docs/python/tf/keras/layers/LSTM
5. https://www.tensorflow.org/api_docs/python/tf/keras/layers/Conv1D
6. https://www.tensorflow.org/api_docs/python/tf/keras/layers/Dense
7. https://arxiv.org/abs/1706.03762 *Attention is All You Need*

To get datasets:

8. https://ieee-dataport.org/documents/nasa-turbofan-jet-engine-data-set#files
9. https://www.kaggle.com/datasets/behrad3d/nasa-cmaps/data

Github: https://github.com/sam-ghala/predictive_maintenance