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**INTRODUCTION**

           The aviation industry is capital intensive, and is subject to stringent environmental and safety regulations. To minimize risk, technological improvements of aircraft engines are generally made incrementally, drawing heavily from experiences and lessons learned. Engine companies have generated and collected large amounts of data over the years. These big data, from various sources such as the database of currently manufactured engines, current development projects, previously completed development projects, and the designs that were not manufactured, are valuable resources of intelligence that can support new engine development. With increasing computational power and employing machine learning, data can be mined to provide valuable insights that could bring high levels of efficiency to engine conceptual des

1.1 **Project Overview**

          Big data and artificial intelligence/machine learning are transforming the global business environment. Data is now the most valuable asset for enterprises in every industry. Companies are using data-driven insights for competitive advantage. With that, the adoption of machine learning-based data analytics is rapidly taking hold across various industries, producing autonomous systems that support human decision-making. This work explored the application of machine learning to aircraft engine conceptual design. Supervised machine-learning algorithms for regression and classification were employed to study patterns in an existing, open-source database of production and research turbofan engines, and resulting in predictive analytics for use in predicting performance of new turbofan designs. Specifically, the author developed machine learning-based analytics to predict cruise thrust specific fuel consumption (TSFC) and core sizes of high-efficiency turbofan engines, using engine design parameters as the input.

   1.2  **Purpose**

           To determine if machine learning-based predictive analytics could be an effective tool for turbofan engine TSFC prediction at the conceptual design stage. In addition to the TSFC predictive-analytics development, It has slightly modified the engine core-size predictive analytics that was developed and to improve its prediction accuracy.

Aircraft maintenance is quickly adopting AI to build predictive maintenance towards “aircraft smart maintenance”. Machine learning algorithms are trained to forecast failure and suggest appropriate actions depending on the predicted failure, which is a step towards smart maintenance solutions.Both TSFC and core-size are key design parameters for any new aircraft engine. TSFC is a measure of fuel efficiency. It affects aircraft range and is a key element in fuel burn. TSFC is also an indicator of engine operating cost. To be able to predict TSFC rapidly and accurately would help to identify the best engine design expeditiously amongst several candidates. Engine core size can affect fuel efficiency. To be able to predict engine core size rapidly and accurately in the design space exploration would facilitate engine core architecture selection in the conceptual stage of engine development.

**2.LITERATURE SURVEY**

**1.Aircraft Engine Remaining Useful Life Prediction Framework for Industry**

The proposed model considers continuous learning and improvement to account for any further operational changes that affect the model prediction ability. This is reached by ingesting the model with the actual RUL during the maintenance of the engine unit, and by comparing it to the predicted one

**Advantages:**

Accuracy - 94%

Comparing multiple algorithms.

**Disadvantages:**  

Need more Down Time.

  Predictive Maintenance of Aircraft Engine using Deep Learning  Technique.

In this paper, an accurate algorithm to estimate remaining useful life of aircraft engine is proposed. Since the aircraftengine has a low fault tolerant, meaning that a little faulty in the

system can lead to catastrophic conditions, an accurate and real-time information about the engine condition is required. This paper utilizesthe combination of CNN and LSTM algorithms in learning the behaviorof the historical data and providing the accurate information about the time to failure of the system. The simulation results demonstrate that the proposed system is able to achieveimproved performance in terms of accuracy rate and computing time compared to the previous works.

**Advantages:**  

Using Deep learning Increasesthe Accuracy and computing time.

**Disadvantages:**  

Didn’t comparemany algorithm to get the best.

A rare failure detection model for aircraftpredictive maintenance usinga deep hybrid learning      approach.

The use of aircraft operation logs to develop a data-driven model to predict probable failuresthat could cause interruption poses many challenges and has yet to be fully explored. Giventhat aircraft is high-integrity assets, failures are exceedingly rare. Hence, the distribution ofrelevant log data containing prior signs will be heavily skewed towards the typical (healthy)scenario. Thus, this study presents a novel deep learning technique based on the auto-encoderand bidirectional gated recurrent unit networks to handle extremely rare failure predictions inaircraft predictive maintenance modelling. The auto-encoder is modified and trained to detectrare failures, and the result from the auto-encoder is fed into the convolutional bidirectionalgated recurrent unit network to predict the next occurrence of failure.

**Advantages:**  

High Accuracy, good recall and G-means

**Disadvantages:**  

Didn’t compare many algorithm to get the best.

  Predictive Maintenance of the AircraftEngine Bleed Air System Component

This paper presents a predictive maintenance solution of an aircraft engine bleed air system component using machine learning approaches on aircraft Quick Access Recorder

(QAR) data. However, when the QAR parameters are not sufficiently representative of thecomponent health,it has been highlighted that there is a need to leverageon more data sourcessuch as Smart Access Recorder (SAR) data.

**Advantages:**  

GoodAccuracy in both training and Validating dataset.

**Disadvantages:**  

Using only one algorithm.

Failure Prediction of Aircraft Equipment Using Machine Learning with a Hybrid Data   Preparation Method

Reliability and availability of aircraft components have always been an important consideration in aviation. Accurate prediction of possible failures will increase the reliability of aircraft components and systems. )e scheduling of maintenance operations help determine the overall maintenance and overhaul costs of aircraft components. Maintenance costs constitute a significant portion of the total operating expenditure of aircraft systems.

**Advantages:**

Accuracy - 0.9316 while using LR and SVR, Comparing multiple modelsto select the best.

**Disadvantages:**  

Consume more time using ReliefFand K - means in data preparation.

`2.**1 Existing problem**

* Airline restrictions on flying. Many airlines will not allow passengers to fly with certain conditions. ...
* Economy Class Syndrome (Deep Vein Thrombosis DVT) ...
* Jet Lag. ...
* Respiratory Infections. ...
* Parasite Infestation. ...
* Altitude sickness on arrival. ...
* Fear of flying. ...
* Air rage.

2.2 **References**

1.Turbofan Engines,” GT2019-91432, ASME Turbo-Expo 2019, June 17-21, 2019. 2. Daly, M., “Jane’s Aero-Engine,” 2017-2018. 3. Meier, N., “Civil turbojet/turbofan specifications.” 2..http://www.jet-engine.net/civtfspec.html. Accessed August, 2018. 4. GE Aviation. 3.https://www.geaviation.com/commercial 5. Pratt and Whitney. 4.https://www.pw.utc.com/products-and-services/products/commercial-engines

5. Google, “TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems. Retrieved on February 20, 2019 from: https://www.tensorflow.org/

**2.3Problem Statement Definition**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Problem Statement (PS)** | **I am (Customer)** | **I’m trying to** | **But** | **Because** | **Which makes me feel** |
| PS-1 | Passenger | Focus on  safety and security | I can’t focus on huge passenger at  the time | Hard to instruct at the same  time | Afraid to travel |
| PS-2 | Pilot | Get the situation underthe  control | Due to some technical issues | Improper monitoring | Frustrated |
| PS-3 | Civilians | Trying to see the safety and security of the  passenger | Inappropriate service concern | Engine beyond the control | Anxiety to travel |

**3.IDEATION & PROPOSED SOLUTION**

**1. Empathy Map Canvas**

**2.Ideation & Brainstorming**

**3.Proposed Solution**

|  |  |  |
| --- | --- | --- |
| **S.No.** | **Parameter** | **Description** |
| 1. | Problem Statement(Problem to besolved) | Predicting the failure of an Aircraft Engine using MachineLearning to save loss of time,  effort and money thusimproving productivity. |
| 2. | Idea / Solution description | The failure can be detected by installing the sensors and keeping a track of the values. The failure detection and predictive maintenance can be for any device, out of which we will be dealing withthe engine failure fora threshold numberof days.  Preventing the structural problems and the fuelproblems such as exhaustion and  contamination. |
| 3. | Novelty / Uniqueness | The engineis the heartof the aircraft were  it converts energyfrom the fuelto mechanical energy by creating motionin the process. |
| 4. | Social Impact / Customer Satisfaction | The Safety and Security playsa major rolein Social impact.The customer expectfor the  Timeliness, Comfort and Convenience. |
| 5. | Business Model (Revenue Model) | The emerging formsof business modelin the airline industry are presented in terms of how the carrier generates revenue and its  product offering. |
| 6. | Scalability of the Solution | This proposed solution is very scalable. i.e., Adding new features to enhance our engineto work withoutany difficulty and  increasing thesafety. |

**4.Problem Solution fit**

|  |  |  |
| --- | --- | --- |
| 1.CUSTOMER SEGMENT(S) (**CS)**  > Customers are businessmen, student, tourist, traveler and all the people  traveling in ﬂight. | 2.JOBS-TO-BE-DONE / PROBLEMS( **J&P**)  > Engine failure occurs when a turbine engine unexpectedly stopsproducing power due to malfunction. This lead to a lot of customer dissatisfaction. | 3. TRIGGERS **(TR)**    > To accurately predict the failure of an engineand track the ﬂight    4.EMOTIONS: BEFORE / AFTER (**EM)**    > The aircraft engine failure occurs, passengers often get annoyed and frustrated. They also might lose to reach on timeto some important occasions. |
| 5. AVAILABLE SOLUTIONS (AS)    > The reliability analysis of aircraft engines is essential for ensuring the smooth functioning of each component of an aircraft engine. | 6.CUSTOMER CONSTRAINTS (CC)    > Customers require accurate and early predictions of the ﬂight engine failure. And they also look for an alternate solution | 7. BEHAVIOUR (BE)  > The purpose of this research is to develop methods that can be used to generate reliable and timely alerts |
| 8. CHANNELS OF BEHAVIOR ( **CH**)    > Check the engine regularly and maintained properly. And also check the fuel and oil levels regularly in the aircraft engine. | 9. PROBLEMROOT CAUSE ( **RC**)    > The root cause of the problem is unforeseen & unpredictable engine failure that cause cancellations and arrival, departure delays. | 10. YOURSOLUTION ( SL )    > Preventable fuel problems such as exhaustion. Structural failures where a broken connecting rod, crank, valve, or camshaft is present account for seventeen percent of engine failures occurs. |

**4.REQUIREMENT ANALYSIS**

**1.Functional requirement**

The input data from jet engine consists of three feature columns named Nozzle Area, Air fuel ration and Throttle\_position and one label column named Fault to train the model and to predict fault for streaming features.

Trained model can predict whether the fault is detected or not based on the Input and time series values of features (Nozzle Area, Air fuel ration, and Throttle\_position).

**2.Non-Functional requirements**

Predicated throttle fault. The recurrent network consists of 22 hidden neurons and four-time delays for each of the inputs. The network is NARX (Nonlinear Autoregressive with External Inputs). The training algorithm utilized is Levenberg-Marquardt is minimizing the MSE. The NN false positives mostly happen at large throttle command changes, however, the overall prediction accuracy achieved is 96.4% over multiple simulation runs. The network is trained to identify the fault in damping of the throttle actuator. After the network is trained, the output is processed with a saturation and relay to achieve discrete outputs such that a logical indication is obtained indicating a fault.

**5.PROJECT DESIGN**

    Data Flow Diagrams

**6.PROJECT PLANNING & SCHEDULING**

**1.Sprint Planning & Estimation**

|  |  |  |
| --- | --- | --- |
| **TITLE** | **DESCRIPTION** | **DATE** |
| Literature Survey &Information Gathering | Literature survey on the selected project & gathering information by referring the, technical papers,research publications etc. | 3 SEPTEMBER 2022 |
| Prepare EmpathyMap | Prepare Empathy Map Canvas to capture the user Pains & Gains, Prepare list of problem statements | 23 SEPTEMBER 2022 |
| Ideation | List the by organizing the brainstorming session and prioritize the top 3 ideas based on the feasibility & importance | 23 SEPTEMBER 2022 |
| Proposed Solution | Prepare the proposed solution document, which includes the novelty, feasibility of idea, business model, social impact, scalability of solution, etc. | 24 SEPTEMBER 2022 |
| Problem Solution Fit | Prepare problem - solution fit document. | 29 SEPTEMBER 2022 |
| Solution Architecture | Prepare solution architecture document. | 19 SEPTEMBER 2022 |
| Customer Journey | Prepare the customer journey maps to understand the user interactions &experiences with the application (entry to exit). | 1 OCTOBER 2022 |
| Functional Requirement | Prepare the functional requirement document. | 2 OCTOBER 2022 |

**2.Sprint Delivery Schedule**

       The main event during agile methodology is the sprint, the stage where ideas turn into innovation and valuable products come to life.

On one hand, agile sprints can be highly effective and collaborative. At the same time, they can be chaotic and inefficient if they lack proper planning and guidance. And for this reason, making a sprint schedule is one of the most important things you can do to ensure that your efforts are successful.

If you’re looking to schedule your next sprint, you’ve come to the right place. Keep reading to learn everything you need to know about sprint scheduling, including some tips to drive the best results.

**3.Reports from JIRA**

          One part of ensuring the success and smooth operations of your projects in JIRA is reporting. It involves gaining the knowledge about the health, progress and overall status of your JIRA projects through Gadgets, report pages or even third party applications. The goal of this guide is to provide an overview of the tools available to JIRA users today and how they can be used to fulfill the different types of reporting needs that users face today.

**7.CODING & SOLUTIONING**

import pandas as pd

import numpy as np

from sklearn.preprocessing import MinMaxScaler

from sklearn.metrics import confusion\_matrix,accuracy\_score

import matplotlib.pyplot as plt

plt.style.use('ggplot')

%matplotlib inline

dataset\_train=pd.read\_csv('PM\_train.txt',sep=' ',header=None).drop([26,27],axis=1)

col\_names=['id','cycle','setting1','setting2','setting3','s1','s2','s3','s4','s5','s6','s7','s8','s9','s10','s11','s1 2','s13','s14','s15','s16','s17','s18','s19','s20','s21']

dataset\_train.columns=col\_names

print('shape of train dataset:',dataset\_train.shape)

dataset\_train.head()

dataset\_test=pd.read\_csv('PM\_test.txt',sep=' ',header=None).drop([26,27],axis=1)

dataset\_test.column=col\_names

#dataset\_test.head()

print('Shape of Test dataset:',dataset\_train.shape)

dataset\_train.head()

pm\_truth=pd.read\_csv('PM\_truth.txt',sep=' ',header=None).drop([1],axis=1)

pm\_truth.columns=['more']

pm\_truth['id']=pm\_truth.index+1

pm\_truth. head ()

rul=pd.DataFrame (dataset\_test.groupby ('id') ['cycle'].max()).reset\_index()

rul.columns=['id','max']

rul. head()

pm\_truth['rtf']=pm\_truth['more']+rul['max']

pm\_truth.head()

pm\_truth.drop('more',axis=1,inplace=True)

dataset\_test=dataset\_test.merge(pm\_truth,on=['id'],how='left')

dataset\_test['ttf']=dataset\_test['rtf']-dataset\_test['cycle']

dataset\_test.drop('rtf',axis=1,inplace=True)

dataset\_test.head()

dataset\_train['ttf']=dataset\_train.groupby(['id'])['cycle'].transform(max)-dataset\_train['cycle']

dataset\_train.head()

df\_train=dataset\_train.copy()

df\_test=dataset\_test.copy()

period=30

df\_train['label\_bc']=df\_train['ttf'].apply(lambds x:1 if x<=period else 0)

df\_test['label\_bc']=df\_test['ttf'].apply(lambda x: 1 if x<= period else 0)

df\_train.head()

x\_train=df\_train.iloc[:,:-1].values

y\_train=df\_train.iloc[:,-1:].values

**8.TESTING**

1.Test Cases

Test Cases for Computation of Internal Flows in aircraft  Engine Components. (Propulsion and Energetics Panel Working Group) (Exemples de Tests pour le Calcul des Ecoulements Internes dans les Organes des Moteurs d'Avion),

2.User Acceptance Testing

**9.  RESULTS**

**10.ADVANTAGES & DISADVANTAGES**

**ADVANTAGES**

* Data can be misinterpreted, leading to false maintenance requests,
* It's costly to establish a complete IoT system with sensors, transmission costs and analysis,
* Predictive analysis may not take contextual information into account, such as equipment age or weather,

**DISADVANTAGES**

* Upfront costs of preventive maintenance—keeping equipment regularly maintained requires a bit of an investment
* More labor-intensive, so you’ll need enough staff on hand
* Potential for over-maintenance

**11.CONCLUSION**

This is a very interesting dataset and a popular one. It tries to solve a real-world problem that really matters. And it is directly related to lives of passengers. I don’t claim to have given the best solution. But I really enjoyed solving it. It is very amazing to see that Deep Learning networks learn the patterns without any feature engineering.

**12.FUTURE SCOPE**

The system can be further trained to predict the remaining useful life (RUL) [7] of the machine before it requires maintenance or replacement. The use of stacked architectures [8] of various models can be used to increase the confidence in classification. Furthermore, use of proactive anomaly detection [9] can be used to send signals to the machine controller tocontrol the machine parameters to prevent bad quality production cycles and hence increase the overall productivity

**13.APPENDIX**

**GITHUB LINK**

**https://github.com/IBM-EPBL/IBM-Project-13043-1659508266**

**DEMO LINK:**

 https://youtu.be/HbEXWSeKW34