Project Documentation Report

Project Name : Machine Learning-Based Predictive Analytics for Aircraft Engine

Team ID: PNT2022TMID27252

Team Members:

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- . Krishna Varshan S
- . Kavya K
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1.INTRODUCTION

1.1 Project Overview

Unexpected failure leads to loss of money and time. Predicting the failure prior will save time, effort, money and sometimes even lives. 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 Engine failure is highly risky and needs a lot of time for repair. which we will be dealing with the engine failure for a threshold number of days.

1.2 Purpose

The project aims to predict the failure of an engine by using Machine Learning to save loss of time & money thus improving productivity.

2. LITERATURE SURVEY

TITLE	FailurePredictionofAircraftEquipmentUsingMachineLe arningwitha HybridData PreparationMethod
AUTHORS	KadirCelikmih,OnurInan,andHarunUguz
YEAROFPUBLICATION	12January2020
ABSTRACT	Reliabilityandavailabilityof aircraftcomponentshavealwaysbeenanimportantconsid erationinaviation. Accurate prediction of possible failures will increase thereliability of aircraft components and systems.)eschedulingofmaintenanceoperationshelpdeterminetheover all maintenance and overhaul costs of aircraftcomponents. Maintenance costs constitute a significant portion of the total operating expenditure of aircraftsystems.
METHODOLOGY	DataMining
MERITS	Accuracy - 0.9316 while using LR and SVR,Comparingmultiplemodelstoselectthebes t.
DEMERITS	Consume more time using ReliefF and K - means in datapreparation.
OVERCOMEDEMERITS	Manuallydeletethefieldswhicharelesscontributed.
LINK	https://pdfs.semanticscholar.org/1462/685c83d65bc9d99d9 227c435e8035a902e7b.pdf

TITLE	AircraftEngineRemainingUsefulLifePredictionFramew orkforIndustry.				
AUTHORS	Hussein A. Taha, Ahmed H. Sakr, Soumaya Yacout.				
YEAROFPUBLICATION	October23-25,2019				
ABSTRACT	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.				
METHODOLOGY	DataAnalysisandDataMining				
MERITS	Accuracy-94% Comparingmultiplealgorithms.				
DEMERITS	NeedmoreDownTime.				
OVERCOMEDEMERITS	UseViewwhichcontainsdatastoredbeforetraining,which leads to use the bw system while training anddowntimerequired.				
LINK	https://www.researchgate.net/publication/337311736_Aircr aft_Engine_Remaining_Useful_Life_Prediction_Framewor k_for_Industry_40				

TITLE	Predictive Maintenance of Aircraft EngineusingDeepLearningTechnique.					
AUTHORS	AdePitraHermawan, <u>Dong-SeongKim</u> , Jae-MinLee.					
YEAROFPUBLICATION	21December 2020					
ABSTRACT	In this paper, an accurate algorithm to estimate remaininguseful life of aircraft engine is proposed. Since the aircraftengine has a low fault tolerant, meaning that a little faulty inthe system can lead to catastrophic conditions, an accurate and real-time information about the engine condition is required. This paper utilizes the combination of CNN and LSTM algorithms in learning the behavior of 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 achieve improved performance in terms of accuracy rate and computing time compared to the previous works.					
METHODOLOGY	MachineLearning					
MERITS	UsingDeeplearningIncreasestheAccuracyandcom putingtime.					
DEMERITS	Didn'tcomparemanyalgorithmtogetthebest.					
OVERCOMEDEMERITS	Comparemoremodelswiththesamedata.					
LINK	https://ieeexplore.ieee.org/document/9289466/authors#authors					

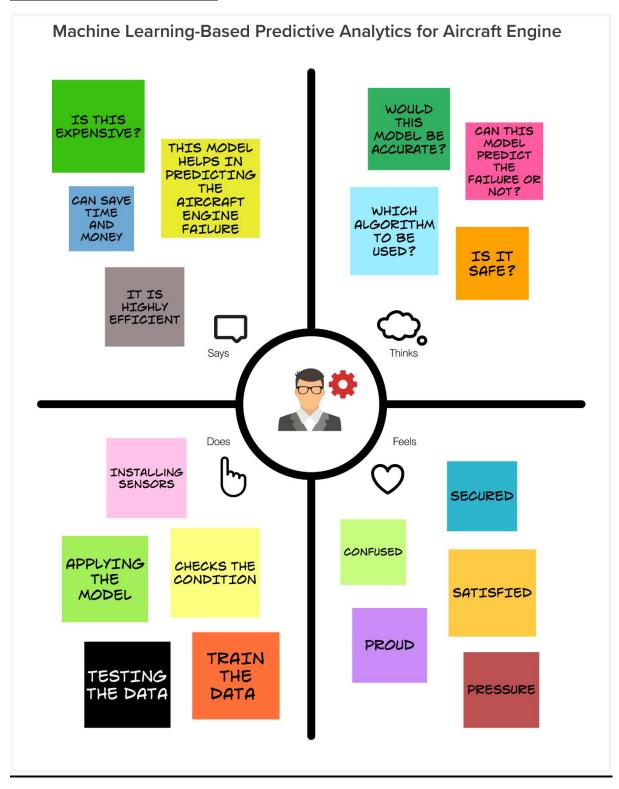
TITLE	Ararefailuredetectionmodelforaircraftpredictivemaintenan ceusingadeephybridlearning approach.
AUTHORS	MarenDavidDangut,IanK.Jennions,SteveKing&ZakwanSkaf.
YEAROFPUBLICATION	Published:26March2022
ABSTRACT	Theuseofaircraftoperationlogstodevelopadata- drivenmodeltopredict probable failures that could cause interruption poses manychallenges and has yet to be fully explored. Given that aircraft ishigh- integrityassets,failuresareexceedinglyrare.Hence,thedistrib utionofrelevantlogdatacontainingpriorsignswillbeheavily skewed towards the typical (healthy) scenario. Thus, thisstudy presents a novel deep learning technique based on the auto-encoder and bidirectional gated recurrent unit networks to handleextremelyrarefailurepredictionsinaircraftpredictivem aintenance modelling. The auto-encoder is modified and trainedto detect rare failures, and the result from the auto-encoder is fedintotheconvolutionalbidirectionalgatedrecurrentunitnet worktopredictthenextoccurrenceoffailure.
METHODOLOGY	MachineLearningandIOT
MERITS	HighAccuracy,goodrecallandG-means.
DEMERITS	Didn'tcomparemanyalgorithmtogetthebest.
OVERCOMEDEMERITS	Comparemoremodelswiththesamedata.

LINK	https://link.springer.com/article/10.1007/s00521-022- 07167-8

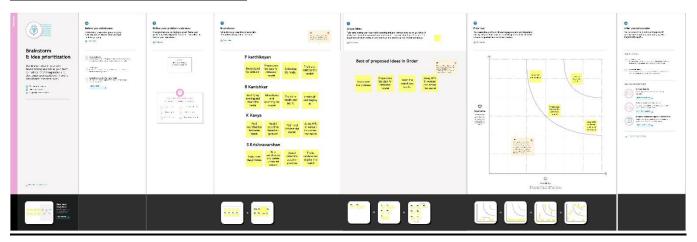
TITLE	PredictiveMaintenanceoftheAircraftEngineBleedAirSyste mComponent					
AUTHORS	SavithaRamasamy,YangXue,RoystonPhoon, Richard Han, Nelson Low andCheeSiangLim.					
YEAROFPUBLICATION	September2018.					
ABSTRACT	Thispaperpresentsapredictivemaintenancesolutionofanaircr aftenginebleedairsystemcomponentusing machine learning approaches on aircraft QuickAccess Recorder (QAR)data.However,whentheQARparametersare not sufficiently representative of the component health,it has been highlighted that there is a need to leverage onmore data sources such as Smart Access Recorder (SAR)data.					
METHODOLOGY	AnalysisandClassification					
MERITS	GoodAccuracyinbothtrainingandValidatingdataset.					
DEMERITS	Usingonlyone algorithm.					
OVERCOMEDEMERITS	Comparemoremodelswiththesamedata.					
LINK	https://www.researchgate.net/publication/330357379_Pred_ictive_Maintenance_of_the_Aircraft_Engine_Bleed_Air_System_Component					

3. IDEATION & PROPOSED SOLUTION

3.1 Empathy Map Canvas



3.2 Ideation & Brainstorming



3.3 Proposed Solution

Abstraction:

A failure in the aircraft engine tends to a huge loss of life and money. There is a need to analyse the condition of Aircraft engine and detect the failure period of it before it happens, which helps in reducing the accident of aircraft due to engine failure. Different aircraft engine uses different settings in each fly. So, there is a task to analyse the data from different sensors with different settings periodically. The idea of this project is to choose a ML model, train & validate it, deploy it with an API with user friendly UI.

Novelty:

In this project the idea is to increase the training speed of the model by recognizing the impactful factors which affect the target field. And to increase the accuracy of the model in the new set of data. Choosing different Time Series algorithm and compare all those to get the best accuracy and performance. The main freshness in the project is:

- Increasing Accuracy,
- Getting better prediction as using time series algorithm,
- Optimized API to get the predictions easily.

Feasibility of Project:

Every aircraft is different from each other in terms of sensor, engine and settings of it. One of the aims of the project is to build the model which is suitable for most of the aircraft engine. The data going to use in the project need

to has data of settings, sensors of different aircrafts engine over the time, which may help in designing the model to work better in different aircraft.

Business Model:

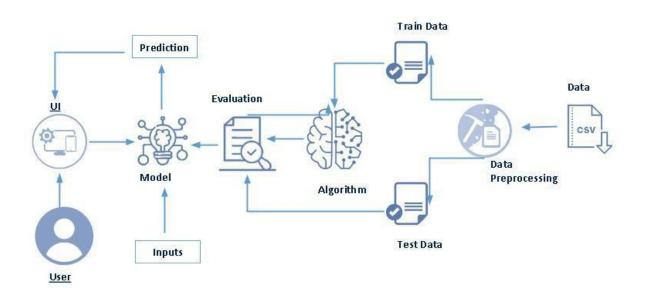
The approach reduces man power which involved in testing the engine each time. It helps in identifying the engine failure or engine maximum cycles before each time of fly. It helps in saving more time and money. And importantly saves more life. It almost reduces 60% of over all process of formal procedures involved in inspecting the aircraft engine.

Social Impact:

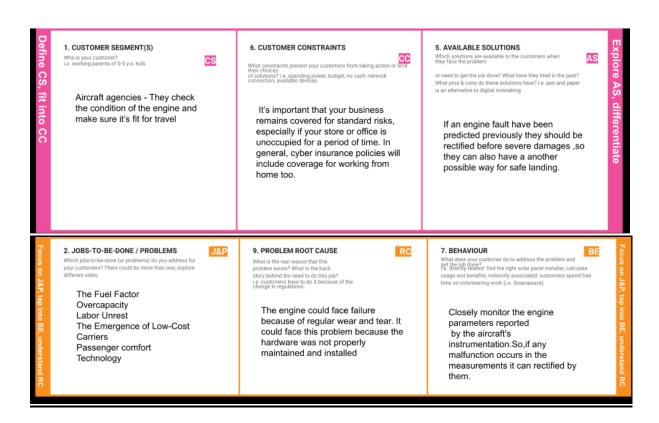
Society wise the project ensure lot of people life who trust the aircraft. As it provides the cycles an aircraft engine can fly helps in schedule the aircraft service early and provide it without any delay. It helps the passengers to reach the destination on time without any delay.

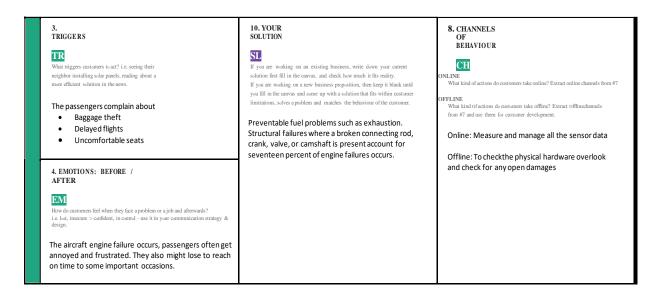
Proposed architecture:

Extract the Data, Pre-process the data for the model, train the data with different algorithm, validate and select the best algorithm, create a API and connect it with the trained model, then connect it with a user friendly UI to get and show the input and result.



3.4 Problem Solution fit





4. REQUIREMENT ANALYSIS

4.1Functional Requirements:

Following are the functional requirements of the proposed solution.

Following are the functional requirements of the proposed solution.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR No.	TT - D	
FR-1	User Registration	Registration through Form.
FR-2	User Confirmation	Confirmation via email. Confirmation via OTP.
FR-3	User Infrastructure	A platform for machine learning. An appropriate GPU and CPU.
FR-4	User Network	Internet access is required for the web server to host the application and send users' test results through email.
FR-5	User Cost	The web server running costs.
FR-6	User Requirements	Understanding of how to enter data into an application.

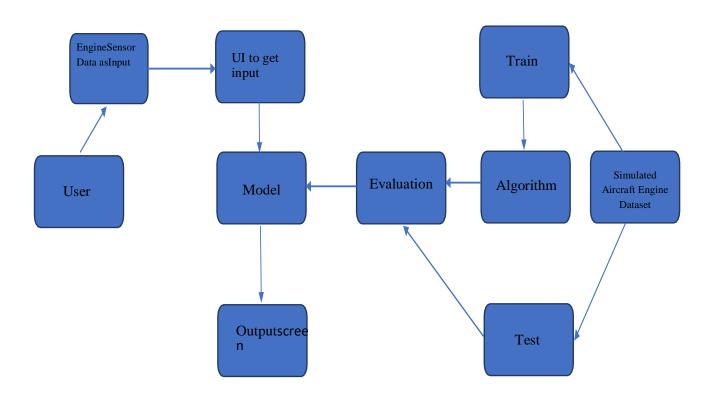
4.2 Non-Functional Requirements

Following are the non-functional requirements of the proposed solution.

FR No.	Non-Functional Requirement	Description
NFR-1	Usability	The application is too simple to use. It does not need special training.
NFR-2	Security	Both the user data and the web server hosting the application are secure.
NFR-3	Reliability	It specifies the probability of the performance of software with no failure for a particular number of uses or amount of time.
NFR-4	Performance	The machine learning model can predict outcomes very rapidly because it is quick.
NFR-5	Availability	All internet users must be able to access the web application, and it must be secure from denial-of-service attacks.
NFR-6	Scalability	The application needs to be flexible enough to scale up or down across various servers in response to demand.

5. PROJECT DESIGN

5.1 Data Flow Diagrams

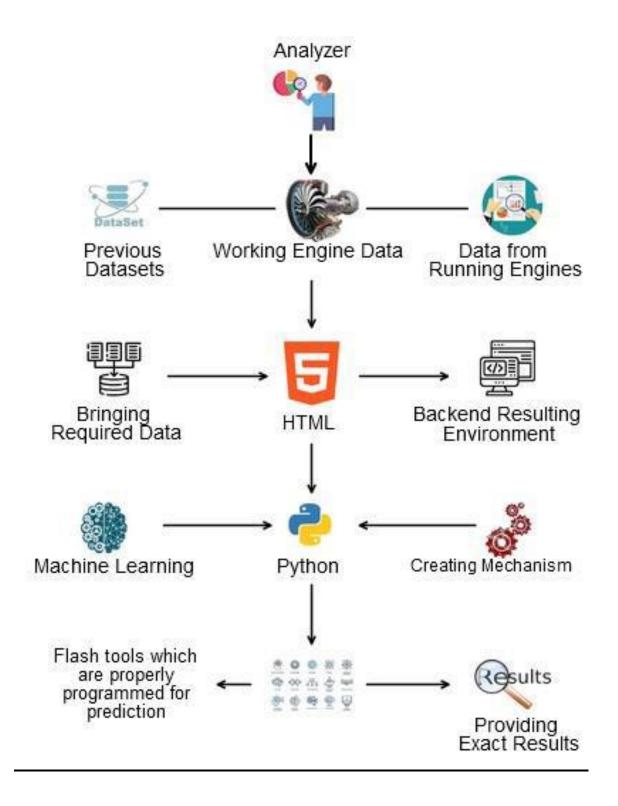


5.2 Solution & Technical Architecture

Solution architecture is a complex process – with many sub-processes – that bridges the gap between business problems and technology solutions. Its goals are to:

are to: \Box Find the best tech solution to solve existing business problems.
☐ Describe the structure, characteristics, behaviour, and other aspects of the software to project stakeholders.
☐ Define features, development phases, and solution requirements.
☐ Provide specifications according to which the solution is defined, managed, and delivered.

Example - Solution Architecture Diagram:



5.3 User Stories

UserType	FunctionalReq uirement (Epic)	User StoryNu mber	UserStory/Task	Acceptancecri teria	Priority	Release
Customer orUser WebUser	Entering Aircraft EngineData	USN -1	Enter the required datarequeste dintheformto predict the remainingcy clesofengine	Feedinput tothemod el forpredict ion	High	Sprint-1
		USN –2	EnterSubm ittogettheo utput	Can get theremainin gcyclesof engine	High	Sprint-1
		USN –3	View the Remaining cyclesofAircra ftengine	Getthepre dictedcycl es	High	Sprint-1

6. PROJECT PLANNING & SCHEDULING

6.1 Sprint Planning & Estimation

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1		USN-1	Download and pre-process the data set	1	High	Kanishkar, Karthikeyan
Sprint-2		USN-2	Train the model	2	High	Krishna Varshan,Kavya
Sprint-3		USN-3	Train, validate the dataset in the IBM Watson	3	Low	Karthikeyan
Sprint-4	Predict the engine's remaining cycle from by entering inputs in created application	USN-4	Develop app using flask and deploy using IBM Watson.	5	Medium	Karthikeyan, Kanishkar, Krishna Varshan, Kavya

6.2 Sprint Delivery Schedule

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Points Completed (as on Planned End Date)	Sprint Release Date (Actual)
Sprint-1	20	6 Days	24 Oct 2022	29 Oct 2022	20	29 Oct 2022
Sprint-2	20	6 Days	31 Oct 2022	05 Nov 2022	20	05 Nov 2022
Sprint-3	20	6 Days	07 Nov 2022	12 Nov 2022	20	12 Nov 2022
Sprint-4	20	6 Days	14 Nov 2022	19 Nov 2022	20	19 Nov 2022

7. CODING & SOLUTIONING

```
from flask import Flask, request, render_template
import pandas as pd
import joblib
import keras
import keras.backend as K
from keras.models import Sequential
from keras.layers import Dense , LSTM, Dropout
from keras.layers.core import Activation
from keras.callbacks import EarlyStopping, ModelCheckpoint
import random
import tensorflow as tf
import os
import numpy as np
from keras.models import load model
# Declare a Flask app
app = Flask( name )
@app.route('/', methods=['GET', 'POST'])
def main():
    if request.method == "POST":
        model = load model(r'C:\karthi\Projects\Nalai Thiran\Final 1\LSTM model.h5')
```

```
sensor 2 = request.form.get("sensor 2")
        sensor_3 = request.form.get("sensor_3")
        sensor_4 = request.form.get("sensor_4")
        sensor_7 = request.form.get("sensor_7")
        sensor_8 = request.form.get("sensor_8")
        sensor_11 = request.form.get("sensor_11")
        sensor_12 = request.form.get("sensor_12")
        sensor_13 = request.form.get("sensor_13")
        sensor_15 = request.form.get("sensor_15")
        sensor_17 = request.form.get("sensor_17")
        sensor_20 = request.form.get("sensor_20")
        sensor_21 = request.form.get("sensor_21")
        # Put inputs to dataframe
        test_seq = pd.DataFrame([[sensor_2,sensor_3,sensor_4,sensor_7,sensor_8,sensor_11,sensor_12,sensor_15,sensor_17,sensor_17,sensor_20,sensor_21]])
        y_pred_test = model.predict(test_seq,verbose=1, batch_size=200)
    else:
        prediction = ""
    return render_template("website.html", output = prediction)
# Running the app
if __name__ == '__main__':
    app.run(debug = True)
```

8. TESTING

Aircraft Engine Failure Prediction



Aircraft Engine Failure Prediction



Aircraft Engine Failure Prediction

cycles: 190

sensor_2: [643.7

sensor_3: [1572

sensor_4: [1384.9

sensor_7: [553.9

sensor_8: [2387.99

sensor_11: [47.05

sensor_12: [521.9

sensor_15: [8.32

sensor_17: [390.14

sensor_20: [38.90

sensor_21: [23.12

Run

Aircraft Engine Failure Prediction

cycles: Enter cy
sensor_2: Enter value
sensor_3: Enter value
sensor_4: Enter value
sensor_7: Enter value
sensor_7: Enter value
sensor_11: Enter value
sensor_12: Enter value
sensor_13: Enter value
sensor_15: Enter value
sensor_15: Enter value
sensor_17: Enter value
sensor_17: Enter value

9. RESULTS

Aircraft Engine Failure Prediction
cycles: Enter cy
sensor_2: Enter value
sensor_3: Enter value <
sensor_4: Enter value c
sensor_7: Enter value
sensor_8: Enter value c
sensor_11: Enter value
sensor_12: Enter value
sensor_13: Enter value c
sensor_15: [Enter valu
sensor_17: [Enter value
sensor_20: Enter value
sensor_21: Enter value
Run
Fly over the sky, long way to go!!! Lot of cycles remainding
Aircraft Engine Failure Prediction
cycles: Enter cy
sensor_2: Enter value
sensor_3: Enter value c
sensor_4: Enter value c
sensor_7: Enter value
sensor_8: Enter value c
sensor_11: Enter value
sensor_12: Enter value
sensor_13: Enter value c
sensor_15: Enter vali
sensor_17: Enter value
sensor_20: Enter value
sensor_21: Enter value
Run
Fly over the sky, Engine has [[68.687386]] cycles more
Aircraft Engine Failure Prediction
cycles: Enter cy
sensor_2: Enter value
sensor_3: Enter value c
sensor_4: Enter value c
sensor_7: Enter value
sensor_8: Enter value c
sensor_11: [Enfer value
sensor_12: Enter value
sensor_13: Enter value c
sensor_15: Enter vali
sensor_17: Entervalue
sensor_20: Enter value
sensor_21: Enter valu
Run
Need to change the engine, Aircraft has less than 20 cycles of lifetime

Aircraft Engine Failure Prediction	
cycles: Enter cy	
sensor_2: Enter value	
sensor_3: Enter value c	
sensor_4: Enter value c	
sensor_7: Enter value	
sensor_8: Enter value c	
sensor_11: Enter value	
sensor_12: Enter value	
sensor_13: Enter value c	
sensor_15: Enter vali	
sensor_17: Enter value	
sensor_20: Enter valur	
sensor_21: Enter value	
Run	
Fly over the sky, Engine has [[68.687386]] cycles more	

10. ADVANTAGES & DISADVANTAGES

ADVANTAGES:

Machine learning and data science can predict future events, trends, and customer behaviour to a certain extent. These predictions can enable businesses to make better decisions about where to allocate resources and how to respond to changes in the market.

Machine learning algorithms use historical data as input to predict new output values. Recommendation engines are a common use case for machine learning. Other popular uses include fraud detection, spam filtering, malware threat detection, business process automation (BPA) and Predictive maintenance

With the ever-growing volume of data generated every day, it is increasingly difficult for humans to process and make sense of all this information. Machine learning can help businesses handle large amounts of data more efficiently and effectively and even use decision trees to take action on the information.

As humans after gaining experience improve themselves in the same way machine learning improve themselves and become more accurate and efficient in work. This led to better decisions. For example, in the weather forecast, the more data and experience the machine gets the more advanced forecast it will provide.

DISADVANTAGES:

Although machine learning is considered to be more accurate it is highly vulnerable. For example, a set of programs provided to the machine may be biased or consist of errors. The same program is used to make another forecast or prediction then there will be a chain of errors that could be formed which may, although recognized but take some time to find out the source of the error.

The more data a machine gets the more accurate and efficient it becomes thus more data is required to input to the machine for better forecasting or decision making. But it may sometimes not be possible. Also, the data must be unbiased and of good quality. Data requirements are problematic sometimes. As we have already seen that a little manipulation or biased data could lead to a long drawn error chain and therefore there are chances of the inaccuracy of interpretation also. Sometimes data without any error could also be interpreted inaccurately by the machine as the data provided previously may not fulfil all the basics of the machine.

11. CONCLUSION

Overall, the results show that by bringing together sufficient (big) high quality data, robust machine learning algorithms, and data science, machine learning-based predictive analytics can be an effective tool for engine design-space exploration during the conceptual design phase. It would help to identify the best engine design expeditiously amongst several candidates. The promising results of the predictive analytics show that machine-learning techniques merit further exploration for application in aircraft engine conceptual design.

To further improve the accuracy (and reduce the uncertainty) of TSFC prediction. the database needs to be expanded However, the limitation of publicly available engine data is a challenge to overcome.

12. FUTURE SCOPE

• Early predictions avoid the accident and other problems.

- The process maintenance become easier...
- Predicting future also saves the money and the resources,
- Controls the machine and its performance.
- Train model in various machines can useful for the performance and maintenance.
- Machine learning algorithms can used for the models and the models monitor the performances.
- The algorithms can be update in high performance like the solution it will find itself.

14. GITHUB AND DEMO LINK

Github Link:

https://github.com/IBM-EPBL/IBM-Project-5357-1658760171

Demo Link:

https://drive.google.com/file/d/1rU3TrQywHG1yYPV9Tk6r6XUanmwwlsr4/view?usp=share_link