

**MACHINE LEARNING – BASED PREDICTIVE ANALYTICS FOR
AIRCRAFT ENGINE**

PROJECT REPORT

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Project Report Format

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1. INTRODUCTION

1.1 Project Overview

Engine failure is highly risky and needs a lot of time for repair. 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 which we will be dealing with the engine failure for a threshold number of days.

1.2 Purpose

The purpose of the project is to predict the failure of the engine using Machine Learning to save loss of time and money thus improving productivity.

2. LITERATURE SURVEY

2.1 Problem Statement Definition

1. +The study critically reviews the techniques and tools, infrastructure and general application architecture for discussing the applicability of data analytics based on both batch processing and real time stream data in general aviation for health monitoring and predictive analysis in order to predict maintenance and optimize the performance of aircrafts.
2. 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.
3. Due to high monitoring costs and restrictions to the monitoring environment, little condition monitoring data exists that can inform maintenance predictions for aircraft engines. As obtaining sufficient monitoring data is important for optimizing maintenance times, this

paper proposes a method for using generative adversarial networks (GANs) to generate condition monitoring data of aircraft engines.

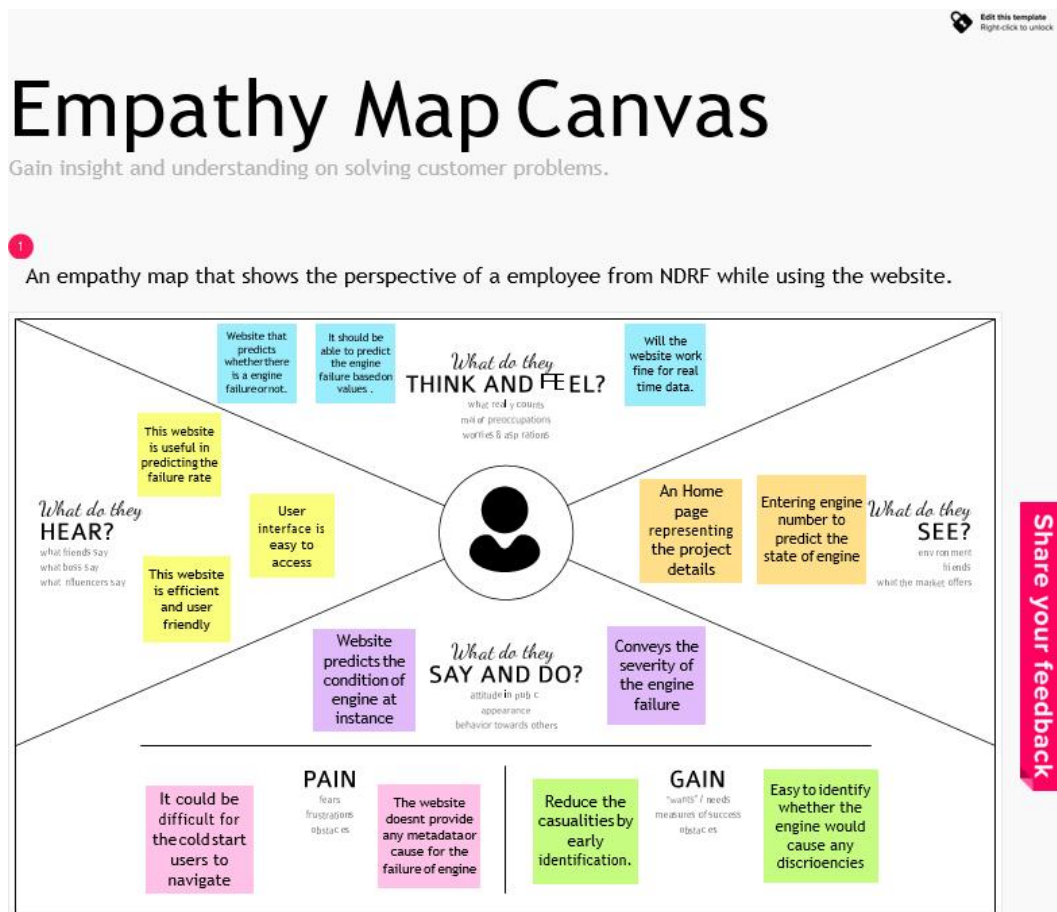
4. Traditional tools can no longer handle the increasing volume and velocity of data collected on modern aircraft. This paper proposes a generic and scalable pipeline for large-scale analytics of operational data from a recent type of aircraft engine, oriented towards health monitoring applications. Based on Hadoop and Spark, this approach enables domain experts to scale their algorithms and extract features from tens of thousands of flights stored on a cluster.
5. This paper addresses the problem of estimating aircraft on-board parameters using ground surveillance available parameters. The proposed methodology consists in training supervised Neural Networks with Flight Data Records to estimate target parameters. This paper investigates the learning process upon three case study parameters: the fuel flow rate, the flap configuration, and the landing gear position.

2.2 References

1. Predictive Maintenance and Performance Optimization in Aircrafts using Data Analytics(Shakthi Weerasinghe, Supunmali Ahangama.) IEEE 2018
2. Machine Learning-Based Predictive Analytics for Aircraft Engine Conceptual Design(Michael T. Tong)
3. A Maintenance-prediction Method for Aircraft Engines using Generative Adversarial Networks (Authors - Qiang Fu, Huawei Wang, Jianhua Zhao, Xiaojing Yan)
4. A Generic and Scalable Pipeline for Large-Scale Analytics of Continuous Aircraft Engine Data (Florent Forest, Jérôme Lacaille, Mustapha Lebbah and Hanene Azzag)
5. Approach And Landing Aircraft on-board Parameters Estimation with LSTM Networks (Author – Gabriel Jarry).

3. IDEATION & PROPOSED SOLUTION

3.1 Empathy Map Canvas



3.2 Ideation & Brainstorming

[illegible]

3.3 Proposed solution

Machine Learning Based Predictive Analytics for Aircraft Engine

Novelty :-

Suggestion of remedy measures for the engine failure while comparing with the threshold values of various parameters that are involved in predicting the engine state .

Feasibility of the project :-

Economical feasibility :

Since the project mainly focuses on software using sensor and no complicated hardware is required the overall cost doesn't get too high.

Technical feasibility|

Python,Flask ,and many machine learning algorithms are used to build the project and is used to achieve the desired result for the proposed model.

Social feasibility:

A proper management is maintained where the task is split into modules and given to individuals or teams based on their area of expertise.

Scheduling Feasibility:

Agile methodology is used and the project is scheduled and the process is monitored regularly within weeks.

Operational Feasibility:

The proposed solution solves the problem by well predicting the failure of engine in prior stages because of the frequent and periodic testing phases.

Social Impacts:-

1. As the failure of a particular engine is previously predicted one could know to not use that specific hardware and this drastically reduces the loss of life if that engine had been used in an aircraft.

[illegible]

3.4 Problem Solution Fit

Define CS, fit into CC	<p>1. CUSTOMER SEGMENT(S) Who is your customer? i.e. working parents of 0-5 y.o. kids CS</p> <p>Aircraft agencies - They check the condition of the engine and make sure it's fit for travel</p>	<p>6. CUSTOMER CONSTRAINTS What constraints prevent your customers from taking action or limit their choices of solutions? i.e. spending power, budget, no cash, network connection, available devices. CC</p> <p>It's important that your business remains covered for standard risks, especially if your store or office is unoccupied for a period of time. In general, cyber insurance policies will include coverage for working from home too.</p>	<p>5. AVAILABLE SOLUTIONS Which solutions are available to the customers when they face the problem? AS</p> <p>or need to get the job done? What have they tried in the past? What pros & cons do these solutions have? i.e. pen and paper is an alternative to digital notetaking</p> <p>If an engine fault have been predicted previously they should be rectified before severe damages, so they can also have a another possible way for safe landing.</p>	Explore AS, differentiate
Focus on J&P, tap into BE, understand R	<p>2. JOBS-TO-BE-DONE / PROBLEMS Which jobs to be done (or problems) do you address for your customers? There could be more than one, explore different sides. J&P</p> <p>The Fuel Factor Overcapacity Labor Unrest The Emergence of Low-Cost Carriers Passenger comfort Technology</p>	<p>9. PROBLEM ROOT CAUSE What is the real reason that this problem exists? What is the back story behind the need to do this job? i.e. customers have to do it because of the change in regulations. RC</p> <p>The engine could face failure because of regular wear and tear. It could face this problem because the hardware was not properly maintained and installed</p>	<p>7. BEHAVIOUR What does your customer do to address the problem and get the job done? i.e. directly related: find the right solar panel installer, calculate usage and benefits; indirectly associated: customers spend free time on volunteering work (i.e. Greenpeace) BE</p> <p>Closely monitor the engine parameters reported by the aircraft's instrumentation. So, if any malfunction occurs in the measurements it can be rectified by them.</p>	
	<p>3. TRIGGERS What triggers customers to act? i.e. seeing their neighbour installing solar panels, reading about a more efficient solution in the news. TR</p> <p>The passenger complain about Baggage Theft. Delayed Flights Uncomfortable seats Hidden charges Customer Service The passenger complain about</p> <p>4. EMOTIONS: BEFORE / AFTER How do customers feel when they face a problem or a job and afterwards? i.e. lost, insecure > confident, in control - use it in your communication strategy & design. EM</p> <p>A justified state of panic arises and the main focus shifts on getting them safely back on the ground without any further discrepancies</p>	<p>10. YOUR SOLUTION If you are working on an existing business, write down your current solution first, fill in the canvas, and check how much it fits reality. If you are working on a new business proposition, then keep it blank until you fill in the canvas and come up with a solution that fits within customer limitations, solves a problem and matches customer behaviour. SL</p> <p>First we have to prepare a clear measurements chart on the data of the engine and to check all the measurements with the recommended sensor values before utilization. Prior organization of these could help reduce any on-air problems or troubles</p>	<p>8. CHANNELS of BEHAVIOUR 8.1 ONLINE What kind of actions do customers take online? Extract online channels from #7 8.2 OFFLINE What kind of actions do customers take offline? Extract offline channels from #7 and use them for customer development. CH</p> <p>Online :Manage and measure all the sensor data Offline :To check the physical hardware overlook and check for any open damages</p>	

4.REQUIREMENT ANALYSIS

4.1 Functional Requirement

- 1.Business Requirement : Products, system, software and processes are ways of how to deliver, satisfy business requirements. Identifies relevant stakeholders. Establishes project goals and objectives. Elicit requirements from stakeholders. Document the requirements. Confirm the requirements. Prioritize the requirements.
- 2.User Requirement : Software should bring valuable results with accurate prediction. Prediction must be on time and should be able to save lives. They need accuracy while predicting with pre-historical datasets.
- 3.Product Requirement : It defines the product you are about to build, its main goal is to predict whether a engine will be in working condition based on the provided sensor values. Its main feature is to give the exact give the remaining time a engine could run for an aircraft.
- 4.Transaction Handling : It means that the user can access multiple data from the database without being interfaced by others. Historical data can be accessed without any issues. Technicians must have access with the database maintenance. Results must be accessible to anyone with the permission to predict the values.
- 5.Business requirement and certification requirement : A proper certificate has to be provided for the project. It must be issued by the proper aviation industry management system under the control of government. Certification enables it as an non-hazardous project. Thus, it increases the trust among the general public.

4.2 Non-functional Requirement

- 1.Usability : Usability is a quality attribute that assesses how easy user interfaces are to use. The word "usability" also refers to methods for improving ease-of-use during the design process.
2. Security : Security consists of the platforms which protect your organization's users, endpoints and their online activity to more efficiently correlate threats. As users are increasingly logging in to networks via their personal devices, securing these is just as important as securing company owned devices.

3. Reliability : Reliability requirements are typically part of a technical specifications document. They can be requirements that a company sets for its product and its own engineers or what it reports as its reliability to its customers. They can also be requirements set for suppliers or subcontractors.

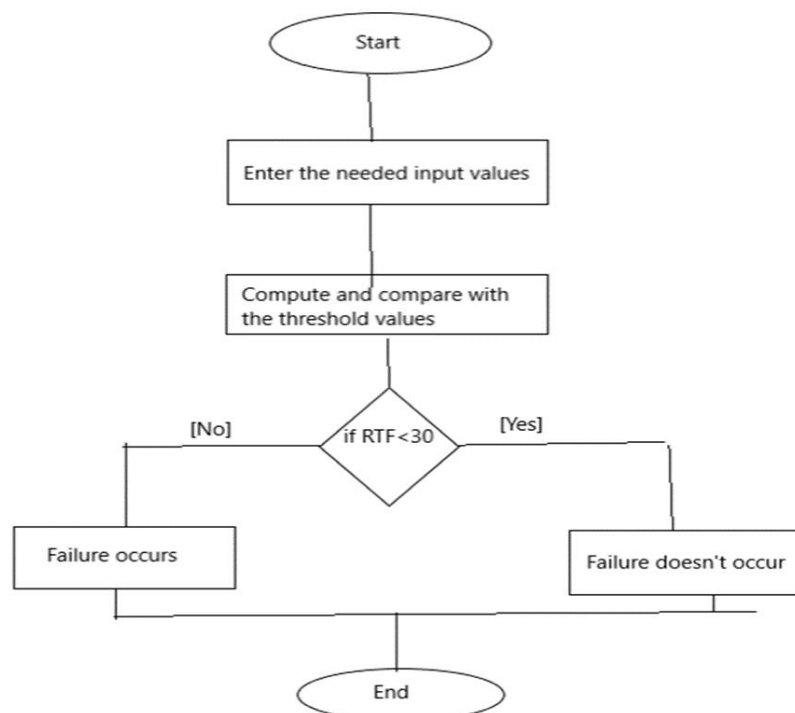
4. Availability : Availability describes how likely the system is accessible to a user at a given point in time. While it can be expressed as an expected percentage of successful requests, you may also define it as a percentage of time the system is accessible for operation during some time period.

5. Scalability : Scalability requirements are, in essence, a reflection of the organization's ambition to grow and the need for a solution to support the growth with minimal changes and disruption to everyday activities.

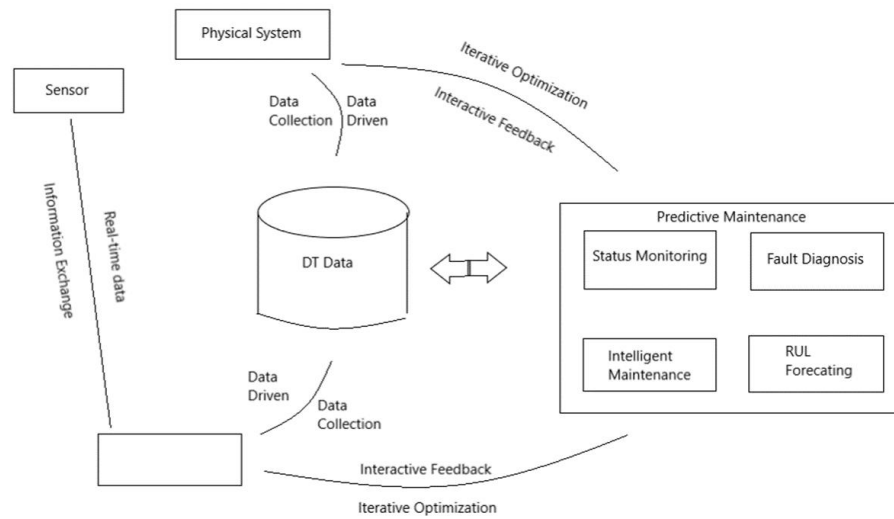
5.PROJECT DESIGN

5.1 Data Flow Diagram

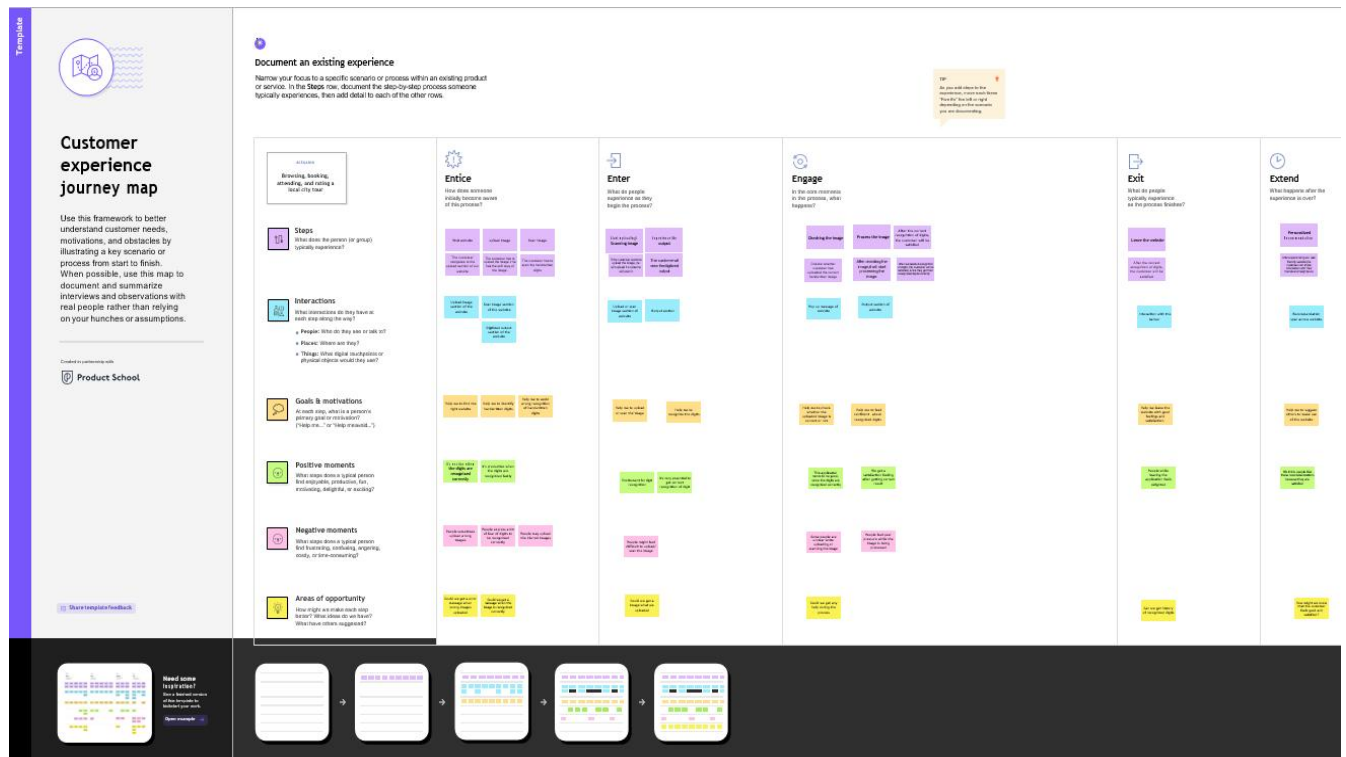
A Data Flow Diagram (DFD) is a traditional visual representation of the information flows within a system. A neat and clear DFD can depict the right amount of the system requirement graphically. It shows how data enters and leaves the system, what changes the information, and where data is store.



5.2 Solution & Technical Architecture



5.3 User Stories



6. PROJECT PLANNING & SCHEDULING

6.1 Sprint planning & estimation

Project Planning (Product Backlog, Spring Planning, Stories, Story Points)

Date	29 th October, 2022
Team ID	PNT2022TMID17747
Project Name	Machine Learning – Based Predictive Analytics for Aircraft Engine
Maximum Marks	8 Marks

Product Backlog, Sprint Schedule and Estimation (4 Marks)

SPRINT NO	FUNCTION PERFORMED	TASK	STORY POINTS	PRIORITY	TEAM MEMBERS
SPRINT-1	Data Collection and processing	The needed data for processing and cleaning of the same has been done	20	High	Swetha R
SPRINT-2	Model Building	Splitting of data into two sets and testing of the data is done	20	High	Sneha Raksha SK
SPRINT-3	Integrating with flask	Python has been integrated with flask framework	20	High	Akila S
SPRINT-4	Deployment of code	Deployment of code has been done	20	High	Kiruthika D

6.2 Sprint Delivery Schedule

Project Tracker, Velocity & Burndown Chart: (4 Marks)

SPRINTS	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	10 NOV 2022	20	10 NOV 2022
Sprint – 4	20	6 DAYS	14 NOV 2022	18 NOV 2022	20	18 NOV 2022

VELOCITY :

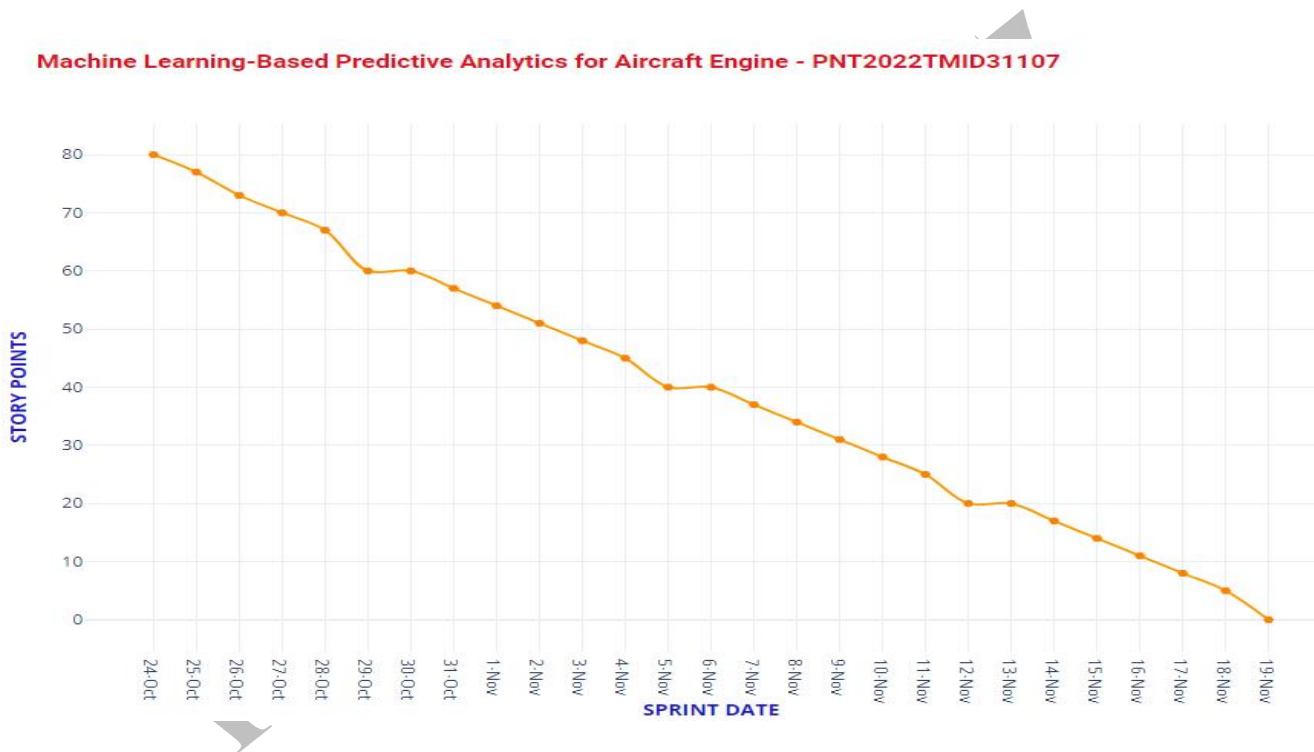
SPRINT DURATION : 6 Days

VELOCITY OF THE TEAM : 20(Points per Sprint)

TOTAL AVERAGE VELOCITY: $AV = \text{sprint valuation} = 20 = 3.3 \text{ Story points per day}$

Velocity 6

BURNDOWN CHART :



7.CODE:

```
# -*- coding: utf-8 -*-  
"""Untitled6.ipynb
```

Automatically generated by Colaboratory.

Original file is located at

<https://colab.research.google.com/drive/14IZpvoMVFe-SjH-G3b4iSTEGA-olFg6N>

```
"""
```

```
def predict(data):  
    try:  
        col_name =  
        ['id','cycle','set1','set2','set3','s1','s2','s3','s4','s5','s6','s7','s8']+['s9',  
        's10','s11','s12','s13','s14','s14','s15','s16','s17','s18','s19','s20']  
        test_dataset = pd.DataFrame([data],columns=col_name)  
        rul=pd.DataFrame(test_dataset.groupby("id")['cycle'].max()).reset_index()  
        rul.columns = ['id','max']  
        truth_ds['rtf']=truth_ds['more']+rul["max"]  
        truth_ds.head()  
        truth_ds['rtf']=truth_ds['more']+rul["max"]  
        test_dataset=test_dataset.merge(truth_ds, on= ['id'], how= "left")  
        test_dataset[ 'ttf']=test_dataset['rtf'] - test_dataset['cycle']  
        test_dataset.drop ('rtf', axis=1, inplace=True)  
        df_test = test_dataset.copy()  
        period = 30  
        df_test['label_bc'] = df_test ['ttf'].apply(lambda x: 1 if x <= period  
else 0)
```

```

        df_test = df_test.dropna()
        if len(df_test.index) == 0 :
            return True
        x_test = df_test.iloc[ : , : -2].values
        y_pred = model.predict(x_test)
        return True if y_pred[0] else False
    except:
        return True

from flask import Flask, render_template
from flask import request
from flask_cors import CORS
import joblib

import requests

# NOTE: you must manually set API_KEY below using information retrieved from your
# IBM Cloud account.
API_KEY = "uRaU-TjwldvnODMwaDakva7BY1NKMjg2n6OFsnMoFrXa"
token_response =
requests.post('https://iam.cloud.ibm.com/identity/token',data={"apikey": API_KEY,
"grant_type": 'urn:ibm:params:oauth:grant-type:apikey'})
mltoken = token_response.json()["access_token"]

header = {'Content-Type': 'application/json', 'Authorization': 'Bearer ' + mltoken}
app = Flask(__name__)
CORS(app)

@app.route('/')
def index():
    return render_template('ibm.html')
@app.route('/pre', methods=['POST'])
def result():
    a="problem"
    b="not a failure"
    c="check the inputs"
    #try:
        #if request.method == 'POST':
            id1=float(request.form['id'])
            cyc=float(request.form['cycle'])
            set1=float(request.form['set1'])
            set2=float(request.form['set2'])
            set3=float(request.form['set3'])
            s1=float(request.form['s1'])
            s2=float(request.form['s2'])
            s3=float(request.form['s3'])
            s4=float(request.form['s4'])
            s5=float(request.form['s5'])
            s6=float(request.form['s6'])
            s7=float(request.form['s7'])
            s8=float(request.form['s8'])
            s9=float(request.form['s9'])
            s10=float(request.form['s10'])
            s11=float(request.form['s11'])
            s12=float(request.form['s12'])
            s13=float(request.form['s13'])

```

```

s14=float(request.form['s14'])
s15=float(request.form['s15'])
s16=float(request.form['s16'])
s17=float(request.form['s17'])
s18=float(request.form['s18'])
s19=float(request.form['s19'])
s20=float(request.form['s20'])
s21=float(request.form['s21'])
last =
predict([[id1,cyc,set1,set2,set3,s1,s2,s3,s4,s5,s6,s7,s8,s9,s10,s11,s12,s13,s14,s15,s16,s17,s18,s19,s20]])

l=[[id1,cyc,set1,set2,set3,s1,s2,s3,s4,s5,s6,s7,s8,s9,s10,s11,s12,s13,s14,s15,s16,s17,s18,s19,s20,s21,last]]
payload_scoring = {"input_data": [{"field":
[['id1','cyc','set1','set2','set3','s1','s2','s3','s4','s5','s6','s7','s8','s9','s10','s11','s12','s13','s14','s15','s16','s17','s18','s19','s20','s21','last']], "values": l}]}
response_scoring = requests.post('https://us-south.ml.cloud.ibm.com/ml/v4/deployments/6b03fb5d-159d-4b31-bfc0-e51cd75e797a/predictions?version=2022-11-21',
json=payload_scoring,headers={'Authorization': 'Bearer ' + mltoken})
print(response_scoring)
print(response_scoring.json())

predictions=response_scoring.json()
predict1=predictions['predictions'][0]['values'][0][0]
print("Final Predictions:",predict1)

if predict1:
    print(a)
    val =a
    #return a
else:
    print(b)
    val =b
    #return b
    return render_template('result.html', ans=val)
if __name__ == "__main__":
    app.run(debug=False)

```

8.TESTING:

8.1 Testing:

- Login Page
- Result Page

8.2 User Acceptance Testing:

1. Purpose of Document

The purpose of this document is to briefly explain the test coverage and open issues of the [ProductName] project at the time of the release to User Acceptance Testing (UAT).

2. Defect Analysis

This report shows the number of resolved or closed bugs at each severity level, and how they were resolved

Resolution	Severity 1	Severity 2	Severity 3	Severity 4	Subtotal
By Design	10	4	2	3	20
Duplicate	1	0	3	0	4
External	2	3	0	1	6
Fixed	11	2	4	20	37
Not Reproduced	0	0	1	0	1
Skipped	0	0	1	1	2
Won't Fix	0	5	2	1	8
Totals	24	14	13	26	77

3. Test Case Analysis



This report shows the number of test cases that have passed, failed, and untested

Section	Total Cases	Not Tested	Fail	Pass
Print Engine	7	0	0	7
Client Application	51	0	0	51
Security	2	0	0	2
Outsource Shipping	3	0	0	3
Exception Reporting	9	0	0	9

Final Report Output	4	0	0	4
Version Control	2	0	0	2

9.RESULTS

9.1 Performance Metrics

S.No.	Parameter	Values	Screenshot
1.	Metrics	Regression Model: MAE - , MSE - , RMSE - , R2 score -	 <pre> from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score # Train the model model = LinearRegression() model.fit(X_train, y_train) # Predict on training data y_train_pred = model.predict(X_train) # Calculate metrics mae = mean_absolute_error(y_train, y_train_pred) mse = mean_squared_error(y_train, y_train_pred) rmse = sqrt(mse) r2 = r2_score(y_train, y_train_pred) print("MAE:", mae) print("MSE:", mse) print("RMSE:", rmse) print("R2 Score:", r2) MAE: 0.0089113332871283 MSE: 0.00004333333333333 RMSE: 0.00658111111111111 R2 Score: 0.9999999999999999 </pre>
2.	Tune the Model	Hyperparameter Tuning - Validation Method -	 <pre> from sklearn.model_selection import GridSearchCV # Logistic Regression logistic = LogisticRegression() grid_logistic = GridSearchCV(logistic, param_grid, cv=5) grid_logistic.fit(X_train, y_train) best_logistic = grid_logistic.best_estimator_ print("Best Logistic Regression Model") # Decision Tree decision_tree = DecisionTreeRegressor() grid_decision_tree = GridSearchCV(decision_tree, param_grid, cv=5) grid_decision_tree.fit(X_train, y_train) best_decision_tree = grid_decision_tree.best_estimator_ print("Best Decision Tree Model") # Support Vector Machines svm = SupportVectorMachine() grid_svm = GridSearchCV(svm, param_grid, cv=5) grid_svm.fit(X_train, y_train) best_svm = grid_svm.best_estimator_ print("Best Support Vector Machine Model") Logistic Regression [1. 0.99999999 0.99999999 0.99999999 0.99999999] Decision Tree [1. 1. 1. 1. 1.] Support Vector Machines [1. 1. 1. 1. 1.] RM [0.00891133 0.00004333 0.00658111 0.99999999 0.99999999] </pre>

Home Page :

← → ↻ File | C:/Users/DELL/Documents/ibm.html

AIR *predict*

SENSOR DATA

S1:	
S2:	
S3:	
S4:	
S5:	
S6:	
S7:	
S8:	
S9:	
S10:	
S11:	
S12:	
S13:	
S14:	
S15:	
S16:	
S17:	
S18:	
S19:	
S20:	
S21:	
Cycle:	

Submit

Result page



Engine might fail in 30 days !!!!

10.ADVANTAGES AND DISADVANTAGES

10.1 Advantages

To a certain extent, machine learning and data science can forecast upcoming occasions, trends, and consumer behaviour. These forecasts can help companies decide more effectively where to deploy their resources and how to react to market changes.

In order to forecast new output values, machine learning algorithms use historical data as input. Machine learning is frequently used in recommendation engines. Other common applications include business process automation (BPA), predictive maintenance, spam filtering, malware threat detection, and fraud detection.

It is becoming more and more challenging for people to interpret and make sense of the vast amount of data generated every day. Businesses can use decision trees and massive volumes of data more effectively and efficiently with machine learning.

10.2 Disadvantages

Even if machine learning is thought to be more accurate, it is very open to attack. For instance, the machine might be given a collection of biased or flawed programmes. When the same programme is used to create multiple forecasts or predictions, a chain of errors may develop that, while recognisable, may take some time to identify the source of.

For better forecasting or decision-making, a computer needs to be fed with more data since the more data it receives, the more accurate and effective it becomes. But occasionally, it might not be achievable. Additionally, the information must be accurate and neutral. Data requirements can be challenging at times.

11.CONCLUSION

Overall, the results demonstrate that machine learning-based predictive analytics can be a useful tool for engine design-space exploration during the conceptual design phase when combined with enough (large) high quality data, reliable machine learning algorithms, and data science. It would be beneficial to quickly choose the best engine design out of multiple

contenders. The positive outcomes of the predictive analytics demonstrate the need for additional research into the use of machine learning techniques in the conceptual design of aviation engines. The database has to be increased in order to further increase the precision (and decrease the uncertainty) of TSFC prediction. However, it is difficult to get beyond the restriction of publicly accessible engine data.

12.FUTURE SCOPE

- Process maintenance has become simpler.
- Making future predictions also helps to conserve resources and money.
- Regulates the machine's operation.
- Train models for various machinery might be helpful for upkeep and performance.
- Models can apply machine learning methods, and the models can track performance.
- High performance algorithm updates are possible, just like the algorithms' self-solving capabilities.