

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

A PROJECT REPORT

Submitted by

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Machine Learning-Based PredictiveAnalytics for Aircraft Engine

Team ID	PNT2022TMID23879
Project Name	Machine Learning-Based Predictive Analytics for AircraftEngine
Team Members	Narmatha D (Team Leader) Srinidi M (Team Member 1) Sowndharya S (Team Member2) Vidhya N (TeamMember 3)

1. INTRODUCTION

1.1 Project overview

Machine learning is a branch of artificial intelligence that uses statistical technique and mathematical algorithms to enable a machine to learn from data, to analyze data patterns, and to make decisions with minimal human intervention. 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 performance prediction. 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.

1.2 Purpose

Predictive analytics help us to understand possible future occurrences by analyzing the past. Predictive modeling solutions are a form of data-mining technology that works by analyzing historical and current data and generating a model to help predict future outcomes. Machine learning, on the other hand, is a subfield of computer science that, as per Arthur Samuel's definition from 1959, gives 'computers the ability to learn without being explicitly programmed'.

2. LITERATURE SURVEY

2.1 Existing problem

The majority of the returns we receive from the field are found not to be issues with the turbocharger itself, but in most cases they are problems with the system's installation, inadequate pre-lubrication, or other operational issues. Typically a mechanic must inspect and diagnose operational issues that may include an inability for the

aircraft to reach altitude; pressurization issues; the system's inability to reach the maximum rated manifold pressure; a surging or dropping off of manifold pressure when climbing or descending; and/or oil leaks from the compressor or turbine side of the turbocharger.

2.2 Reference

- <https://ntrs.nasa.gov/api/citations/20205007448/>
- <https://youtu.be/qYhTdcYhhk8>
- <https://www.geeksforgeeks.org/deploy-machine-learning-model-using-flask/>
- <https://towardsdatascience.com/building-a-machine-learning-web-application-using-flask29fa9ea11dac> https://www.youtube.com/watch?v=wUPreN43_dY

2.3 Problem Statement Definition

This article aims to prove that Machine Learning (ML) methods are effective for Predictive Maintenance (PdM) and to obtain other developing methods that suitable applied on PdM, especially for aircraft engine, and potential method that can apply on future research, and also compared between articles in International and Indonesia institution. Maintenance factors are important to prognostic the states of a machine. PdM is one of the factor strategies based on real time data to diagnosis a failure of the machine through forecasting remaining useful life (RUL), especially on aircraft machine where the safety is priority due to enormous cost and human life. ML is the technique that accurately prediction through the data. Applied ML on PdM is the huge contribution for saving cost and human life guarantee of safety. The capacity of machinery working cannot last forever, sometimes it will be broken-down because of out-date operation. Machinery system that included sensors are just monitoring state of the machine, but cannot make a report the machine in good or bad condition.

3. IDEATION & PROPOSED SOLUTION

3.1 Empathy Mapcanvas

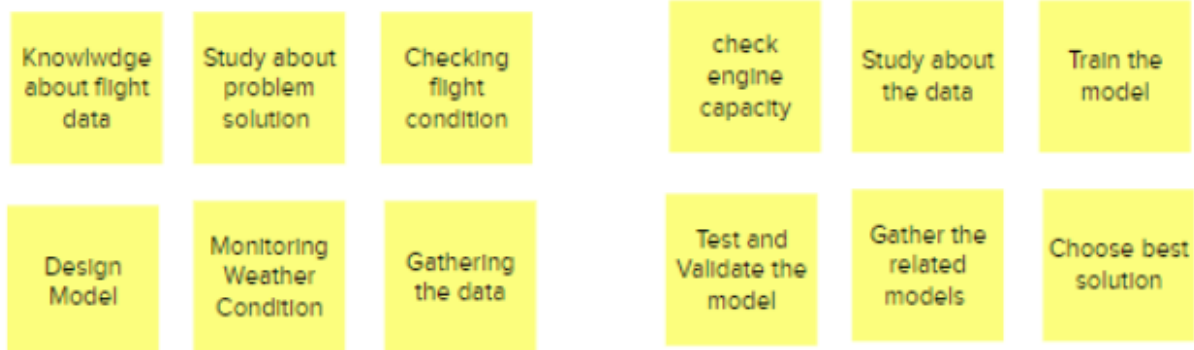
MACHINE LEARNING-BASED PREDICTIVE ANALYSIS FOR AIRCRAFT ENGINE



3.2 Ideation&Brainstorming

NARMATHA D

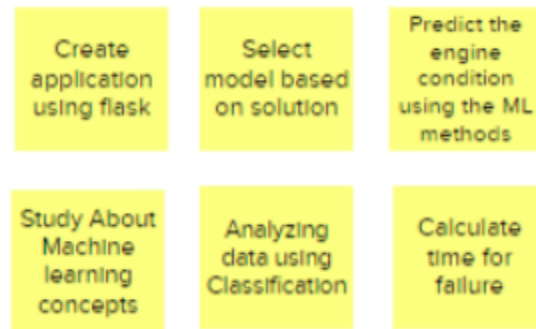
SRINIDI M



SOWNDHARYA S



VIDHYA N



3.3 Proposed Solution

To predict the failure of an engine by using Machine Learning to save loss of time & money thus improving productivity. Machine learning (ML) is a type of artificial intelligence (AI) that allows software applications to become more accurate at predicting outcomes without being explicitly programmed to do so. The failure can be predicted by installing the sensors and keeping a track of the values.

3.4 Proposed Solution Fit

To predict the failure of an engine by using Machine Learning to save loss of time & money thus improving productivity. Novelty / Uniqueness : Gas-turbine engines are critical to the operation of most industrial plants, aircraft, and heavy vehicles such as military armor and transport ships, and their associated maintenance costs can be high. Social Impact / Customer : Satisfaction Unhappy or disengaged customers naturally mean fewer passengers and less revenue. It's important that customers have an excellent experience every time they travel. Business Model (Revenue Model) : While safety and performance are the primary goals of aircraft maintenance. Scalability of the Solution : The Scalability calculated by machine learning methods.

4. REQUIREMENT ANALYSIS

4.1 Functional requirement

Following are the functional requirements of the proposed solution.

FR-1 User Registration ,Registration through Form Registration through Gmail

Registration through LinkedIn

FR-2 User Confirmation ,via Email Confirmation via OTP

FR-3 Tracking Expense Helpful insights about money management

FR-4 Alert Message Give alert mail if the amount exceeds the budget limit

FR-5 Category This application shall allow users to add categories of their expenses

4.2 Non Functional requirement

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

NFR-1 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.

NFR-2 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.

NFR-3 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.

NFR-4 Performance requirements define how well the software system accomplishes certain functions under specific conditions. Examples include the software's speed of response, throughput, execution time and storage capacity. The service levels comprising performance requirements are often based on supporting end-user tasks.

NFR-5 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.

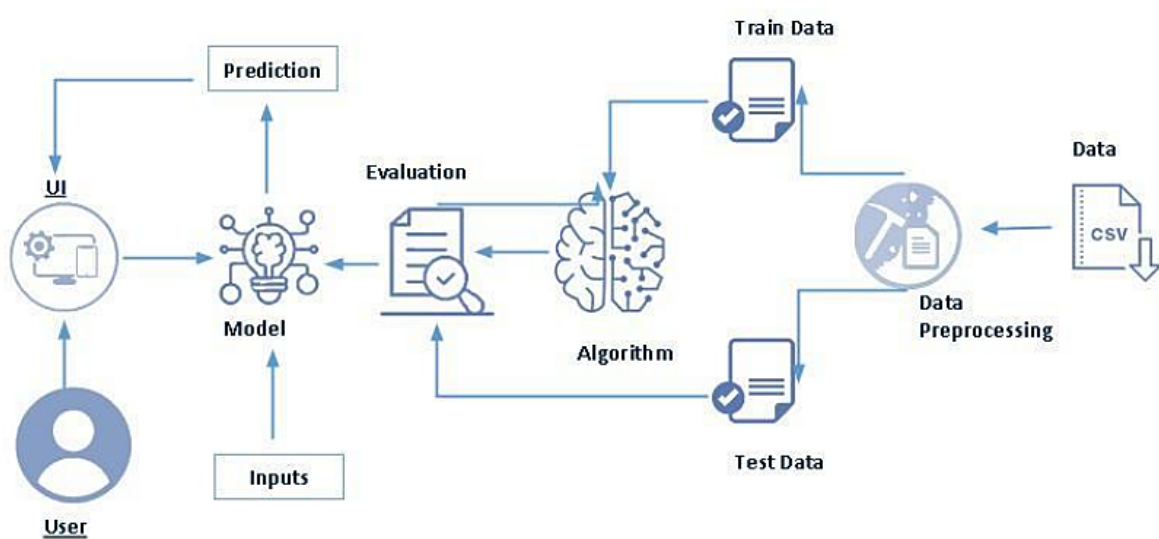
NFR-6 Scalability Scalability requirements are, in essence, a reflection of the organization's ambition to grow and the need for a solution to support the growth with minimal changes and disruption to everyday activities

5. PROJECT DESIGN

5.1 Data Flow Diagrams

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 AND TECHNICAL ARCHITECTURE



5.3 User Stories

Use the below template to list all the user stories for the product.

User Type	Functional Requirement(Epic)	User Story Number	User Story/ Task	Acceptance criteria	Priority	Release
Customer (Mobile user)	Registration	USN-1	As a user,I can register for the application	I can access my account / dashboard	High	Sprint
			by entering my email,			

			password			
--	--	--	----------	--	--	--

			and confir mi ng my password.			
		USN-2	As a user, I canregister for the application through Facebook	I can register &access the dashboard withFacebo ok Login	Medium	Sprint-1
		USN-3	As a user, I can registerfor the application through Gmail	I can register by entering the details	Low	Sprint-2
	Login	USN-4	As a user, I can loginto the application by entering email & password	I can accessmy dashboard	High	Sprint 1
	Facebo oklogin	USN-5	As a user, I can loginto the application by using facebook	I can accessmy dashboard	Medium	Sprint 1

	Gmail login	USN-6	As a user, I can loginto the application by using gmail	I can access my account / dashboard	Low	Sprint 1
	Analyze or detect problems	USN-7	As a user, I can able to analyze the problem in aircraft engine.	I can analyze the problem	High	Sprint 1
	Identify the fault engine	USN-8	As a user, I can identify the engine that is get fault	I can access the engine data	Medium	Sprint 1
	Solution	USN-9	As a user, I can view the solutionfor minad and major problems	I can receive alertemail	High	Sprint 1
	solution	USN-10	As a user I can find the solution and suggestion for maintainthe engine	I can track expense	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	Registration	USN-1	As a user, I can register for the application by entering my email, password, and confirming my password.	3	High	4
Sprint-1	Facebook Registration	USN-2	As a user, I can register for the application through Facebook	1	Medium	4

Sprint-1	Gmail registration	USN-3	As a user, I can register for the application through Gmail	3	Low	4
Sprint-2	Login	USN-4	As a user,I can log into the application by entering email & password	3	High	4
Sprint-2	Facebook	USN-5	As a user, I can log in intothis application through Facebook	2	Medium	4
Sprint-2	Gmail	USN-6	As a user, I can log in into this application through Gmail	1	Low	4
Sprint-3	Analyzing /Detecting Problems	USN-7	As a user, I can ableanalyze the defectsin Aircraft Engine	3	High	4

Sprint-3	Analyzing /Detecting Problems	USN-8	As a user, I can able to viewthe repeated problems occurs in Aircraft Engine	2	Medium	4
Sprint-3	Analyzing /Detecting Problems	USN-9	As a user, I can able to findthe defects occurs in Aircraft Engine	1	Low	4

Sprint-4	Solution	USN-10	As a user, I can viewthe solution for minor problems of theAircraft Engine	3	High	4
Sprint-4	Solution	USN-11	As a user, I can view the solution for major problems of the Aircraft Engine	2	Medium	4
Sprint-4	Solution	USN-12	As a user, I can find the solution and suggestion to maintain for regular services	1	Low	4

6.2 Sprint Delivery Schedule

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint EndDate (Planned)	Story Points Completed(asonPlanned End Date)	Sprint ReleaseDate(Actual)
Sprint-1	20	6 Days	24Oct2022	29Oct2022	20	29Oct2022
Sprint-2	20	6 Days	31Oct2022	05Nov2022	18	06Nov2022
Sprint-3	20	6 Days	07Nov2022	12Nov2022	15	14Nov2022
Sprint-4	20	6 Days	14Nov2022	19Nov2022	19	21Nov2022

7 Coding and Solutioning:

7.1 Features

Feature 1: Trained Model

Feature 2: Prediction

Feature 3: Engine

Feature 4: Send Alert Emails to users

7.2 Other Features:

Analyse the data that gives as an input and predict it using the model trained in the IBM cloud. It let the uses to know about the engine performance using the sensor values. Alerts if any performance fault is found in data. It helps to maintain the engine in an proper state.

```
1 from flask import Flask, render_template, request
2 import numpy as np
```



```
3
4
5 import requests
6
7 # NOTE: you must manually set API_KEY below using information
  retrieved from your IBM Cloud account.
8 API_KEY = "<Your API>"
9 token_response =
  requests.post('https://iam.cloud.ibm.com/identity/token',
  data={"apikey":
10 API_KEY, "grant_type": 'urn:ibm:params:oauth:grant-
  type:apikey'})
11 mltoken = token_response.json()["access_token"]
12
13 header = {'Content-Type': 'application/json', 'Authorization':
  'Bearer ' + mltoken}
14
15 app = Flask(__name__)
16
17
18 #home page
19 @app.route('/')
20 def home():
21     return render_template('home.html')
22
23
24 #signup page
25 @app.route('/register')
26 def register():
27     return render_template('register.html')
28
29
30 #login page
31 @app.route('/login')
32 def login():
33     return render_template('login.html')
34
35
36 #prediction page
37 @app.route('/index')
```

```
38 def index():
39     return render_template('index.html')
40
41
42 #result page prediction function
43 @app.route('/result', methods= ['POST'])
44 def result():
45     try:
46         if request.methods == 'POST':
47             l=[]
48             l.append(float(request.form['id']))
49             l.append(float(request.form['cycle']))
50             l.append(float(request.form['set1']))
51             l.append(float(request.form['set2']))
52             l.append(float(request.form['set3']))
53             l.append(float(request.form['s1']))
54             l.append(float(request.form['s2']))
55             l.append(float(request.form['s3']))
56             l.append(float(request.form['s4']))
57             l.append(float(request.form['s5']))
58             l.append(float(request.form['s6']))
59             l.append(float(request.form['s7']))
60             l.append(float(request.form['s8']))
61             l.append(float(request.form['s9']))
62             l.append(float(request.form['s10']))
63             l.append(float(request.form['s11']))
64             l.append(float(request.form['s12']))
65             l.append(float(request.form['s13']))
66             l.append(float(request.form['s14']))
67             l.append(float(request.form['s15']))
68             l.append(float(request.form['s16']))
69             l.append(float(request.form['s17']))
70             l.append(float(request.form['s18']))
71             l.append(float(request.form['s19']))
72             l.append(float(request.form['s20']))
73             l.append(float(request.form['s21']))
74             l.append(float(request.form['s22']))
75             print(l)
76             # NOTE: manually define and pass the array(s) of
values to be scored in the next line
```

```

77         payload_scoring = {"input_data": [{"fields":
    ['f0','f1','f2','f3','f4','f5','f6','f7','f8','f9','f10','f11','f
    12','f13','f14','f15','f16','f17','f18','f19','f20','f21','f22','
    f23','f24','f25','f26'], "values": [1]}]}
78
79         response_scoring =
    requests.post('https://south.ml.cloud.ibm.com/ml/v4/deployments/c
    870b-1697-49d5-86e7-302bd8fccd/predictions?version=2022-11-14',
    json=payload_scoring,
80         headers={'Authorization': 'Bearer ' + mltoken})
81         print("Scoring response")
82         print(response_scoring.json())
83         pred = response_scoring.json()
84         output = pred['predictions'][0]['values'][0][0]
85         print(output)
86
87         if output >=1 and output <=2 :
88             return
    render_template('result.html',data="normal")
89         elif output >2:
90             return
    render_template('result.html',data="excess")
91         else :
92             return render_template('result.html',data="low")
93     except:
94         return render_template('result.html',data="error")
95 if __name__=="__main__":
96     app.run(debug=True)

```

TESTING:

8 TESTING:

8.1 TESTING:

- i. Login Page

ii. Prediction Page

iii. Result Page

User Acceptance Testing:

Purpose of Document

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

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	8	15
Duplicate	1	0	3	0	4
External	2	3	0	1	6
Fixed	9	2	4	11	20
Not Reproduced	0	0	1	0	1
Skipped	0	0	1	1	2
Won't Fix	0	5	0	1	8
Totals	22	14	11	22	51

Test Case Analysis

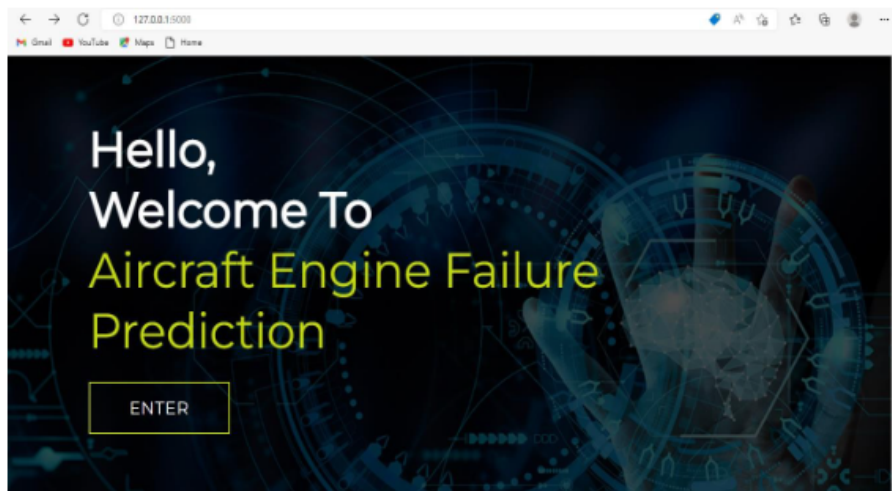
This report shows the number of test cases that have passed, failed, and untested

Section	Total Cases	Not Tested	Fail	Pass
Login	7	0	0	7

Prediction	27	0	0	27
Result	4	0	0	4

9 RESULTS

9.1 Homepage



9.2 SIGN UP PAGE



9.3 LOGIN PAGE

Enter Engine Parameters		
1	14.62	8134.97
2	21.61	8.1914
3	554.89	0.08
4	2988.05	491
5	9071.59	2988
6	140	100.00
7	47.31	38.85
8	522.01	23.8952
9	2388.06	0

Evaluate

9.4 PREDICTION PAGE

Limit Page

PREDICTIVE ANALYSIS FOR AIRCRAFT ENGINE
USING MACHINE LEARNING

Done

THE ENGINE IS NORMAL

NO ANOMALIES FOUND IN THE GIVEN DATA

GO BACK

10. ADVANTAGES AND DISADVANTAGES

10.1. ADVANTAGES:

Machine learning and data science can predict future events, trends, and customer behavior 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.

10.2 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 fulfill all the basics of the machine.

8. 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.

9. 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.

10. APPENDIX:

GITHUB & PROJECT DEMO LINK:

The GitHub link: <https://github.com/IBM-EPBL/IBM-Project-36928-1660298939/blob/main/FINAL%20DELIVERABLES/output%20video.mp4>