PREDICTIVE ANALYTICS FOR AIRCRAFT ENGINE

USING CLOUD

A Project report submitted in partial fulfilment of 7th semester in degree of

BACHELOR OF ENGINEERING

IN

COMPUTER SCIENCE AND ENGINEERING

Submitted by

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BONAFIDE CERTIFICATE

Certified this Report "PREDICTIVE ANALYTICS FOR AIRCRAFT ENGINE", for the project, is the bonafied work of **R.ABBROSE BARVIN(950619104001),S.ALAGURAMALAKSHMI(950619104004) N.ARUNA LAKSHMI(950619104008),S.HARINI(950619104024)** who carried out the project work under my supervision. Certified further that to the best of my knowledge the work reported here in does not form part of any other thesis or dissertation on the basis of which a degree or award was co-offerred on the earlier occasion on this or any other candidate.

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CHAPTER 1

INTRODUCTION

The aircraft control system completes flight attitude and trajectory control and achieves specific flight actions, which is closely linked with flight safety. In recent years, with the rapid development of aviation technology, the performance of control system has been significantly improved. But as the airborne system with the highest safety level requirements, the sudden failure of this system is very likely to cause harm to pilots and passengers, leading to disastrous consequences in the face ofcomplex high-altitude flight conditions . Therefore, it is crucial to establish an efficient fault detection method to cover more faults to ensure the0 safety and reliability of aircraft.In view of this, many scholars in the world are committed to solving the problem of aircraft control system fault detection. Xu and Sun optimized the traditional fault detection method by adopting the neural networks to simplify the detection steps of the expert system. Duan and Zhang took the system modeling and FMECA as the theoretical basis to realize the detection, and Cheng analyzed the flight parameter data from QAR and found the flap extracting and retracting time can be applied to realize the flap system fault detection. But in general, these traditional model-based fault detection methods are required a large number of observers; the diagnosis process is so complicated and inefficient. Furthermore, the fault detection coverage cannot be guaranteed by the sole feature parameter, while these problems can be solved well by the artificial immune system.

1.1 PROJECT OVERVIEW

There is a large amount of information and maintenance data in the aviation industry that could be used to obtain meaningful result in the forecasting future actions.This study aims to introduce machine learning model based on feature selection and data elimination to predict failure of aircraft systems. Maintenanace and failure data for aircraft equipments across a period of two years were collected, and nine input and one output variable were meticulously identified. A hybrid data preparation model is proposed to improve the success of failure count prediction in two stages. In the first stage, ReliefF, a feature selection method for attribute evaluation, is used to find the most effective and ineffective parameters. In the second stage, a K-means algorithm is modified to eliminate noisy or inconsistent data. Performance of the hybrid data preparation model on the maintenance dataset on the equipments in evaluated by multilayer perception(MLP),as Artificial Neural Network(ANN), Support Vector Regression(SVR) and Linear Regression(LR)as machine learning algorithm. Moreover, performance criteria such as the Correlation Coefficient(CC), Mean Absolute Error(MAE), and Root Man Square Error(RMSE) are used to evaluate the models. The results indicate that the hybrid data preparation model is successful in predicting the failure count of the equipment.

1.2 PURPOSE

Predicting supports the development of critical thinking skills by requiring students to draw upon their prior knowledge and experiences as well as observations to anticipate what might happen. The ability to make logical predictions supports the development of the ability to formulate hypotheses. Prediction engine is a tool which can forecast a future outcome using a set of past observation. In present days Prediction engines have become increasingly popular as they are producing accurate and affordable predictions almost similar to human.and safe people life from predicting the engine failure.

CHAPTER 2
LITERATURE SURVEY

2.1 EXISTING PROBLEM

The predictive maintenance strategies are based on real time data for diagnosis of impending failures and prognosis of machine health.It is a proactive process,which needs predictive modelling to trigger an alarm for maintenance activities and anticipate a failure before it occurs. Use off data recognition has shown good results in detecting the failure well in advance..The model is capable of correctly predicting engine behavior.

2.2REFERENCES

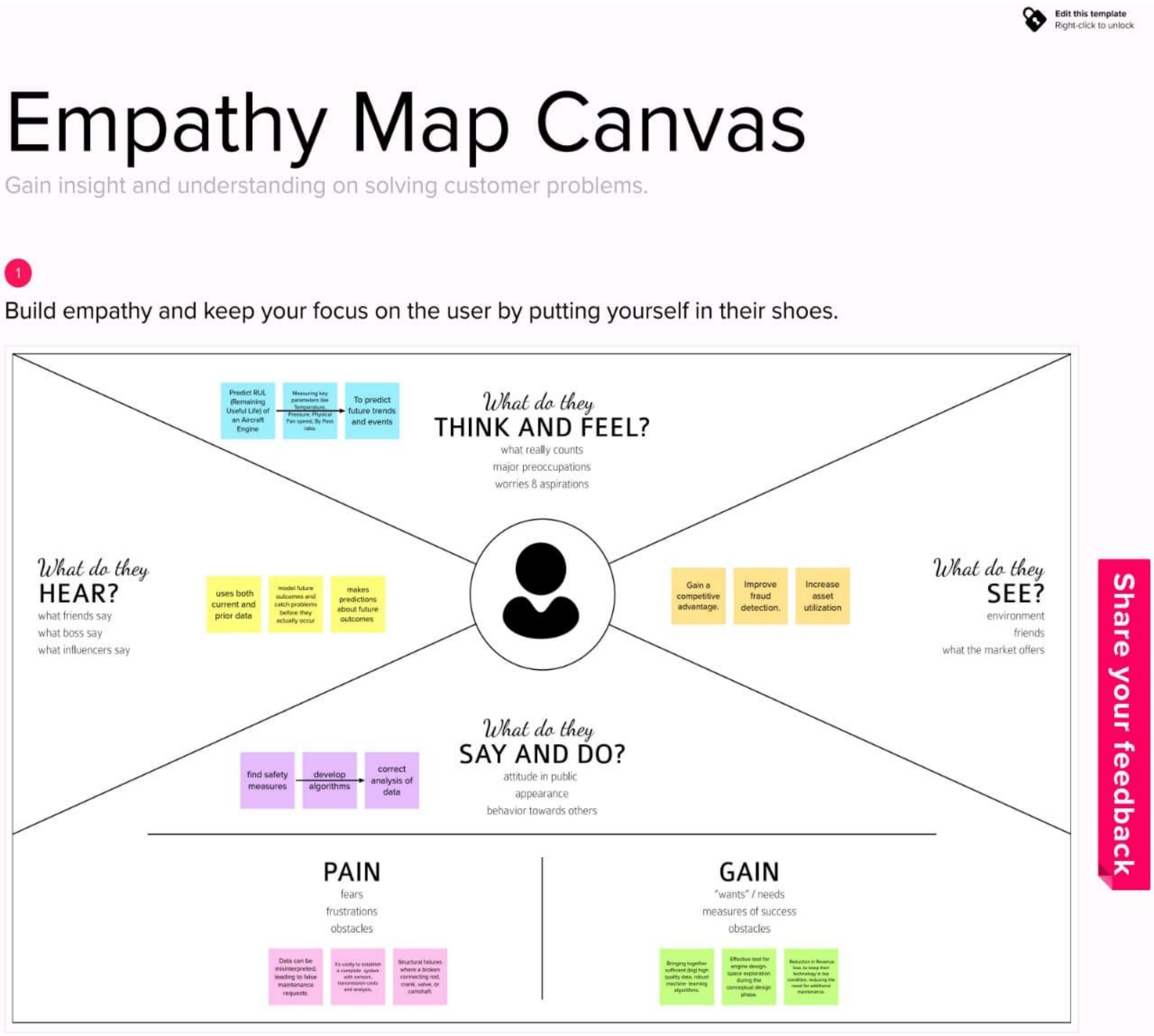
- Adams, S., .Meekins, R., Beling, P. A., Farinholt, K., Brown, N., Polter, S., & Dong, Q. (2017). A comparison of feature selection and feature extraction techniques for condition monitoring of a hydraulic actuator. Annual Conference of the Prognostics and Health Management Society, 2017.
- ASF-230, O. (2004, April). Ac 120-82 - flight operational quality assurance (Tech. Rep.). Federal Aviation Administration.

2.3PROBLEM STATEMENT DEFINITION

This project combats the problem of overflowing solid waste bins which pollute the surroundings. The level of garbage present in any bin is determined by the ultrasonic distance measuring sensor. When the garbage level in any garbage bin exceeds a pre-defined level, then the microcontroller send an alert message to the e-monitoring station, and, the workstation then assigns the nearest garbage collecting truck to collect the garbage from such bins, which have sent an alert message. It informs when the container is at full capacity and when it needs to be emptied, thus allowing the sanitation specialists to work more efficiently and cut unnecessary costs.

CHAPTER 3
IDEATION & PROPOSED SOLUTION

3.1 EMPATHY MAP CANVAS



3.2 IDEATION & BRAINSTORMING

Effective tool for engine design space exploration during the conceptual design phase.	Sensors can be used to predict	A portion of the data is selected and obtained, the next step is to process it. Follow the standard approach and test splits are selected and normalized.
Proposed analysis shows that XGBoost and LightGBM is a better choice for predicting the RUL	The main topics studied Where engine health monitoring, deep learning (DL) for anomaly detection, and aviation software simulation.	A review of state-of-the-art predictive maintenance techniques in use for aircrafts hydraulic system and engine has been explored in this work
LSTM based prognostics technique for aircraft fault prediction.The model is capable of correctly predicting engine behavior.	Backpropagation, dropout, RNN and LSTM to include the mathematical and historical line in the development of algorithms used in this work.	Proposed analysis shows that XGBoost and LightGBM is a better choice for predicting the RUL.

- The predictive maintenance strategies are based on real time data for diagnosis of impending failures and prognosis of machine health.
- The model is capable of correctly predicting engine behavior.
- This also presents an LSTM based prognostics technique for aircraft fault prediction.
- It can be an effective tool for engine design space exploration during the conceptual design phase.
- This model aims to predict the fuel mass flow rate having as an input

3.3 PROPOSED SOLUTION

S.No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	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. .
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 with the engine failure for a threshold number of days.Based on machine learning applied data science it aims to predict the failure of an engine.th sustainability of waste services.
3.	Novelty / Uniqueness	Predicting the failure prior will save time, effort, money and sometimes even

		lives.Through its predictive analysis techn iques we can easily detect the failures and take appropriate measures.
4.	Social Impact / Customer Satisfaction	Using IoT and smart sensors, waste management companies can increase
5.	Business Model (Revenue Model)	Machine Learning generates revenue through the provision of various aircraft management and other services and provide solutions to residential, commercial, industrial, and all other aircraft managements. The Company derives its revenue in the form of various fees associated with its service offerings.
5.	Scalability of the Solution	It is found that scaling down of engines is detrimental to SFC and fuel burn, mainly due to the Reynolds number effect. The more scaling done, the more prominent the effect. It is determined that new technology such as higher TIT, OPR and turbomachinery [eta]poly's for aircraft engines enable the operation of larger bypass ratios, which is the most influential parameter to SFC and fuel bum. The increase of bypass ratio up to a value of 8 is found to be effective for such improvement. SFC decrease from the current to mid-term model is found to be ~20% and ~9% from mid-term to far-term. Range and endurance improvements are found to be ~30% and ~10% respectively for the mission examined. Finally, the mid-term

		engine model has performance comparable to that of a current, larger state-of-the-art engine, thus suggesting that improvement in small gas turbine technology in the next 10 years will make the application of commodity thrust or distributed propulsion an attractive option for future aircraft.

3.4 PROBLEM SOLUTION FIT

Project Title: Predictive Analytics for Aircraft Engine

Project Design Phase-I - Solution Fit Template

Team ID:

Define CS, fit into CC

1. CUSTOMER SEGMENT(S) CS

Who is your customer?
i.e. working parents of 0-5 y.o. kids

Old Travelers They are aged customers probably retired and go on holidays frequently.
Business Travelers They are frequent flyers and form a large segment.
Budget Conscious Travelers They look for the most inexpensive airline without knowing much about the different airline services.

6. CUSTOMER CONSTRAINTS CC

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.

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.

5. AVAILABLE SOLUTIONS AS

Which solutions are available to the customers when they face the problem
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

If an engine fault have been predicted previously they have rectify from the severe damage ,so they can also have a another possible way for safest landing.

Explore AS, differentiate

Focus on J&P, tap into BE, understand RC

2. JOBS-TO-BE-DONE / PROBLEMS J&P

Which jobs-to-be-done (or problems) do you address for your customers? There could be more than one; explore different sides.

The Fuel Factor
Overcapacity
Labor Unrest
The Emergence of Low-Cost Carriers
Passenger comfort
Technology

9. PROBLEM ROOT CAUSE RC

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.

If the problem occurs than the customer has to inform to the engine controller ,and they have to take all measurement instrumentation previously.

7. BEHAVIOUR BE

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)

Closely monitor the engine parameters reported by the aircraft's instrumentation.So,if there is any malfunction occurs in the measurements it can rectified by them.

Focus on J&P, tap into BE, understand RC

Identify strong TR & EM

3. TRIGGERS TR

What triggers customers to act? i.e. seeing their neighbour installing solar panels, reading about a more efficient solution in the news.

Baggage Theft.
Delayed Flights
Uncomfortable seats
Hidden charges. ...
Customer Service.

4. EMOTIONS: BEFORE / AFTER EM

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.

they got fear,and make loud and think how to releive from that.

10. YOUR SOLUTION SL

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.

First we have to prepare a clear measurements of all engine and to check all the measurements with the fixed (occurate)measurements while starting the aircraft.

8. CHANNELS of BEHAVIOUR CH

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.

online works:manage the all measurements
offline works:to check the appearance correctness

Identify strong TR & EM

CHAPTER 4
REQUIREMENT ANALYSIS

4.1.Functional Requirements

Following are the functional requirements of the proposed solution.

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	Registration through Form Registration through Gmail Registration through LinkedIN
FR-2	User Confirmation	Confirmation via Email Confirmation via OTP
FR-3	User dashboard	Can access the dashboard

4.2.Non-functional Requirements:

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

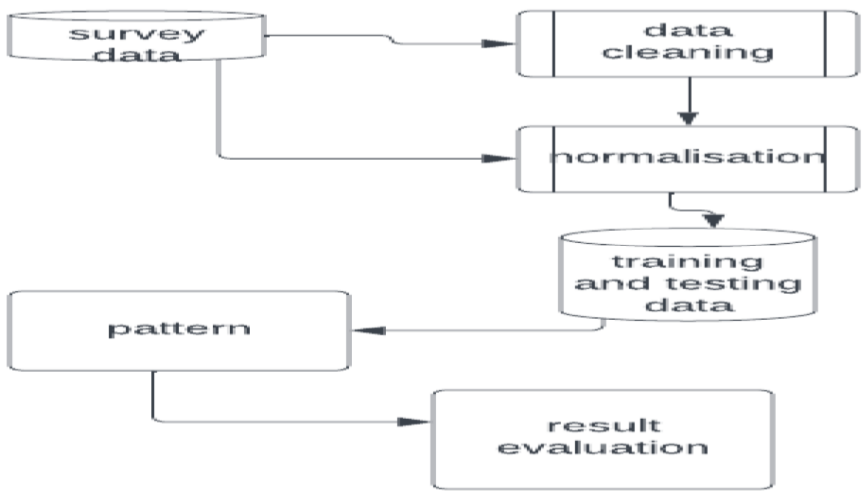
FR No.	Non-Functional Requirement	Description
NFR-1	**Usability**	For detecting the faults occurance in aircraft engine
NFR-2	**Security**	Manage the safety and security of passengers life
NFR-3	**Reliability**	The system is more reliable because of it is system adequacy and system security.
NFR-4	**Performance**	High performance because of the system efficiency.
NFR-5	**Availability**	High availability because it allows continuous functioning.
NFR-6	**Scalability**	More number of aircrafts can be secured

CHAPTER 5

PROJECT DESIGN

5.1.Data flowDiagrams

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 stored.



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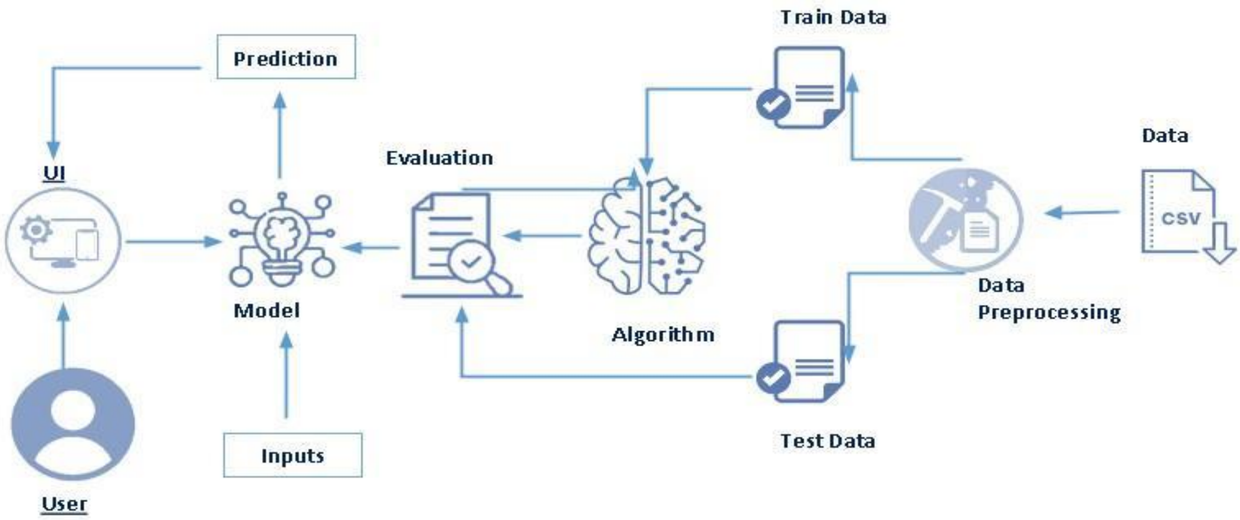
5.2.Solution and Technical Architecture

Predictive Analysis for aircraft engine using machine learning



5.3.User Stories

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

		USN-2	As a user, I will receive confirmation email once I have registered for the application	I can receive confirmation email & click confirm	High	Sprint-1
		USN-3	As a user, I can register for the application through Facebook	I can register & access the dashboard Facebook Login	Low	Sprint-2
		USN-4	As a user, I can register for the application through Gmail		Medium	Sprint-1
	Login	USN-5	As a user, I can log into the application by entering email & password		High	Sprint-1
Administrator	Maintain data		Have to calculate the data according to ddefault values		High	

CHAPTER 6

Project Planning and Scheduling

6.1.Sprint Planning &Estimation

Sprint	Functional Requirement(Epic)	User Story Number	User Story/Task	Story point	Priority	Team Members
Sprint-1	Registration	USN-2	As a user, I can register for the application by entering my email, password, and confirming my password.	2	High	Abbrose Barvin.R
Sprint-1		USN-2	As a user, I will receive confirmation email once I have register for the application	1	High	Aruna Lakshmi.N
Sprint-2		USN-3	As a user, I can register for the application through Facebook	2	Low	Alagu Ramalakshmi.S
Sprint-1		USN-4	As a user, I can register for the application through	2	Medium	Harini.S

			Gmail			
Sprint-1	Login	USN-5	As a user, I can log into the application by entering email & password	1	High	Abbrose Barvin.R

6.2.Sprint Delivery Schedule

Sprint	Total Story point	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Point Completed (as on Planned End Date)	Sprint Release Date (Actual)
Sprint-1	20	6 Days	26 Oct 2022	31 Oct 2022	20	31 Oct 2022
Sprint-2	20	6 Days	1 Nov 2022	6 Nov 2022	20	6 Nov 2022
Sprint-3	20	6 Days	7 Nov 2022	12 Nov 2022	20	12 Nov 2022
Sprint-4	20	6 Days	13 Nov 2022	18 Nov 2022	20	18 Nov 2022

CHAPTER 7

Coding &Solutioning

```
# Importing modules
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
from pysurvival.datasets import Dataset
%pylab inline
# Reading the dataset
raw_dataset = Dataset('maintenance').load()
print("The raw_dataset has the following shape: {}.".format(raw_dataset.shape))
raw_dataset.head(3)
# Defining the time and event column
time_column = 'lifetime'
event_column = 'broken'
# Encoding the categorical variables as one-hot vectors
categories = ['provider', 'team']
dataset = pd.get_dummies(raw_dataset, columns = categories, drop_first=True)
# Defining the modeling features
features = np.setdiff1d(dataset.columns, ['lifetime', 'broken']).tolist()
# Checking for null values
N_null = sum(dataset[features].isnull().sum())
print("The dataset contains {} null values".format(N_null)) #0 null values
# Removing duplicates if there exist
N_dupli = sum(dataset.duplicated(keep='first'))
dataset = dataset.drop_duplicates(keep='first').reset_index(drop=True)
print("The dataset contains {} duplicates".format(N_dupli))
# Number of samples in the dataset
N = dataset.shape[0]
for feature in ['pressureInd','moistureInd','temperatureInd']:
 # Creating an empty chart
  fig, ((ax1, ax2)) = plt.subplots(1, 2,  figsize=(15, 4))
# Extracting the feature values
 x = raw_dataset[feature].values
```

```
    # Boxplot
    ax1.boxplot(x)
    ax1.set_title( 'Boxplot for {}'.format(feature) )
    # Histogram
    ax2.hist(x, bins=20)
    ax2.set_title( 'Histogram for {}'.format(feature) )
    # Display
    plt.show()
from collections import Counter
for feature in ['team','provider']:
    # Creating an empty chart
    fig, ax = plt.subplots(figsize=(15, 4))
    # Extracting the feature values
    x = raw_dataset[feature].values
    # Counting the number of occurrences for each category
    data = Counter(x)
    category = list(data.keys())
    counts = list(data.values())
    # Boxplot
    ax.bar(category, counts)
    # Display
    plt.title( 'Barchart for {}'.format(feature) )
    plt.show()
```

CHAPTER 8

TESTING

8.1.Test Cases

Test case ID	Feature Name	Actual Result
Test Case_1	Set1	Above the range , predicted to be fault
Test Case_2	Set2	Below the range , Predicted to be correct range
Test Case_3	Set 3	At the equal range , Predicted to be in dangerous condition

8.2.User Acceptance Testing

1.Purpose of Document

The purpose of this document is to briefly explain the aircraft engine and the issues of the aircraft model,at the the release to time of User Acceptance Testing (UST)

.

2.Defect Analysis

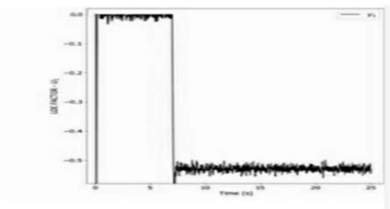
Having the ability to identify potential repeating defects on an aircraft can greatly contribute to increasing the overall fleet availability of any airline. However, the ability to identify such repeating defects on individual aircraft is also dependant on several variables in the aircraft complaint registration process being properly manager.we can find the engine fault using this predictive analytic model.

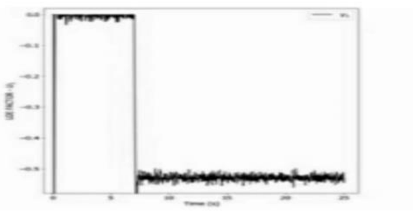
CHAPTER 9

RESULTS

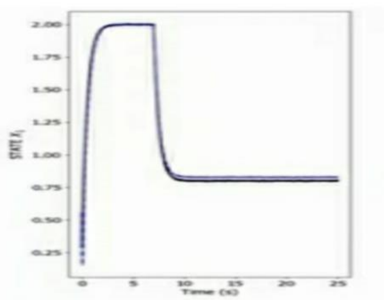
9.1.PERFORMANCE METRICS

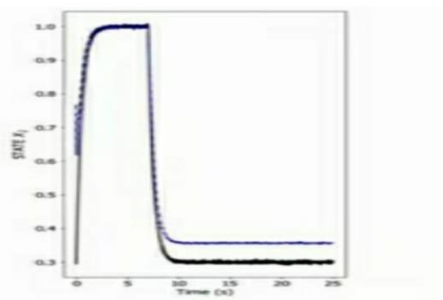
RESULT-1





RESULT -2





10.ADVANTAGES

- Reduction or near elimination of unscheduled equipment downtime caused by equipment or system failure;
- Increased labor utilization
- Increased production capacity
- Reduced maintenance costs
- Increased equipment lifespan
- Maintenance frequency is minimal and reliability is as high as possible
- Eliminating unnecessary costs.

10. DISADVANTAGES

- Required correct datasets
- System will provide inaccurate results if data entered incorrectly
- Datasets varies according to the aircrafts

11.CONCLUSION

The machine-learning predictive analytics for engine respectively. predictive analytics show remarkable prediction accuracy. To further improve the accuracy (and reduce the uncertainty) of prediction, the database needs to be expanded. However, the limitation of publicly available engine data is a challenge to overcome. 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

12.FUTURE SCOPE

An interesting approach to test the methodology developed in this work would be to test the models on data collected from a larger time spectrum, which would include more maintenance dates. This would lead to validate the fuel consumption pattern occurring pre and post maintenance. The inclusion of other useful features on the model would provide more consistency to the predictions. It's important to mention that some features were excluded because their use was not beneficial to the prediction. Other ideas for future future work include use of different architectures for the model selected, such as gated recurring units or attention models which have had great success in other areas of ML. With respect to external factors affecting the data, one approach could be the normalization of data considering these factors (weight of the plane at departure, weather conditions, etc. Other options not considering specialized software include the use of a neural network (NN) to extract information from raw data and then train a second NN with the extracted features. To generate a more robust method it would be interesting to include typical analyses performed prior to the maintenance of an engine, such as analysis of lubrica.

13.APENDIX

SOURCE CODE

```
# Importing modules
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
from pysurvival.datasets import Dataset
%pylab inline
# Reading the dataset
raw_dataset = Dataset('maintenance').load()
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event_column = 'broken'
```

```
# Encoding the categorical variables as one-hot vectors
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# Extracting the feature values
x = raw_dataset[feature].values

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# Histogram
ax2.hist(x, bins=20)
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# Display
plt.show()
from collections import Counter
for feature in ['team','provider']:
# Creating an empty chart
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# Extracting the feature values
x = raw_dataset[feature].values
# Counting the number of occurrences for each category
data = Counter(x)
category = list(data.keys())
```

```
counts = list(data.values())
# Boxplot
ax.bar(category, counts)
# Display
plt.title( 'Barchart for {}'.format(feature) )
```

GITHUB AND PROJECT DEMO LINK

https://github.com/IBM-EPBL/IBM-Project-45965-1660733782