CONTENT

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.

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

1.2 PURPOSE

- **To understand the problem to classify if it is a regression or a classification kind of problem.**
- **To pre-process/clean the data using different data pre-processing techniques.**
- **To apply different algorithms according to the dataset and will be able to know how to find the accuracy of a model.**

  You will be able to build web applications using the Flask framework.

2. LITERATURE SURVEY

2.1 PROBLEM STATEMENT DEFINITION:

Problem-Statement: **"How might we help the Flight Safety Officer, who wants to improve the engine reliability and flight safety by using a predictive analysis to replace vulnerable components?"**

Although the flight safety officer thoroughly inspects the engine before takeoff, he or she cannot guarantee that no failure will occur during flight. To overcome this problem, predictive analytics comes in and predicts the accuracy or gives us prior information on the flight engine. To avoid accidents during flight, this is a good solution to use.

This section includes a literature survey of research on the assessment of student enrollment opportunities in universities.

2.2 REFERENCES

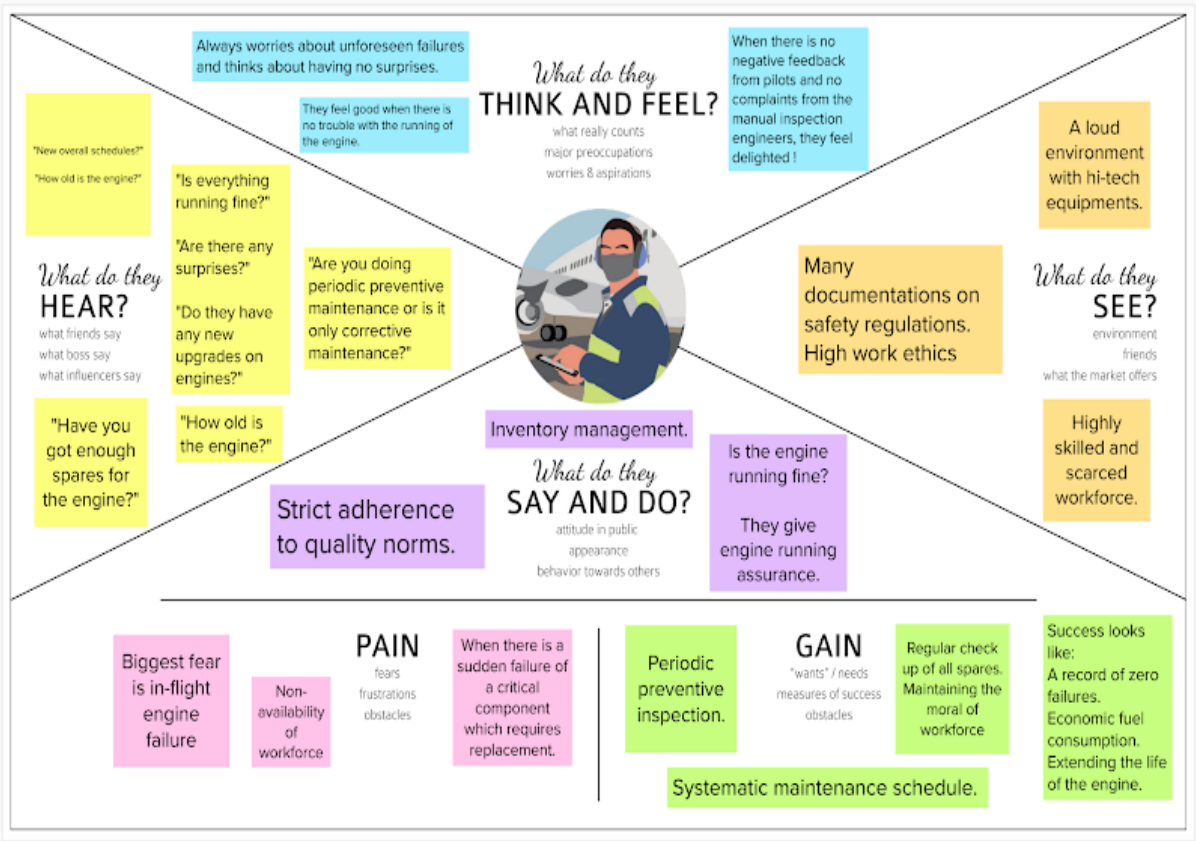
Michael T. Tong Glenn Research Center, Cleveland, Ohio : Machine Learning-Based Predictive Analytics for Aircraft Engine Conceptual Design

https://ntrs.nasa.gov/api/citations/20205007448/downloads/TM-20205007448.pdf

3. IDEATION & PROPOSED SOLUTION

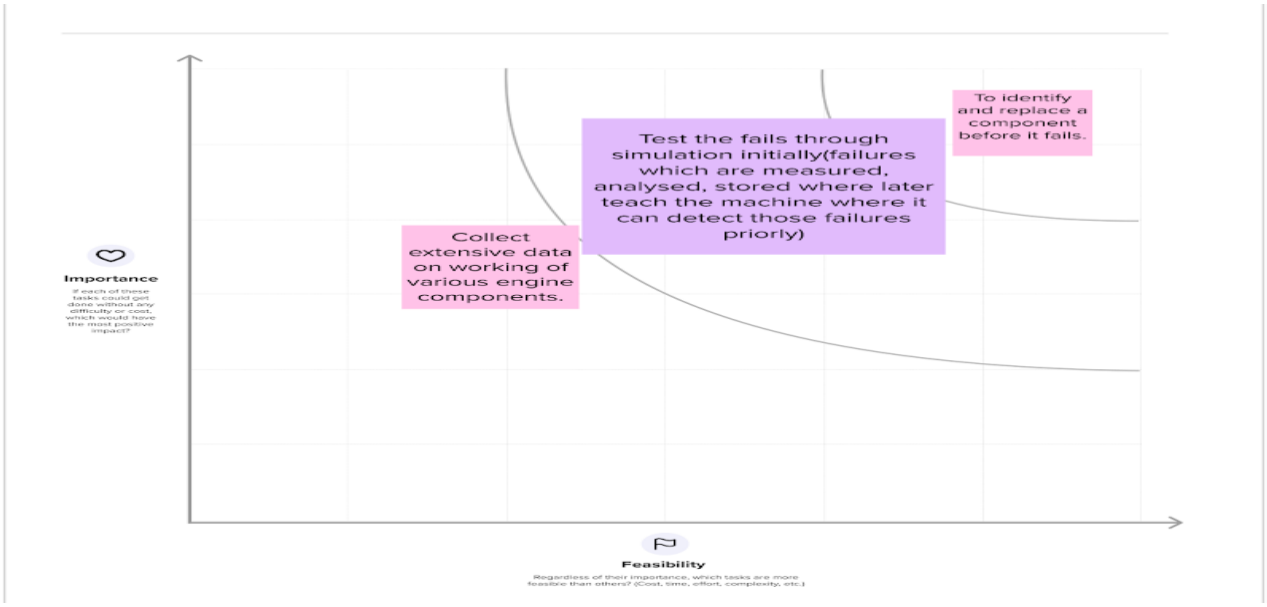
3.1 EMPATHY MAP CANVAS

This map is created with view of the project in user's perspective, to find pain & gain points and to summarize it with a list of problem statements.



3.2 IDEATION & BRAINSTORMING

Brainstorming provides a free and open environment that encourages everyone within a team to participate in the creative thinking process that leads to problem solving. Prioritizing volume over value, out-of-the-box ideas are welcome and built upon, and all participants are encouraged to collaborate, helping each other develop a rich amount of creative solutions.



3.3 PROPOSED SOLUTION:

S.No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	How might we help the Flight Safety Officer who wants to improve the engine reliability and flight safety by using a predictive analysis to replace vulnerable components.
2.	Idea / Solution description	Collect extensive data on working of engines, develop a Machine Learning Program and train it with failure data generated through a simulation model. The program would then predict on the working of the engine.
3.	Novelty / Uniqueness	Identifying interdependencies between component which would result with the most economical solution.
4.	Social Impact / Customer Satisfaction *(FLIGHT SAFETY OFFICEER)*	The Flight Safety Officer is now able to *avoid* Engine failure instead of solving the failure after it occurs. Accurate results as a machine can analyse extensive amount of data. The customer is able to produce Engine Assurance quickly.
5.	Business Model (Revenue Model)	The materials, cost of resources and our initial investments are negligible.
6.	Scalability of the Solution	The solution is highly scalable, it can accommodate a large set of data for any type of engine.

3.4 PROBLEM SOLUTION FIT:

4. REQUIREMENT ANALYSIS

4.1 FUNCTIONAL REQUIREMENTS:

FR No.	Non-Functional Requirement	Description
NFR-1	**Usability**	The fight safety officer is provided with an undisturbed ambience, a system with a condition for the officer to perform the tasks safely, effectively, and efficiently.
NFR-2	**Security**	Assuring all data inside the system or its part will be protected against malware attacks or unauthorized access.
NFR-3	**Reliability**	A good working system with adequate ML datasets that predict engine failure.
NFR-4	**Performance**	It defines how fast a software system or a particular piece of it responds to the flight safety officer. This metric explains how long a user must wait before the target operation happens given the overall number of users at the moment. As backup will be provided during the process, performance is adequate.
NFR-5	**Availability**	Highly available.
NFR-6	**Scalability**	The solution is highly scalable, it can accommodate a large set of data for any type of engine

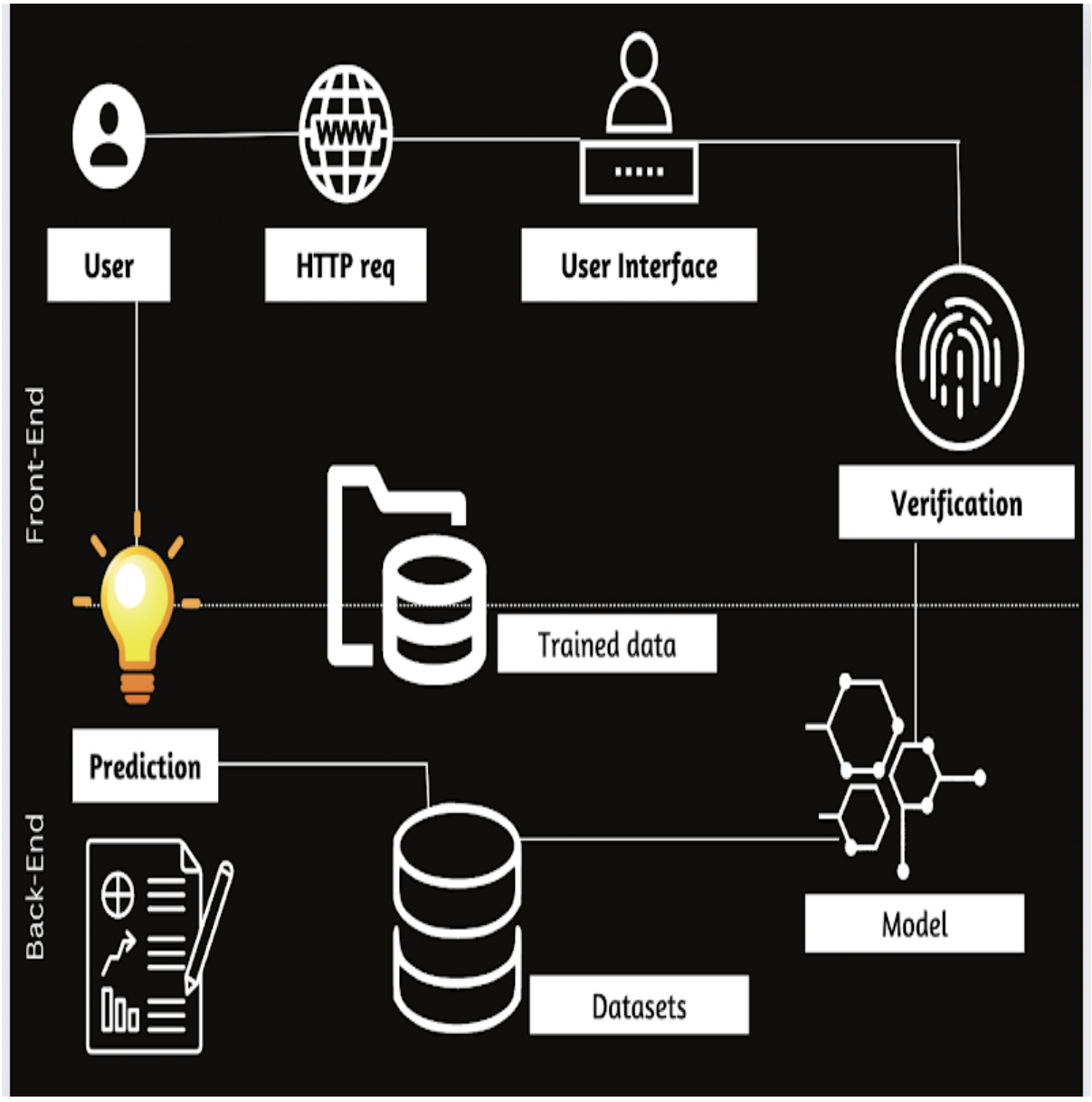
4.2 NON-FUNCTIONAL REQUIREMENTS:

FR No.	Functional Requirement (Epic) *[User – Flight Safety Officer]*	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	Registration through website
FR-2	User Confirmation	Confirmation via Email Confirmation via OTP
FR-3	User Verification	Fingerprint Verification
FR-4	Inputs/Data	Data generated through a simulation model and engine data.
FR-5	Data processing	Displays the components lifespan, detects errors.
FR-6	Prediction	Notifies when there's a flaw in components and displays the engine failure rate.

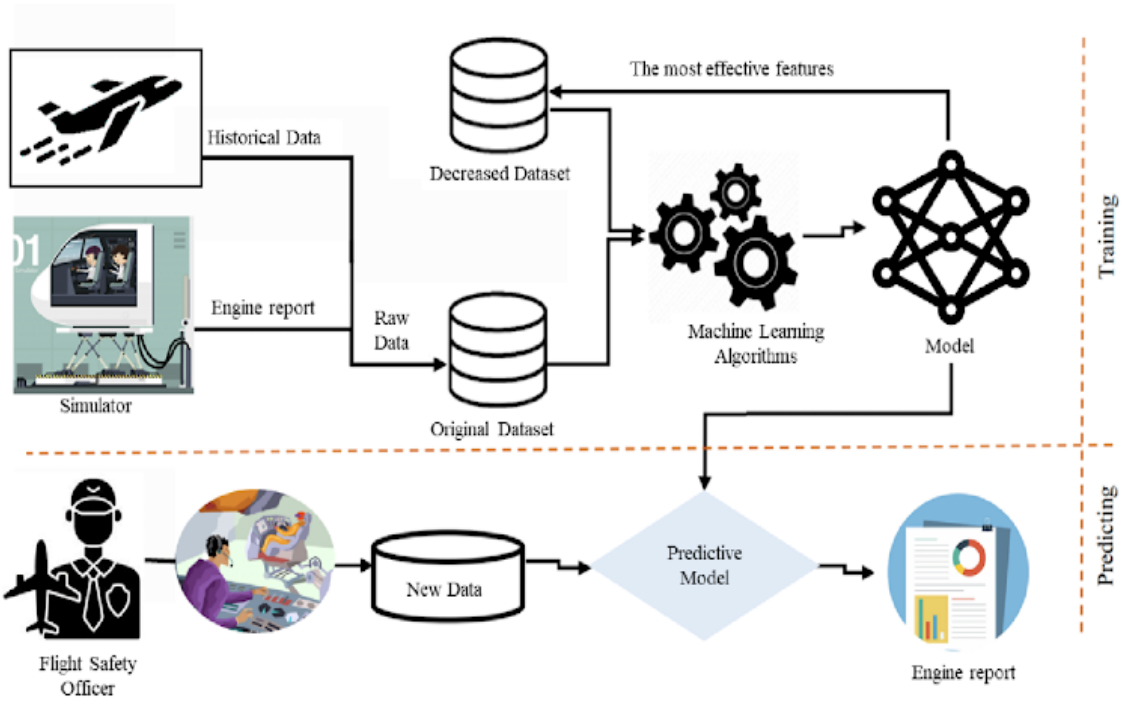
5. PROJECT DESIGN

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 datais stored.



5.2 SOLUTION ARCHITECTURE:



5.2 USER STORIES:

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Customer (Web 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 with 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
	Dashboard					
Customer (Web Verification)	Fingerprint biometric sensor		As a user, I can verify through my fingerprint for security purpose	For authentication	Medium	Sprint 1
Customer Care Executive	Customer service		If any issues arises	Customer Care Excecutive will solve the issues/errors		

6.PROJECT PLANNING & SCHEDULING

6.1 SPRINT PLANNING & ESTIMATION:

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		19 Nov 2022
Sprint-2	20	6 Days	31 Oct 2022	05 Nov 2022	20	19 Nov 2022
Sprint-3	20	6 Days	07 Nov 2022	12 Nov 2022	20	19 Nov 2022
Sprint-4	20	6 Days	14 Nov 2022	19 Nov 2022	20	19 Nov 2022

6.2 SPRINT DELIVERY SCHEDULE:

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint - 1	Modules	USN-1	The module which are used to be imported	2	High	NithyaLakshmi Yugalakshmi
Sprint - 1	Data Ingestion	USN-2	Instead of a CSV file, text file is added	1	High	Preethi Yugalakshmi
Sprint - 2	Data Pre-processing	USN-3	A data mining technique	2	Medium	Reethika NithyaLakshmi
Sprint - 3	Modelling	USN-4	Data Modeling in software engineering is the process of simplifying the diagram or data model of a software system by applying certain formal techniques.	2	Medium	Yugalakshmi Preethi
Sprint - 4	LSTM Network	USN-5	LSTMs are predominately used to learn, process, and classify sequential data	1	High	Preethi Reethika
Sprint - 4	Model Training	USN-6	Training the model		High	Nithyalakshmi Yugalakshmi Preethi Reethika
Sprint - 4	Model Testing	USN-7	Test and validation of model	2	High	Preethi Reethika

7. CODING

7.1 FINAL CODE:

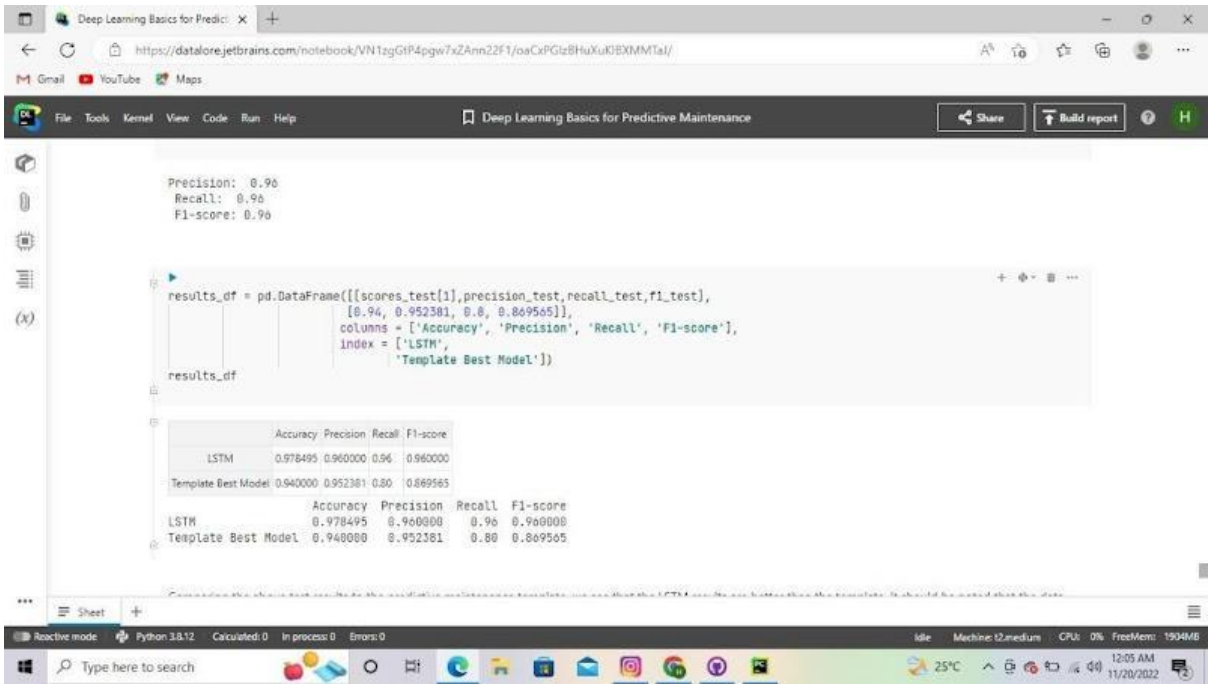
```
import keras
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
np.random.seed(1234)
PYTHONHASHSEED = 0
from sklearn import preprocessing
from sklearn.metrics import confusion_matrix, recall_score, precision_score
from keras.models import Sequential
from keras.layers import Dense, Dropout, LSTM, Activation
%matplotlib inline

# read training data
train_df = pd.read_csv('PM_train.txt', sep=" ", header=None)
train_df.drop(train_df.columns[[26, 27]], axis=1, inplace=True)
train_df.columns = ['id', 'cycle', 'setting1', 'setting2', 'setting3', 's1', 's2', 's3',
                    's4', 's5', 's6', 's7', 's8', 's9', 's10', 's11', 's12', 's13', 's14',
                    's15', 's16', 's17', 's18', 's19', 's20', 's21']

# read test data
test_df = pd.read_csv('PM_test.txt', sep=" ", header=None)
test_df.drop(test_df.columns[[26, 27]], axis=1, inplace=True)
test_df.columns = ['id', 'cycle', 'setting1', 'setting2', 'setting3', 's1', 's2', 's3',
                    's4', 's5', 's6', 's7', 's8', 's9', 's10', 's11', 's12', 's13', 's14',
                    's15', 's16', 's17', 's18', 's19', 's20', 's21']


# read ground truth data
truth_df = pd.read_csv('PM_truth.txt', sep=" ", header=None)
truth_df.drop(truth_df.columns[[1]], axis=1, inplace=True)

train_df = train_df.sort_values(['id','cycle'])
train_df.head()

rul = pd.DataFrame(train_df.groupby('id')['cycle'].max()).reset_index()
rul.columns = ['id', 'max']
train_df = train_df.merge(rul, on=['id'], how='left')
train_df['RUL'] = train_df['max'] - train_df['cycle']
train_df.drop('max', axis=1, inplace=True)
train_df.head()
```

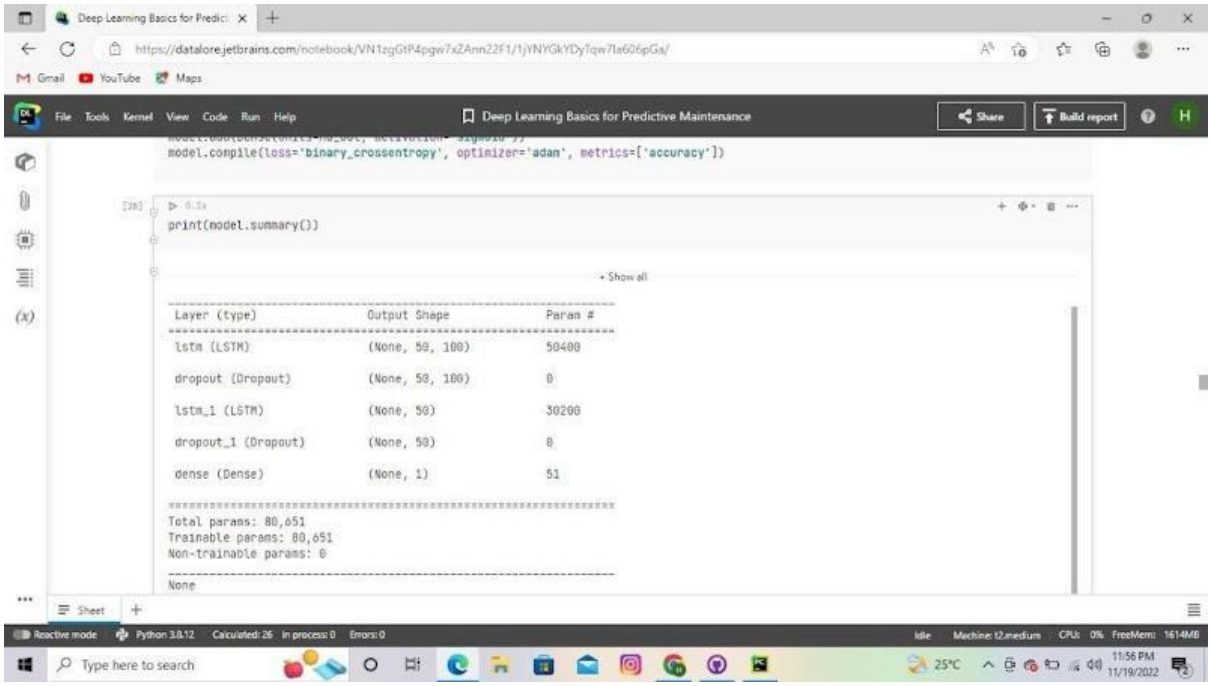
```
test_df.head()

test_df['label1'] = np.where(test_df['RUL'] <= w1, 1, 0 )
test_df['label2'] = test_df['label1']
test_df.loc[test_df['RUL'] <= w0, 'label2'] = 2
test_df.head()test_df['label1'] = np.where(test_df['RUL'] <= w1, 1, 0 )
test_df['label2'] = test_df['label1']
test_df.loc[test_df['RUL'] <= w0, 'label2'] = 2
test_df.head()

sequence_length = 50

engine_id3 = test_df[test_df['id'] == 3]
engine_id3_50cycleWindow = engine_id3[engine_id3['RUL'] <= engine_id3['RUL'].min() + 50]
cols1 = ['s1', 's2', 's3', 's4', 's5', 's6', 's7', 's8', 's9', 's10']
engine_id3_50cycleWindow1 = engine_id3_50cycleWindow[cols1]
cols2 = ['s11', 's12', 's13', 's14', 's15', 's16', 's17', 's18', 's19', 's20', 's21']
engine_id3_50cycleWindow2 = engine_id3_50cycleWindow[cols2]

ax1 = engine_id3_50cycleWindow1.plot(subplots=True, sharex=True, figsize=(20,20))
ax2 = engine_id3_50cycleWindow2.plot(subplots=True, sharex=True, figsize=(20,20))

def gen_sequence(id_df, seq_length, seq_cols):
    data_array = id_df[seq_cols].values
    num_elements = data_array.shape[0]
    for start, stop in zip(range(0, num_elements-seq_length), range(seq_length, num_elements)):
        yield data_array[start:stop, :]



sensor_cols = ['s' + str(i) for i in range(1,22)]
sequence_cols = ['setting1', 'setting2', 'setting3', 'cycle_norm']
sequence_cols.extend(sensor_cols)
seq_gen = (list(gen_sequence(train_df[train_df['id']==id], sequence_length, sequence_cols))
           for id in train_df['id'].unique())

seq_array = np.concatenate(list(seq_gen)).astype(np.float32)
seq_array.shape
```

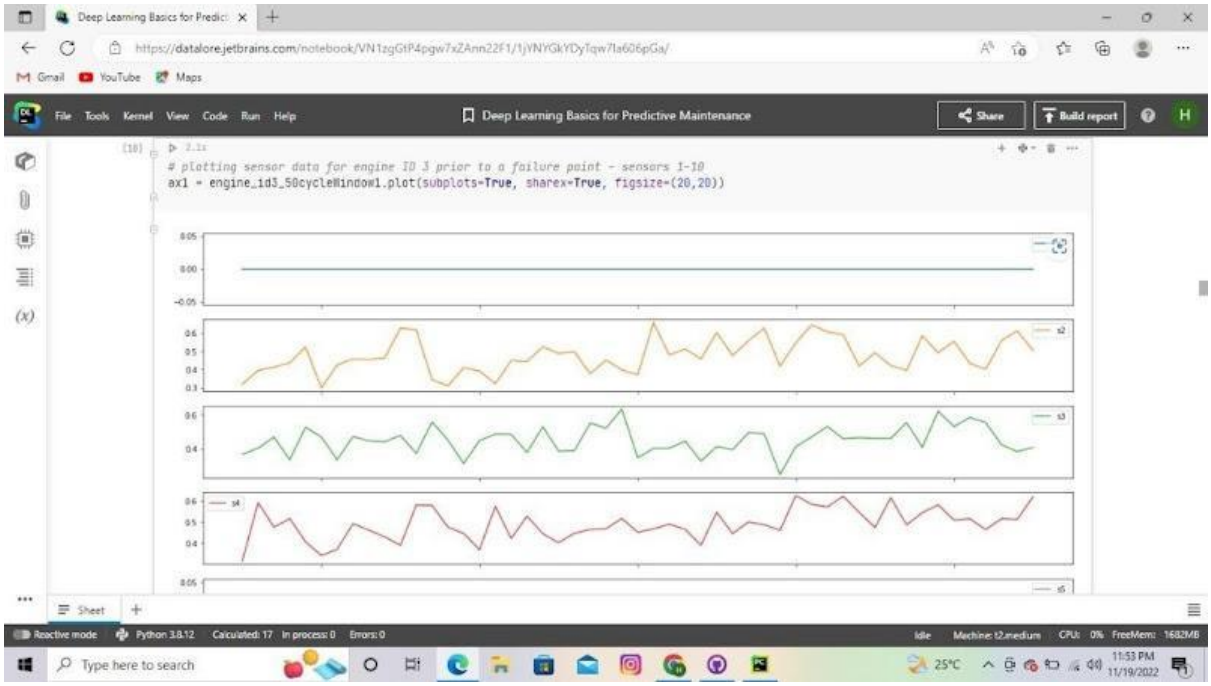
```
y_pred = model.predict_classes(seq_array,verbose=1, batch_size=200)
y_true = label_array
print('Confusion matrix\n- x-axis is true labels.\n- y-axis is predicted labels')
cm = confusion_matrix(y_true, y_pred)
print(cm)

precision = precision_score(y_true, y_pred)
recall = recall_score(y_true, y_pred)
print( 'precision = ', precision, '\n', 'recall = ', recall)
seq_array_test_last = [test_df[test_df['id']==id][sequence_cols].values[-sequence_length:]
                       for id in test_df['id'].unique() if len(test_df[test_df['id']==id]) >= sequence_length]

seq_array_test_last = np.asarray(seq_array_test_last).astype(np.float32)
seq_array_test_last.shape

y_mask = [len(test_df[test_df['id']==id]) >= sequence_length for id in test_df['id'].unique()]

label_array_test_last = test_df.groupby('id')['label1'].nth(-1)[y_mask].values
label_array_test_last = label_array_test_last.reshape(label_array_test_last.shape[0],1).astype(np.float32)
label_array_test_last.shape

print(seq_array_test_last.shape)
print(label_array_test_last.shape)
scores_test = model.evaluate(seq_array_test_last, label_array_test_last, verbose=2)
print('Accurracy: {}'.format(scores_test[1]))

y_pred_test = model.predict_classes(seq_array_test_last)
y_true_test = label_array_test_last
print('Confusion matrix\n- x-axis is true labels.\n- y-axis is predicted labels')
cm = confusion_matrix(y_true_test, y_pred_test)
print(cm)

precision_test = precision_score(y_true_test, y_pred_test)
recall_test = recall_score(y_true_test, y_pred_test)
f1_test = 2 * (precision_test * recall_test) / (precision_test + recall_test)
print( 'Precision: ', precision_test, '\n', 'Recall: ', recall_test,'\n', 'F1-score:', f1_test )
```

```
y_pred_test = model.predict_classes(seq_array_test_last)
y_true_test = label_array_test_last
print('Confusion matrix\n- x-axis is true labels.\n- y-axis is predicted labels')
cm = confusion_matrix(y_true_test, y_pred_test)
print(cm)

precision_test = precision_score(y_true_test, y_pred_test)
recall_test = recall_score(y_true_test, y_pred_test)
f1_test = 2 * (precision_test * recall_test) / (precision_test + recall_test)
print( 'Precision: ', precision_test, '\n', 'Recall: ', recall_test,'\n', 'F1-score:', f1_test )

results_df = pd.DataFrame([[scores_test[1],precision_test,recall_test,f1_test],
                           [0.94, 0.952381, 0.8, 0.869565]],
                          columns = ['Accuracy', 'Precision', 'Recall', 'F1-score'],
                          index = ['LSTM',
                                   'Template Best Model'])
print(results_df)
```

8 SCREENSHOTS:




Deep Learning Basics for Predictive Maintenance
https://datalore.jetbrains.com/notebook/VN1zgGtP4pgw7xZAnn22F1/1jYNYGkYDyTqw7Ia606pGa/
File Tools Kernel View Code Run Help
Deep Learning Basics for Predictive Maintenance
Share
Build report
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
print(model.summary())
+ Show all
Layer (type) Output Shape Param #
lstm (LSTM) (None, 50, 100) 50400
dropout (Dropout) (None, 50, 100) 0
lstm_1 (LSTM) (None, 50) 30200
dropout_1 (Dropout) (None, 50) 0
dense (Dense) (None, 1) 51
Total params: 80,651
Trainable params: 80,651
Non-trainable params: 0
None
Sheet
Reactive mode
Python 3.8.12
Calculated: 26
In process: 0
Errors: 0
Idle
Machine: t2.medium
CPU: 0%
FreeMem: 1614MB
Type here to search
25°C
11:56 PM
11/19/2022


Deep Learning Basics for Predictive Maintenance
https://datalore.jetbrains.com/notebook/VN1zgGtP4pgw7xZAnn22F1/1jYNYGkYDyTqw7Ia606pGa/
File Tools Kernel View Code Run Help
Deep Learning Basics for Predictive Maintenance
Share
Build report
# plotting sensor data for engine ID 3 prior to a failure point - sensors 1-10
ax1 = engine_id3_50cycleWindow1.plot(subplots=True, sharex=True, figsize=(20,20))
Sheet
Reactive mode
Python 3.8.12
Calculated: 17
In process: 0
Errors: 0
Idle
Machine: t2.medium
CPU: 0%
FreeMem: 1682MB
Type here to search
25°C
11:53 PM
11/19/2022

9 ADVANTAGES :

Integration with IOT devices to address specific business problem related to Engine.
• Ability to view Engine Component Health.
• The solution can be used / deployed on PC or an iOS device (iPad).
• Ability to create Maintenance Work Orders in S/4 HANA or Gen2iMRO
• Integration with R to utilize its clustering algorithms; Uses PdMS / PAL (Predictive Analysis Library) in SAP HANA for RUL calculation Instead of R model to utilize the algorithms available in PAL (Predictive Analysis Library) in SAP HANA
• Proactive alerts based on user defined parameters Supports Proactive Maintenance of Engines to ensure that the Aircrafts have maximum Airtime.
• Ability to Predict RUL (Remaining Useful Life) of an Aircraft Engine by measuring key parameters like Temperature, Pressure, Physical Fan speed, By Pass Ratio to predict remaining usable life of an Aircraft Engine.
• Reduction in Revenue loss by predicting failures of Aircraft Engines and optimizing service windows.

10 CONCLUSION:

In aviation, the use of maintenance data is highly critical in the analysis of reliability and maintenance costs. Is is because predictive maintenance scheduling can be planned in line with estimates. Main target of predictive maintenance is to predict equipment failures and planning strategies for spare parts of the system com-ponents to analyse the reliability and maintainability of a complex repairable system. In this study, a hybrid data preparation model was applied to the landing gear system maintenance dataset using feature selection ReliefF
al-gorithm to select attributes and a modified K-means al-gorithm to eliminate noisy and inconsistent data. Proposed hybrid data preparation method was put into practice through LR, SVR, and MLP models. Results indicated that the LR model had better performance thanMLP and SVR models in predicting the failure counts. Results indicate that the proposed hybrid data preparation model significantly improves the accurate prediction of failure counts. His study could function as a guide for using hybrid data preparation methods in machine learning algorithms and data mining.

11 FUTURE SCOPE:

Our recent experience with players in this space, however, suggests the opposite. While certain "moonshot" (unproven, capital- intensive) predictive maintenance
efforts may be less likely, many airlines and MRO organizations, seeking to avoid building back overhead organizations that were sharply reduced as air travel
plummeted, are now even more eager to find cost-efficient ways to improve maintenance performance.

Many airlines have already, in recent years, benefited from the use of AI in engine health monitoring (EHM) and have embarked on program optimization campaigns designed to contain costs and increase aircraft reliability. But relatively few have succeeded in early attempts to apply AI to the much more complex component
and line maintenance environments. We believe the predictive power of AI could contribute to a step change in airline profitability by removing maintenance-caused
disruption from the operation.
The airlines already exploring the potential of predictive maintenance have found their attempts plagued by inadequate sponsorship at the executive level,
data fragmentation and usability issues, and myriad downstream implementation challenges.