Machine Learning-Based Predictive Analytics for Aircraft Engine

PROJECT TITLE	Machine Learning-Based Predictive Analysis for Aircraft Engine
TEAM ID	PNT2022TMID31107
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BRANCH	Computer Science and Engineering

1.ABSTRACT

An essential aspect of air safety is making sure the engines run properly for their entire lifespan. The number of accidents caused by a poor crew response after an engine malfunction has remained constant for many years,despite the fact that modern engines are very reliable. Engine failure is highly risky and needs numerous time for repair. Unexpected failure leads to loss of money and time. Predicting the failure prior will savetime, effort, money and sometimes even lives. The failure can be detected by installingthe 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 anengine by using MachineLearning to save loss of time & money thus improving productivity. especially on aircraft machine where the safety is priority due to enormouscost and human life. ML is the technique that accurately prediction through the data. Processing of real-time sensor data is frequently used in fault diagnosis and predictive analytics of high-value engineering systems to identify obstructive or covert issues withthe underlying system. To accomplish this, it is required to condition the sensor data before combining it with the system's existing design knowledge to produce insightfulinformation. These analytics have the potential to avoid expensive breakdowns and schedule maintenance cycles efficiently. A configuration that can efficientlyenable datacollecting, data conditioning, secure transmission, database storage, and the executionof real-time data analytics algorithms is required to develop such a system.

2.INTRODUCTION

2.1 Project Overview:

The ability of machinery to function cannot be guaranteed; occasionally, it will fail due to outdated operation. Sensor-equipped machinery systems can only monitor a machine's condition; they cannot determine if it is in excellent or bad shape.

Maintenance strategy must be applied to scheduled machinery systems in order to prevent the worst event (failure) and obtain information about a machine's status. There are three maintenance strategies that are best practices. Maintenance that is corrective, preventive, and predictive. The fundamental maintenance method is corrective maintenance (CM), which is carried out when a machine stops functioning. Corrective maintenance (CM) can be carried out when a machine has spare components; otherwise, it has drawbacks whereas predictive maintenance (PM) is scheduled. Machine learning (ML), a branch of artificial intelligence, is a technique or algorithm that can pick up knowledge based on training, or information that is provided about something, and use that knowledge later when the algorithm is use. Due to its impact on human and economic safety, prognostic and health management (PHM) in the aviation sector will develop. Advance maintenance will be used in this sector to inform of the state of the aircraft engines.PdM is an advanced maintenance method that can be used in the aviation industry due to its high accuracy forecast, which can lower operating costs and increase safety by calculating remaining usable life.

2.2 Purpose:

Making sure the engines function effectively for their lives is a crucial component of air safety. Even though modern engines are relatively reliable, the number of accidents resulting from a subpar crew response to an engine breakdown has remained steady for many years. Engine failure is quite dangerous and takes a long time to fix. Unexpected failure results in time and money losses.Saving time, effort,money, and occasionally even lives can be done by anticipating failure. By putting in the sensors and monitoring the values, the failure can be found. By putting in the sensors and monitoring the values, the fault can be found. Any device may be subject to failure detection and preventive maintenance, but we will be dealing with engine failure for a predetermined number of days. There can be various factors in which aircraft engines malfunctions, the main motive of the project is to predict the cause of the failure to improve the quality of flying experience and extricate capital loss.

3.LITERATURE SURVEY

3.1 Existing Problem:

The zero-engine system is complex, and the working environment is harsh. As the fundamental component of the zero-engine control system, the sensor must monitor its health status. Traditional sensor fault detection algorithms often have many parameters, complex architecture, and low detection accuracy There are earlier works on the same subject as the fundamental details of this page. A thorough analysis of PdM system architecture has been conducted somewhere, and it provides a review of the variousPdM approaches currently in use, ranging from the traditional base to the use of ML and DL approaches. This work also places emphasis on DL due to its accuracy and the rise in popularity of the method among researchers over the past five years. The most often used techniques are k-means, RF, ANN, and SVM.Additionally, because the model can accurately anticipate engine activity, other researchers have provided Long Short-Term Memory (LSTM) method for prognostic methodology for aircraft fault prediction and suggested it.

3.2 References:

Dubrovnik Miljković; He told in their research paper on “Detecting AircraftPiston Engine Problems by Analysis of Engine Parameters” Most general aviation aircrafts use piston engines that are considerably less reliable than turbine engines. Most problems of aircraft piston engines are reflected in engine temperature parameters like cylinder head temperature (CHT) and exhaust gas temperature (EGT) that are recorded by engine monitor. Three approaches fordetection of engine problems are presented. Many problems may be detected by comparison of statistical distributions of CHTs and EGTs from individual cylinders. Incipient exhaust valve failure may be detected from temporal EGT pattern containing low frequency fluctuations. The life of the exhaust valve depends on its operating temperature. Because EGT is the major contributor to the overheating of the exhaust valve and it’s cooling mostly depends on the CHT,the remaining life of exhaust valve may be assessed from cumulative sum of EGT and CHT during the period of use. Veer Markup, Madurai Mokashi, “Predicting Aircraft Equipment Failureusing Machine Learning Classification Algorithms “published in April 2021 proposed enormousamount of information and maintenance data exists in the aviation industry that can be utilized to draw meaningful insights in forecasting the future course of action. In this study, our prime objective is to use machine learning classification models to perform feature selection and predictive analysis to predict failures of aircraft systems. Maintenance and failure data for aircraft equipment across a period of two years were collected, and cleaned, which was followed by application feature engineering and feature election techniques before model building and evaluation. We compute a metric known as Remaining Useful Life (RUL) to predictthe failure of aircraft equipment, since this is a continuous variable, we then convert it into a binary classification problem by setting a threshold RUL value to indicate an impending failure so that our classification model flags a warning well in advance to the point of breakdown, thereby giving response teams sufficient time to act upon the warning. Experimental results of our classification model demonstrate the effectiveness of our model to forecast the failure of aircraft equipment. Xiao Du, Jiajie Chen, Haibo Zhang and Jiqiang Wang; ": Fault Detection of AeroEngine Sensor Based on Inception-CNN" in this research paper they told the engineer system is complex, and the working environment is harsh. As the fundamental component of the zero-engine control system, the sensor must monitor its health status. Traditional sensor fault detection algorithms often have many parameters, complex architecture, and low detection accuracy. Aiming at this problem, a convolution al neural network (CNN) whose basic unit is an inception block composed of convolution kernels of different sizes in parallel is proposed. Three The network fully extracts redundant analytical information between sensors through different size convolution kernels and uses it for zero-engine sensor fault detection. On the sensor failure dataset generated by the Monte Carlo simulation method, the detection accuracy of Inception-CNN is 95.41%, which improves the prediction accuracy by 17.27% and 12.69% compared with the best-performing non-neural network algorithm and simple BP neural networks tested in thepaper, respectively. In addition, the method simplifies the traditional fault detection unit composed of multiple fusion algorithms into one detection algorithm, which reduces the complexity of the algorithm. Finally, the effectiveness and feasibility of the method are verified in two aspects of the typical sensor fault detection effect and fault detection and isolation process. Arunvinthan Shan, 2015, they told in their survey that Ensuring a proper operation of the engines over their lifetime is an important air safety aspect. Even though the recent engines are highly reliable the number of accidents due to an incorrect crew response following an Engine malfunction has remained constant for many years. This prompted this study and it reveals that flight crews are not always able to identify and understand engine malfunctions precisely which leads to needless engine shutdowns, incidents, and accidents. The scope of this Book is to provide basic guidelines to identify Engine failures/malfunctions and to give operational recommendations in case of Engine malfunction. This can be accomplished using

SOM maps. Clustering the various engine parameters based on the parametric variations influencedby the faults, SOM maps are generated and they are stored as the failure template. In addition to their traditional tool based quantitative inspection of some measured variables to detect any deviation from the normal behavior making it possible to anticipate possible faults. By proper detection of the faults suitable malfunction response for the crew will be displayed for their crew assistance. It ensures further reliability and passenger safety. Xiaoping Liu, Siqi An, in the year 2014 proposed the method to find the failure propagation mechanism from the complex system of aircraft engine, this paper used the topological structure to describe the coupling relations, discussing the role of topological geometry method in the failure propagation. The topological structure statistical properties of the system were analyzed with small world net theory, and a failure propagation model based on the small world clustering was proposed, and the failure propagation paths and relevant key nodes with high pervasive ability were found with the Dijkstra algorithm. The results verify that this method can effectively find the weak point in the system, and provide an important basis for design improvements and failure prevention.

3.3 Problem Statement Definition:

1. Need of more Data:

Our first step is to identify the target variable which we want to predict. Since our dataset consists of columns containing sensor readings, it initially is not intuitive as to what will help us arrive at our target variable. Through some analysis, we realized that based on the maximum number of cycles until failure, we can compute the Remaining useful life or RUL. After which we will approach predictive maintenance as a binary classification problem.

2. Need of code for perfect results :

The problem can be posed as a regression or binary classification or multi-class classification for this dataset. In this case study, binary classification is done and the code predicts whether the Engine will fail in next 30 cycles or not. Class label 1 represents that it will fail in next 30 cycles and class label 0 represents that it won't. These labels are not given by dataset but are generated by code. As it is more important to correctly classify it as failure when it is going to fail, Recall is considered as the performance metrics in this case study.

3. Problem with Engines :

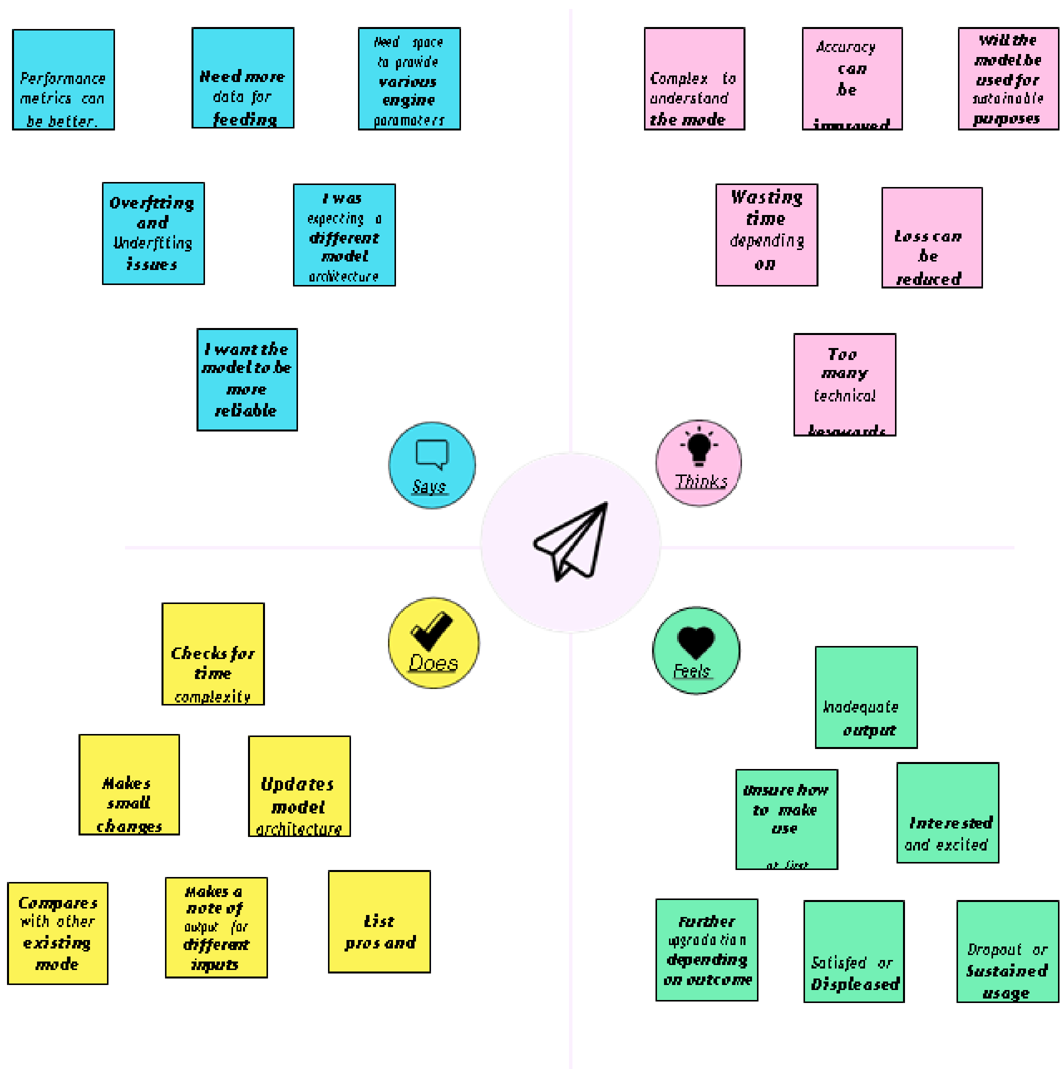
Preventable fuel problems such as exhaustion, mismanagement, contamination, or miss-fueling . Structural failures where a broken connecting rod, crank, valve, or camshaft is present account for seventeen percent of engine failures, primarily in Continental engines.

4. Problem with Human resources:
It is better to record and maintain data and the malfunction with systems through machine learning with the Aid of Artificial Intelligence. But there is a need of Human resource is needed to maintain the datasets preferably exact ones. There is such need of pilot and second officers are needed to maintain the customers. There is no one to have a look on condition of airplane, pilots concentration is fully focused on flights stability. There is no possibility to have a look on engines condition. So machine learning can help to read the data.

4. IDEATION & PROPOSEDSOLUTION

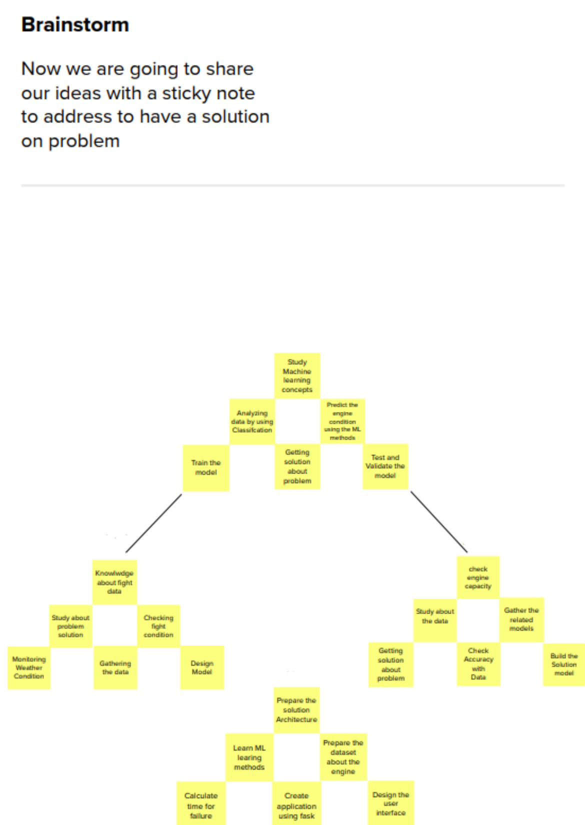
4.1 Empathy Map Canvas:

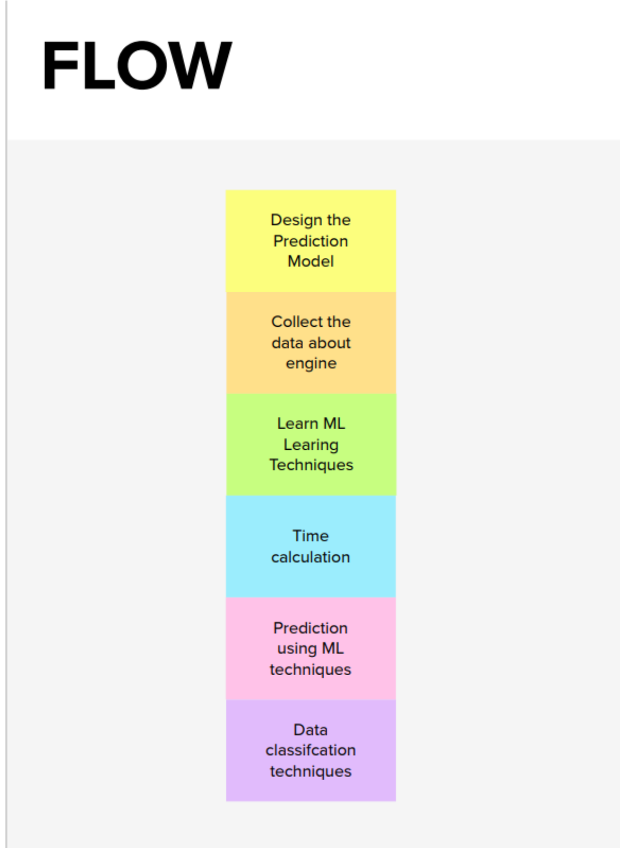
Machine Learning-Based Predictive Analytics for Aircraft Engine



4.2 Ideation &Brainstorming:

An essential aspect of air safety is making sure the engines run properly for their entire lifespan. Making sure the engines function effectively for their lives is a crucial component of air safety. The number of accidents caused by a poor crew response after an engine malfunction has remained constant for many years. Engine failure is highly risky and needs numerous 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 predictivemaintenance 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 MachineLearning to save loss of time & money thus improving productivity. especially on aircraft machine where the safety is priority due to enormous cost and human life. ML is the techniquethat accurately prediction through the data. Processing of real-time sensor data is frequently used in fault diagnosis and predictive analytics of high-value engineering systems to identify obstructive or covert issues with the underlying system. Engine failure is very dangerous and requires significant time for repair. Loss of time and money results from an unexpected failure.Time, effort, money, and occasionally even lives can be saved by predicting failure beforehand.Installing the sensors and monitoring the values will allow you to find the failure.





4.3Proposed Solution

S. No	Parameter	Description
1	Problem Statement(Problem to be solved)	There can be various factors in which aircraft engines malfunctions, the main motive of the project is to predict the cause of the failure to improve the quality of flying experience and extricate capital loss.
2	Idea / Solution description	The project aims to predict the failure of an engine by taking engine parameters, flight trajectory and other external testing parameters using Machine Learning to save

		loss of time and money thus improving productivity.
3	Novelty / Uniqueness	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.
4	Social Impact/ Customer Satisfaction	As the failure of a particular engine segment ispreviously predicted one could have an idea to usethe affected-hardware aptly and this could drastically reduce the loss of life. On encountering the plane crash,one could observe the ecosystem surrounding the crash would be seriously affected due to gregariousness chemical-emission. Bird strikes occur at various wing and fuselage locations, but they usually inflict most damage to the jet engines, composed as they are of intricate high-speed rotating parts, and this is specially termed as bird ingestion engine damage.
5	Scalability of the Solution	The solution of the project "Machine learning based predictive analysis for aircraft engines" isflexible enough to meet the clients or customer requirements.

Feasibilityof the project:

a. Economic feasibility: Since the project mainly focuses on software using sensor and no complicated hardware is required. Thus, the overall cost does not get too high.

b. Technical feasibility: Python, flask and many machine learning algorithms are used to build theproject and is used to achieve the desired result for the proposed model.

c. Operational feasibility: The proposed solution solves the problem by well predicting the failure ofengine in prior stages because of the frequent and periodic testing phases.

5. REQUIREMENT ANALYSIS

5.1 Functional Requirement

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 Password	Set Password Confirm Password
FR-4	User Verification	Email Verification
FR-5	User Dataset	Add to Prediction System
FR-6	Dataset Pre-processing	Apply 80-20 rule on the dataset Transform Categorical data into Numerical values
FR-7	User Engine Data Intake	Get data input through Web Interface Communicate data to ML model
FR-8	Display Engine Failure Rate	Process input to arrive at a conclusion Display Probability of Engine Failure in Web Interface

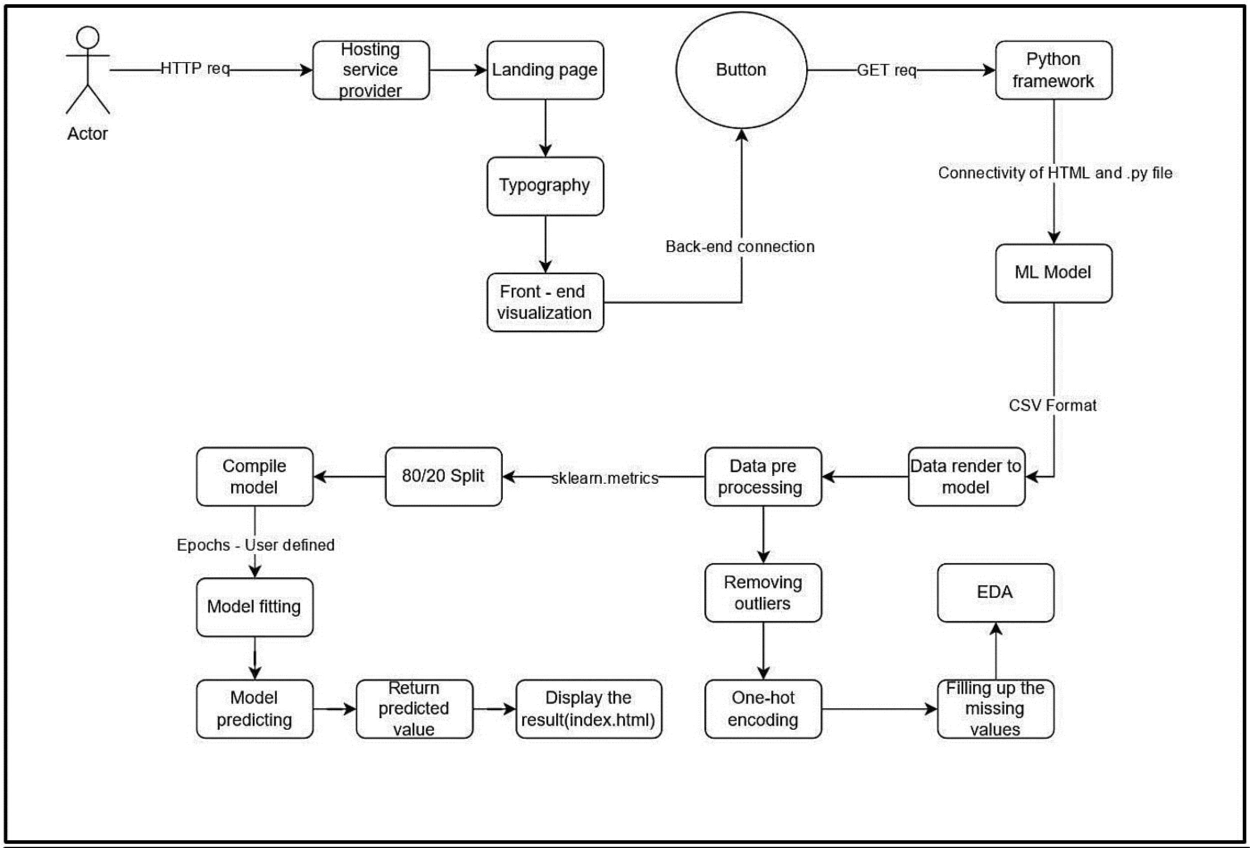
5.1 Non-Functional Requirement

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

FR No.	Non-Functional Requirement	Description
NFR-1	**Usability**	Usability is a non-functional requirement, because in its essence it doesn't specify parts of the system functionality, only how that functionality is to be perceived by the user, for instance how easy it must be to learn and how efficient it must be for carrying out user tasks.
NFR-2	**Security**	Functional security requirements describe functional behaviour that enforces security. Functional requirements can be directly tested and observed. Requirements related to access control, data integrity, authentication and wrong password lockouts fall under functional requirements.
NFR-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.
NFR-4	**Performance**	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 compromising performance requirements are often based on supporting end-user Tasks.

6. PROJECT DESIGN

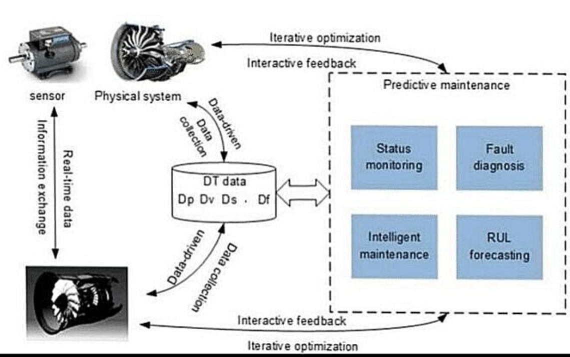
6.1 Data Flow Diagram



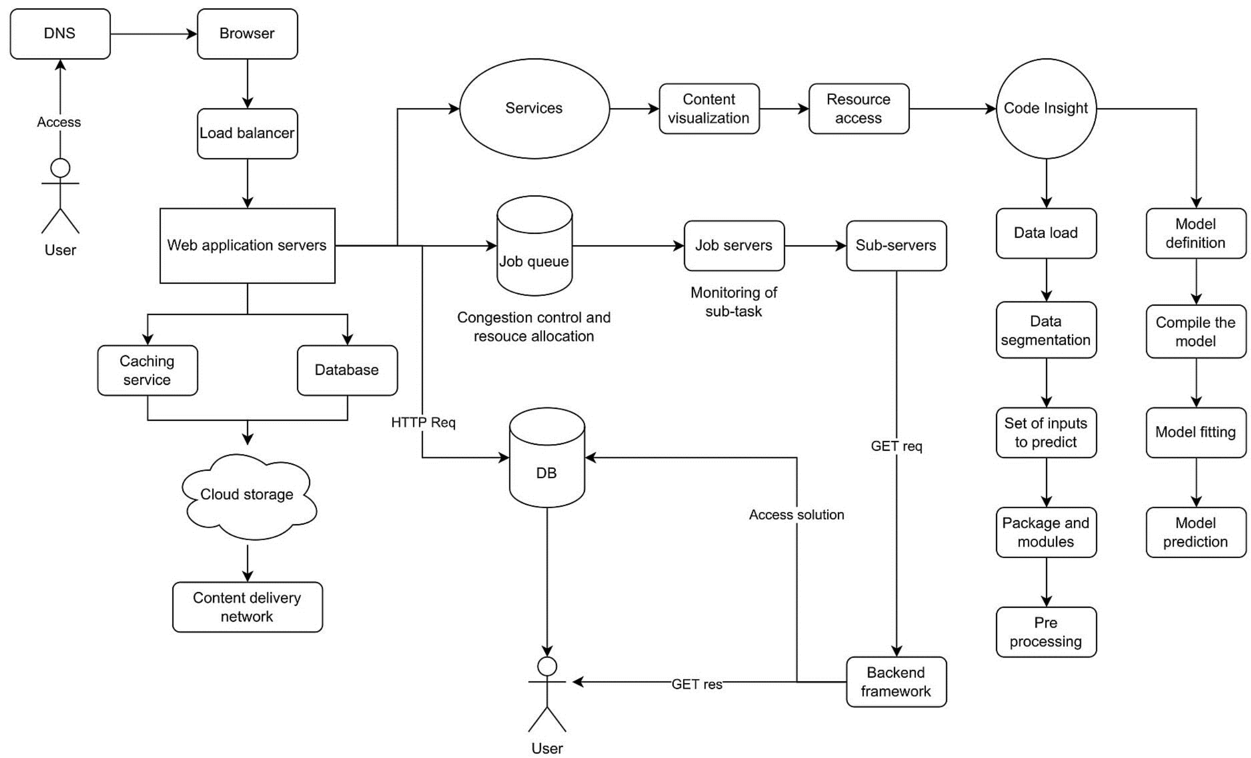
Data Flow Diagrams:

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 stored.

EXAMPLE: **Data flow diagram for Machine Learning-Based Predictive Analytics for Aircraft Engine**



6.2 SOLUTION ARCHITECTURE



7. PROJECT PLANNING & SCHEDULING

7.1 Sprint Planning & Estimation

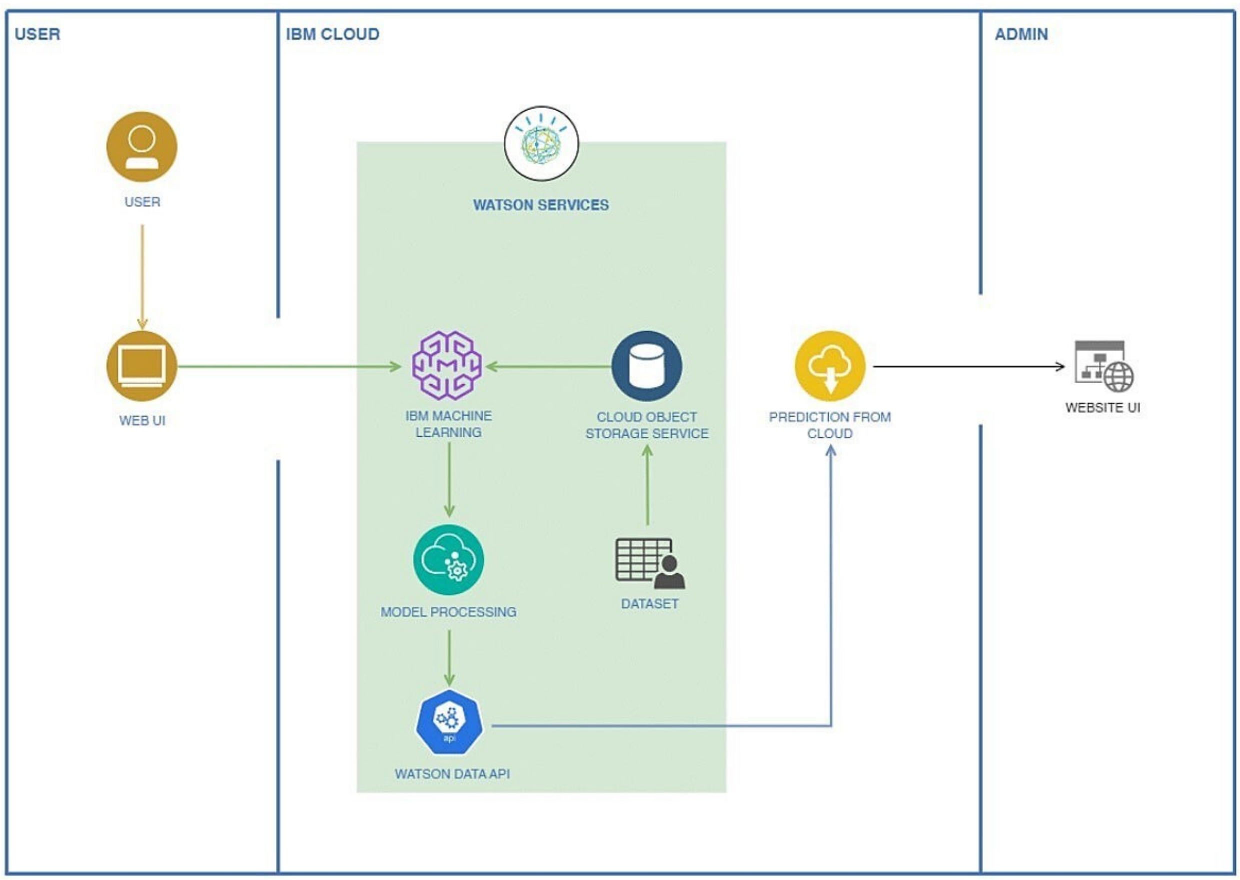
i. SPRINT PLAN
ii. ANALYZE THE PROBLEM
iii. PREPARE AN ABSTRACT, PROBLEM STATEMENT
iv. LIST A REQUIRED OBJECTNEEDED
v. CREATE A PROGRAM CODE AND RUN IT
vi. MAKE A PROTOTYPE TO IMPLEMENT
vii. TEST WITH THE CREATEDCODE AND CHECK THE DESIGNEDPROTOTYPE

7.2 Sprint Delivery Schedule

i. Sprint 1
ii. Sprint 2
iii. Sprint 3
iv. Sprint 4

8. SCHEMATIC DIAGRAM OF PROJECT & COMPONENTS:

8.1 Technical Architecture



8.2.Components Used

S.No	Component	Description	Technology
1.	User Interface	The User interacts via a web UI	HTML, CSS, JavaScript
2.	Application Logic-1	Running the web server and UI for website	Flask, Python
3.	Application Logic-2	Running the Machine Learning Model	IBM Watson Studio , Machine Learning
4.	Application Logic-3	Logic for a process in the application	IBM Watson Assistant
5.	Cloud Database	Database Service on Cloud	IBM DB2, IBM Cloudant etc.
6.	File Storage	Storage for storing Dataset	Cloud object storage service
7.	Internal API	API Used for getting the predicted data from machine learning model in watson	Watson Data API
8.	Machine Learning Model	Machine Learning Model for predicting Aircraft Engine Failure	Object Recognition Model, etc.
9.	Infrastructure (Server / Cloud)	Application Deployment on Cloud Cloud Server Configuration : Intel Xeon E3-1270 v6 4 Cores, 3.80 GHz 16 GB RAM 1 x 1 TB HDD CentOS 20 TB bandwidth*	Web hosting on IBM Cloud

Application Characteristics

S.No	Characteristics	Description	Technology
1.	Open-Source Frameworks	List the open-source frameworks used	Python, GIt, Github, Keras, Tensorflow, Jupyter Notebooks
2.	Security Implementations	In the web server created by the team will be secure and when deployed on cloud the cloud security will cover the web app	HTTPS, IBM Cloud Web Hosting
3.	Scalable Architecture	This is a 3 Tier Architecture	IBM Watson Studio, Python,Flask
4.	Availability	Taken care by the cloud provider, availability required is high	IBM Cloud Load Balancers, Multiple Data Servers
5.	Performance	High performance rate is required to provide accurate predictions	Watson Machine Learning on Cloud Pak

9. CONCLUSION

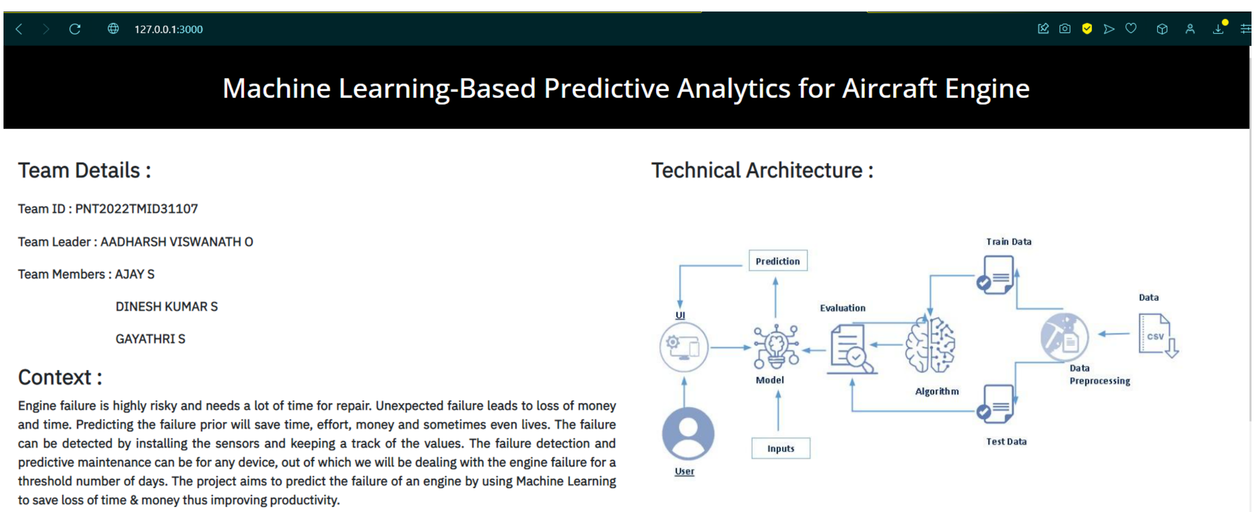
Engine failure is highly risky and needs numerous time for repair. Unexpected failure leads to lossof money and time. Predicting the failure prior will save time, effort,money and sometimes even lives. The failure can be detected by installing the sensors and keeping a track of the values. The main objective of predictive maintenance is to predict when equipment failures can occur. Then prevent that failure by taking relevant actions.

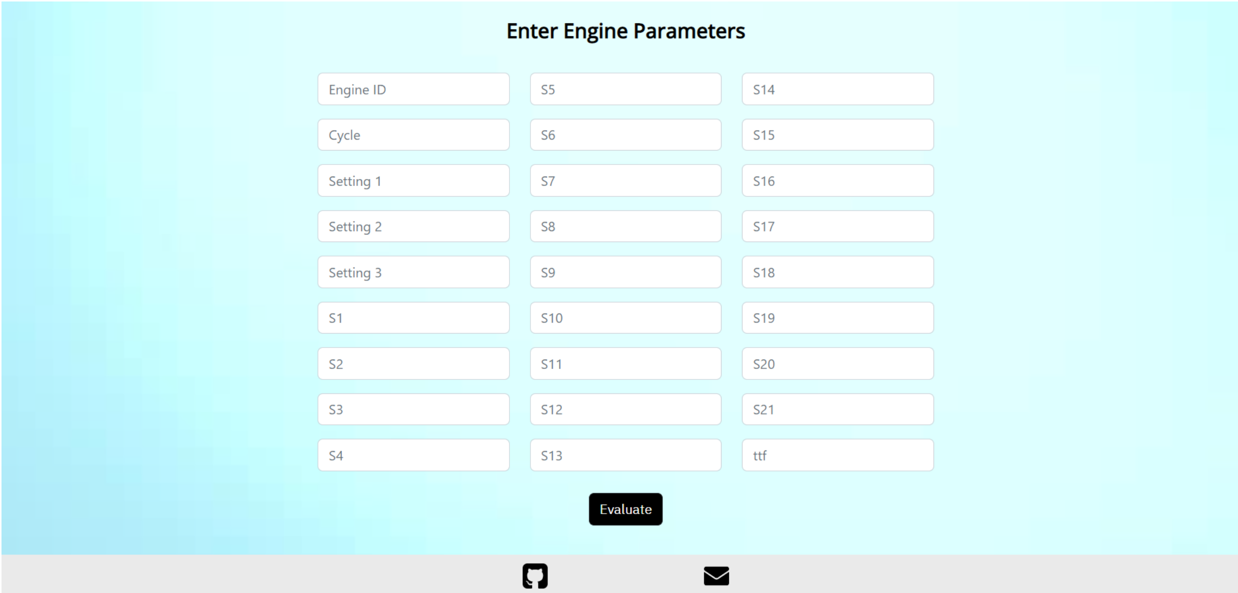
10.FUTURE SCOPE

By reducing the likelihood of a serious engine failure and the need for the pilot to shut down an engine during flight with all the potential emergency ramifications that can result,the ability to detect an impending failure in an aircraft engine mechanical power system at an early stage, where expensive and potentially catastrophic system failures can be prevented, will improve aircraft safety. Various other algorithms can be used to predict the aircraft engine failure more accurately and prevent this failure before it happens.

11. APPENDIX

11.1 Screen Shorts:





11.2 Source code:

For source code please check out our github repositories.

https://github.com/IBM-EPBL/IBM-Project-5755-1658814367