Developing A Flight Delay Prediction Model

Using Machine Learning

Project domain : Data science

Team ID : PNT2022TMID24557

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VELAMMAL INSTITUTE OF TECHNOLOGY

PONNERI -601 204

DEVELOPING A FLIGHT DELAY PREDICTION MODEL USING MACHINE LEARNING

Bonafide record of work done by

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CONTENTS

CHAPTER 1
INTRODUCTION

Travelers have begun to favor air travel more and more over the past 20 years, primarily due to its quickness and occasional comfort. Both on the ground and in the air, as a result, have experienced amazing growth. Massive amounts of ground and airborne aircraft delays have also been brought on by an increase in air traffic. Large economic and environmental losses are the result of these delays. The model's primary goal is to correctly forecast flight delays in order to improve aircraft operations and reduce delays.

1.1. PROJECT OVERVIEW

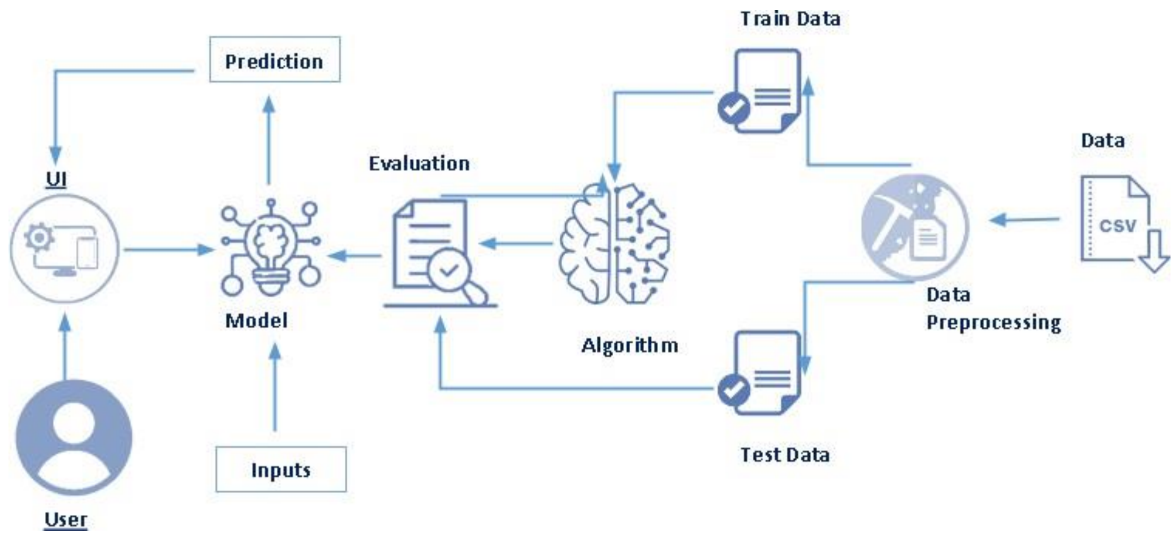


Figure 1.1. Technical Architecture

Flight arrival delays can be predicted using a machine learning algorithm. Rows of feature vectors, such as departure date, delay, travel time between the two airports, and scheduled arrival time, provide the input to our algorithm. The decision tree classifier is then used to determine whether or not the flight arrival will be delayed. When there is more than a 15-minute gap between the scheduled and actual arrival timings, a flight is deemed to be delayed. For various figures of merit, we contrast the decision tree classifier with logistic regression and a straightforward neural network.

1.2. PURPOSE

The main goal of this project is to predict the flight delay using machine learning algorithms. Flight planning is one of the difficulties in the industrial environment because there are many unpredictabilities. One such condition is the incidence of delays, which can result from a variety of causes and impose significant expenses on airlines, operators, and passengers. Delays in departure can be brought on by inclement weather, seasonal and holiday demands, airline policies, technical issues with airport infrastructure, baggage handling, and mechanical equipment, and a buildup of delays from earlier flights. Hence Predicting flight delays can improve airline operations and passenger satisfaction, which will result in a positive impact on the economy.

CHAPTER 2

LITERATURE SURVEY

[1] H. Khaksar and A. Sheikholeslami, “Airline delay prediction by machine learning algorithms”, Scientia Iranica, Transactions A: Civil Engineering 26 (2019) 2689-2702.

Proposed work: This paper proposes a flight delay prediction model through different methods which includes Bayesian modeling, decision tree, cluster classification, random forest, and hybrid methods. These methods were applied to estimate the occurrences and magnitude of delay in a network.

[2] Miguel Lambelho, Mihaela Mitici, Simon Pickup, Alan Marsden,”Assessing strategic flight schedules at an airport using machine learning-based flight delay and cancellation predictions”, Journal of Air Transport Management, Volume 82, 2020, 101737, ISSN 0969-6997.

Proposed work: This paper provides a machine learning- based approach to assess the strategic flight schedules in terms of potential arrival/departure flight delays and cancellations. This paper also provides an approach that supports an integrated strategic flight schedule assessment, where strategic flight schedules are evaluated withrespect to flight delays and cancellations.

[3] Navoneel Chakrabarty, ”A Data Mining Approach to Flight Arrival Delay Prediction for American Airlines“, The 9th Annual Information Technology, Electromechanical and Microelectronics Conference (IEMECON 2019).

Proposed work: This paper aims at analyzing flight information of US domestic flights operated by American Airlines, covering top 5 busiest airports of the US and predicting possible arrival delay of the flight using Data Mining and Machine Learning Approaches.

[4] Kaiquan Cai, Yue Li, Yiping Fang, Yanbo Zhu,” A Deep Learning Approach for Flight Delay PredictionthroughTime-EvolvingGraphs”.IEEE Transactions on Intelligent Transportation Systems,IEEE,In press,pp.1-11.ff10.1109/TITS.2021.3103502ff. ffhal-03428046f.

Proposed work: This paper is about the flight delay prediction problem is investigated from a network perspective (i.e., multi-airport scenario). To model the time-evolving and periodic graph-structured information in the airport network, a flight delay prediction approach based on the graph convolutional neural network (GCN) is developed in this paper.

[5] Yi Ding," Predicting flight delay based on multiple linear regression" ,2017 IOP Conf. Ser.: Earth Environ. Sci. 81 012198

Proposed work: This paper proposes a method to model the arriving flights and a multiple linear regression algorithm to predict delay, comparing with Naive-Bayes and C4.5 approach.

[6] Qu, J., Zhao, T., Ye, M. et al. "Flight Delay Prediction Using Deep Convolutional Neural Network Based on Fusion of Meteorological Data.", Neural Process Lett 52, 1461–1484 (2020).

Proposed work: This paper provides two flight delay prediction models using deep convolutional neural networks based on fusion of meteorological data. The first model is DCNN (Dual- channel Convolutional Neural Network), which refers to the ResNet network structure. The second model is SE- DenseNet (Squeeze and ExcitationDensely Connected Convolutional Network).

[7] G. Gui, F. Liu, J. Sun, J. Yang, Z. Zhou and D. Zhao, "Flight Delay Prediction Based on Aviation Big Data and Machine Learning," in IEEE Transactions on Vehicular Technology, vol. 69, no. 1, pp. 140-150, Jan. 2020, doi: 10.1109/TVT.2019.2954094.

Proposed work: This paper explores a broader scope of factors which may potentially influence the flight delay, and compares several machine learning-based models in designed generalized flight delay prediction tasks. To build a dataset for the proposed scheme, automatic dependent surveillance-broadcast (ADS-B) messages are received, pre- processed, and integrated with other information such as weather condition, flight schedule, and airport information.

[8] Yu, Bin; Guo, Zhen; Asian, Sobhan; Wang, Huaizhu; Chen, Gang (2019),"Flight delay prediction for commercial air transport: A deep learning approach." Transportation Research Part E: Logistics and Transportation Review.

Proposed work: This paper analyzes high-dimensional data from Beijing International Airport and presents a practical flight delay prediction model. Following a multifactor approach, a novel deep belief network method is employed to mine the inner patterns of flight delays. Support vector regression is embedded in the developed model to perform a supervised fine-tuning within the presented predictive architecture

[9] Esmaeilzadeh, Ehsan; Mokhtarimousavi, Seyedmirsajad (2020).“Machine Learning Approach for Flight Departure Delay Prediction and Analysis”. Transportation Research Record: Journal of the Transportation Research Board.

Proposed work: This paper employs a support vector machine (SVM) model to explore the non- linear relationship between flight delay outcomes. Individual flight data were gathered from 20 days in 2018 to investigate causes and patterns of air traffic delay at three major New York City airports

[10] Etani, Noriko (2019),”Development of a predictive model for on-time arrival flight of airliners by discovering correlation between flight and weather data.”, Journal of Big Data,2019.

Proposed work:This paper aims to discover the correlation between fight data and weather data. A predictive model of on-time arrival flight is proposed using flight data and weather data. The feasibility of the predictive model is evaluated by developing a tool of on-time arrival fight prediction.

CHAPTER 3

IDEATION & PROPOSED SOLUTION

3.1. EMPATHY MAP CANVAS

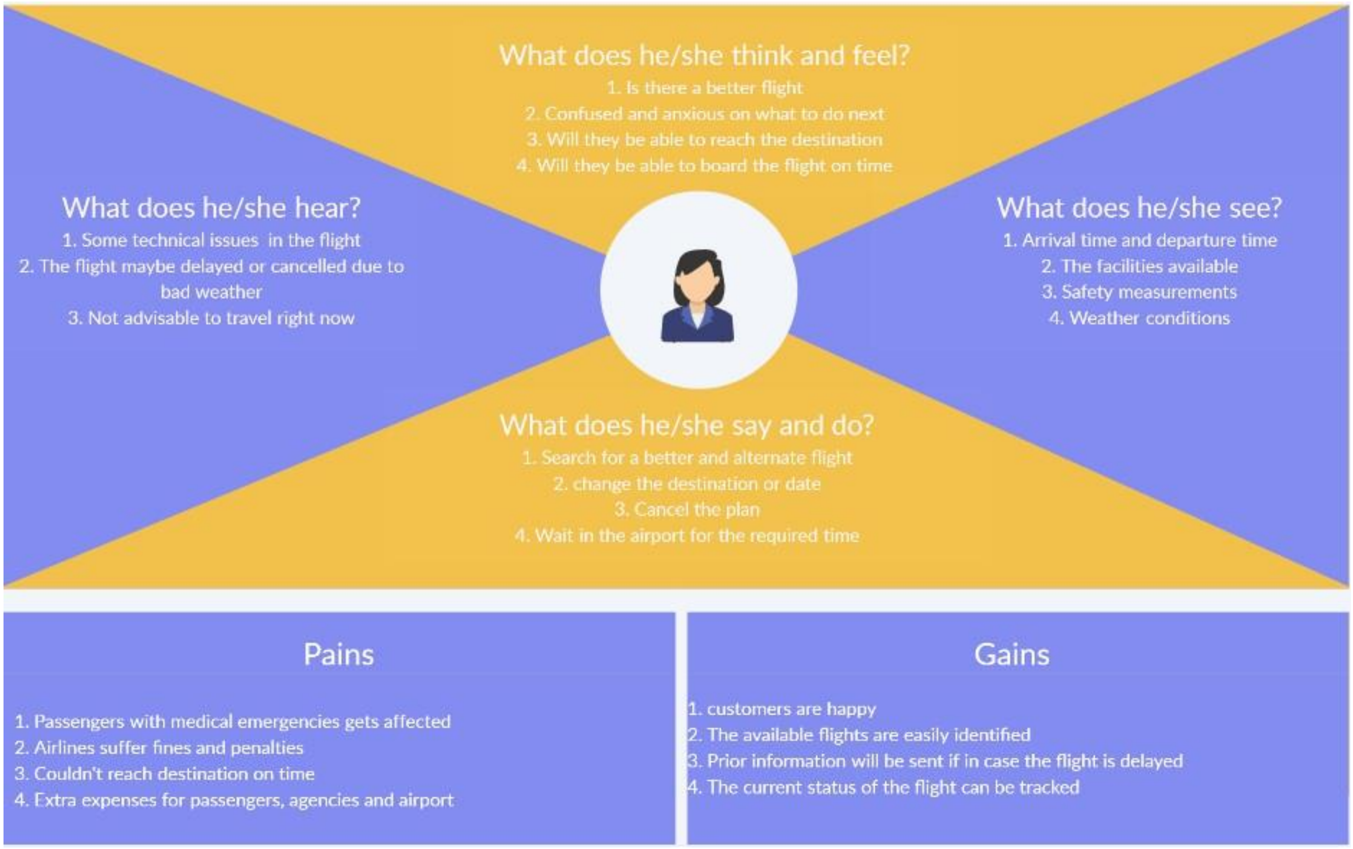
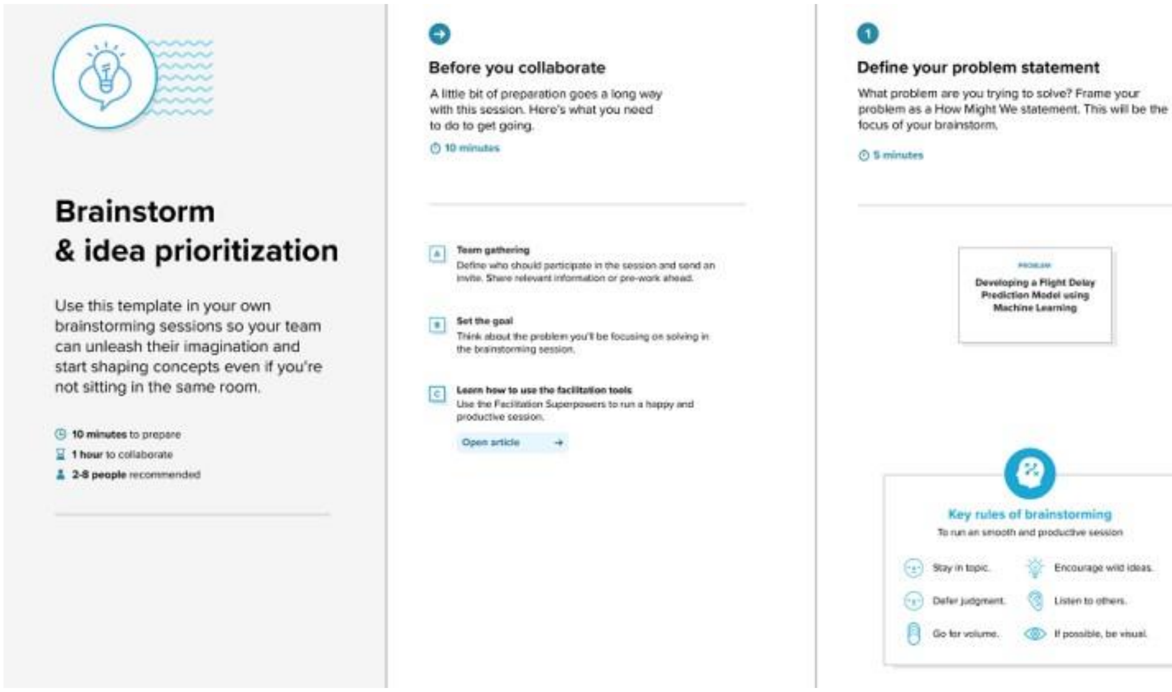


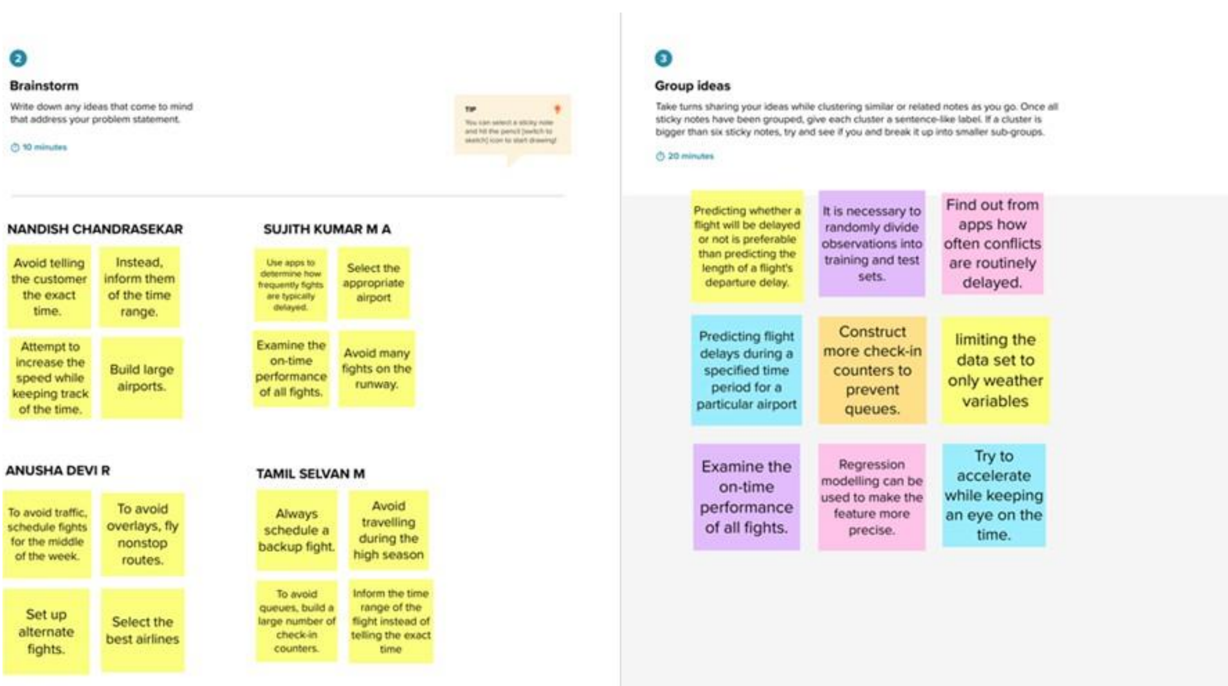
Figure 3.1. Empathy Map

3.2. IDEATION & BRAINSTORMING

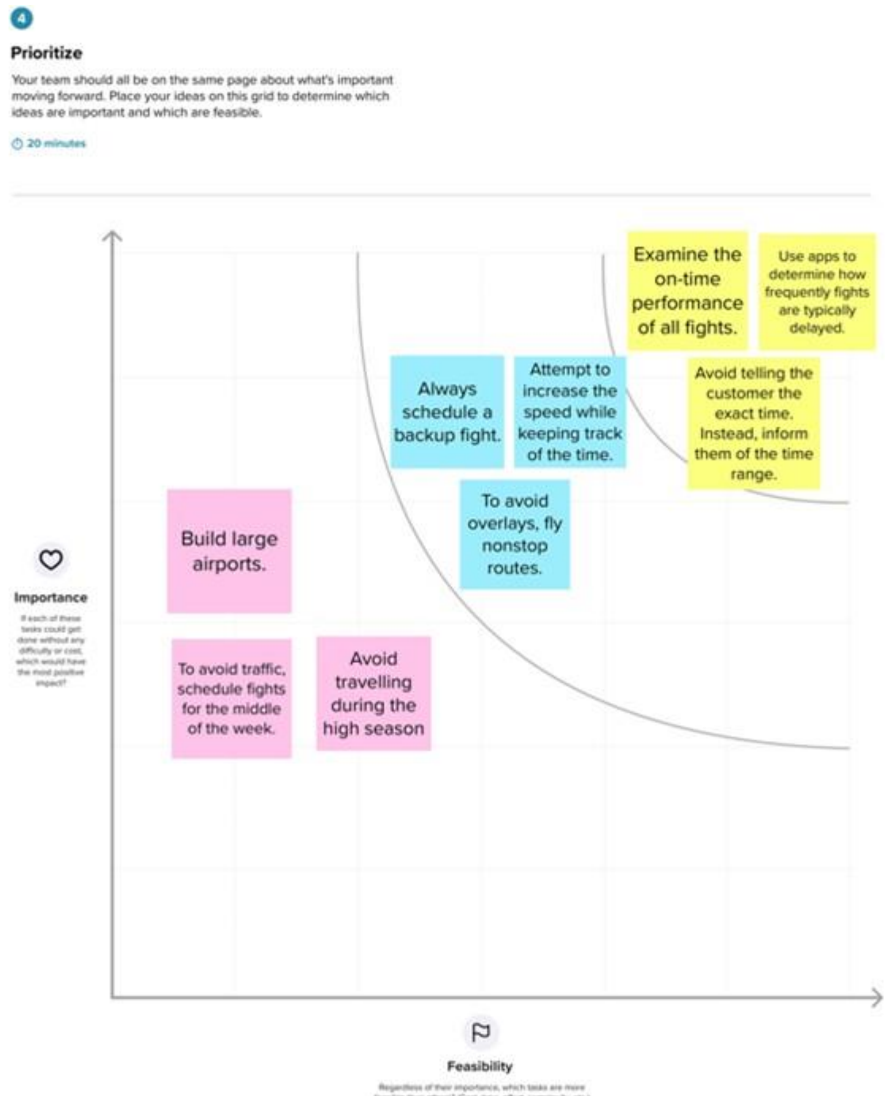
Step 1 - Team Gathering, Collaboration and Selecting the Problem Statement



Step 2 - Brainstorm, Idea Listing and Grouping



Step 3 - Idea Prioritization

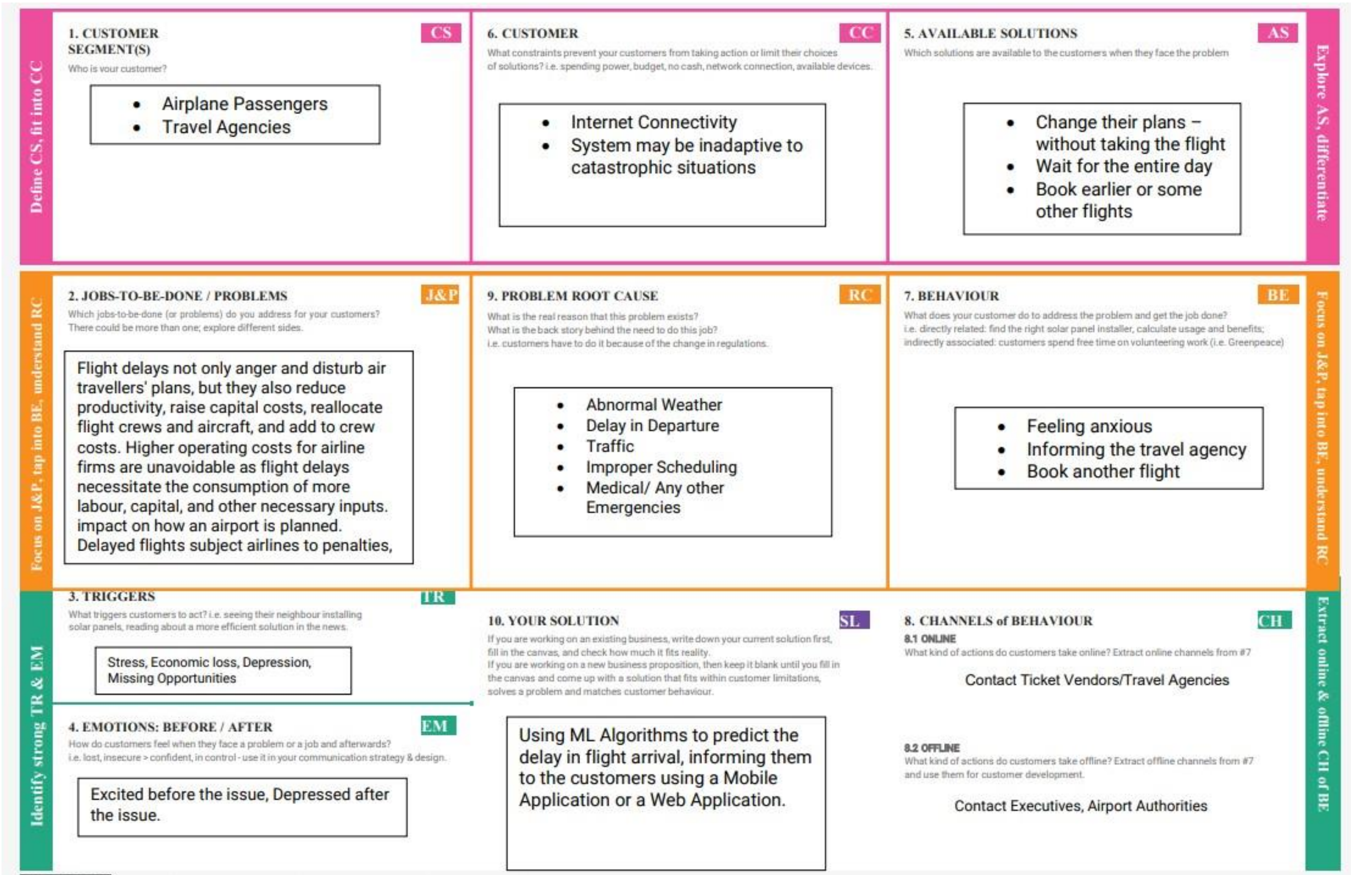


3.3. PROPOSED SOLUTION

S.No.	Parameter	Description
1	Problem Statement (Problem to be solved)	Flight arrival delays can be predicted using a machine learning algorithm. Rows of feature vectors, such as departure date, delay, travel time between the two airports, and scheduled arrival time, provide the input to our algorithm. The decision tree classifier is then used to determine whether or not the flight arrival will be delayed. When there is more than a 15-minute gap between the scheduled and actual arrival timings, a flight is deemed to be delayed. Additionally, for various figures of merit, we contrast the decision tree classifier with logistic regression and a straightforward neural network.
2	Idea / Solution description	Using ML Algorithms to predict the delay in flight arrival, informing them to the customers using a Mobile Application or a Web Application. We are developing a software that will allow passengers who use airplanes to foresee flight delays. They may effectively plan their travel using this application, which will help them save time. The tool will have an intuitive user interface. To estimate delays and execute the most effective and efficient methods in the tool, we will use a variety of machine learning algorithms.
3	Novelty / Uniqueness	1. Building a full-fledged application in which the customers can track whether the flights will be delayed or not. 2. Combining the results of one or more ML models using the techniques of ensembling
4	Social Impact / Customer Satisfaction	Flight delays not only anger and disturb air travelers' plans, but they also reduce productivity, raise capital costs, reallocate flight crews and aircraft, and add to crew costs. Higher operating costs for airline firms are

		unavoidable as flight delays necessitate the consumption of more labor, capital, and other necessary inputs. Flight delays could make the transportation system less effective and have a negative impact on how an airport is planned. Delayed flights subject airlines to penalties, fines, and additional expenses.
5	Business Model (Revenue Model)	The cost of airline tickets and flight delays are now uncertain. Even for the same airplane and seat class, ticket costs are dynamic and frequently change. To increase their revenue, airline firms use a variety of algorithms to adjust the prices dynamically. These modelsare not accessible to the general public due to the intensecompetition among airline operators. Additionally, the flight is delayed due to a number of micro and macro causes. The air route status, the prior flight's delay, airplane capacity, air traffic management, airline properties, etc. are the main elements that have an impact on airlines. To save "Time and Money," it is necessary to forecast airline flight delays and ticket costs.
6	Scalability of the Solution	The proposed system can be scaled up to take actions – book another flight for passengers or if a particular flight is getting delayed often, the same can be examined by memorizing the outputs of this system. This can be scaled up to predict the delay of flights in every airport.

3.4. PROBLEM SOLUTION FIT



CHAPTER 4
REQUIREMENT ANALYSIS

4.1. FUNCTIONAL REQUIREMENT

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	Registration through Form Registration through Gmail Registration through LinkedIN Registration through Facebook
FR-2	User Confirmation	Confirmation via Email Confirmation via OTP
FR-3	Data Management	The administrator of the mobile portal can add, amend, or remove the department data.
FR-4	Data Storage	• Application system under consideration manages the archival, retrieval, and retention of historical data • Sufficient information comprising these
FR-5	Process for Exporting Flight Data	A procedure where mobile client users obtain flight data from a web server for web client analysis.
FR-6	Flight Data	The administrator of the mobile portal can add, amend, or remove passenger's data.
FR-7	Regulatory Conditions	This paper proposes a model for predicting the flight delay based on the decision tree. A decision tree is a supervised machine learning tool that may be used to classify or forecast data based on how queries from the past have been answered. The model is supervised learning in nature, which means that it is trained and tested using data sets that contain the required categorisation.

4.2. NON-FUNCTIONAL REQUIREMENTS

FR No.	Non-Functional Requirement	Description
NFR-1	**Usability**	Knowing when the flight will be delayed enables improved operational planning at the airport of destination based on anticipated flight delay at origin.
NFR-2	**Security**	It is highly secure and the passengers who log in to the application will be able to view the status
NFR-3	**Reliability**	As we train with more data the model will be reliable.
NFR-4	**Performance**	• This was done statistically, and the delay time was thought to be shorter. • Using variables that occur close to the destination's arrival time, it has projected the delay at the destination.
NFR-5	**Availability**	The mobile application must be accessible to users in India 99.98% of the time each month between EST and IST business hours.
NFR-6	**Scalability**	• The main problem for airlines and travellers is flight delay. • According to the flight schedule, the anticipated arrival delay considers both flight information and the weather at the airports of origin and destination.

CHAPTER 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 stored.

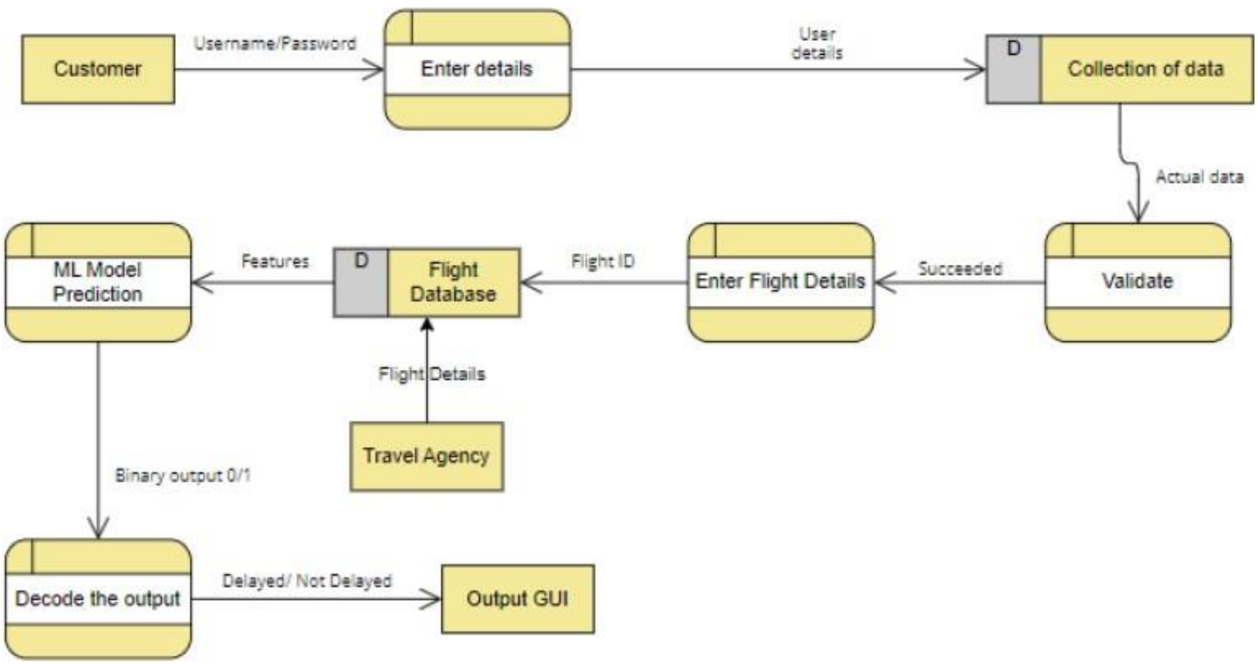


Figure 5.1. Data flow diagram

5.2. SOLUTION & TECHNICAL ARCHITECTURE

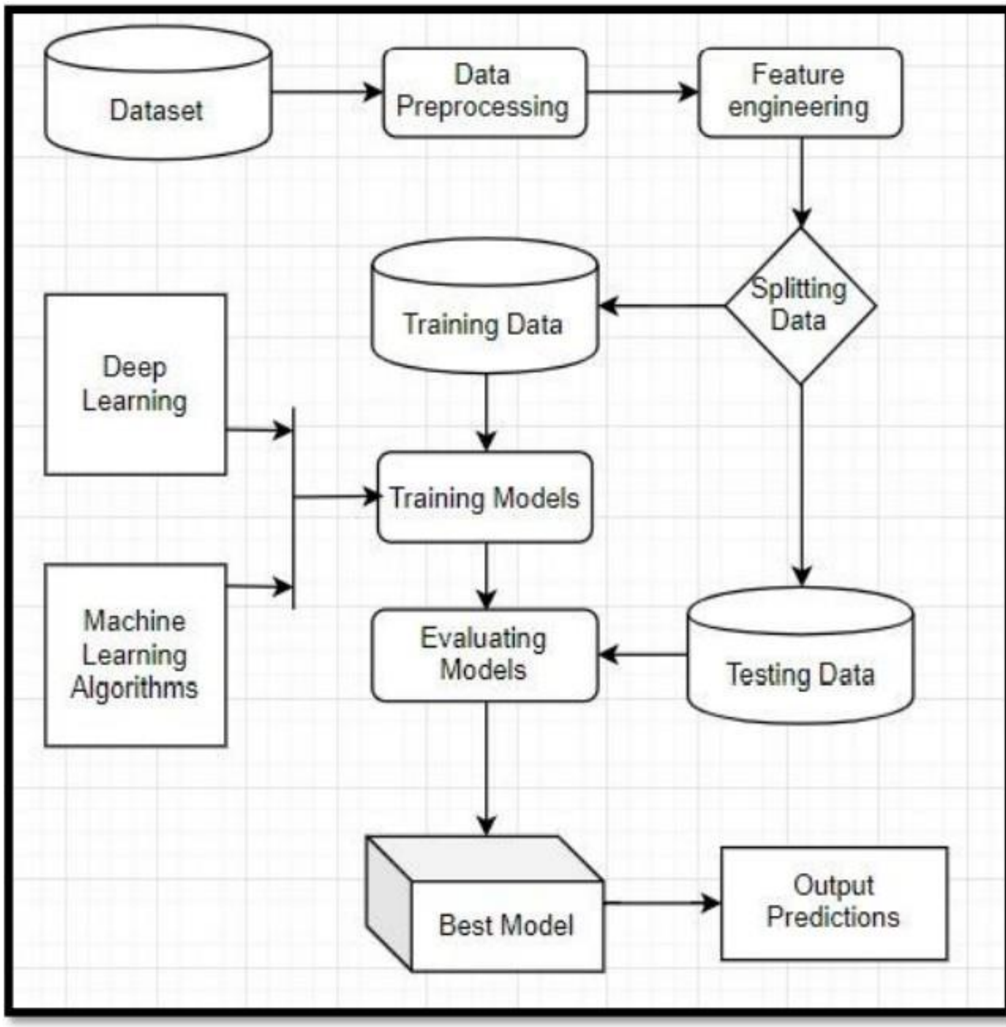


Figure 5.2. Solution Architecture

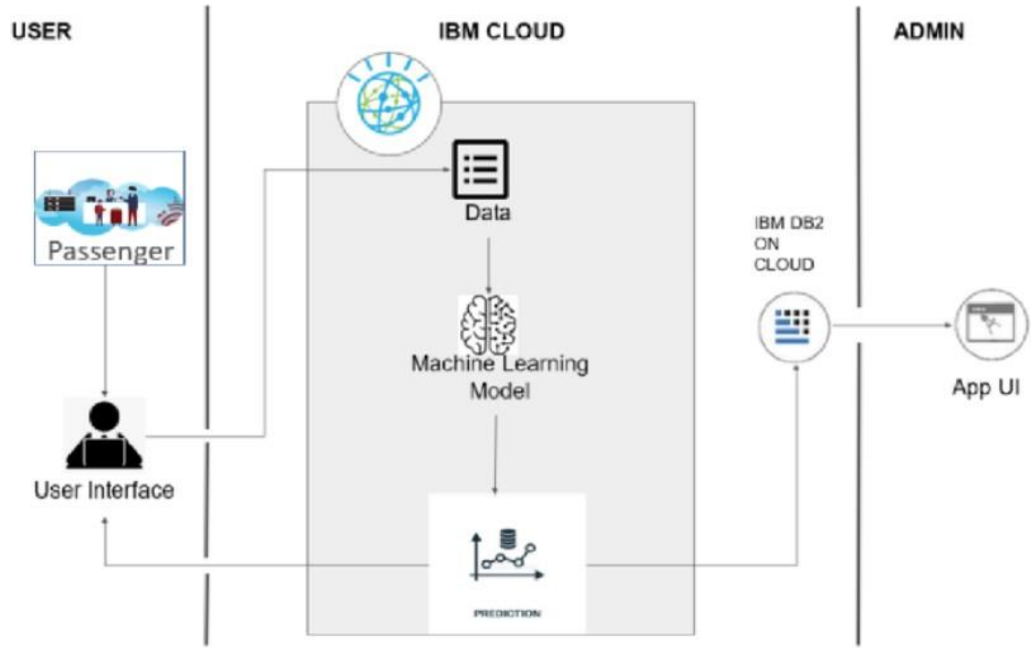


Figure 5.3. Technology Stack

Components & Technologies

S.No	Component	Description	Technology
1.	User Interface	Web Application to interact with the user.	Flask
2.	Login/Sign up	Login/ Sign up – The user can enter the details and get them validated	Python
3.	Database	The Database to store the login details of the user	MySQL
4.	Cloud Database	The database to keep track of the flight details from the travel agency, input to the Machine Learning Model	Firebase
5.	Machine Learning Model	To Predict whether the flight will get delayed or not.	SVM, KNN Classifier, Logistic Regression, Decision Trees
6.	Deep Learning Model	To Predict whether the flight will get delayed or not	Fully Connected Neural Networks
7.	Infrastructure (Server / Cloud)	Application Deployment on Local System / Cloud Local Server Configuration: Cloud Server Configuration :	IBM Cloud

Application Characteristics

S.No	Characteristics	Description	Technology
1.	Open-Source Frameworks	Web application – Flask ML – Sklearn, Tensorflow, Keras API	Deep Learning, Python
2.	Security Implementations	The data is secured that it is encrypted in IBM cloud	AES (256-bit)
3.	Scalable Architecture	Can be scaled upto many airports, many users with more training	Firebase
4.	Availability	The status will be updated frequently	IBM Cloud
5.	Performance	Can make as many number of requests per second to get the prediction	IBM Cloud

5.3. User Stories

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 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	I can register & access the dashboard with Gmail Login	Medium	Sprint-1
	Login	USN-5	As a user, I can log into the application by entering email & password	I can login & access the dashboard	High	Sprint-1
	Core	USN-6	As a user, I can enter my flight details	I can feed the inputs to the system	High	Sprint-2
		USN-7	As a user, I can look at the flight details	I can see whether my flight is getting delayed or not	High	Sprint-3

CHAPTER 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	Data Engineering	USN-1	Data Collection, Data Preprocessing and Feature Extraction	4	High	Sujith Kumar M A
Sprint-1	Machine Learning Prediction Model	USN-2	Building a Machine Model for Flight Delay Prediction, Testing with different metrics.	4	High	Anusha Devi R
Sprint-2	Flask Web Page	USN-3	Building Home Page and Prediction Page.	4	Low	Nandish Chandrasekar
Sprint-1	Integration.	USN-4	Integrating the flask pages with the ML Model and IBM Cloud Deployment	4	Medium	Tamilselvan M

6.2. SPRINT DELIVERY SCHEDULE

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	4	6 Days	24 Oct 2022	29 Oct 2022	4	29 Oct 2022
Sprint-2	4	6 Days	31 Oct 2022	05 Nov 2022	4	05 Nov 2022
Sprint-3	4	6 Days	07 Nov 2022	12 Nov 2022	4	12 Nov 2022
Sprint-4	4	6 Days	14 Nov 2022	19 Nov 2022	4	19 Nov 2022

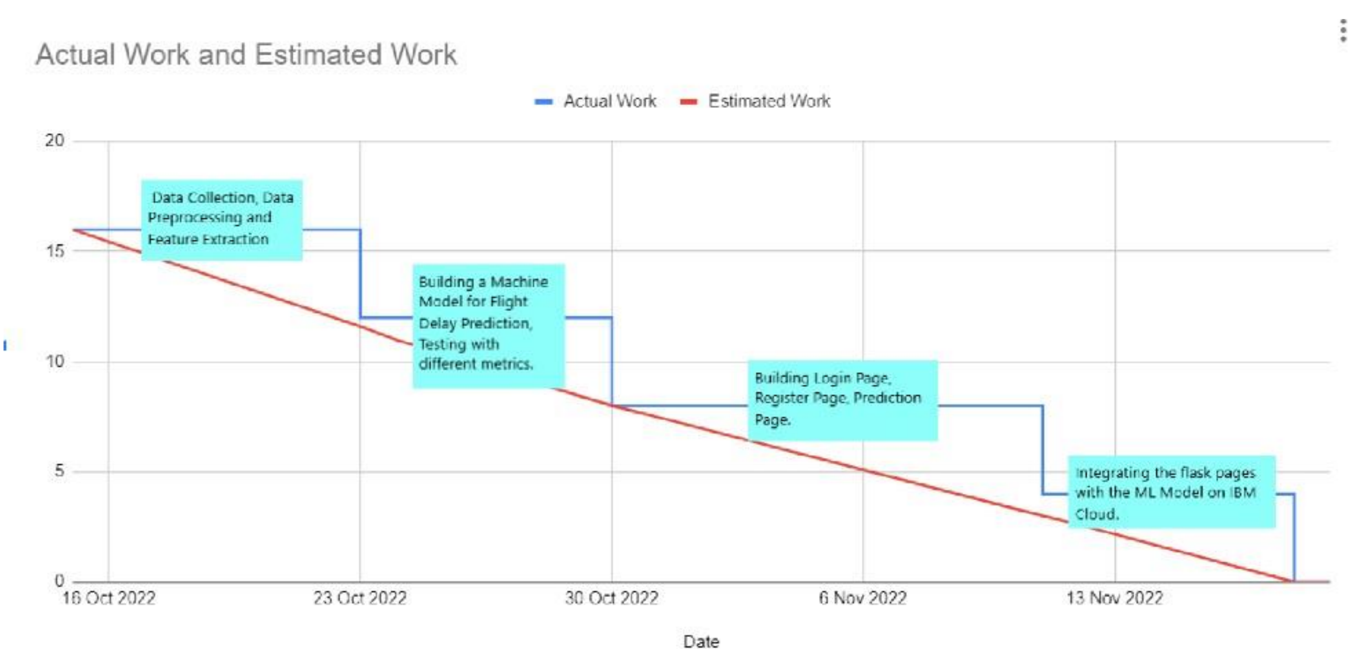


Figure 6.1 - Burndown Chart

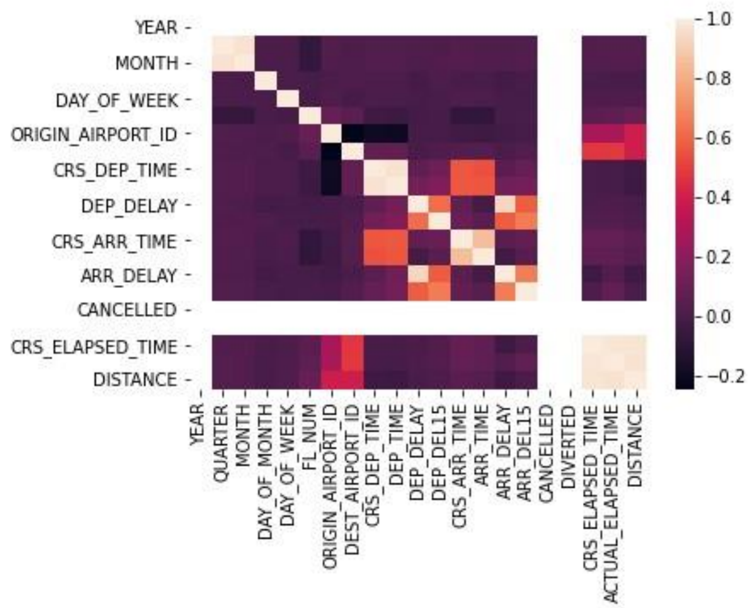
CHAPTER 7

CODING AND SOLUTIONING

7.1. FEATURE 1 - CORRELATION BETWEEN THE VARIABLES IN THE DATASET

```
In [19]: sns.heatmap(data.corr())

Out[19]: <AxesSubplot:>
```



This will help us to find out the correlation between the variables in the dataset which would help us to find out the columns that are unnecessary and hence to be dropped.

7.2. FEATURE 2 - ONE HOT ENCODING

```
In [39]: data=pd.get_dummies(data,columns=['ORIGIN','DEST'])

In [40]: data['ARR_DEL15'].value_counts()

Out[40]: 0.0    9668
         1.0    1375
         Name: ARR_DEL15, dtype: int64

In [41]: data.tail()

Out[41]:
```

	FL_NUM	MONTH	DAY_OF_MONTH	DAY_OF_WEEK	CRS_ARR_TIME	DEP_DEL15	ARR_DEL15	ORIGIN_0	ORIGIN_1	ORIGIN_2	ORIGIN_3	ORIGIN_4
11226	1715	12	30	5	12	0.0	0.0	0	1	0	0	0
11227	1770	12	30	5	20	1.0	0.0	0	0	0	0	1
11228	1823	12	30	5	22	0.0	0.0	0	1	0	0	0
11229	1901	12	30	5	18	0.0	0.0	1	0	0	0	0
11230	2005	12	30	5	9	0.0	0.0	1	0	0	0	0

The cities in both Origin and Destination are one-hot encoded using the above code.

7.3. FEATURE 3 - SAVING THE MODEL WEIGHTS FOR DEPLOYMENT

SAVING THE MODEL

```
In [63]: pickle.dump(classifier,open('flight_new.pk1','wb'))

In [64]: from sklearn.metrics import confusion_matrix
         confusion_matrix(predicted, y_test)

Out[64]: array([[1825,  129],
                [ 138,  117]], dtype=int64)

In [66]: from sklearn.metrics import classification_report
         print(classification_report(predicted, y_test, labels=[1, 2]))

                      precision    recall  f1-score   support

                   1       0.48      0.46      0.47       255
                   2       0.00      0.00      0.00         0

           micro avg       0.48      0.46      0.47       255
           macro avg       0.24      0.23      0.23       255
        weighted avg       0.48      0.46      0.47       255
```

The above code will save the model weights for further deployment in IBM Cloud and also measure the performance metrics.

7.4. FEATURE 4 - FLASK INTERFACE - UI

```
from flask import Flask, request, render_template
import numpy as np
import pandas as pd
import pickle
import os
model = pickle.load(open('flight_new.pk1','rb'))
app = Flask(__name__)
@app.route('/')
def home():
    return render_template("mainpage.html")

@app.route('/prediction',methods=['GET','POST'])
def predict():
    name = request.form['fname']
    month = request.form['month']
    dayofmonth = request.form['daymonth']
    dayofweek = request.form['dayweek']
    origin = request.form['origin']
```

```
    if(origin == "msp"):
        origin1, origin2, origin3, origin4, origin5 = 0,0,0,0,1
    if(origin == "dtw"):
        origin1, origin2, origin3, origin4, origin5 = 1,0,0,0,0
    if(origin == "jfk"):
        origin1, origin2, origin3, origin4, origin5 = 0,0,1,0,0,
    if(origin == "sea"):
        origin1, origin2, origin3, origin4, origin5 = 0,1,0,0,0
    if(origin == "atl"):
        origin1, origin2, origin3, origin4, origin5 = 0,0,0,1,0
    destination = request.form['destination']
    if(destination == "msp"):
        destination1,destination2,destination3,destination4,destination5 = 0,0,0,0,1
    if(destination == "dtw"):
        destination1,destination2,destination3,destination4,destination5 = 1,0,0,0,0
    if(destination == "jfk"):
        destination1,destination2,destination3,destination4,destination5 = 0,0,1,0,0
    if(destination == "sea"):
        destination1,destination2,destination3,destination4,destination5 = 0,1,0,0,0
    if(destination == "atl"):
        destination1,destination2,destination3,destination4,destination5 = 0,0,0,1,0
    dept = request.form['sdeparttime']
    arrtime = request.form['sarrivaltime']
    actdept = request.form['adeparttime']
    dept15 = int(dept)-int(actdept)
    total =
[[name,month,dayofmonth,dayofweek,arrtime,dept15,origin1,origin2,origin3,origin4,origi
n5,destination1,destination2,destination3,destination4,destination5]]
    y_pred = model.predict(total)
    print(y_pred)
    if(y_pred == [0.]):
        ans = "The Flight will be on time"
    else:
        ans = "The Flight will be delayed"
    return render_template("index.html",data = ans)

app.run(debug=True)
```

Explanation:

The above code will be able to get the details of the flight from the user in the respective text fields created using the HTML, scale the inputs and give the inputs to the model which has been developed already. The predictions are shown in another HTML page.

7.5. FEATURE 5 - HTML PAGES FOR FRONTEND DESIGN

```
<html>
<div align="center" class="logbg">
<head>
<meta charset="UTF-8">
<center>
<table>
<tr>
<td><h1><br>Prediction of Flight Delay<br><br></h1></td>
</tr>
</table>
</center>
</head>
<body background='C:\Users\Public\project\templates\flight_4.jpg'>
<form action="http://localhost:5000/prediction" method="POST" >
<center>
<table>
<tr>
<td>Enter the flight number:</td>
<td><input type="number" name="fname"><br></td>
</tr>
<tr>
<td>Month:</td>
<td><input type="number" name="month"><br></td>
</tr>
<tr>
<td>Day of Month:</td>
<td><input type="number" name="daymonth"><br></td>
</tr>
<tr>
<td>Day of Week:</td>
<td><input type="number" name="dayweek"><br></td>
</tr>
<tr>
<td>Origin:</td>
```

```
<td><select name="origin">
<option value="atl">ATL</option>
<option value="dtw">DTW</option>
<option value="sea">SEA</option>
<option value="msp">MSP</option>
<option value="jfk">JFK</option>
</select></td>
<tr>
<tr>
<td>Destination:</td>
<td><select name="destination">
<option value="atl">ATL</option>
<option value="dtw">DTW</option>
<option value="sea">SEA</option>
<option value="msp">MSP</option>
<option value="jfk">JFK</option>
</select></td>
<tr>
<tr>
<td>Scheduled Departure Time:</td>
<td><input type="number" name="sdeparttime"><br></td>
</tr>
<tr>
<td>Scheduled Arrival Time:</td>
<td><input type="number" name="sarrivaltime"><br></td>
</tr>
<tr>
<td>Actual Departure Time:</td>
<td><input type="number" name="adeparttime"><br></td>
</tr>
<tr>
<td><br><input type="submit" class="btn" value="SUBMIT"></br>
</tr>
</table>
</center>
</form>
</body>
</div>
</html>
```

CHAPTER 8
TESTING

8.1. TEST

User No	Flight No	Month	Day of month	Day of week	Origin	Destination	Scheduled Departure Time	Scheduled Arrival Time	Actual Departure Time	Actual Inputs
1	1232	1	1	1	ATL	MSP	1905	2305	1945	Delayed
2	1399	1	1	1	ATL	SEA	1805	2410	1855	Delayed
3	2351	1	2	3	ATL	DTW	1305	2305	1305	Not Delayed
4	2637	2	1	3	DTW	ATL	1500	2410	1505	Not Delayed

8.2. USER ACCEPTANCE TESTING

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

User No	Flight No	Month	Day Of Month	Day Of Week	Origin	Destin -ation	Scheduled Departure Time	Scheduled Arrival Time	Actual Departure Time	Actual Output	Predict -ed Output	Correct-ne ss
1	1232	1	1	1	ATL	MSP	1905	2305	1945	Delayed	Delayed	Correct
2	1399	1	1	1	ATL	SEA	1805	2410	1855	Delayed	Delayed	Correct
3	2351	1	2	3	ATL	DTW	1305	2305	1305	Not Delayed	Not Delayed	Correct
4	2637	2	1	3	DTW	ATL	1500	2410	1505	Not Delayed	Not Delayed	Correct

CHAPTER 9
RESULTS

9.1. PERFORMANCE METRICS

Training Accuracy

MODEL EVALUATION

```
acc=accuracy_score(predicted,y_test)
```

```
acc
```

```
0.8791308284291535
```

Confusion Matrix

```
from sklearn.metrics import confusion_matrix
confusion_matrix(predicted, y_test)
```

```
array([[1825,  129],
       [ 138,  117]], dtype=int64)
```

Classification Model

```
from sklearn.metrics import classification_report
print(classification_report(predicted, y_test, labels=[1, 2, 3]))
```

```
              precision    recall  f1-score   support

           1       0.48      0.46      0.47       255
           2       0.00      0.00      0.00         0
           3       0.00      0.00      0.00         0

   micro avg       0.48      0.46      0.47       255
   macro avg       0.16      0.15      0.16       255
weighted avg       0.48      0.46      0.47       255
```

CHAPTER 10
ADVANTAGES AND DISADVANTAGES

Advantages

- Customers are happy
- The available flights are easily identified
- Prior information will be sent if in case the flight is delayed
- The current status of the flight can be tracked

Disadvantages

- Wrong prediction due to noise of input data
- If the prediction is wrong, then there will be extra expenses for the agencies, passengers and airport
- Passengers with medical emergencies gets affected

CHAPTER 11
CONCLUSION

In this project, we use flight data, weather, and demand data to predict flight departure delay. In the end, our model correctly predicts the delayed and non-delayed flights correctly. As a result, there can be additional features related to the causes of flight delay that are not yet discovered using our existing data sources.

CHAPTER 12
FUTURE SCOPE

Based on data analysis from the year 2008, this project. There is a sizable dataset accessible from 1987 to 2008, but managing a larger dataset necessitates extensive preprocessing and purification of the data Therefore, adding a larger dataset is a part of this project's future effort. Preprocessing a bigger dataset can be done in a variety of methods, such as establishing a Spark cluster on a computer or using cloud services like AWS and Azure. Now that deep learning has advanced, we can employ neural networks algorithms to analyze aviation and meteorological data. Neural networks employ a form of pattern matching.

The project's focus is primarily on flight and weather data for India, but we can also include data from other nations like China, the United States, and Russia. We can broaden the project's scope by including flight information from international flights rather than just domestic flights.

CHAPTER 13
APPENDIX

13.1 Source codes

13.1.2 Exploratory Data Analysis

```
#!/usr/bin/env python
# coding: utf-8

# **Importing all the libraries**

# In[1]:

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import pickle
get_ipython().run_line_magic('matplotlib', 'inline')
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
import sklearn.metrics as metrics

# **Importing the dataset**

# In[2]:

data=pd.read_csv("flightdata.csv")

# In[3]:

data.head()

# In[4]:

data.info()
```

```
# In[5]:

data=data.drop('Unnamed: 25',axis=1)

# In[6]:

data.info()

# In[7]:

data.describe()

# In[ ]:

# **Handling Missing Values**

# In[8]:

data=data.dropna()

# In[9]:

data.info()

# **Analysis**

# In[10]:

plt.scatter(data.index,data['ARR_TIME'])
plt.ylabel('Arrival Time')
plt.title('Distribution of the Arrival Time')

# In[11]:

plt.hist(data['FL_NUM'])

# In[12]:

columns=list(data.columns)
```

```
# In[13]:

sns.scatterplot(x='ARR_DELAY',y='ARR_DEL15',data=data)

# In[14]:

sns.catplot(x='ARR_DELAY',y='ARR_DEL15',data=data,kind='bar')

# In[15]:

data['ARR_DEL15'].nunique()

# In[16]:

# In[17]:

data.describe()

# **Dropping off unnecessary columns**

# In[18]:

data.corr()['ARR_DEL15']

# In[19]:

sns.heatmap(data.corr())

# In[20]:

new_data=data.drop(['ORIGIN_AIRPORT_ID','DEST_AIRPORT_ID','FL_NUM','YEAR','
CANCELLED','DIVERTED','DISTANCE','DAY_OF_MONTH','QUARTER','MONTH','DAY
_OF_WEEK','UNIQUE_CARRIER','TAIL_NUM'],axis=1)

# In[21]:

new_data.head()

# **Label Encoding**

# In[22]:
```

```
cities=new_data['ORIGIN'].unique()

# In[23]:

cities

# In[24]:

new_data['DEST'].unique()

# In[25]:

city_map={cities[i]:i for i in range(0,len(cities))}

# In[26]:

city_map

# In[27]:

def encode(c):
  return city_map[c]

# In[28]:

new_data['ORIGIN']=new_data['ORIGIN'].apply(encode)

# In[29]:

new_data['DEST']=new_data['DEST'].apply(encode)

# In[30]:

new_data.head()

# In[31]:

new_data.corr()['ARR_DEL15']
```

```
# In[32]:

#data=data.drop('Unnamed: 25',axis=1)
data.isnull().sum()

# In[33]:

data=data[["FL_NUM","MONTH","DAY_OF_MONTH","DAY_OF_WEEK","ORIGIN","DE
ST","CRS_ARR_TIME","DEP_DEL15","ARR_DEL15"]]
data.isnull().sum()

#

# In[34]:

data=data.fillna({'ARR_DEL15': 1})
data=data.fillna({'DEP_DEL15': 0})
data.iloc[177:185]

# In[35]:

import math
for index, row in data.iterrows():
  data.loc[index,'CRS_ARR_TIME'] = math.floor(row['CRS_ARR_TIME'] / 100)
data.head()

# In[36]:

from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
data['DEST'] = le.fit_transform(data['DEST'])
data['ORIGIN'] = le.fit_transform(data['ORIGIN'])

# In[37]:

data.head()

# In[38]:
```

```
from sklearn.preprocessing import OneHotEncoder
oh = OneHotEncoder()
z=oh.fit_transform(data['ORIGIN'].values.reshape(-1,1)).toarray()
t=oh.fit_transform(data['DEST'].values.reshape(-1,1)).toarray()

# In[ ]:

# In[ ]:

# In[39]:

data=pd.get_dummies(data,columns=['ORIGIN','DEST'])

# In[40]:

data['ARR_DEL15'].value_counts()

# In[41]:

data.tail()

# **Split the data into dependent and independent variables**
#
# In[42]:

x=data[[i for i in data.columns if i!='ARR_DEL15']].values
y=data[[i for i in data.columns if i=='ARR_DEL15']].values

# In[43]:

x.shape

# In[44]:

y.shape

# In[ ]:
```

CHAPTER 13
APPENDIX

13.1. SOURCE CODE

13.1.1. Train the ML Model

```
# # SPRINT-2

# **TRAIN-TEST-SPLIT**

# In[45]:

x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=0)

# In[46]:

x_test.shape

# In[47]:

x_train.shape

# In[48]:

y_test.shape

# In[49]:

y_train.shape

# **Scaling**

# In[50]:

sc = StandardScaler()

# In[51]:

x_train=sc.fit_transform(x_train)
```

```
# In[52]:

x_test=sc.fit_transform(x_test)

# **Model Building**

# In[53]:

classifier = DecisionTreeClassifier(random_state=0)

# In[54]:

classifier.fit(x_train,y_train)

# In[55]:

predicted = classifier.predict(x_test)

# In[56]:

predicted

# In[57]:

y_test

# **MODEL EVALUATION**

# In[58]:

acc=accuracy_score(predicted,y_test)

# In[59]:

acc

# In[ ]:


# In[60]:
```

```
data[data['ARR_DEL15']>0].iloc[33].values

# In[61]:

sample=[[1.187e+03, 1.000e+00, 1.500e+01, 5.000e+00, 1.900e+01, 1.000e+00,
0.000e+00, 0.000e+00, 0.000e+00, 1.000e+00, 0.000e+00,
       0.000e+00, 0.000e+00, 0.000e+00, 0.000e+00, 1.000e+00]]

# In[62]:

classifier.predict(sample)

# **SAVING THE MODEL**

# In[63]:

pickle.dump(classifier,open('flight_new.pk1','wb'))

# In[64]:

from sklearn.metrics import confusion_matrix
confusion_matrix(predicted, y_test)

# In[66]:

from sklearn.metrics import classification_report
print(classification_report(predicted, y_test, labels=[1, 2]))

# In[ ]:
```

13.1.2. Mainpage – HTML Code

```html
<html>
<div align="center" class="logbg">
<head>
<meta charset="UTF-8">
<center>
<table>
<tr>
<td><h1><br>Prediction of Flight Delay<br><br></h1></td>
</tr>
</table>
</center>
</head>
<body background='C:\Users\Public\project\templates\flight_4.jpg'>
<form action="http://localhost:5000/prediction" method="POST" >
<center>
<table>
<tr>
<td>Enter the flight number:</td>
<td><input type="number" name="fname"><br></td>
</tr>
<tr>
<td>Month:</td>
<td><input type="number" name="month"><br></td>
</tr>
<tr>
<td>Day of Month:</td>
<td><input type="number" name="daymonth"><br></td>
</tr>
<tr>
<td>Day of Week:</td>
<td><input type="number" name="dayweek"><br></td>
</tr>
<tr>
<td>Origin:</td>
<td><select name="origin">
<option value="atl">ATL</option>
<option value="dtw">DTW</option>
<option value="sea">SEA</option>
<option value="msp">MSP</option>
```

```
<option value="jfk">JFK</option>
</select></td>
<tr>
<tr>
<td>Destination:</td>
<td><select name="destination">
<option value="atl">ATL</option>
<option value="dtw">DTW</option>
<option value="sea">SEA</option>
<option value="msp">MSP</option>
<option value="jfk">JFK</option>
</select></td>
<tr>
<tr>
<td>Scheduled Departure Time:</td>
<td><input type="number" name="sdeparttime"><br></td>
</tr>
<tr>
<td>Scheduled Arrival Time:</td>
<td><input type="number" name="sarrivaltime"><br></td>
</tr>
<tr>
<td>Actual Departure Time:</td>
<td><input type="number" name="adeparttime"><br></td>
</tr>
<tr>
<td><br><input type="submit" class="btn" value="SUBMIT"></br>
</tr>
</table>
</center>
</form>
</body>
</div>
</html>
```

13.1.3 Prediction Page - HTML Code

```
<!doctype html>
<html>
  <body background="C:\Users\Public\project\templates\flight_2.jpg">
        <center>
    <h1><strong>Thanks for asking</strong></h1>
    <h2>{{data}}</h2>
    <a href='/'>Go back to home page</a>
        </center>
  </body>
</html>
```

13.1.4. Flask Application

```
from flask import Flask, request, render_template
import numpy as np
import pandas as pd
import pickle
import os
model = pickle.load(open('flight_new.pk1','rb'))
app = Flask(__name__)
@app.route('/')
def home():
    return render_template("mainpage.html")

@app.route('/prediction',methods=['GET','POST'])
def predict():
    name = request.form['fname']
    month = request.form['month']
    dayofmonth = request.form['daymonth']
    dayofweek = request.form['dayweek']
    origin = request.form['origin']
    if(origin == "msp"):
        origin1, origin2, origin3, origin4, origin5 = 0,0,0,0,1
    if(origin == "dtw"):
        origin1, origin2, origin3, origin4, origin5 = 1,0,0,0,0
    if(origin == "jfk"):
        origin1, origin2, origin3, origin4, origin5 = 0,0,1,0,0,
    if(origin == "sea"):
        origin1, origin2, origin3, origin4, origin5 = 0,1,0,0,0
```

```
    if(origin == "atl"):
        origin1, origin2, origin3, origin4, origin5 = 0,0,0,1,0
    destination = request.form['destination']
    if(destination == "msp"):
        destination1,destination2,destination3,destination4,destination5 = 0,0,0,0,1
    if(destination == "dtw"):
        destination1,destination2,destination3,destination4,destination5 = 1,0,0,0,0
    if(destination == "jfk"):
        destination1,destination2,destination3,destination4,destination5 = 0,0,1,0,0
    if(destination == "sea"):
        destination1,destination2,destination3,destination4,destination5 = 0,1,0,0,0
    if(destination == "atl"):
        destination1,destination2,destination3,destination4,destination5 = 0,0,0,1,0
    dept = request.form['sdeparttime']
    arrtime = request.form['sarrivaltime']
    actdept = request.form['adeparttime']
    dept15 = int(dept)-int(actdept)
    total =
[[name,month,dayofmonth,dayofweek,arrtime,dept15,origin1,origin2,origin3,origin4,origi
n5,destination1,destination2,destination3,destination4,destination5]]
    y_pred = model.predict(total)
    print(y_pred)
    if(y_pred == [0.]):
        ans = "The Flight will be on time"
    else:
        ans = "The Flight will be delayed"
    return render_template("index.html",data = ans)

app.run(debug=True)
```