IBM – NALAIYA THIRAN PROJECT

DEVELOPING A FLIGHT DELAY PREDICTION MODEL USING MACHINE LEARNING

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Dissertation submitted in partial fulfillment of the requirements for the degree of

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Branch: INFORMATION TECHNOLOGY
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DEVELOPING A FLIGHT DELAY PREDICTION MODEL USING MACHINE LEARNING

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ABSTRACT
Over the last twenty years, air travel has been increasingly preferred among travelers, mainly because of its speed and in some cases comfort. This has led to phenomenal growth in air traffic and on the ground. An increase in air traffic growth has also resulted in massive levels of aircraft delays on the ground and in the air. These delays are responsible for large economic and environmental losses. The main objective of the model isto predict flight delays accurately in order to optimize flight operations and minimize delays.

Using a machine learning model, we can predict flight arrival delays. The input to our algorithm is rows of feature vector like departure date, departure delay, distance between the two airports, scheduled arrival time etc. We then use decision tree classifier to predict if the flight arrival will be delayed or not. A flight is considered to be delayed when difference between scheduled and actual arrival times is greater than 15 minutes. Furthermore, we compare decision tree classifier with logistic regression and a simple neural network for various figures of merit.

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

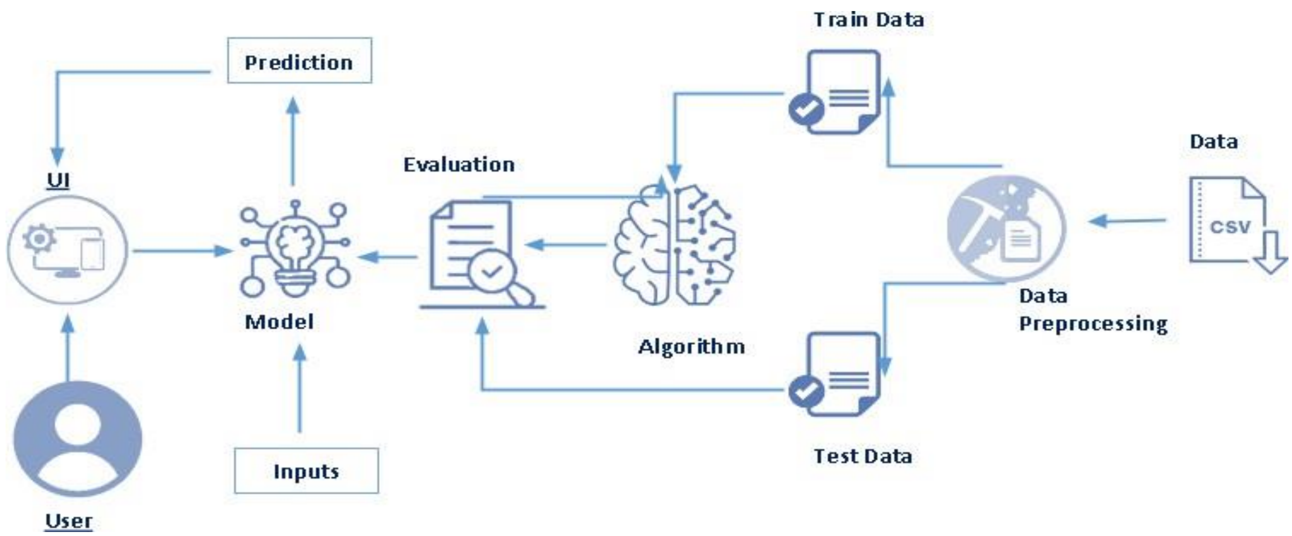

Figure 1.1. Technical Architecture

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 with respect 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.

[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

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CHAPTER 3

IDEATION & PROPOSED SOLUTION

3.1. EMPATHY MAP CANVAS

An empathy map helps to map what a design team knows about the potential audience. This tool helps to understand the reason behind some actions a user takes deeply. This tool helps build Empathy towards users and helps design teams shift focus from the product to the users who are going to use the product.

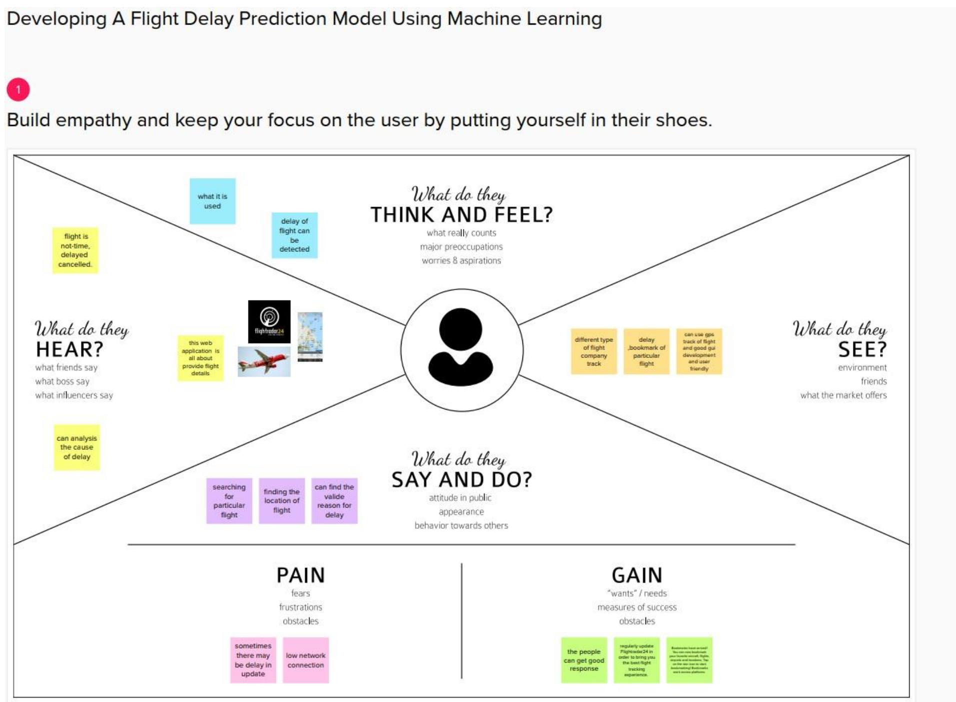


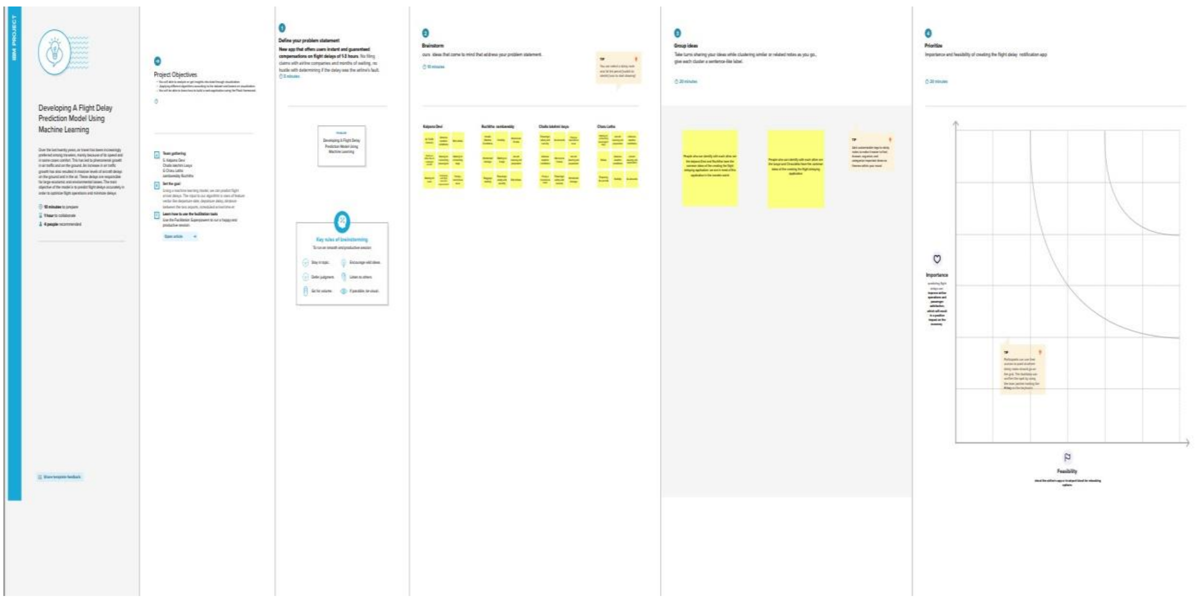
Figure 3.1. Empathy Map

3.2. IDEATION & BRAINSTORMING

Brainstorm is a collaborative, open-source application dedicated to the analysis of brain recordings: MEG, EEG, fNIRS, ECoG, depth electrodes and animal invasive neurophysiology.
They can also be used to keep track of all the ideas and make sure that these ideas are available to everyone
If brainstorming does not work for a group, there are some alternatives.

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

Step 2 - Brainstorm, Idea Listing and Grouping



3.3. 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 he 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 models are not accessible to the general public due to the intense competition 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

Project Title: Developing a flight delay model using Machine Learning **Project Design Phase-I - Solution Fit Template** **Team ID: PNT2022TMID24528**

Define CS, fit into CC	**1. CUSTOMER SEGMENT(S)** CS - Normal flight users - Business professionals having meetings - People boarding a lay-over flight - Logistics incharge at airport Airport catering manager	**6. CUSTOMER CONSTRAINTS** CC - Refund/Partial Refund - Not knowing the exact time of delay - Unavailability of alternate flights or accommodation	**5. AVAILABLE SOLUTIONS** AS - May take alternate flights - Ask for an alternate flight/schedule - Wait for the delayed schedule - Enjoy airline benefits - Report airline - Cancel the flight - Search for specific reasons for delay	Explore AS, differentiat
Focus on J&P, tap into BE, understand RC	**2. JOBS-TO-BE-DONE / PROBLEMS** J&P - To know if a flight is delayed - To make alternate arrangements to reach the destination in case the flight is delayed - To know other things that can be done when the flight is delayed	**9. PROBLEM ROOT CAUSE** RC - Unavailability of means to estimate delays occurring in airplanes - Large scale economic loss for both airlines and the customers - Degradation in airline's reputation when many flights are delayed	**7. BEHAVIOUR** BE - Use the app deployed to know the approximate delay - Find alternate travel options - Find hotel accommodations for overnight delays - Fill ratings and feedbacks to help other users	Focus on J&P, tap into BE, understand RC

3.5. PROBLEM SOLUTION FIT

Identify strong TR & EM

3. TRIGGERS TR

- Cancellation of flights
- Extreme boredom
- Guilt of wasting time
- Thought of missing important meetings
- Missing layover flight
- Uncertainty in deciding if the flight is delayed when they start late for the airport

10. YOUR SOLUTION SL

- The aim is to develop an application that predicts flight delays using a supervised machine learning model (a decision tree classifier) with the data of flights and delays so far and estimate the time of delay taking spatial dependencies of flights into account.

8. CHANNELS of BEHAVIOUR CH

8.1 ONLINE

- Check if a particular flight will be delayed and the estimated time of arrival
- Giving ratings and feedbacks for various flights so as to improve the app's performance in predicting further delays
- Check for other specific reasons for delay

Identify strong TR & EM

4. EMOTIONS: BEFORE / AFTER EM

Before:

- Worried
  - About missing important events
  - About missing layover flights
  - If the flight is gonna be canceled
- Frustrated
  - About the unexpected delay/cancellation
  - Not knowing the news of delay beforehand
  - About the weather

8.2 OFFLINE

- Finding alternate travel routes in the airport
- Hotels near the airport can be visit for overnight stays during delays

3.6. PROBLEM SOLUTION FIT

  - Not knowing the news of delay beforehand
  - About the weather
- Bored
  - Don't know how to make use of time

After:

- Gets to enjoy the airline benefits
- Stay relaxed after getting a proper update from the airline
- Relieved if an alternate solution can be found

CHAPTER 4
REQUIREMENT ANALYSIS

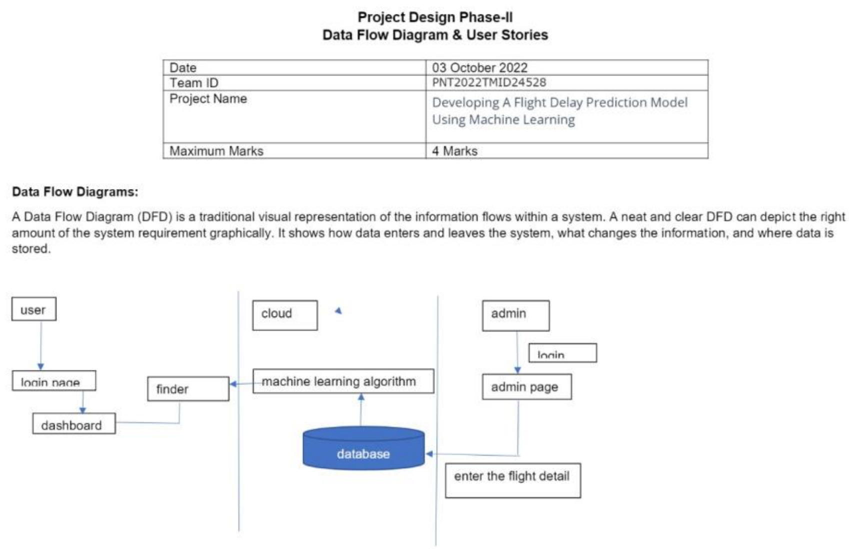
4.1. FUNCTIONAL REQUIREMENT

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	Registration through Form Registration through Gmail Registration through LinkedIN
FR-2	User Confirmation	Confirmation via Email Confirmation via OTP
FR-3	Log In	• Log in with give user credentials
FR-4	Support	• Support option provided for queries and contact customer support team
FR-5	Prediction of delay	• Requesting for prediction by providing details of flight • Shows prediction results
FR-6	Trust ability of prediction	• Gives the confidence percentage about their prediction

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.



Project Design Phase-II
Data Flow Diagram & User Stories

Date	03 October 2022
Team ID	PNT2022TMID24528
Project Name	Developing A Flight Delay Prediction Model Using Machine Learning
Maximum Marks	4 Marks

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

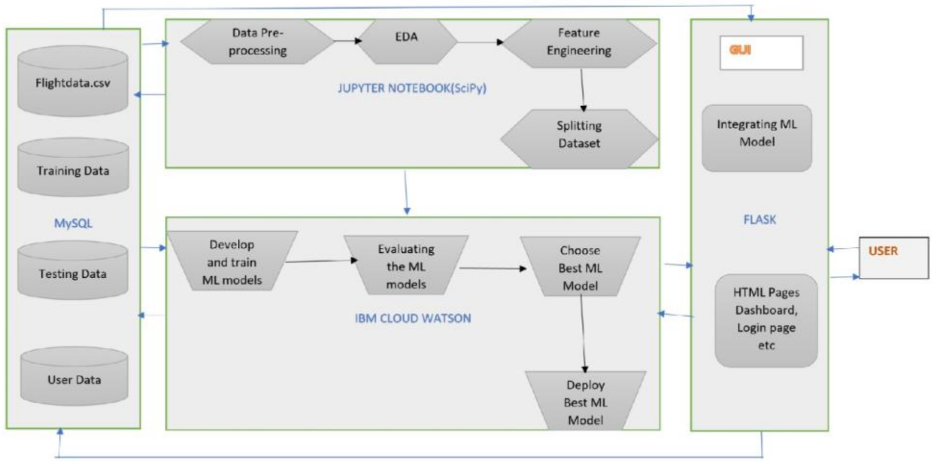


Figure 5.2. Solution Architecture

Components & Technologies

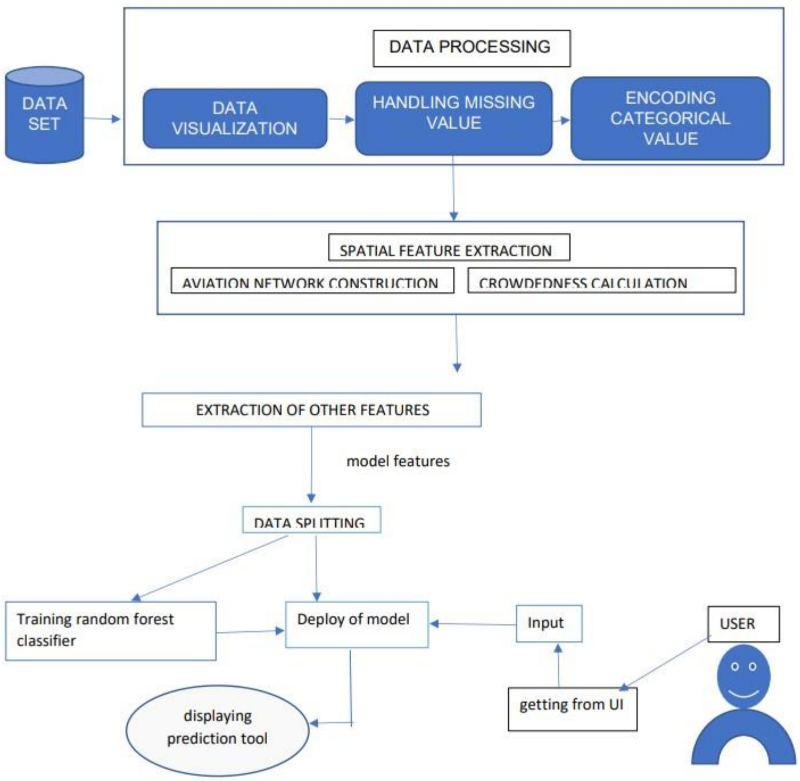
S.No	Component	Description	Technology
1.	User Interface	Web Application to interact with the user.	Flask
2.	Login/Sign up	Login/ Sign up – The user can enter the details and get them validated	Python
3.	Database	The Database to store the login details of the user	MySQL
4.	Cloud Database	The database 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

A user story is an informal, general explanation of a software feature written from the perspective of the end user or customer. The purpose of a user story is to articulate how a piece of work will deliver a particular value back to the customer



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 Collection and Pre-processing	USN-1	As a user, I can't interact anything. Waiting is user's task. User can listen the relationship exist between the various attributes of data by presentation of developer	**2**	high	KALPANA DEVI S CHARU LATHA G
Sprint-1	Model Building	USN-2	As a user, I can predict flight delay by various developed ML models by console	**1**	high	CHELLA LAKSHMI LASYA SAMBAREDDY RUCHITHA
Sprint-2	Model Evaluation	USN-3	As a user, I can predict flight delay by best Model in various developed ML model by console	**2**	high	KALPANA DEVI S CHARU LATHA G
						SAMBAREDDY RUCHITHA
Sprint-2	Basic user interaction Dashboard	USN-5	As a user, I can use the model or prediction from model by interacting with dashboard	2	High	KALPANA DEVI S CHARU LATHA G
Sprint-3	improved Dashboard and GUI	USN-6	As a user, I can use the model or prediction from model by interacting with improved dashboard	1	Medium	CHELLA LAKSHMI LASYA SAMBAREDDY RUCHITHA
Sprint-3	registration	USN-7	As a user, I can register for the application by entering my email, password, and confirming my password.	2	High	KALPANA DEVI S CHARU LATHA G
Sprint-3	Registration	USN-7	As a user, I can register for the application through Gmail	2	High	CHELLA LAKSHMI LASYA SAMBAREDDY RUCHITHA

6.2. SPRINT DELIVERY SCHEDULE

Project Tracker, Velocity & Burndown Chart: (4 Marks)

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	20	29 Oct 2022
Sprint-2	20	6 Days	31 Oct 2022	05 Nov 2022	20	07 Nov 2022
Sprint-3	20	6 Days	07 Nov 2022	12 Nov 2022	20	12 Nov 2022
Sprint-4	20	6 Days	14 Nov 2022	19 Nov 2022	20	19 Nov 2022

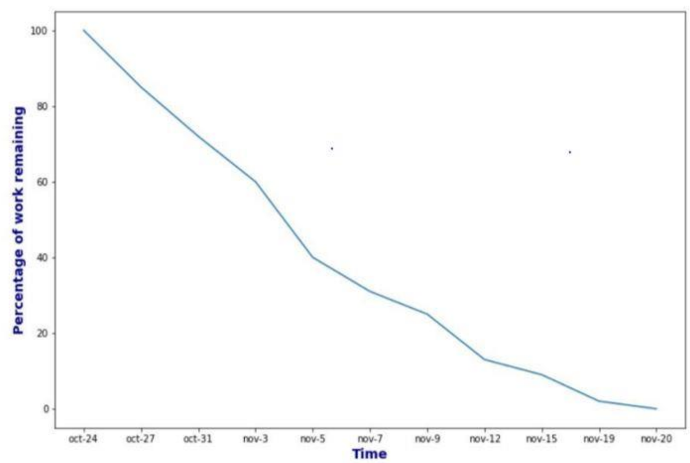
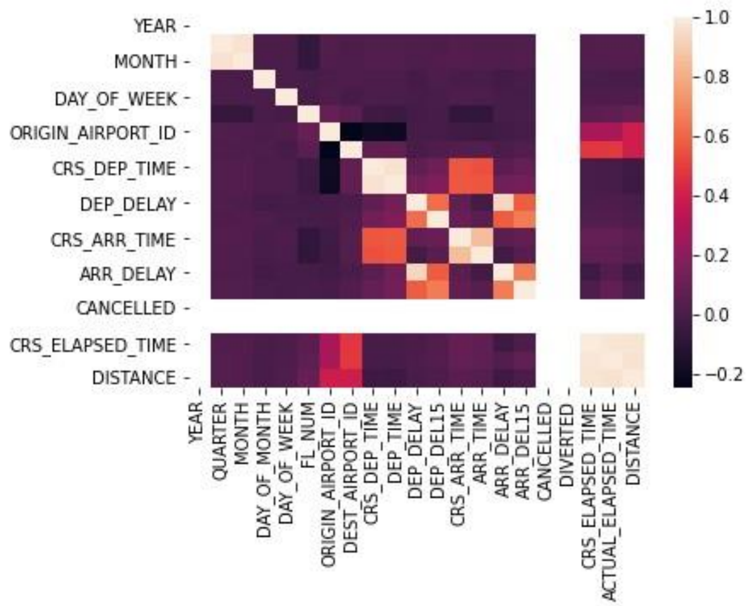


Figure 6.1 - Burndown Chart

CHAPTER 7

CODING AND SOLUTIONING

```
In [19]: sns.heatmap(data.corr())
Out[19]: <AxesSubplot:>
```



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

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, render_template, request
import pandas as pd
import joblib
import numpy as np


app = Flask(__name__)


@app.route('/')
def home():
    return render_template('Flightdelay.html')


@app.route('/result', methods = ['POST'])
def predict():
    fl_num = int(request.form.get('fno'))
    month = int(request.form.get('month'))
    dayofmonth = int(request.form.get('daym'))
    dayofweek = int(request.form.get('dayw'))
    sdeptime = request.form.get('sdt')
    adeptime = request.form.get('adt')
    arrtime = int(request.form.get('sat'))
    depdelay = int(adeptime) - int(sdeptime)
    inputs = list()
    inputs.append(fl_num)
    inputs.append(month)
    inputs.append(dayofmonth)
    inputs.append(dayofweek)
    if (depdelay < 15):
        inputs.append(0)
    else:
        inputs.append(1)
    inputs.append(arrtime)
    origin = str(request.form.get("org"))
    dest = str(request.form.get("dest"))
    if(origin=="ATL"):
        a=[1,0,0,0,0]
        inputs.extend(a)
    elif(origin=="DTW"):
        a=[0,1,0,0,0]
        inputs.extend(a)
    elif(origin=="JFK"):
        a=[0,0,1,0,0]
        inputs.extend(a)
```

```
elif(origin=="MSP"):
    a=[0,0,0,1,0]
    inputs.extend(a)
elif(origin=="SEA"):
    a=[0,0,0,0,1]
    inputs.extend(a)
```

```
    if(dest=="ATL"):
        b=[1,0,0,0,0]
        inputs.extend(b)
    elif(dest=="DTW"):
        b=[0,1,0,0,0]
        inputs.extend(b)
    elif(dest=="JFK"):
        b=[0,0,1,0,0]
        inputs.extend(b)
    elif(dest=="MSP"):
        b=[0,0,0,1,0]
        inputs.extend(b)
    elif(dest=="SEA"):
        b=[0,0,0,0,1]
        inputs.extend(b)


    prediction = preprocessAndPredict(inputs)
    #Pass prediction to prediction template
    print(inputs)
    return render_template('/result.html', prediction = prediction)
    def preprocessAndPredict(inputs):
    test_data = np.array(inputs).reshape((1,16))

    model_file = open('D:\\IBM-Project-25904-1659976941\\Final Deliverables\\model.pkl', 'rb')

    trained_model = joblib.load(model_file)


    df = pd.DataFrame(data=test_data[0:, 0:], columns=['FL_NUM', 'MONTH', 'DAY_OF_MONTH',
'DAY_OF_WEEK', 'DEP_DEL15', 'CRS_ARR_TIME', 'ORIGIN_ATL', 'ORIGIN_DTW', 'ORIGIN_JFK', 'ORIGIN_MSP',
'ORIGIN_SEA', 'DEST_ATL', 'DEST_DTW', 'DEST_JFK', 'DEST_MSP', 'DEST_SEA'])


    data = df.values


    result = trained_model.predict(data)


    print(result)
    return result


if __name__ == '__main__':
```

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.

FEATURE 5 - HTML PAGES FOR FRONTEND DESIGN

```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta http-equiv="X-UA-Compatible">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <link rel="stylesheet" href="C:\Users\Arunjana\Desktop\flight delay development\styles.css">
    <script src="C:\Users\Arunjana\Desktop\flight delay development\delaypredicts.js"></script>
    <title>Flight Delay Prediction</title>
</head>
<body id="flight-form">
<h2 id="main-head" class="centered-head">FLIGHT DELAY PREDICTION</h2>
<img src="C:\Users\Arunjana\Desktop\flight delay development\pexels-asad-photo-maldives-2245279.JPG"
id="bgimg">
<form name="flightForm" action="/result" method="POST" target="_blank">
    <div id="form-content">
        <div id="block1">
            <div class="detail-container">
                <label for="fno" class="label-item">Enter the Flight Number</label>
                <br>
                <input type="number" id="fno" name="fno" class="text-input">
            </div>
            <div class="detail-container">
                <label for="month" class="label-item">Month</label>
                <br>
                <input type="number" id="month" name="month" class="text-input"
onblur="checkValid('month');" placeholder="Enter the Month Number">
                <div class="alert-text" id="month-valid">Enter a valid month between 1 to 12.</div>
            </div>
            <div class="detail-container">
                <label for="daym" class="label-item">Day of Month</label>
```

```html
                <br>
                <input type="number" id="daym" name="daym" class="text-input"
onblur="checkValid('daym');">
                <div class="alert-text" id="daym-valid">Enter a valid day of month.</div>
            </div>
            <div class="detail-container">
                <label for="dayw" class="label-item">Day of Week</label>
                <br>
                <input type="number" id="dayw" name="dayw" class="text-input"
onblur="checkValid('dayw');">
                <div class="alert-text" id="dayw-valid">Enter a valid day between 1 to 7.</div>
            </div>
            <div class="detail-container">
                <label for="org" class="label-item">Origin</label>
                <br>
                <select id="org" name="org" class="select-input">
                    <option value="ATL" class="option-item">ATL</option>
                    <option value="SEA" class="option-item">SEA</option>
                    <option value="DTW" class="option-item">DTW</option>
                    <option value="MSP" class="option-item">MSP</option>
                    <option value="JFK" class="option-item">JFK</option>
                </select>
            </div>
```

```
            <div class="detail-container">
                <label for="dest" class="label-item">Destination</label>
                <br>
                <select id="dest" name="dest" class="select-input" onblur="checkValid('dest');">
                    <option value="ATL" class="option-item">ATL</option>
                    <option value="SEA" class="option-item">SEA</option>
                    <option value="DTW" class="option-item">DTW</option>
                    <option value="MSP" class="option-item">MSP</option>
                    <option value="JFK" class="option-item">JFK</option>
                </select>
                <div class="alert-text" id="dest-valid">Enter different Origin and
Destination.</div>
            </div>
        </div>
        <div id="block2">
            <div class="detail-container">
                <label for="sdt" class="label-item">Scheduled Departure Time</label>
                <br>
                <input type="number" id="sdt" name="sdt" class="text-input"
onblur="checkValid('sdt');" placeholder="Enter in the format HHMM">
                <div class="alert-text" id="sdt-valid">Enter a valid time between 500 to 2359.</div>
            </div>
            <div class="detail-container">
                <label for="sat" class="label-item">Scheduled Arrival Time</label>
                <br>
                <input type="number" id="sat" name="sat" class="text-input"
onblur="checkValid('sat');" placeholder="Enter in the format HHMM">
                <div class="alert-text" id="sat-valid">Enter a valid time between 500 to 2359.</div>
            </div>
            <div class="detail-container">
                <label for="adt" class="label-item">Actual Departure Time</label>
                <br>
                <input type="number" id="adt" name="adt" class="text-input"
onblur="checkValid('adt');" placeholder="Enter in the format HHMM">
                <div class="alert-text" id="adt-valid">Enter a valid time between 500 to 2359.</div>
            </div>
        </div>
    </div>
    <div id="submit-button">
        <input type="submit" value="Submit" id="submit" class="button" onclick="validateForm()">
    </div>
</form>
</body>
</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

```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta http-equiv="X-UA-Compatible">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <link rel="stylesheet" href="C:\Users\Arunjana\Desktop\flight delay development\styles.css">
    <script src="C:\Users\Arunjana\Desktop\flight delay development\delaypredicts.js"></script>
    <title>Flight Delay Prediction</title>
</head>
<body id="flight-form">
<h2 id="main-head" class="centered-head">FLIGHT DELAY PREDICTION</h2>
<img src="C:\Users\Arunjana\Desktop\flight delay development\pexels-asad-photo-maldives-2245279.JPG"
id="bgimg">
<form name="flightForm" action="/result" method="POST" target="_blank">
    <div id="form-content">
        <div id="block1">
            <div class="detail-container">
                <label for="fno" class="label-item">Enter the Flight Number</label>
                <br>
                <input type="number" id="fno" name="fno" class="text-input">
            </div>
            <div class="detail-container">
                <label for="month" class="label-item">Month</label>
                <br>
                <input type="number" id="month" name="month" class="text-input"
onblur="checkValid('month');" placeholder="Enter the Month Number">
                <div class="alert-text" id="month-valid">Enter a valid month between 1 to 12.</div>
            </div>
            <div class="detail-container">
                <label for="daym" class="label-item">Day of Month</label>
                <br>
                <input type="number" id="daym" name="daym" class="text-input"
onblur="checkValid('daym');">
                <div class="alert-text" id="daym-valid">Enter a valid day of month.</div>
            </div>
            <div class="detail-container">
                <label for="dayw" class="label-item">Day of Week</label>
                <br>
                <input type="number" id="dayw" name="dayw" class="text-input"
onblur="checkValid('dayw');">
                <div class="alert-text" id="dayw-valid">Enter a valid day between 1 to 7.</div>
            </div>
            <div class="detail-container">
                <label for="org" class="label-item">Origin</label>
```

```
      <br>
                <select id="org" name="org" class="select-input">
                    <option value="ATL" class="option-item">ATL</option>
                    <option value="SEA" class="option-item">SEA</option>
                    <option value="DTW" class="option-item">DTW</option>
                    <option value="MSP" class="option-item">MSP</option>
                    <option value="JFK" class="option-item">JFK</option>
                </select>
            </div>
            <div class="detail-container">
                <label for="dest" class="label-item">Destination</label>
                <br>

<select id="dest" name="dest" class="select-input" onblur="checkValid('dest');">
                    <option value="ATL" class="option-item">ATL</option>
                    <option value="SEA" class="option-item">SEA</option>
                    <option value="DTW" class="option-item">DTW</option>
                    <option value="MSP" class="option-item">MSP</option>
                    <option value="JFK" class="option-item">JFK</option>
                </select>
                <div class="alert-text" id="dest-valid">Enter different Origin and
Destination.</div>
            </div>
        </div>
        <div id="block2">
            <div class="detail-container">
                <label for="sdt" class="label-item">Scheduled Departure Time</label>
                <br>
                <input type="number" id="sdt" name="sdt" class="text-input"

onblur="checkValid('sdt');" placeholder="Enter in the format HHMM">
                <div class="alert-text" id="sdt-valid">Enter a valid time between 500 to 2359.</div>
            </div>
            <div class="detail-container">
                <label for="sat" class="label-item">Scheduled Arrival Time</label>
                <br>
                <input type="number" id="sat" name="sat" class="text-input"
onblur="checkValid('sat');" placeholder="Enter in the format HHMM">
                <div class="alert-text" id="sat-valid">Enter a valid time between 500 to 2359.</div>
            </div>
            <div class="detail-container">
                <label for="adt" class="label-item">Actual Departure Time</label>
                <br>
                <input type="number" id="adt" name="adt" class="text-input"
onblur="checkValid('adt');" placeholder="Enter in the format HHMM">
```

```html
                <div class="alert-text" id="adt-valid">Enter a valid time between 500 to 2359.</div>
            </div>
        </div>
    </div>
    <div id="submit-button">
        <input type="submit" value="Submit" id="submit" class="button" onclick="validateForm()">
    </div>
</form>
</body>
</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)
```

13.2. GITHUB & PROJECT DEMO LINK

Github link

https://github.com/IBM-EPBL/IBM-Project-53409-1661400534