PROJECT BASED EXPERIENTIAL LEARNING - PROGRAM (NALAIYA THIRAN)

DEVELOPING A FLIGHT DELAY PREDICTION MODEL USING MACHINE LEARNING

A PROJECT REPORT

Submitted by

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CONTENTS

1. INTRODUCTION

- 1. Project Overview
- 2. Purpose

2. LITERATURE SURVEY

- 1. Existing problem
- 2. References
- 3. . Problem Statement Definition

3. IDEATION & PROPOSED SOLUTION

- 1. Empathy Map Canvas
- 2. . Ideation & Brainstorming
- 3. . Proposed Solution
- 4. Problem Solution fit

4. REQUIREMENT ANALYSIS

- 1. . Functional requirement
- 2. . Non-Functional requirements

5. PROJECT DESIGN

- 1. Data Flow Diagrams
- 2. . Solution & Technical Architecture
- 3. . User Stories

6. PROJECT PLANNING & SCHEDULING

- 1. Sprint Planning & Estimation
- 2. . Sprint Delivery Schedule
- 3. Reports from JIRA

7. CODING & SOLUTIONING (Explain the features added in the project along with code)

- 1. Feature 1
- 2. Feature 2
- 3. . Database Schema (if Applicable)
- 8. TESTING
 - 1. Test Cases
 - 2. . User Acceptance Testing
- 9. RESULTS
 - 1. Performance Metrics
- **10.ADVANTAGES & DISADVANTAGES**
- 11. CONCLUSION
- **12.FUTURE SCOPE**
- 13. APPENDIX

1. 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

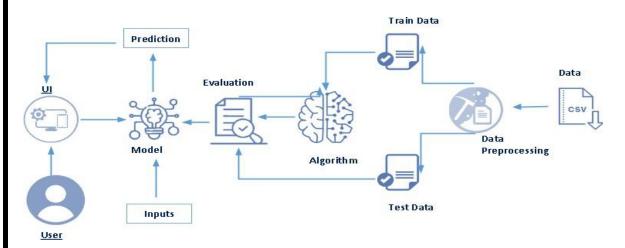


Figure 1.1. Technical Architecture

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.

2. LITERATURE SURVEY

S. NO	TITLE	AUTHOR	ABSTRACT	DRAWBACKS
1.	Flight Delay Prediction	Alice Sternberg, Jorge Soares, Diego Carvalho, Eduardo Ogasawara	Flight delays hurt airlines, airports, and passengers. Their prediction is crucial during the decision-making process for all players of commercial aviation. Moreover, the development of accurate prediction models for flight delays became cumbersome due to the complexity of air transportation system, the number of methods for prediction, and the deluge of flight data. In this context, this paper presents a thorough literature review of approaches used to build flight delay prediction models from the Data Science perspective. Here , proposed a taxonomy and summarize the initiatives used to address the flight delay prediction problem, according to scope, data, and computational methods, giving particular attention to an increased usage of machine learning methods. Besides , also present a timeline of significant works that depicts relationships between flight delay prediction problems and research trends to address them.	Dimensions were not directly related to the type of problem, but to the scope of application. This characteristic is notable in this case. Attributes such as weather, capacity, and demand were characteristics of airport or enroute airspace scopes. On the other hand, airlines schedules indicated scopes that considered airlines elements. It was also observed several ensembles of different dimensions, showing that prediction models may be improved through the selection of different attributes.
2.	Flight Delay Prediction System	Mrs Yogita Borse, Dhruvin Jain, Shreyash Sharma, Viral Vora, Aakash Zaveri	Flight Planning is one of the challenges in industrial world which faces many uncertain conditions. One such condition is delay occurrence, which stems from various factors and imposes considerable costs on airlines, operators, and travelers. Delays in departure can occur due to bad weather conditions, seasonal and holiday demands, airline policies, technical issue such as problems in airport facilities, luggage handling and mechanical apparatus, and accumulation of delays from preceding flights. Here in flight delay prediction system based on the weather parameters which can result in delays. The system considers the temperature, humidity, rain in mm, visibility and month number as important parameters for prediction of delay.	Results in this system is not so accurate. Although weather conditions are the major reasons for flight delay, other unprecedented events such as major calamities , natural or man-made can cause major delay in flight which is not considered in this Prediction System.
3.	Flight Delay Prediction	Vishrut Raj , Viran Raj, Satyam Singh , Adityanath Mishra	Fight delay prediction is fundamental to establish the more efficient airline business. The development of accurate prediction models for flight delays became cumbersome due to the complexity of air transportation system, the number of	This model only included one-year data due to our computation capability, as more years of data included, the prediction could be

methods for prediction, and the deluge of flight data. The paper presents a thorough literature review of approaches used to build flight delay prediction model. Airlines delays make immense loss for business field as well as in budget loss for a country. Flight delays hurt airlines, airports, and passengers. Here, proposing a machine learning algorithms like Linear regression Techniques. The aim of this research work is to predict Flight Delay, which is highest economy producing field for many countries and among many transportations this one is fastest and comfort, so to identify and reduce flight delays, can dramatically reduce the flight delays to saves huge number of turnovers, using machine-learning algorithms. Flight delays could always be annoying, especially in the case when the period of delay was so long that there was even a danger to miss the next flight. However, if there was a way to predict whether there would be a delay or even better - how long the delay could be, then people could make earlier preparation to reschedule following flights in an earlier manner.

easier. In addition, some other related information such as airplane type, e.g., detailed weather data specific to airport were not included. Therefore, researchers could try to collect more related data and deploy better computational powers to build a better mode.

CHAPTER 3: IDEATION AND PROPOSED SOLUTION

3.1 EMPATHY MAP CANVAS

Build empathy and keep your focus on the user by putting yourself in their shoes.

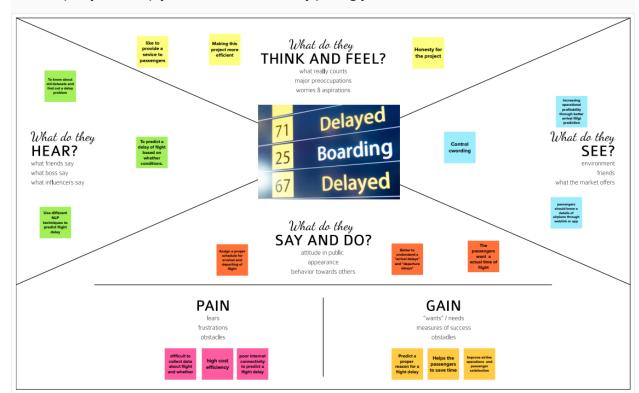
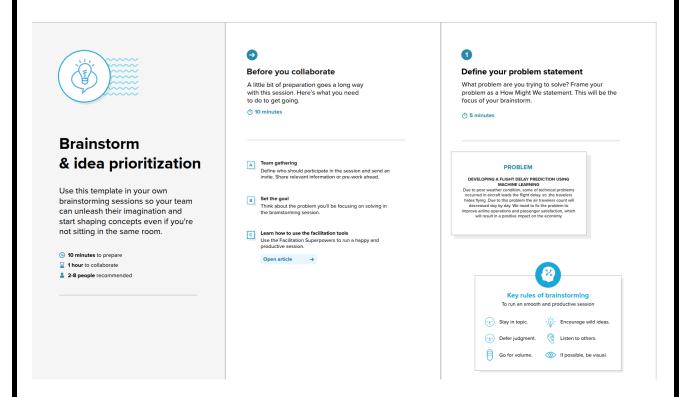


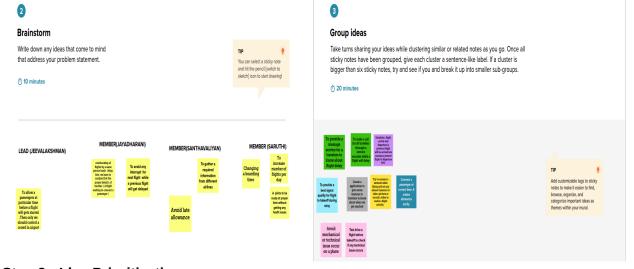
Figure 3.1. Empathy Map

3.2. IDEATION AND BRAINSTORMING

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



Step 2 - Brainstorm, Idea Listing and Grouping



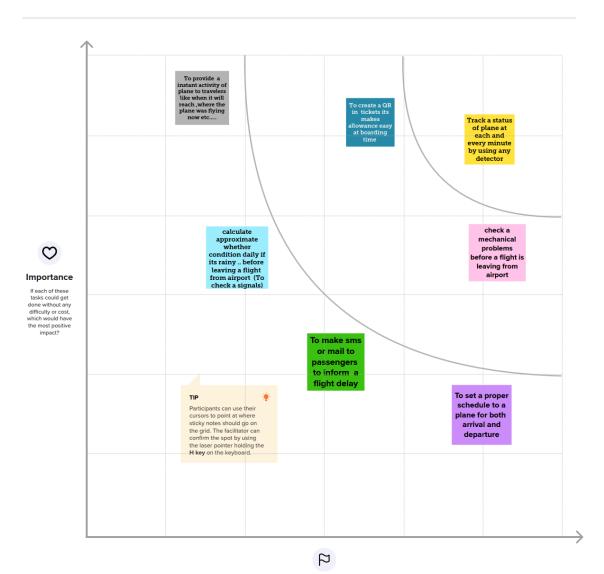
Step 3 - Idea Prioritization



Prioritize

Your team should all be on the same page about what's important moving forward. Place your ideas on this grid to determine which ideas are important and which are feasible.

① 20 minutes



Feasibility

Regardless of their importance, which tasks are more

3.3. PROPOSED SOLUTION

Date	24 September 2022
Team ID	PNT2022TMID16204
Project Name	Developing a flight delay prediction model using Machine learning
Maximum Marks	2 Marks

Proposed Solution Template:

S.No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	 Flight delays have been the most challenging area for airlines to improve. They have been affecting the air industry directly and indirectly causing unforeseen expenses thereby reducing the reputation of the industry and the airlines. Thus, knowing if a flight would be delayed beforehand can let passengers and airlines be prepared for the circumstances. This solution aims at making it possible by predicting arrival and departure delays using Machine learning.
2.	Idea / Solution description	 Building an application interface for customers(passengers and airlines) to know if a flight is delayed by implementing a machine learning based model to predict departure and arrival delays of an aircraft considering spatial, temporal and other dependencies causing the delay.
3.	Novelty / Uniqueness	 The solution takes into account all possible reasons for delay(crew delys, weather, air traffic, aircraft type) to provide an accurate prediction. Apart from predicting arrival delays, departure delays are also predicted in order for the passengers to prepare accordingly and for the airline to make arrangements suitably.
4.	Social Impact / Customer Satisfaction	 A lot of time and money can be saved for the customers and the loyalty and trust of customers towards the company increases.

		 Improves airline operations by letting the company prepare in advance to adversaries (like crew illness, timeouts, rescheduling) leading to passenger satisfaction which will result positively on the economy and brand value.
5.	Business Model (Revenue Model)	 Business to Consumer model The solution is a low-cost airline model planned to be created as an application with which the consumers can interact directly to know the details of their flight. It follows a non-monetary revenue model where the consumers aren't charged for what they get but are asked to provide their flight details and ratings which can be used to improve the model and shared with the airline in return for the airline's flight data.
6.	Scalability of the Solution	 The present solution is drafted with the aim of experimenting with airlines based out of the United States of America. If there is a possibility to acquire data of a broader region (say North America, other continents), then the solution can be developed to benefit a wider range of people. International flight dependencies in both temporal and spatial focus can be derived from that data to provide more accurate predictions. Presence of ADS-B data can further increase the efficiency of the system making it reach a global audience and live time tracking of flights.

Relieved if an alternate solution can be

found

	6. CUSTOMER CONSTRAINTS CC	5. AVAILABLE SOLUTIONS AS
Normal flight users Business professionals having meetings People boarding a lay-over flight Logistics incharge at airport Airport catering manager	- Refund/Partial Refund - Not knowing the exact time of delay - Unavailability of alternate flights or accommodation	- 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
2. JOBS-TO-BE-DONE / PROBLEMS - 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 - 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 - 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
3. TRIGGERS	10, YOUR SOLUTION SL	8.CHANNELS of BEHAVIOUR
- 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	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.	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
4. EMOTIONS: BEFORE / AFTER Before: - Worried - About missing important events - About missing layover flights - If the flight is gonna be canceled - Frustrated - About the unexpected		Finding alternate travel routes in the airport Hotels near the airport can be visit for overnight stays during delays

CHAPTER 4 REQUIREMENT ANALYSIS

4.1. 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 Web app
FR-2	User Login	User is confirmed using the login credentials given at the time of registration
FR-3	Inputs for prediction	Inputs are given by the User through the form displayed in the web application
FR-4	Prediction	The ML model predicts if the flight will be delayed or not
FR-5	User Logout	The User is logged out from the application after timeout period or through manual logout

4.2. NON-FUNCTIONAL REQUIREMENTS

Non-functional Requirements:

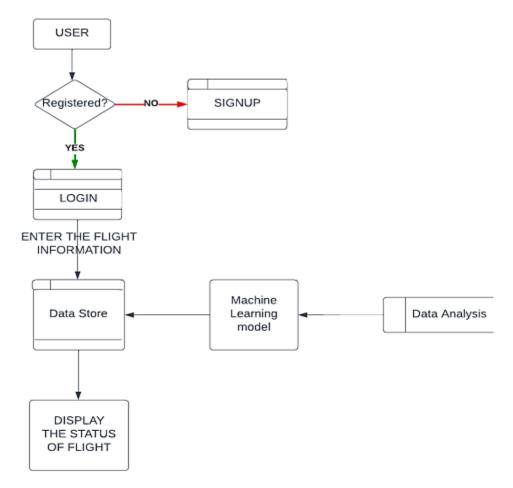
Following are the non-functional requirements of the proposed solution.

FR No.	Non-Functional Requirement	Description
NFR-1	Usability	Interactive and simple UI makes the application user friendly
NFR-2	Security	User authentication using email and password provides high security
NFR-3	Reliability	Usage of ML for prediction makes the predictions highly reliable and accurate
NFR-4	Performance	The application predicts the output in few seconds
NFR-5	Availability	Since the web application can be hosted online, it can be made available anywhere anytime
NFR-6	Scalability	The application can be scaled for any number of users and complexity

CHAPTER 5 PROJECT DESIGN

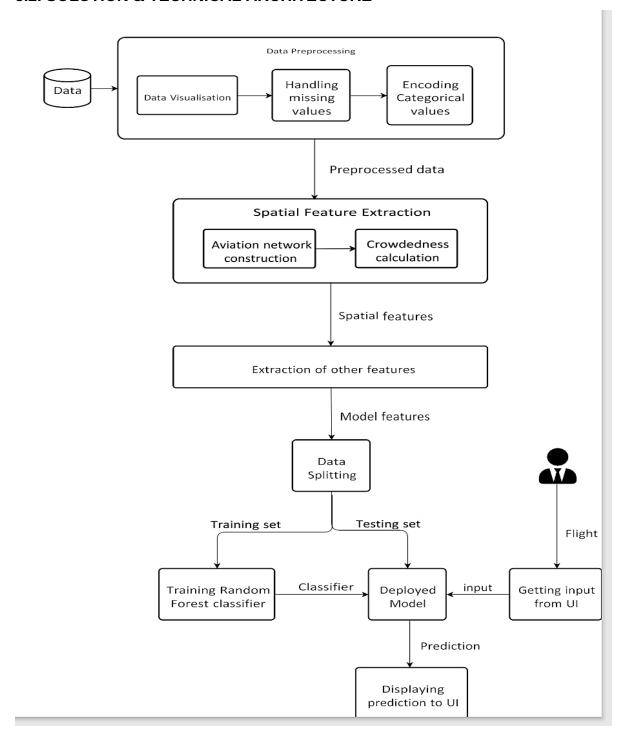
5.1. DATA FLOW DIAGRAMS

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.

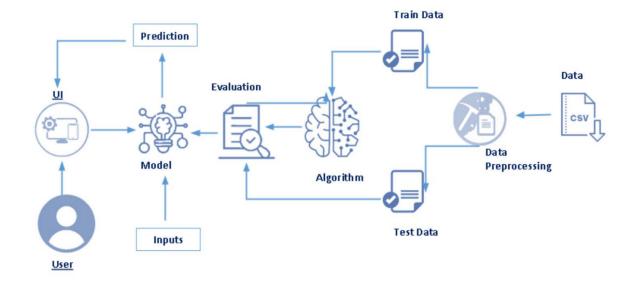


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5.2. SOLUTION & TECHNICAL ARCHITECTURE



Technology Stack



Components and 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.	SQLite
4.	Machine Learning Model	To Predict whether the flight will get delayed or not	Decision Trees,SVM,KNN Classifier
5.	Infrastructure (Server/ Cloud)	Application Deployment on Local System / Cloud Local Server Configuration Cloud Server Configuration	IBM Cloud

5.3. User Stories

User Type	Functional Requirement	User Story	User Story / Task	Acceptance criteria	Priority	Release
	(Epic)	Number				
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 Gmail		Medium	Sprint-1
	Login	USN-4	As a user, I can log into the application by entering email & password		High	Sprint-1
Customer (Web user)	Registration	USN-1	As a web 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 web user, I will receive confirmation email once I have registered for the application	I can receive confirmation email & click confirm	High	Sprint-1
	Login	USN-3	As a web user, I can log into the application by entering email & password		High	Sprint-1
	Screen space	USN-5	As a web user, I can have a better illumination	I can have a good interaction with website	Medium	Sprint-1

User Type	Functional Requirement	User Story	User Story / Task	Acceptance criteria	Priority	Release
	(Epic)	Number				
Executive			a very strong functional knowledge about	understanding about the		
			the website.	website		
		USN-2	As a customer care executive, I must have	I receive good feedback	High	Sprint-2
			patience, people management qualities	from customers		
		USN-3	As a customer care executive, I will help	Clarity about the	Medium	Sprint-2
			the customer in all possible ways.	website		
Administrator	Management	USN-1	As an administrator, I would provide	Allows growth and	High	Sprint-3
			specific IT support and advice for	success of the website		
			different management activities			
		USN-2	As an administrator, I would describe the	Mutual benefits of both	High	Sprint-3
			requirements of inputs, behavior and	customers and websites		
			outcomes of the actions performed.			
	Coordination	USN-1	As an administrator, I would act as a	Untroubled workflow	Medium	Sprint-3
			bridge connecting the user and website.	for customer side		
		USN-2	As an administrator, I would verify the	Website is being used	High	Sprint-3
			identity of users.	only by certified users		

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 Preprocessing	USN-1	Datasets collected from various online resources are preprocessed, cleaned so as to provide valid data to the Machine learning model for training.	2	high	Tamil Mani P, Saravana Kumar P B, Srikanth M U, Suriya Raaj P
Sprint-1	Model Building	USN-2	Machine Learning models are built using Python Notebook available in the Watson Studio.	1	high	Tamil Mani P, Saravana Kumar P B, Srikanth M U, Suriya Raaj P
Sprint-2	Model Evaluation	USN-3	Many different models are trained and evaluated and the model with the best performance metrics is chosen for deployment.	2	high	Tamil Mani P, Saravana Kumar P B, Srikanth M U, Suriya Raaj P
Sprint-2	Model Deployment on IBM Cloud using IBM Watson	USN-4	The selected model is deployed in the IBM cloud using the deployment space available in the Watson Studio.	1	Medium	Tamil Mani P, Saravana Kumar P B, Srikanth M U, Suriya Raaj P
Sprint-2	Basic user interaction Dashboard	USN-5	Dashboard is provided for each user which is interactive and informative.	2	high	Tamil Mani P, Saravana Kumar P B,
Sprint-3	Improved Dashboard and GUI	USN-6	The dashboard can be further improved to provide more interactivity.	1	Medium	Saravana Kumar P B, Srikanth M U, Suriya Raaj P
Sprint-3	Registration	USN-7	As a user, I can register a new account by providing E-mail, password and name.	2	High	Tamil Mani P, Saravana Kumar P B,
Sprint-3	Login	USN-8	As a user, I can login to my registered account by providing e-mail and password which is already available in the stored database.	2	Medium	Tamil Mani P, Saravana Kumar P B,

						Suriya Raaj P
Sprint-4	Raise query/complaint	USN-9	As a user, I can raise queries related to the	1	Medium	Tamil Mani P,
	and give feedback		service provided and also provide feedback on			Saravana
			the performance of the web-application.			Kumar P B
Sprint-4	Improve overall	USN-10	Taking into account the feedback provided	1	High	Tamil Mani P,
	web app		by various users, the overall performance			Saravana
			and the usability of the app can be			Kumar P B,
			improved.			Srikanth M U,
						Suriya Raaj P

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	20	6 Days	24 Oct 2022	29 Oct 2022	20	31 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

Burndown Chart

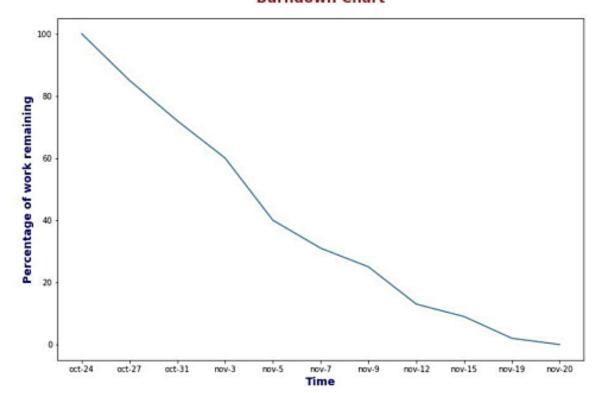
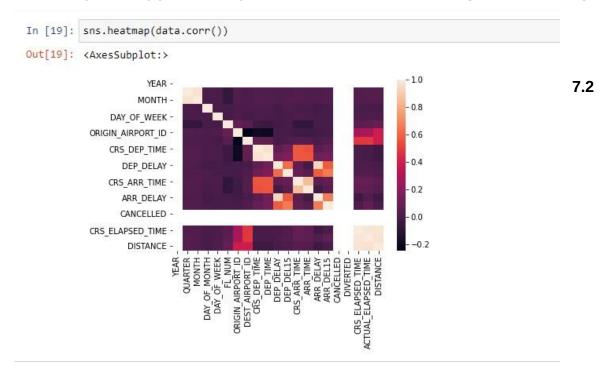


Figure 6.1 - Burndown Chart

CHAPTER 7 CODING AND SOLUTIONING

7.1 FEATURE 1 - CORRELATION BETWEEN THE VARIABLES IN THE DATASET



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
            1375
       1.0
      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 I
                        30
                                              12 0.0 0.0
       11226 1715 12
                                         5
                                                                        0
                                                                                             0
       11227
              1770
                               30
                                         5
                                                   20
                                                          1.0
                                                                  0.0
                                                                          0
                                                                                0
                                                                                       0
             1823 12
                                                 22
                                                         0.0
       11228
       11229
             1901
                                                   18
                                                          0.0
                                                                          1
                                                                                0
                                                                                             0
       11230 2005 12 30
                                         5 9 0.0 0.0 1 0 0
```

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
                            0.48
                                      0.46 0.47
                                                             255
                             0.00
                                      0.00
                                                  0.00
                                                                 a
                           0.48 0.46
0.24 0.23

    0.48
    0.46
    0.47

    0.24
    0.23
    0.23

    0.48
    0.46
    0.47

             micro avg
                                                               255
             macro avg
                                                               255
          weighted avg
                                                               255
```

7.4 FEATURE 4 - FLASK INTERFACE - UI

from flask import Blueprint, render_template,request,redirect,url_for from flask_login import login_required, current_user from . import db

```
import requests
import flask
from flask_cors import CORS
from datetime import datetime
API_KEY = "b1papptuFebhE9mB86BRaPcjkCS3jwsVV_69I5w3os7E"
token_response = requests.post('https://iam.cloud.ibm.com/identity/token', data={"apikey": API_KEY,
"grant_type": 'urn:ibm:params:oauth:grant-type:apikey'})
mltoken = token_response.json()["access_token"]
header = {'Content-Type': 'application/json', 'Authorization': 'Bearer ' + mltoken}
main = Blueprint('main', __name__)
@main.route('/')
def index():
  return render_template('index.html')
@main.route('/profile')
@login_required
def profile():
  return render_template('profile.html', name=current_user.name)
@main.route('/prediction')
@login_required
def prediction():
  return render_template('prediction.html')
@main.route('/prediction',methods=['POST'])
```

```
@login_required
def prediction_post():
  departure_date=request.form['date_flight']
  departure_time=request.form['time_flight']
  departure_date_lis=departure_date.split('-')
  departure_date_str=departure_date_lis[2]+"/"+departure_date_lis[1]+"/"+departure_date_lis[0]
  origin=request.form['source']
  destination=request.form['destination']
  departure_date_time=departure_date_str+" "+departure_time
  try:
     departure_date_time_parsed = datetime.strptime(departure_date_time, '%d/%m/%Y
%H:%M:%S')
except ValueError as e:
     return 'Error parsing date/time - {}'.format(e)
  month = departure date time parsed.month
  day = departure_date_time_parsed.day
  day_of_week = departure_date_time_parsed.isoweekday()
  hour = departure_date_time_parsed.hour
  origin = origin.upper()
  destination = destination.upper()
  X= [[month, day, day of week, hour, 1 if origin == 'ATL' else 0, 1 if origin == 'DTW' else 0,
  1 if origin == 'JFK' else 0, 1 if origin == 'MSP' else 0, 1 if origin == 'SEA' else 0,
  1 if destination == 'ATL' else 0, 1 if destination == 'DTW' else 0, 1 if destination == 'JFK' else 0,
  1 if destination == 'MSP' else 0, 1 if destination == 'SEA' else 0 ]]
  print(X)
  #predict= model.predict(X)[0]
  #print(predict)
```

```
pred=['Flight is on Time', 'Flight is Delayed']
  payload_scoring = {"input_data": [{"field":
[['MONTH','DAY','DAY_OF_WEEK','CRS_DEP_TIME','ORIGIN_ATL',
'ORIGIN_DTW','ORIGIN_JFK','ORIGIN_MSP','ORIGIN_SEA','DEST_ATL','DEST_DTW','DEST_JFK'
,'DEST_MSP','DEST_SEA']], "values": X}]}
  response_scoring = requests.post('https://us-
south.ml.cloud.ibm.com/ml/v4/deployments/82a07ea5-a22b-4882-acc3-
7edb67a61b88/predictions?version=2022-11-15', json=payload_scoring,
  headers={'Authorization': 'Bearer ' + mltoken})
  print(response_scoring)
  predictions = response_scoring.json()
  print(predictions)
  predict = int(predictions['predictions'][0]['values'][0][0])
  predict_str=pred[predict]
  print("Final prediction :",predict str)
  # showing the prediction results in a UI# showing the prediction results in a UI
  return render_template('output.html', predict_str=predict_str)
@main.route('/output')
@login_required
def predict_again():
  return render_template('prediction.html')
```

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 prediction.html page

```
{% extends "base.html" %}
{% block content%}
<div class="column is-4 is-offset-4">
  <h3 class="title">Enter the details of your scheduled flight</h3>
  <div class="box">
    <form method="POST" action="" class="">
       Enter the Date of the Flight:
       <div class="input-field">
         <input name="date_flight" input type='date' required>
       </div>
       Enter the Departure Time in 24 hour format:
       <input name="time_flight" input type='time' value='13:45:00' step='1' required>
       Enter the Source:
    <!--input name="source" required-->
       <select name="source" id="source" class="form-select" >
         <option value="ATL">ATL-Hartsfield-Jackson Atlanta International Airport,
Atlanta/option>
         <option value="JFK">JFK-John F kennedy International Airport, New York
         <option value="DTW">DTW-Detroit Metropolitan Wayne County Airport-Detroit,
Michigan</option>
         <option value="MSP">MSP-Minneapolis-Saint Paul International Airport,
```

```
Minnesota
         <option value="SEA">SEA-Seattle-Tacoma International Airport, Washington
       </select>
       <br>
       Enter the Destination:
       <select name="destination" id="source" class="form-select">
         <option value="ATL">ATL-Hartsfield-Jackson Atlanta International Airport,
Atlanta/option>
         <option value="JFK">JFK-John F kennedy International Airport, New York
         <option value="DTW">DTW-Detroit Metropolitan Wayne County Airport-Detroit,
Michigan</option>
         <option value="MSP">MSP-Minneapolis-Saint Paul International Airport,
Minnesota</option>
         <option value="SEA">SEA-Seattle-Tacoma International Airport, Washington/option>
<br>
       <br>
       <!--button class="button is-block is-info is-large is-fullwidth" type="submit" >Submit</br/>/button--
       <button class="btn btn-link" type="submit">Predict</button>
  </form>
  </div>
</div>
<style>
  input{
    -webkit-text-fill-color:gray;
  }
  .checkbox{
    -webkit-text-fill-color: gray;
  }
  button{
```

```
background-color: black !important;
  }
  button a:hover{
     color:aqua !important;
  }
  option{
    color:black;
     background-color:white;
  }
  option :hover{
     background-color:aqua!important;
  }
  p{
    text-align:left;
}
</style>
{% endblock %}
```

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 form and provides it to the back end flask framework.

ouput.html Page

```
</form>
<style>
  input{
     -webkit-text-fill-color:gray;
  }
  .checkbox{
     -webkit-text-fill-color: gray;
  }
  button{
     background-color: black !important;
  }
  button a:hover{
     color:aqua !important;
  }
  option{
     color:black;
     background-color:white;
  }
  option :hover{
     background-color:aqua!important;
  }
</style>
{% endblock %}
```

Explanation:

The above page loads when the user submits the form and provides the output predicted classification as whether the flight is delayed or not.

CHAPTER 8 TESTING

8.1 TEST

Us er No	Flight No	Mon th	Day of mon th	D ay of we ek	Orig in	Destinati on	Schedul ed Departu re Time	Schedul ed Arrival Time	Actual Depart ure Time	Act ual Inpu ts
1	1232	1	1	1	ATL	MSP	1905	2305	19 45	Delayed
2	1399	1	1	1	ATL	S E A	1805	2410	18 55	Delayed
3	2351	1	2	3	ATL	DTW	1305	2305	13 05	Not Delayed
4	2637	2	1	3	D TW	A T L	1500	2410	15 05	Not Delayed

8.2 USER ACCEPTANCE TESTING

Us er No	Flig ht No	Mon th	Day Of Mon th	D ay Of We ek	Orig in	Destin -ation	Schedul ed Departu re Time	Schedu led Arrival Time	Actual Depart ure Time	Actu al Out put	Predict -ed Outp ut	Correc t-ne ss
1	1232	1	1	1	ATL	M SP	19 05	23 05	1945	Delayed	Delay ed	Corr ect
2	1399	1	1	1	ATL	S EA	18 05	24 10	1855	Delayed	Delay ed	Corr ect

3	2351	1	2	3	ATL	D T W	13 05	23 05	1305	Not Delayed	Not Delay ed	Corr ect
4	2637	2	1	3	DTW	A TL	15 00	24 10	1505	Not Delayed	Not Delay ed	Corr ect

CHAPTER 9 RESULTS

9.1 PERFORMANCE METRICS

Training Accuracy

MODEL EVALUATION

```
acc=accuracy_score(predicted,y_test)
acc
0.8791308284291535
```

Confusion Matrix

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

- Passengers can identify easily if their flights will be delayed or not.
- Passengers become aware of the delays early and can be composed in crunch situations.
- The current status of the flight can also be tracked.
- Helps passengers plan their journey prior to their travel.

Disadvantages

- Biased prediction due to the presence of outliers.
- Passengers might miss their flights due to incorrect prediction of the model that the flight will be delayed.
- Incorrect prediction leads to various confusions including the loss of capital for

the trave agency.

CHAPTER 11 CONCLUSION

The created web-application makes use of Machine Learning model trained on the dataset of previous flights and predicts the status of the flights in the current time. Using our Flight Delay Predictor application, the users can be benefitted by getting know the delay status of their scheduled flights.

Since the application is web based, any person can access and get the information at anytime anywhere.

CHAPTER 12 FUTURE SCOPE

Based on data analysis between the years 2016-2018, this project was made. There is a sizable dataset accessible from 1987 to 2020, 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 also 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 specific airports of USA, but we can also include data from other nations like China, Europe, Russia and also

India. 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

```
!curl https://topcs.blob.core.windows.net/public/FlightData.csv -o
flightdata.csv
 % Total % Received % Xferd Average Speed Time Time Time
                                 Dload Upload Total Spent Left
Speed
 0 0 0 0 0 0 0 0 0 0 --:--:--
-:--:- Ocurl: (6) Could not resolve host:
-----
topcs.blob.core.windows.net
import os, types
import pandas as pd
from botocore.client import Config
import ibm boto3
def___iter__(self): return 0
# @hidden_cell
# The following code accesses a file in your IBM Cloud Object Storage.
It includes your credentials.
# You might want to remove those credentials before you share the
cos_client = ibm_boto3.client(service_name='s3',
    ibm_api_key_id='qbgeU05njYh_u7o7DjiZtO-jZaiGeNf8OWmacgANzHjR',
    ibm_auth_endpoint="https://iam.cloud.ibm.com/oidc/token",
    config=Config(signature_version='oauth'),
    endpoint_url='https://s3.private.us.cloud-object-
storage.appdomain.cloud')
bucket = 'flightdelay-donotdelete-pr-ti12fkh98hxjhh'
object_key = 'flightdata.csv'
body = cos_client.get_object(Bucket=bucket, Key=object_key)['Body']
# add missing iter method, so pandas accepts body as file-likeobje
if not hasattr(body, "__iter__"): body.__iter__ = types.MethodType(
__iter__, body )
```

N813DN							
3 2016 N587NW	1	1		1	5	DI	L
4 2016	1	1		1	5	DI	r.
N836DN	-	-		-	-		-
FL_NUM ARR_DELAY 0 1399 41.0 1 1476 4.0 2 1597 33.0 3 1768		RPORT_ID 07 10397 11433 10397 14747	ATL DTW ATL		2143 1435 1215	R_TIME 3 2102.0 5 1439.0 5 1142.0 5 1345.0	-
10.0 4 1823		14747	CPA		607	7 615.0	
8.0	•	14/4/	SEA		60	615.0	
ACTUAL_EL	APSED_TIME	LED DIVERT	ED CRS	ELAPSED_T	IME		
0 295.0	0.0	0.0	0.0		338.0		
1	0.0	0.0	0.0		110.0		
115.0	0.0	0.0	0.0		335.0		
300.0							
3 205.0	0.0	0.0	0.0		196.0		
	0.0	0.0	0.0		247.0		
259.0							
DISTAN	ICE Unname	d · 25					
0 2182		NaN					
1 528	.0	NaN					
2 2182		NaN					
3 1399		NaN					
4 1927	.0	NaN					
[5 rows x	26 column	s]					
df.shape							
(11231, 2	6)						
df.isnull	().values.	any()					
True							

```
df.isnull().sum()
YEAR
QUARTER
MONTH
DAY_OF_MONTH
DAY_OF_WEEK
UNIQUE CARRIER
TAIL NUM
FL NUM
ORIGIN_AIRPORT_ID
ORIGIN
DEST_AIRPORT_ID
                         0
DEST
CRS_DEP_TIME
DEP_TIME
DEP_DELAY
                        107
                        107
DEP DEL15
                     115
CRS ARR TIME
ARR_TIME
                       188
188
ARR DELAY
ARR DEL15
CANCELLED
                        0
DIVERTED
CRS_ELAPSED_TIME
CRS_ELAPSED_TIME 0
ACTUAL_ELAPSED_TIME 188
             11231
DISTANCE
Unnamed: 25
dtype: int64
df = df.drop('Unnamed: 25', axis=1)
df.isnull().sum()
YEAR
QUARTER
                        0
MONTH
DAY OF MONTH
DAY_OF_WEEK
UNIQUE_CARRIER
TAIL_NUM
FL NUM
ORIGIN_AIRPORT_ID
ORIGIN
DEST_AIRPORT_ID
                      0
DEST
CRS DEP TIME
DEP_TIME
DEP_DELAY
DEP_DEL15
                     107
                      107
                     107
CRS ARR TIME
ARR TIME
                      115
```

13.1.2 Train the ML Model

```
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier(random_state=13)
model.fit(train_x, train_y)
RandomForestClassifier(random_state=13)
```

```
predicted = model.predict(test x)
model.score(test x, test y)
 0.8642634623943035
 from sklearn.metrics import roc auc score
 probabilities = model.predict proba(test x)
 from sklearn.metrics import confusion matrix
 confusion_matrix(test_y, predicted)
 array([[1903,
                33],
                39]])
        [ 272,
 from sklearn.metrics import precision score
 train_predictions = model.predict(train_x)
 precision score(train y, train predictions)
 1.0
 from sklearn.metrics import recall_score
 recall_score(train_y, train_predictions)
 0.9992012779552716
 def predict_delay(departure_date_time, origin, destination):
     from datetime import datetime
        departure_date_time_parsed =
 datetime.strptime(departure_date_time, '%d/%m/%Y %H:%M:%S')
     except ValueError as e:
         return 'Error parsing date/time - {}'.format(e)
     month = departure_date_time_parsed.month
     day = departure_date_time_parsed.day
     day_of_week = departure_date_time_parsed.isoweekday()
     hour = departure date time parsed.hour
     origin = origin.upper()
     destination = destination.upper()
     input = [{'MONTH': month,
                'DAY': day,
                'DAY_OF_WEEK': day_of_week,
                'CRS_DEP_TIME': hour,
                'ORIGIN ATL': 1 if origin == 'ATL' else 0,
                'ORIGIN DTW': 1 if origin == 'DTW' else 0, 'ORIGIN JFK': 1 if origin == 'JFK' else 0,
                'ORIGIN MSP': 1 if origin == 'MSP' else 0,
```

```
'ORIGIN SEA': 1 if origin == 'SEA' else 0,
              'DEST ATL': 1 if destination == 'ATL' else 0,
              'DEST_DTW': 1 if destination == 'DTW' else 0,
              'DEST JFK': 1 if destination == 'JFK' else 0,
              'DEST MSP': 1 if destination == 'MSP' else 0,
              'DEST SEA': 1 if destination == 'SEA' else 0 }]
    return model.predict proba(pd.DataFrame(input))[0][0]
predict delay('1/10/2018 21:45:00', 'JFK', 'ATL')
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/sklearn/
base.py:493: FutureWarning: The feature names should match those that
were passed during fit. Starting version 1.2, an error will be raised.
Feature names unseen at fit time:

    DAY

Feature names seen at fit time, yet now missing:
- DAY_OF_MONTH
  warnings.warn(message, FutureWarning)
predict delay('2/10/2018 21:45:00', 'JFK', 'ATL')
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/sklearn/
base.py:493: FutureWarning: The feature names should match those that
were passed during fit. Starting version 1.2, an error will be raised.
Feature names unseen at fit time:
- DAY
Feature names seen at fit time, yet now missing:
- DAY_OF_MONTH
  warnings.warn(message, FutureWarning)
0.87
predict_delay('2/10/2018 10:00:00', 'ATL', 'SEA')
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/sklearn/
base.py:493: FutureWarning: The feature names should match those that
were passed during fit. Starting version 1.2, an error will be raised.
Feature names unseen at fit time:
- DAY
Feature names seen at fit time, yet now missing:
- DAY_OF_MONTH
  warnings.warn(message, FutureWarning)
0.99
train x
```

13.1.3 Mainpage – HTML Code

```
{% extends "base.html" %}
{% block content%}
```

```
<div class="column is-4 is-offset-4">
  <h3 class="title">Enter the details of your scheduled flight</h3>
  <div class="box">
    <form method="POST" action="" class="">
      Enter the Date of the Flight:
      <div class="input-field">
         <input name="date_flight" input type='date' required>
      </div>
      Enter the Departure Time in 24 hour format:
      <input name="time_flight" input type='time' value='13:45:00' step='1' required>
      Enter the Source:
    <!--input name="source" required-->
      <select name="source" id="source" class="form-select" >
         <option value="ATL">ATL-Hartsfield-Jackson Atlanta International Airport,
Atlanta
         <option value="JFK">JFK-John F kennedy International Airport, New York/option>
         <option value="DTW">DTW-Detroit Metropolitan Wayne County Airport-Detroit,
Michigan
         <option value="MSP">MSP-Minneapolis-Saint Paul International Airport,
Minnesota
         <option value="SEA">SEA-Seattle-Tacoma International Airport, Washington
      </select>
      <br>
      Enter the Destination:
      <select name="destination" id="source" class="form-select">
         <option value="ATL">ATL-Hartsfield-Jackson Atlanta International Airport,
```

```
Atlanta/option>
         <option value="JFK">JFK-John F kennedy International Airport, New York
         <option value="DTW">DTW-Detroit Metropolitan Wayne County Airport-Detroit,
Michigan</option>
         <option value="MSP">MSP-Minneapolis-Saint Paul International Airport,
Minnesota</option>
         <option value="SEA">SEA-Seattle-Tacoma International Airport, Washington
       </select>
       <br>
       <br>
       <!--button class="button is-block is-info is-large is-fullwidth" type="submit" >Submit</button--
       <button class="btn btn-link" type="submit">Predict</button>
  </form>
  </div>
</div>
<style>
  input{
    -webkit-text-fill-color:gray;
  }
  .checkbox{
    -webkit-text-fill-color: gray;
  }
  button{
    background-color: black !important;
  }
  button a:hover{
    color:aqua !important;
  }
  option{
```

```
color:black;
     background-color:white;
  }
  option :hover{
    background-color:aqua !important;
  }
  p{
    text-align:left;
  }
</style>
{% endblock %}
13.1.4 Prediction Output Page – HTML Code
{% extends "base.html" %}
{% block content %}
<h2>{{predict_str}}</h2>
<form action="/prediction">
  <button class="btn btn-link" type="submit"><a hef="/prediction">Predict Again</a></button>
</form>
<style>
  input{
    -webkit-text-fill-color:gray;
  }
  .checkbox{
    -webkit-text-fill-color: gray;
  }
  button{
```

```
background-color: black !important;
  }
  button a:hover{
    color:aqua !important;
  }
  option{
    color:black;
    background-color:white;
  }
  option :hover{
    background-color:aqua !important;
  }
</style>
{% endblock %}
13.1.5 Flask Application
main.py
from flask import Blueprint, render_template,request,redirect,url_for
from flask_login import login_required, current_user
from . import db
import requests
import flask
from flask_cors import CORS
from datetime import datetime
API_KEY = "b1papptuFebhE9mB86BRaPcjkCS3jwsVV_69I5w3os7E"
token_response = requests.post('https://iam.cloud.ibm.com/identity/token', data={"apikey": API_KEY,
"grant_type": 'urn:ibm:params:oauth:grant-type:apikey'})
```

```
mltoken = token_response.json()["access_token"]
header = {'Content-Type': 'application/json', 'Authorization': 'Bearer ' + mltoken}
main = Blueprint('main', __name__)
@main.route('/')
def index():
return render_template('index.html')
@main.route('/profile')
@login_required
def profile():
  return render_template('profile.html', name=current_user.name)
@main.route('/prediction')
@login_required
def prediction():
  return render_template('prediction.html')
@main.route('/prediction',methods=['POST'])
@login_required
def prediction_post():
  departure_date=request.form['date_flight']
  departure_time=request.form['time_flight']
  departure_date_lis=departure_date.split('-')
  departure_date_str=departure_date_lis[2]+"/"+departure_date_lis[1]+"/"+departure_date_lis[0]
  origin=request.form['source']
  destination=request.form['destination']
  departure_date_time=departure_date_str+" "+departure_time
    departure_date_time_parsed = datetime.strptime(departure_date_time, '%d/%m/%Y
%H:%M:%S')
  except ValueError as e:
```

```
return 'Error parsing date/time - {}'.format(e)
  month = departure_date_time_parsed.month
  day = departure_date_time_parsed.day
  day_of_week = departure_date_time_parsed.isoweekday()
  hour = departure_date_time_parsed.hour
  origin = origin.upper()
  destination = destination.upper()
  X= [[month, day, day_of_week, hour, 1 if origin == 'ATL' else 0, 1 if origin == 'DTW' else 0,
  1 if origin == 'JFK' else 0, 1 if origin == 'MSP' else 0, 1 if origin == 'SEA' else 0,
  1 if destination == 'ATL' else 0, 1 if destination == 'DTW' else 0, 1 if destination == 'JFK' else 0,
  1 if destination == 'MSP' else 0, 1 if destination == 'SEA' else 0 ]]
  print(X)
  #predict= model.predict(X)[0]
  #print(predict)
  pred=['Flight is on Time','Flight is Delayed']
  payload_scoring = {"input_data": [{"field":
[['MONTH','DAY','DAY_OF_WEEK','CRS_DEP_TIME','ORIGIN_ATL',
'ORIGIN_DTW','ORIGIN_JFK','ORIGIN_MSP','ORIGIN_SEA','DEST_ATL','DEST_DTW','DEST_JFK'
,'DEST_MSP','DEST_SEA']], "values": X}]}
  response_scoring = requests.post('https://us-
south.ml.cloud.ibm.com/ml/v4/deployments/82a07ea5-a22b-4882-acc3-
7edb67a61b88/predictions?version=2022-11-15', json=payload scoring,
  headers={'Authorization': 'Bearer ' + mltoken})
  print(response_scoring)
  predictions = response_scoring.json()
  print(predictions)
```

```
predict = int(predictions['predictions'][0]['values'][0][0])
  predict_str=pred[predict]
  print("Final prediction :",predict_str)
  # showing the prediction results in a UI# showing the prediction results in a UI
  return render_template('output.html', predict_str=predict_str)
@main.route('/output')
@login_required
def predict_again():
  return render_template('prediction.html')
auth.py
from flask import Blueprint, render_template,redirect,url_for,request, flash
from werkzeug.security import generate_password_hash, check_password_hash
from . import db
from .models import User
from flask_login import login_user, login_required, logout_user
auth = Blueprint('auth', __name__)
@auth.route('/login')
def login():
  return render_template('login.html')
@auth.route('/login', methods=['POST'])
def login_post():
  # login code goes here
  email = request.form.get('email')
  password = request.form.get('password')
```

```
remember = True if request.form.get('remember') else False
  user = User.query.filter_by(email=email).first()
  # check if the user actually exists
  # take the user-supplied password, hash it, and compare it to the hashed password in the
database
  if not user or not check_password_hash(user.password, password):
     flash('Please check your login details and try again.')
     return redirect(url_for('auth.login')) # if the user doesn't exist or password is wrong, reload the
page
  # if the above check passes, then we know the user has the right credentials
  login_user(user, remember=remember)
  return redirect(url_for('main.profile'))
@auth.route('/signup')
def signup():
  return render_template('sign_up.html')
@auth.route('/signup', methods=['POST'])
def signup_post():
  email = request.form.get('email')
  name = request.form.get('name')
  password = request.form.get('password')
  user = User.query.filter_by(email=email).first() # if this returns a user, then the email already exists
in database
```

```
if user: # if a user is found, we want to redirect back to signup page so user can try again
     flash('Email address already exists')
     return redirect(url_for('auth.signup')
  new_user = User(email=email, name=name, password=generate_password_hash(password,
method='sha256'))
  # add the new user to the database
  db.session.add(new_user)
  db.session.commit()
  return redirect(url_for('auth.login'))
@auth.route('/logout')
@login_required
def logout():
  logout_user()
  return redirect(url_for('main.index'))
Init.py
from flask import Flask
from flask_sqlalchemy import SQLAlchemy
from flask_login import LoginManager
# init SQLAlchemy so we can use it later in our models
db = SQLAlchemy()
def create_app():
```

```
app = Flask(__name__)
  app.config['SECRET_KEY'] = 'secret-key-goes-here'
  app.config['SQLALCHEMY_DATABASE_URI'] = 'sqlite:///db.sqlite'
  db.init_app(app)
  login_manager = LoginManager()
  login_manager.login_view = 'auth.login'
  login_manager.init_app(app)
  from . import models
  with app.app_context():
    db.create_all()
  from .models import User
  @login_manager.user_loader
  def load_user(user_id):
    # since the user_id is just the primary key of our user table, use it in the query for the user
    return User.query.get(int(user_id))
  # blueprint for auth routes in our app
  from .auth import auth as auth_blueprint
  app.register_blueprint(auth_blueprint)
  # blueprint for non-auth parts of app
  from .main import main as main_blueprint
  app.register_blueprint(main_blueprint)
  return app
models.py
```

from . import db
from flask_login import UserMixin
from . import db

class User(UserMixin, db.Model):

id = db.Column(db.Integer, primary_key=True) # primary keys are required by SQLAlchemy
email = db.Column(db.String(100), unique=True)
password = db.Column(db.String(100))
name = db.Column(db.String(1000))

13.2 GITHUB & PROJECT DEMO LINK

GITHUB LINK:

https://github.com/IBM-EPBL/IBM-Project-30699-1660155180

PROJECT DEMO LINK:

