You Choose, We Do it

St. JOSEPH'S COLLEGE OF ENGINEERING

(An Autonomous Institution)

St. Joseph's Group of Institutions

Jeppiaar Educational Trust

OMR, Chennai-119

Team ID	PNT2022TMID00047
Project Name	Developing a Flight Delay Prediction Model using Machine Learning

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1. INTRODUCTION

1. Project Overview

One of the key business issues that airlines face is that the vital prices that are related to flights being delayed because of natural occurrences and operational shortcomings that is an upscale affair for the airlines, making issues in scheduling and operations for the end users therefore inflicting unhealthy name and client discontent. As we all know that we have a tendency to not get the flight delay before departure as customers of the Airline Company neither the airline company's ground staff gets the airline delay prediction supported varied conditions. However, we all know that one in all the most reasons for delay in flights is that the weather. This motivates us to use the live weather knowledge in conjunction with different metrics to calculate the delay on the wing before departure. Indian state of affairs, in 2017, in line with the reports by the directorate General of Civil Aviation (DGCA), between January and April, close to 5.12 hundred thousand domestic passengers in India faced issues because of airline corporations denying boarding, moreover as flight cancellations and delays [2]. Airline corporations had to pay the passengers compensations of over Rs. twenty five core for varied inconveniences throughout the first four months of this year. Hence, the prediction analysis retrieved from this project can contribute within the form of a prototype in helping to identify operational variables that contribute to delays in any country scenario[2] The main issues associated with flight delay prediction are known and arranged in taxonomy. It includes the problem that causes the flight delay, the range of institution it affects, and ways that of handling flight delay prediction downside. It considers flight domain options, like problem and scope. Major problem which causes delay in flights can be delay propagation, delay caused on the departure point or the root of the flight, and cancellation of flights. These problems cannot be eliminated forever, but a delay prediction tool will allow the operator and the administrators to take the concerned actions for smooth operation. This problem that is causes delay affects Airline, Airport and the enroute airspace which are independent entities which works in synchronization and hence delay in flight causes issues in all the sectors. Various methods that can be used to develop a system which predicts the delay in flights can be Machine Learning, Probabilistic models, Statistical analysis or Network Representations.

2. LITERATURE SURVEY

Flight Delay Prediction Based on Aviation Big Data and Machine Learning

Accurate flight delay prediction is fundamental to establish the more efficient airline business. Recent studies have been focused on applying machine learning methods to predict the flight delay. Most of the previous prediction methods are conducted in a single route or airport. 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. The designed prediction tasks contain different classification tasks and a regression task. Experimental results show that long short-term memory (LSTM) is capable of handling the obtained aviation sequence data, but overfitting problem occurs in our limited dataset. Compared with the previous schemes, the proposed random forest-based model can obtain higher prediction accuracy (90.2% for the binary classification) and can overcome the overfitting problem.

Machine Learning Model - based Prediction of Flight Delay

Prior prediction of flight arrival delays is necessary for both travellers and airlines because delays in flights not only trigger huge economic loss but also airlines end up losing their reputation that was built for several years and passengers lose their valuable time. Our paper aims at predicting the arrival delay of a scheduled individual flight at the destination airport by utilizing available data. The predictive model presented in this work is to foresee airline arrival delays by employing supervised machine learning algorithms. US domestic flight data along with the weather data from July 2019 to December 2019 were acquired and are used while training the predictive model. XG Boost and linear regression algorithms were applied to develop the predictive model that aims at predicting flight delays. The performance of each algorithm was analyzed. Flight data along with the weather data was given to the model. Using this data, binary classification was carried out by the XG Boost trained model to predict whether there would be any arrival delay or not, and then linear regression model predicts the delay time of the flight. the estimation of delay time in minutes using machine learning algorithms namely Decision Tree Algorithm (XGBoost) and Linear regression. Data set of both flights and weather will be taken to compare with the given inputs and validate them by applying classification and Regression concepts of Machine Learning. Also having done feature extraction, handling missing values using appropriate methods, sampling to handle imbalanced data and also tuning the hyperparameters with which better accuracy was able to be achieved.

A Deep Learning Approach to Flight Delay Prediction

Deep learning has achieved significant improvement in various machine learning tasks including image recognition, speech recognition, machine translation and etc. Inspired by the huge success of the paradigm, there have been lots of tries to apply deep learning algorithms to data analytics problems with big data including traffic flow prediction. However, there has been no attempt to apply the deep learning algorithms to the analysis of air traffic data. This paper investigates the effectiveness of the deep learning models in the air traffic delay prediction tasks. By combining multiple models based on the deep learning paradigm, an accurate and robust prediction model has been built which enables an elaborate analysis of the patterns in air traffic delays. In particular, Recurrent Neural Networks (RNN) has shown its great accuracy in modeling sequential data. Day - to-day sequences of the departure and arrival flight delays of an individual airport have been modeled by the Long Short Term Memory RNN architecture. It has been shown that the accuracy of RNN improves with deeper architectures. In this study, four different ways of building deep RNN architecture are also discussed. Finally, the accuracy of the proposed prediction model was measured, analyzed and compared with previous prediction methods. It shows best accuracy compared with all other methods.

Prediction of Weather-induced Airline Delays Based on Machine Learning Algorithms

The primary goal of the model proposed in this paper is to predict airline delays caused by inclement weather conditions using data mining and supervised machine learning algorithms. US domestic flight data and the weather data from 2005 to 2015 were extracted and used to train the model. To overcome the effects of imbalanced training data, sampling techniques are applied. Decision trees, random forest, the AdaBoost and the k Nearest-Neighbors were implemented to build models which can predict delays of individual flights. Then, each of the algorithms' prediction accuracy and the receiver operating characteristic (ROC) curve were compared. In the prediction step, flight schedule and weather forecast were gathered and fed into the model. Using those data, the trained model performed a binary classification to predicted whether a scheduled flight will be delayed or on-time.

The model was built on historical weather and traffic data of individual OD pair by utilizing machine learning algorithms. Supervised machine learning algorithms implemented in this study includes random forest, AdaBoost, k Nearest-Neighbors and Decision Trees. Because the data was imbalanced, the combination of SMOTE and random under sampling were applied. The model's prediction performance on the validation set and the test set was analyzed. There are still possible approaches that can improve the model in the future. If the costs of false positive and false negative are taken into account, preferred performance of classifiers could be clearly determined. Then it could be a solid foundation for a decision support tool for predicting aircraft arrival. Also a thorough consideration of uncertainty in forecast would enhance the model's predictive performance.

2.1 Existing problem

As discussed, considering the standard taxonomy of the flight delay and its problems, one will contemplate the scope of prediction to be one in every of these factors or combination of those factors[3]. The models developed during this system may be applied to predict the incidence of flight delay at airports. Such prognosticative capabilities would facilitate traffic managers and airline dispatchers to organize mitigation methods for reducing traffic disruptions. This issue can be reduced by developing the flight delay prediction tool which can be developed using following methods.

2.2 References

[1] Kuhn, Nathalie and Navaneeth Jamadagni. "Application of Machine Learning Algorithms to Predict Flight Arrival Delays." (2017).

[2] N, Prabakaran & Kannadasan, Rajendran. (2018). Airline Delay Predictions using Supervised Machine Learning. International Journal of Pure and Applied Mathematics. 119.

[3] A Review on Flight Delay Prediction Alice Sternberg, Jorge Soares, Diego Carvalho, Eduardo Ogasawara _ CEFET/RJ Rio de Janeiro, Brazil November 6, 2017 International Journal of Engineering Research & Technology (IJERT) http://www.ijert.org ISSN: 2278-0181 IJERTV9IS030148 (This work is licensed under a Creative Commons Attribution 4.0 International License.) Published by : www.ijert.org Vol. 9 Issue 03, March-2020 91

[4] Gopalakrishnan, Karthik and Hamsa Balakrishnan. "A Comparative Analysis of Models for Predicting Delays in Air Traffic Networks." Air Traffic Management Research and Development Seminar, June 2017, Seattle, Washington, USA, ATM Seminar, June 2017 © 2017 ATM Seminar

[5] Rebollo, Juan Jose and Balakrishnan, Hamsa. "Characterization and Prediction of Air Traffic Delays." Transportation Research Part C: Emerging Technologies 44 (July 2014): 231–241 © 2014 Elsevier LtdA model for acurracy prediction using geoRSS using naive bayes

https://doi.org/10.24200/sci.2017.20020

https://doi.org/10.1177/0361198120930014

2.3 Problem Statement definition

In this project, the goal is to use exploratory analysis and to build machine learning models to predict airline departure and arrival delays.

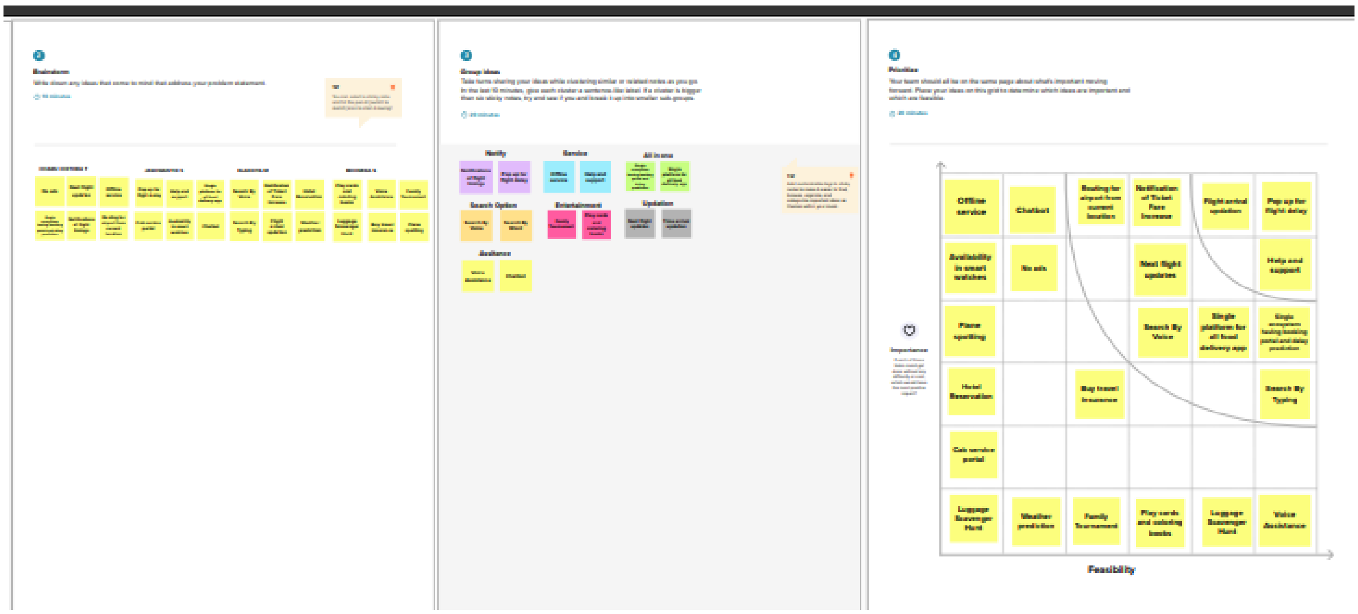
OBJECTIVES:

- Flight delays are gradually increasing and bring more financial difficulties and customer dissatisfaction to airline companies.
- To resolve this situation, supervised machine learning models were implemented to predict flight delays.
- The data set that records information of flights departing from JFK airport during one year was used for the prediction.
- The comparative analysis showed that the Decision Tree algorithm has the best performance with an accuracy of 0.9777, and the KNN algorithm has the worst performance with an f1-score of 0.8039.
- Tree-based ensemble classifiers generally have better performance over other base classifiers.

3. IDEATION & PROPOSED SOLUTION

1. Empathy Map Canvas

2. Ideation & Brainstorming

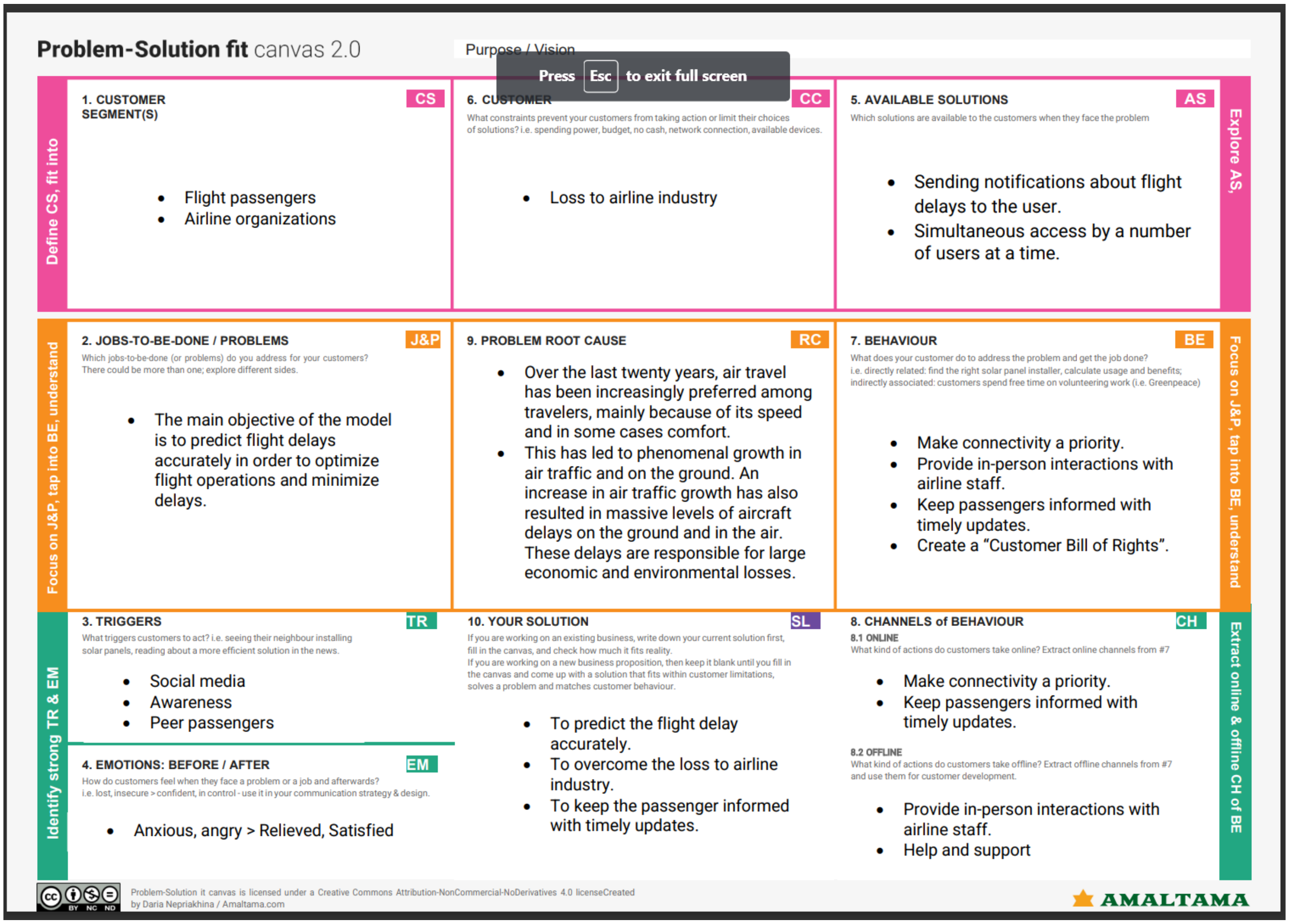


3. Proposed Solution

S.NO.	PARAMETER	DESCRIPTION
1.	**Problem statement**	• 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 is to predict flight delays accurately in order to optimize flight operations and minimize delays.
2.	**Idea / solution description**	• 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. •Provides a help and support corner.
3.	**Novelty/Uniqueness**	• Sending notifications about flight delays to the user. • Simultaneous access by a number of users at a time.
4.	**Social impact**	• This model is beneficial for both aviation industry and passenger travel. • Delays are calculated against scheduled block times as well as against more idealized feasible flight times. • Based on econometric estimations, welfare impacts of flight delays are calculated. • We find that flight delays on a route reduce passenger demand and raise airfares, producing significant decreases in both consumer and producer welfare. • Since producer welfare effects are estimated to be three times as large as consumer welfare effects

5.	**Business model**	• Flight delay has become widespread in the United States with nearly one-quarter of all flights delayed by more than 15 minutes in 2007. • US net welfare would increase by $17.6 billion for a 10 per cent reduction in flight delay and by $38.5 billion for a 30 per cent reduction.
6.	**Feasibility of idea**	• Compatibility with all devices. • The assessment of all the contributing factors is proposed. • This model can be used to obtain future flight fluctuations before scheduling future flights, then guide the allocation of airport resources such as parking spaces and optimize resource utilization.
7.	**Scalability of solution**	• Two open datasets of airline flights and weather observations have been collected and exploratory data analysis has been performed to discover initial insights, evaluate the quality of data, and identify potentially interesting subsets. • Then, data pre-processing and transformation (joining and balancing operations) have been performed to make data ready for modelling. Finally, a parallel version of the Random Forest data classification algorithm has been implemented, iteratively calibrating its settings to optimize results in terms of accuracy and recall. • The data preparation and mining tasks have been implemented on a Cloud infrastructure. • Other than providing the necessary computing resources for our experiments, the Cloud makes the proposed process more general: in fact, if the amount of data increases (e.g., by extending the analysis to many years of flight and weather data), the Cloud can provide the required resources with a high level of elasticity, reliability, and scalability

4. Problem Solution fit



4. REQUIREMENT ANALYSIS

Functional Requirements:

Following are the functional requirements of the proposed solution.

FR.NO.	FUNCTIONAL REQUIREMENT	SUB REQUIREMENT
FR-1	User Registration	Registration through Gmail.
FR-2	User Confirmation	Confirmation through Gmail.
FR-3	User Login	Login through Credentials.
FR-4	Authorization	Acceptance of Terms and Conditions.
FR-5	Flight Data	Enter Flight Details.
FR-6	Prediction	Prediction through Model.
FR-7	End Process	Logout.

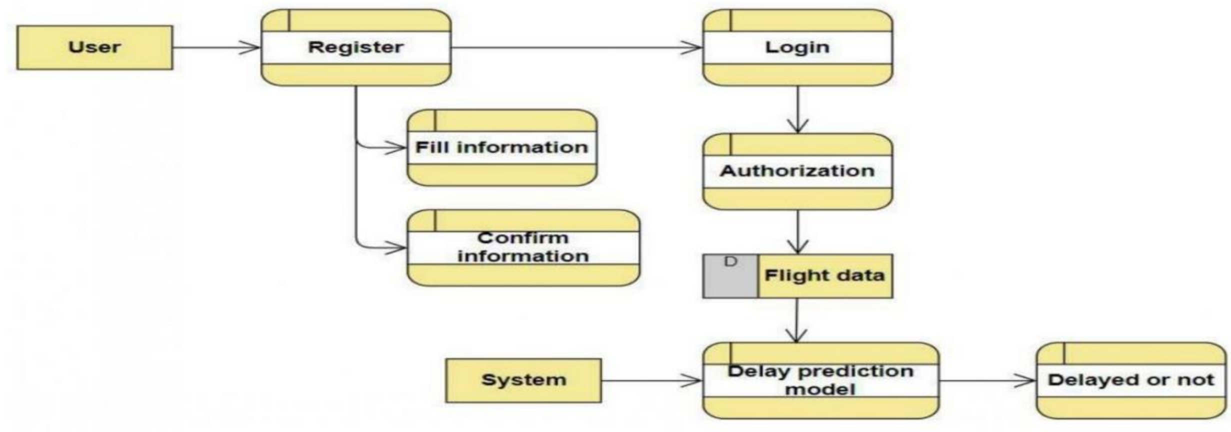
Non-Functional Requirements:

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

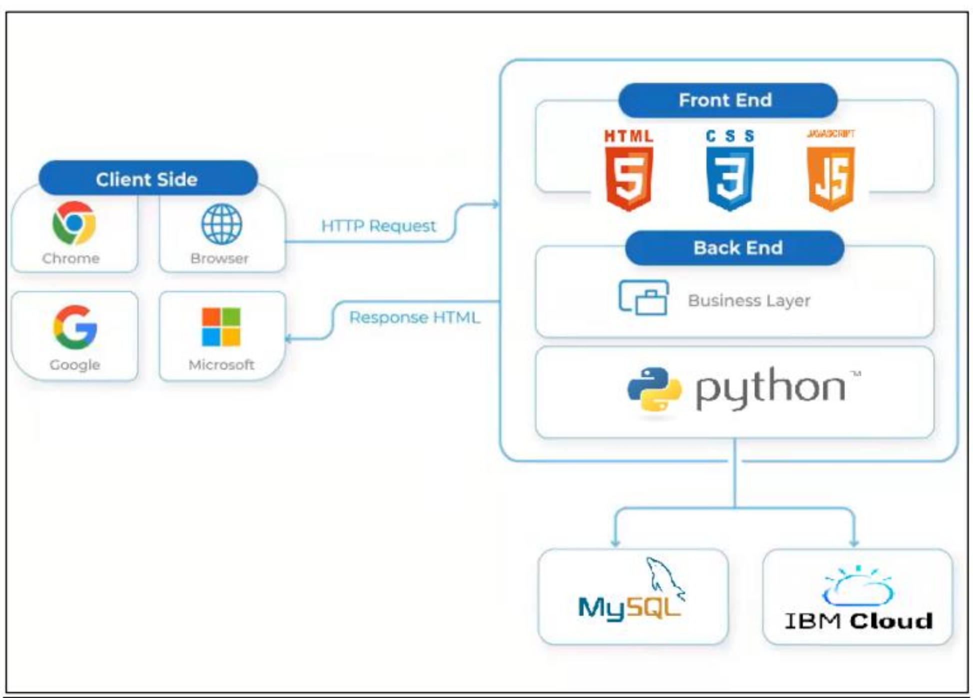
NFR No.	NON-FUNCTIONAL REQUIREMENT	DESCRIPTION
NFR-1	Usability	Effectiveness, efficiency, and overall satisfaction of the user while interacting with the application.
NFR-2	Security	Authentication and encryption of the application.
NFR-3	Reliability	Probability of failure-free operations in a specified environment for a specified time.
NFR-4	Performance	How the application is functioning and how responsive the application is to the end-users.
NFR-5	Availability	In spite of the lack of an active internet connection all features of the application are accessible. Synchronization of data cannot be done.
NFR-6	Scalability	The capacity of the application to handle growth, especially in handling more users.

5. PROJECT DESIGN

DATA FLOW DIAGRAM:



Technical Architecture:



1. User Stories

USER STORIES:

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Priority	Release
Customer (mobile user)	Registration andLogin	USN-1	As a new user, I can register for the applicationby entering my email and my password.	High	Sprint-1
Administrator	Confirmation email	USN-2	As a user, I will receive confirmation email onceI have registered for the application	Medium	Sprint-2
Customer (mobile user)	User login	USN-3	As a user, I can login into the application by entering the registered email-id and password	High	Sprint-1
Administrator	Admin Panel	USN-4	As an admin, I can authenticate the registrationand login credentials of the passengers	High	Sprint-2
	Arrival and Departuretime of flights	USN-5	As a user, I can find all the details of a specificflight with its number or name	High	Sprint-3
		USN-6	As a user, I can find exactly how long the flightwill be delayed	High	Sprint-3
Customer Care Executive	Helpdesk	USN-7	As a customer care executive, I can provide thecontact details of the airlines	Medium	Sprint-4

6. PROJECT PLANNING & SCHEDULING

1. Sprint Planning & Estimation

Product Backlog, Sprint Schedule, and Estimation (4 Marks)

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Registration	USN-1	As a new user, I can register for the application by entering my email and my password.	4	High	Charu Chithra.T
Sprint-2	User login	USN-2	As a user, I can login into the application by entering the registered email-id and password	4	High	Boomika .S
Sprint-3	Prediction page creation	USN-3	As a user, I can enter all the details of a specific flight	4	High	Elakkiya .M
Sprint-4	Accuracy	USN-4	As a user, I can find exactly how long the flight will be delayed	4	High	Jashwanthi .S

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

Velocity:

We have a 24-day sprint duration, and the velocity of the team is 4 (points per sprint). Thus the team's average velocity (AV) per iteration unit (story points per day) is as follows

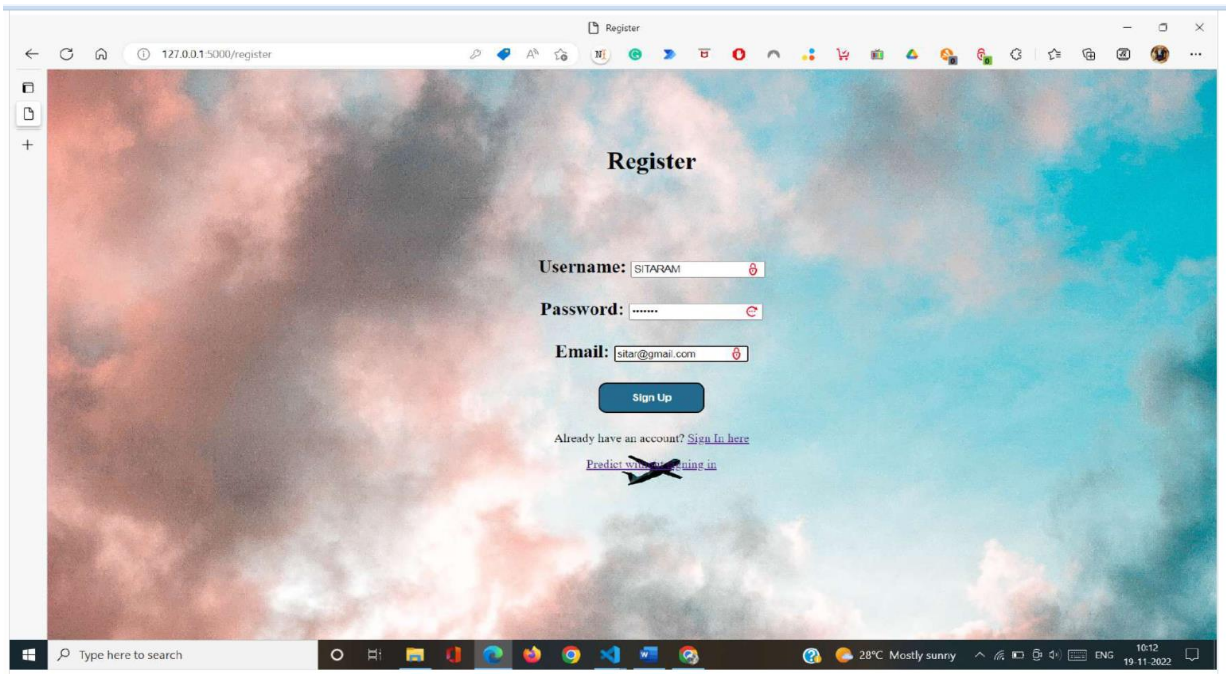
AV = sprint duration / velocity

= 24/16

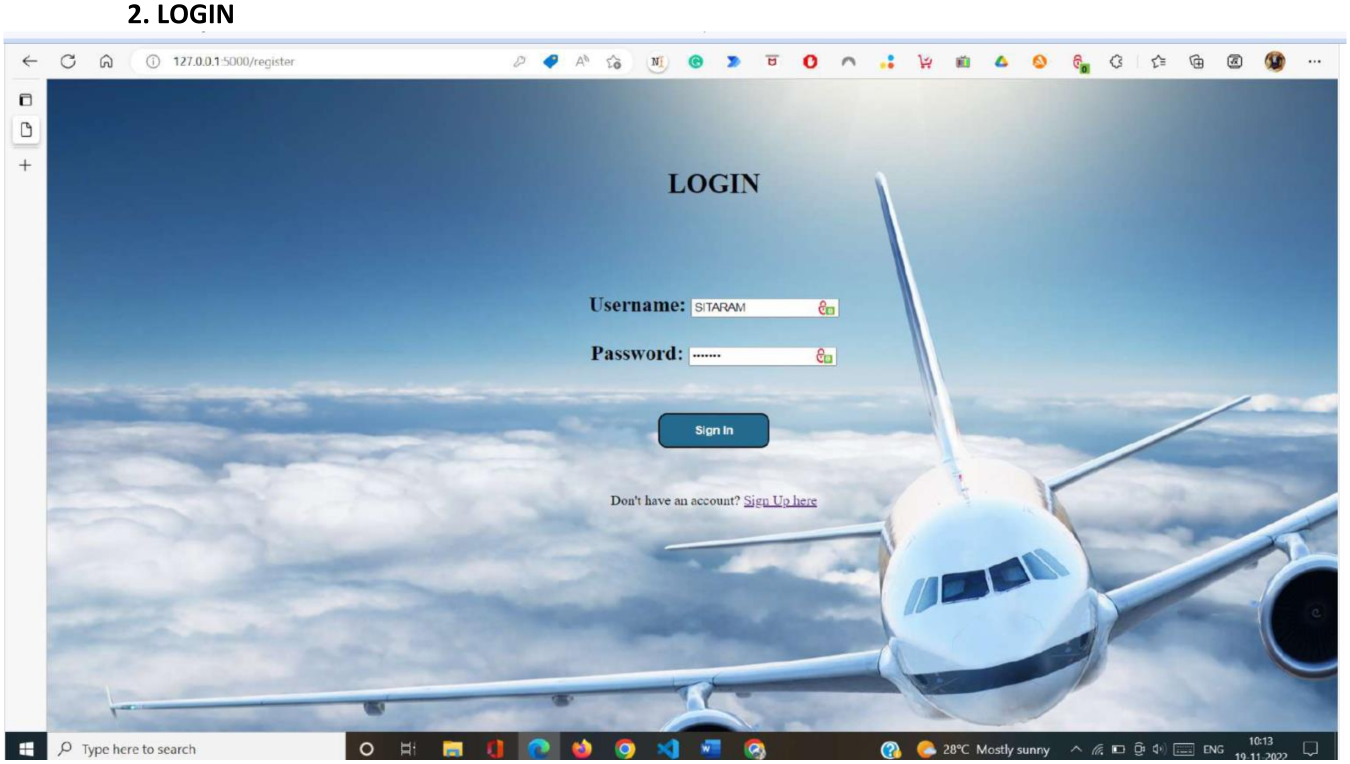
= 1.5

7. CODING & SOLUTIONING

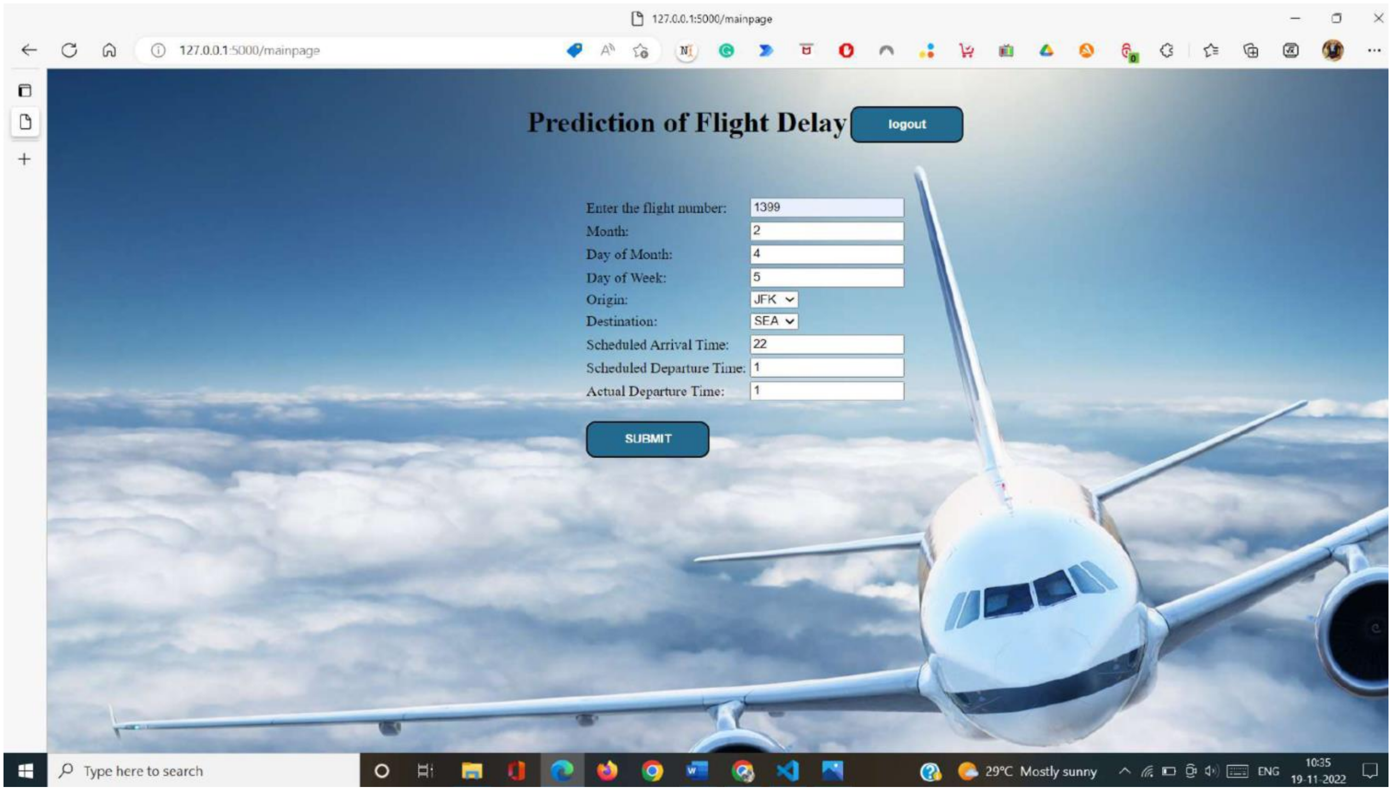
1. REGISTER



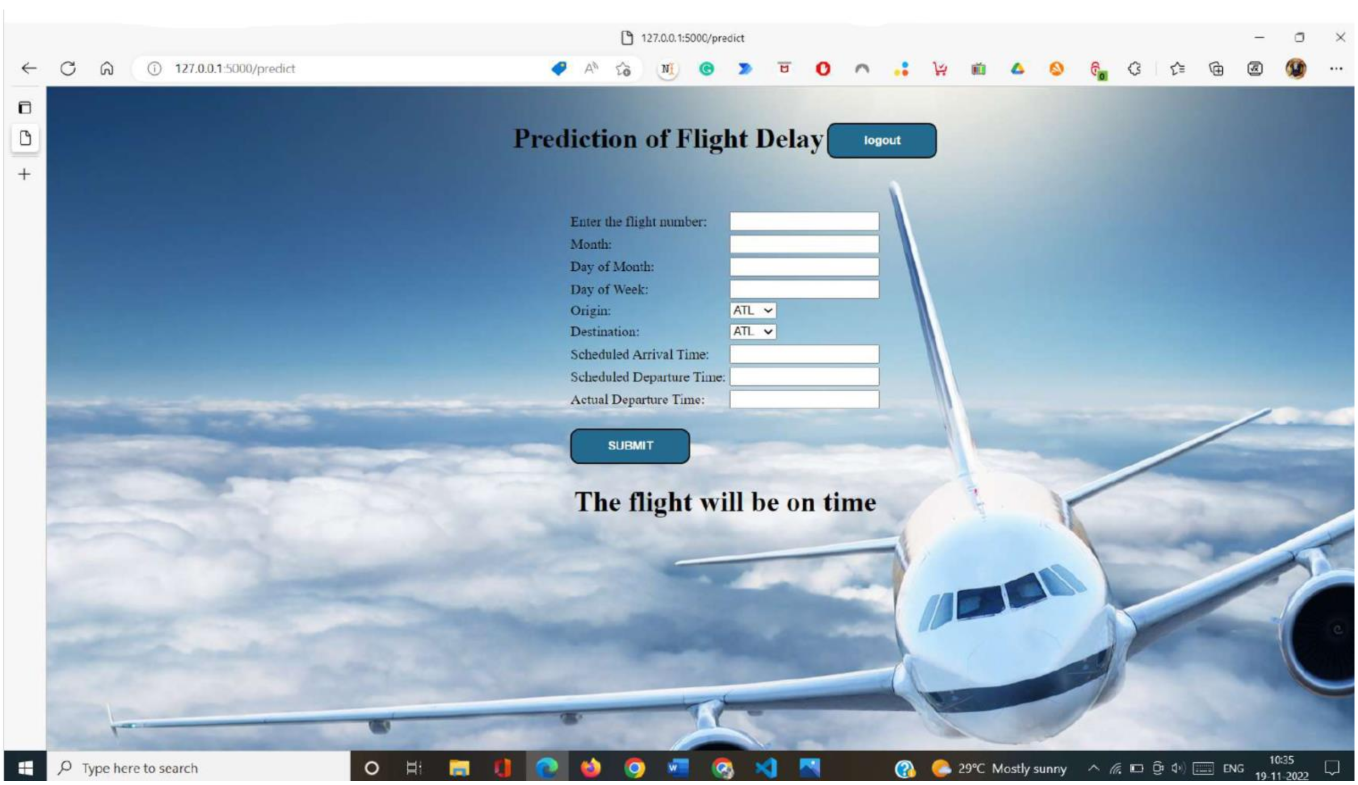
2. LOGIN



3. ENTER FLIGHT DATA



1. GET THE PREDICTION



8. TESTING

1. Test Cases

Resolution	Severity 1	Severity 2	Severity 3	Severity 4	Subtotal
By Design	11	4	3	7	25
Duplicate	2	1	1	2	6
External	3	3	0	2	8
Fixed	10	5	3	18	38
Not Reproduced	1	1	0	0	2
Skipped	0	0	1	1	2
Won't Fix	0	5	3	0	8
Totals	27	19	11	30	87

2. User Acceptance Testing

Section	Total Cases	Not Tested	Fail	Pass
Login	4	0	0	4
Sign-up	7	0	0	7
Security	2	0	0	2
Prediction	9	0	0	9
Final Report Output	2	0	0	2

9. RESULTS

This paper presented the need to develop a system to predict the delay in flights along with its methodology. The paper gives details about the range of different methodology that is used or can be used to find out the delay in flights. As flight delay cost a lot to the airlines as well as passangers in financial and environmental terms, flight delay is a the talk of the hour. Flight delay causes surging of prices by costing a lot on operational purpose They may increase prices to customers and operational prices to airlines. As the outcome is directly associated with the passanger and the airlines which inturn is liked to another set of airline and passangers it is very crucial to get real time delay for each player within the air transport system. hence there is a requirement to develop a system to predict the delay in flights to scale back monetory loss and for the higher and smooth operation. Classification or reggrerssion ways are often accustomed determine the delay which includes Feed forward network, Neural Network, Random Forrest, decision tress, Naïve Bayes Classification Tree, Regression Tree, etc. As seen from the articles and papers these methodologies offer virtually identical accuracy however we want an algorithmic rule that is good with real world prediction and analysis and thus: naïve Bayes.Except being smart with real time prediction algorithmic rule that considers or assumes independence among predictors that makes the system scalable as other independent attribute may be superimposed up to the algorithmic rule for computation of the delay. the expected delay can thus facilitate the ground employees for creating correct and smooth operation plans and therefore the data if sent to the passengers will profit the airlines also because the passengers.

10. FUTURE SCOPE

Further supportive study is required to correlate all the problem, scope and method for getting most accurate result. 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.

APPENDIX:

```
from flask import Flask, render_template, request, redirect, url_for, session
from flask_mysqldb import MySQL
import MySQLdb.cursors
import re

import flask
from flask import request,render_template
from flask_cors import CORS
import numpy as np
import pandas as pd
import requests

import mysql.connector

mydb = mysql.connector.connect(
    host = "localhost",
    user = "root",
    password = "Lokesh@2005",
    database = "userlogin"
)



app = Flask(__name__)


app.secret_key = 'london'

app.config['MYSQL_HOST'] = 'localhost'
app.config['MYSQL_USER'] = 'root'
app.config['MYSQL_PASSWORD'] = 'Lokesh@2005'
app.config['MYSQL_DB'] = 'userlogin'

mysql = MySQL(app)
CORS(app)

@app.route('/')
@app.route('/login', methods =['GET', 'POST'])
def login():
    msg = ''
    if request.method == 'POST' and 'username' in request.form and 'password' in
request.form:
        username = request.form['username']
        password = request.form['password']
        #cursor = mysql.connection.cursor()
        cursor = mysql.connection.cursor(MySQLdb.cursors.DictCursor)
```

```
        cursor.execute('SELECT * FROM accounts WHERE username = % s AND password = % s', (username, password, ))
        account = cursor.fetchone()
        if account:
            session['loggedin'] = True
            #session['id'] = account['id']
            session['username'] = account['username']
            msg = 'Logged in successfully !'
            return render_template('mainpage.html', msg = msg)
        else:
            msg = 'Incorrect username / password !'
    return render_template('login.html', msg = msg)

@app.route('/logout')
def logout():
    session.pop('loggedin', None)
    session.pop('id', None)
    session.pop('username', None)
    return redirect(url_for('login'))#change{}
    #return render_template('login.html', msg = msg)

@app.route('/')
@app.route('/register', methods =['GET', 'POST'])
def register():
    msg = ''
    if request.method == 'POST' and 'username' in request.form and 'password' in request.form and 'email' in request.form :
        username = request.form['username']
        password = request.form['password']
        email = request.form['email']
        print(username)
        cursor = mysql.connection.cursor()
        #cursor = mydb.cursor(MySQLdb.cursors.DictCursor)
        cursor.execute('SELECT * FROM accounts WHERE username = % s;', (username, ))
        #cursor.execute('SELECT * FROM accounts')
        account = cursor.fetchone()
        if account:
            msg = 'Account already exists !'
        elif not re.match(r'[^@]+@[^@]+\.[^@]+', email):
            msg = 'Invalid email address !'
        elif not re.match(r'[A-Za-z0-9]+', username):
            msg = 'Username must contain only characters and numbers !'
        elif not username or not password or not email:
            msg = 'Please fill out the form !'
        else:
            cursor.execute('INSERT INTO accounts VALUES (NULL, % s, % s, % s);', (username, password, email, ))
            mysql.connection.commit()
            cursor.close()
```

```
            msg = 'You have successfully registered !'
            return render_template('login.html', msg = msg)
    elif request.method == 'POST':
        msg = 'Please fill out the form !'
    return render_template('register.html', msg = msg)

@app.route('/')
@app.route('/mainpage', methods =['GET', 'POST'])
def mainpage():
    msg=''
    return render_template('mainpage.html', msg = msg)

API_KEY = "2AjKeBOMtc_4WMPYUQe2GI-opbRdU3E0q7VEZkBiPUkA"
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"]

@app.route('/')
def sendHomePage():
    return render_template('index.html')

@app.route('/predict', methods=['POST'])
def predict():
    fname = float (request.form['fname'])
    month = float (request.form['month'])
    daymonth = float (request.form['daymonth'])
    dayweek = float (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 == "alt":
        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 == "alt":
```

```
        destination1,destination2,destination3,destination4,destination5 = 0,0,0,1,0

    sarrivaltime = float (request.form['sarrivaltime'])
    sdeparttime = float (request.form['sdeparttime'])
    adeparttime = float (request.form['adeparttime'])
    dept15=int(sdeparttime)-int(adeparttime)

    X = [[fname, month, daymonth, dayweek, sarrivaltime, dept15, origin1, origin2,
origin3, origin4, origin5, destination1, destination2, destination3, destination4,
destination5]]

    payload_scoring = {"input_data": [{"field": [["FL_NUM", "MONTH", "DAY_OF_MONTH",
"DAY_OF_WEEK", "CRS_ARR_TIME", "DEP_DEL15", "ORIGIN_0", "ORIGIN_1", "ORIGIN_2",
"ORIGIN_3", "ORIGIN_4", "DEST_0", "DEST_1", "DEST_2", "DEST_3", "DEST_4"]], "values":
X}]}

    response_scoring = requests.post('https://us-
south.ml.cloud.ibm.com/ml/v4/deployments/70ba7f52-fcd7-4553-bc8b-
afbc37d1a0be/predictions?version=2022-11-18', json=payload_scoring,
headers={'Authorization': 'Bearer ' + mltoken})
    predictions = response_scoring.json()

    pred = predictions['predictions'][0]['values'][0][0]

    if pred == 0:
        ans = "The flight will be on time"
    else :
        ans = "The flight will be delayed"

    return render_template("mainpage.html",predict = ans)

if __name__ == '__main__':
    app.debug = True
    app.run()
```

Project Demonstration Video Link :

https://drive.google.com/file/d/1CjAFD3CoUN_dP97-tVZBhewRntgq6dhs/view?usp=share_link