

# **DEVELOPING A FLIGHT PREDICTION MODEL WITH MACHINE LEARNING**

*Submitted by*

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# CHAPTER-1

## Introduction

The goal of this Machine Learning model is to predict whether a flight you are considering to book is likely to arrive on time. You might decide to book another flight if you are aware that the flight will probably be delayed. The unique public huge dataset of flight delays will serve as the model's foundation. Only domestic flights are included in this dataset, which includes information from all major carriers. Short-term delay forecasting has already received extensive research. In fact, since some of the factors affecting current and potential delays are known, even though they still have components, it is possible to anticipate future delays rather well using information on weather, airport congestion, and current flight delays. The field of short-term delay prediction has already been extensively studied. Given that some factors influencing future delays are known, even though they still have components, it is possible to predict them fairly accurately using information about weather, airport traffic, and current flight delays.

### 1.1 Project Overview

Average aircraft delay is regularly referred to as an indication of airport capacity. Flight delay is a prevailing problem in this world. It's very tough to explain the reason for a delay. A few factors responsible for the flight delays like runway construction and excessive traffic are rare, but bad weather seems to be a common cause. Some flights are delayed because of the reactionary delays, due to the late arrival of the previous flight. It hurts airports, airlines, and affects a company's marketing strategies as companies rely on customer loyalty to support their frequent flying programs. The classification and regression results obtained in these studies generate an estimate for individual flight delay in the form of a class or a point estimate, respectively.

### 1.2 Purpose

The details about the range of different methodology that is used or can be used to find out the delay in flights. The purpose is to establish a delay prediction model based on a machine learning algorithm to predict the departure delay at an airport. Predicting the likelihood of delay based on flights' features bridges an important information asymmetry between airlines and passengers. This document is to look at the approaches used to build models for predicting flight delays that occur due to bad weather conditions. Reduce further economic loss for airlines.

## **CHAPTER-2**

### **LITERATURE SURVEY**

#### **1. Flight Delay Prediction System**

Authors: Mrs Yogita Borse , Dhruvin Jain, Shreyash Sharma, Viral Vora, Aakash Zaveri

Year: 2020

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. 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. The models developed during this system may be applied to predict the incidence of flight delay at airports. This issue can be reduced by developing the flight delay prediction tool which can be developed using statistical analysis, probabilistic models and classification approach or methods like Naïve Bayes Classification , Bayesian Network Algorithm, decision tree, logistic regression etc. We propose a flight delay prediction system which focuses mainly on predicting delay of a flight based on the weather situation .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 the talk of the hour.

#### **2. Flight Delay Prediction Based with Machine Learning.**

Authors: Irmak Hatipoglu, Omur Tosun, Nedret Tosun

Year: 2022

The delay of a planned flight causes many undesirable situations such as cost, customer satisfaction, environmental pollution. There is only one way to prevent these problems before they occur, and that is to know which flights will be delayed. The aim of this study is to predict delayed flights. For this, the use of machine learning techniques, which have become widespread with the development of computer capacities and data storage systems, is preferred. Estimations are made with three up-to-date techniques XGBoost, LightGBM, and CatBoost techniques based on Gradient Boosting from machine learning techniques. The bayesian technique is used for hyper-parameter settings. The results are analyzed and

shared with and without SMOTE. Hence, these are the following methods we use in this paper. The application of machine learning techniques to anticipate flight delays is new, but it has a lot of potential. Companies will be able to avert problems before they develop if delays are correctly estimated, which can generate plenty of issues. As a result, concrete advantages such as lower costs and higher customer satisfaction will emerge. Improvements will be made at the most vulnerable place in the aviation business. This paper has developed a new approach for airline companies to detect delayed flights. In order to achieve these different approaches, which are XGBoost, LightGBM, and CatBoost, were used.

### **3. Flight Delay Predictions and The Study of Its Casual Factors Using Machine Learning Algorithms.**

Authors: Cho Yin Yiu, Kam K.H. Ng, Kin Chung Kwok, Wing Tung Lee, Ho Tung Mo

Year: 2021

The term ‘flight delay’ is the measure of actual arrival/departure time compared to the scheduled arrival/departure time, while the actual time is later than the scheduled time. However, different stakeholders may have different interpretations. The Federal Aviation Administration defines a flight delay as having an actual arrival/departure time that is 15 minutes later than the scheduled arrival/departure time. Much research attempted to deal with flight delay issue by formulating various models to predict their occurrence. In this paper we adopted several machine learning algorithms to predict flight delay and compared their performances in the case of the HKIA. The analysis concluded that the ANNs algorithm is the most effective in predicting flight delay. During flight planning, these important contributing factors could be emphasized. A dataset with a longer duration might aid in further development. Some data is also missing due to flight cancellation, etc., causing reduction in accuracy. the current model could be improved to provide a comprehensive analysis and accurate prediction of flight delay. The number of take-off and landing flights shall also be further balanced to enhance the robustness of the results.

## 2.1 Existing Problem

First, this paper summarizes the factors affecting flight operation in existing research results, and analyzes and filters the factors, so as to determine the factors affecting flight operation. Then, the GRU neural network model is established, which is verified by the real flight data. Finally, compared with several commonly used neural network models and random forest models in machine learning, the advantages of the model built in this paper are highlighted.

## 2.2 References

1. Bo Zhang School of Traffic and Transportation Beijing Jiao tong University Zhang [bo@bjtu.edu.cn](mailto:bo@bjtu.edu.cn)
2. Dan dan Ma School of Traffic and Transportation Beijing Jiao tong University Beijing, China.

## 2.1 Problem Statement Definition

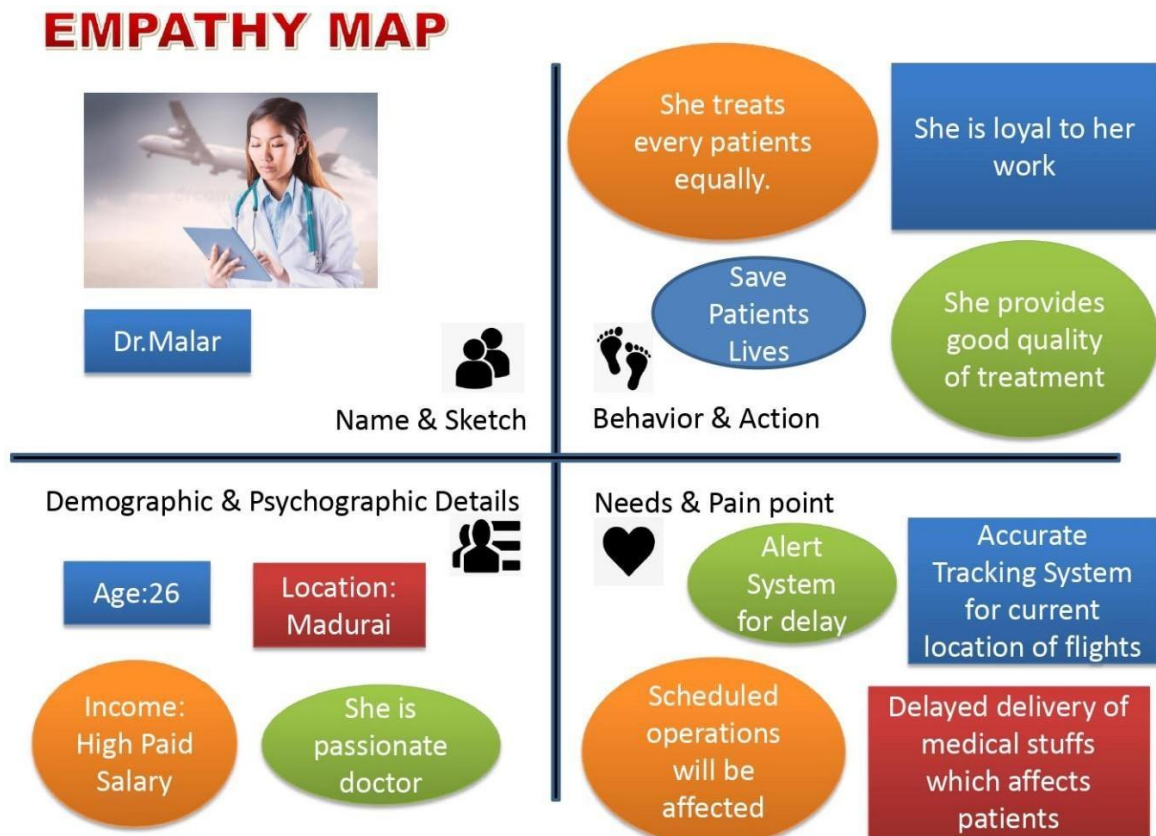
Air travel has been increasingly preferred among travelers, mainly because of its speed and in some cases comfort. This has led to phenomenal growth in air traffic and on the ground, An Increase in air traffic growth has also resulted in massive levels of aircraft delays on the ground and in the air. 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.

## CHAPTER-3

### IDEATION AND PROPOSED SOLUTION

#### 3.1 Empathy Map Canvas

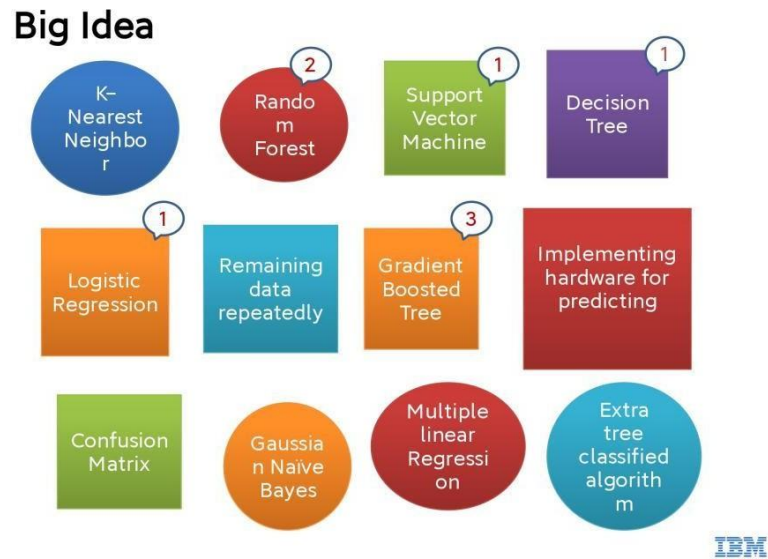
An empathy map is a collaborative tool teams can use to gain a deeper insight into their customers. Much like a user persona, an empathy map can represent a group of users, such as a customer segment.





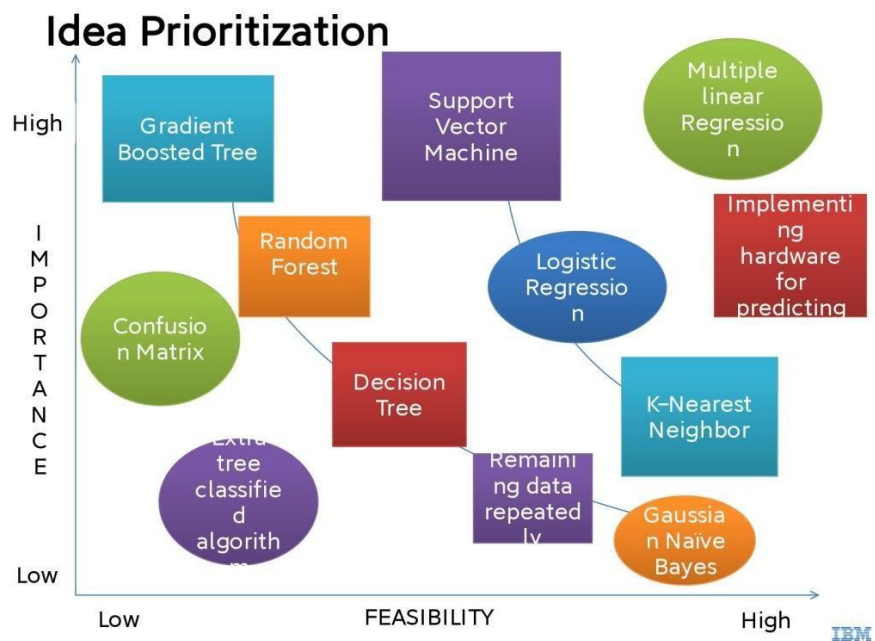
### 3.2 Big Ideas

It consists of all the ideas of instruments and equipments that we are going to implement in this project.

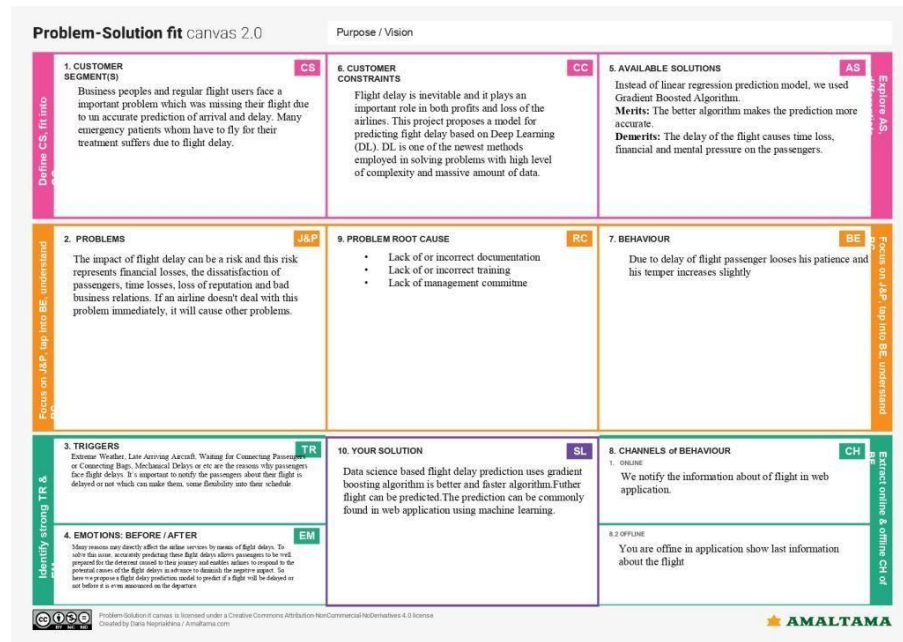


### 3.3 Idea Prioritization

It deals with the prioritizing of the big ideas in order of highest to lowest likes.




### 3.4 Problem Solution Fit



### 3.5 Proposed Solution

S.No	Parameter	Description
1.	<b>Problem Statement (Problem to be solved)</b>	Developing a flight delay prediction model,
2.	<b>Idea / Solution description</b>	<p>The main objective of the model is to predict flight delays accurately in order to optimize flight operations and minimize delays.</p> <p>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.</p>

		Furthermore, we compare decision tree classifier with logistic regression and a simple neural network for various figures of Merit
3.	<b>Novelty / Uniqueness</b>	Delay Prediction using <b>Deep Learning</b> .
4.	<b>Social Impact / Customer Satisfaction</b>	By predicting the flight delay with more accuracy, the optimised results will help the passengers by alerting them, which will not lead them to miss the flight. In the case of the medical field, if a doctor misses a flight, it can cause issues in the life or health of a patient. Our project helps them to stay aware of their flights.
5.	<b>Business Model (Revenue Model)</b>	 <pre> graph TD     KP((Key partners • Technology • Business)) --&gt; BM((Business model))     KA((Key activities • Time management • Business Value)) --&gt; BM     VP((Value proposition • Targeted marketing • Risk marketing)) --&gt; BM     R((Relationships • Regional • Institutions • attendance)) --&gt; BM     CH((Channels • Internet • Cooperation in grants)) --&gt; BM     CS((Customer segments • All age customer • Structure • Logistic way)) --&gt; BM     CST((Cost structure • Employees • Technologies)) --&gt; BM     RS((Revenue streams • Promoted trends • Employer branding)) --&gt; BM </pre>
6.	<b>Scalability of theSolution</b>	This makes the passengers to take preventive action when the status of the flight is notified and this improves the business value of the passengers, time management, and more.

## CHAPTER-4

### REQUIREMENT ANALYSIS

#### 4.1 Functional Requirements

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	Registration through Form Registration through Gmail Registration through LinkedIN
FR-2	User Confirmation	Confirmation via Email Confirmation via OTP
FR-3	User requirements	Collecting information like date of travel, departing & arrival destination, flight number or booking number, etc for providing the status of the flight.
FR-4	User friendliness	This system is easy to learn and understand.

#### 4.2 Non-Functional Requirements

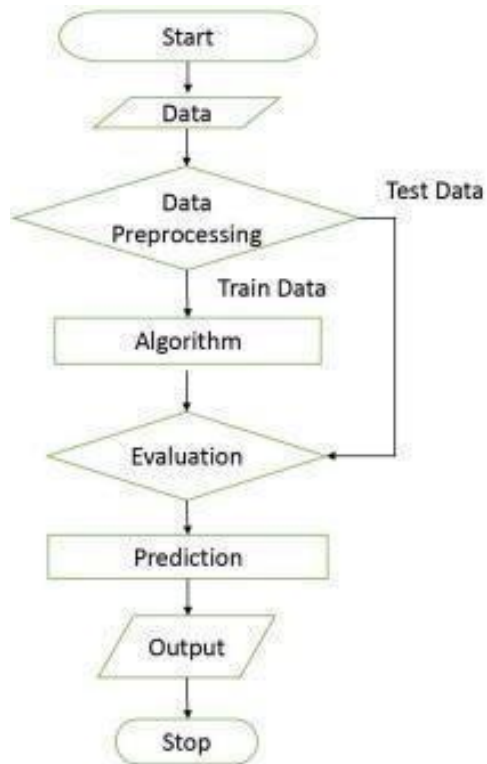
FR No.	Non-Functional Requirement	Description
NFR-1	<b>Usability</b>	How easy is it for a customer to use the system?
NFR-2	<b>Security</b>	<b>Security's</b> part will be protected against malware attacks or unauthorized access. But there's a catch. The lion's share of security non-functional requirements can be translated into concrete functional counter parts. If you want to protect the admin panel from unauthorized access, you would define the login flow and different user roles as system behavior or user actions.
NFR-3	<b>Reliability</b>	<b>Reliability</b> specifies how likely the system or its element would run without a failure for a given period of time under predefined conditions.  Traditionally, this probability is expressed in percentages. For instance, if the system has 85 percent

		reliability for a month, this means that during this month, under normal usage conditions, there's an 85 percent chance that the system won't experience critical failure.
NFR-4	<b>Performance</b>	<b>Performance</b> defines how fast a software system or a particular piece of it responds to certain users' actions under a certain workload. In most cases, this metric explains how long a user must wait before the target operation happens (the page renders, a transaction is processed, etc.) given the overall number of users at the moment. But it's not always like that. Performance requirements may describe background processes invisible to users, e.g. backup. But let's focus on user-centric performance.
NFR-5	<b>Availability</b>	<b>Availability</b> describes how likely the system is accessible to a user at a given point in time. While it can be expressed as an expected percentage of successful requests, you may also define it as a percentage of time the system is accessible for operation during some time period. For instance, the system may be available 98 percent of the time during a month. Availability is perhaps the most <b>business - critical requirement</b> , but to define it, you also must have estimations for reliability and maintainability.
NFR-6	<b>Scalability</b>	<b>Scalability</b> assesses the highest workloads under which the system will still meet the performance requirements. There are two ways to enable your system scale as the workloads get higher horizontal and vertical scaling.

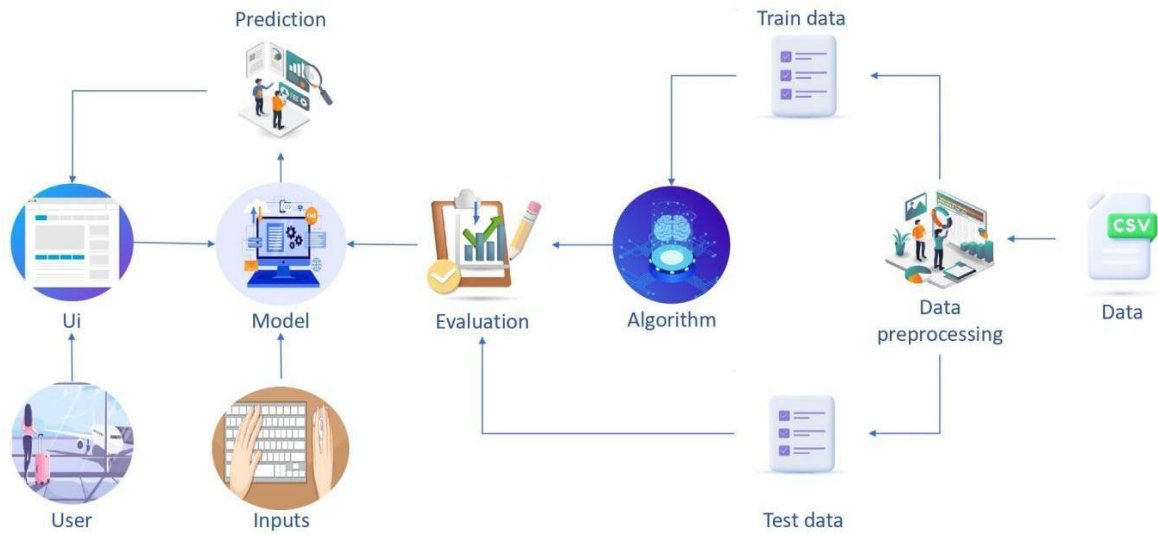
## CHAPTER-5

### PROJECT DESIGN








#### 5.1 Data Flow Diagram



## 5.2 Solution Architecture



## 5.3 Customer Journey Map

Journey Steps Which step of the experience are you describing?	Discovery Why do they even start the journey?	Onboarding and First Use How can they feel successful?	Sharing Why would they invite others?
<b>Actions</b> What does the customer do? What information do they look for? What is their context?	Starts to look for flight's status	Search for flights Explore the web application Find information on other flights	User Friendliness Invite others Correctness of the prediction
<b>Needs and Pains</b> What does the customer want to achieve or avoid? <i>Tip: Reduce ambiguity, e.g. by using the first person narrator.</i>	Wants to avoid dealing with flight delays in the last minute Get ample time to look for other resources in case of any emergency	Helps me to get proper information Helps me to plan my journey better Helps in changing flights or informed earlier Can stop last minute stress at session	I can always get proper information I can see some other works done I can claim compensation
<b>Touchpoint</b> What part of the service do they interact with?	Search and explore flights' status	The list of flights Maps that help in choosing a location	Sharing
<b>Customer Feeling</b> What is the customer feeling? <i>Tip: Use the <b>emoji app</b> to express more emotions</i>			
<b>Backstage</b>			
<b>Opportunities</b> What could we improve or introduce?	Better accuracy High Value Low Confidence Low Reach	Ample time to look for other resources High Confidence High Value Low Reach	Avoid cancellations and waste of money
<b>Process ownership</b> Who is in the lead on this?	 User	 User	 User and Admin 



## CHAPTER-6

### PROJECT PLANNING PHASE

#### 6.1 Sprint Planning, Schedule & Estimation

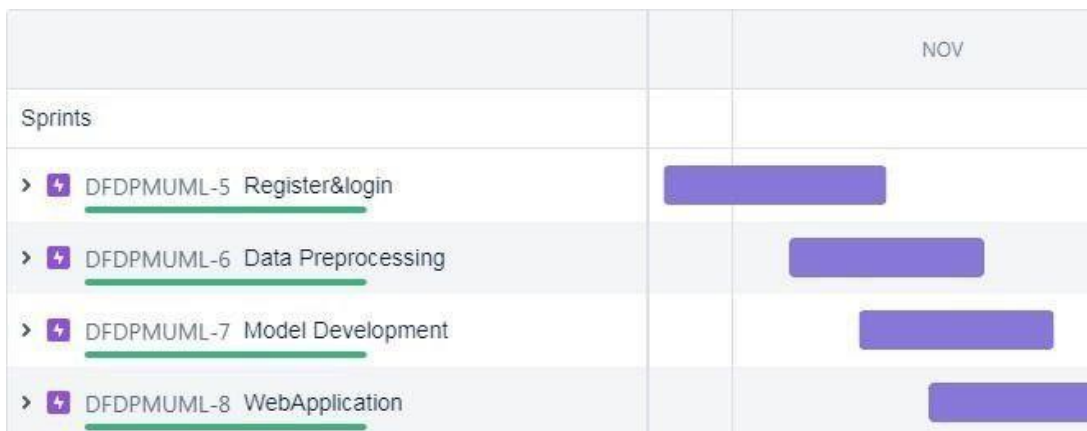
Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Registration	USN-1	As a user, I can register for the application by entering my email, password, and Confirming my password.	2	High	Jeyaprasanna S
Sprint-1	User Confirmation	USN-2	As a user, I will receive confirmation email once I have registered for the Web application.	1	Medium	Karuppaiya I Naveen Kumar S
Sprint-1	Login	USN-3	As a user, I can login to the application by entering my email & password.	1	High	Varun Kumar V
Sprint-2	Analyse the dataset	USN-4	I can analyse the data set.	2	High	Jeyaprasanna S Karuppaiya I
Sprint-3	Developing and Training the model	USN-5	I can develop and train the prediction model.	2	High	Naveen Kumar S Varun Kumar V
Sprint-4	Web	USN-6	View the current information of the	2	High	Jeyaprasanna S Karuppaiya I

	Application		flight.			Naveen Kumar S Varun Kumar V
--	-------------	--	---------	--	--	---------------------------------

## 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	4 Days	24 Oct 2022	27 Oct 2022	20	29 Oct 2022
Sprint-2	20	5 Days	28 Oct 2022	01 Nov 2022	20	04 Nov 2022
Sprint-3	20	8 Days	02 Nov 2022	09 Nov 2022	20	11 Nov 2022
Sprint-4	20	9 Days	10 Nov 2022	18 Nov 2022	20	19 Nov 2022

## 6.3 Reports From JIRA



## CHAPTER-7

### CODING AND SOLUTION

#### 7.1 Feature

- ✓ The database used in this project are Xampp and MySQL
- ✓ We provide lots of facilities in our page anybody can access any time anywhere
- ✓ First you have to register on our page. Registration process is very simple. Language is not a barrier in our page. We used simple understandable language.
- ✓ After the registration process is finished, the login page will appear in which you have to enter your email id or username as you wish.
- ✓ After that you have to create very strong password in our login page

#### 7.2 Feature 2

- ✓ In this feature you can click the about and services pages to know more about our details.

#### 7.3 Database Scheme

```
-- phpMyAdmin SQL Dump
-- version 5.1.1
-- https://www.phpmyadmin.net/
--
-- Host: 127.0.0.1
-- Generation Time: Aug 14, 2021 at 07:07 PM
-- Server version: 10.4.20-MariaDB
-- PHP Version: 8.0.9

SET SQL_MODE = "NO_AUTO_VALUE_ON_ZERO";
START TRANSACTION;
SET time_zone = "+00:00";
```

```
--
-- Database: `login`
--
```

-----

```

--
-- Table structure for table `users`
--

CREATE TABLE `users` (
  `id` int(11) NOT NULL,
  `name` varchar(255) NOT NULL,
  `email` varchar(255) NOT NULL,
  `password` varchar(255) NOT NULL,
) ENGINE=InnoDB DEFAULT CHARSET=utf8mb4;

--
-- Indexes for dumped tables
--

--
-- Indexes for table `users`
--
ALTER TABLE `users`
  ADD PRIMARY KEY (`id`);

--
-- AUTO_INCREMENT for dumped tables
--

--
-- AUTO_INCREMENT for table `users`
--
ALTER TABLE `users`
  MODIFY `id` int(11) NOT NULL AUTO_INCREMENT;
COMMIT;

```

# CHAPTER-8

## TESTING

## 8.1 Test cases

[illegible]

## 8.2 User Acceptance Testing

### 8.2.1 Purpose of Document

The purpose of this document is to briefly explain the test coverage and open issues of the [Developing a flight delay prediction model using machine learning] project at the time of the release to User Acceptance Testing (UAT).

## 8.2.2 Defect Analysis

This report shows the number of resolved or closed bugs at each severity level, and how

Resolution	Severity 1	Severity 2	Severity 3	Severity 4	Subtotal
By Design	7	3	6	5	21
Duplicate	4	0	3	0	7
External	1	2	0	1	4
Fixed	14	1	3	8	26
Not Reproduced	0	0	1	0	1
Skipped	0	0	1	1	2
Won't Fix	0	4	2	0	6
Totals	26	11	18	19	67

## 8.2.3 Test Case Analysis

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

Section	Total Cases	Not Tested	Fail	Pass
Print Engine	5	0	0	5
Client Application	30	0	0	30
Security	2	0	0	2
Outsource Shipping	1	0	0	1
Exception Reporting	7	0	0	7
Final Report Output	9	0	0	9
Version Control	1	0	0	1

## CHAPTER-9

### RESULTS

- Predicting flight delays by expanding the list of variables included in the classification and prediction models.
- Show comparable efficacy of classification rates by using only decision control variables as compared models reported in prior studies.
- Examine the cause of delays and evaluate delays as a multi group classification problem.

### 9.1 Performance Metrics

- The problem of traffic congestion, the traffic prediction using machine learning which contains regression models and libraries like pandas, NumPy, matplotlib. are used to predict the traffic.
- This has to be implemented so that the traffic congestion is controlled and can be accessed easily.
- Predictive maintenance in the airplane business is machine learning. With predictive analytics, sensory equipment gathers information from each aircraft's systems, and sends that information to a cloud.

#### Model Performance Testing:

Project team shall fill the following information in model performance testing template.

S.No.	Parameter	Values	Screenshot
1	Metrics	<b>Classification Model:</b> Confusion Matrix, Accuracy Score & Classification Report	<pre>from sklearn.metrics import accuracy_score, confusion_matrix, classification_report print(accuracy_score(y_test, yhat))  0.7019318889988636  print(confusion_matrix(y_test, yhat))  [[49358  9472]  [14921  8086]]</pre>

2	Tune theModel	Hyperparameter Tuning , Validation Method	<pre>print(classification_report(y_test, yhat))</pre> <table><tr><td></td><td>precision</td><td>recall</td><td>f1-score</td><td>support</td></tr><tr><td>0</td><td>0.77</td><td>0.84</td><td>0.80</td><td>58830</td></tr><tr><td>1</td><td>0.46</td><td>0.35</td><td>0.40</td><td>23007</td></tr><tr><td>accuracy</td><td></td><td></td><td>0.70</td><td>81837</td></tr><tr><td>macro avg</td><td>0.61</td><td>0.60</td><td>0.60</td><td>81837</td></tr><tr><td>weighted avg</td><td>0.68</td><td>0.70</td><td>0.69</td><td>81837</td></tr></table>		precision	recall	f1-score	support	0	0.77	0.84	0.80	58830	1	0.46	0.35	0.40	23007	accuracy			0.70	81837	macro avg	0.61	0.60	0.60	81837	weighted avg	0.68	0.70	0.69	81837
	precision	recall	f1-score	support																													
0	0.77	0.84	0.80	58830																													
1	0.46	0.35	0.40	23007																													
accuracy			0.70	81837																													
macro avg	0.61	0.60	0.60	81837																													
weighted avg	0.68	0.70	0.69	81837																													



## **CHAPTER 10**

### **ADVANTAGES & DISADVANTAGES**

#### **10.1 ADVANTAGE:**

- ✓ Flight delay is inevitable and it plays an important role in both profits and loss of the airlines.
- ✓ Predicting flight delays can improve airline operations and passenger satisfaction, which will result in a positive impact on the economy.
- ✓ An accurate estimation of flight delay is critical for airlines because the results can be applied to increase customer satisfaction and incomes of airline agencies.
- ✓ Flight delays hurt airlines, airports, and passengers. Their prediction is crucial during the decision-making process for all players of commercial aviation.
- ✓ A model that can enable the airline company to better predict if a flight will be on time or will be delayed.
- ✓ It significantly improves service quality.

#### **10.2 DISADVANTAGE:**

- ✓ Flight delays not only irritate air passengers and disrupt their schedules but also cause a decrease in efficiency, an increase in capital costs, reallocation of flight crews and aircraft, and additional crew expenses.
- ✓ Improved scheduling and operations management can assist the industry in improving on-time flight performance.
- ✓ Delay results in the dissatisfaction of trusted customers and sometimes even marketing strategies.

## **CHAPTER-11**

### **CONCLUSION**

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 costs a lot to the airlines as well as passengers in financial and environmental terms, flight delay is 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 passenger and the airlines which in turn is linked to another set of airline and passengers 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 monetary loss and for the higher and smoother operation. Classification or regression ways are often accustomed to determine the delay which includes Feed forward network, Neural Network, Random methodologies offer virtually identical accuracy however we want an algorithmic rule that is good with real. 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.

## **CHAPTER-12**

### **FUTURE SCOPE**

This project is based on data analysis from 2013. Therefore, the future work of this project includes incorporating a larger dataset. There are many different ways to preprocess a larger dataset like running a Spark cluster over a server or using a cloud-based services like AWS and Azure to process the data. With the new advancement in the field of deep learning, we can use Neural Networks algorithm on flight and weather data. Neural Network works on the pattern matching methodology. It is divided into three basic parts for data modeling that includes feed forward networks, feedback networks, and self-organization networks. Feed-forward and feedback networks are generally used in the areas of prediction, pattern recognition, associative memory, and optimization calculation, whereas self-organization networks are generally used in cluster analysis. Neural Network offers distributed computer architecture with important learning abilities to represent nonlinear relationships. Also, the scope of this project is very much confined to flight and weather data of the United States, but we can include more countries like China, India, and Russia. Expanding the scope of this project, we can also add the flight data from international flights and not just restrict ourselves to the domestic flights.

## CHAPTER-13

### APPENDIX

#### Source Code

##### App.py

```
from flask import Flask, render_template, request

import requests

# NOTE: you must manually set API_KEY below using information retrieved from your IBM Cloud
account.
API_KEY = "gyOvc0l0Hde4zdTmNc47N4Vh1zmMTFh7FlK8BEcKPADB"
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}

import mysql.connector

app = Flask(__name__)

conn=mysql.connector.connect(host="localhost", user="root", password="", database="login")
cursor=conn.cursor()

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

@app.route('/login')
def login(): # put application's code here
    return render_template('login.html')

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

@app.route('/home')
def home():
```

```

    return render_template('home.html')

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

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

@app.route('/login_validation', methods=['POST'])
def login_validation():
    email=request.form.get('email')
    password=request.form.get('password')

    cursor.execute("""SELECT * FROM `users` WHERE `email` LIKE'{}' AND `password` LIKE
'{}'""".format(email,password))
    users = cursor.fetchall()

    if len(users)>0:
        return render_template('home.html')
    else:
        return render_template('login.html', prediction_text = "1" )

@app.route('/add_user', methods=['POST'])
def add_user():
    name= request.form.get('name')
    email = request.form.get('email')
    password = request.form.get('password')

    cursor.execute("""INSERT INTO `users`(`id`, `name`, `email`, `password`) VALUES
(NULL,'{}','{}','{}')""".format(name,email,password))
    conn.commit()
    return render_template('login.html', prediction_text = "0")

@app.route('/predict',methods=['POST'])
def predict():

    year = request.form['year']
    month = request.form['month']
    day = request.form['day']
    carrier = request.form['carrier']
    origin = request.form['origin']
    dest = request.form['dest']

    if (carrier=="UA"):
        carrier=11
    if (carrier=="AA"):

```

```

    carrier=1
    if (carrier=="B6"):
        carrier=3
    if (carrier=="DL"):
        carrier=4
    if (carrier=="EV"):
        carrier=8
    if (carrier=="MQ"):
        carrier=9
    if (carrier=="US"):
        carrier=12
    if (carrier=="WN"):
        carrier=14
    if (carrier=="VX"):
        carrier=13
    if (carrier=="FL"):
        carrier=7
    if (carrier=="AS"):
        carrier=2
    if (carrier=="9E"):
        carrier=0
    if (carrier=="F9"):
        carrier=9
    if (carrier=="HA"):
        carrier=4
    if (carrier=="OO"):
        carrier=5
    if (carrier=="YV"):
        carrier=15

    if (origin=="EWR"):
        origin=0
    if (origin=="LGA"):
        origin=2
    if (origin=="JFK"):
        origin=1

    if (dest=="ATL"):
        dest=4
    if (dest=="IAH"):
        dest=43
    if (dest=="MIA"):
        dest=57
    if (dest=="BQN"):
        dest=12
    if (dest=="ORD"):
        dest=68
    if (dest=="FLL"):

```

```
    dest=35
if (dest=="IAD"):
    dest=42
if (dest=="MCO"):
    dest=53
if (dest=="PBI"):
    dest=70
if (dest=="TPA"):
    dest=99
if (dest=="LAX"):
    dest=49
if (dest=="SFO"):
    dest=89
if (dest=="DFW"):
    dest=30
if (dest=="BOS"):
    dest=11
if (dest=="LAS"):
    dest=48
if (dest=="MSP"):
    dest=60
if (dest=="DTW"):
    dest=32
if (dest=="RSW"):
    dest=82
if (dest=="SJU"):
    dest=91
if (dest=="PHX"):
    dest=73
if (dest=="BWI"):
    dest=16
if (dest=="CLT"):
    dest=23
if (dest=="BOS"):
    dest=11
if (dest=="BUF"):
    dest=14
if (dest=="DEN"):
    dest=29
if (dest=="SNA"):
    dest=94
if (dest=="LAS"):
    dest=48
if (dest=="MSY"):
    dest=61
if (dest=="SLC"):
    dest=92
if (dest=="SEA"):
```

```
    dest=88
if (dest=="ROC"):
    dest=99
if (dest=="ATL"):
    dest=4
if (dest=="DCA"):
    dest=33
if (dest=="RDU"):
    dest=4
if (dest=="BNA"):
    dest=4
if (dest=="CLE"):
    dest=88
if (dest=="STL"):
    dest=82
if (dest=="MDW"):
    dest=99
if (dest=="CVG"):
    dest=68
if (dest=="CMH"):
    dest=68
if (dest=="CHS"):
    dest=99
if (dest=="PIT"):
    dest=1
if (dest=="SAN"):
    dest=82
if (dest=="MKE"):
    dest=11
if (dest=="JAX"):
    dest=88
if (dest=="BTV"):
    dest=4
if (dest=="AUS"):
    dest=23
if (dest=="RIC"):
    dest=64
if (dest=="PWM"):
    dest=83
if (dest=="HOU"):
    dest=89
if (dest=="IND"):
    dest=47
if (dest=="MCI"):
    dest=80
if (dest=="SYR"):
    dest=78
if (dest=="BWI"):
```



```
    dest=4
if (dest=="MEM"):
    dest=23
if (dest=="PHL"):
    dest=14
if (dest=="GSO"):
    dest=96
if (dest=="ORF"):
    dest=23
if (dest=="DAY"):
    dest=57
if (dest=="PDX"):
    dest=83
if (dest=="SRQ"):
    dest=91
if (dest=="SDF"):
    dest=29
if (dest=="XNA"):
    dest=88
if (dest=="MHT"):
    dest=43
if (dest=="BDL"):
    dest=23
if (dest=="OMA"):
    dest=4
if (dest=="GSP"):
    dest=57
if (dest=="SAV"):
    dest=28
if (dest=="GRR"):
    dest=16
if (dest=="HNL"):
    dest=24
if (dest=="SAT"):
    dest=30
if (dest=="TYS"):
    dest=99
if (dest=="MSN"):
    dest=55
if (dest=="DSM"):
    dest=23
if (dest=="STT"):
    dest=23
if (dest=="ALB"):
    dest=99
if (dest=="BUR"):
    dest=41
if (dest=="PVD"):
```

```

        dest=32
    if (dest=="PSE"):
        dest=96
    if (dest=="OKC"):
        dest=61
    if (dest=="TUL"):
        dest=60
    if (dest=="SMF"):
        dest=88
    if (dest=="ACK"):
        dest=11
    if (dest=="AVL"):
        dest=10
    if (dest=="ABQ"):
        dest=30
    if (dest=="MVY"):
        dest=68
    if (dest=="EGE"):
        dest=32
    if (dest=="CRW"):
        dest=4
    if (dest=="ILM"):
        dest=79
    if (dest=="CAE"):
        dest=69

t=[[int(year),int(month),int(day),int(carrier),int(origin),int(dest)]]

payload_scoring = {"input_data": [{"fields": ["f0","f1","f2","f3","f4","f5"]}, {"values":t }]}
#payload_scoring = {"input_data": [{"fields": [array_of_input_fields], "values":
[array_of_values_to_be_scored, another_array_of_values_to_be_scored]}]}

response_scoring = requests.post('https://us-south.ml.cloud.ibm.com/ml/v4/deployments/f4014f53-
d84e-4c2a-9dd2-e36cd70e6b22/predictions?version=2022-11-04', json=payload_scoring,
headers={'Authorization': 'Bearer ' + mltoken})

print("Scoring response")

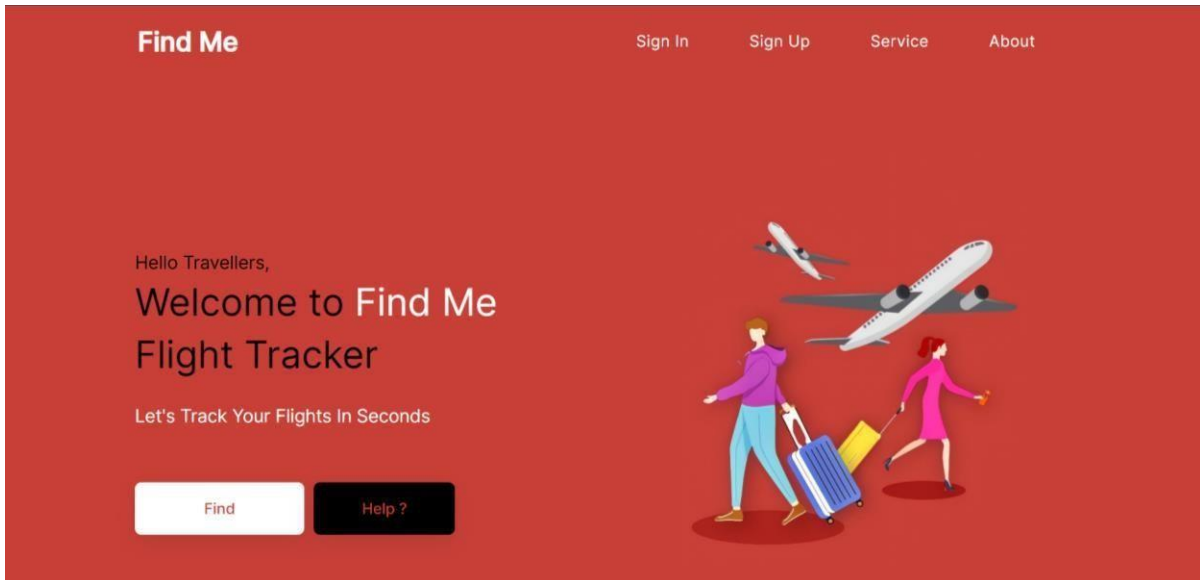
payload_scoring = {"input_data": [{"fields": ["f0","f1","f2","f3","f4","f5"]}, {"values":t }]}
pred= response_scoring.json()
output=pred['predictions'][0]['values'][0][0]print(output)
return render_template('home.html', prediction_text = output)

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

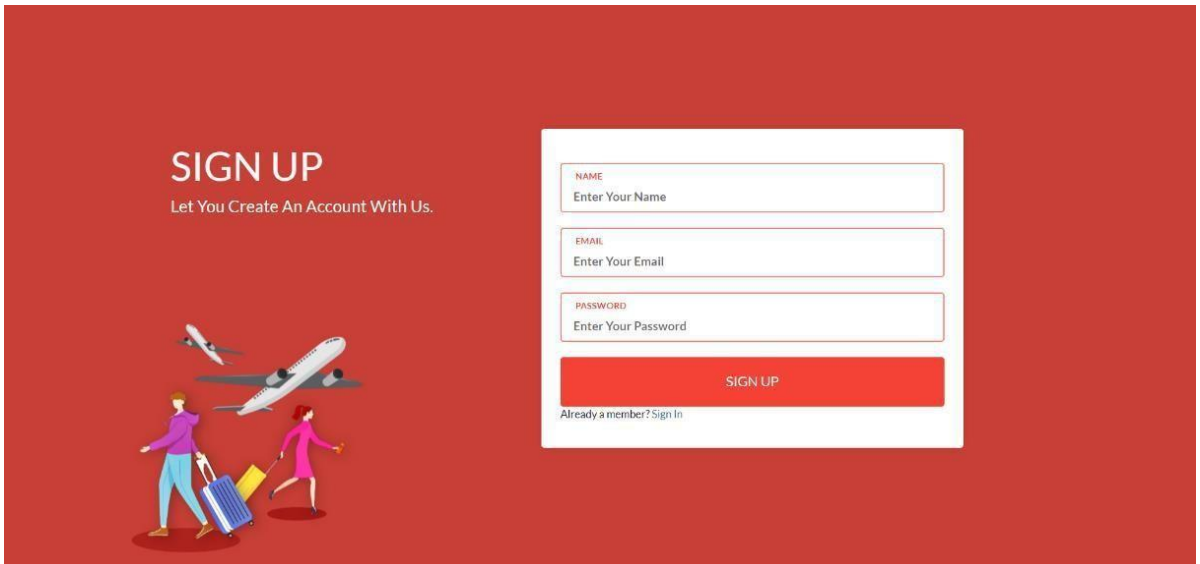
```

## Screenshots:

### Home Page



### Sign Up page:



## SIGN UP

Let You Create An Account With Us.



NAME

Karuppaiya

EMAIL

karuppaiyappan@gmail.com

PASSWORD

•••

SIGN UP

Already a member? [Sign In](#)

## SIGN IN

Let You Create An Account With Us.

"Account Successfully Created"



EMAIL

Enter Your Email

PASSWORD

Enter Your Password


SIGN IN

Not a member? [Create Account](#)

## Sign in Page:

# SIGN IN

Let You Create An Account With Us.



EMAIL

Enter Your Email

PASSWORD

Enter Your Password


SIGN IN

Not a member? [Create Account](#)

# SIGN IN

Let You Create An Account With Us.

"Account Successfully Created"



EMAIL

karuppalaiyappan@gmail.com

PASSWORD

...


SIGN IN

Not a member? [Create Account](#)

## Prediction Page:

# FIND ME

Let's Track Your Flights In Seconds.



YEAR

Enter year

MONTH

Enter month

DATE

Enter date

SELECT AN AIRLINE

United Air Lines Inc.(UA)

FLYING FROM

Newark Liberty International Airp


FLYING TO

Hartsfield-Jackson Atlanta Interna

PREDICT

# FIND ME

Let's Track Your Flights In Seconds.



YEAR

2013

MONTH

05

DATE

20

SELECT AN AIRLINE

United Air Lines Inc.(UA)

FLYING FROM

Newark Liberty International Airp

FLYING TO

Hartsfield-Jackson Atlanta Interna

PREDICT

# FIND ME

Let's Track Your Flights In Seconds.

" Sorry, The Flight Is Delayed "



YEAR  
Enter year

MONTH  
Enter month

DATE  
Enter date

SELECT AN AIRLINE  
United Air Lines Inc.(UA)

FLYING FROM  
Newark Liberty International Airp

FLYING TO  
Hartsfield-Jackson Atlanta Interna

PREDICT

# FIND ME

Let's Track Your Flights In Seconds.



YEAR  
2013

MONTH  
1

DATE  
1

SELECT AN AIRLINE  
Alaska Airlines Inc.(AS)

FLYING FROM  
Newark Liberty International Airp


FLYING TO  
Hartsfield-Jackson Atlanta Interna

PREDICT

# FIND ME

Let's Track Your Flights In Seconds.

" The Flight Will Be OnTime "



YEAR

Enter year

MONTH

Enter month

DATE

Enter date

SELECT AN AIRLINE

United Air Lines Inc.(UA)

FLYING FROM

Newark Liberty International Airp

FLYING TO

Hartsfield-Jackson Atlanta Interna

PREDICT

## Service Page:

Service


HomeSign UpSign InAbout

We are providing the

# Flight Delay Prediction Service

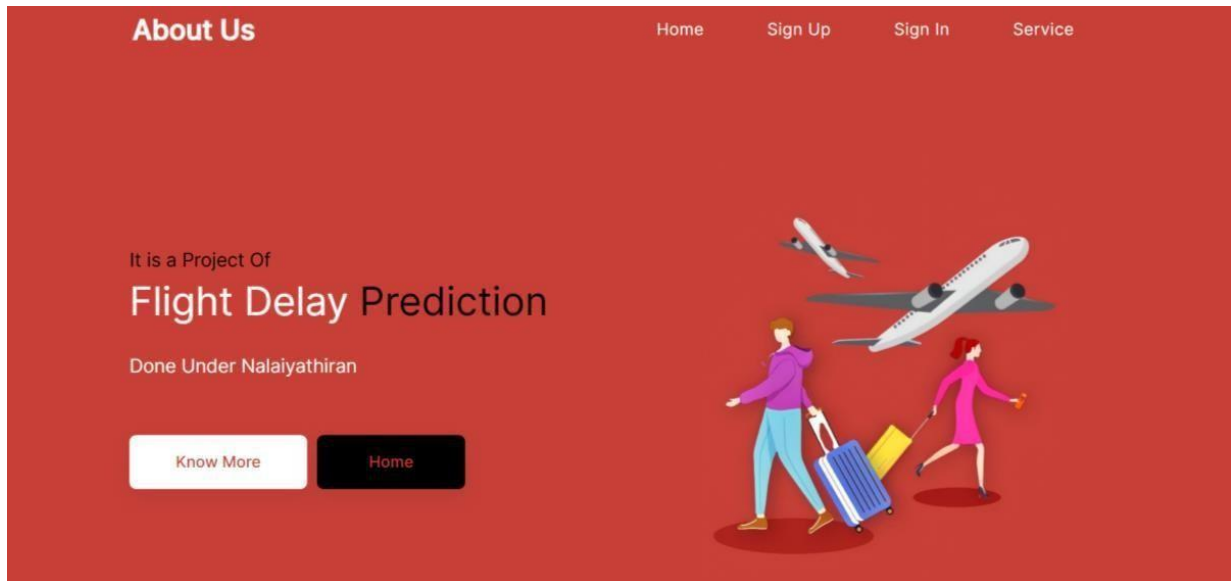
Using Machine Learning

[GitHub Repo](#)
[Back](#)





## About Us Page:



## LINKS:

<b>Github Repo Link</b>	<a href="#"><u>Click Here</u></a>
<b>Demo Video Link</b>	<a href="#"><u>Click Here</u></a>