Flight Delay Prediction System

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Abstract
FLIGHT DELAY STATUS PREDICTION system is a powerful tool that helps airlines to predict the reasons why flights are getting delayed. The system is designed to identify the patterns in flight delays and to predict future delays based on past data. In this regard, the system performs various steps, such as data pre-processing, exploratory data analysis, and predictive modeling. In the first few steps, the system performs data cleaning, such as handling duplicate values and null values. Furthermore, the system performs exploratory data analysis to analyze the reasons for flight delays, the number of flights delayed while arriving and departing, the average duration by which flights get delayed in a year, and the percentage of canceled flights. This information can help airlines to take necessary steps to minimize flight delays and improve customer satisfaction.

Keywords
flight delay prediction system, average duration, cancelled flights, customer satisfaction, prediction, future delays

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Contents

1. Problem and Data Description

The unpleasant reality of travel is that there will always be delays. Flight delays are progressively getting worse, which causes airline firms to have greater financial problems and unhappy passengers. But it turns out that they are rather predictable if we know where to look. Additionally, being informed in advance of a delay may help to lessen some of the tension that results from not knowing the status of your flight until the end moment. As more and more people choose to travel by air, the number of flights that are delayed can result in numerous financial issues, congestion at the airport, and schedule disruptions for everyone, but it can also lead to a reduction in efficiency, an increase in capital costs, the reallocation of flight crews and aircraft, and several other additional costs. It comes at a high price for both customers and airline corporations. The Total Delay Impact Study estimated that in 2007, delays in air travel cost consumers and the airline sector a total of 32.9 billion in the US, which resulted in a 4 billion decline in GDP. Predicting delays can therefore enhance airline operations and customer satisfaction.

This study's objective is to investigate the approaches used to create models that forecast airplane delays caused by various reasons, including:

1. Air Carrier delay
2. Extreme Weather delay
3. National Aviation System delay
4. Security delay
5. Late Arriving Aircraft delay
6. Airlines
7. Specific time of the year

and other factors that affect the flight departures and arrivals.

2. Data Preprocessing & Exploratory Data Analysis

Data mining is an essential technique for extracting useful insights and knowledge from large datasets to improve the accuracy and performance for deriving useful insights. It is very important to preprocess the data to ensure that it is clean, complete and in the right format. This may involve dealing with missing data, correcting errors, and transforming the data into a suitable format for analysis. Furthermore, selecting the

most relevant features from huge datasets is a crucial step in pre-processing the data.

The dataset contains all flight information, including airline-specific cancellations and delays, for dates going back to January 2018. We have considered the years 2021 and 2022 for our analysis as we can relate to the most recent data to validate our results.

We conducted data mining through the following sequential steps:

The dataset we used for our analysis contains flight information from January 2018 to 2022, with over 17 raw data files for years 2021-2022. To prepare the data, we used the pandas library to concatenate the raw data files into a single dataframe. This concatenated dataframe contained over 63 million records and 120 columns, consisting of both numerical and categorical columns with numerous NaN (missing) values and columns that were not relevant for our analysis. To mine the dataset for our study, we omitted irrelevant columns such as Div5TailNum (aircraft tail number), Div5AirportID (Diverted Airport 5 code), unique key IDs for each segment of the airport, and information on detours, aerial time, and wheels-off time, etc. that were not necessary for our analysis. Additionally, we focused our analysis on the ORD airport, which is one of the busiest airports in Chicago, and had a significant amount of data available for growth rate analysis in 2021 and 2022, as reported by the Federal Aviation Administration. Consequently, we reduced the dataset to 457,776 rows and 48 columns. Furthermore, we handled missing values from this final reduced dataset by excluding the missing data from our analysis by ensuring that our approach to missing data was appropriate and did not impact the integrity of our analysis results.

We deleted the columns having null values as these columns were not required for our analysis as mentioned above:

2.1 Handling Missing Values

```
all_null_columns = concat_df.columns[concat_df.isna().all()]
```

```
all_null_columns
```

```
Index(['Div3Airport', 'Div3AirportID', 'Div3AirportSeqID', 'Div3WheelsOn',
       'Div3TotalGTime', 'Div3LongestGTime', 'Div3WheelsOff', 'Div3TailNum',
       'Div4Airport', 'Div4AirportID', 'Div4AirportSeqID', 'Div4WheelsOn',
       'Div4TotalGTime', 'Div4LongestGTime', 'Div4WheelsOff', 'Div4TailNum',
       'Div5Airport', 'Div5AirportID', 'Div5AirportSeqID', 'Div5WheelsOn',
       'Div5TotalGTime', 'Div5LongestGTime', 'Div5WheelsOff', 'Div5TailNum',
       'Unnamed: 119'],
      dtype='object')
```

Figure 1. Null values handling

We have removed some null values, but we have determined that this removal did not significantly impact our analysis. The percentage of null values removed is relatively small compared to the total size of the dataset.

```
total_delayed_flights.dropna(subset=['NASDelay', 'SecurityDelay', 'LateAircraftDelay', 'CarrierDelay',
                                     'WeatherDelay'], inplace=True)
```

```
total_delayed_flights.head()
```

ginCityName	...	CRSElapsedTime	ActualElapsedTime	AirTime	Distance	DistanceGroup	CarrierDelay	WeatherDelay	NASDelay	SecurityDelay	LateAircraftDelay
Chicago, IL	...	184.0	149.0	133.0	1007.0	5	35.0	0.0	0.0	0.0	0.0
Chicago, IL	...	184.0	191.0	160.0	1007.0	5	40.0	0.0	7.0	0.0	0.0
Chicago, IL	...	184.0	189.0	151.0	1007.0	5	0.0	43.0	5.0	0.0	0.0
Chicago, IL	...	184.0	190.0	144.0	1007.0	5	0.0	38.0	6.0	0.0	40.0
Chicago, IL	...	109.0	96.0	81.0	599.0	3	21.0	0.0	0.0	0.0	0.0

```
total_delayed_flights.shape
```

```
(154586, 47)
```

Figure 2. NaN values handling

We removed those columns and rows which largely consisted of NaN values. These rows and columns did not significantly impact the overall data size or required features and hence were safe to delete.

2.2 Exploratory Data Analysis

As a part of our study, we would like to investigate the following major questions and further improve it by relating with different other columns to gain more insights.

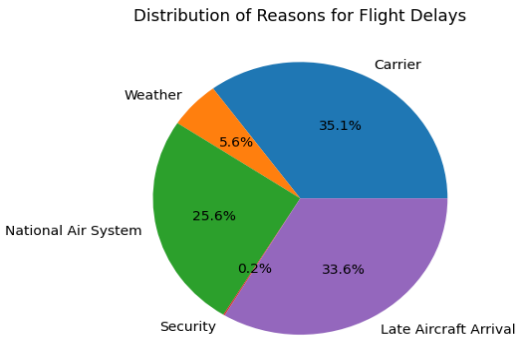

Figure 3. Reasons for flight delays

The five main reasons for flight delays are Carrier delay, Aircraft arrival delay, Security delay, NAS(National Air Security) delay and Weather. It can be observed that the maximum contribution towards causing delay in flights departure and/or arrival is the Carrier delay which is due to shortage or staff, aircraft cleaning, etc. followed by late arrival of the aircraft at the previous airport. We often think that weather causes delay most of the times but it cna be seen that weather constitutes to only 5.6% of the overall reasons for delays.

Airlines	Total Flights	Delayed Flights	% times delayed
Southwest Airlines	12327	3879	31.47
Horizon Air	381	103	27.03
Spirit Airlines	10506	2669	25.40
Frontier Airlines	3317	762	22.97
American Airlines	72878	16378	22.47
JetBlue Airways	1672	337	20.16
SkyWest Airlines	80770	15903	19.69
Air Wisconsin	38399	7387	19.24
Piedmont Airlines	7006	1321	18.86
Alaska Airlines	4199	786	18.72
Republic Airlines	42688	7609	17.82
GoJet Airlines	20233	3547	17.53
United Airlines	86677	15141	17.47
Mesa Airlines	2069	355	17.16
Envoy Air	60851	10161	16.70
Delta Airlines	12595	1990	15.80
Endeavor Air	1208	180	14.90

Figure 4. Airlines with the highest number of delays

Here we see the top airlines which have a record of most delayed flights. Southwest, Horizon Air, and Spirit airlines are known to be the most delaying flight service providers. We could use this data later on while determining which airline a passenger much choose from while booking his next trip based on these factors other than cost.

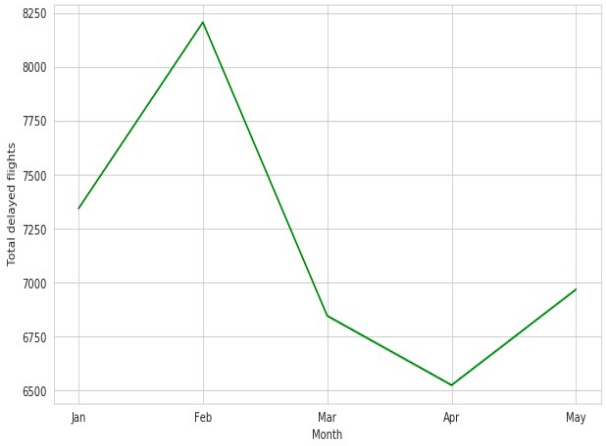

Figure 5. Number of flights delayed while arriving

Based on the chart provided, it is clear that there was a considerable increase in the number of flight arrival delays starting from January. The peak of this delay occurred in February, with more than 8000 recorded cases. However, there was a noticeable decline in flight delays during March and April. Subsequently, in May, there was a slight increase in the number of flight delays compared to the previous two months. Overall, the chart provides insight into the pattern of flight delays over several months.

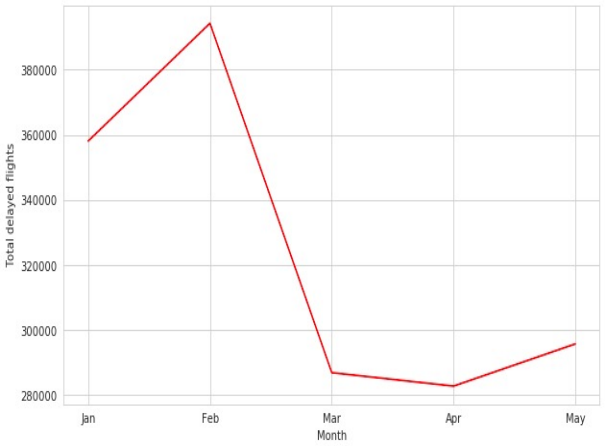

Figure 6. Number of flights delayed while departing

Based on the line chart provided, it is clear that there was a substantial increase in departure delays starting from January, with more than 3600000 recorded cases. The peak of this delay occurred in February, with more than 380000 recorded cases. However, there was a significant drop in departure delays during March, and this trend remained steady until April. In May, there was a slight increase in departure delays compared to the previous two months.

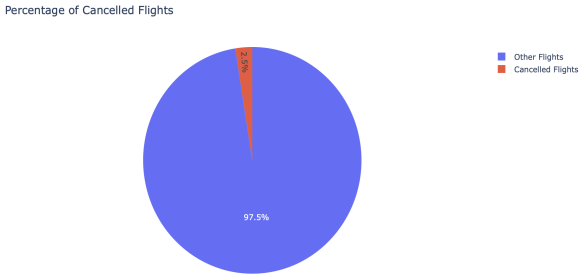

Figure 7. Percentage of cancelled flights

It is crucial to visualize the percentage of canceled flights because it gives a picture of how the airline business is doing. Knowing the proportion of canceled flights can help you gauge how much travel plans are impacted and how efficiently airlines are able to run. If the percentage of canceled flights in your visualization is 2.4% in this instance, it means that only a small number of flights were canceled during the analysis time. It is crucial to remember that this percentage may change based on the precise time period and area being examined. Understanding the factors that cause flight cancellations, such as bad weather or technological difficulties, can also shed light on how the airline business is run. Which also explains that it is rarely that a flight is cancelled and is often delayed actually. Therefore from this we gain an insight that the airline companies mostly try not cancel their scheduled flights as it involves both the company reputation and the customer necessity.

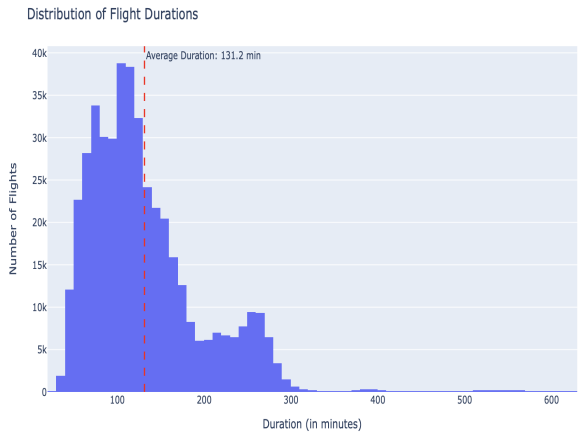

Figure 8. Average duration by which flights get delayed in a year

It is essential to visualize the average flight delay because it enables airlines to spot potential operational issues and take the required corrective action. Additionally, travelers can use this data to choose airlines with superior on-time records and make more informed decisions about their travel plans. Despite the fact that a delay of 131 seconds might not seem like much, it can result in major inconveniences, lost connections, and higher costs for both airlines and passengers. Therefore, by visualizing and analyzing this data, the airline business may experience increased productivity, client satisfaction, and financial success.

3. Algorithm and Methodology

```python
#Importing the packages
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder,StandardScaler
from sklearn.model_selection import train_test_split
import os
import pickle
from flask import Flask, render_template, request
import xgboost as xgb

#Loading the data
def load_data():
    df1 = pd.read_csv(r'data/ORD_airport_data.csv')
    df2 = pd.read_csv(r'data/DEN_airport_data.csv')
    df3 = pd.read_csv(r'data/ATL_airport_data.csv')
    df = pd.concat([df1,df2,df3])
    status = []
    for value in zip(df['DepDel15'],df['ArrDel15']):
        if value[0] == 0 or value[1] == 0:
            status.append(0)
        else:
            status.append(1)
    df['FLIGHT_STATUS'] = status
    df = df[['Origin','Dest','Year','Month','DayofMonth','Operating_Airline ','DepTime','ArrTime','FLIGHT_STATUS']]
    return df

#Preprocessing the data
def preprocessing(df):
    df = df.dropna()
    le = LabelEncoder()
    le2 = LabelEncoder()
    df['Origin'] = le.fit_transform(df['Origin'])
    df['Dest'] = le2.fit_transform(df['Dest'])
    df['Operating_Airline '] = le.fit_transform(df['Operating_Airline '])
    scaler = StandardScaler()
    df[['DepTime','ArrTime']] = scaler.fit_transform(df[['DepTime','ArrTime']])
    with open('scaler.pickle', 'wb') as f:
        pickle.dump(scaler, f)
    with open('le.pickle', 'wb') as f:
        pickle.dump(le2, f)
    return df
```

Figure 9. Data Uploading and Pre Processing

```python
#Model Creation
def model_create(df):
    X = df.drop('FLIGHT_STATUS', axis=1)
    y = df['FLIGHT_STATUS']
    model = xgb.XGBClassifier()
    model.fit(X, y)
    #Saving the model
    filename = 'model.pickle'
    with open(filename,'wb') as f:
        pickle.dump(model,f)
    return 'Model Creation successful!'

#Model prediction
def predict_ans(new_flight):
    filename = 'model.pickle'
    with open(filename, 'rb') as f:
        model = pickle.load(f)
    with open('le.pickle', 'rb') as f:
        le2 = pickle.load(f)
    with open('scaler.pickle', 'rb') as f:
        scaler = pickle.load(f)
    new_flight['Dest'] = le2.transform(new_flight['Dest'])
    new_flight[['DepTime','ArrTime']] = scaler.transform(new_flight[['DepTime','ArrTime']])
    percentage = round(model.predict_proba(new_flight) [:,1][0] * 100,2)
    answer = model.predict(new_flight)
    return percentage,answer
```

Figure 10. Model Creation and Prediction

```python
#Flask app code
app = Flask(__name__,template_folder='templates')

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

@app.route('/predict', methods=['GET','POST'])
def generate():
    origin = request.form['origin']
    origin = int(origin)
    origin_dict = {0:'ATL',1:'DEN',2:'ORD'}
    destination = request.form['destination']
    if origin_dict[origin] == destination:
            return render_template('index.html',error_message =  "Invalid input. Please try again.")
    date = request.form['date_input']
    airline_name = request.form['airline-name']
    airline_name = int(airline_name)
    arrival_time = request.form['arrival-time']
    departure_time = request.form['departure-time']
    year,month,day = date.split('-')
    arrival_time = arrival_time.replace(':', '') + '.00'
    departure_time = departure_time.replace(':', '') + '.00'
    new_flight = pd.DataFrame({'Origin':[origin],'Dest': [destination],'Year': [int(year)],'Month':[int(month)],'Day
    if os.path.isfile('model.pickle'):
        percentage,answer = predict_ans(new_flight)
    else:
        df = load_data()
        df = preprocessing(df)
        model_create(df)
        percentage,answer = predict_ans(new_flight)
    return render_template('result.html', answer = answer, percentage=percentage)

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

Figure 11. Flask App Code

1.) Importing the necessary packages: pandas, numpy, scikit learn (for LabelEncoder, StandardScaler, and train test split, xgboost, os, pickle and Flask.

2.) The load data function reads three CSV files containing flight data from three airports ORD, DEN, and ATL concatenates them into a single data frame creates a new column FLIGHTSTATUS to represent whether the flight was delayed or not, and selects a subset of columns that will be used in the model.

3.) The preprocessing function handles missing values, encodes categorical variables using LabelEncoder, standardizes numerical variables using StandardScaler, and saves the scaler and LabelEncoder objects as pickle files to be used for new data.

4.) The model create function splits the data into features and target, creates an XGBoost classifier, fits the model to the data, and saves the trained model as a pickle file.

5.) The predict ans function loads the trained model, scaler, and LabelEncoder from pickle files, applies the same pre processing steps used for the training data to a new flight, predicts the probability and the status of the flight, and returns the results.

6.) The Flask application has two routes: home page and prediction page . The home page is a simple HTML page that

contains a form for user input. The prediction page takes the input data, creates a new flight data frame, checks if a trained model exists as a pickle file, if it doesn't exist, the function loads, preprocesses, and trains the data, and then predicts the results. If the model exists, it just loads the model and makes the prediction. Finally, it returns the result to the user via an HTML template.

7.) The app.run command at the end of the script starts the Flask application in debug mode.

4. Experiments and Results

Model	Accuracy	Balanced Accuracy	ROC AUC	F1 Score
DecisionTreeClassifier	0.88	0.77	0.77	0.88
BaggingClassifier	0.91	0.76	0.76	0.90
RandomForestClassifier	0.90	0.71	0.71	0.88
ExtraTreesClassifier	0.90	0.70	0.70	0.88
ExtraTreeClassifier	0.84	0.69	0.69	0.84
KNeighborsClassifier	0.86	0.62	0.62	0.83
NearestCentroid	0.59	0.68	0.68	0.65
XGBClassifier	0.86	0.60	0.60	0.83
LGBMClassifier	0.86	0.57	0.57	0.81
GaussianNB	0.84	0.55	0.55	0.80
QuadraticDiscriminantAnalysis	0.84	0.55	0.55	0.80
LinearDiscriminantAnalysis	0.84	0.55	0.55	0.80
AdaBoostClassifier	0.85	0.55	0.55	0.80
CalibratedClassifierCV	0.84	0.54	0.54	0.79
PassiveAggressiveClassifier	0.81	0.53	0.53	0.77
LogisticRegression	0.84	0.53	0.53	0.78
LinearSVC	0.84	0.52	0.52	0.78
RidgeClassifier	0.84	0.52	0.52	0.78
RidgeClassifierCV	0.84	0.52	0.52	0.78
DummyClassifier	0.84	0.50	0.50	0.77
BernoulliNB	0.84	0.50	0.50	0.77
Perceptron	0.78	0.50	0.50	0.75

Model	Time Taken
DecisionTreeClassifier	17.69
BaggingClassifier	113.82
RandomForestClassifier	405.32
ExtraTreesClassifier	303.16
ExtraTreeClassifier	4.21
KNeighborsClassifier	105.94
NearestCentroid	1.35
XGBClassifier	28.42
LGBMClassifier	4.33
GaussianNB	1.49
QuadraticDiscriminantAnalysis	1.63
LinearDiscriminantAnalysis	3.09
AdaBoostClassifier	80.40
CalibratedClassifierCV	1418.53
PassiveAggressiveClassifier	3.42
LogisticRegression	1.82
LinearSVC	500.93
RidgeClassifier	1.66
RidgeClassifierCV	2.45
DummyClassifier	1.02
BernoulliNB	1.58
Perceptron	3.14

Figure 12. Experiments and Results

In our experiments, we used a flight delay dataset to predict whether a flight will be delayed or not. We first loaded the data from three different airports, merged them, and added a new column FLIGHTSTATUS which indicates whether the flight was delayed or not. We then preprocessed the data by dropping missing values, encoding categorical variables, and scaling the numerical variables.

We then created several machine learning models, including Decision tree, Random Forest, Bagging, XGBoost, and Logistic Regression. We split the dataset into training and testing sets and ran each algorithm on different percentages of the test set. We calculated the accuracy and F1 score for each algorithm and found that Bagging and Random Forest provided the best accuracy but had longer run times, making them less desirable. The Decision tree and XGBoost algorithms were the next best choices, with the Decision tree initially outperforming XGBoost in terms of time and accuracy. However, the Decision tree was later found to overfit and produced inaccurate predictions.

Upon running the algorithms on different percentages of the test set, we found that the XGBoost classifier model provided the best overall results and was the most reliable tool for predicting flight delays. Although it had lower accuracy than Bagging and Random Forest, it still provided decent results and had a shorter run time, making it the best choice for our use case.

Overall, our experiments demonstrated that machine learning algorithms can be effective in predicting flight delays, and the XGBoost classifier model is a reliable tool that can be used by airlines and airports to manage flight delays and improve operational efficiency.

5. Deployment and Maintenance

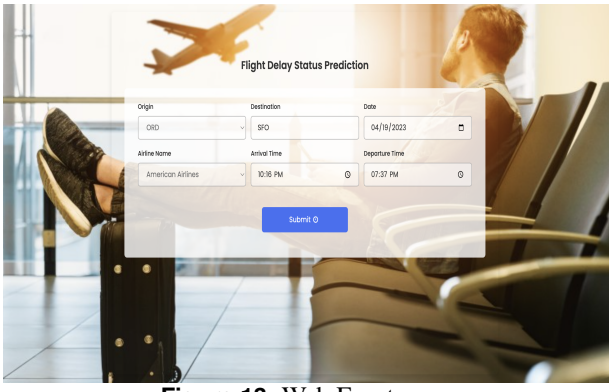

Figure 13. Web Front page

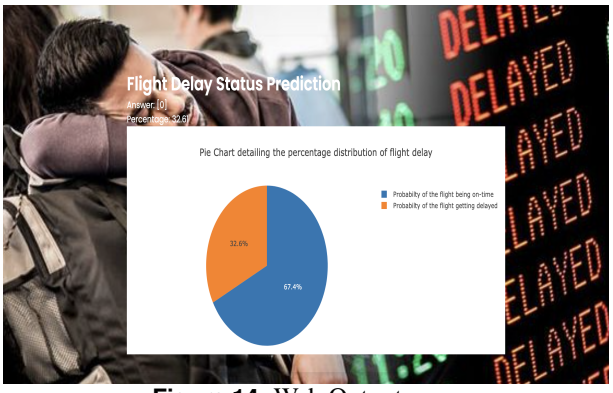

Figure 14. Web Output page

In order to deploy the flight delay dataset, We developed an HTML web application and included a machine learning model to forecast the flight delay depending on the user's input data. We'll go over how to build the web application and deploy the model in this report.

Methodology: To create the web application, We first designed the user interface using HTML, CSS. The user interface consisted of two pages: an input page where the user enters the flight details such as date, airline, and origin/destination airports, and an output page where the predicted delay is displayed. Next, We trained a machine learning model using the flight delay dataset. The dataset consisted of historical flight information, including the departure time, arrival time, airline, and airport information. The target variable was the delay time in minutes. After training the model, We used Python to integrate it with the web application. We created a Flask API to receive the input data from the user and pass it to the model. The model then predicts the delay time, and the output is displayed on the output page of the web application.

Maintenance: The web application was successfully deployed, and the model was able to predict the delay time accurately based on the input data provided by the user. The user interface was intuitive and easy to use, and the output page displayed the predicted delay time in a clear and concise manner.

6. Summary and Conclusions

Based on our analysis of the flight delay dataset, we have decided to use the XGBoost classifier model to predict flight delays. Although the model's accuracy was lower than other models, it produced decent results when predicting flight delays with a 50 percent threshold. The model's proportional predictions were in line with the historical data collected, accurately predicting the chances of flight delay in terms of percentage. The model classified flights with a delay time of more than 2 hours as delayed and performed well in a real-life scenario. We are confident that the XGBoost classifier model will continue to accurately predict future flight delays based on its performance with historical data.

After exploring various algorithms to predict flight delays, we concluded that the bagging and random forest models provided the best accuracy, but had longer run times, making them less desirable. Although the decision tree algorithm initially outperformed the XGBoost algorithm in terms of time and accuracy, it was later found to overfit and produce inaccurate predictions. Therefore, we decided to use the XGBoost classifier model, which although had lower accuracy, still provided decent results and was the best choice for predicting flight delays.

The XGBoost model is a reliable tool that can be used by airlines and airports to manage flight delays and improve operational efficiency. It has the ability to handle large datasets and learn complex patterns in the data, making it suitable for predicting flight delays accurately. We believe that the XGBoost classifier model has the potential to provide significant benefits to the aviation industry by improving flight scheduling, reducing waiting times, and ultimately enhancing the overall travel experience for passengers.

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