ARIGNAR ANNA GOVERNMENT ARTS COLLEGE VILLUPURAM – 605602

DEPARTMENT OF COMPUTER APPLICATION

MACHINE LEARNING WITH PYTHON

Project Title: *Flight delay prediction For Aviation Industry Using Machine Learning*

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Overview:

- The flight delay prediction project using machine learning involves the development of a model that can accurately predict flight delays. This project utilizes historical flight data and machine learning techniques to identify patterns and factors that contribute to flight delays.

- The model is trained on a large dataset of flight information, which includes various features such as departure and arrival times, weather conditions, airline and airport operations, and other relevant factors that may impact flight delays.

- Once the model is trained, it can be used to predict the likelihood and duration of flight delays for future flights. This information can be used by airlines and passengers to better plan their travel schedules, reduce the impact of flight delays, and improve overall flight efficiency.

- The project aims to improve the accuracy of flight delay predictions by utilizing advanced machine learning techniques such as neural networks and decision trees. By doing so, the model can identify complex relationships and interactions between various factors that may impact flight delays.

- Overall, the flight delay prediction project using machine learning has the potential to greatly improve the efficiency and reliability of air travel by providing more accurate and timely information on flight delays.

Purpose :

- ✓ Improving airline operations: By accurately predicting flight delays, airlines can better manage their resources, such as gate assignments, crew scheduling, and aircraft utilization. This can lead to improved efficiency and cost savings for airlines.

- ✓ Enhancing customer experience: Accurate flight delay predictions can help airlines to proactively communicate with customers about potential delays and provide alternative travel options. This can help to reduce stress and frustration for travelers, improving their overall experience

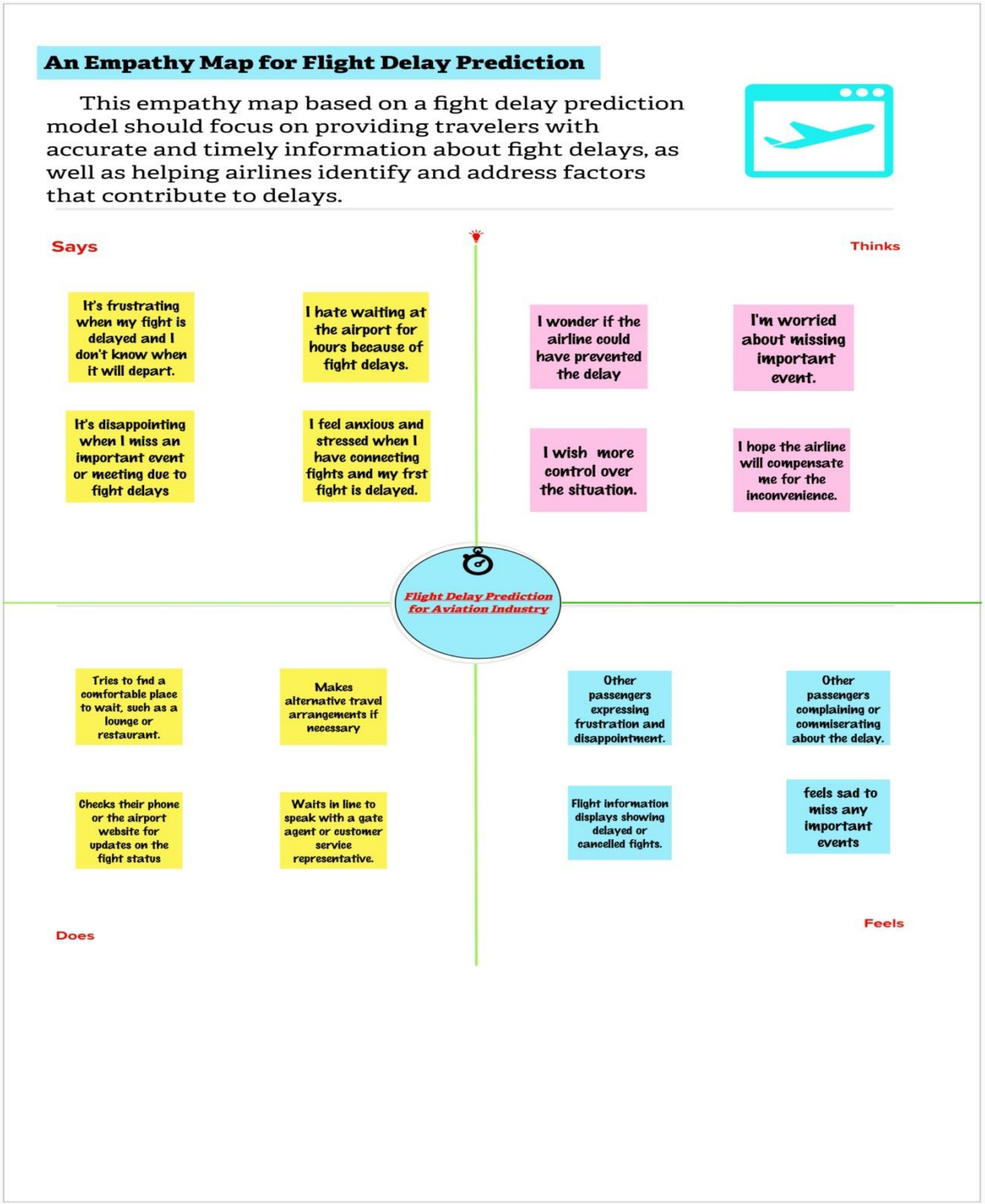
.

- ✓ Increasing safety: Machine learning models can be used to predict potential safety hazards, such as adverse weather conditions, which could impact flight operations. By identifying these hazards in advance, airlines can take appropriate safety measures to protect passengers and crew.

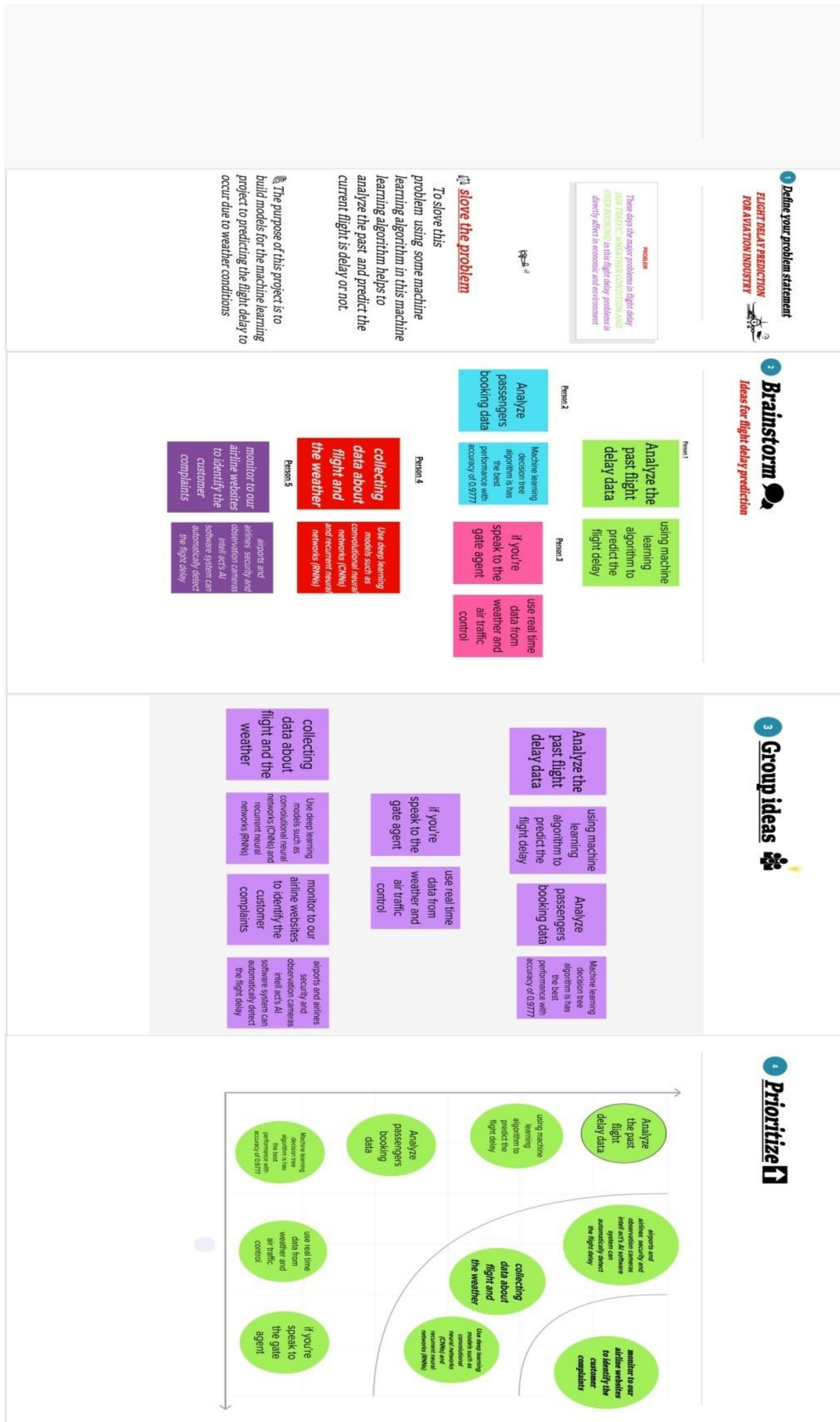
- ✓ Supporting airport planning: Flight delay prediction can help airports to better manage their operations and resources, such as ground handling and gate assignments. This can lead to improved efficiency and reduced congestion at airports.

Problem Defining & Design Thinking:

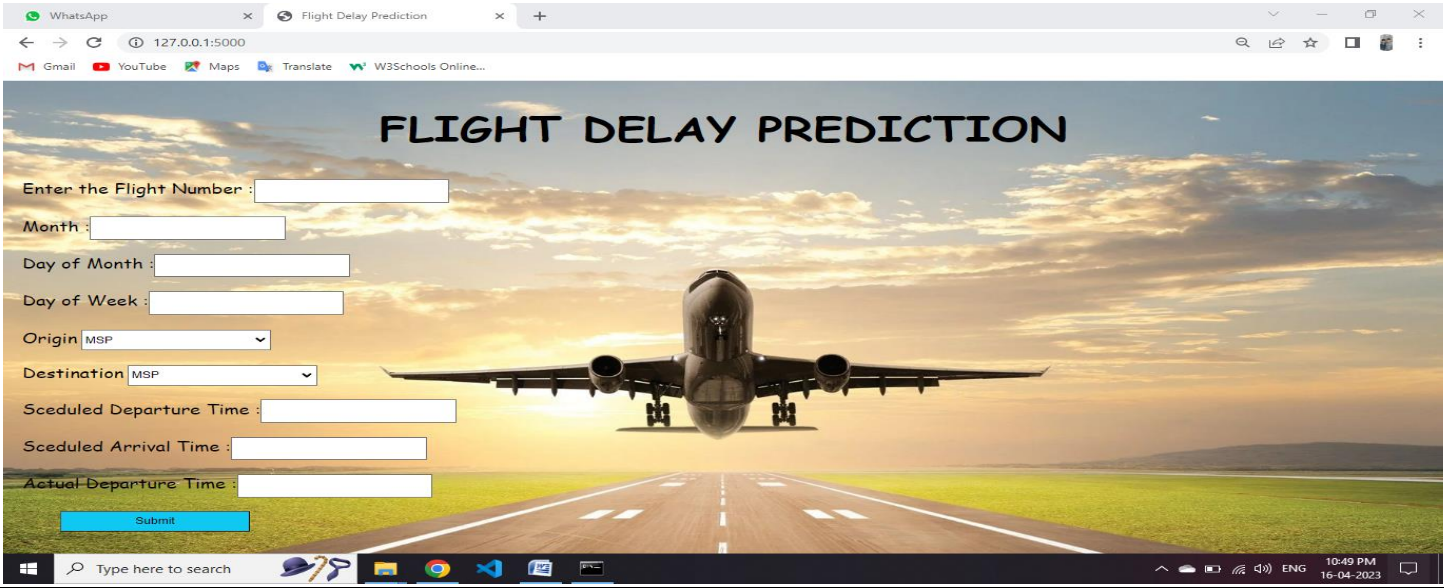
Empathy Map:

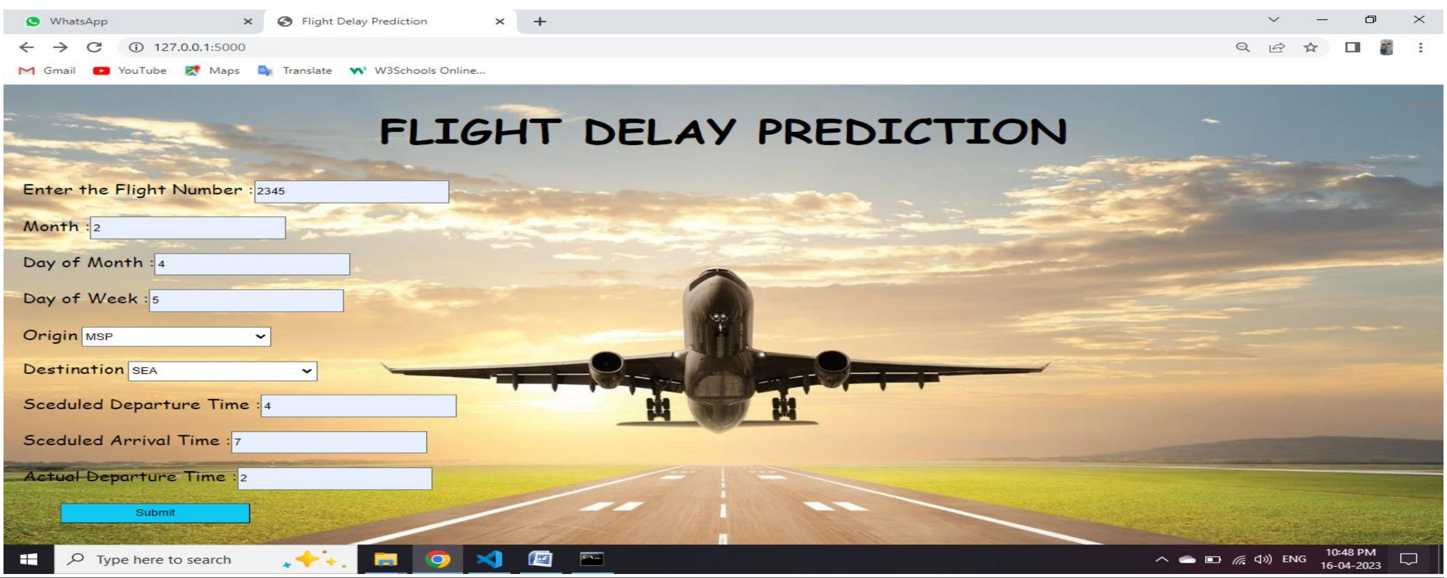


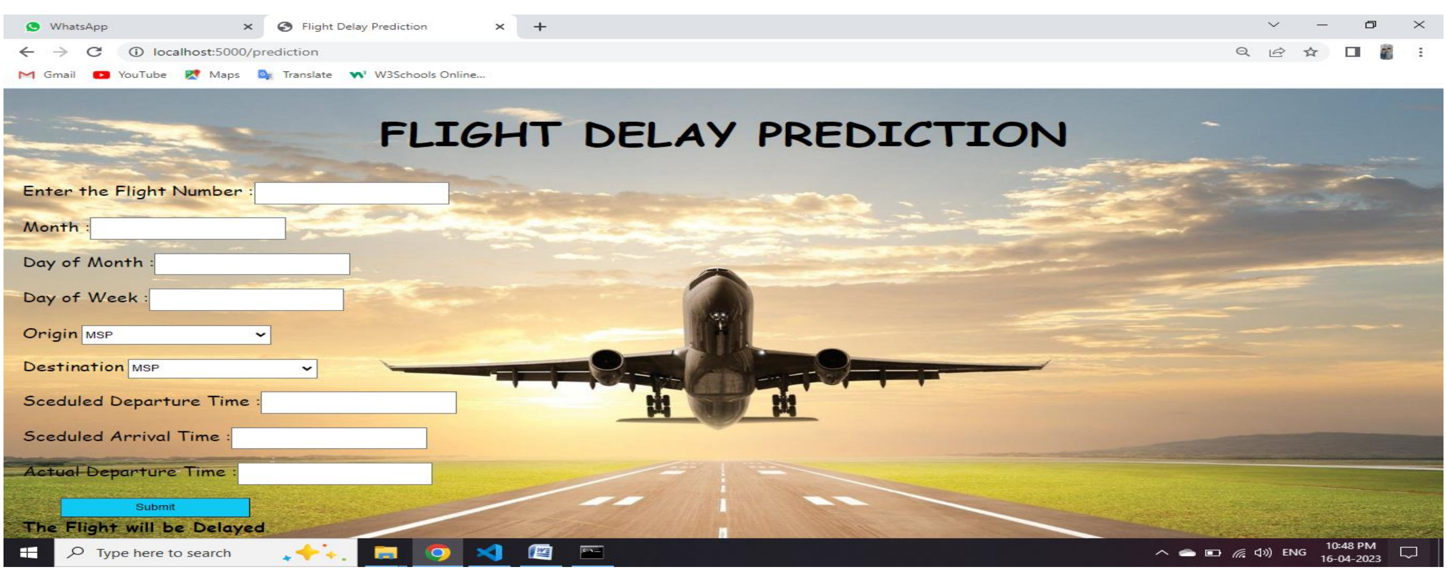
Ideation & Brainstorming Map:



RESULTS IMAGE:







Advantages of flight delay:

- ✓ Reimbursement of your ticket and a return flight to your departure airport if you have a connecting flight.

- ✓ Rerouting to your final destination.

- ✓ Rerouting at a later date under comparable transportation conditions.

- ✓ When we traveling by air, can sit comfortable in an armchair, reading magazines, listen to music, read books, play games or watching a free film on television.

Disadvantages of flight delay:

- ✓ 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.

- ✓ There are plane crashes in which the crew and passengers have died.

- ✓ Airports can often be several miles from city center.

Applications for Flight Delay:

✓ It is widely used by aircraft operators throughout the world to inform and facilitate corrective actions in a range of operational areas by offering the ability to track and evaluate flight operations trends, identify risk precursors, and take the appropriate remedial action.

✓ Therefore, predicting flight delays can improve airline operations and passenger satisfaction, which will result in a positive impact on the economy. In this study, the main goal is to compare the performance of machine learning classification algorithms when predicting flight delays.

✓ With predictive analytics, sensory equipment gathers information from each aircraft's systems, and sends that information to a cloud. That data is then analyzed and used to determine everything from fleet maintenance schedules to marketing strategies.

✓ In case of a delay of over 24 hours, the passenger should be offered free hotel accommodation.

✓ Customers should also be offered a free stay if a flight departs between 8 pm and 3 am and is delayed for over six hours.

Conclusion:

- ✓ In this project, we use flight data, weather, and demand data to predict flight departure delay. Our result shows that the Random Forest method yields the best performance compared to the SVM model.
- ✓ Somehow the SVM model is very time consuming and does not necessarily produce better results. In the end, our model correctly predicts 91% of the non-delayed flights.
- ✓ However, the delayed flights are only correctly predicted 41% of time. As a result, there can be additional features related to the causes of flight delay that are not yet discovered using our existing data sources.
- ✓ In the second part of the project, we can see that it is possible to predict flight delay patterns from just the volume of concurrently published tweets, and their sentiment and objectivity.
- ✓ This is not unreasonable; people tend to post about airport delays on Twitter; it stands to reason that these posts would become more frequent, and more profoundly emotional, as the delays get worse. Without more data, we cannot make a robust model and find out the role of related factors and chance on these results.
- ✓ However, as a proof of concept, there is potential for these results. It may be possible to routinely use tweets to ascertain an understanding of concurrent airline delays and traffic patterns, which could be useful in a variety of circumstances.

Future scope:

- This project is based on data analysis from year 2008. A large dataset is available from 1987-2008 but handling a bigger dataset requires a great amount of preprocessing and cleaning of the data.

- 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 the flight and weather data. Neural Network works on the pattern matching methodology. It is divided into three basic parts for data modelling that includes feed forward networks, feedback networks, and self organization network.

APPENDIX:

Source code

Milestone 2:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import math
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
oh=OneHotEncoder()
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix

#Read the dataset
dataset = pd.read_csv("flightdata.csv")
#dataset.head()
print(dataset.head())

#removing a last column
dataset = dataset.drop('Unnamed: 25', axis=1)
dataset.info()
```

```
#checking the null values
dataset.isnull().sum()
#get the wanted columns in dataset
dataset = dataset[["FL_NUM", "MONTH", "DAY_OF_MONTH", "DAY_OF_WEEK", "ORIGIN", "DEST", "CRS_ARR_TIME", "DEP_DEL15", "ARR_DEL15"]]
#fill the null values in columns ARR_DEL15 ,DEP_DEL15
dataset = dataset.fillna({"ARR_DEL15" : 1})
dataset = dataset.fillna({"DEP_DEL15" : 0})
dataset.iloc[177:189]
```

```
   YEAR  QUARTER  MONTH  DAY_OF_MONTH  DAY_OF_WEEK UNIQUE_CARRIER TAIL_NUM  \
0  2016        1      1             1            5             DL   N836DN
1  2016        1      1             1            5             DL   N964DN
2  2016        1      1             1            5             DL   N813DN
3  2016        1      1             1            5             DL   N587NW
4  2016        1      1             1            5             DL   N836DN

   FL_NUM  ORIGIN_AIRPORT_ID ORIGIN  ...  CRS_ARR_TIME ARR_TIME  ARR_DELAY  \
0    1399              10397    ATL  ...          2143   2102.0      -41.0
1    1476              11433    DTW  ...          1435   1439.0        4.0
2    1597              10397    ATL  ...          1215   1142.0      -33.0
3    1768              14747    SEA  ...          1335   1345.0       10.0
4    1823              14747    SEA  ...           607    615.0        8.0

   ARR_DEL15  CANCELLED  DIVERTED  CRS_ELAPSED_TIME  ACTUAL_ELAPSED_TIME  \
0        0.0        0.0       0.0             338.0                295.0
1        0.0        0.0       0.0             110.0                115.0
2        0.0        0.0       0.0             335.0                300.0
3        0.0        0.0       0.0             196.0                205.0
4        0.0        0.0       0.0             247.0                259.0

   DISTANCE  Unnamed: 25
0    2182.0          NaN
1     528.0          NaN
2    2182.0          NaN
3    1399.0          NaN
4    1927.0          NaN
```

```
[5 rows x 26 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11231 entries, 0 to 11230
Data columns (total 25 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   YEAR                 11231 non-null  int64
 1   QUARTER              11231 non-null  int64
 2   MONTH                11231 non-null  int64
 3   DAY_OF_MONTH         11231 non-null  int64
 4   DAY_OF_WEEK          11231 non-null  int64
 5   UNIQUE_CARRIER       11231 non-null  object
 6   TAIL_NUM             11231 non-null  object
 7   FL_NUM               11231 non-null  int64
 8   ORIGIN_AIRPORT_ID    11231 non-null  int64
 9   ORIGIN               11231 non-null  object
 10  DEST_AIRPORT_ID      11231 non-null  int64
 11  DEST                 11231 non-null  object
 12  CRS_DEP_TIME         11231 non-null  int64
 13  DEP_TIME             11124 non-null  float64
 14  DEP_DELAY            11124 non-null  float64
 15  DEP_DEL15            11124 non-null  float64
 16  CRS_ARR_TIME         11231 non-null  int64
 17  ARR_TIME             11116 non-null  float64
 18  ARR_DELAY            11043 non-null  float64
 19  ARR_DEL15            11043 non-null  float64
 20  CANCELLED            11231 non-null  float64
 21  DIVERTED             11231 non-null  float64
 22  CRS_ELAPSED_TIME     11231 non-null  float64
 23  ACTUAL_ELAPSED_TIME  11043 non-null  float64
 24  DISTANCE             11231 non-null  float64
dtypes: float64(11), int64(10), object(4)
memory usage: 2.1+ MB
```

	FL_NUM	MONTH	DAY_OF_MONTH	DAY_OF_WEEK	ORIGIN	DEST	CRS_ARR_TIME	DEP_DEL15	ARR_DEL15
177	2834	1	9	6	MSP	SEA	852	0.0	1.0
178	2839	1	9	6	DTW	JFK	1724	0.0	0.0
179	86	1	10	7	MSP	DTW	1632	0.0	1.0
180	87	1	10	7	DTW	MSP	1649	1.0	0.0
181	423	1	10	7	JFK	ATL	1600	0.0	0.0
182	440	1	10	7	JFK	ATL	849	0.0	0.0
183	485	1	10	7	JFK	SEA	1945	1.0	0.0
184	557	1	10	7	MSP	DTW	912	0.0	1.0
185	589	1	10	7	MSP	SEA	1100	0.0	0.0
186	744	1	10	7	MSP	ATL	1334	0.0	0.0
187	789	1	10	7	SEA	MSP	1837	0.0	0.0
188	8	1	9	6	MSP	ATL	2103	0.0	0.0

[2]
```
#change the CRS_ARR_TIME values
for index, row in dataset.iterrows():
    dataset.loc[index, 'CRS_ARR_TIME'] = math.floor(row['CRS_ARR_TIME'] / 100)
dataset.head()
```

	FL_NUM	MONTH	DAY_OF_MONTH	DAY_OF_WEEK	ORIGIN	DEST	CRS_ARR_TIME	DEP_DEL15	ARR_DEL15
0	1399	1	1	5	ATL	SEA	21	0.0	0.0
1	1476	1	1	5	DTW	MSP	14	0.0	0.0
2	1597	1	1	5	ATL	SEA	12	0.0	0.0
3	1768	1	1	5	SEA	MSP	13	0.0	0.0
4	1823	1	1	5	SEA	DTW	6	0.0	0.0

```
#convert DEST & ORIGIN using LabelEncoder
le = LabelEncoder()
dataset['DEST'] = le.fit_transform(dataset['DEST'])
dataset['ORIGIN'] = le.fit_transform(dataset['ORIGIN'])
dataset.head()
```

	FL_NUM	MONTH	DAY_OF_MONTH	DAY_OF_WEEK	ORIGIN	DEST	CRS_ARR_TIME	DEP_DEL15	ARR_DEL15
0	1399	1	1	5	0	4	21	0.0	0.0
1	1476	1	1	5	1	3	14	0.0	0.0
2	1597	1	1	5	0	4	12	0.0	0.0
3	1768	1	1	5	4	3	13	0.0	0.0
4	1823	1	1	5	4	1	6	0.0	0.0

0s [4]
```
dataset["ORIGIN"].unique()
```

```
array([0, 1, 4, 3, 2])
```

```
dataset.iloc[:,8:9]
```

	ARR_DEL15
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
...	...
11226	0.0
11227	0.0
11228	0.0
11229	0.0
11230	0.0

11231 rows × 1 columns

Milestone 3:

task 3:

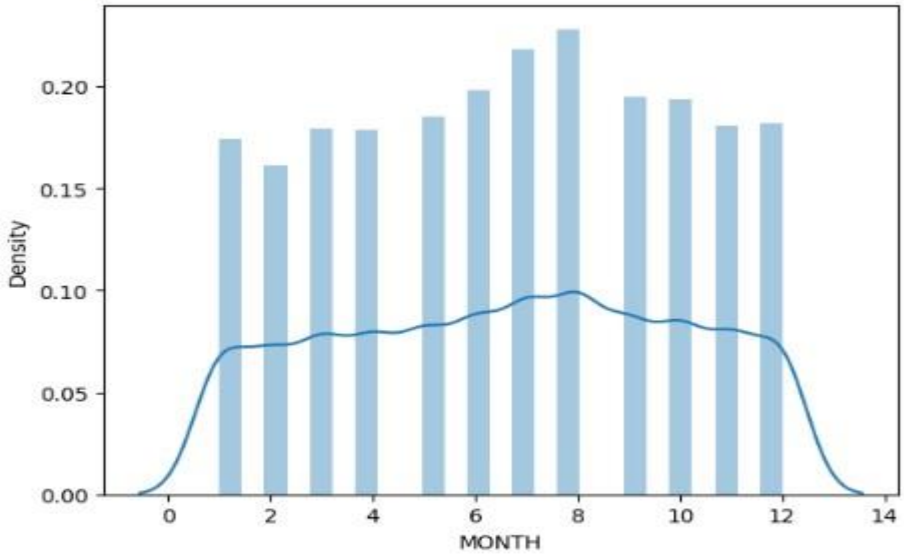
```
[6] org_data=pd.read_csv("flightdata.csv")
    org_data.describe()
```

	YEAR	QUARTER	MONTH	DAY_OF_MONTH	DAY_OF_WEEK	FL_NUM	ORIGIN_AIRPORT_ID	DEST_AIRPORT_ID	CRS_DEP_TIME	DEP_TIME	...
count	11231.0	11231.000000	11231.000000	11231.000000	11231.000000	11231.000000	11231.000000	11231.000000	11231.000000	11124.000000	...
mean	2016.0	2.544475	6.628973	15.790758	3.960199	1334.325617	12334.516695	12302.274508	1320.798326	1327.189410	...
std	0.0	1.090701	3.354678	8.782056	1.995257	811.875227	1595.026510	1601.988550	490.737845	500.306462	...
min	2016.0	1.000000	1.000000	1.000000	1.000000	7.000000	10397.000000	10397.000000	10.000000	1.000000	...
25%	2016.0	2.000000	4.000000	8.000000	2.000000	624.000000	10397.000000	10397.000000	905.000000	905.000000	...
50%	2016.0	3.000000	7.000000	16.000000	4.000000	1267.000000	12478.000000	12478.000000	1320.000000	1324.000000	...
75%	2016.0	3.000000	9.000000	23.000000	6.000000	2032.000000	13487.000000	13487.000000	1735.000000	1739.000000	...
max	2016.0	4.000000	12.000000	31.000000	7.000000	2853.000000	14747.000000	14747.000000	2359.000000	2400.000000	...

8 rows × 22 columns

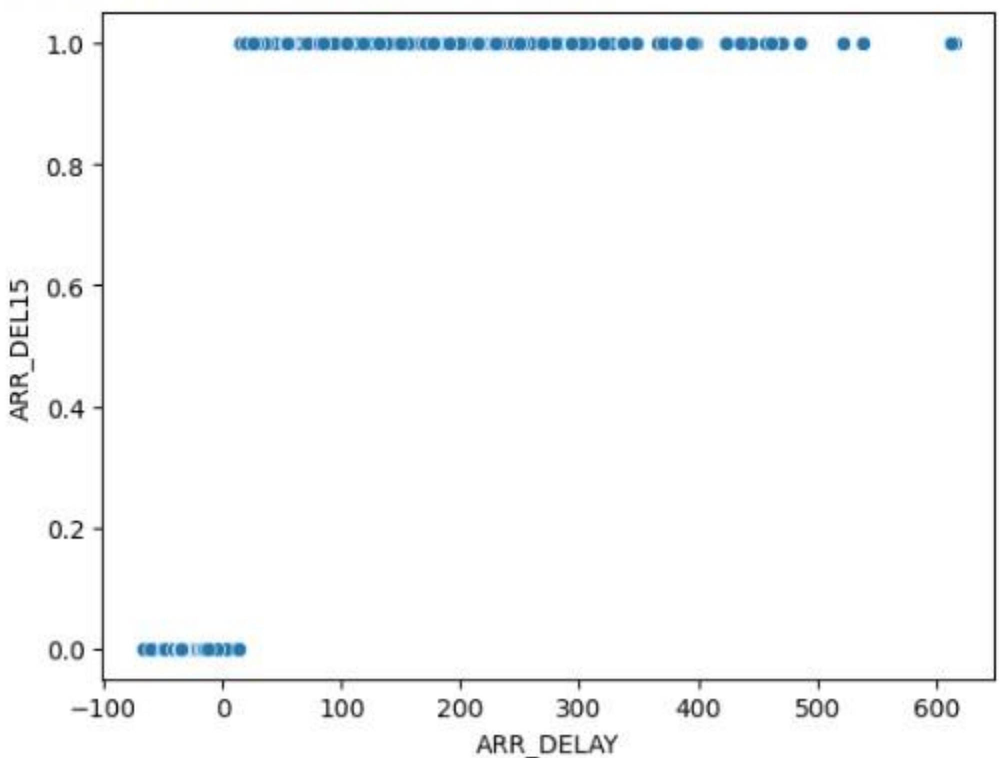
```
sns.distplot(dataset.MONTH)
```

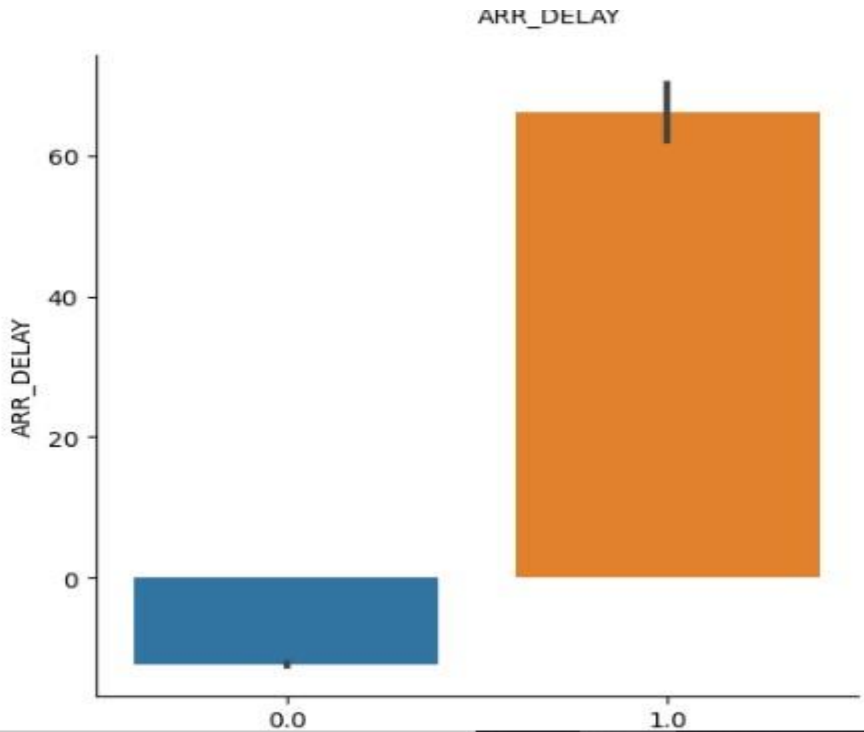
<Axes: xlabel='MONTH', ylabel='Density'>




```
[70] sns.scatterplot(x='ARR_DELAY', y='ARR_DEL15', data=org_data)
     sns.catplot(x='ARR_DEL15', y='ARR_DELAY', kind='bar', data=org_data)
```

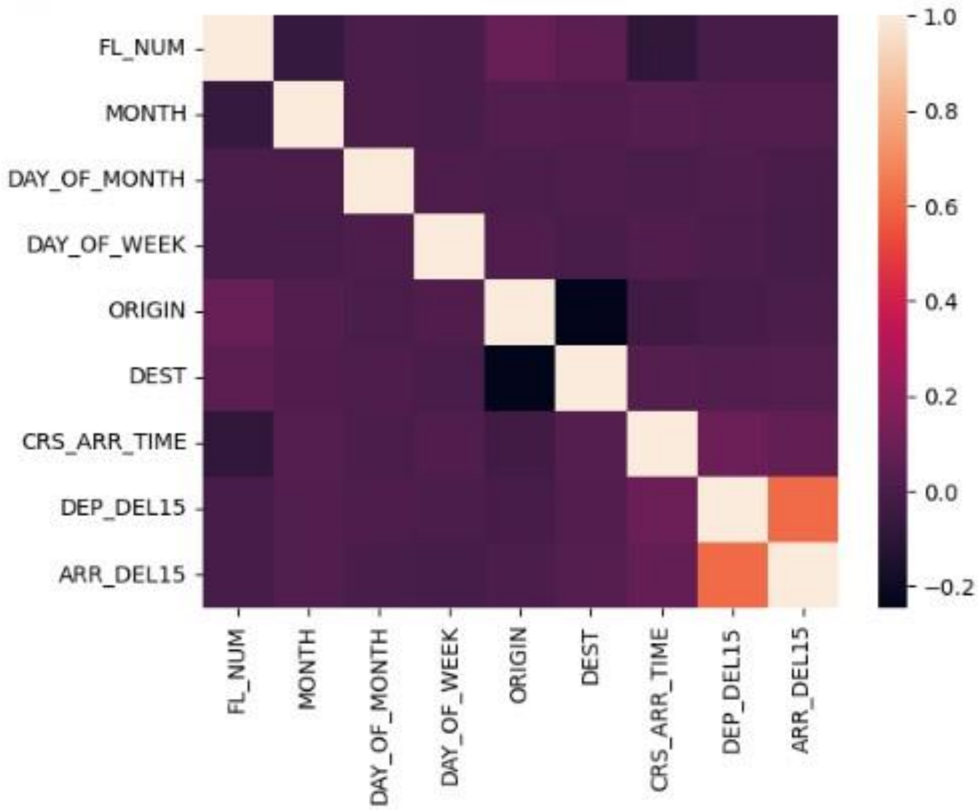
<seaborn.axisgrid.FacetGrid at 0x7fcecda9df40>






```
sns.heatmap(dataset.corr())
```

```
<Axes: >
```



```
#spilting data
x = dataset.iloc[:, 0:8].values
y = dataset.iloc[:, 8:9].values
x
```

```
array([[1.399e+03, 1.000e+00, 1.000e+00, ..., 4.000e+00, 2.100e+01,
        0.000e+00],
       [1.476e+03, 1.000e+00, 1.000e+00, ..., 3.000e+00, 1.400e+01,
        0.000e+00],
       [1.597e+03, 1.000e+00, 1.000e+00, ..., 4.000e+00, 1.200e+01,
        0.000e+00],
       ...,
       [1.823e+03, 1.200e+01, 3.000e+01, ..., 4.000e+00, 2.200e+01,
        0.000e+00],
       [1.901e+03, 1.200e+01, 3.000e+01, ..., 4.000e+00, 1.800e+01,
        0.000e+00],
       [2.005e+03, 1.200e+01, 3.000e+01, ..., 1.000e+00, 9.000e+00,
        0.000e+00]])
```

```
[73] y
```

```
array([[0.],
       [0.],
       [0.],
       ...,
       [0.],
       [0.],
       [0.]])
```

```
[76] z = oh.fit_transform(x[:,4:5]).toarray()
     t = oh.fit_transform(x[:,5:6]).toarray()
     #x = np.delete(x,[4,7],axis=1)
```

```
z
```

```
array([[1., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       ...,
       [0., 1., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.]])
```

```
[78] t
```

```
array([[0., 0., 0., 0., 1.],
       [0., 0., 0., 1., 0.],
       [0., 0., 0., 0., 1.],
       ...,
       [0., 0., 0., 0., 1.],
       [0., 0., 0., 0., 1.],
       [0., 1., 0., 0., 0.]])
```

```
[79] x = np.delete(x, [4,5], axis=1)
```

```
x.shape
```

```
(11231, 6)
```

```
[81] #using concatenate
     x=np.concatenate((t,z,x),axis=1)
```

```
[82] x.shape
```

```
(11231, 16)
```

get **dummies:**

```
[83] dataset=pd.get_dummies(dataset,columns=['ORIGIN','DEST'])
```

```
#Splitting data into train and test
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=0.2, random_state=0)
```

```
[85] x_test.shape
```

```
(2247, 16)
```

```
[86] x_train.shape
```

```
(8984, 16)
```

```
[87] y_test.shape
```

```
(2247, 1)
```

```
[88] y_train.shape
```

```
(8984, 1)
```

```
[89] #StandardScaler scaling the data
     x_train = sc.fit_transform(x_train)
     x_test = sc.fit_transform(x_test)
```

Milestone 4:

```
##TASK 4 - Model building
#Decision tree model
classifier = DecisionTreeClassifier(random_state = 0)
classifier.fit(x_train, y_train)
decisiontree = classifier.predict(x_test)
decisiontree
```

```
array([1., 0., 0., ..., 0., 0., 1.])
```

```
[91] #check accuracy
desacc = accuracy_score(y_test, decisiontree)
desacc
```

```
0.8673787271918113
```

```
#RandomForestClassifier
from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier(n_estimators=10,criterion='entropy')
rfc.fit(x_train,y_train)
```

```
RandomForestClassifier
RandomForestClassifier(criterion='entropy', n_estimators=10)
```

```
[96] y_predict=rfc.predict(x_test)
y_predict
```

```
array([0., 0., 0., ..., 0., 0., 1.])
```

```
[97] #ANN model
import tensorflow
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
#creating ANN skleton view
classification=Sequential()
classification.add(Dense(30,activation='relu'))
classification.add(Dense(128,activation='relu'))
classification.add(Dense(64,activation='relu'))
classification.add(Dense(32,activation='relu'))
classification.add(Dense(1,activation='sigmoid'))
```

```
[98] #compilling the ANN model
classification.compile(optimizer='adam',loss='binary_crossentropy',metrics=['accuracy'])
#Training the model
classification.fit(x_train, y_train, batch_size=4, validation_split=0.2, epochs=100)
```

```
Epoch 1/100
1797/1797 [==============================] - 4s 2ms/step - loss: 0.2878 - accuracy: 0.8948 - val_loss: 0.2802 - val_accuracy: 0.9060
Epoch 2/100
1797/1797 [==============================] - 4s 2ms/step - loss: 0.2708 - accuracy: 0.9051 - val_loss: 0.2767 - val_accuracy: 0.9065
Epoch 3/100
1797/1797 [==============================] - 3s 2ms/step - loss: 0.2672 - accuracy: 0.9055 - val_loss: 0.2723 - val_accuracy: 0.9076
```

```
Epoch 96/100
1797/1797 [==============================] - 3s 2ms/step - loss: 0.0535 - accuracy: 0.9809 - val_loss: 1.3290 - val_accuracy: 0.8720
Epoch 97/100
1797/1797 [==============================] - 3s 2ms/step - loss: 0.0555 - accuracy: 0.9773 - val_loss: 1.2785 - val_accuracy: 0.8798
Epoch 98/100
1797/1797 [==============================] - 3s 2ms/step - loss: 0.0531 - accuracy: 0.9800 - val_loss: 1.3200 - val_accuracy: 0.8726
Epoch 99/100
1797/1797 [==============================] - 4s 2ms/step - loss: 0.0516 - accuracy: 0.9800 - val_loss: 1.3804 - val_accuracy: 0.8737
Epoch 100/100
1797/1797 [==============================] - 3s 2ms/step - loss: 0.0447 - accuracy: 0.9837 - val_loss: 1.3087 - val_accuracy: 0.8653
<keras.callbacks.History at 0x7fce603f3190>
```

[99]
```
#Activity 2: Test the model
#Decision tree
y_pred=classifier.predict([[129,99,1,0,0,1,0,1,1,1,0,1,1,1,1,1]])
y_pred
```

```
array([0.])
```

[100]
```
#RandomForest
y_pred=rfc.predict([[129,99,1,0,0,1,0,1,1,1,0,1,1,1,1,1]])
y_pred
```

```
array([0.])
```

[101]
```
classification.save('flight.h5')
```

[102]
```
#Testing the model
y_pred=classification.predict(x_test)
```

```
y_pred
```

```
array([[9.9998450e-01],
       [2.0697034e-06],
       [6.7771194e-03],
       ...,
       [2.6455763e-15],
       [4.0001239e-16],
       [9.9998057e-01]], dtype=float32)
```

[104]
```
y_pred=(y_pred>0.5)
y_pred
```

```
array([[ True],
       [False],
       [False],
       ...,
       [False],
       [False],
       [ True]])
```

[105]
```
def predict_exit(sample_value):
  #convert list to numpy array
  sample_value=np.array(sample_value)
  #Reshape because sample_value is contains only 1 value
  sample_value=sample_value.reshape(1,-1)
  #Feature scaling
  sample_value=sc.transform(sample_value)
  return classifier.predict(sample_value)
```

```
test=classification.predict([[1,1,121.000000,36.0,0,0,1,0,1,1,1,1,1,1,1,1,]])
if test==1:
  print('prediction: Chance Of Delay')
else:
  print('prediction: No Chance Of Delay')
```

```
1/1 [==============================] - 0s 27ms/step
prediction: No Chance Of Delay
```

Milestone 5:

```
#task 5 Performance Testing & Hyperparameter Tuning
#Compare the model
from sklearn import model_selection
from sklearn.neural_network import MLPClassifier
def classification_report():
  dfs=[]
  models=[
        ('RF',RandomForestClassifier()),
        ('DecisionTree',DecisionTreeClassifier()),
        ('ANN',MLPClassifier())
      ]
  results=[]
  names=[]
  scoring=['accuracy','precision_weighted','recall_weighted','f1_weighted','roc_auc']
  target_names=['no delay','delay']
  for name,model in models:
    kfold=model_selection.KFold(n_splits=5, shuffle=True, random_state=90210)
    cv_results=model_selection.cross_validate(model,x_train, y_train, cv=kfold, scoring=scoring)
    clf=model.fit(x_train, y_train)
    y_pred=clf.predict(x_test)
    print(name)
    print(classification_report(y_test,y_pred,target_names=target_names))
    results.append(cv_results)
    names.append(name)
    this_df=pd.DataFrame(cv_results)
    this_df['models']=name
    dfs.append(this_df)
    final=pd.concat(dfs,ignore_index=True)
  return final
```

```
[108] #RandomForest Accuracy
      print('Training accuracy: ',accuracy_score(y_pred,y_predict))
      print('Testing accuracy: ',accuracy_score(y_test,y_predict))
```

```
Training accuracy:  0.9185580774365821
Testing accuracy:  0.8976412995104583
```

```
[109] #making the confusion matrix
      from sklearn.metrics import confusion_matrix
      cm= confusion_matrix(y_test,y_predict)
      cm
```

```
array([[1872,   64],
       [ 166,  145]])
```

```
[110] #accuracy score of desiciontree
      from sklearn.metrics import accuracy_score
      desacc=accuracy_score(y_test,decisiontree)
      desacc
```

```
0.8673787271918113
```

```
from sklearn.metrics import confusion_matrix
cm=confusion_matrix(y_test,decisiontree)
cm
```

```
array([[1778,  158],
       [ 140,  171]])
```

```
[112] #calculate the accuracy of ANN
      from sklearn.metrics import accuracy_score,classification_report
      score=accuracy_score(y_pred,y_test)
      print('The accuracy for ANN model is :{}%'.format(score*100))
```

```
The accuracy for ANN model is :87.49443702714731%
```

```
[113] #making the confusion matrix
      cm=confusion_matrix(y_test,y_pred)
      cm
```

```
array([[1803,  133],
       [ 148,  163]])
```

```
[114] #giving some parameters that can be used in randized search cv
      parameters={
                   'n_estimators' :[1,20,30,55,68,74,90,120,115],
                   'criterion':['gini','entropy'],
                   'max_features':["auto","sqrt","log2"],
                 'max_depth':[2,5,8,10],'verbose':[1,2,3,4,6,8,9,10]
      }
```

```
[115] # Performing the randomized cv
      from sklearn.model_selection import RandomizedSearchCV
      RCV = RandomizedSearchCV(estimator = rfc, param_distributions = parameters, cv = 10, n_iter = 4)
```

```
[116] RCV.fit(x_train,y_train)
```

```
building tree 1 of 68
building tree 2 of 68
building tree 3 of 68
building tree 4 of 68
building tree 5 of 68
building tree 6 of 68
building tree 7 of 68
building tree 8 of 68
building tree 9 of 68
building tree 10 of 68
building tree 11 of 68
building tree 12 of 68
```

```
building tree 81 of 90
building tree 82 of 90
building tree 83 of 90
building tree 84 of 90
building tree 85 of 90
building tree 86 of 90
building tree 87 of 90
building tree 88 of 90
building tree 89 of 90
building tree 90 of 90
building tree 1 of 68
building tree 2 of 68
```

```
[117] #getting the best paarmets from the giving list and best score from them
      bt_params=RCV.best_params_
      bt_score=RCV.best_score_
      bt_params
```

```
building tree 83 of 90
building tree 84 of 90
building tree 85 of 90
building tree 86 of 90
building tree 87 of 90
building tree 88 of 90
```

```
[120] y_predict_rf=RCV.predict(x_test)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   3 out of   3 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   4 out of   4 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:    0.0s remaining:    0.0s
[Parallel(n_jobs=1)]: Done  68 out of  68 | elapsed:    0.0s finished
```

```
[121] RCV=accuracy_score(y_test,y_predict_rf)
RCV
```

```
0.910547396528705
```

```
import pickle
pickle.dump(RCV,open('flight.pkl','wb'))
```

Milestone 6:

```
from flask import Flask,render_template,request
import pickle
import numpy as np

model = pickle.load(open('flight.pkl', 'rb'))

app = Flask(__name__, template_folder='template')

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

@app.route('/prediction', methods = ['POST'])
def predict():
    name = request.form['name']
    month = request.form['month']
    dayofmonth = request.form['dayofmonth']
    dayofweek = request.form['dayofweek']
    origin = request.form['origin']
    if(origin == "msp"):
        origin0,origin1,origin2,origin3,origin4 = 0,0,0,0,1
    if(origin == "dtw"):
        origin0,origin1,origin2,origin3,origin4 = 1,0,0,0,0
    if(origin == "jfk"):
        origin0,origin1,origin2,origin3,origin4 = 0,0,1,0,0
    if(origin == "sea"):
        origin0,origin1,origin2,origin3,origin4 = 0,1,0,0,0
    if(origin == "alt"):
```

```
        origin0,origin1,origin2,origin3,origin4 = 0,1,0,0,0
    if(origin == "alt"):
        origin0,origin1,origin2,origin3,origin4 = 0,0,0,1,0

    destination = request.form['destination']
    if(destination == "msp"):
        destination0,destination1,destination2,destination3,destination4 = 0,0,0,0,1
    if(destination == "dtw"):
        destination0,destination1,destination2,destination3,destination4 = 1,0,0,0,0
    if(destination == "jfk"):
        destination0,destination1,destination2,destination3,destination4 = 0,0,1,0,0
    if(destination == "sea"):
        destination0,destination1,destination2,destination3,destination4 = 0,1,0,0,0
    if(destination == "alt"):
        destination0,destination1,destination2,destination3,destination4 = 0,0,0,1,0
    dept = request.form['dept']
    arrtime = request.form['arrtime']
    actdept = request.form['actdept']
    dept15 = int(dept) - int(actdept)
    total = [[name,month,dayofmonth,dayofweek,origin0,origin1,origin2,origin3,origin4,destination0,de
    print(total)
    y_pred = model.predict(total)
    print(y_pred)
    y_pred = [0.]
    if(y_pred == [0.]):
        ans = "The Flight will be On Time"
    else:
```

```
    y_pred = model.predict(total)
    print(y_pred)
    y_pred = [0.]
    if(y_pred == [0.]):
        ans = "The Flight will be On Time"
    else:
        ans = "The Flight will be Delayed"
    return render_template('index.html', showcase = ans)

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

User interface wep page code:

```
<!DOCTYPE html>
<html>
    <style>
    @import url('https://fonts.google.com/specimen/Balsamiq+Sans');
        body{
            width: 100%;
            margin: 0px;
            background-image: url('https://wallpaperaccess.com/full/1470798.jpg');
        }
        .header{
            top: 0;
            width: 100%;
            height: 90px;
            font-family: 'Balsamiq Sans',cursive;
            font-size: 25px;
            font-weight: 800px;
            text-align: center;
        }
        .MAIN p,label{
            font-size: 20px;
            margin-left: 20px;
            font-family: 'Balsamiq Sans',cursive;
        }
        .MAIN input,select{
            height: 30px;
            width: 200px;
        }
```

```
        }
        .MAIN button{
            height: 30px;
            width: 200px;
            margin-left: 60px;
            background-color: #daa520;
        }
        .MAIN b{
            font-size: 20px;
            font-weight: 800px;
            text-align: center;
            font-family: 'Balsamiq Sans',cursive;
            margin-left: 20px;
        }
    </style>
    <title>Flight Delay Prediction</title>
    <body background="1470798.jpg">
        <div class="header">
        <h1>FLIGHT DELAY PREDICTION</h1>
        </div>
        <div class="MAIN">
            <form action="http://localhost:5000/prediction" method="post">
                <p> Enter the Flight Number :<span><input type="text" name="name"/></span></p>
                <p> Month :<span><input type="text" name="month"/></span></p>
                <p> Day of Month :<span><input type="text" name="dayofmonth"/></span></p>
                <p> Day of Week :<span><input type="text" name="dayofweek"/></span></p>
                <label for="origin">Origin</label>
                <select name="origin">
```

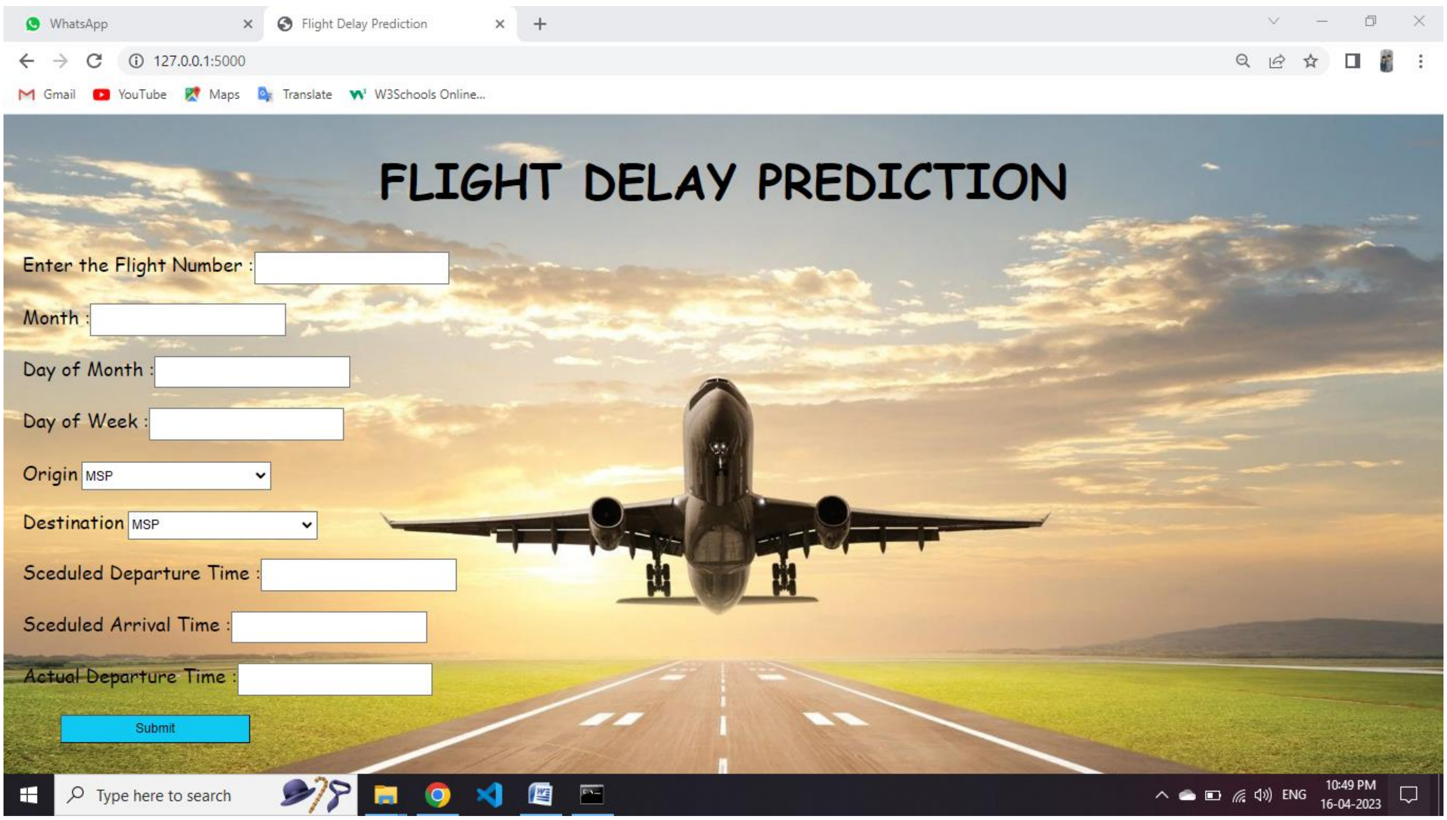
```html
                <label for="origin">Origin</label>
                <select name="origin">
                    <option value="msp">MSP</option>
                    <option value="dtw">DTW</option>
                    <option value="jfk">JFK</option>
                    <option value="sea">SEA</option>
                    <option value="alt">ALT</option>
                </select>
                <br><br>
                <label for="destination">Destination</label>
                <select name="destination">
                    <option value="msp">MSP</option>
                    <option value="dtw">DTW</option>
                    <option value="jfk">JFK</option>
                    <option value="sea">SEA</option>
                    <option value="alt">ALT</option>
                </select>
                <p> Sceduled Departure Time :<span><input type="text" name="dept"/></span></p>
                <p> Sceduled Arrival Time :<span><input type="text" name="arrtime"/></span></p>
                <p> Actual Departure Time :<span><input type="text" name="actdept"/></span></p>
                <div class="form-btn">
                    <button class="submit-btn">Submit</button>
                    <br><br><br><br>
                </div>
            </form>
        </div>
    </body>
</html>
```

Output:

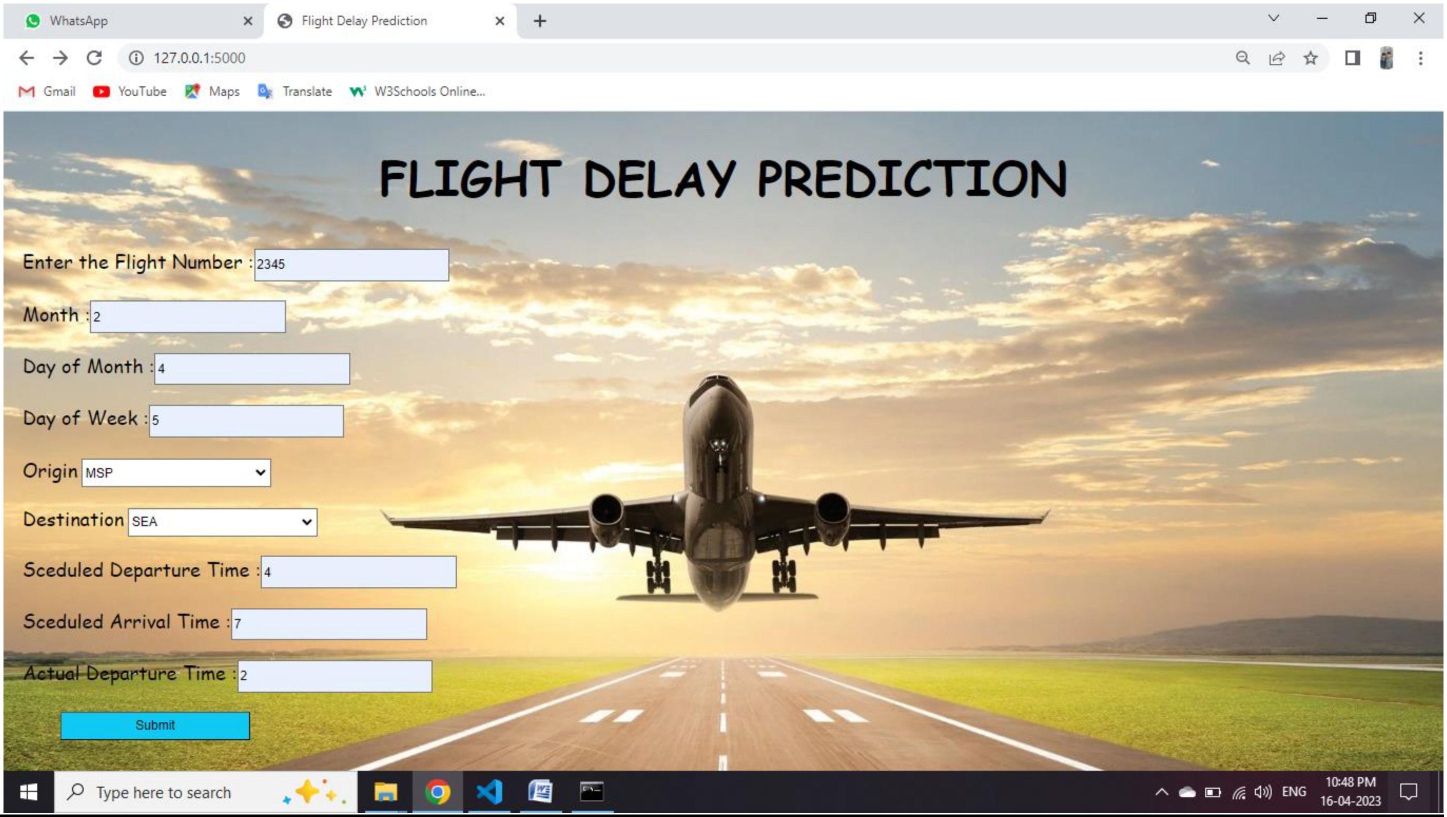
C:\Windows\System32\cmd.exe - python app.py

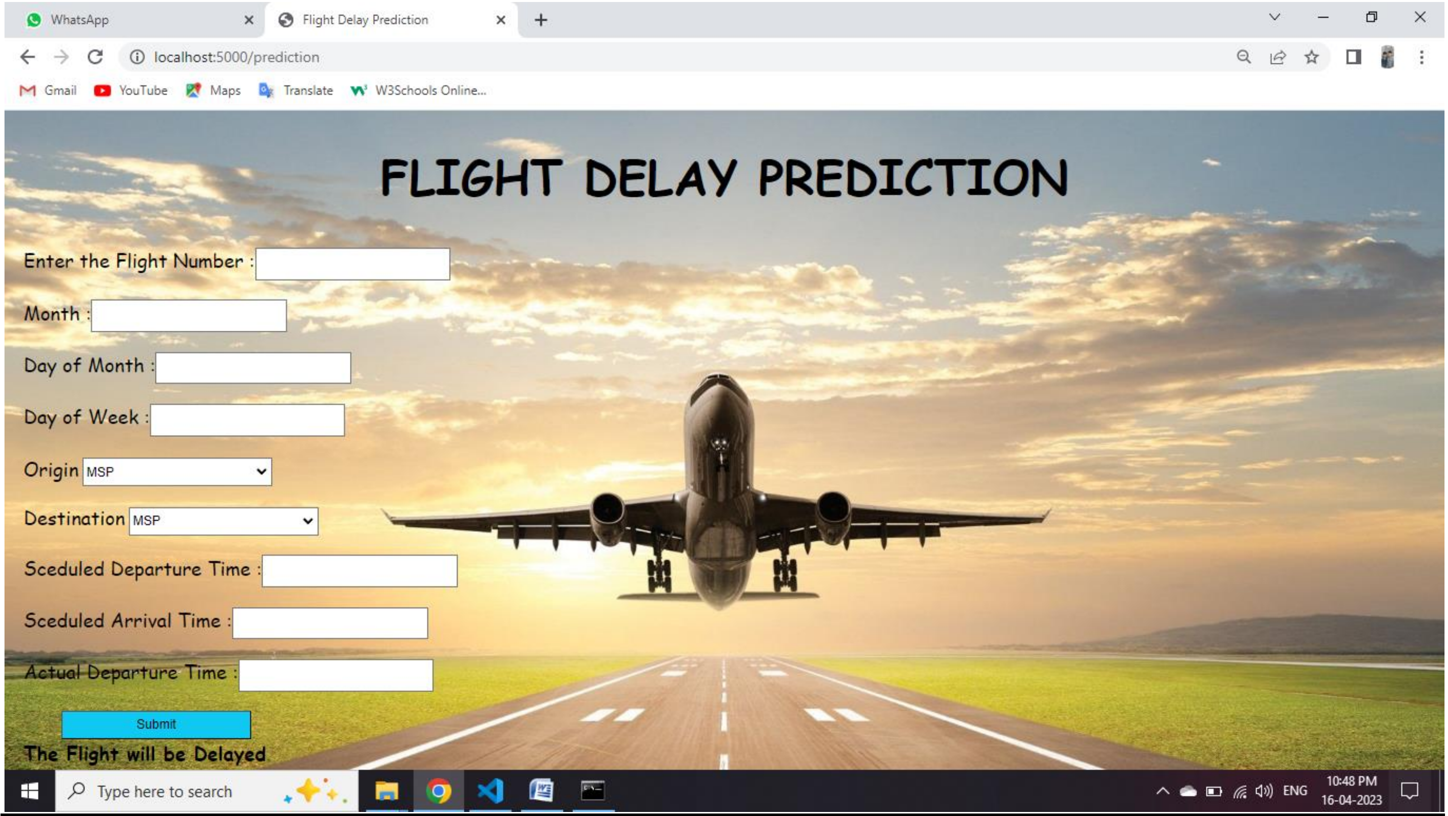
```
Microsoft Windows [Version 10.0.19045.2846]
(c) Microsoft Corporation. All rights reserved.

E:\ML project\flight_delay_prediction 1\flask>python app.py
 * Serving Flask app 'app'
 * Debug mode: on
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on http://127.0.0.1:5000
Press CTRL+C to quit
 * Restarting with stat
 * Debugger is active!
 * Debugger PIN: 533-497-909
```

Then the next step is go to web browser and write the localhost URL (http://127.0.0.1:5000) to get the below result.



The user will give input to get the predicted result after clicking the submit button.


WhatsApp
Flight Delay Prediction
127.0.0.1:5000
Gmail
YouTube
Maps
Translate
W3Schools Online...
FLIGHT DELAY PREDICTION
Enter the Flight Number :
2345
Month :
2
Day of Month :
4
Day of Week :
5
Origin
MSP
Destination
SEA
Sceduled Departure Time :
4
Sceduled Arrival Time :
7
Actual Departure Time :
2
Submit
Type here to search
ENG
10:48 PM
16-04-2023


WhatsApp
Flight Delay Prediction
localhost:5000/prediction
Gmail
YouTube
Maps
Translate
W3Schools Online...
FLIGHT DELAY PREDICTION
Enter the Flight Number :
Month :
Day of Month :
Day of Week :
Origin
MSP
Destination
MSP
Sceduled Departure Time :
Sceduled Arrival Time :
Actual Departure Time :
Submit
The Flight will be Delayed
Type here to search
ENG
10:48 PM
16-04-2023

<u>Thank you..</u>