ARIGNAR ANNA GOVERNMENT ARTS COLLEGE

VILLUPURAM – 605 602.

DEPARTMENT OF COMPUTER APPLICATIONS

MACHINE LEARNING WITH PYTHON

Project Title : Optimizing Flight Booking Decisions through Machine Learning Price Predictions

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1. INTRODUCTION

1.1 Overview:

Perfect time for purchasing plane ticket by the passenger's view is difficult since passengers get very less information of future business price rates. Different models figure out future business price on plane and categorise the best time to obtain flight ticket. Airlines use different strategies of pricing for their tickets, later taking the decision on price because order shows higher value for the approximation models. The causes behind the difficult system is each Planes has limited number of seats to be filed, so airlines must regulate demand. Suppose when demand is expected to increase capacity, the airline may increase prices, to decrease the rate at which seats fill.

Also, seating arrangements in flight which is not occupied shows the loss of the amount invested for the business airline companies and making them purchase the ticket to fill the seats for any price this would be the best idea to get profit in loss too. Passengers should be compatible with the airline companies to get adjusted for the increase and decrease of the price. Passengers or customers should make their own planning to get the best offers available on different airlines and travel through less price. Planes ticket prices changes as time passes, pulling out the elements which creates the difference. Reporting the correlated and models which is used to price the flight tickets. Then, using that information, building the model which helps passengers to make pull out the ticket to buy and predicting air ticket prices which progresses in the future. Duration, Arrival time, Price, Source, Destination and much more these are the attribute used for flight price prediction.

1.2 Purpose

- The primary purpose of flight price prediction is to help travelers save money by predicting when prices are likely to go up or down. By using this information, travelers can time their purchases to get the best possible deals on flights.

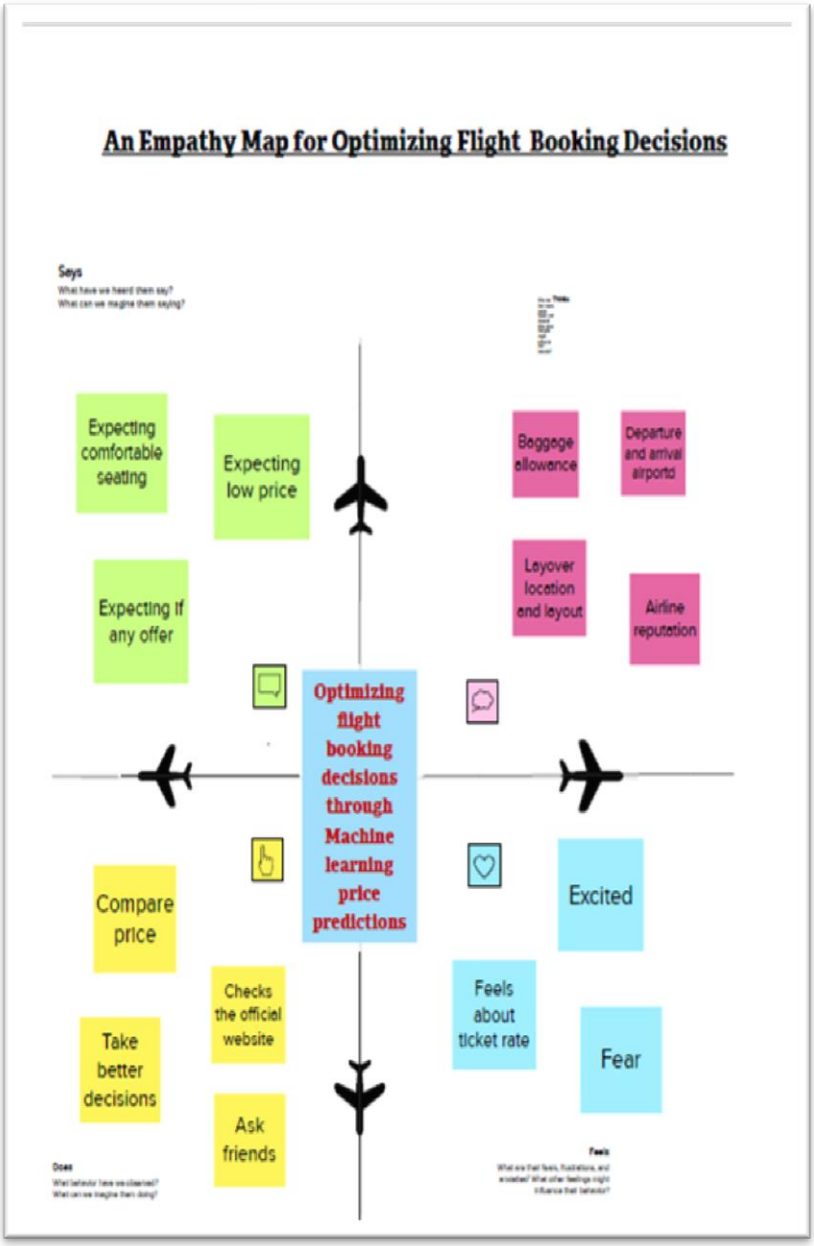
- A Flight price prediction application which predicts fares of flight for a particular date based on various parameters like source, Destination, Stops and Airlines. The prediction will help a traveller to decide a specific airline as per his/her budget.

- The main purpose of out system is to predict the flight prices with comparison of today to another any day because of this customer can be book their tickets of Flight according to their comfortably, according to their affordability, Means whichever cheaper cost they want they can be easily choose. The purpose is to provide customers with the relevant information they need to decide the best time to purchase a ticket.

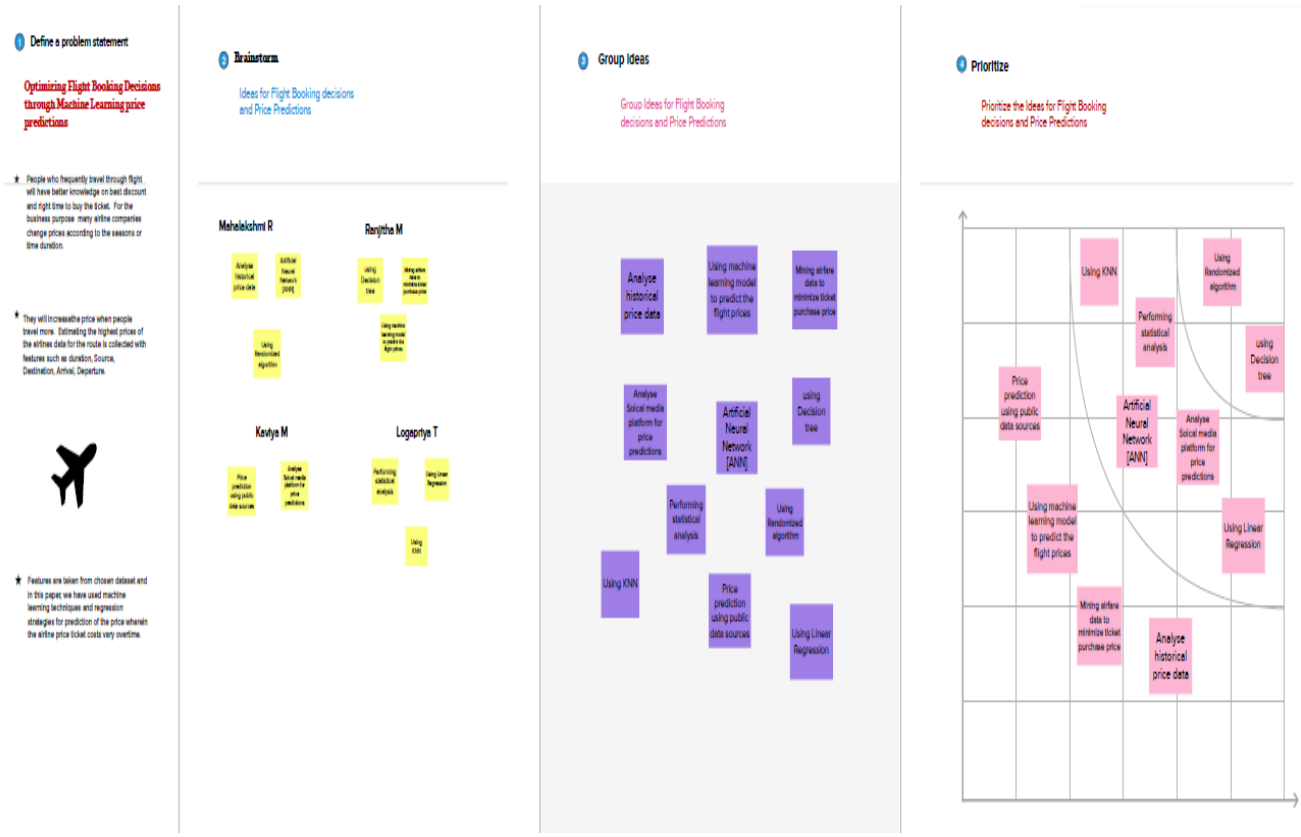
- By helping travelers save money and plan their trips more effectively, flight price prediction tools can improve overall travel experiences. This reduces stress and enhances enjoyment, making travel more accessible and enjoyable for everyone.

2. PROBLEM DEFINITION AND DESIGN THINKING

2.1 Empathy map

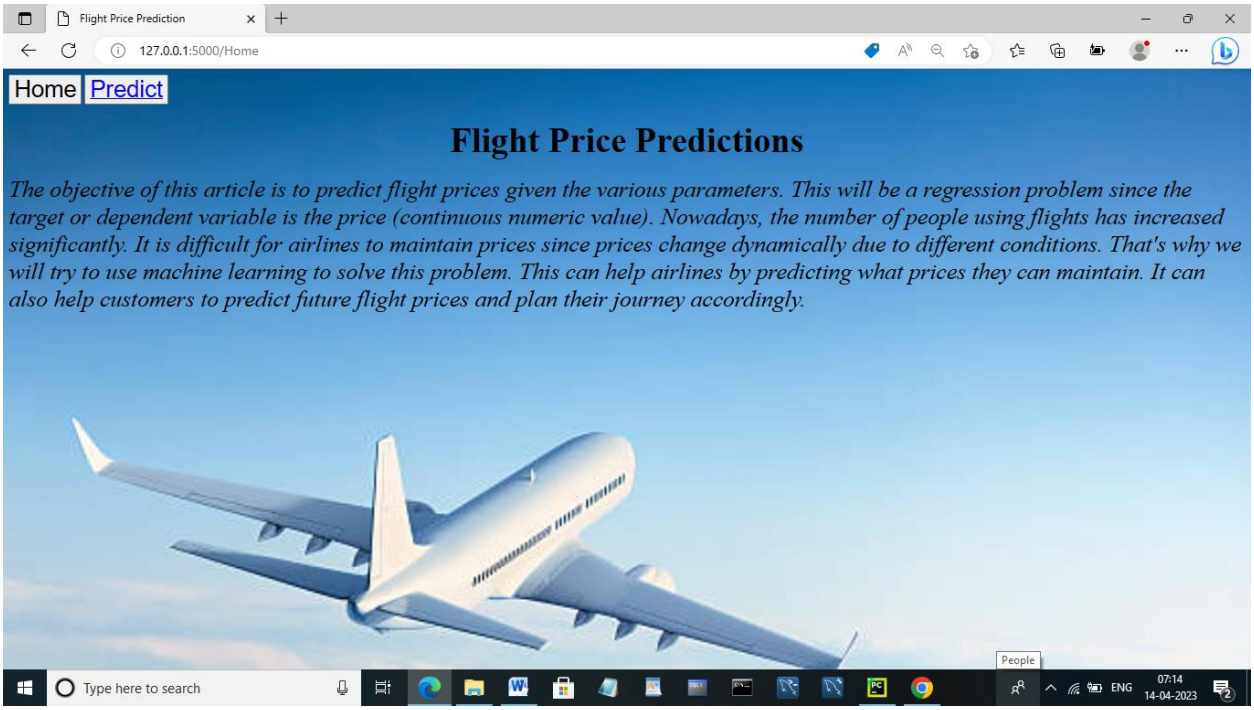


2.2 Ideation & Brainstorming Map

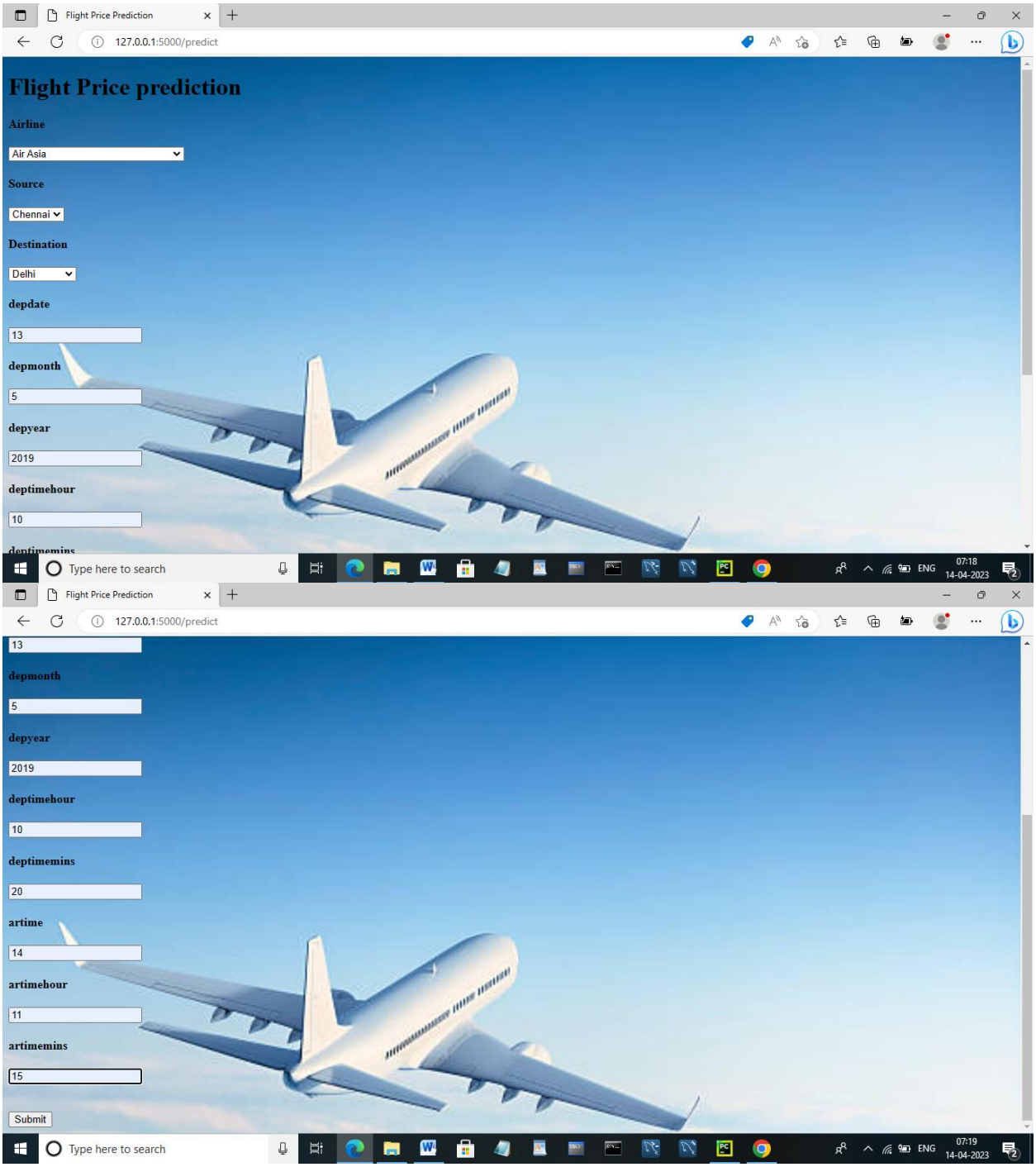


3. RESULT

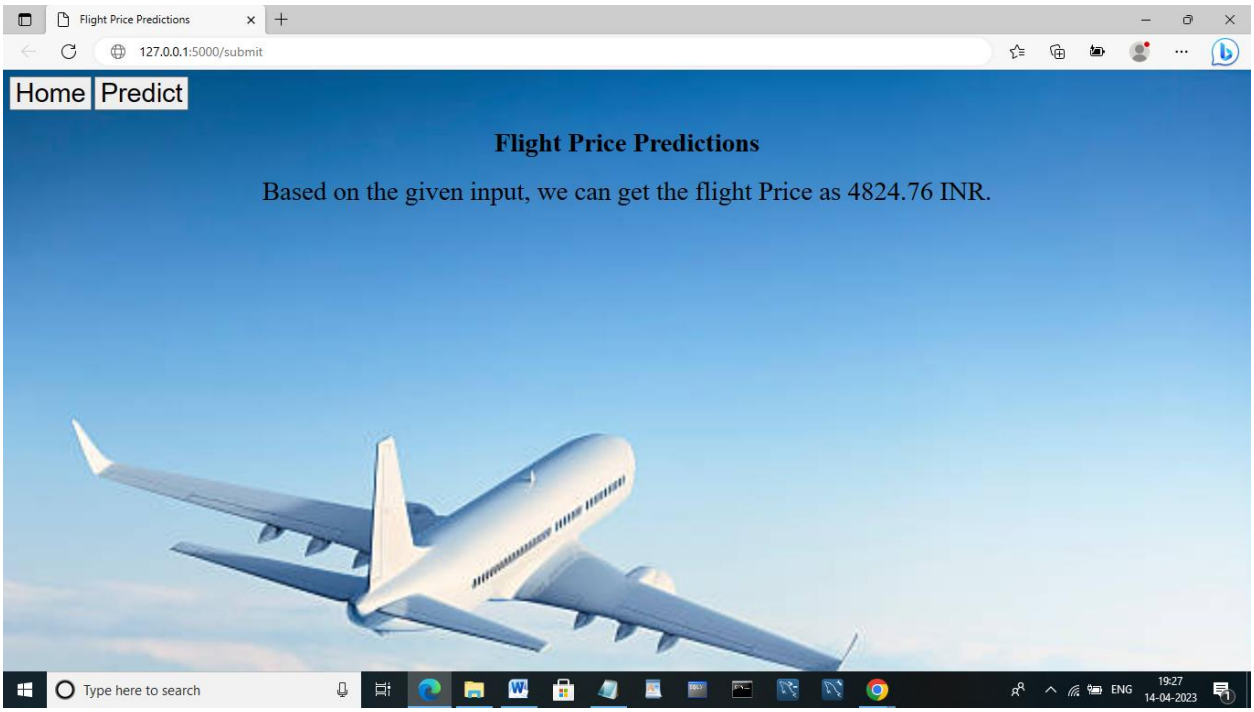
Home Page:



Predict page:



Submit Page (Final Output):



4. ADVANTAGES AND DISADVANTAGES

Advantages:

- Traveler get the fare prediction handy using which it's easy to decide the airlines.
- Saves time in searching/deciding for airlines.
- Flight price prediction tools can help you save money on your flights by alerting you to when the prices are expected to drop, allowing you to book your flights as the optimal time.
- Flight price prediction tools allow you to track multiple flights and airlines at once, so you can easily compare price and choose the best option for you.
- Rather than spending hours searching for the best deals on flights, you can use a flight price prediction tool to do the work for you, giving you more time to focus on planning the rest of your trip.
- If you have flexible travel dates, flight price prediction tools can help you find the cheapest times to travel, allowing you to adjust your plans accordingly.
- Knowing that you got the best deal possible on your flights can provide a sense of satisfaction and peace of mind, making your travel experience more enjoyable overall.

Disadvantages:

- Improper data will result in incorrect fare predictions.
- Flight price prediction tools use historical data and algorithms to predict future prices, but there are many factors that can influence the accuracy of these predictions, including unexpected events such as natural disasters or political unrest.
- Not all airlines or flights are covered by flight price prediction tools, so travelers may not be able to get accurate predictions for every flight they are interested in.
- Flight price prediction tools can provide travelers with information about when to book their flights, but they cannot control the actual prices or availability of flights. This means that even if a prediction suggests that prices will drop in the future, there is no guarantee that this will happen.
- Some travelers may become too reliant on flight price prediction tools and may miss out on good deals if they rely solely on these tools rather than actively searching for the best deals.
- Some flight price prediction tools may collect personal data from travelers, raising concerns about privacy and data protection.

5. APPLICATIONS

Flight price prediction has several applications for both individual travelers and travel companies:

- **Personal travel planning:** Individuals can use flight price prediction tools to find the best deals on flights for personal travel. By monitoring prices and predicting future changes, travelers can save money and plan their trips more effectively.

- **Business travel planning:** Companies can use flight price prediction tools to find the best deals on flights for business travel. This can help reduce travel costs and increase overall efficiency.

- **Travel agency services:** Travel agencies can use flight price predictions tools to offer their clients the best possible deals on flights. This can help increase customer satisfaction and loyalty.

- **Airline revenue management:** Airlines can use flight price prediction tools to adjust prices in real-time based on predicted demand. This can help airlines optimize revenue and increase profitability.

- **Tourism industry:** Flight price prediction tools can help the tourism industry plan and promote travel packages and events more effectively. By understanding future price changes, travel companies can tailor their offerings to meet the needs of their customers.

6. CONCLUSION

Evaluating the algorithmic rule, a dataset is collected, pre-processed, performed data modelling and studied a value difference for the number of restricted days by the passengers for travelling. Machine Learning algorithms with square measure for forecasting the accurate fare of airlines and it gives accurate value of plane price ticket at limited and highest value. Information is collected from Kaggle websites that sell the flight tickets therefore restricting data which are often accessed. The results obtained by the random forest and decision tree algorithm has better accuracy, but best accuracy is predicted by random Forest algorithm to fitting/split the train & test data, (x_train, y_train) accuracy= 93%, (x_test, y_test)accuracy = 77%.

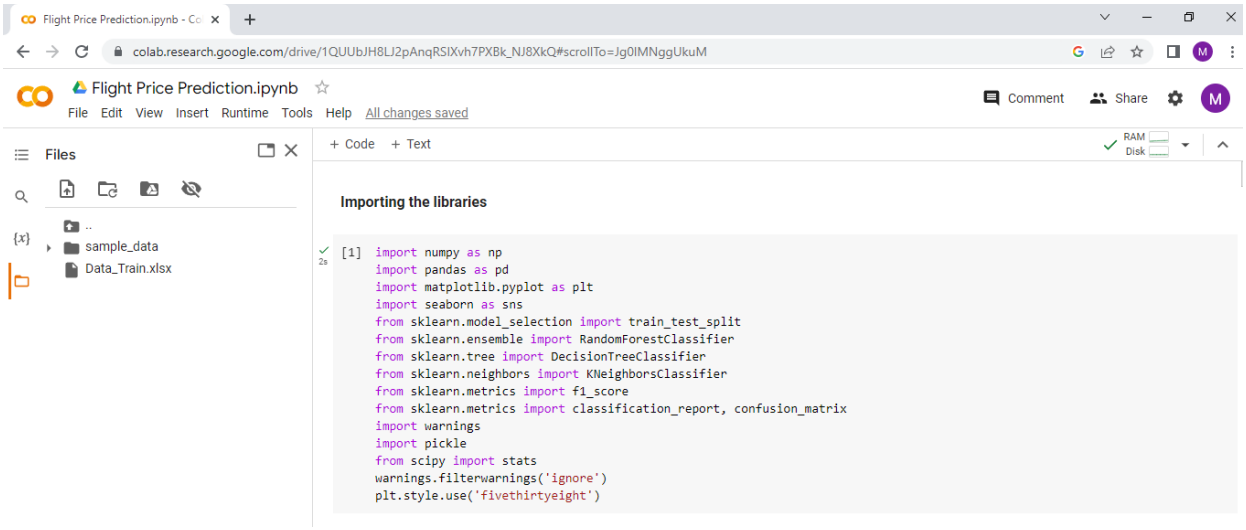
7. FUTURE SCOPE

In Upcoming days when huge amount of information is accessed as in detailed information in the dataset, the expected results in future are highly correct. For further research anyone desire to expand upon it ought to request different sources of historical data or be a lot of organized in collection knowledge manually over amount of your time to boot, a lot of different combination of plane are going to be traversed. There is whole possibility that planes differ their execution ideas consisting characteristics of the plane. At last, it is curious to match our model accuracy with that of the business models accuracy offered nowadays.

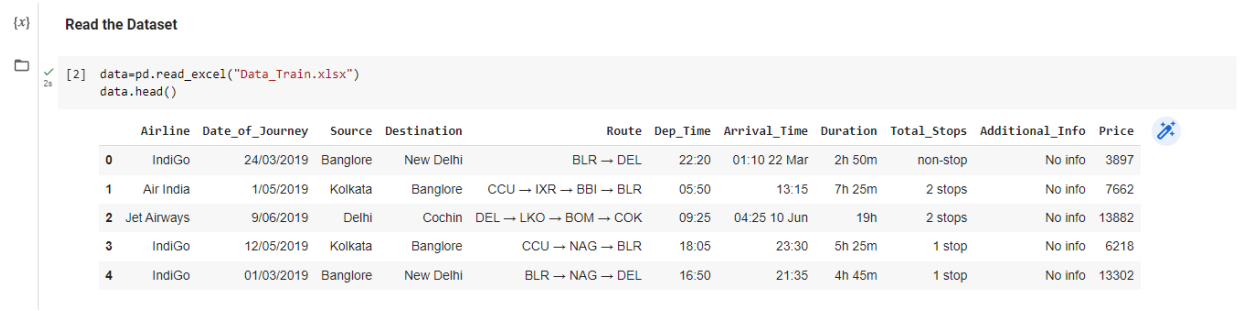
8. APPENDIX

A. Source Code :

Import the libraries:

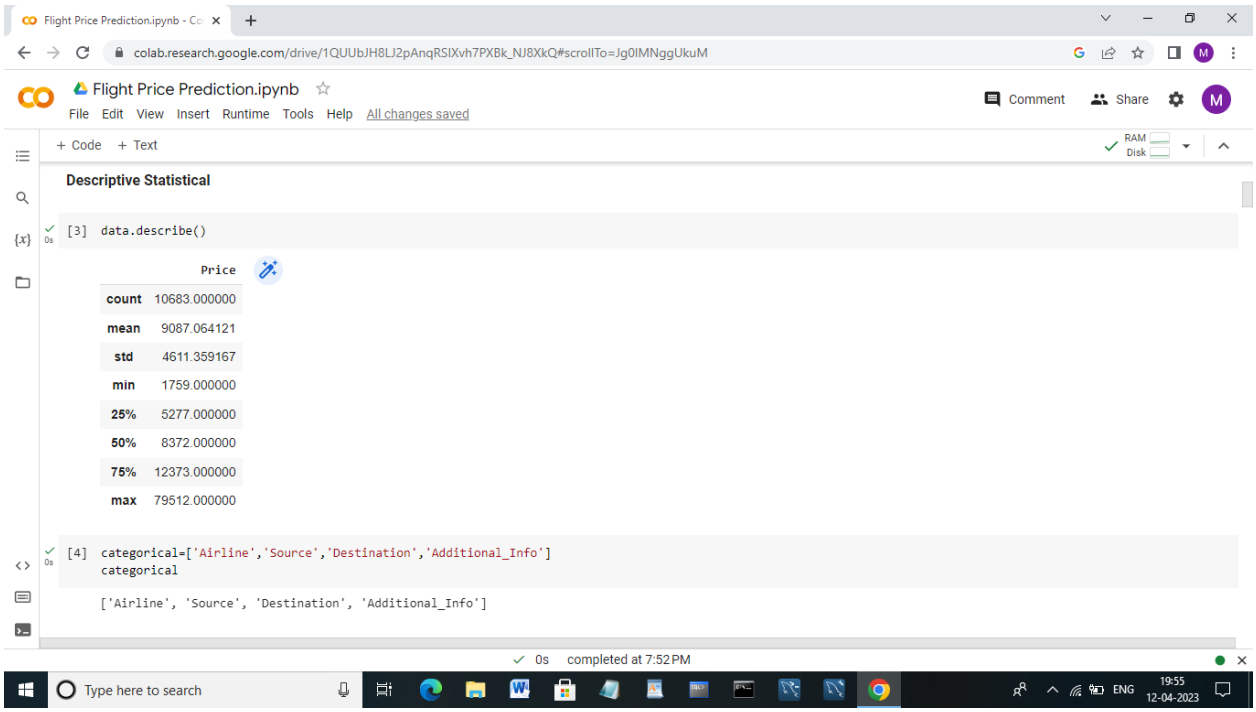


Read the data set:



	Airline	Date_of_Journey	Source	Destination	Route	Dep_Time	Arrival_Time	Duration	Total_Stops	Additional_Info	Price
0	IndiGo	24/03/2019	Banglore	New Delhi	BLR → DEL	22:20	01:10 22 Mar	2h 50m	non-stop	No info	3897
1	Air India	1/05/2019	Kolkata	Banglore	CCU → IXR → BBI → BLR	05:50	13:15	7h 25m	2 stops	No info	7662
2	Jet Airways	9/06/2019	Delhi	Cochin	DEL → LKO → BOM → COK	09:25	04:25 10 Jun	19h	2 stops	No info	13882
3	IndiGo	12/05/2019	Kolkata	Banglore	CCU → NAG → BLR	18:05	23:30	5h 25m	1 stop	No info	6218
4	IndiGo	01/03/2019	Banglore	New Delhi	BLR → NAG → DEL	16:50	21:35	4h 45m	1 stop	No info	13302

Descriptive Statistical:



Flight Price Prediction.ipynb

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Descriptive Statistical

```
[3] data.describe()
```

	Price
count	10683.000000
mean	9087.064121
std	4611.359167
min	1759.000000
25%	5277.000000
50%	8372.000000
75%	12373.000000
max	79512.000000

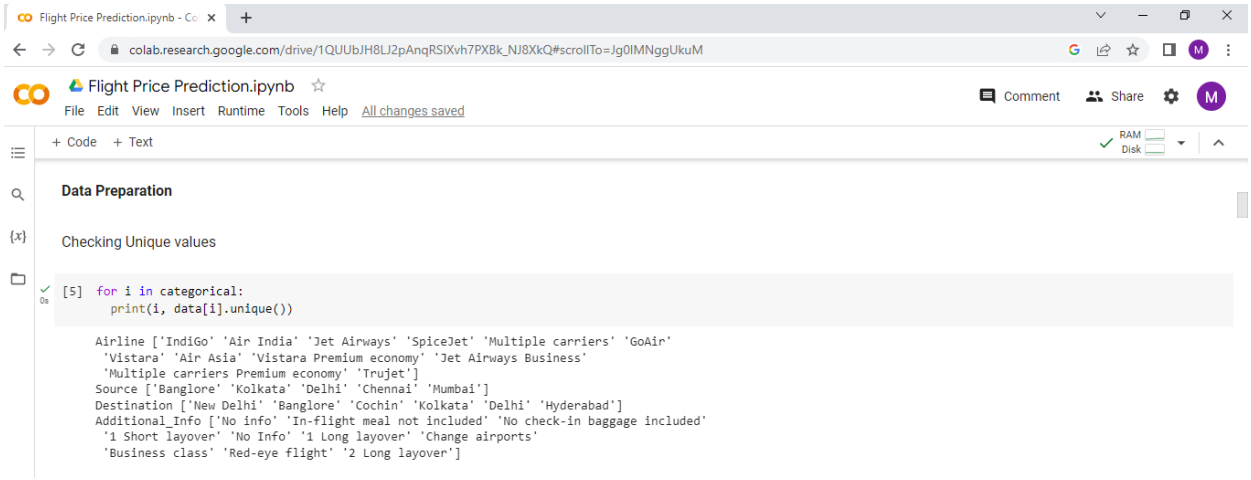
```
[4] categorical=['Airline','Source','Destination','Additional_Info']
    categorical
```

```
['Airline', 'Source', 'Destination', 'Additional_Info']
```

0s completed at 7:52 PM

Data Preparation:

Check the unique values:



Flight Price Prediction.ipynb

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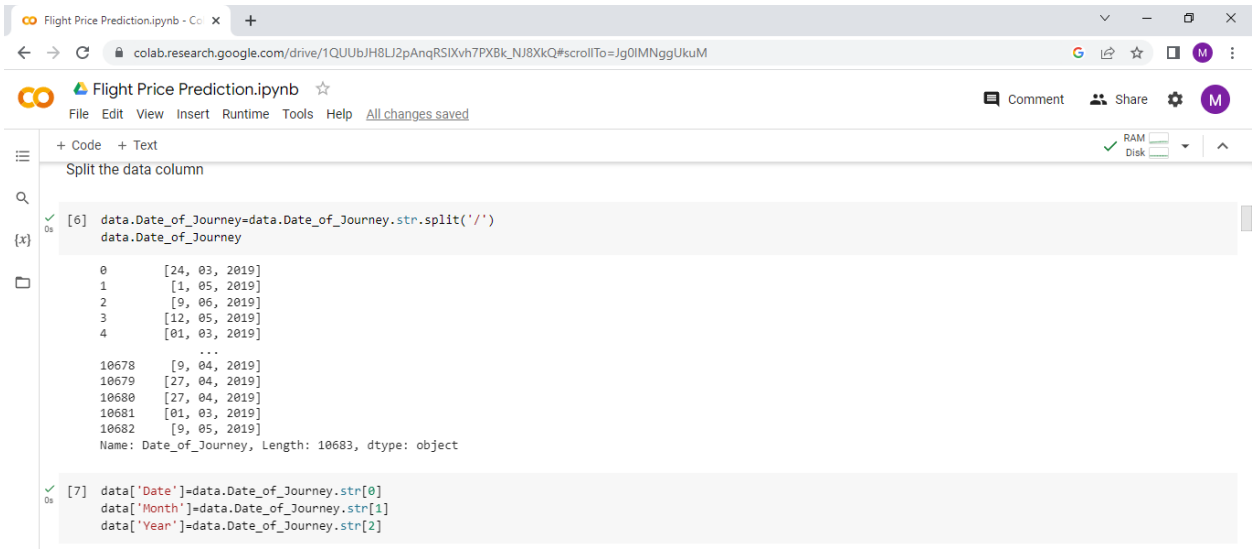
Data Preparation

Checking Unique values

```
[5] for i in categorical:
      print(i, data[i].unique())
```

```
Airline ['IndiGo' 'Air India' 'Jet Airways' 'SpiceJet' 'Multiple carriers' 'GoAir'
 'Vistara' 'Air Asia' 'Vistara Premium economy' 'Jet Airways Business'
 'Multiple carriers Premium economy' 'Trujet']
Source ['Banglore' 'Kolkata' 'Delhi' 'Chennai' 'Mumbai']
Destination ['New Delhi' 'Banglore' 'Cochin' 'Kolkata' 'Delhi' 'Hyderabad']
Additional_Info ['No info' 'In-flight meal not included' 'No check-in baggage included'
 '1 Short layover' 'No Info' '1 Long layover' 'Change airports'
 'Business class' 'Red-eye flight' '2 Long layover']
```

Split the data column:



Flight Price Prediction.ipynb - Co

colab.research.google.com/drive/1QUUbJH8LJ2pAnqRSIXvh7PXBk_NJ8XkQ#scrollTo=Jg0IMNggUkuM

Flight Price Prediction.ipynb

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RAM Disk

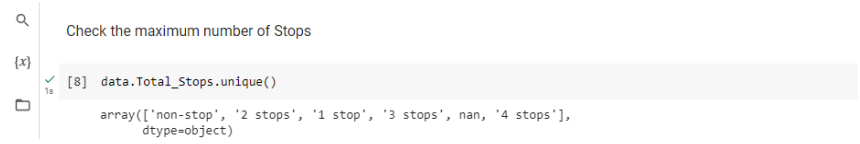
Split the data column

```
[6] data.Date_of_Journey=data.Date_of_Journey.str.split('/')
    data.Date_of_Journey
```

```
0        [24, 03, 2019]
1         [1, 05, 2019]
2         [9, 06, 2019]
3        [12, 05, 2019]
4        [01, 03, 2019]
              ...
10678     [9, 04, 2019]
10679    [27, 04, 2019]
10680    [27, 04, 2019]
10681    [01, 03, 2019]
10682     [9, 05, 2019]
Name: Date_of_Journey, Length: 10683, dtype: object
```

```
[7] data['Date']=data.Date_of_Journey.str[0]
    data['Month']=data.Date_of_Journey.str[1]
    data['Year']=data.Date_of_Journey.str[2]
```

Check the maximum Number of stops:

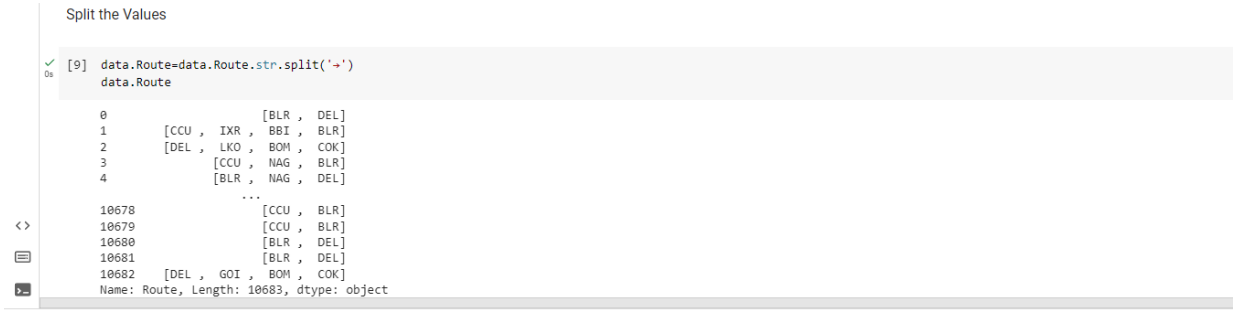


Check the maximum number of Stops

```
[8] data.Total_Stops.unique()
```

```
array(['non-stop', '2 stops', '1 stop', '3 stops', nan, '4 stops'],
      dtype=object)
```

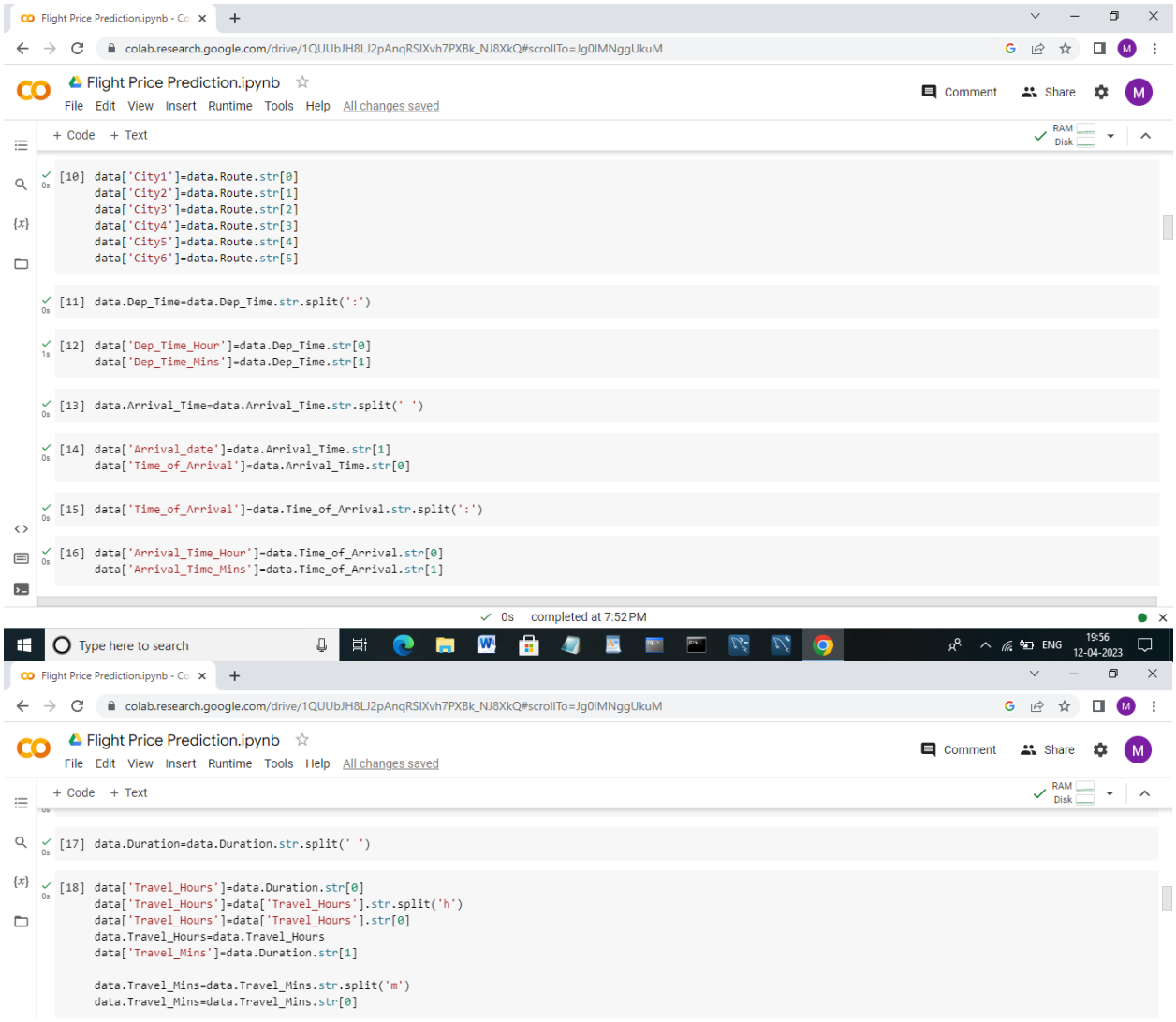
Split the Values:



Split the Values

```
[9] data.Route=data.Route.str.split('→')
    data.Route
```

```
0                   [BLR ,  DEL]
1           [CCU ,  IXR ,  BBI ,  BLR]
2           [DEL ,  LKO ,  BOM ,  COK]
3                 [CCU ,  NAG ,  BLR]
4                 [BLR ,  NAG ,  DEL]
                      ...
10678                 [CCU ,  BLR]
10679                 [CCU ,  BLR]
10680                 [BLR ,  DEL]
10681                 [BLR ,  DEL]
10682       [DEL ,  GOI ,  BOM ,  COK]
Name: Route, Length: 10683, dtype: object
```



Replace non-stop flights with o value:

Replace non-stop flights with 0 value

```
[19] data.Total_Stops.replace('non_stop',0,inplace=True)
     data.Total_Stops=data.Total_Stops.str.split(' ')
     data.Total_Stops=data.Total_Stops.str[0]
```

Check the additional information:

```
[20] data.Additional_Info.unique()

array(['No info', 'In-flight meal not included',
       'No check-in baggage included', '1 Short layover', 'No Info',
       '1 Long layover', 'Change airports', 'Business class',
       'Red-eye flight', '2 Long layover'], dtype=object)
```

```
[21] data.Additional_Info.replace('No Info','No Info',inplace=True)
```

Check the null values:

Check the null values

```
[ ] data.isnull().sum()

Airline               0
Date_of_Journey       0
Source                0
Destination           0
Route                 1
Dep_Time              0
Arrival_Time          0
Duration              0
Total_Stops           1
Additional_Info       0
Price                 0
Date                  0
Month                 0
Year                  0
City1                 1
City2                 1
City3              3492
City4              9117
City5             10637
City6             10682
Dep_Time_Hour         0
Dep_Time_Mins         0
Arrival_date       6348
Time_of_Arrival       0
Arrival_Time_Hour     0
Arrival_Time_Mins     0
Travel_Hours          0
Travel_Mins        1032
dtype: int64
```

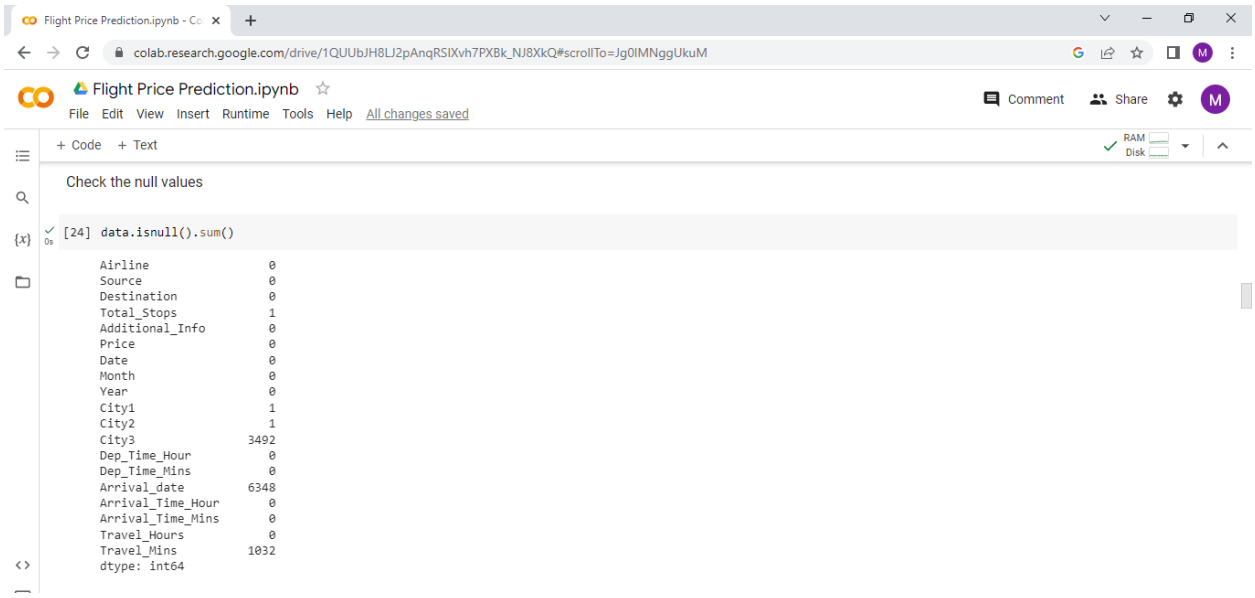
Drop the columns:

Drop the columns

```
[22] data.drop(['City4','City5','City6'],axis=1,inplace=True)
```

```
[23] data.drop(['Date_of_Journey','Route','Dep_Time','Arrival_Time','Duration'],axis=1,inplace=True)
     data.drop(['Time_of_Arrival'],axis=1,inplace=True)
```

Checking null values:



Flight Price Prediction.ipynb

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RAM Disk

Check the null values

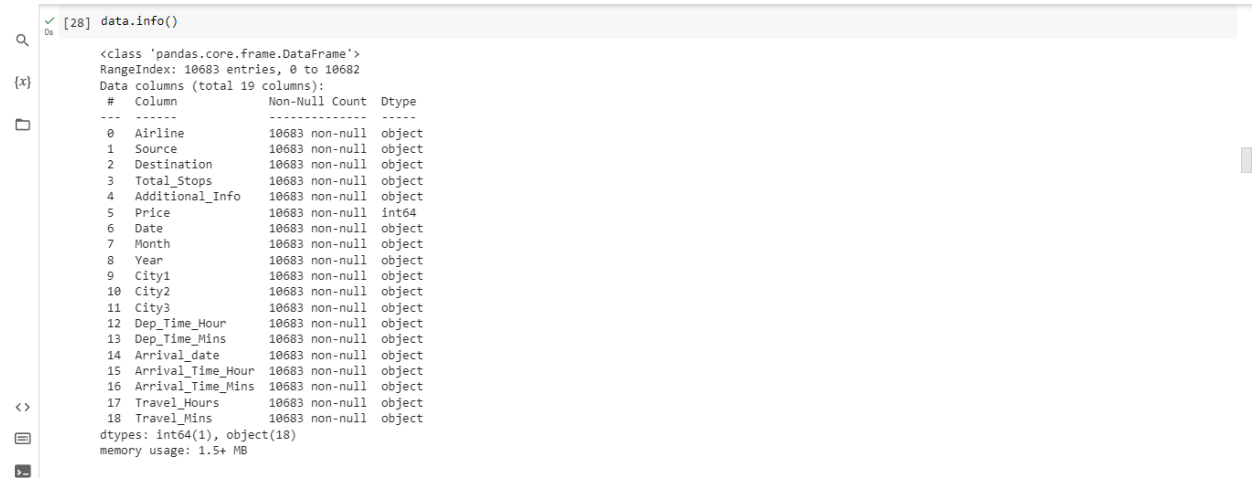
```
[24] data.isnull().sum()

Airline               0
Source                0
Destination           0
Total_Stops           1
Additional_Info       0
Price                 0
Date                  0
Month                 0
Year                  0
City1                 1
City2                 1
City3              3492
Dep_Time_Hour         0
Dep_Time_Mins         0
Arrival_date       6348
Arrival_Time_Hour     0
Arrival_Time_Mins     0
Travel_Hours          0
Travel_Mins        1032
dtype: int64
```

Replacing missing values:

Replacing missing values

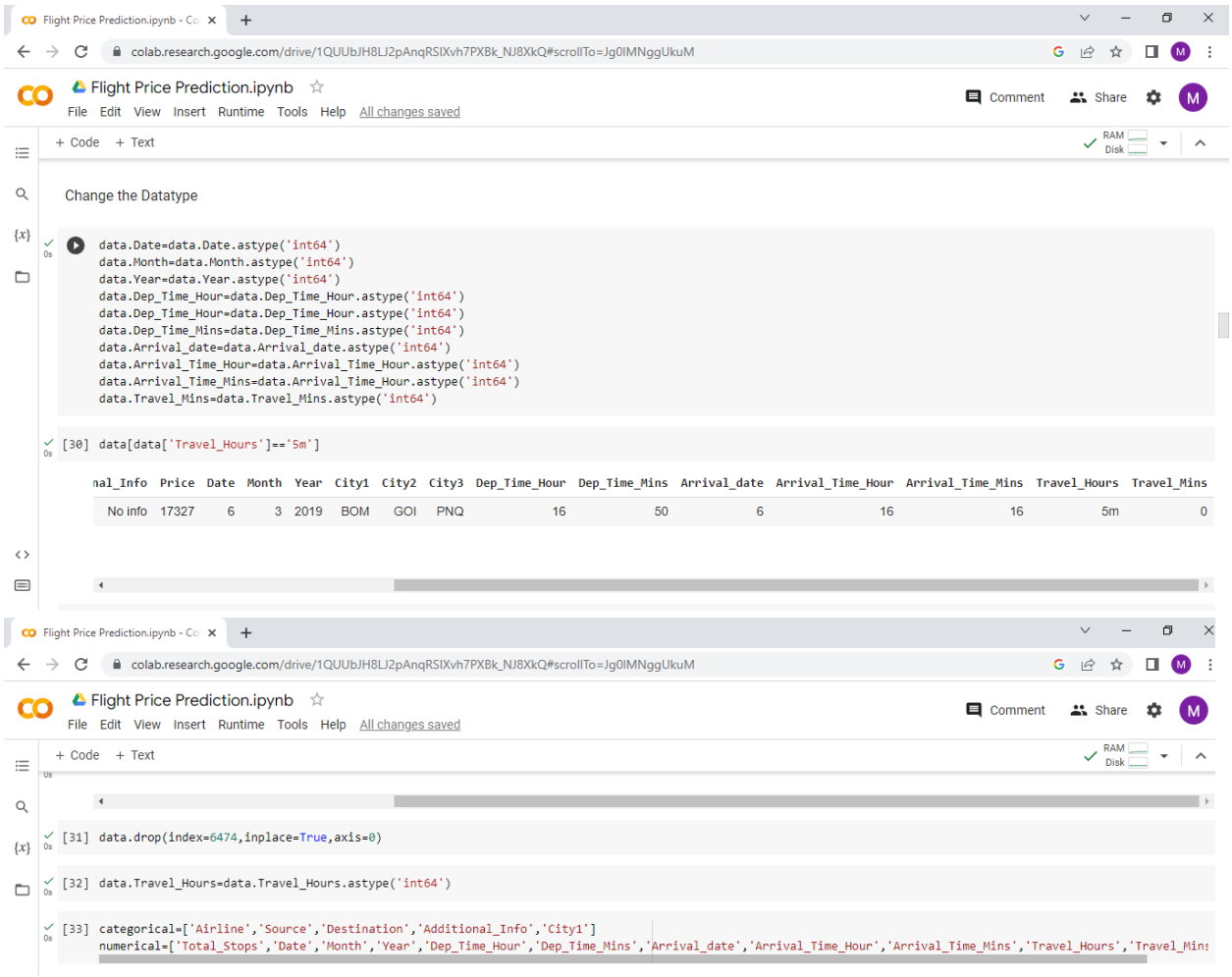
```
[25] data['City1'].fillna('None',inplace=True)
     data['City2'].fillna('None',inplace=True)
     data['City3'].fillna('None',inplace=True)
     data['Total_Stops'].fillna('None',inplace=True)

[26] data['Arrival_date'].fillna(data['Date'],inplace=True)

[27] data['Travel_Mins'].fillna(0,inplace=True)
```

Check Info:



```
[28] data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10683 entries, 0 to 10682
Data columns (total 19 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Airline            10683 non-null  object
 1   Source             10683 non-null  object
 2   Destination        10683 non-null  object
 3   Total_Stops        10683 non-null  object
 4   Additional_Info    10683 non-null  object
 5   Price              10683 non-null  int64
 6   Date               10683 non-null  object
 7   Month              10683 non-null  object
 8   Year               10683 non-null  object
 9   City1              10683 non-null  object
 10  City2              10683 non-null  object
 11  City3              10683 non-null  object
 12  Dep_Time_Hour      10683 non-null  object
 13  Dep_Time_Mins      10683 non-null  object
 14  Arrival_date       10683 non-null  object
 15  Arrival_Time_Hour  10683 non-null  object
 16  Arrival_Time_Mins  10683 non-null  object
 17  Travel_Hours       10683 non-null  object
 18  Travel_Mins        10683 non-null  object
dtypes: int64(1), object(18)
memory usage: 1.5+ MB
```

Change the Datatype:



Label Encoding:

Label Encoding

```
[34] from sklearn.preprocessing import LabelEncoder
     le=LabelEncoder()
```

```
[35] data.Airline=le.fit_transform(data.Airline)
     data.Source=le.fit_transform(data.Source)
     data.Destination=le.fit_transform(data.Destination)
     data.Total_Stops=le.fit_transform(data.Total_Stops)
     data.City1=le.fit_transform(data.City1)
     data.City2=le.fit_transform(data.City2)
     data.City3=le.fit_transform(data.City3)
     data.Additional_Info=le.fit_transform(data.Additional_Info)
     data.head()
```

	Airline	Source	Destination	Total_Stops	Additional_Info	Price	Date	Month	Year	City1	City2	City3	Dep_Time_Hour	Dep_Time_Mins	Arrival_date	Arrival_T
0	3	0	5	5	8	3897	24	3	2019	0	13	29	22	20	22	
1	1	3	0	1	8	7662	1	5	2019	2	25	1	5	50	1	
2	4	2	1	1	8	13882	9	6	2019	3	32	4	9	25	10	
3	3	3	0	0	8	6218	12	5	2019	2	34	3	18	5	12	
4	3	0	5	0	8	13302	1	3	2019	0	34	8	16	50	1	

```
[36] data.head()
```

	Airline	Source	Destination	Total_Stops	Additional_Info	Price	Date	Month	Year	City1	City2	City3	Dep_Time_Hour	Dep_Time_Mins	Arrival_date	Arrival_T
0	3	0	5	5	8	3897	24	3	2019	0	13	29	22	20	22	
1	1	3	0	1	8	7662	1	5	2019	2	25	1	5	50	1	
2	4	2	1	1	8	13882	9	6	2019	3	32	4	9	25	10	
3	3	3	0	0	8	6218	12	5	2019	2	34	3	18	5	12	
4	3	0	5	0	8	13302	1	3	2019	0	34	8	16	50	1	

Output columns:

Output Columns

```
[37] data.head()
```

	Airline	Source	Destination	Total_Stops	Additional_Info	Price	Date	Month	Year	City1	City2	City3	Dep_Time_Hour	Dep_Time_Mins	Arrival_date	Arrival_T
0	3	0	5	5	8	3897	24	3	2019	0	13	29	22	20	22	
1	1	3	0	1	8	7662	1	5	2019	2	25	1	5	50	1	
2	4	2	1	1	8	13882	9	6	2019	3	32	4	9	25	10	
3	3	3	0	0	8	6218	12	5	2019	2	34	3	18	5	12	
4	3	0	5	0	8	13302	1	3	2019	0	34	8	16	50	1	

Descriptive Statistical:

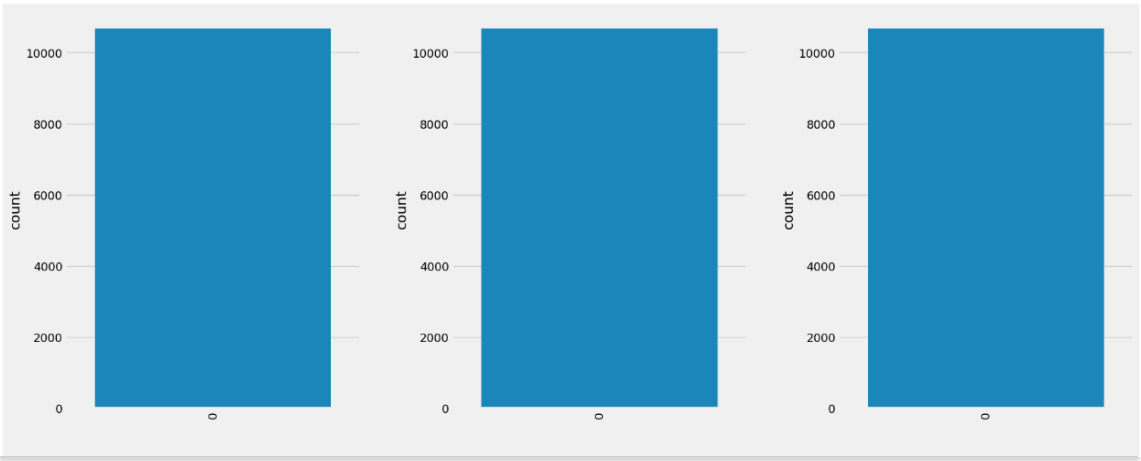
Visual Analysis:

Descriptive statistical

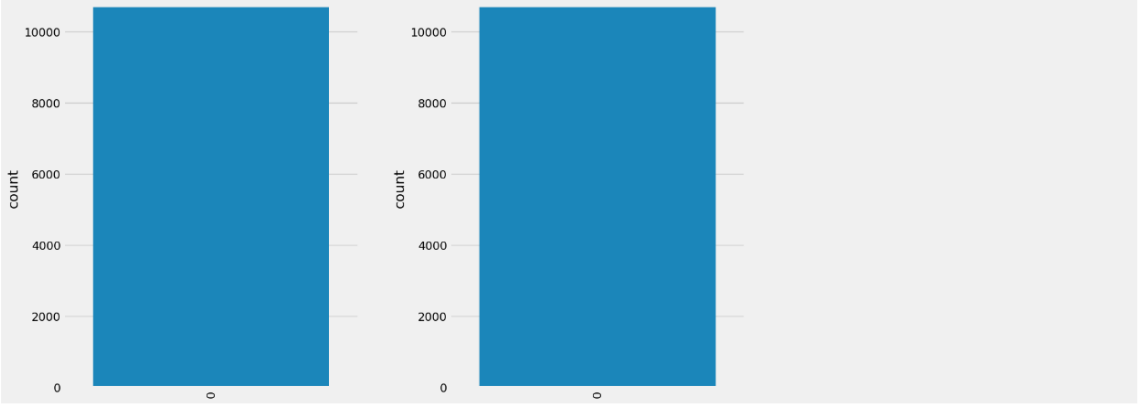
Visual analysis

```
[38] c=1
     plt.figure(figsize=(20,45))

     for i in categorical:
       plt.subplot(6,3,c)
       sns.countplot(data[i])
       plt.xticks(rotation=90)
       plt.tight_layout(pad=3.0)
       c=c+1

     plt.show()
```

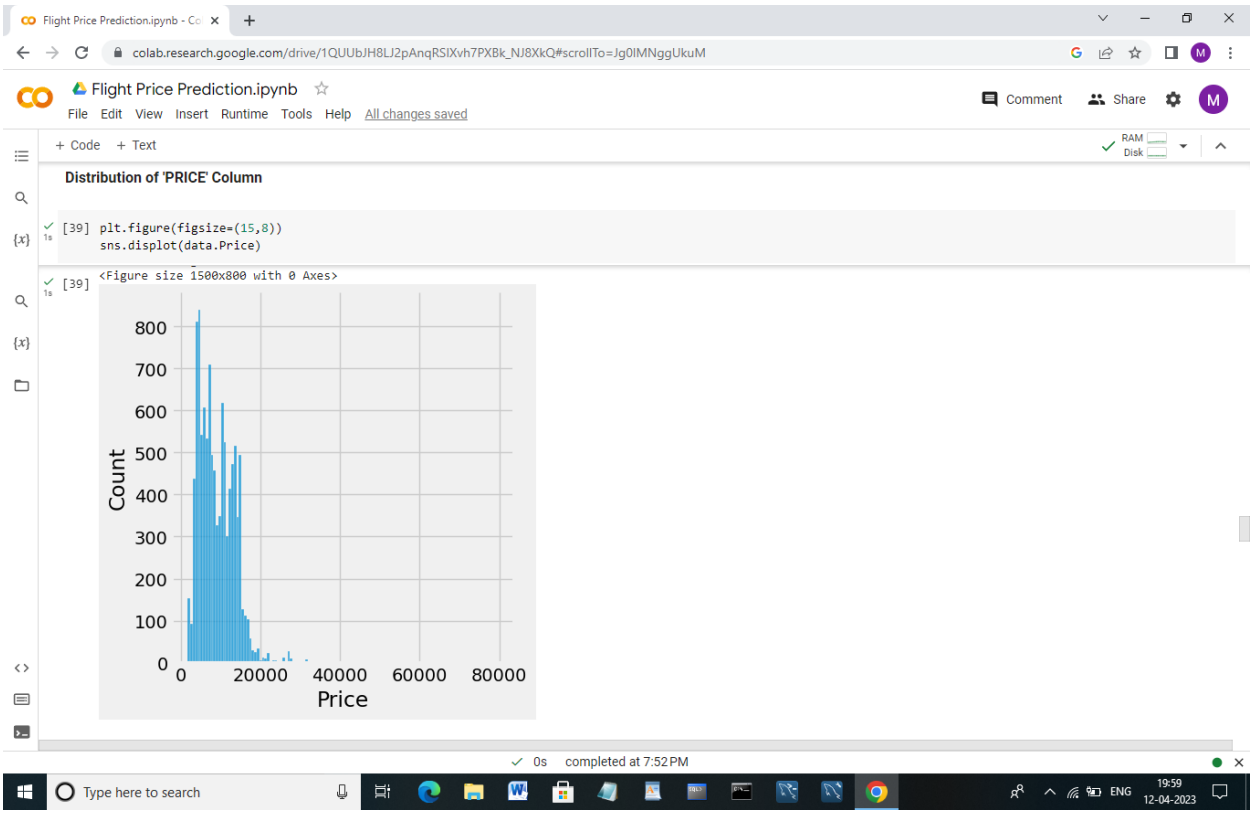
[38]



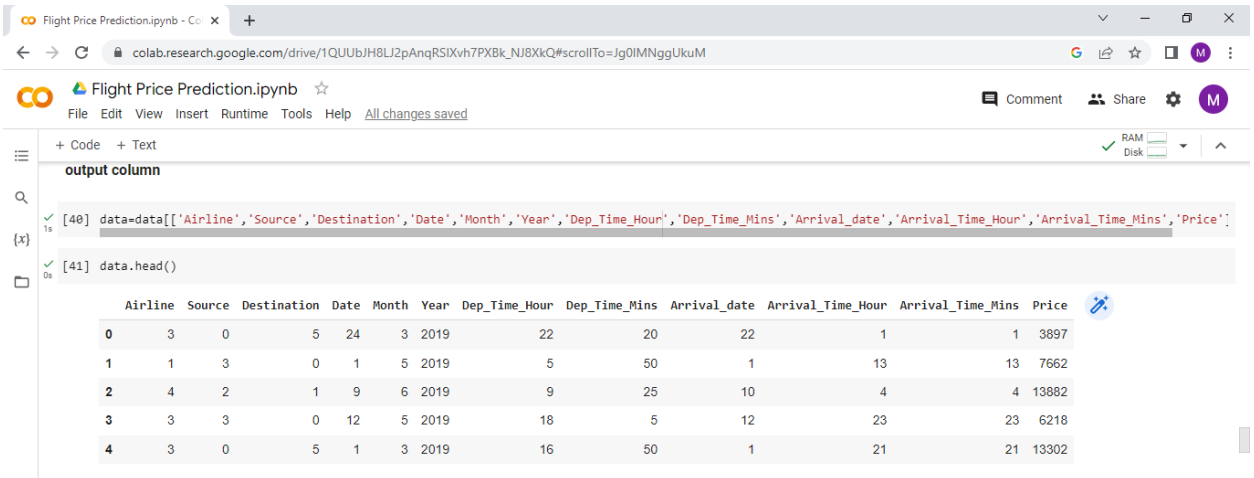
[38]



Distribution of ‘PRICE’ Column:

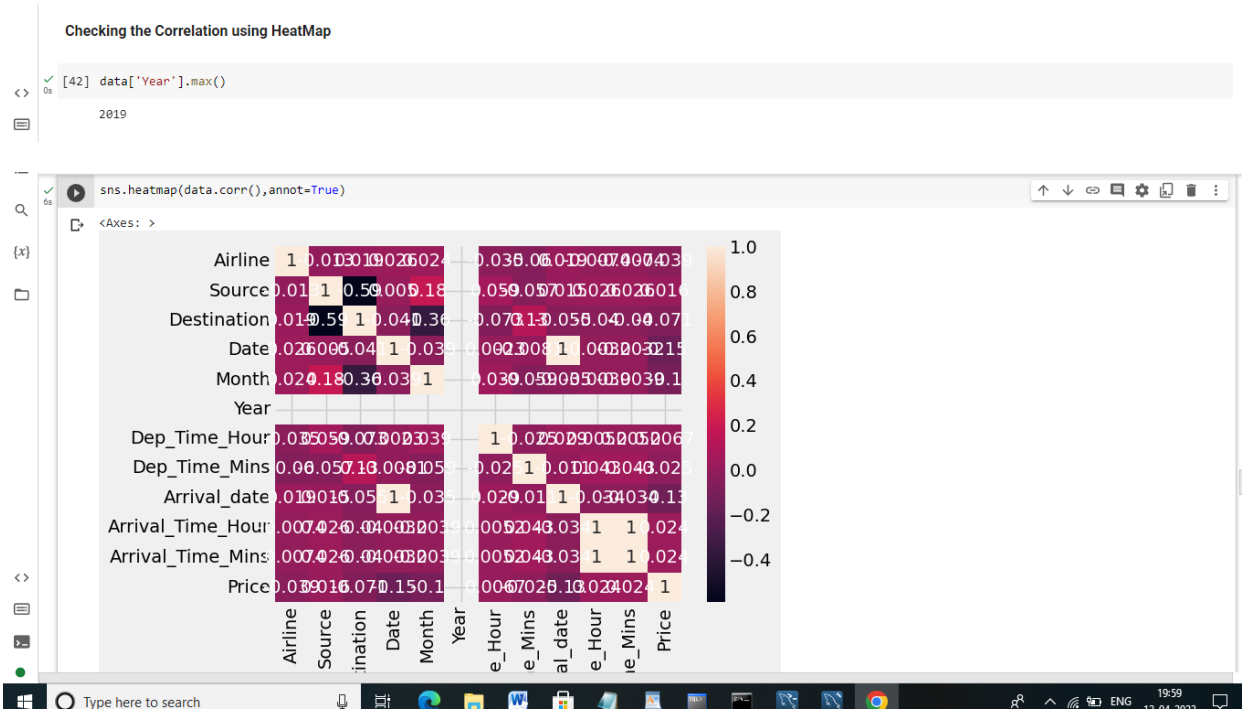


Output Column:

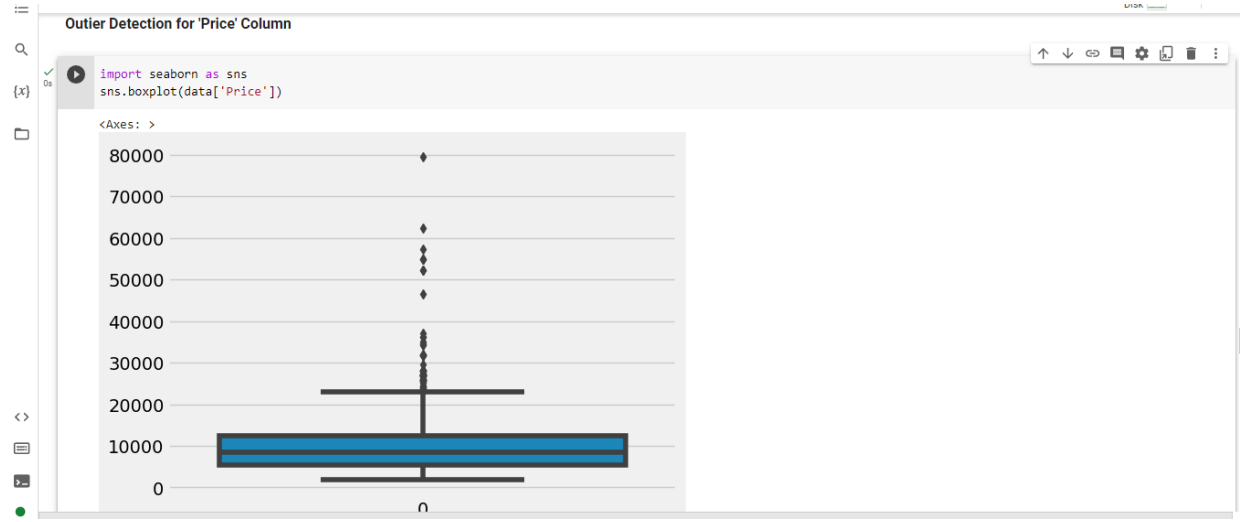


	Airline	Source	Destination	Date	Month	Year	Dep_Time_Hour	Dep_Time_Mins	Arrival_date	Arrival_Time_Hour	Arrival_Time_Mins	Price
0	3	0	5	24	3	2019	22	20	22	1	1	3897
1	1	3	0	1	5	2019	5	50	1	13	13	7662
2	4	2	1	9	6	2019	9	25	10	4	4	13882
3	3	3	0	12	5	2019	18	5	12	23	23	6218
4	3	0	5	1	3	2019	16	50	1	21	21	13302

Checking the correlation using HeatMap:



Outlier Detection for ‘PRICE’ column:



Scaling the data:

Scaling the Data

```
[45] y=data['Price']
     x=data.drop(columns=['Price'],axis=1)
```

```
[46] from sklearn.preprocessing import StandardScaler
     ss=StandardScaler()
```

```
[47] x_scaled=ss.fit_transform(x)
```

```
[48] x_scaled=pd.DataFrame(x_scaled,columns=x.columns)
     x_scaled.head()
```

	Airline	Source	Destination	Date	Month	Year	Dep_Time_Hour	Dep_Time_Mins	Arrival_date	Arrival_Time_Hour	Arrival_Time_Mins
0	-0.410805	-1.658435	2.416778	1.237288	-1.467707	0.0	1.654268	-0.234932	0.955750	-1.800319	-1.800319
1	-1.261152	0.890299	-0.973732	-1.475307	0.250153	0.0	-1.303000	1.363674	-1.524648	-0.050813	-0.050813
2	0.014369	0.040721	-0.295630	-0.531796	1.109082	0.0	-0.607172	0.031502	-0.461621	-1.362943	-1.362943
3	-0.410805	0.890299	-0.973732	-0.177979	0.250153	0.0	0.958440	-1.034235	-0.225392	1.407109	1.407109
4	-0.410805	-1.658435	2.416778	-1.475307	-1.467707	0.0	0.610527	1.363674	-1.524648	1.115525	1.115525

Splitting data into train and test:

Splitting data into train and test

```
[49] from sklearn.model_selection import train_test_split
     x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=42)
```

```
[50] x_train.head()
```

	Airline	Source	Destination	Date	Month	Year	Dep_Time_Hour	Dep_Time_Mins	Arrival_date	Arrival_Time_Hour	Arrival_Time_Mins
10005	6	2	1	27	5	2019	8	30	27	19	19
3684	4	2	1	9	5	2019	11	30	10	12	12
1034	8	2	1	24	4	2019	15	45	24	22	22
3909	6	2	1	21	3	2019	12	50	22	1	1
3088	1	2	1	24	6	2019	17	15	25	19	19

Using Ensemble techniques:

Using Ensemble Technique

```
[51] from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor, AdaBoostRegressor
     rfr=RandomForestRegressor()
     gb=GradientBoostingRegressor()
     ad=AdaBoostRegressor()
```

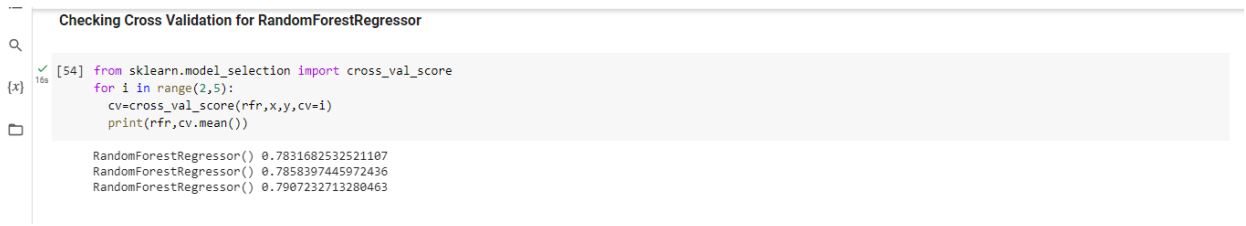
```
[52] from sklearn.metrics import r2_score,mean_absolute_error,mean_squared_error

     for i in [rfr,gb,ad]:
       i.fit(x_train,y_train)
       y_pred=i.predict(x_test)
       test_score=r2_score(y_test,y_pred)
       train_score=r2_score(y_train,i.predict(x_train))
       if abs(train_score-test_score)<=0.2:
         print(i)

         print("R2 score is",r2_score(y_test,y_pred))
         print("R2 for train data",r2_score(y_train,i.predict(x_train)))
         print("Mean Absolute Error is",mean_absolute_error(y_pred,y_test))
         print("Mean Squared Error is",mean_squared_error(y_pred,y_test))
         print("Root Mean Squared Error is",(mean_squared_error(y_pred,y_test,squared=False)))

RandomForestRegressor()
R2 score is 0.8412340005067588
R2 for train data 0.9469745512589411
Mean Absolute Error is 1227.442066923497
Mean Squared Error is 3356157.945718379
Root Mean Squared Error is 1831.9819719960071
GradientBoostingRegressor()
R2 score is 0.7659806545178971
R2 for train data 0.730149720400205
Mean Absolute Error is 1687.5222333706563
Mean Squared Error is 4946940.077210986
Root Mean Squared Error is 2224.171773314954
```

Regression Model:

Regression Model

```
[53] from sklearn.neighbors import KNeighborsRegressor
     from sklearn.svm import SVR
     from sklearn.tree import DecisionTreeRegressor

     from sklearn.metrics import r2_score,mean_absolute_error,mean_squared_error

     knn=KNeighborsRegressor()
     svr=SVR()
     dt=DecisionTreeRegressor()

     for i in [knn,svr,dt]:
       i.fit(x_train,y_train)
       y_pred=i.predict(x_test)
       test_score=r2_score(y_test,y_pred)
       train_score=r2_score(y_train,i.predict(x_train))
       if abs(train_score-test_score)<=0.1:
         print(i)

         print("R2 score is",r2_score(y_test,y_pred))
         print("R2 for train data",r2_score(y_train,i.predict(x_train)))
         print("Mean Absolute Error is",mean_absolute_error(y_test,y_pred))
         print("Mean Squared Error is",mean_squared_error(y_test,y_pred))
         print("Root Mean Squared Error is",(mean_squared_error(y_test,y_pred,squared=False)))

SVR()
R2 score is -0.03013111523471812
R2 for train data -0.023072501115390276
Mean Absolute Error is 3629.626247681
Mean Squared Error is 21775964.240214497
Root Mean Squared Error is 4666.4723550252065
```

Checking cross validation for RandomForestRegressor:



Checking Cross Validation for RandomForestRegressor

```
[54] from sklearn.model_selection import cross_val_score
     for i in range(2,5):
       cv=cross_val_score(rfr,x,y,cv=i)
       print(rfr,cv.mean())
```

```
RandomForestRegressor() 0.7831682532521107
RandomForestRegressor() 0.7858397445972436
RandomForestRegressor() 0.7907232713280463
```

Hypertuning the Model:

Hypertuning the model

```
[55] from sklearn.model_selection import RandomizedSearchCV
```

```
[56] param_grid={'n_estimators':[10,30,50,70,100],'max_depth':[None,1,2,3],'max_features':['auto','sqrt']}
     rfr=RandomForestRegressor()
     rf_res=RandomizedSearchCV(estimator=rfr,param_distributions=param_grid,cv=3,verbose=2,n_jobs=-1)

     rf_res.fit(x_train,y_train)
```

```
[56] Fitting 3 folds for each of 10 candidates, totalling 30 fits
RandomizedSearchCV(cv=3, estimator=RandomForestRegressor(), n_jobs=-1,
                   param_distributions={'max_depth': [None, 1, 2, 3],
                                        'max_features': ['auto', 'sqrt'],
                                        'n_estimators': [10, 30, 50, 70, 100]},
                   verbose=2)
  estimator: RandomForestRegressor
    RandomForestRegressor
```

```
[57] gb=GradientBoostingRegressor()
     gb_res=RandomizedSearchCV(estimator=gb,param_distributions=param_grid,cv=3,verbose=2,n_jobs=-1)

     gb_res.fit(x_train,y_train)
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
RandomizedSearchCV(cv=3, estimator=GradientBoostingRegressor(), n_jobs=-1,
                   param_distributions={'max_depth': [None, 1, 2, 3],
                                        'max_features': ['auto', 'sqrt'],
                                        'n_estimators': [10, 30, 50, 70, 100]},
                   verbose=2)
  estimator: GradientBoostingRegressor
    GradientBoostingRegressor
```

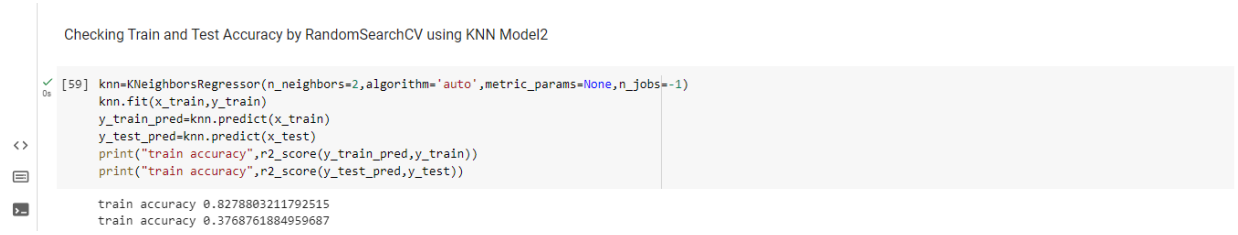
Accuracy:

Accuracy

```
[58] rfr=RandomForestRegressor(n_estimators=10,max_features='sqrt',max_depth=None)
     rfr.fit(x_train,y_train)
     y_train_pred=rfr.predict(x_train)
     y_test_pred=rfr.predict(x_test)
     print("train accuracy",r2_score(y_train_pred,y_train))
     print("train accuracy",r2_score(y_test_pred,y_test))
```

```
train accuracy 0.9226894111129454
train accuracy 0.7530453919241885
```

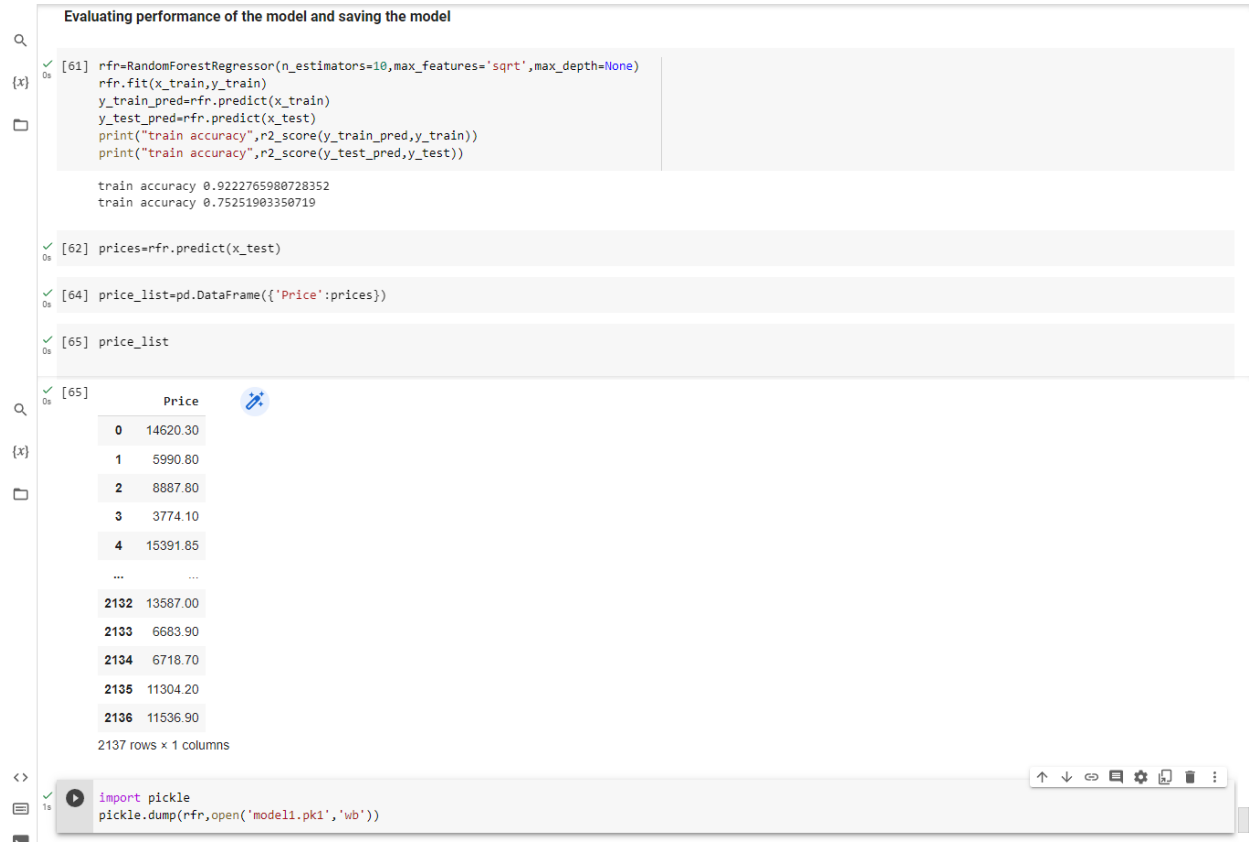
Checking Train and Test Accuracy by RandomSearch using KNN Model2:



Checking Train and Test Accuracy by RandomSearchCV using KNN Model2

```
[59] knn=KNeighborsRegressor(n_neighbors=2,algorithm='auto',metric_params=None,n_jobs=-1)
     knn.fit(x_train,y_train)
     y_train_pred=knn.predict(x_train)
     y_test_pred=knn.predict(x_test)
     print("train accuracy",r2_score(y_train_pred,y_train))
     print("train accuracy",r2_score(y_test_pred,y_test))

     train accuracy 0.8278803211792515
     train accuracy 0.3768761884959687
```

Evaluating performance of the model and saving the model:



Evaluating performance of the model and saving the model

```
[61] rfr=RandomForestRegressor(n_estimators=10,max_features='sqrt',max_depth=None)
     rfr.fit(x_train,y_train)
     y_train_pred=rfr.predict(x_train)
     y_test_pred=rfr.predict(x_test)
     print("train accuracy",r2_score(y_train_pred,y_train))
     print("train accuracy",r2_score(y_test_pred,y_test))

     train accuracy 0.9222765980728352
     train accuracy 0.75251903350719
```

```
[62] prices=rfr.predict(x_test)
```

```
[64] price_list=pd.DataFrame({'Price':prices})
```

```
[65] price_list
```

[65]

	Price
0	14620.30
1	5990.80
2	8887.80
3	3774.10
4	15391.85
...	...
2132	13587.00
2133	6683.90
2134	6718.70
2135	11304.20
2136	11536.90

2137 rows × 1 columns

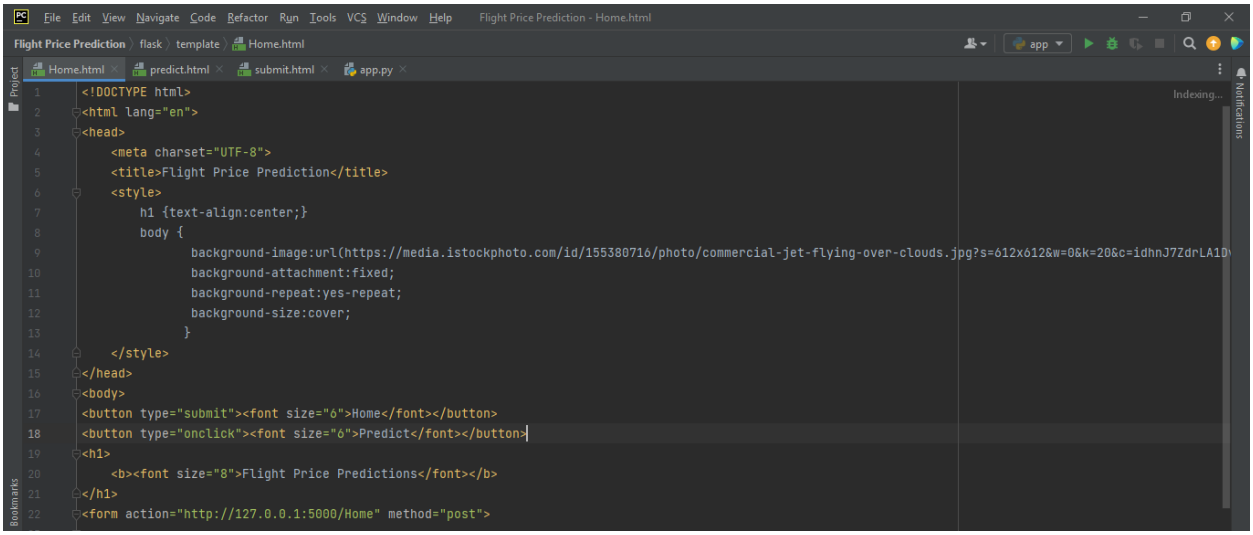
```
import pickle
pickle.dump(rfr,open('model1.pk1','wb'))
```

Save the best model:

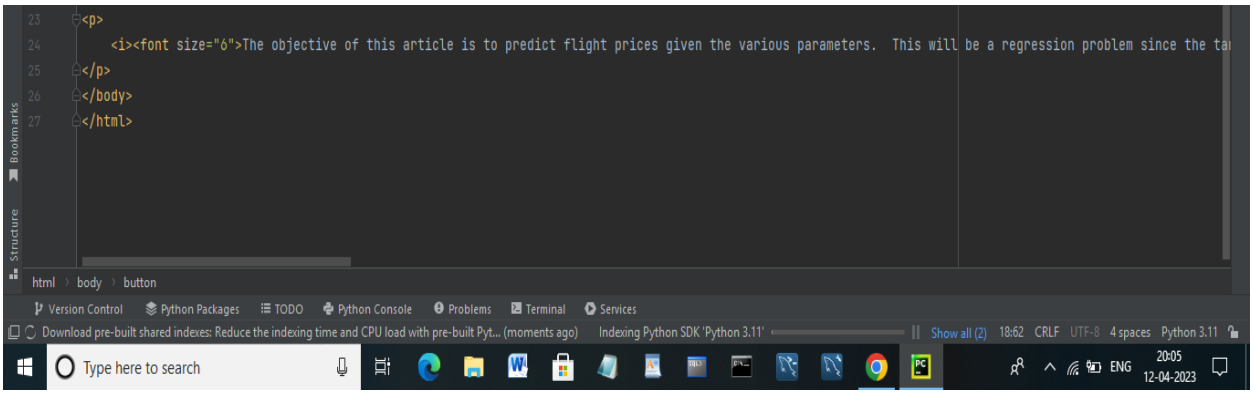
Save the best model

```
[67] import pickle
     pickle.dump(rfr,open('model1.pk1','wb'))
```

Home.html:

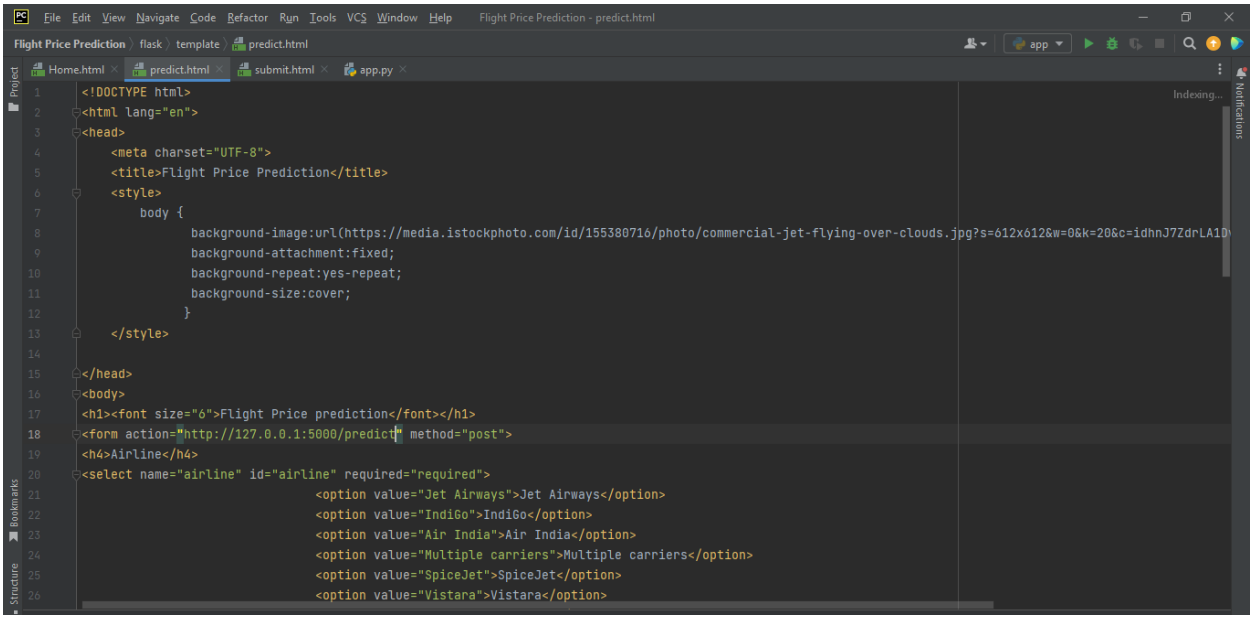


```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <title>Flight Price Prediction</title>
    <style>
        h1 {text-align:center;}
        body {
              background-image:url(https://media.istockphoto.com/id/155380716/photo/commercial-jet-flying-over-clouds.jpg?s=612x612&w=0&k=20&c=idhnJ7ZdrLA1
              background-attachment:fixed;
              background-repeat:yes-repeat;
              background-size:cover;
             }
    </style>
</head>
<body>
<button type="submit"><font size="6">Home</font></button>
<button type="onclick"><font size="6">Predict</font></button>
<h1>
    <b><font size="8">Flight Price Predictions</font></b>
</h1>
<form action="http://127.0.0.1:5000/Home" method="post">
```

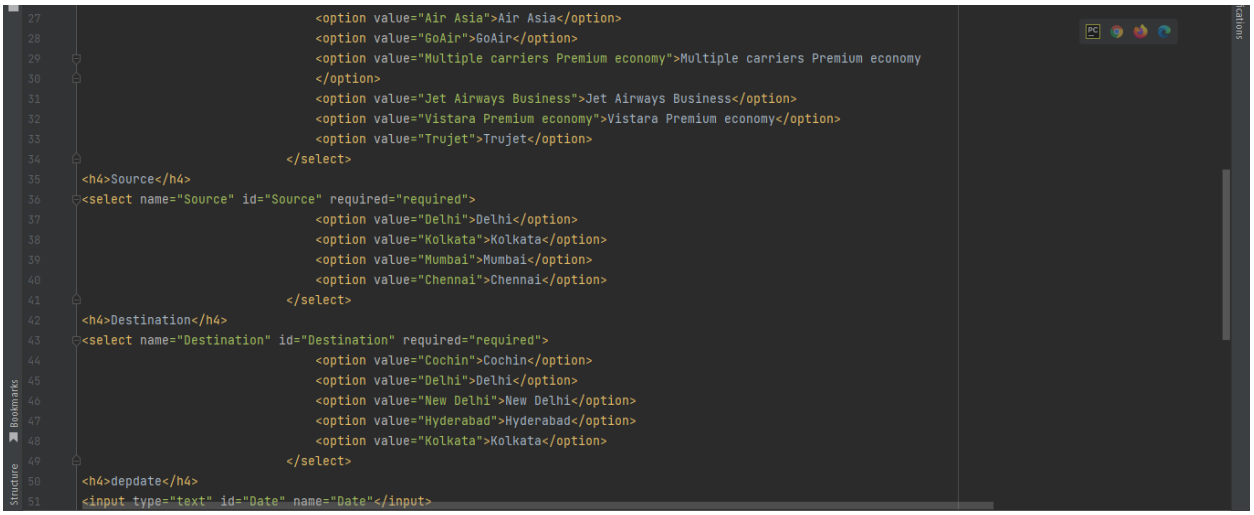


```
<p>
    <i><font size="6">The objective of this article is to predict flight prices given the various parameters.  This will be a regression problem since the ta
</p>
</body>
</html>
```

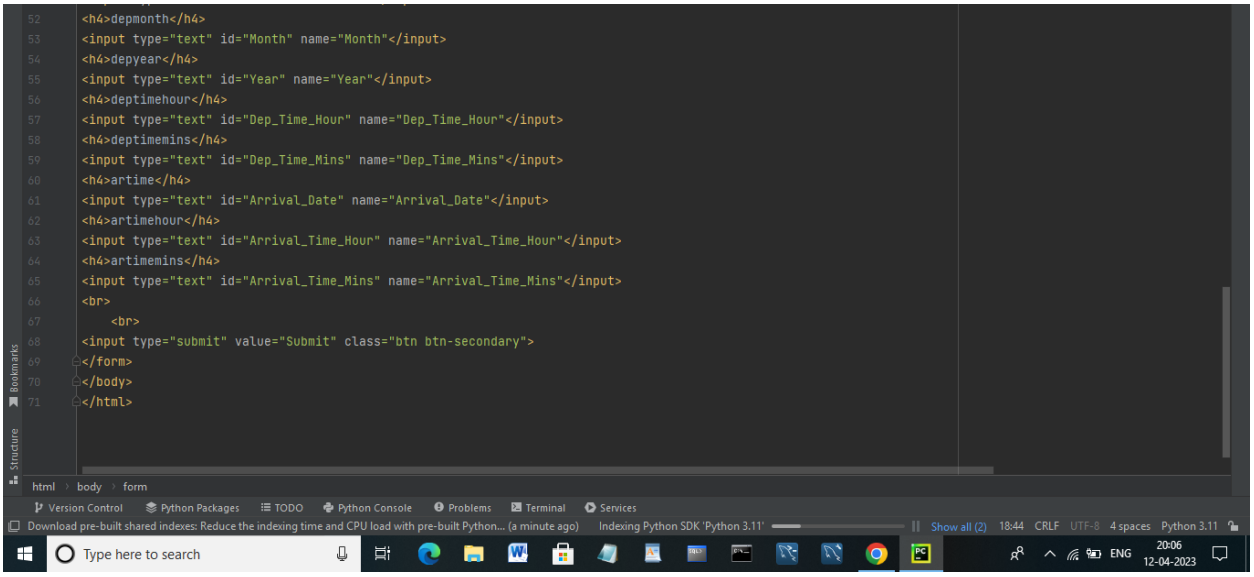
predict.html:



```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <title>Flight Price Prediction</title>
    <style>
        body {
               background-image:url(https://media.istockphoto.com/id/155380716/photo/commercial-jet-flying-over-clouds.jpg?s=612x612&w=0&k=20&c=idhnJ7ZdrLA10
               background-attachment:fixed;
               background-repeat:yes-repeat;
               background-size:cover;
              }
    </style>

</head>
<body>
<h1><font size="6">Flight Price prediction</font></h1>
<form action="http://127.0.0.1:5000/predict" method="post">
<h4>Airline</h4>
<select name="airline" id="airline" required="required">
                                <option value="Jet Airways">Jet Airways</option>
                                <option value="IndiGo">IndiGo</option>
                                <option value="Air India">Air India</option>
                                <option value="Multiple carriers">Multiple carriers</option>
                                <option value="SpiceJet">SpiceJet</option>
                                <option value="Vistara">Vistara</option>
```

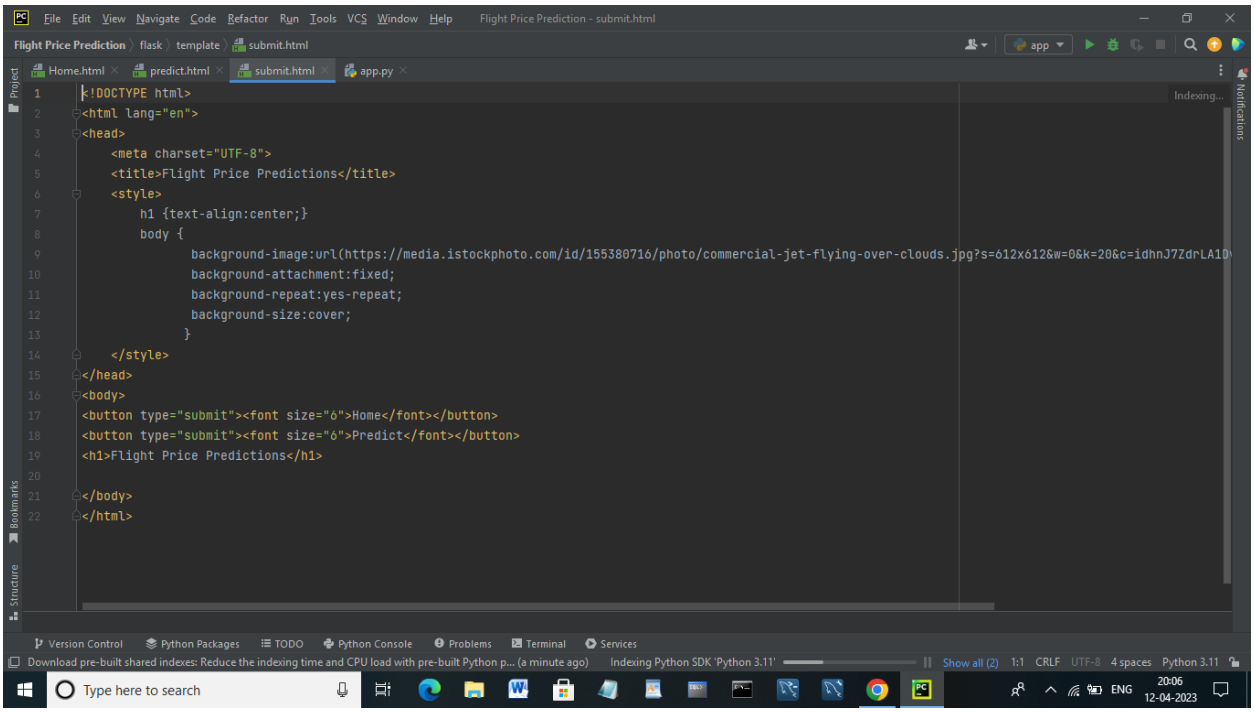


```
                                <option value="Air Asia">Air Asia</option>
                                <option value="GoAir">GoAir</option>
                                <option value="Multiple carriers Premium economy">Multiple carriers Premium economy
                                </option>
                                <option value="Jet Airways Business">Jet Airways Business</option>
                                <option value="Vistara Premium economy">Vistara Premium economy</option>
                                <option value="Trujet">Trujet</option>
                            </select>
<h4>Source</h4>
<select name="Source" id="Source" required="required">
                                <option value="Delhi">Delhi</option>
                                <option value="Kolkata">Kolkata</option>
                                <option value="Mumbai">Mumbai</option>
                                <option value="Chennai">Chennai</option>
                            </select>
<h4>Destination</h4>
<select name="Destination" id="Destination" required="required">
                                <option value="Cochin">Cochin</option>
                                <option value="Delhi">Delhi</option>
                                <option value="New Delhi">New Delhi</option>
                                <option value="Hyderabad">Hyderabad</option>
                                <option value="Kolkata">Kolkata</option>
                            </select>
<h4>depdate</h4>
<input type="text" id="Date" name="Date"</input>
```

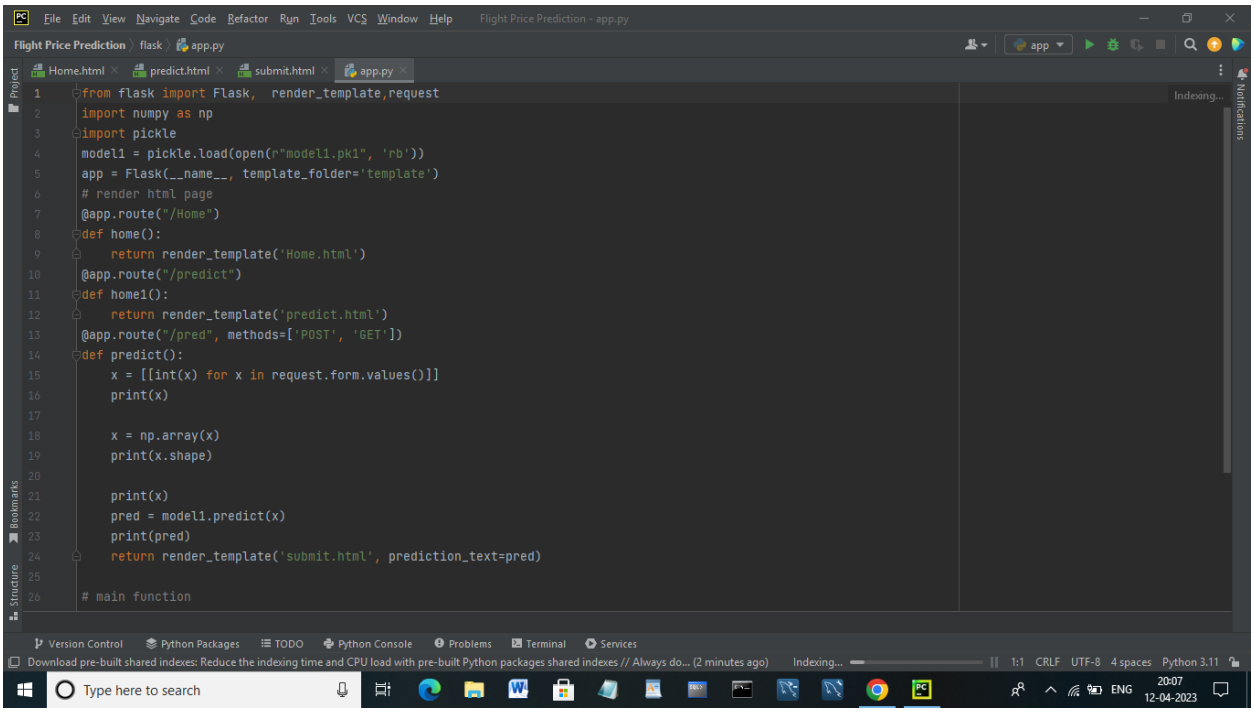


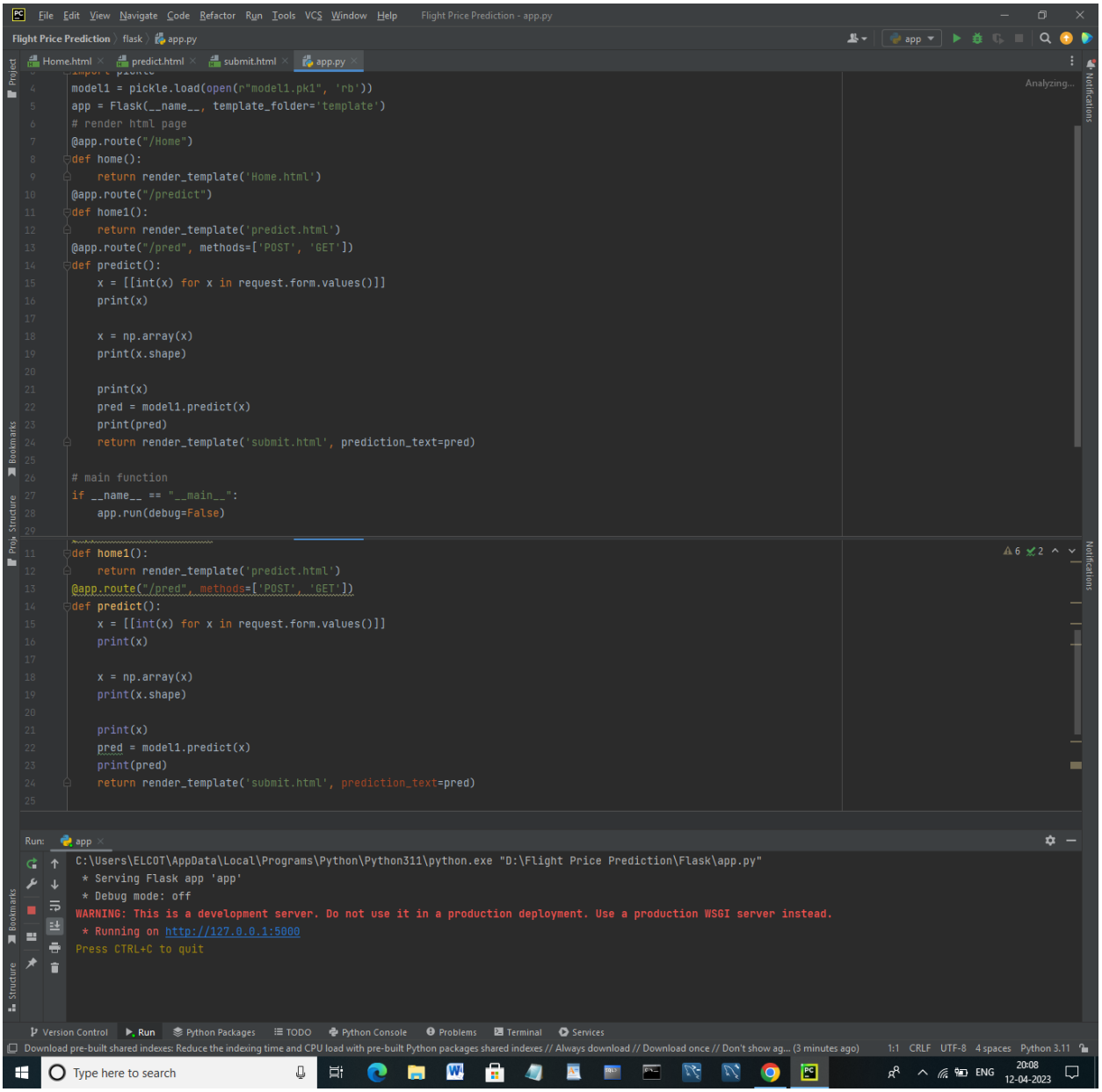
```
<h4>depmonth</h4>
<input type="text" id="Month" name="Month"</input>
<h4>depyear</h4>
<input type="text" id="Year" name="Year"</input>
<h4>deptimehour</h4>
<input type="text" id="Dep_Time_Hour" name="Dep_Time_Hour"</input>
<h4>deptimemins</h4>
<input type="text" id="Dep_Time_Mins" name="Dep_Time_Mins"</input>
<h4>artime</h4>
<input type="text" id="Arrival_Date" name="Arrival_Date"</input>
<h4>artimehour</h4>
<input type="text" id="Arrival_Time_Hour" name="Arrival_Time_Hour"</input>
<h4>artimemins</h4>
<input type="text" id="Arrival_Time_Mins" name="Arrival_Time_Mins"</input>
<br>
    <br>
<input type="submit" value="Submit" class="btn btn-secondary">
</form>
</body>
</html>
```

submit.html:



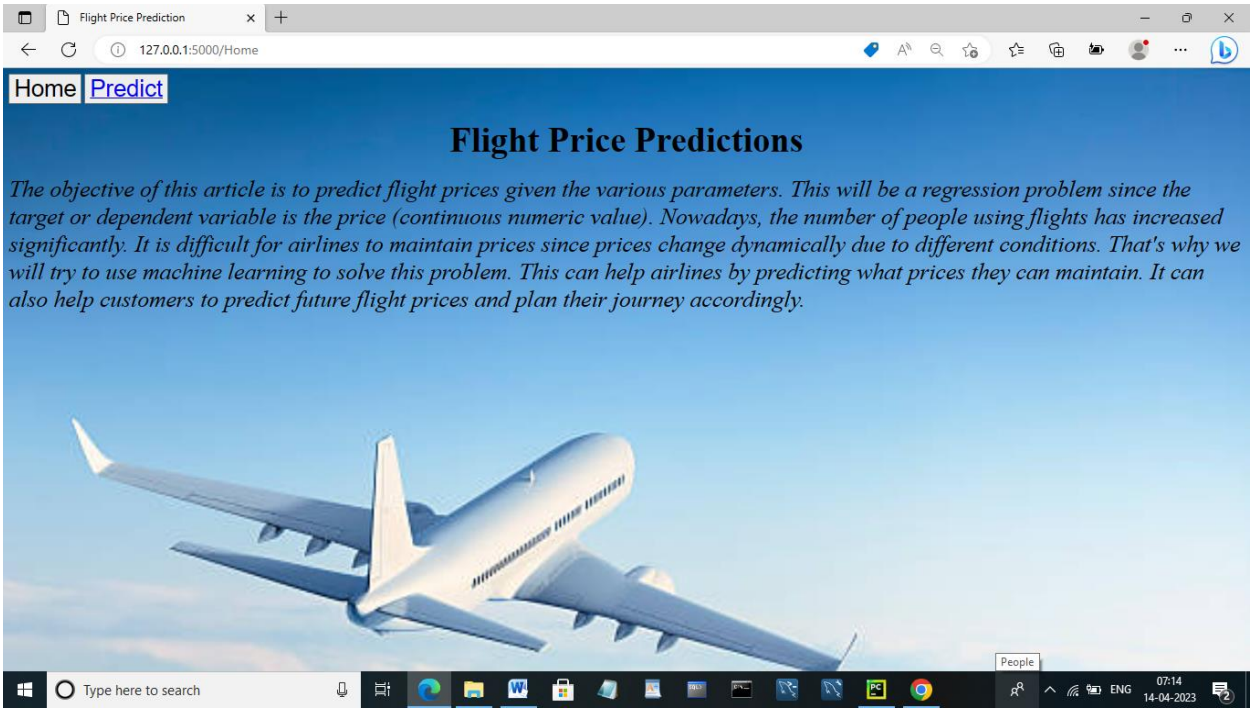
app.py:



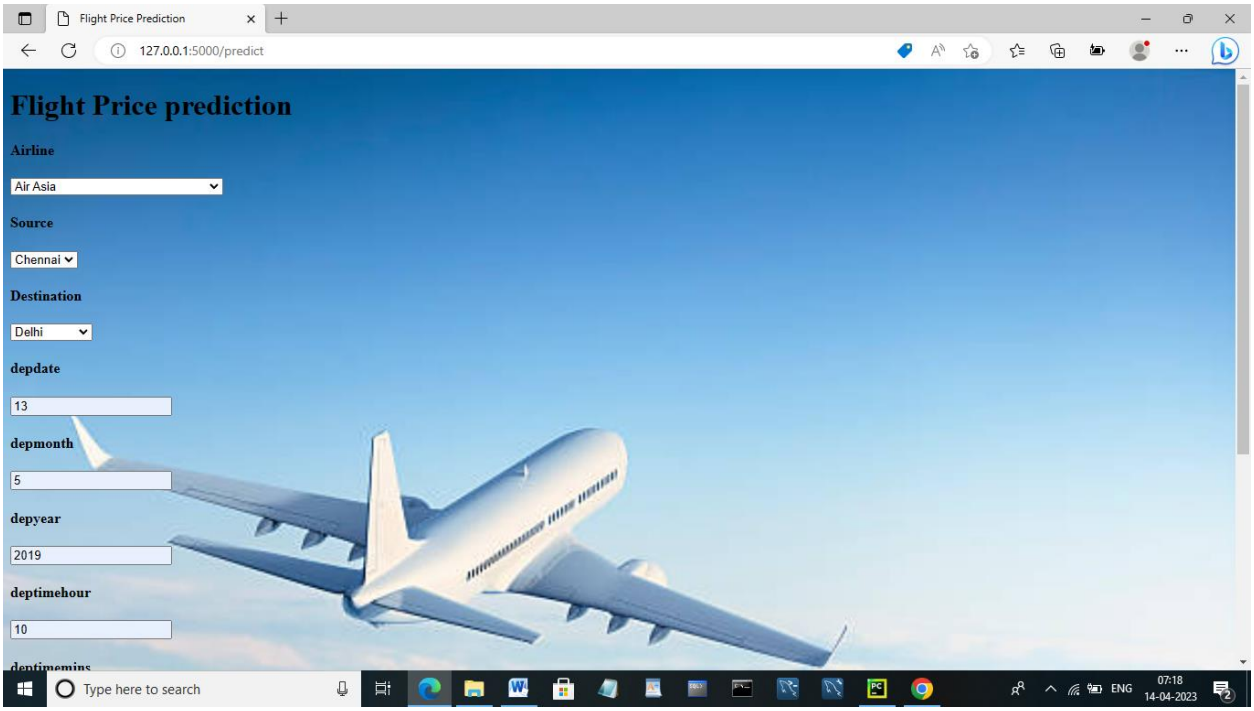

File Edit View Navigate Code Refactor Run Tools VCS Window Help
Flight Price Prediction - app.py
Flight Price Prediction
flask
app.py
Home.html
predict.html
submit.html
app.py
Analyzing...
model1 = pickle.load(open(r"model1.pk1", 'rb'))
app = Flask(__name__, template_folder='template')
# render html page
@app.route("/Home")
def home():
return render_template('Home.html')
@app.route("/predict")
def home1():
return render_template('predict.html')
@app.route("/pred", methods=['POST', 'GET'])
def predict():
x = [[int(x) for x in request.form.values()]]
print(x)
x = np.array(x)
print(x.shape)
print(x)
pred = model1.predict(x)
print(pred)
return render_template('submit.html', prediction_text=pred)
# main function
if __name__ == "__main__":
app.run(debug=False)
Run:
app
C:\Users\ELCOT\AppData\Local\Programs\Python\Python311\python.exe "D:\Flight Price Prediction\Flask\app.py"
* Serving Flask app 'app'
* Debug mode: off
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
Version Control
Run
Python Packages
TODO
Python Console
Problems
Terminal
Services
Type here to search
ENG
20:08
12-04-2023

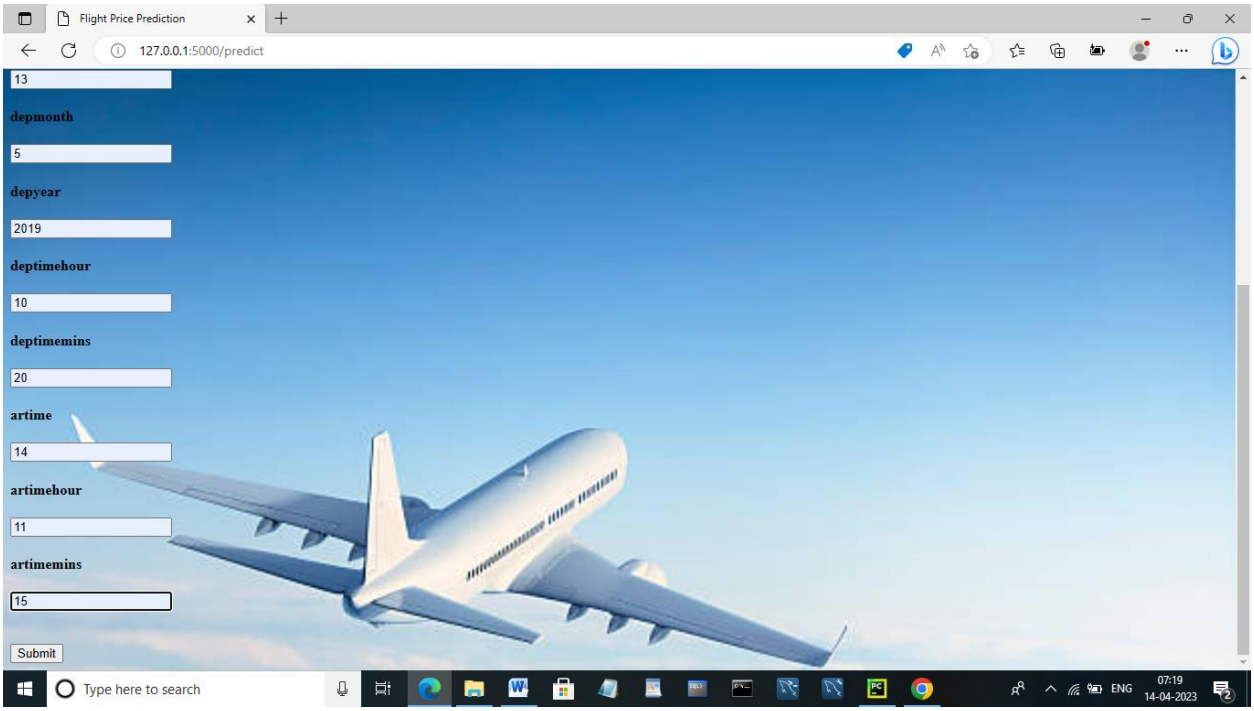
OUTPUT

Home Page:



Predict page:





Summit Page (Final Output):