

This notebook contains the ML Model for predicting flight delay

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import necessary libraries
```

```
!pip install catboost
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting catboost
  Downloading catboost-1.2-cp310-cp310-manylinux2014_x86_64.whl (98.6 MB)
    98.6/98.6 MB 8.4 MB/s eta 0:00:00
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from catboost) (1.10.1)
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.10/dist-packages (from catboost) (1.22.4)
Requirement already satisfied: pandas>=0.24 in /usr/local/lib/python3.10/dist-packages (from catboost) (1.5.3)
Requirement already satisfied: graphviz in /usr/local/lib/python3.10/dist-packages (from catboost) (0.20.1)
Requirement already satisfied: plotly in /usr/local/lib/python3.10/dist-packages (from catboost) (5.13.1)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from catboost) (1.16.0)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (from catboost) (3.7.1)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.24->catboost) (2022.7.1)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.24->catboost) (2.8)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (1.0.7)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (4.39.3)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (8.4.0)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (23.1)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (3.0.9)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (0.11.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->catboost) (1.4.4)
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from plotly->catboost) (8.2.2)
Installing collected packages: catboost
Successfully installed catboost-1.2
```

```
import pandas as pd
from sklearn.inspection import permutation_importance
from matplotlib import pyplot as plt
#from matplotlib import pyplot
import numpy as np
import seaborn as sns

from sklearn.model_selection import train_test_split, GridSearchCV
from catboost import CatBoostClassifier, Pool
from sklearn.metrics import confusion_matrix
from sklearn import preprocessing
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.exceptions import DataConversionWarning
```

```
df=pd.read_csv('/content/drive/MyDrive/ML Project/Result.csv')
```

```
df
```

```

    Unnamed: 0      Unnamed: 0 x      Date      Flight      Destination      Scheduled      Actual      Departure      Wheels-      Taxi-Out
    0              0 x      (MM/DD/YYYY)      Number      Airport      elapsed      elapsed      delay      off      time      ...      winddir      seal
df.columns

Index(['Unnamed: 0', 'Unnamed: 0_x', 'Date (MM/DD/YYYY)', 'Flight Number',
      'Destination Airport', 'Scheduled elapsed time (Minutes)',
      'Actual elapsed time (Minutes)', 'Departure delay (Minutes)',
      'Wheels-off time', 'Taxi-Out time (Minutes)',
      'Delay Carrier (Minutes)_x', 'Delay Weather (Minutes)_x',
      'Delay National Aviation System (Minutes)_x',
      'Delay Security (Minutes)_x', 'Delay Late Aircraft Arrival (Minutes)_x',
      'Origin Airport', 'Arrival Delay (Minutes)', 'Wheels-on Time',
      'Taxi-In time (Minutes)', 'month', 'day', 'year', 'Unnamed: 0_y',
      'tempmax', 'tempmin', 'temp', 'feelslikemax', 'feelslikemin',
      'feelslike', 'dew', 'humidity', 'precip', 'precipprob', 'precipcover',
      'snow', 'snowdepth', 'windgust', 'windspeed', 'winddir',
      'sealevelpressure', 'cloudcover', 'visibility', 'solarradiation',
      'solarenergy', 'uvindex', 'severerisk', 'moonphase', 'icon'],
      dtype='object')

1011      1011      1020      10/28/22      2198.0      0      71.0      63.0      -13.0      22:25      18.0      ...      30.9
drop unnecessary columns

```

```
df=df.drop(columns=['Unnamed: 0', 'Unnamed: 0_x','Unnamed: 0_y'])
```

Rename the Delay column to Target

```
df1 = df.rename(columns={'Arrival Delay (Minutes)':'TARGET'})
```

```
target = pd.cut(df1.TARGET,bins=[-500,-10,10,30,1000],labels=['0','1','2','3'])
```

```
df1.insert(45,'TARGET1',target)
```

```
df1.columns
```

```

Index(['Date (MM/DD/YYYY)', 'Flight Number', 'Destination Airport',
      'Scheduled elapsed time (Minutes)', 'Actual elapsed time (Minutes)',
      'Departure delay (Minutes)', 'Wheels-off time',
      'Taxi-Out time (Minutes)', 'Delay Carrier (Minutes)_x',
      'Delay Weather (Minutes)_x',
      'Delay National Aviation System (Minutes)_x',
      'Delay Security (Minutes)_x', 'Delay Late Aircraft Arrival (Minutes)_x',
      'Origin Airport', 'TARGET', 'Wheels-on Time', 'Taxi-In time (Minutes)',
      'month', 'day', 'year', 'tempmax', 'tempmin', 'temp', 'feelslikemax',
      'feelslikemin', 'feelslike', 'dew', 'humidity', 'precip', 'precipprob',
      'precipcover', 'snow', 'snowdepth', 'windgust', 'windspeed', 'winddir',
      'sealevelpressure', 'cloudcover', 'visibility', 'solarradiation',
      'solarenergy', 'uvindex', 'severerisk', 'moonphase', 'icon', 'TARGET1'],
      dtype='object')

```

Define Features and Labels for training testing data

```

X1=df1[['Origin Airport', 'tempmax', 'tempmin', 'temp',
      'feelslikemax', 'feelslikemin', 'feelslike', 'dew', 'humidity',
      'precip', 'precipprob', 'precipcover', 'snow', 'snowdepth', 'windgust',
      'windspeed', 'winddir', 'sealevelpressure', 'cloudcover', 'visibility',
      'solarradiation', 'solarenergy', 'uvindex', 'severerisk', 'moonphase',
      'icon', 'day', 'month', 'year', 'Flight Number']]

```

```
y = df1['TARGET1']
```

```
X1_train, X1_test, y_train, y_test = train_test_split(X1,y, test_size=0.2, random_state=20)
```

```

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X1_train = pd.DataFrame(sc.fit_transform(X1_train), columns = X1_train.columns, index = X1_train.index)
X1_test = pd.DataFrame(sc.transform(X1_test), columns = X1_test.columns, index = X1_test.index)

```

```
X1_train
```

	Origin Airport	tempmax	tempmin	temp	feelslikemax	feelslikemin	feelslike	dew	humidity	precip	...	solarradiati
206	0.982572	0.949510	1.590662	1.272104	1.312042	1.460623	1.322399	1.738199	1.313543	0.255621	...	-1.1682
893	0.196126	0.780303	1.386212	1.086312	0.786974	1.293867	1.039039	1.347958	0.720380	0.640197	...	-0.9985
150	0.982572	0.667498	1.230440	0.959191	0.651473	1.166814	0.922361	1.443139	1.332678	1.045286	...	-0.8301
895	0.196126	0.930709	0.918897	1.017862	0.914007	0.912709	0.980700	1.081452	0.190997	-0.374755	...	-0.5304
438	-1.376767	-0.723761	-1.008778	-0.849840	-0.601914	-0.961315	-0.852807	-1.041077	-0.746585	-0.374755	...	1.6184
...
924	0.196126	1.297325	1.434891	1.409004	1.549169	1.333571	1.439077	1.623982	0.694867	0.503740	...	-0.9711
223	0.982572	0.789703	0.918897	0.900520	0.710755	0.912709	0.864022	0.843501	0.006032	-0.374755	...	-0.2279
271	0.982572	0.827305	0.782597	0.841848	0.803912	0.801538	0.830686	1.052898	0.592817	-0.374755	...	-0.5728
474	-1.376767	0.554693	-0.658292	0.088900	0.549847	-0.572217	0.097283	-1.060113	-1.607629	-0.374755	...	2.0372
...

```
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression(random_state=20).fit(X1_train, y_train)

/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
https://scikit-learn.org/stable/modules/linear\_model.html#logistic-regression
n_iter_i = _check_optimize_result(
```

```
lr.score(X1_train,y_train)
```

0.49135802469135803

```
lr.score(X1_test,y_test)
```

0.458128078817734

```
importance = lr.coef_[0]
# summarize feature importance
for i,v in enumerate(importance):
    print('Feature: %0d, Score: %.5f' % (i,v))
# plot feature importance
plt.bar([x for x in range(len(importance))], importance)
plt.show()
```

```
Feature: 0, Score: 0.52421
Feature: 1, Score: -0.09852
Feature: 2, Score: -0.32440
Feature: 3, Score: -0.27824
Feature: 4, Score: 0.42868
Feature: 5, Score: 0.15797
Feature: 6, Score: 0.23195
Feature: 7, Score: -0.12714
Feature: 8, Score: -0.06830
Feature: 9, Score: -0.05962
Feature: 10, Score: 0.00200
Feature: 11, Score: 0.01525
Feature: 12, Score: 0.13324
Feature: 13, Score: -0.02470
Feature: 14, Score: 0.08387
Feature: 15, Score: -0.07289
Feature: 16, Score: -0.08252
Feature: 17, Score: 0.12474
Feature: 18, Score: 0.16798
Feature: 19, Score: 0.01411
Feature: 20, Score: 0.16845
Feature: 21, Score: 0.03440

test_output = pd.DataFrame(lr.predict(X1_test), index = X1_test.index, columns = ['pred'])

test_output
```

	pred
320	0
346	0
832	1
471	1
935	1
...	...
36	0
137	0
132	0
677	1
296	0

203 rows × 1 columns

```
test_output = test_output.merge(y_test, left_index = True, right_index = True)
test_output
```

	pred	TARGET1
320	0	0
346	0	2
832	1	1
471	1	1
935	1	3
...
36	0	1
137	0	1
132	0	0
677	1	1
296	0	0

203 rows × 2 columns

```
y_pred1=lr.predict(X1_test)

from sklearn.metrics import *

cm1 = confusion_matrix(y_test, y_pred1)
print('Classification Report:\n',classification_report(y_test, y_pred1))
```

```

Classification Report:
              precision    recall  f1-score   support

     0       0.45         0.42         0.43         65
     1       0.48         0.72         0.58         86
     2       0.00         0.00         0.00         25
     3       0.33         0.15         0.21         27

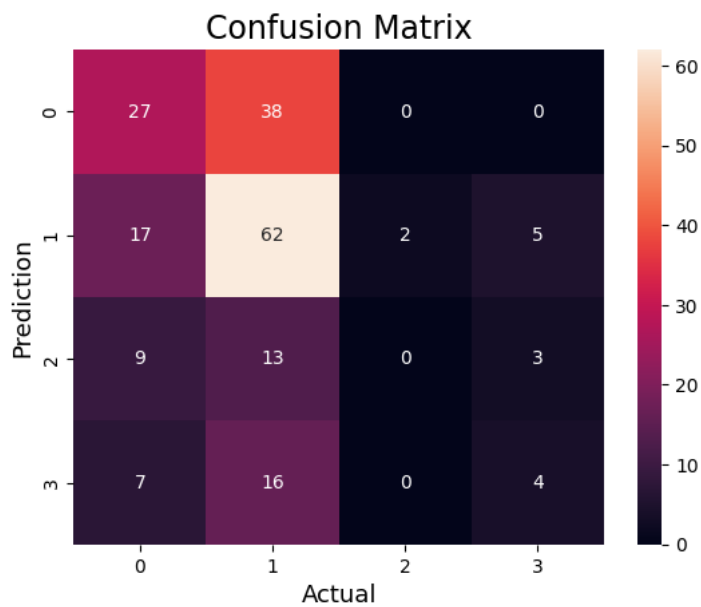
 accuracy          0.32          0.32          0.30         203
 macro avg          0.32          0.32          0.30         203
 weighted avg          0.39          0.46          0.41         203

```

```

sns.heatmap(cm1,
             annot=True,
             fmt='g')
plt.ylabel('Prediction',fontsize=13)
plt.xlabel('Actual',fontsize=13)
plt.title('Confusion Matrix',fontsize=17)
plt.show()

```



```

catboost = CatBoostClassifier(random_state=20)
catboost.fit(X1_train, y_train, verbose=False)

<catboost.core.CatBoostClassifier at 0x7f7494535fc0>

```

```

catboost.score(X1_test , y_test)

0.42857142857142855

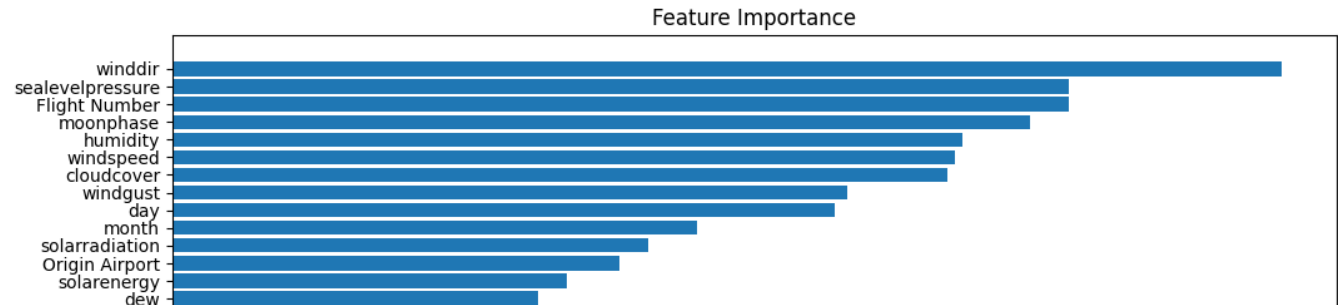
```

```

feature_importance = catboost.feature_importances_
sorted_idx = np.argsort(feature_importance)
fig = plt.figure(figsize=(12, 6))
plt.barh(range(len(sorted_idx)), feature_importance[sorted_idx], align='center')
plt.yticks(range(len(sorted_idx)), np.array(X1_test.columns)[sorted_idx])
plt.title('Feature Importance')

```

```
Text(0.5, 1.0, 'Feature Importance')
```



Double-click (or enter) to edit



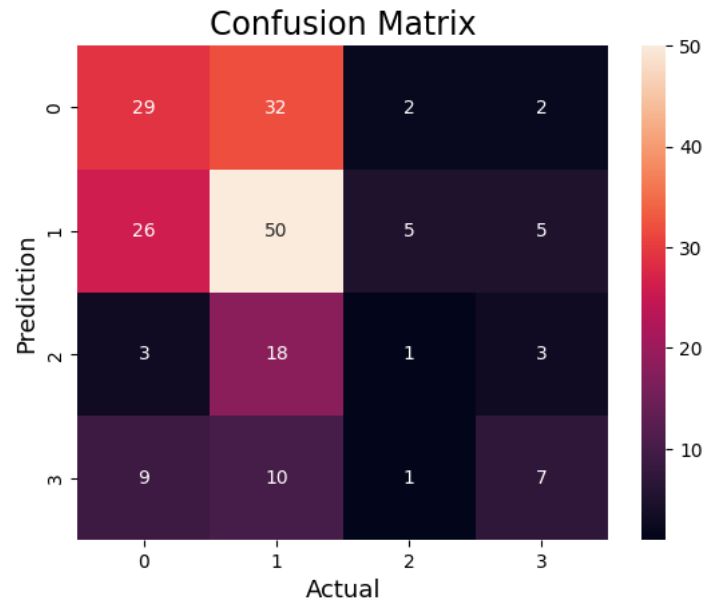
```
y_pred2=catboost.predict(X1_test)
```



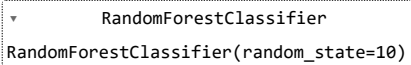
```
cm2 = confusion_matrix(y_test, y_pred2)
print('Classification Report:\n',classification_report(y_test, y_pred2))
```

Classification Report:					
	precision	recall	f1-score	support	
0	0.43	0.45	0.44	65	
1	0.45	0.58	0.51	86	
2	0.11	0.04	0.06	25	
3	0.41	0.26	0.32	27	
accuracy			0.43	203	
macro avg	0.35	0.33	0.33	203	
weighted avg	0.40	0.43	0.41	203	

```
sns.heatmap(cm2,
             annot=True,
             fmt='g')
plt.ylabel('Prediction',fontsize=13)
plt.xlabel('Actual',fontsize=13)
plt.title('Confusion Matrix',fontsize=17)
plt.show()
```



```
rf = RandomForestClassifier(random_state=10)
rf.fit(X1_train, y_train)
```



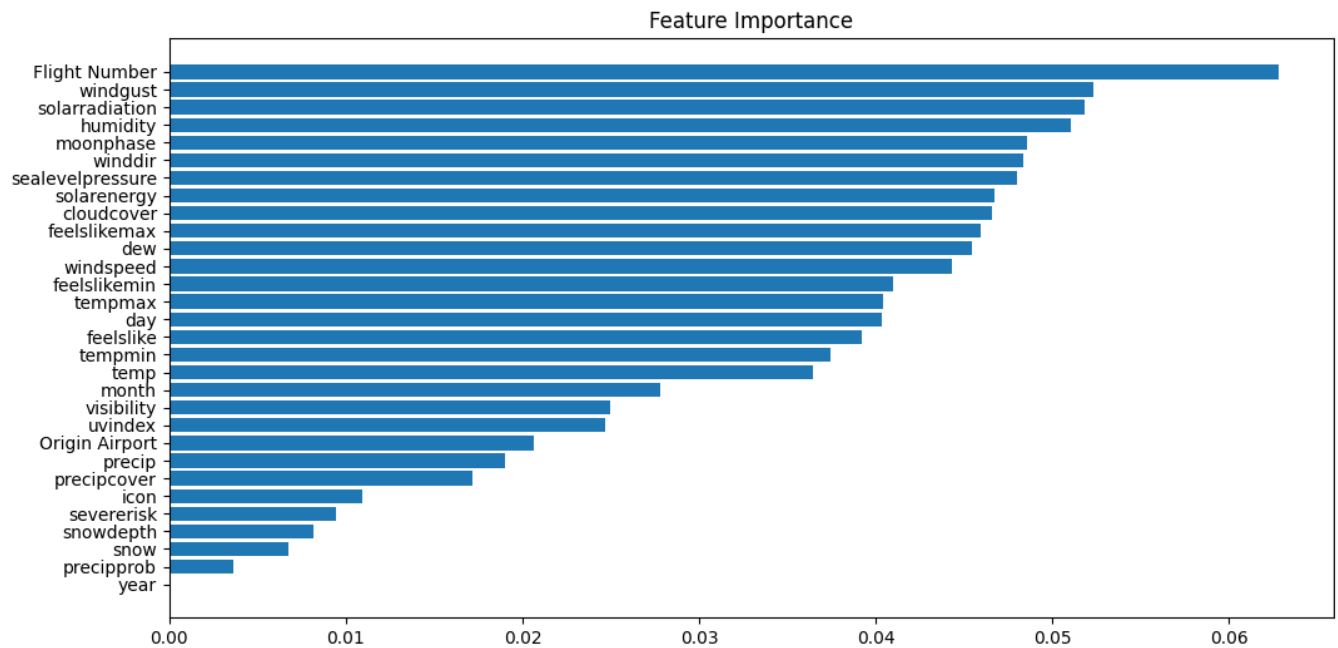
```
rf.score(X1_test,y_test)
```

0.43349753694581283

```
y_pred3=rf.predict(X1_test)
```

```
feature_importance = rf.feature_importances_
sorted_idx = np.argsort(feature_importance)
fig = plt.figure(figsize=(12, 6))
plt.barh(range(len(sorted_idx)), feature_importance[sorted_idx], align='center')
plt.yticks(range(len(sorted_idx)), np.array(X1_test.columns)[sorted_idx])
plt.title('Feature Importance')
```

```
Text(0.5, 1.0, 'Feature Importance')
```



```
cm3 = confusion_matrix(y_test, y_pred3)
print('Classification Report:\n',classification_report(y_test, y_pred3))
```

```
Classification Report:
              precision    recall  f1-score   support

     0       0.41         0.37         0.39         65
     1       0.46         0.65         0.54         86
     2       0.33         0.12         0.18         25
     3       0.33         0.19         0.24         27

 accuracy          0.39         0.33         0.43        203
 macro avg         0.39         0.33         0.34        203
 weighted avg      0.41         0.43         0.41        203
```

```
sns.heatmap(cm3,
            annot=True,
            fmt='g')
plt.ylabel('Prediction',fontsize=13)
plt.xlabel('Actual',fontsize=13)
plt.title('Confusion Matrix',fontsize=17)
plt.show()
```

Confusion Matrix



##FORECASTING

```
ic
f1=pd.read_csv('/content/drive/MyDrive/ML Project/WeatherDataF21-24.csv')
re
f1
```

	Unnamed: 0	Origin Airport	tempmax	tempmin	temp	feelslikemax	feelslikemin	feelslike	dew	humidity	...	visibility	solarradiatio
0	0	ORD	16.6	7.1	11.2	16.6	5.4	10.2	2.0	55.1	...	16.0	115.
1	1	ORD	8.7	3.9	5.9	6.6	-1.2	2.6	-1.2	60.5	...	15.8	69.
2	2	ORD	5.7	2.3	4.3	3.7	-1.5	1.2	-2.2	63.2	...	16.0	35.
3	3	ORD	11.8	2.2	7.1	11.8	-0.8	5.2	-3.8	47.6	...	16.0	91.
4	0	DEN	8.8	-3.4	2.7	6.2	-7.4	-0.7	-12.5	36.0	...	14.7	127.
5	1	DEN	1.4	-5.2	-1.7	1.3	-10.3	-5.5	-4.4	82.5	...	9.5	105.
6	2	DEN	12.6	-3.6	4.3	12.6	-7.3	2.3	-4.8	57.0	...	15.9	295.
7	3	DEN	16.5	2.6	9.7	16.5	-0.6	8.6	-4.2	41.7	...	15.9	266.
8	0	EWR	20.0	10.7	14.9	20.0	10.7	14.9	8.9	68.2	...	16.0	255.
9	1	EWR	20.5	11.6	15.5	20.5	11.6	15.5	11.8	79.3	...	13.4	156.
10	2	EWR	20.4	12.7	16.2	20.4	12.7	16.2	8.5	65.6	...	13.1	189.
11	3	EWR	16.6	7.7	12.3	16.6	5.0	11.6	-0.1	45.3	...	16.0	240.
12	0	IAD	31.1	14.1	22.0	29.3	14.1	21.8	12.9	60.6	...	15.4	221.
13	1	IAD	22.8	14.8	18.9	22.8	14.8	18.9	12.5	68.5	...	15.3	60.
14	2	IAD	17.8	9.9	14.2	17.8	6.7	14.1	5.3	57.2	...	16.0	117.
15	3	IAD	16.0	8.1	11.6	16.0	5.5	10.8	-1.3	41.5	...	16.0	205.

16 rows x 30 columns

```
f1['day'] = f1['day'].astype(str)
f1['month'] = f1['month'].astype(str)
f1['year'] = f1['year'].astype(str)
```

f1.dtypes

Unnamed: 0	int64
Origin Airport	object
tempmax	float64
tempmin	float64
temp	float64
feelslikemax	float64
feelslikemin	float64
feelslike	float64
dew	float64
humidity	float64
precip	float64


```
precipprob          int64
precipcover         float64
snow                float64
snowdepth           float64
windgust             float64
windspeed           float64
winddir             float64
sealevelpressure    float64
cloudcover          float64
visibility           float64
solarradiation       float64
solarenergy         float64
uvindex             int64
severerisk           int64
moonphase           float64
icon                object
day                 object
month               object
year                object
dtype: object

f2=pd.read_csv('/content/drive/MyDrive/ML Project/project csv(Apr 21-24).csv')

f2

   Date      Day  Origin Airport  Flight Number  Arrival Time  Status (Early, On-time, Late, Severly Late)
0  4/21/23  Friday           ORD           3839    10:00 AM                               NaN
1  4/21/23  Friday           ORD           3524     4:50 PM                               NaN
2  4/21/23  Friday           ORD            538     9:34 PM                               NaN
3  4/22/23  Saturday          ORD           3839    10:00 AM                               NaN
4  4/22/23  Saturday          ORD           3524     4:50 PM                               NaN
5  4/22/23  Saturday          ORD            538     9:34 PM                               NaN
6  4/23/23  Sunday           ORD           3839    10:00 AM                               NaN
7  4/23/23  Sunday           ORD           3524     4:55 PM                               NaN
8  4/23/23  Sunday           ORD            538     9:34 PM                               NaN
9  4/24/23  Monday           ORD           3839    10:00 AM                               NaN
10 4/24/23  Monday           ORD           3524     4:50 PM                               NaN
11 4/24/23  Monday           ORD            538     9:34 PM                               NaN
12 4/21/23  Friday           DEN            604     3:12 PM                               NaN
13 4/22/23  Saturday          DEN            604     3:12 PM                               NaN
14 4/23/23  Sunday           DEN            604     3:12 PM                               NaN
15 4/24/23  Monday           DEN            604     3:12 PM                               NaN
16 4/21/23  Friday           EWR           4189    10:46 AM                               NaN
17 4/21/23  Friday           EWR           1412    11:42 PM                               NaN
18 4/22/23  Saturday          EWR           4189    10:46 AM                               NaN
19 4/22/23  Saturday          EWR           1412    11:17 PM                               NaN
20 4/23/23  Sunday           EWR           4189    10:46 AM                               NaN
21 4/23/23  Sunday           EWR           1412    11:42 PM                               NaN
22 4/24/23  Monday           EWR           4189    10:46 AM                               NaN
23 4/24/23  Monday           EWR           1412    11:42 PM                               NaN
24 4/21/23  Friday           IAD           4490     1:57 PM                               NaN
25 4/21/23  Friday           IAD           4165     6:59 PM                               NaN
26 4/22/23  Saturday          IAD           3805     1:58 PM                               NaN
27 4/22/23  Saturday          IAD           4165     6:59 PM                               NaN
28 4/23/23  Sunday           IAD           4490     1:57 PM                               NaN
29 4/23/23  Sunday           IAD           4165     6:59 PM                               NaN
30 4/24/23  Monday           IAD           4490     1:57 PM                               NaN
31 4/24/23  Monday           IAD           4165     6:59 PM                               NaN

f2[["month", "day", "year"]] = f2["Date"].str.split("/", expand = True)
```

f2

	Date	Day	Origin Airport	Flight Number	Arrival Time	Status (Early, On-time, Late, Severly Late)	month	day	year
0	4/21/23	Friday	ORD	3839	10:00 AM	NaN	4	21	23
1	4/21/23	Friday	ORD	3524	4:50 PM	NaN	4	21	23
2	4/21/23	Friday	ORD	538	9:34 PM	NaN	4	21	23
3	4/22/23	Saturday	ORD	3839	10:00 AM	NaN	4	22	23
4	4/22/23	Saturday	ORD	3524	4:50 PM	NaN	4	22	23
5	4/22/23	Saturday	ORD	538	9:34 PM	NaN	4	22	23
6	4/23/23	Sunday	ORD	3839	10:00 AM	NaN	4	23	23
7	4/23/23	Sunday	ORD	3524	4:55 PM	NaN	4	23	23
8	4/23/23	Sunday	ORD	538	9:34 PM	NaN	4	23	23
9	4/24/23	Monday	ORD	3839	10:00 AM	NaN	4	24	23
10	4/24/23	Monday	ORD	3524	4:50 PM	NaN	4	24	23
11	4/24/23	Monday	ORD	538	9:34 PM	NaN	4	24	23
12	4/21/23	Friday	DEN	604	3:12 PM	NaN	4	21	23
13	4/22/23	Saturday	DEN	604	3:12 PM	NaN	4	22	23
14	4/23/23	Sunday	DEN	604	3:12 PM	NaN	4	23	23
15	4/24/23	Monday	DEN	604	3:12 PM	NaN	4	24	23
16	4/21/23	Friday	EWR	4189	10:46 AM	NaN	4	21	23
17	4/21/23	Friday	EWR	1412	11:42 PM	NaN	4	21	23
18	4/22/23	Saturday	EWR	4189	10:46 AM	NaN	4	22	23
19	4/22/23	Saturday	EWR	1412	11:17 PM	NaN	4	22	23
20	4/23/23	Sunday	EWR	4189	10:46 AM	NaN	4	23	23
21	4/23/23	Sunday	EWR	1412	11:42 PM	NaN	4	23	23
22	4/24/23	Monday	EWR	4189	10:46 AM	NaN	4	24	23
23	4/24/23	Monday	EWR	1412	11:42 PM	NaN	4	24	23
24	4/21/23	Friday	IAD	4490	1:57 PM	NaN	4	21	23
25	4/21/23	Friday	IAD	4165	6:59 PM	NaN	4	21	23
26	4/22/23	Saturday	IAD	3805	1:58 PM	NaN	4	22	23
27	4/22/23	Saturday	IAD	4165	6:59 PM	NaN	4	22	23
28	4/23/23	Sunday	IAD	4490	1:57 PM	NaN	4	23	23
29	4/23/23	Sunday	IAD	4165	6:59 PM	NaN	4	23	23
30	4/24/23	Monday	IAD	4490	1:57 PM	NaN	4	24	23
31	4/24/23	Monday	IAD	4165	6:59 PM	NaN	4	24	23

f2.columns

```
Index(['Date', 'Day', 'Origin Airport', 'Flight Number', 'Arrival Time',  
      'Status (Early, On-time, Late, Severly Late)', 'month', 'day', 'year'],  
      dtype='object')
```

drop unnecessary columns

```
f2=f2.drop(columns=['Date', 'Day','Arrival Time','Status (Early, On-time, Late, Severly Late)'])
```

f2

	Origin Airport	Flight Number	month	day	year
0	ORD	3839	4	21	23
1	ORD	3524	4	21	23
2	ORD	538	4	21	23
3	ORD	3839	4	22	23
4	ORD	3524	4	22	23
5	ORD	538	4	22	23
6	ORD	3839	4	23	23
7	ORD	3524	4	23	23
8	ORD	538	4	23	23
9	ORD	3839	4	24	23
10	ORD	3524	4	24	23
11	ORD	538	4	24	23
12	DEN	604	4	21	23
13	DEN	604	4	22	23
14	DEN	604	4	23	23
15	DEN	604	4	24	23
16	EWR	4189	4	21	23
17	EWR	1412	4	21	23
18	EWR	4189	4	22	23
19	EWR	1412	4	22	23
20	EWR	4189	4	23	23
21	EWR	1412	4	23	23
22	EWR	4189	4	24	23
23	EWR	1412	4	24	23
24	IAD	4490	4	21	23
25	IAD	4165	4	21	23
26	IAD	3805	4	22	23

merge the files on origin airport and date

```
ff=pd.merge(f1,f2,on=['Origin Airport','day','month','year'])
```

ff

	Unnamed: 0	Origin Airport	tempmax	tempmin	temp	feelslikemax	feelslikemin	feelslike	dew	humidity	...	solarradiation	solarer
0	0	ORD	16.6	7.1	11.2	16.6	5.4	10.2	2.0	55.1	...	115.2	
1	0	ORD	16.6	7.1	11.2	16.6	5.4	10.2	2.0	55.1	...	115.2	
2	0	ORD	16.6	7.1	11.2	16.6	5.4	10.2	2.0	55.1	...	115.2	
3	1	ORD	8.7	3.9	5.9	6.6	-1.2	2.6	-1.2	60.5	...	69.4	
4	1	ORD	8.7	3.9	5.9	6.6	-1.2	2.6	-1.2	60.5	...	69.4	
5	1	ORD	8.7	3.9	5.9	6.6	-1.2	2.6	-1.2	60.5	...	69.4	
6	2	ORD	5.7	2.3	4.3	3.7	-1.5	1.2	-2.2	63.2	...	35.6	
7	2	ORD	5.7	2.3	4.3	3.7	-1.5	1.2	-2.2	63.2	...	35.6	
8	2	ORD	5.7	2.3	4.3	3.7	-1.5	1.2	-2.2	63.2	...	35.6	
9	3	ORD	11.8	2.2	7.1	11.8	-0.8	5.2	-3.8	47.6	...	91.1	
10	3	ORD	11.8	2.2	7.1	11.8	-0.8	5.2	-3.8	47.6	...	91.1	
11	3	ORD	11.8	2.2	7.1	11.8	-0.8	5.2	-3.8	47.6	...	91.1	
12	0	DEN	8.8	-3.4	2.7	6.2	-7.4	-0.7	-12.5	36.0	...	127.2	
13	1	DEN	1.4	-5.2	-1.7	1.3	-10.3	-5.5	-4.4	82.5	...	105.5	
14	2	DEN	12.6	-3.6	4.3	12.6	-7.3	2.3	-4.8	57.0	...	295.9	
15	3	DEN	16.5	2.6	9.7	16.5	-0.6	8.6	-4.2	41.7	...	266.5	
16	0	EWR	20.0	10.7	14.9	20.0	10.7	14.9	8.9	68.2	...	255.1	
17	0	EWR	20.0	10.7	14.9	20.0	10.7	14.9	8.9	68.2	...	255.1	
18	1	EWR	20.5	11.6	15.5	20.5	11.6	15.5	11.8	79.3	...	156.0	
19	1	EWR	20.5	11.6	15.5	20.5	11.6	15.5	11.8	79.3	...	156.0	
20	2	EWR	20.4	12.7	16.2	20.4	12.7	16.2	8.5	65.6	...	189.6	
21	2	EWR	20.4	12.7	16.2	20.4	12.7	16.2	8.5	65.6	...	189.6	
22	3	EWR	16.6	7.7	12.3	16.6	5.0	11.6	-0.1	45.3	...	240.6	
23	0	EWR	16.6	7.7	12.3	16.6	5.0	11.6	-0.1	45.3	...	240.6	

perform label encoding

```
from sklearn.preprocessing import LabelEncoder
```

```
le=LabelEncoder()
```

```
ff['Origin Airport'] = le.fit_transform(ff['Origin Airport'])
ff['icon'] = le.fit_transform(ff['icon'])
```

```
ff
```

	Unnamed: 0	Origin Airport	tempmax	tempmin	temp	feelslikemax	feelslikemin	feelslike	dew	humidity	...	solarradiation	solarer
0	0	3	16.6	7.1	11.2	16.6	5.4	10.2	2.0	55.1	...	115.2	
1	0	3	16.6	7.1	11.2	16.6	5.4	10.2	2.0	55.1	...	115.2	
2	0	3	16.6	7.1	11.2	16.6	5.4	10.2	2.0	55.1	...	115.2	
3	1	3	8.7	3.9	5.9	6.6	-1.2	2.6	-1.2	60.5	...	69.4	
4	1	3	8.7	3.9	5.9	6.6	-1.2	2.6	-1.2	60.5	...	69.4	
5	1	3	8.7	3.9	5.9	6.6	-1.2	2.6	-1.2	60.5	...	69.4	
6	2	3	5.7	2.3	4.3	3.7	-1.5	1.2	-2.2	63.2	...	35.6	
7	2	3	5.7	2.3	4.3	3.7	-1.5	1.2	-2.2	63.2	...	35.6	
8	2	3	5.7	2.3	4.3	3.7	-1.5	1.2	-2.2	63.2	...	35.6	
9	3	3	11.8	2.2	7.1	11.8	-0.8	5.2	-3.8	47.6	...	91.1	
10	3	3	11.8	2.2	7.1	11.8	-0.8	5.2	-3.8	47.6	...	91.1	
11	3	3	11.8	2.2	7.1	11.8	-0.8	5.2	-3.8	47.6	...	91.1	
12	0	0	8.8	-3.4	2.7	6.2	-7.4	-0.7	-12.5	36.0	...	127.2	
13	1	0	1.4	-5.2	-1.7	1.3	-10.3	-5.5	-4.4	82.5	...	105.5	
14	2	0	12.6	-3.6	4.3	12.6	-7.3	2.3	-4.8	57.0	...	295.9	
15	3	0	16.5	2.6	9.7	16.5	-0.6	8.6	-4.2	41.7	...	266.5	
16	0	1	20.0	10.7	14.9	20.0	10.7	14.9	8.9	68.2	...	255.1	
17	0	1	20.0	10.7	14.9	20.0	10.7	14.9	8.9	68.2	...	255.1	
18	1	1	20.5	11.6	15.5	20.5	11.6	15.5	11.8	79.3	...	156.0	
19	1	1	20.5	11.6	15.5	20.5	11.6	15.5	11.8	79.3	...	156.0	
20	2	1	20.4	12.7	16.2	20.4	12.7	16.2	8.5	65.6	...	189.6	
21	2	1	20.4	12.7	16.2	20.4	12.7	16.2	8.5	65.6	...	189.6	
22	3	1	16.6	7.7	12.3	16.6	5.0	11.6	-0.1	45.3	...	240.6	
23	3	1	16.6	7.7	12.3	16.6	5.0	11.6	-0.1	45.3	...	240.6	
24	0	2	31.1	14.1	22.0	29.3	14.1	21.8	12.9	60.6	...	221.4	
25	0	2	31.1	14.1	22.0	29.3	14.1	21.8	12.9	60.6	...	221.4	
26	1	2	22.8	14.8	18.9	22.8	14.8	18.9	12.5	68.5	...	60.5	
27	1	2	22.8	14.8	18.9	22.8	14.8	18.9	12.5	68.5	...	60.5	
28	2	2	17.8	9.9	14.2	17.8	6.7	14.1	5.3	57.2	...	117.7	
29	2	2	17.8	9.9	14.2	17.8	6.7	14.1	5.3	57.2	...	117.7	
30	3	2	16.0	8.1	11.6	16.0	5.5	10.8	-1.3	41.5	...	205.9	

```
ff.columns
```

```
Index(['Unnamed: 0', 'Origin Airport', 'tempmax', 'tempmin', 'temp',
      'feelslikemax', 'feelslikemin', 'feelslike', 'dew', 'humidity',
      'precip', 'precipprob', 'precipcover', 'snow', 'snowdepth', 'windgust',
      'windspeed', 'winddir', 'sealevelpressure', 'cloudcover', 'visibility',
      'solarradiation', 'solarenergy', 'uvindex', 'severerisk', 'moonphase',
      'icon', 'day', 'month', 'year', 'Flight Number'],
      dtype='object')
```

```
ff=ff.drop(columns=['Unnamed: 0'])
```

Fit the data into our pretrained model

```
ff=pd.DataFrame(sc.transform(ff),columns=ff.columns)
```

```
ff
```

	Origin Airport	tempmax	tempmin	temp	feelslikemax	feelslikemin	feelslike	dew	humidity	precip	...	solarradia
0	0.982572	-0.263142	-0.181241	-0.272906	-0.186942	-0.119592	-0.211080	-0.232041	-0.121530	-0.374755	...	0.000
1	0.982572	-0.263142	-0.181241	-0.272906	-0.186942	-0.119592	-0.211080	-0.232041	-0.121530	-0.374755	...	0.000
2	0.982572	-0.263142	-0.181241	-0.272906	-0.186942	-0.119592	-0.211080	-0.232041	-0.121530	-0.374755	...	0.000
3	0.982572	-1.005773	-0.492784	-0.791169	-1.033825	-0.643684	-0.844473	-0.536619	0.222887	-0.215823	...	-0.620
4	0.982572	-1.005773	-0.492784	-0.791169	-1.033825	-0.643684	-0.844473	-0.536619	0.222887	-0.215823	...	-0.620
5	0.982572	-1.005773	-0.492784	-0.791169	-1.033825	-0.643684	-0.844473	-0.536619	0.222887	-0.215823	...	-0.620
6	0.982572	-1.287785	-0.648556	-0.947626	-1.279421	-0.667506	-0.961151	-0.631800	0.395096	-0.374755	...	-1.080
7	0.982572	-1.287785	-0.648556	-0.947626	-1.279421	-0.667506	-0.961151	-0.631800	0.395096	-0.374755	...	-1.080
8	0.982572	-1.287785	-0.648556	-0.947626	-1.279421	-0.667506	-0.961151	-0.631800	0.395096	-0.374755	...	-1.080
9	0.982572	-0.714361	-0.658292	-0.673826	-0.593446	-0.611920	-0.627786	-0.784089	-0.599888	-0.374755	...	-0.320
10	0.982572	-0.714361	-0.658292	-0.673826	-0.593446	-0.611920	-0.627786	-0.784089	-0.599888	-0.374755	...	-0.320
11	0.982572	-0.714361	-0.658292	-0.673826	-0.593446	-0.611920	-0.627786	-0.784089	-0.599888	-0.374755	...	-0.320
12	-1.376767	-0.996373	-1.203493	-1.104082	-1.067700	-1.136012	-1.119499	-1.612161	-1.339749	-0.145722	...	0.160
13	-1.376767	-1.692003	-1.378736	-1.534338	-1.482673	-1.366294	-1.519537	-0.841198	1.626071	0.140748	...	-0.130
14	-1.376767	-0.639158	-1.222964	-0.947626	-0.525695	-1.128071	-0.869476	-0.879270	-0.000346	-0.374755	...	2.470
15	-1.376767	-0.272542	-0.619349	-0.419584	-0.195410	-0.596039	-0.344426	-0.822161	-0.976197	-0.374755	...	2.070
16	-0.590320	0.056472	0.169245	0.088900	0.100999	0.301269	0.180624	0.424706	0.714001	-0.374755	...	1.910
17	-0.590320	0.056472	0.169245	0.088900	0.100999	0.301269	0.180624	0.424706	0.714001	-0.374755	...	1.910
18	-0.590320	0.103474	0.256867	0.147572	0.143343	0.372736	0.230629	0.700730	1.421971	2.910015	...	0.550
19	-0.590320	0.103474	0.256867	0.147572	0.143343	0.372736	0.230629	0.700730	1.421971	2.910015	...	0.550
20	-0.590320	0.094074	0.363960	0.216021	0.134874	0.460085	0.288968	0.386633	0.548171	4.996285	...	1.010
21	-0.590320	0.094074	0.363960	0.216021	0.134874	0.460085	0.288968	0.386633	0.548171	4.996285	...	1.010
22	-0.590320	-0.263142	-0.122826	-0.165342	-0.186942	-0.151355	-0.094402	-0.431921	-0.746585	-0.374755	...	1.710
23	-0.590320	-0.263142	-0.122826	-0.165342	-0.186942	-0.151355	-0.094402	-0.431921	-0.746585	-0.374755	...	1.710
24	0.196126	1.099917	0.500260	0.783177	0.888600	0.571256	0.755679	0.805428	0.229265	-0.374755	...	1.450
25	0.196126	1.099917	0.500260	0.783177	0.888600	0.571256	0.755679	0.805428	0.229265	-0.374755	...	1.450
26	0.196126	0.319683	0.568411	0.480042	0.338126	0.626841	0.513989	0.767356	0.733136	1.478201	...	-0.740
27	0.196126	0.319683	0.568411	0.480042	0.338126	0.626841	0.513989	0.767356	0.733136	1.478201	...	-0.740
28	0.196126	-0.150337	0.091360	0.020450	-0.085316	-0.016362	0.113951	0.082055	0.012410	-0.374755	...	0.030
29	0.196126	-0.150337	0.091360	0.020450	-0.085316	-0.016362	0.113951	0.082055	0.012410	-0.374755	...	0.030

```
test1=catboost.predict(ff)
```

```
test1
```

```
array([[ '1'],
       [ '1'],
       [ '0'],
       [ '1'],
       [ '1'],
       [ '1'],
       [ '0'],
       [ '0'],
       [ '1'],
       [ '1'],
       [ '1'],
       [ '1'],
       [ '0'],
       [ '1'],
       [ '3'],
       [ '1'],
       [ '1'],
       [ '1'],
       [ '1'],
       [ '1'],
       [ '1'],
       [ '1'],
       [ '1'],
       [ '1'],
       [ '1'],
       [ '1'],
       [ '1'],
       [ '3'],
```