1. INITIAL EXPLORATION

1.1 Generic Inputs for Building Model

In [1]:
```
# Generic inputs for ML task
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn import tree

from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.ensemble import RandomForestClassifier

pd.options.display.float_format = '{:,.2f}'.format

# setup interactive notebook mode
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"

import plotly.io as pio
pio.renderers.default='notebook'

from IPython.display import display, HTML
```

1.2 Loading the dataset

In [2]:
```
# Loading csv file into dataframe
airline_data = pd.read_csv('Detailed_Statistics_Arrivals.csv')

# printing loaded data frame
airline_data
```

Out[2]:

	Carrier Code	Date (MM/DD/YYYY)	Flight Number	Tail Number	Origin Airport	Scheduled Arrival Time	Actual Arrival Time	Scheduled Elapsed Time (Minutes)	Actu Elaps Tir (Minut
0	UA	1/1/2000	356	N306UA	ORD	17:03	16:49	105	
1	UA	1/1/2000	1498	N976UA	ORD	19:25	19:15	101	
2	UA	1/1/2001	356	N981ä1	ORD	17:00	16:56	109	1
3	UA	1/1/2001	1498	N985ä1	ORD	23:32	0:13	107	1
4	UA	1/1/2001	1620	N991ä1	ORD	9:03	8:57	103	1
...	...	...	...	...	...	...	...	...	
5339	UA	12/31/2019	1460	N838UA	EWR	18:15	18:14	75	
5340	UA	12/31/2021	467	N872UA	IAD	18:38	18:32	78	
5341	UA	12/31/2022	604	N801UA	DEN	14:58	14:46	193	1
5342	UA	12/31/2022	1998	N23707	ORD	21:08	20:44	113	
5343	UA	12/31/2022	2488	N37427	EWR	23:14	0:46	75	

5344 rows × 17 columns

2. DATA PREPROCESSING

2.1 Handling Missing Data: Dealing with Null Values

In [3]:

```
# printing the number of rows in the data frame
print("Number of rows in the data frame:", len(airline_data))

print("(Rows,Columns) = ", airline_data.shape)
print("\n")

# check for NaN values
print("NaN values in the file are:\n", airline_data.isna().any())

print("\n Count of NaN values in each column (feature):\n", airline_data.isna().sum
print("\nCount of total NaN values in entire file:", airline_data.isna().sum().sum(
```

```
Number of rows in the data frame: 5344
(Rows,Columns) =  (5344, 17)


NaN values in the file are:
 Carrier Code                              False
Date (MM/DD/YYYY)                         False
Flight Number                             False
Tail Number                                True
Origin Airport                            False
Scheduled Arrival Time                    False
Actual Arrival Time                       False
Scheduled Elapsed Time (Minutes)          False
Actual Elapsed Time (Minutes)             False
Arrival Delay (Minutes)                   False
Wheels-on Time                            False
Taxi-In time (Minutes)                    False
Delay Carrier (Minutes)                   False
Delay Weather (Minutes)                   False
Delay National Aviation System (Minutes)  False
Delay Security (Minutes)                  False
Delay Late Aircraft Arrival (Minutes)     False
dtype: bool

 Count of NaN values in each column (feature):
 Carrier Code                              0
Date (MM/DD/YYYY)                         0
Flight Number                             0
Tail Number                              63
Origin Airport                            0
Scheduled Arrival Time                    0
Actual Arrival Time                       0
Scheduled Elapsed Time (Minutes)          0
Actual Elapsed Time (Minutes)             0
Arrival Delay (Minutes)                   0
Wheels-on Time                            0
Taxi-In time (Minutes)                    0
Delay Carrier (Minutes)                   0
Delay Weather (Minutes)                   0
Delay National Aviation System (Minutes)  0
Delay Security (Minutes)                  0
Delay Late Aircraft Arrival (Minutes)     0
dtype: int64

Count of total NaN values in entire file: 63
```

In [4]:

```
# dropping null values
airline_data.dropna(inplace=True)
print("\nCount of total NaN values in entire file:", airline_data.isna().sum().sum(

# rechecking for any null values
airline_data.isna().any()
```

```
Count of total NaN values in entire file: 0
```

```
Out[4]: Carrier Code                                False
        Date (MM/DD/YYYY)                           False
        Flight Number                               False
        Tail Number                                 False
        Origin Airport                              False
        Scheduled Arrival Time                      False
        Actual Arrival Time                         False
        Scheduled Elapsed Time (Minutes)            False
        Actual Elapsed Time (Minutes)               False
        Arrival Delay (Minutes)                     False
        Wheels-on Time                              False
        Taxi-In time (Minutes)                      False
        Delay Carrier (Minutes)                     False
        Delay Weather (Minutes)                     False
        Delay National Aviation System (Minutes)    False
        Delay Security (Minutes)                    False
        Delay Late Aircraft Arrival (Minutes)       False
        dtype: bool
```

```
In [5]: # checking data types of all columns
        airline_data.dtypes
```

```
Out[5]: Carrier Code                                object
        Date (MM/DD/YYYY)                           object
        Flight Number                                int64
        Tail Number                                 object
        Origin Airport                              object
        Scheduled Arrival Time                      object
        Actual Arrival Time                         object
        Scheduled Elapsed Time (Minutes)             int64
        Actual Elapsed Time (Minutes)                int64
        Arrival Delay (Minutes)                      int64
        Wheels-on Time                              object
        Taxi-In time (Minutes)                       int64
        Delay Carrier (Minutes)                      int64
        Delay Weather (Minutes)                      int64
        Delay National Aviation System (Minutes)     int64
        Delay Security (Minutes)                     int64
        Delay Late Aircraft Arrival (Minutes)        int64
        dtype: object
```

2.2 Parsing and Sorting Data

```
In [6]: # parsing the Timestsamp column as a date
        airline_data['Date'] = pd.to_datetime(airline_data['Date (MM/DD/YYYY)'])
        airline_data.insert(2, 'Date', airline_data.pop('Date'))
        airline_data = airline_data.sort_values(by='Date', ascending=False)

        # printing column names
        airline_data.columns
```

Out[6]:
```
Index(['Carrier Code', 'Date (MM/DD/YYYY)', 'Date', 'Flight Number',
       'Tail Number', 'Origin Airport', 'Scheduled Arrival Time',
       'Actual Arrival Time', 'Scheduled Elapsed Time (Minutes)',
       'Actual Elapsed Time (Minutes)', 'Arrival Delay (Minutes)',
       'Wheels-on Time', 'Taxi-In time (Minutes)', 'Delay Carrier (Minutes)',
       'Delay Weather (Minutes)', 'Delay National Aviation System (Minutes)',
       'Delay Security (Minutes)', 'Delay Late Aircraft Arrival (Minutes)'],
      dtype='object')
```

2.3 Data Cleaning: Removing unwanted Columns

In [7]:
```python
# dropping column Date (MM/DD/YYYY)
airline_data = airline_data.drop(['Date (MM/DD/YYYY)'], axis = 1)

# printing the header
airline_data.head()
```

Out[7]:

	Carrier Code	Date	Flight Number	Tail Number	Origin Airport	Scheduled Arrival Time	Actual Arrival Time	Scheduled Elapsed Time (Minutes)	Actual Elapsed Time (Minutes)	Arri De (Minut
454	UA	2023-01-31	1998	N808UA	ORD	21:17	20:52	113	97	-
455	UA	2023-01-31	2617	N68807	EWR	23:12	22:59	74	66	-
453	UA	2023-01-31	604	N851UA	DEN	14:59	14:47	193	175	-
438	UA	2023-01-30	604	N882UA	DEN	14:59	14:35	193	172	-
439	UA	2023-01-30	1998	N836UA	ORD	21:17	21:21	113	103	

2.4 Data Transformation: Converting Data Types and Formats

In [8]:
```python
# replaces any occurrence of '24:00:00' in following 2 columns with '00:00:00'
airline_data['Actual Arrival Time'] = airline_data['Actual Arrival Time'].str.repla
airline_data['Wheels-on Time'] = airline_data['Wheels-on Time'].str.replace('24:00:

# convert time column to datetime format
airline_data['Scheduled Arrival Time'] = pd.to_datetime(airline_data['Scheduled Arr
airline_data['Actual Arrival Time'] = pd.to_datetime(airline_data['Actual Arrival T
airline_data['Wheels-on Time'] = pd.to_datetime(airline_data['Wheels-on Time'])

# convert time to AM/PM format
airline_data['Scheduled Arrival Time'] = airline_data['Scheduled Arrival Time'].dt.
airline_data['Actual Arrival Time'] = airline_data['Actual Arrival Time'].dt.strfti
airline_data['Wheels-on Time'] = airline_data['Wheels-on Time'].dt.strftime('%I:%M
```

```
# printing data frame
print(airline_data)
```

```
    Carrier Code       Date  Flight Number Tail Number Origin Airport  \
454           UA 2023-01-31           1998      N808UA            ORD
455           UA 2023-01-31           2617      N68807            EWR
453           UA 2023-01-31            604      N851UA            DEN
438           UA 2023-01-30            604      N882UA            DEN
439           UA 2023-01-30           1998      N836UA            ORD
..           ...        ...            ...         ...            ...
14            UA 2000-01-02            356      N361UA            ORD
15            UA 2000-01-02           1498      N994UA            ORD
16            UA 2000-01-02           1620      N994UA            ORD
1             UA 2000-01-01           1498      N976UA            ORD
0             UA 2000-01-01            356      N306UA            ORD

    Scheduled Arrival Time Actual Arrival Time  \
454               09:17 PM            08:52 PM
455               11:12 PM            10:59 PM
453               02:59 PM            02:47 PM
438               02:59 PM            02:35 PM
439               09:17 PM            09:21 PM
..                     ...                 ...
14                05:03 PM            04:59 PM
15                07:26 PM            08:22 PM
16                09:25 AM            09:10 AM
1                 07:25 PM            07:15 PM
0                 05:03 PM            04:49 PM

     Scheduled Elapsed Time (Minutes)  Actual Elapsed Time (Minutes)  \
454                               113                             97
455                                74                             66
453                               193                            175
438                               193                            172
439                               113                            103
..                                ...                            ...
14                                105                             81
15                                101                             92
16                                 95                             82
1                                 101                             92
0                                 105                             91

     Arrival Delay (Minutes) Wheels-on Time  Taxi-In time (Minutes)  \
454                      -25       08:48 PM                       4
455                      -13       10:55 PM                       4
453                      -12       02:40 PM                       7
438                      -24       02:30 PM                       5
439                        4       09:16 PM                       5
..                       ...            ...                     ...
14                        -4       04:56 PM                       3
15                        56       08:17 PM                       5
16                       -15       09:06 AM                       4
1                        -10       07:09 PM                       6
0                        -14       04:44 PM                       5

     Delay Carrier (Minutes)  Delay Weather (Minutes)  \
454                        0                        0
455                        0                        0
453                        0                        0
```

```
438                         0                        0
439                         0                        0
..                        ...                      ...
14                          0                        0
15                          0                        0
16                          0                        0
1                           0                        0
0                           0                        0

     Delay National Aviation System (Minutes)  Delay Security (Minutes)  \
454                                         0                         0
455                                         0                         0
453                                         0                         0
438                                         0                         0
439                                         0                         0
..                                        ...                       ...
14                                          0                         0
15                                          0                         0
16                                          0                         0
1                                           0                         0
0                                           0                         0

     Delay Late Aircraft Arrival (Minutes)
454                                      0
455                                      0
453                                      0
438                                      0
439                                      0
..                                     ...
14                                       0
15                                       0
16                                       0
1                                        0
0                                        0

[5281 rows x 17 columns]
```

2.5 Data Filtering: Verifying Columns with Specific Data Types

In [9]:

```
# checking data types
airline_data.dtypes

# Select columns with float data type
float_columns = airline_data.select_dtypes(include=['float'])

# Print the resulting float columns
print(float_columns)
```

Out[9]:
```
Carrier Code                                          object
Date                                          datetime64[ns]
Flight Number                                          int64
Tail Number                                           object
Origin Airport                                        object
Scheduled Arrival Time                                object
Actual Arrival Time                                   object
Scheduled Elapsed Time (Minutes)                       int64
Actual Elapsed Time (Minutes)                          int64
Arrival Delay (Minutes)                                int64
Wheels-on Time                                        object
Taxi-In time (Minutes)                                 int64
Delay Carrier (Minutes)                                int64
Delay Weather (Minutes)                                int64
Delay National Aviation System (Minutes)               int64
Delay Security (Minutes)                               int64
Delay Late Aircraft Arrival (Minutes)                  int64
dtype: object
Empty DataFrame
Columns: []
Index: [454, 455, 453, 438, 439, 440, 425, 426, 410, 411, 409, 394, 395, 396, 381,
380, 379, 366, 365, 364, 350, 351, 349, 334, 335, 336, 322, 321, 320, 305, 307, 30
6, 291, 290, 292, 277, 276, 275, 262, 261, 260, 247, 246, 245, 230, 232, 231, 218,
217, 216, 203, 202, 201, 188, 187, 186, 173, 172, 171, 156, 157, 158, 141, 142, 14
3, 140, 127, 126, 125, 113, 112, 99, 98, 84, 85, 71, 70, 55, 56, 42, 41, 28, 27, 2
6, 13, 11, 12, 5343, 5341, 5342, 5331, 5329, 5330, 5317, 5318, 5319, 5307, 5306, 5
305, 5293, ...]

[5281 rows x 0 columns]
```

In [10]:
```
# checking dataframe info
airline_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5281 entries, 454 to 0
Data columns (total 17 columns):
 #   Column                                    Non-Null Count  Dtype
---  ------                                    --------------  -----
 0   Carrier Code                              5281 non-null   object
 1   Date                                      5281 non-null   datetime64[ns]
 2   Flight Number                             5281 non-null   int64
 3   Tail Number                               5281 non-null   object
 4   Origin Airport                            5281 non-null   object
 5   Scheduled Arrival Time                    5281 non-null   object
 6   Actual Arrival Time                       5281 non-null   object
 7   Scheduled Elapsed Time (Minutes)          5281 non-null   int64
 8   Actual Elapsed Time (Minutes)             5281 non-null   int64
 9   Arrival Delay (Minutes)                   5281 non-null   int64
 10  Wheels-on Time                            5281 non-null   object
 11  Taxi-In time (Minutes)                    5281 non-null   int64
 12  Delay Carrier (Minutes)                   5281 non-null   int64
 13  Delay Weather (Minutes)                   5281 non-null   int64
 14  Delay National Aviation System (Minutes)  5281 non-null   int64
 15  Delay Security (Minutes)                  5281 non-null   int64
 16  Delay Late Aircraft Arrival (Minutes)     5281 non-null   int64
dtypes: datetime64[ns](1), int64(10), object(6)
memory usage: 742.6+ KB
```

2.6 Other Data Preprocessing Steps

In [11]:

```
# removing unnecessary features
airline_data = airline_data.drop(['Carrier Code', 'Tail Number'], axis = 1)
airline_data
```

Out[11]:

	Date	Flight Number	Origin Airport	Scheduled Arrival Time	Actual Arrival Time	Scheduled Elapsed Time (Minutes)	Actual Elapsed Time (Minutes)	Arrival Delay (Minutes)	Wheels-on Time	Ta (Mir
454	2023-01-31	1998	ORD	09:17 PM	08:52 PM	113	97	-25	08:48 PM	
455	2023-01-31	2617	EWR	11:12 PM	10:59 PM	74	66	-13	10:55 PM	
453	2023-01-31	604	DEN	02:59 PM	02:47 PM	193	175	-12	02:40 PM	
438	2023-01-30	604	DEN	02:59 PM	02:35 PM	193	172	-24	02:30 PM	
439	2023-01-30	1998	ORD	09:17 PM	09:21 PM	113	103	4	09:16 PM	
...	...	...	...	...	...	...	...	...	...	
14	2000-01-02	356	ORD	05:03 PM	04:59 PM	105	81	-4	04:56 PM	
15	2000-01-02	1498	ORD	07:26 PM	08:22 PM	101	92	56	08:17 PM	
16	2000-01-02	1620	ORD	09:25 AM	09:10 AM	95	82	-15	09:06 AM	
1	2000-01-01	1498	ORD	07:25 PM	07:15 PM	101	92	-10	07:09 PM	
0	2000-01-01	356	ORD	05:03 PM	04:49 PM	105	91	-14	04:44 PM	

5281 rows × 15 columns

3. FEATURE ENGINEERING

3.1 Creating a New Feature for Flight Status Classification:

In [12]:

```
# creating a new feature 'Status' using 'Arrival Delay (Minutes)'
airline_data['Status'] = pd.cut(airline_data['Arrival Delay (Minutes)'],
                                bins=[float('-inf'), -10, 10, 30, float('inf')],
                                labels=['Early', 'On-time', 'Late', 'Severely Late'
```

In [13]:

```
# checking column names
airline_data.columns

# checking presence of null values in the entire file
airline_data.isna().sum().sum()
```

```
Out[13]: Index(['Date', 'Flight Number', 'Origin Airport', 'Scheduled Arrival Time',
       'Actual Arrival Time', 'Scheduled Elapsed Time (Minutes)',
       'Actual Elapsed Time (Minutes)', 'Arrival Delay (Minutes)',
       'Wheels-on Time', 'Taxi-In time (Minutes)', 'Delay Carrier (Minutes)',
       'Delay Weather (Minutes)', 'Delay National Aviation System (Minutes)',
       'Delay Security (Minutes)', 'Delay Late Aircraft Arrival (Minutes)',
       'Status'],
      dtype='object')
```

```
Out[13]: 0
```

```
In [14]: # verifying unique values of columng 'Delay Weather (minutes)'
airline_data['Delay Weather (Minutes)'].unique()
```

```
Out[14]: array([  0,  11, 985,  30,  82,  85,  41, 162, 115,  38,  34,  42,  24,
        92,  22, 143,   2,   4, 594, 134,  18,  15,  20,   1,  66,  19,
         3,  43,  59,  21,   7], dtype=int64)
```

3.2 Creating "Weather_Delay" Feature:

```
In [15]: # creating new features named 'Weather_Delay' from existing column 'Delay Weather (
airline_data['Weather_Delay'] = np.where(airline_data['Delay Weather (Minutes)'] >
```

```
In [16]: # checking unique values of column 'Weather_Delay'
airline_data['Weather_Delay'].unique()
```

```
Out[16]: array([0, 1])
```

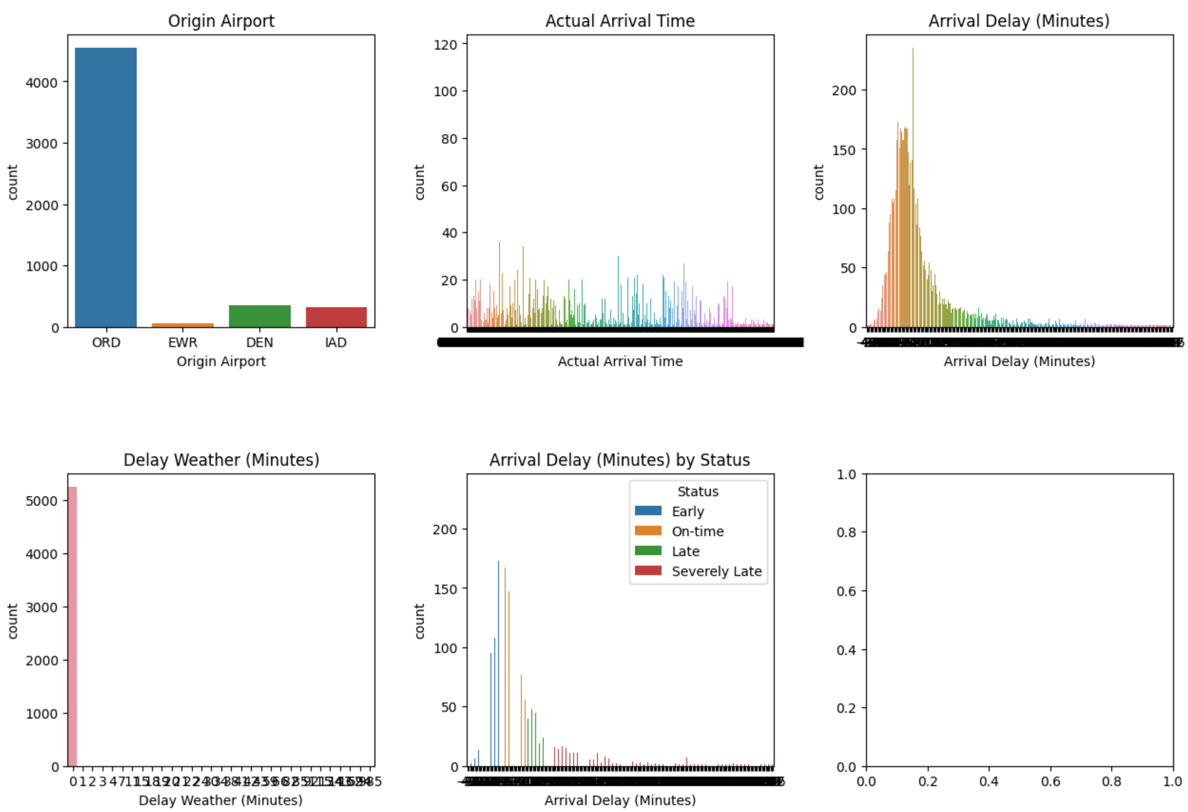
4. EXPLORATORY DATA ANALYSIS (Visualization)

4.1 Bar plots of airline data features

```
In [17]: import seaborn as sns
import matplotlib.pyplot as plt

# create subplots
fig, axs = plt.subplots(nrows=2, ncols=3, figsize=(15, 10))

# plot bar plots for each feature
sns.countplot(x='Origin Airport', data=airline_data, ax=axs[0, 0])
sns.countplot(x='Actual Arrival Time', data=airline_data, ax=axs[0, 1])
sns.countplot(x='Arrival Delay (Minutes)', data=airline_data, ax=axs[0, 2])
sns.countplot(x='Delay Weather (Minutes)', data=airline_data, ax=axs[1, 0])
sns.countplot(x='Arrival Delay (Minutes)', hue='Status', data=airline_data, ax=axs[

# add titles to each plot
axs[0, 0].set_title('Origin Airport')
axs[0, 1].set_title('Actual Arrival Time')
axs[0, 2].set_title('Arrival Delay (Minutes)')
axs[1, 0].set_title('Delay Weather (Minutes)')
axs[1, 1].set_title('Arrival Delay (Minutes) by Status')
```

```python
# adjust spacing between subplots
plt.subplots_adjust(wspace=0.3, hspace=0.5)

# show the plots
plt.show()
```

```
Out[17]: <AxesSubplot: xlabel='Origin Airport', ylabel='count'>

Out[17]: <AxesSubplot: xlabel='Actual Arrival Time', ylabel='count'>

Out[17]: <AxesSubplot: xlabel='Arrival Delay (Minutes)', ylabel='count'>

Out[17]: <AxesSubplot: xlabel='Delay Weather (Minutes)', ylabel='count'>

Out[17]: <AxesSubplot: xlabel='Arrival Delay (Minutes)', ylabel='count'>

Out[17]: Text(0.5, 1.0, 'Origin Airport')

Out[17]: Text(0.5, 1.0, 'Actual Arrival Time')

Out[17]: Text(0.5, 1.0, 'Arrival Delay (Minutes)')

Out[17]: Text(0.5, 1.0, 'Delay Weather (Minutes)')

Out[17]: Text(0.5, 1.0, 'Arrival Delay (Minutes) by Status')
```



4.2 Exploring Correlations in Airline Data Using a Heatmap

```python
In [18]: import seaborn as sns
import matplotlib.pyplot as plt

# calculating correlation
correl = airline_data.corr()
```

```
# visualizing heatmap
sns.heatmap(correl, cmap="YlGnBu")
plt.title("Airline Data Correlation Matrix Heatmap")
plt.show()
```

```
C:\Users\chait\AppData\Local\Temp\ipykernel_15872\1557080848.py:5: FutureWarning:

The default value of numeric_only in DataFrame.corr is deprecated. In a future ver
sion, it will default to False. Select only valid columns or specify the value of
numeric_only to silence this warning.
```

Out[18]: `<AxesSubplot: >`

Out[18]: `Text(0.5, 1.0, 'Airline Data Correlation Matrix Heatmap')`

5. FEATURE SELECTION

5.1 Removing Unnecessary Features:

In [19]:
```
# dropping unwanted features
airline_data.drop(columns=['Actual Arrival Time', 'Arrival Delay (Minutes)',
```

```
       'Scheduled Elapsed Time (Minutes)', 'Actual Elapsed Time (Minutes)',
       'Wheels-on Time', 'Taxi-In time (Minutes)',
       'Delay Carrier (Minutes)', 'Delay Weather (Minutes)',
       'Delay National Aviation System (Minutes)', 'Delay Security (Minutes)',
       'Delay Late Aircraft Arrival (Minutes)'],inplace=True)

# printing header of the dataframe after dropping features
airline_data.head()
```

Out[19]:

	Date	Flight Number	Origin Airport	Scheduled Arrival Time	Status	Weather_Delay
454	2023-01-31	1998	ORD	09:17 PM	Early	0
455	2023-01-31	2617	EWR	11:12 PM	Early	0
453	2023-01-31	604	DEN	02:59 PM	Early	0
438	2023-01-30	604	DEN	02:59 PM	Early	0
439	2023-01-30	1998	ORD	09:17 PM	On-time	0

In [20]:
```
# converting 'Status' from categorical to numerical
status_map = {'Early': 0, 'Severely Late': 1, 'Late': 2, 'On-time': 3}
airline_data['Status'] = airline_data['Status'].map(status_map)
```

5.2 Modifying Features in the Airline Dataset

In [21]:
```
# Extract the scheduled arrival hour and minutes from the 'Scheduled Arrival Time'
airline_data['Scheduled Arrival Hour']= pd.to_datetime(airline_data['Scheduled Arri
airline_data['Scheduled Arrival Minutes']= pd.to_datetime(airline_data['Scheduled A

# dropping features Scheduled Arrival Time and Date columns
airline_data.drop(columns=['Scheduled Arrival Time','Date'],inplace=True)
```

In [22]:
```
# printing header of airline_data data frame
airline_data.head()

# checking column names
airline_data.columns
```

Out[22]:

	Flight Number	Origin Airport	Status	Weather_Delay	Scheduled Arrival Hour	Scheduled Arrival Minutes
454	1998	ORD	0	0	21	17
455	2617	EWR	0	0	23	12
453	604	DEN	0	0	14	59
438	604	DEN	0	0	14	59
439	1998	ORD	3	0	21	17

Out[22]:

```
Index(['Flight Number', 'Origin Airport', 'Status', 'Weather_Delay',
       'Scheduled Arrival Hour', 'Scheduled Arrival Minutes'],
      dtype='object')
```

6. ONE-HOT ENCODING CATEGORICAL FEATURES

6.1 Creating Dummy Variables

In [23]:

```
#dummy variables (one-hot encoding)
cat_cols = airline_data.select_dtypes(include=['object']).columns.tolist()
airline_data = pd.get_dummies(airline_data, columns=cat_cols, drop_first=True)

# printing header of airline_data data frame
airline_data.head()
```

Out[23]:

	Flight Number	Status	Weather_Delay	Scheduled Arrival Hour	Scheduled Arrival Minutes	Origin Airport_EWR	Origin Airport_IAD	Ori Airport_O
454	1998	0	0	21	17	0	0	
455	2617	0	0	23	12	1	0	
453	604	0	0	14	59	0	0	
438	604	0	0	14	59	0	0	
439	1998	3	0	21	17	0	0	

7. FEATURE SCALING

7.1 Standardization and Transformation of Features

In [24]:

```
# Separate the features and the target variable
X = airline_data.drop(columns=["Status"])
y = airline_data["Status"]

# performing feature scaling
```

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
airline_data = pd.DataFrame(sc.fit_transform(airline_data), columns = airline_data.
airline_data.head()
```

Out[24]:

	Flight Number	Status	Weather_Delay	Scheduled Arrival Hour	Scheduled Arrival Minutes	Origin Airport_EWR	Origin Airport_IAD	Ori Airport_O
454	1.18	-1.31	-0.09	0.91	-0.69	-0.11	-0.26	(
455	2.18	-1.31	-0.09	1.32	-0.93	9.17	-0.26	-2
453	-1.08	-1.31	-0.09	-0.55	1.34	-0.11	-0.26	-2
438	-1.08	-1.31	-0.09	-0.55	1.34	-0.11	-0.26	-2
439	1.18	0.98	-0.09	0.91	-0.69	-0.11	-0.26	(

8. MODEL SELECTION AND EVALUATION

8.1 Splitting Data (Test and Train)

In [25]:

```
# splitting data into train and test (with 20% used as testing data)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_st

# print the length of the train and test data
print("Length of train data:", len(X_train))
print("Length of test data:", len(X_test))

print("\n")

# representing all four variable values
X_train
X_test
y_train
y_test
```

```
Length of train data: 4224
Length of test data: 1057
```

Out[25]:

	Flight Number	Weather_Delay	Scheduled Arrival Hour	Scheduled Arrival Minutes	Origin Airport_EWR	Origin Airport_IAD	Origin Airport_ORD
590	1498	0	20	10	0	0	1
1135	607	0	21	50	0	0	1
4268	1730	0	16	54	0	0	1
5276	1498	0	9	44	0	0	1
4937	342	0	15	58	0	0	1
...	...	...	...	...	...	...	...
4395	1094	0	15	54	0	0	1
112	604	0	15	2	0	0	0
5152	2488	0	23	14	1	0	0
3387	1500	0	16	50	0	0	1
4450	1260	0	16	37	0	0	1

4224 rows × 7 columns

Out[25]:

	Flight Number	Weather_Delay	Scheduled Arrival Hour	Scheduled Arrival Minutes	Origin Airport_EWR	Origin Airport_IAD	Origin Airport_ORD
2463	356	0	15	58	0	0	1
4529	1620	0	8	48	0	0	1
4825	1498	0	23	23	0	0	1
3645	1498	0	21	1	0	0	1
722	356	0	20	32	0	0	1
...	...	...	...	...	...	...	...
4610	342	0	16	3	0	0	1
3686	1730	0	16	49	0	0	1
829	1498	0	20	41	0	0	1
541	1620	0	9	4	0	0	1
693	1620	0	9	13	0	0	1

1057 rows × 7 columns

Out[25]:
```
590     0
1135    3
4268    3
5276    3
4937    3
       ..
4395    0
112     2
5152    2
3387    0
4450    3
Name: Status, Length: 4224, dtype: category
Categories (4, int64): [0 < 3 < 2 < 1]
```

Out[25]:
```
2463    0
4529    3
4825    3
3645    1
722     3
       ..
4610    3
3686    2
829     2
541     3
693     0
```

8.2 Random Forest Classifier for Predicting Airline Delays

In [26]:
```python
# importing RandomForestClassifier
from sklearn.ensemble import RandomForestClassifier

# create a Random Forest Classifier object
rf_clf = RandomForestClassifier(n_estimators=1000,
                                random_state=50,
                                max_depth=10,
                                min_samples_split=5,
                                min_samples_leaf=3,
                                max_features=10)

# fit the model to the training data
rf_clf.fit(X_train, y_train)

# make predictions on the testing data
y_pred = rf_clf.predict(X_test)
```

Out[26]:

RandomForestClassifier

```
RandomForestClassifier(max_depth=10, max_features=10, min_samples_leaf=3,
                       min_samples_split=5, n_estimators=1000, random_stat
e=50)
```

8.3 Performance Evaluation

In [27]:
```
# creating new DataFrame called test_output containing the predicted values of the
test_output = pd.DataFrame(rf_clf.predict(X_test), index = X_test.index, columns =

# checking the head of predicted values
test_output.head()
```

Out[27]:

	pred_Status
2463	0
4529	3
4825	3
3645	3
722	3

In [28]:
```
# merging the predicted output of the random forest classifier with the actual labe
test_output = test_output.merge(y_test, left_index = True, right_index = True)

# checking the head of the merged data frame
test_output.head()
```

Out[28]:

	pred_Status	Status
2463	0	0
4529	3	3
4825	3	3
3645	3	1
722	3	3

9. PERFORMING PREDICTIONS (April 21 – April 24)

9.1 Loading Test Data for Prediction

In [29]:
```
# Loading Test Dataset for performing predictions
april_test_data = pd.read_csv('project csv(Apr 21-24).csv')

# second data frame Output_data is used in future for storing actual predictions
Output_data = pd.read_csv('project csv(Apr 21-24).csv')
april_test_data.head()
```

Out[29]:

	Date	Day	Origin Airport	Flight Number	Arrival Time	Status (Early, On-time, Late, Severly Late)
0	4/21/2023	Friday	ORD	UA 3839	10:00 AM	Early
1	4/21/2023	Friday	ORD	UA 3524	4:50 PM	Severely Late
2	4/21/2023	Friday	ORD	UA 538	9:34 PM	On-time
3	4/22/2023	Saturday	ORD	UA 3839	10:00 AM	Early
4	4/22/2023	Saturday	ORD	UA 3524	4:50 PM	Early

9.2 Data-Preprocessing on Test Data

In [30]:

```
# dropping unwanted feature 'Status (Early, On-time, Late, Severly Late)' as this i
april_test_data.head()
april_test_data = april_test_data.drop(columns = 'Status (Early, On-time, Late, Sev

# checking the header of the dataframe april_test_data
april_test_data.head()
```

Out[30]:

	Date	Day	Origin Airport	Flight Number	Arrival Time	Status (Early, On-time, Late, Severly Late)
0	4/21/2023	Friday	ORD	UA 3839	10:00 AM	Early
1	4/21/2023	Friday	ORD	UA 3524	4:50 PM	Severely Late
2	4/21/2023	Friday	ORD	UA 538	9:34 PM	On-time
3	4/22/2023	Saturday	ORD	UA 3839	10:00 AM	Early
4	4/22/2023	Saturday	ORD	UA 3524	4:50 PM	Early

Out[30]:

	Date	Day	Origin Airport	Flight Number	Arrival Time
0	4/21/2023	Friday	ORD	UA 3839	10:00 AM
1	4/21/2023	Friday	ORD	UA 3524	4:50 PM
2	4/21/2023	Friday	ORD	UA 538	9:34 PM
3	4/22/2023	Saturday	ORD	UA 3839	10:00 AM
4	4/22/2023	Saturday	ORD	UA 3524	4:50 PM

In [31]:

```
# checking feature names and data types of all features
april_test_data.columns
april_test_data.dtypes
```

Out[31]:

```
Index(['Date', 'Day', 'Origin Airport', 'Flight Number', 'Arrival Time'], dtype='o
bject')
```

Out[31]:
```
Date              object
Day               object
Origin Airport    object
Flight Number     object
Arrival Time      object
dtype: object
```

In [32]:
```
# dropping null values
april_test_data.dropna(inplace = True)

# checking for presence of null values in each column
april_test_data.isna().any()

# checking for presence of null values in entire file
april_test_data.isna().sum().sum()
```

Out[32]:
```
Date              False
Day               False
Origin Airport    False
Flight Number     False
Arrival Time      False
dtype: bool
```

Out[32]:
```
0
```

In [33]:
```
# checking Train Data and Test Data column names
airline_data.columns
april_test_data.columns
```

Out[33]:
```
Index(['Flight Number', 'Status', 'Weather_Delay', 'Scheduled Arrival Hour',
       'Scheduled Arrival Minutes', 'Origin Airport_EWR', 'Origin Airport_IAD',
       'Origin Airport_ORD'],
      dtype='object')
```

Out[33]:
```
Index(['Date', 'Day', 'Origin Airport', 'Flight Number', 'Arrival Time'], dtype='o
bject')
```

In [34]:
```
import datetime

# converting the 'Arrival Time' column from string format to datetime format
april_test_data['Scheduled Arrival Time'] = april_test_data['Arrival Time'].str.str

# checking the header of this data frame
april_test_data.head()
```

Out[34]:

	Date	Day	Origin Airport	Flight Number	Arrival Time	Scheduled Arrival Time
0	4/21/2023	Friday	ORD	UA 3839	10:00 AM	10:00
1	4/21/2023	Friday	ORD	UA 3524	4:50 PM	16:50
2	4/21/2023	Friday	ORD	UA 538	9:34 PM	21:34
3	4/22/2023	Saturday	ORD	UA 3839	10:00 AM	10:00
4	4/22/2023	Saturday	ORD	UA 3524	4:50 PM	16:50

In [35]:
```python
# dropping other unwanted features
april_test_data.drop(columns=['Date','Day','Arrival Time'],inplace=True)
```

9.3 Feature Engineering on Test Data

In [36]:
```python
# creating a list of values for new column
weather_delay_list = [0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0

# creating new column 'Weather_Delay'
april_test_data['Weather_Delay'] = weather_delay_list
```

In [37]:
```python
# parsing datetime columns
april_test_data['Scheduled Arrival Hour']= pd.to_datetime(april_test_data['Schedule
april_test_data['Scheduled Arrival Minutes']= pd.to_datetime(april_test_data['Sched
april_test_data.drop(columns=['Scheduled Arrival Time'],inplace=True)
```

In [38]:
```python
# converting column Flight Number to Numerical
april_test_data['Flight Number'] = april_test_data['Flight Number'].str.extract('(\
```

9.4 One-Hot Encoding of Categorical Variables in Test Data

In [39]:
```python
#dummy variables (one-hot encoding)
cat_cols = april_test_data.select_dtypes(include=['object']).columns.tolist()
april_test_data = pd.get_dummies(april_test_data, columns=cat_cols, drop_first=True

# checking header
april_test_data.head()
```

Out[39]:

	Flight Number	Weather_Delay	Scheduled Arrival Hour	Scheduled Arrival Minutes	Origin Airport_EWR	Origin Airport_IAD	Origin Airport_ORD
0	3839	0	10	0	0	0	1
1	3524	1	16	50	0	0	1
2	538	0	21	34	0	0	1
3	3839	0	10	0	0	0	1
4	3524	0	16	50	0	0	1

9.5 Comparing Data Distributions of Train and Test Sets

In [40]:
```python
# comapring Train data and Test data headers
april_test_data.head()
airline_data.head()
```

Out[40]:

	Flight Number	Weather_Delay	Scheduled Arrival Hour	Scheduled Arrival Minutes	Origin Airport_EWR	Origin Airport_IAD	Origin Airport_ORD
0	3839	0	10	0	0	0	1
1	3524	1	16	50	0	0	1
2	538	0	21	34	0	0	1
3	3839	0	10	0	0	0	1
4	3524	0	16	50	0	0	1

Out[40]:

	Flight Number	Status	Weather_Delay	Scheduled Arrival Hour	Scheduled Arrival Minutes	Origin Airport_EWR	Origin Airport_IAD	Origin Airport_O
454	1.18	-1.31	-0.09	0.91	-0.69	-0.11	-0.26	(
455	2.18	-1.31	-0.09	1.32	-0.93	9.17	-0.26	-2
453	-1.08	-1.31	-0.09	-0.55	1.34	-0.11	-0.26	-2
438	-1.08	-1.31	-0.09	-0.55	1.34	-0.11	-0.26	-2
439	1.18	0.98	-0.09	0.91	-0.69	-0.11	-0.26	(

9.6 Predicting Flight Status for April (21-24) Test Data

In [41]:
```
# performing predictions
rf_clf.predict(april_test_data)
```

Out[41]:
```
array([0, 1, 3, 0, 0, 3, 1, 0, 1, 0, 0, 3, 3, 1, 3, 3, 0, 2, 1, 1, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0], dtype=int64)
```

In [42]:
```
# creating DataFrame containing predictions made by a random forest classifier
test_output = pd.DataFrame(rf_clf.predict(april_test_data), index = april_test_data
test_output.head()

# test_output is merged with april_test_data based on their indices, creating a new
test_data = test_output.merge(april_test_data, left_index = True, right_index = Tru

# the Weather_Delay column is dropped from test_data
test_data = test_data.drop(columns = ['Weather_Delay'])
```

Out[42]:

	Status
0	0
1	1
2	3
3	0
4	0

9.7 Label Encoding of Predicted Status Values in Test Data

In [43]:

```
# converting predicted column from numerical to categorical
test_data['Status'].replace(0,"Early",inplace=True)
test_data['Status'].replace(1,"Severely Late",inplace=True)
test_data['Status'].replace(2,"Late",inplace=True)
test_data['Status'].replace(3,"On-time",inplace=True)
```

9.8 Saving Predictions to a CSV File

In [44]:

```
# making predictions and storing them in a list or series
Output_data['Status (Early, On-time, Late, Severly Late)'] = test_data['Status']

# writing the updated dataframe to the CSV file
Output_data.to_csv('Output.csv', index=False)
```