# Project Development Phase

# Sprint-1-Data Prepossessing

| | |
|---|---|
| Date | 9 November 2022 |
| Team ID | PNT2022TMID54451 |
| Project Name | Project -Developing a Flight Delay Prediction Model using Machine Learning |
| Maximum Marks | 8 Marks |

We have created a model with the help of Pre-processed data. We have used Decision Tree Classifier algorithm for model development. Also we have implemented the model to check the accuracy of our model. With the help of pickle model file the prediction is performed by flask app

## Screenshots

```
In [18]:
#import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import rcParams
```

```
In [19]:
import os, types
import pandas as pd
from botocore.client import Config
import ibm_boto3

def __iter__(self): return 0

# @hidden_cell
# The following code accesses a file in your IBM Cloud Object Storage. It includes your credentials.
# You might want to remove those credentials before you share the notebook.
cos_client = ibm_boto3.client(service_name='s3',
    ibm_api_key_id='9a5kuMDufRQ-_cGNUo8i7lt6cBI_rKUlI_yar-AAorx',
    ibm_auth_endpoint="https://iam.cloud.ibm.com/oidc/token",
    config=Config(signature_version='oauth'),
    endpoint_url='https://s3.private.us.cloud-object-storage.appdomain.cloud')

bucket = 'flightdelayprediction-donotdelete-pr-ocgt3ilwhtnvuj'
object_key = 'Flightdata2.xlsx'

body = cos_client.get_object(Bucket=bucket,Key=object_key)['Body']
df= pd.read_excel(body.read())
```

```
In [20]:
df.head()
```

Out[20]:

| | YEAR | QUARTER | MONTH | DAY_OF_MONTH | DAY_OF_WEEK | UNIQUE_CARRIER | TAIL_NUM | FL_NUM | ORIGIN_AIRPORT_ID | ORIGIN | ... | ARR_TIME.1 | ARR_DELAY | ARR_DEL15 | C |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 2016 | 1 | 1 | 1 | 5 | DL | N836DN | 1399 | 10397 | ATL | ... | 2102.0 | -41.0 | 0.0 | |
| 1 | 2016 | 1 | 1 | 1 | 5 | DL | N964DN | 1476 | 11433 | DTW | ... | 1439.0 | 4.0 | 0.0 | |
| 2 | 2016 | 1 | 1 | 1 | 5 | DL | N813DN | 1597 | 10397 | ATL | ... | 1142.0 | -33.0 | 0.0 | |
| 3 | 2016 | 1 | 1 | 1 | 5 | DL | N587NW | 1768 | 14747 | SEA | ... | 1345.0 | 10.0 | 0.0 | |
| 4 | 2016 | 1 | 1 | 1 | 5 | DL | N836DN | 1823 | 14747 | SEA | ... | 615.0 | 8.0 | 0.0 | |

In [21]:
```
from datetime import datetime
```

In [22]:
```
import datetime as dt
```

In [23]:
```
from datetime import datetime
```

In [ ]:
```

```

In [41]:
```
pwd
```

Out[41]:
```
'/home/wsuser/work'
```

In [24]:
```
df.shape
```

Out[24]:
```
(11231, 31)
```

In [25]:
```
df.info()
```

```
RangeIndex: 11231 entries, 0 to 11230
Data columns (total 31 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   YEAR                  11231 non-null  int64  
 1   QUARTER               11231 non-null  int64  
 2   MONTH                 11231 non-null  int64  
 3   DAY_OF_MONTH          11231 non-null  int64  
 4   DAY_OF_WEEK           11231 non-null  int64  
 5   UNIQUE_CARRIER        11231 non-null  object 
 6   TAIL_NUM              11231 non-null  object 
 7   FL_NUM                11231 non-null  int64  
 8   ORIGIN_AIRPORT_ID     11231 non-null  int64  
 9   ORIGIN                11231 non-null  object 
 10  DEST_AIRPORT_ID       11231 non-null  int64  
 11  DEST                  11231 non-null  object 
 12  CRS_DEP_TIME          11231 non-null  object 
 13  CRS_DEP_TIME.1        11231 non-null  int64  
 14  DEP_TIME              11124 non-null  object 
 15  DEP_TIME.1            11124 non-null  float64
 16  DEP_DELAY             11124 non-null  float64
 17  DEP_DEL15             11124 non-null  float64
 18  CRS_ARR_TIME          11231 non-null  object 
 19  CRS_ARR_TIME.1        11231 non-null  int64  
 20  ARR_TIME              11116 non-null  object 
 21  ARR_TIME.1            11116 non-null  float64
 22  ARR_DELAY             11043 non-null  float64
 23  ARR_DEL15             11043 non-null  float64
 24  CANCELLED             11231 non-null  int64  
 25  DIVERTED              11231 non-null  int64  
 26  CRS_ELAPSED_TIME1     11231 non-null  object 
 27  ACTUAL_ELAPSED_TIME1  11231 non-null  object 
 28  CRS_ELAPSED_TIME      11231 non-null  int64  
 29  ACTUAL_ELAPSED_TIME   11043 non-null  float64
 30  DISTANCE              11231 non-null  int64  
dtypes: float64(7), int64(14), object(10)
memory usage: 2.7+ MB
```

In [26]:
```
df.isnull().any()
```

Out[26]:
```
YEAR                  False
QUARTER               False
MONTH                 False
DAY_OF_MONTH          False
DAY_OF_WEEK           False
UNIQUE_CARRIER        False
TAIL_NUM              False
FL_NUM                False
ORIGIN_AIRPORT_ID     False
ORIGIN                False
DEST_AIRPORT_ID       False
DEST                  False
CRS_DEP_TIME          False
CRS_DEP_TIME.1        False
DEP_TIME               True
DEP_TIME.1             True
DEP_DELAY              True
DEP_DEL15              True
CRS_ARR_TIME          False
CRS_ARR_TIME.1        False
ARR_TIME               True
ARR_TIME.1             True
ARR_DELAY              True
ARR_DEL15              True
CANCELLED             False
DIVERTED              False
CRS_ELAPSED_TIME1     False
ACTUAL_ELAPSED_TIME1  False
CRS_ELAPSED_TIME      False
ACTUAL_ELAPSED_TIME    True
DISTANCE              False
dtype: bool
```

In [31]:
```
df['DEP_DELAY'].fillna(df['DEP_DELAY'].median(),inplace=True)
```

In [32]:
```
df.describe()
```

Out[32]:

| | YEAR | QUARTER | MONTH | DAY_OF_MONTH | DAY_OF_WEEK | FL_NUM | ORIGIN_AIRPORT_ID | DEST_AIRPORT_ID | CRS_DEP_TIME.1 | DEP_TIME.1 | ... | DEP_DEL1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 11231.0 | 11231.000000 | 11231.000000 | 11231.000000 | 11231.000000 | 11231.000000 | 11231.000000 | 11231.000000 | 11231.000000 | 11124.000000 | ... | 11231.00000 |
| **mean** | 2016.0 | 2.544475 | 6.628973 | 15.790758 | 3.960199 | 1334.325617 | 12334.516695 | 12302.274508 | 1320.798326 | 1327.189410 | ... | 0.14148 |
| **std** | 0.0 | 1.090701 | 3.354678 | 8.782056 | 1.995257 | 811.875227 | 1595.026510 | 1601.988550 | 490.737845 | 500.306462 | ... | 0.34853 |
| **min** | 2016.0 | 1.000000 | 1.000000 | 1.000000 | 1.000000 | 7.000000 | 10397.000000 | 10397.000000 | 10.000000 | 1.000000 | ... | 0.00000 |
| **25%** | 2016.0 | 2.000000 | 4.000000 | 8.000000 | 2.000000 | 624.000000 | 10397.000000 | 10397.000000 | 905.000000 | 905.000000 | ... | 0.00000 |
| **50%** | 2016.0 | 3.000000 | 7.000000 | 16.000000 | 4.000000 | 1267.000000 | 12478.000000 | 12478.000000 | 1320.000000 | 1324.000000 | ... | 0.00000 |
| **75%** | 2016.0 | 3.000000 | 9.000000 | 23.000000 | 6.000000 | 2032.000000 | 13487.000000 | 13487.000000 | 1735.000000 | 1739.000000 | ... | 0.00000 |
| **max** | 2016.0 | 4.000000 | 12.000000 | 31.000000 | 7.000000 | 2853.000000 | 14747.000000 | 14747.000000 | 2359.000000 | 2400.000000 | ... | 1.00000 |

8 rows × 21 columns

In [33]:
```
df.ORIGIN.value_counts()
```

Out[33]:
```
ATL    3180
MSP    2538
DTW    2201
SEA    2018
JFK    1374
Name: ORIGIN, dtype: int64
```

In [34]:
```
df.UNIQUE_CARRIER.value_counts()
```

Out[34]:
```
DL    11231
Name: UNIQUE_CARRIER, dtype: int64
```

In [35]:
```
df.ORIGIN_AIRPORT_ID.value_counts()
```

Out[35]:
```
10397    3180
13487    2538
11433    2201
14747    2018
12478    1374
Name: ORIGIN_AIRPORT_ID, dtype: int64
```

In [36]:
```
df.ORIGIN.unique()
```

Out[36]:
```
array(['ATL', 'DTW', 'SEA', 'MSP', 'JFK'], dtype=object)
```

In [37]:
```
df.ORIGIN_AIRPORT_ID.unique()
```

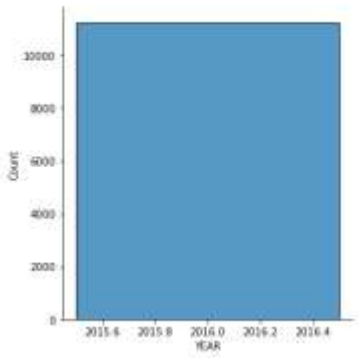
Out[37]:
```
array([10397, 11433, 14747, 13487, 12478])
```

In [38]:
```
df.UNIQUE_CARRIER.unique()
```

Out[38]:
```
array(['DL'], dtype=object)
```

In [39]:
```
sns.displot(df.YEAR)
```

Out[39]:

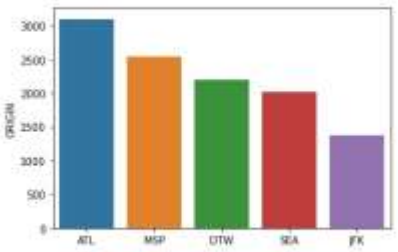


In [40]:
```
plt.pie(df.ORIGIN.value_counts(),labels=['ATL', 'DTW', 'SEA', 'MSP', 'JFK'],autopct='%1.1f%%')
plt.title('AIRPORT')
```

Out[40]:
```
Text(0.5, 1.0, 'AIRPORT')
```


In [41]:
```
sns.barplot(df.ORIGIN.value_counts().index,df.ORIGIN.value_counts())
```

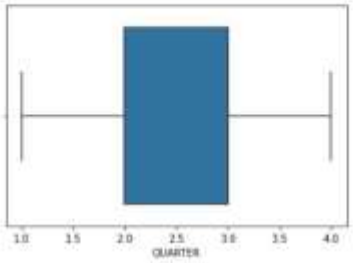
Out[41]:




In [42]:
```
df.hist(figsize=(20,20))
```

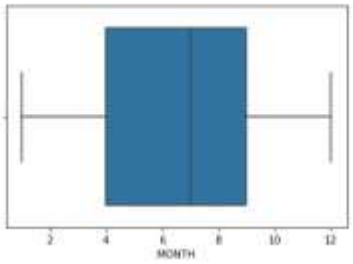
In [43]:
```
sns.boxplot(df.QUARTER)
```

Out[43]:



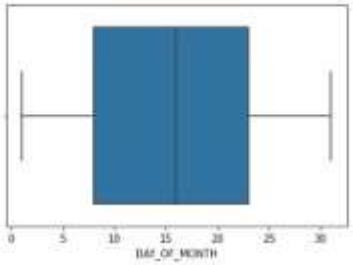

In [44]:
```
sns.boxplot(df.MONTH)
```

Out[44]:



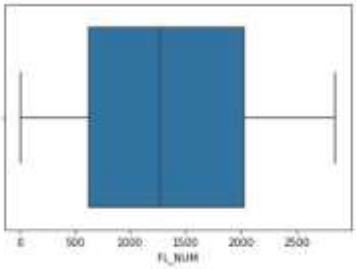

In [45]:
```
sns.boxplot(df.DAY_OF_MONTH)
```

Out[45]:



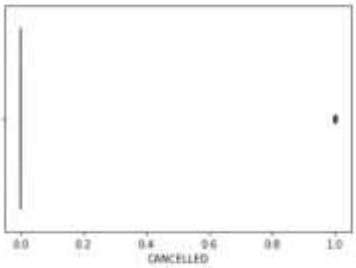
In [46]:
```
sns.boxplot(df.FL_NUM)
```

Out[46]:



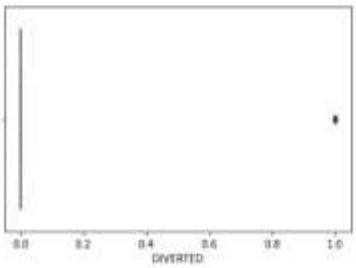

In [47]:
```
sns.boxplot(df.CANCELLED)
```

Out[47]:



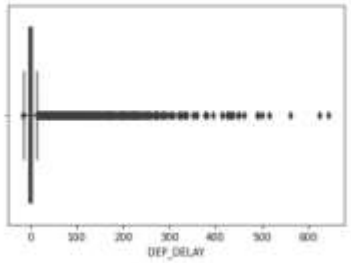

In [48]:
```
sns.boxplot(df.DIVERTED)
```

Out[48]:



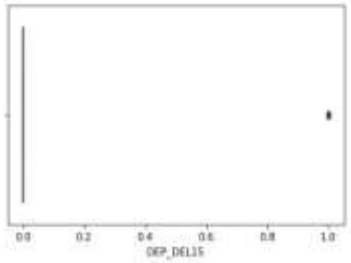
In [94]:
```
sns.boxplot(df.DEP_DELAY)
```

Out[94]:



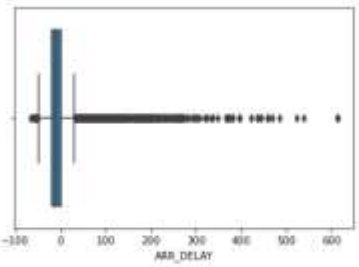

In [95]:
```
sns.boxplot(df.DEP_DEL15)
```

Out[95]:




In [120...
```
sns.boxplot(df.ARR_DELAY)
```

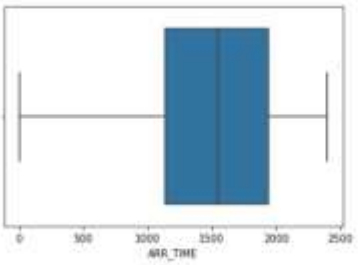
Out[120...



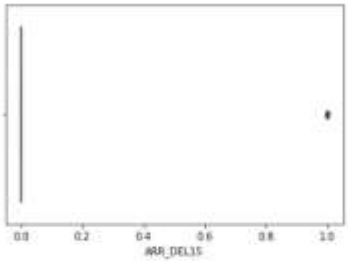

In [130...
```
sns.boxplot(df.ARR_TIME)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.1
2, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretat
ion.
  warnings.warn(
```

Out[130...



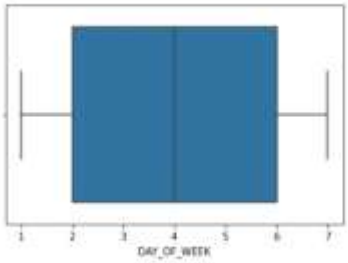

In [131...
```
sns.boxplot(df.ARR_DEL15)
```




In [132]:
```
sns.boxplot(df.DAY_OF_WEEK)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.1
2, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretat
ion.
  warnings.warn(
```

Out[132]:




In [133]:
```
sns.boxplot(df.ORIGIN_AIRPORT_ID)
```

In [56]:
```
df.groupby(by="DAY_OF_WEEK")["DEP_DEL15"].sum()
```

Out[56]:
```
DAY_OF_WEEK
1    253.0
2    213.0
3    204.0
4    245.0
5    250.0
6    198.0
7    226.0
Name: DEP_DEL15, dtype: float64
```

In [57]:
```
df.groupby(by="MONTH")["DEP_DEL15"].sum()
```

Out[57]:
```
MONTH
1     113.0
2     115.0
3     104.0
4      96.0
5      86.0
6     168.0
7     219.0
8     246.0
9      88.0
10     86.0
11     68.0
12    282.0
Name: DEP_DEL15, dtype: float64
```

In [58]:
```
df[df["ARR_DELAY"]>300]
```

Out[58]:

| | YEAR | QUARTER | MONTH | DAY_OF_MONTH | DAY_OF_WEEK | UNIQUE_CARRIER | TAIL_NUM | FL_NUM | ORIGIN_AIRPORT_ID | ORIGIN | ... | ARR_TIME.1 | ARR_DELAY | ARR_DEL1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **202** | 2016 | 1 | 1 | 10 | 7 | DL | N125DL | 1893 | 11433 | DTW | ... | 1815.0 | 326.0 | 1. |
| **565** | 2016 | 1 | 1 | 24 | 7 | DL | N3753 | 463 | 12478 | JFK | ... | 2127.0 | 470.0 | 1. |
| **1189** | 2016 | 1 | 2 | 16 | 2 | DL | N935DL | 86 | 13487 | MSP | ... | 2140.0 | 300.0 | 1. |
| **1605** | 2016 | 1 | 2 | 24 | 3 | DL | N983DL | 1156 | 10397 | ATL | ... | 218.0 | 371.0 | 1. |
| **2535** | 2016 | 1 | 3 | 18 | 5 | DL | N809DN | 2330 | 14747 | SEA | ... | 246.0 | 615.0 | 1. |
| **2723** | 2016 | 2 | 4 | 10 | 7 | DL | N624AG | 1336 | 14747 | SEA | ... | 2317.0 | 437.0 | 1. |
| **4814** | 2016 | 2 | 6 | 16 | 4 | DL | N319NB | 2818 | 12478 | JFK | ... | 2318.0 | 301.0 | 1. |
| **5336** | 2016 | 3 | 7 | 1 | 5 | DL | N171DN | 43 | 12478 | JFK | ... | 27.0 | 374.0 | 1. |
| **5340** | 2016 | 3 | 7 | 1 | 5 | DL | N355NB | 2214 | 13487 | MSP | ... | 307.0 | 335.0 | 1. |
| **5378** | 2016 | 3 | 7 | 1 | 5 | DL | N377NW | 964 | 10397 | ATL | ... | 604.0 | 380.0 | 1. |
| **5524** | 2016 | 3 | 7 | 7 | 4 | DL | N684DA | 2219 | 14747 | SEA | ... | 2354.0 | 539.0 | 1. |
| **5561** | 2016 | 3 | 7 | 8 | 5 | DL | N343NB | 2816 | 12478 | JFK | ... | 3.0 | 348.0 | 1. |
| **5751** | 2016 | 3 | 7 | 13 | 3 | DL | N991AT | 1126 | 13487 | MSP | ... | 2355.0 | 370.0 | 1. |
| **6092** | 2016 | 3 | 7 | 25 | 1 | DL | N910DE | 220 | 12478 | JFK | ... | 421.0 | 366.0 | 1. |

In [58]:
```
df[df["ARR_DELAY"]>=300]
```

Out[58]:

| | YEAR | QUARTER | MONTH | DAY_OF_MONTH | DAY_OF_WEEK | UNIQUE_CARRIER | TAIL_NUM | FL_NUM | ORIGIN_AIRPORT_ID | ORIGIN | ... | ARR_TIME.1 | ARR_DELAY | ARR_DEL1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **202** | 2018 | 1 | 1 | 10 | 7 | DL | N125DL | 1893 | 11433 | DTW | ... | 1615.0 | 326.0 | 1. |
| **565** | 2018 | 1 | 1 | 24 | 7 | DL | N375S | 483 | 12478 | JFK | ... | 2127.0 | 470.0 | 1. |
| **1199** | 2018 | 1 | 2 | 16 | 2 | DL | N935DL | 66 | 13487 | MSP | ... | 2140.0 | 300.0 | 1. |
| **1605** | 2018 | 1 | 2 | 24 | 3 | DL | N988DL | 1156 | 10397 | ATL | ... | 218.0 | 371.0 | 1. |
| **2535** | 2018 | 1 | 3 | 16 | 5 | DL | N809DN | 2330 | 14747 | SEA | ... | 346.0 | 615.0 | 1. |
| **2723** | 2018 | 2 | 4 | 10 | 7 | DL | N624AG | 1336 | 14747 | SEA | ... | 2317.0 | 437.0 | 1. |
| **4814** | 2018 | 2 | 6 | 16 | 4 | DL | N319NB | 2816 | 12478 | JFK | ... | 2318.0 | 301.0 | 1. |
| **5336** | 2018 | 3 | 7 | 1 | 5 | DL | N171DN | 43 | 12478 | JFK | ... | 27.0 | 374.0 | 1. |
| **5340** | 2018 | 3 | 7 | 1 | 5 | DL | N335NB | 2214 | 13487 | MSP | ... | 307.0 | 335.0 | 1. |
| **5378** | 2018 | 3 | 7 | 1 | 5 | DL | N377NW | 984 | 10397 | ATL | ... | 604.0 | 380.0 | 1. |
| **5524** | 2018 | 3 | 7 | 7 | 4 | DL | N884DA | 2218 | 14747 | SEA | ... | 2354.0 | 539.0 | 1. |
| **5561** | 2018 | 3 | 7 | 8 | 5 | DL | N343NB | 2816 | 12478 | JFK | ... | 3.0 | 348.0 | 1. |
| **5751** | 2018 | 3 | 7 | 13 | 3 | DL | N991AT | 1126 | 13487 | MSP | ... | 2355.0 | 370.0 | 1. |
| **6092** | 2018 | 3 | 7 | 25 | 1 | DL | N910DE | 220 | 12478 | JFK | ... | 421.0 | 366.0 | 1. |
| **6195** | 2018 | 3 | 7 | 28 | 4 | DL | N988DL | 433 | 12478 | JFK | ... | 5.0 | 457.0 | 1. |
| **6662** | 2018 | 3 | 8 | 8 | 1 | DL | N855DN | 173 | 10397 | ATL | ... | 140.0 | 398.0 | 1. |
| **6672** | 2018 | 3 | 8 | 8 | 1 | DL | N923DL | 2590 | 10397 | ATL | ... | 1723.0 | 423.0 | 1. |
| **6688** | 2018 | 3 | 8 | 9 | 2 | DL | N376SD | 420 | 10397 | ATL | ... | 2253.0 | 395.0 | 1. |
| **6693** | 2018 | 3 | 8 | 8 | 1 | DL | N587NW | 784 | 10397 | ATL | ... | 1741.0 | 444.0 | 1. |
| **6696** | 2018 | 3 | 8 | 8 | 1 | DL | N946DL | 902 | 10397 | ATL | ... | 2333.0 | 370.0 | 1. |
| **6701** | 2018 | 3 | 8 | 8 | 1 | DL | N339NW | 987 | 10397 | ATL | ... | 1741.0 | 320.0 | 1. |
| **6744** | 2018 | 3 | 8 | 9 | 2 | DL | N121DE | 2827 | 10397 | ATL | ... | 239.0 | 309.0 | 1. |
| **6767** | 2018 | 3 | 8 | 11 | 4 | DL | N936DL | 52 | 11433 | DTW | ... | 1507.0 | 357.0 | 1. |
| **6790** | 2018 | 3 | 8 | 11 | 4 | DL | N884DA | 1444 | 14747 | SEA | ... | 1958.0 | 423.0 | 1. |
| **7129** | 2018 | 3 | 8 | 19 | 3 | DL | N695DL | 1542 | 14747 | SEA | ... | 606.0 | 612.0 | 1. |
| **7198** | 2018 | 3 | 8 | 4 | 4 | DL | N550NW | 1232 | 14747 | SEA | ... | 420.0 | 461.0 | 1. |
| **7259** | 2018 | 3 | 8 | 22 | 1 | DL | N537US | 1444 | 14747 | SEA | ... | 2101.0 | 486.0 | 1. |
| **9239** | 2018 | 4 | 10 | 30 | 7 | DL | N710TW | 494 | 12478 | JFK | ... | 20.0 | 302.0 | 1. |
| **10598** | 2018 | 4 | 12 | 11 | 7 | DL | N6709Y | 2174 | 11433 | DTW | ... | 440.0 | 522.0 | 1. |
| **10754** | 2018 | 4 | 12 | 17 | 6 | DL | N988DL | 33 | 13487 | MSP | ... | 129.0 | 436.0 | 1. |
| **10761** | 2018 | 4 | 12 | 17 | 6 | DL | N988DL | 603 | 11433 | DTW | ... | 339.0 | 381.0 | 1. |

In [58]:
```
sm=[6,7,8]
wt=[9,10,11]
sp=[12,1,2,3]
fl=[4,5]
```

In [60]:
```
df["SEASON"]=np.where(df["MONTH"].isin(sm),0,np.where(df["MONTH"].isin(wt),1,np.where(df["MONTH"].isin(sp),2,3)))
```

In [61]:
```
df["SEASON"].value_counts()
```

Out[61]:
```
2    3441
0    3164
1    2888
3    1738
Name: SEASON, dtype: int64
```

In [141...
```
#Encoding categorial columns into numerical
```

In [62]:
```
df["CANCELLED"]=np.where(df["CANCELLED"]==1,0,0)
```

In [63]:
```
df["DIVERTED"]=np.where(df["DIVERTED"]==1,3,0)
```

In [64]:
```
df.CANCELLED.unique(),df.DIVERTED.unique()
```

Out[64]:
```
(array([0, 4]), array([0, 3]))
```

In [65]:
```
df["DELAY_15"]=df["ARR_DEL15"]+df["DEP_DEL15"]
df.DELAY_15.unique()
```

Out[65]:
```
array([ 0.,  1.,  2., nan])
```

In [66]:
```
df["DELAY_15"].fillna(0,inplace=True)
df.DELAY_15.unique()
```

Out[66]:
```
array([0., 1., 2.])
```

In [67]:
```
df["NDELAY"]=df["DELAY_15"]+df["CANCELLED"]+df["DIVERTED"]
```

In [68]:
```
df.NDELAY.unique()
```

Out[68]:
```
array([0., 1., 2., 3., 4.])
```

In [69]:
```
len(df["TAIL_NUM"].value_counts()),len(df["FL_NUM"].value_counts())
```

Out[69]:
```
(789, 690)
```

In [70]:
```
df.info()
```

```
RangeIndex: 11231 entries, 0 to 11230
Data columns (total 34 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   YEAR                 11231 non-null  int64
 1   QUARTER              11231 non-null  int64
 2   MONTH                11231 non-null  int64
 3   DAY_OF_MONTH         11231 non-null  int64
 4   DAY_OF_WEEK          11231 non-null  int64
 5   UNIQUE_CARRIER       11231 non-null  object
 6   TAIL_NUM             11231 non-null  object
 7   FL_NUM               11231 non-null  int64
 8   ORIGIN_AIRPORT_ID    11231 non-null  int64
 9   ORIGIN               11231 non-null  object
 10  DEST_AIRPORT_ID      11231 non-null  int64
 11  DEST                 11231 non-null  object
 12  CRS_DEP_TIME         11231 non-null  object
 13  CRS_DEP_TIME.1       11231 non-null  int64
 14  DEP_TIME             11114 non-null  object
 15  DEP_TIME.1           11114 non-null  float64
 16  DEP_DELAY            11231 non-null  float64
 17  DEP_DEL15            11231 non-null  float64
 18  CRS_ARR_TIME         11231 non-null  object
 19  CRS_ARR_TIME.1       11231 non-null  int64
 20  ARR_TIME             11116 non-null  object
 21  ARR_TIME.1           11116 non-null  float64
 22  ARR_DELAY            11043 non-null  float64
 23  ARR_DEL15            11043 non-null  float64
 24  CANCELLED            11231 non-null  int64
 25  DIVERTED             11231 non-null  int64
 26  CRS_ELAPSED_TIME1    11231 non-null  object
 27  ACTUAL_ELAPSED_TIME1 11231 non-null  object
 28  CRS_ELAPSED_TIME     11231 non-null  int64
 29  ACTUAL_ELAPSED_TIME  11043 non-null  float64
 30  DISTANCE             11231 non-null  int64
 31  SEASON               11231 non-null  int64
 32  DELAY_15             11231 non-null  float64
 33  NDELAY               11231 non-null  float64
dtypes: float64(9), int64(15), object(10)
memory usage: 2.9+ MB
```

In [73]:
```
df1.head()
```

Out[73]:

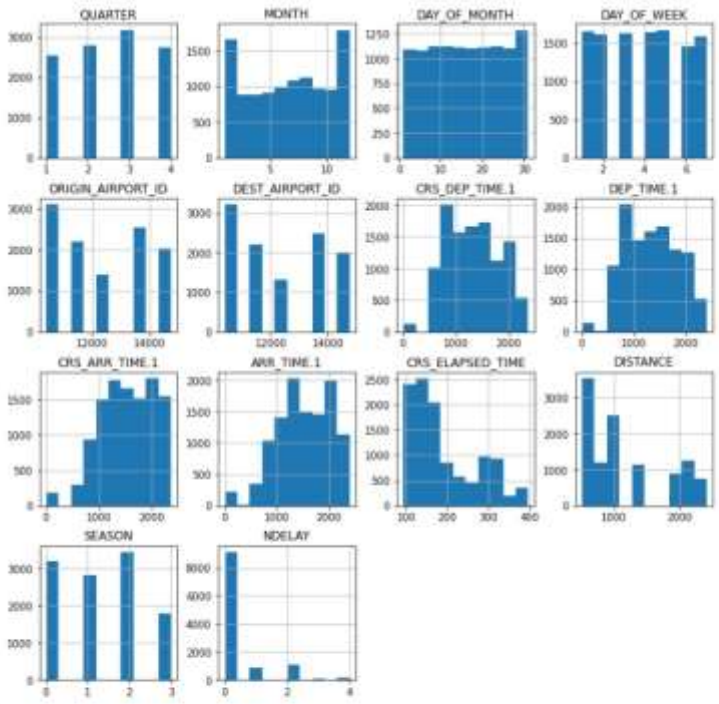
| | QUARTER | MONTH | DAY_OF_MONTH | DAY_OF_WEEK | TAIL_NUM | FL_NUM | ORIGIN_AIRPORT_ID | ORIGIN | DEST_AIRPORT_ID | DEST | ... | DEP_TIME.1 | CRS_ARR_TIME | CRS_ARR_TI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 1 | 1 | 5 | N836DN | 1399 | 10397 | ATL | 14747 | SEA | ... | 1907.0 | 21:43:00 | |
| 1 | 1 | 1 | 1 | 5 | N964DN | 1476 | 11433 | DTW | 13487 | MSP | ... | 1344.0 | 14:35:00 | |
| 2 | 1 | 1 | 1 | 5 | N813DN | 1597 | 10397 | ATL | 14747 | SEA | ... | 942.0 | 12:15:00 | |
| 3 | 1 | 1 | 1 | 5 | N587NW | 1768 | 14747 | SEA | 13487 | MSP | ... | 820.0 | 13:55:00 | |
| 4 | 1 | 1 | 1 | 5 | N836DN | 1823 | 14747 | SEA | 11433 | DTW | ... | 2256.0 | 06:07:00 | |

5 rows × 22 columns

In [74]:
```
df2=df1.drop(columns=["TAIL_NUM","FL_NUM"])
```

In [75]:
```
df2.info()
```

```
RangeIndex: 11231 entries, 0 to 11230
Data columns (total 20 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   QUARTER              11231 non-null  int64
 1   MONTH                11231 non-null  int64
 2   DAY_OF_MONTH         11231 non-null  int64
 3   DAY_OF_WEEK          11231 non-null  int64
 4   ORIGIN_AIRPORT_ID    11231 non-null  int64
 5   ORIGIN               11231 non-null  object
 6   DEST_AIRPORT_ID      11231 non-null  int64
 7   DEST                 11231 non-null  object
 8   CRS_DEP_TIME         11231 non-null  object
 9   CRS_DEP_TIME.1       11231 non-null  int64
 10  DEP_TIME.1           11124 non-null  float64
 11  CRS_ARR_TIME         11231 non-null  object
 12  CRS_ARR_TIME.1       11231 non-null  int64
 13  ARR_TIME.1           11116 non-null  float64
 14  CRS_ELAPSED_TIME1    11231 non-null  object
 15  ACTUAL_ELAPSED_TIME1 11231 non-null  object
 16  CRS_ELAPSED_TIME     11231 non-null  int64
 17  DISTANCE             11231 non-null  int64
 18  SEASON               11231 non-null  int64
 19  NDELAY               11231 non-null  float64
dtypes: float64(3), int64(11), object(6)
memory usage: 1.7+ MB
```




In [77]:
```
df2.NDELAY.value_counts()
```

Out[77]:

```
0.0    9130
1.0    1035
2.0     870
4.0     114
3.0      74
Name: NDELAY, dtype: int64
```

## Spliting Dependent and Independent Variables

In [79]:
```
x=df1.drop(columns=["NDELAY","TAIL_NUM"])
y=df1.NDELAY
```

## Encoding Categorical columns to numerical

In [80]:
```
x["ORIGIN"].replace({"ATL":1,'DTW':2,'JFK':3,'MSP':4,'SEA':5},inplace=True)
x["DEST"].replace({"ATL":1,'DTW':2,'JFK':3,'MSP':4,'SEA':5},inplace=True)
```

In [81]:
```
import os, types
import pandas as pd
from botocore.client import Config
import ibm_boto3

def __iter__(self): return 0

# @hidden_cell
# The following code accesses a file in your IBM Cloud Object Storage. It includes your credentials.
# You might want to remove those credentials before you share the notebook.
cos_client = ibm_boto3.client(service_name='s3',
    ibm_api_key_id='9a5kuMDufRQ-_cOhUo8s7Lt6oBI_rXUIZ_ywo-U4uncs',
    ibm_auth_endpoint="https://iam.cloud.ibm.com/oidc/token",
    config=Config(signature_version='oauth'),
    endpoint_url='https://s3.private.us.cloud-object-storage.appdomain.cloud')

bucket = 'flightdelayprediction-donotdelete-pr-ocgt3z2vnznocj'
object_key = 'X.csv'

body = cos_client.get_object(Bucket=bucket,Key=object_key)['Body']
# add missing __iter__ method, so pandas accepts body as file-like object
if not hasattr(body, "__iter__"): body.__iter__ = types.MethodType( __iter__, body )

x1 = pd.read_csv(body)
x1.head()
```

Out[81]:

| | QUARTER | MONTH | DAY_OF_MONTH | DAY_OF_WEEK | FL_NUM | ORIGIN | DEST | CRS_DEP_TIME.1 | CRS_ARR_TIME.1 | CRS_ELAPSED_TIME | DISTANCE | SEASON |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 1 | 1 | 5 | 1399 | 1 | 5 | 1935 | 2143 | 338 | 2182 | 2 |
| 1 | 1 | 1 | 1 | 5 | 1476 | 2 | 4 | 1345 | 1435 | 110 | 528 | 2 |
| 2 | 1 | 1 | 1 | 5 | 1597 | 1 | 5 | 940 | 1215 | 335 | 2182 | 2 |
| 3 | 1 | 1 | 1 | 5 | 1768 | 5 | 4 | 819 | 1335 | 196 | 1399 | 2 |
| 4 | 1 | 1 | 1 | 5 | 1823 | 5 | 2 | 2330 | 827 | 237 | 1927 | 2 |

In [82]:
```
import os, types
import pandas as pd
from botocore.client import Config
import ibm_boto3

def __iter__(self): return 0

# @hidden_cell
# The following code accesses a file in your IBM Cloud Object Storage. It includes your credentials.
# You might want to remove those credentials before you share the notebook.
cos_client = ibm_boto3.client(service_name='s3',
    ibm_api_key_id='9a5kuMDuFRQ-_cGNUo81Lt6oBI_rKUIZ_yao-U4oncs',
    ibm_auth_endpoint="https://iam.cloud.ibm.com/oidc/token",
    config=Config(signature_version='oauth'),
    endpoint_url='https://s3.private.us.cloud-object-storage.appdomain.cloud')

bucket = 'flightdelayprediction-donotdelete-pr-ocgt3s2vhinocj'
object_key = 'Y.csv'

body = cos_client.get_object(Bucket=bucket,Key=object_key)['Body']
# add missing __iter__ method, so pandas accepts body as file-like object
if not hasattr(body, "__iter__"): body.__iter__ = types.MethodType( __iter__, body )

y2 = pd.read_csv(body)
y2.head()
```

Out[82]:

| | NDELAY |
|---|---|
| 0 | 0.0 |
| 1 | 0.0 |
| 2 | 0.0 |
| 3 | 0.0 |
| 4 | 0.0 |

In [83]:
```
from sklearn.utils import shuffle
X,Y=shuffle(x1,y2,random_state=72)
X.head()
```

Out[83]:

| | QUARTER | MONTH | DAY_OF_MONTH | DAY_OF_WEEK | FL_NUM | ORIGIN | DEST | CRS_DEP_TIME.1 | CRS_ARR_TIME.1 | CRS_ELAPSED_TIME | DISTANCE | SEASON |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5816 | 3 | 8 | 18 | 2 | 786 | 2 | 1 | 1400 | 1603 | 123 | 594 | 0 |
| 475 | 1 | 1 | 25 | 1 | 1173 | 4 | 2 | 830 | 1114 | 104 | 528 | 2 |
| 10952 | 2 | 6 | 25 | 2 | 2547 | 5 | 4 | 1894 | 18 | 197 | 1399 | 0 |
| 8363 | 4 | 11 | 14 | 1 | 1247 | 5 | 1 | 900 | 1653 | 293 | 2182 | 1 |
| 11452 | 1 | 2 | 19 | 2 | 1232 | 1 | 4 | 2079 | 2209 | 149 | 744 | 2 |

## Splitting Dataset as Training and Testing data

In [84]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x1,y2,test_size=0.2,random_state=42)
```

In [85]:
```
x_train.shape,x_test.shape
```

Out[85]: ((9858, 12), (2464, 12))

## Model Building

## DecisionTree

In [86]:
```
from sklearn.tree import DecisionTreeClassifier
dc=DecisionTreeClassifier()
dc.fit(x_train,y_train)
dc.score(x_test,y_test)
```

Out[86]: 0.7568993506493507

## RandomForest

In [87]:
```
from sklearn.ensemble import RandomForestClassifier
rf=RandomForestClassifier(n_estimators=50,random_state=42)
rf.fit(x_train,y_train.values.ravel())
rf.score(x_test,y_test)
```

Out[87]: 0.8368506493506493

In [88]:
```
x_train.shape,x_test.shape
```

Out[88]: ((9858, 12), (2464, 12))

# Model Building

## Decision Tree

In [89]:
```
from sklearn.tree import DecisionTreeClassifier
dc=DecisionTreeClassifier()
dc.fit(x_train,y_train)
dc.score(x_test,y_test)
```

Out[89]: 0.7495941558441559

## Random Forest

In [90]:
```
from sklearn.ensemble import RandomForestClassifier
rf=RandomForestClassifier(n_estimators=50,random_state=42)
rf.fit(x_train,y_train)
rf.score(x_test,y_test)
```

```
/tmp/wsuser/ipykernel_164/905497165.py:3: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of
y to (n_samples,), for example using ravel().
  rf.fit(x_train,y_train)
```

Out[90]: 0.8368586493586493

In [89]:
```
pd.DataFrame(rf.predict(x_test)).value_counts()
```

Out[89]:
```
0.0    1881
1.0     223
2.0     213
4.0     106
3.0      41
dtype: int64
```

In [91]:
```
x_test.iloc[[99,21,23],:]
```

Out[91]:

| | QUARTER | MONTH | DAY_OF_MONTH | DAY_OF_WEEK | FL_NUM | ORIGIN | DEST | CRS_DEP_TIME.1 | CRS_ARR_TIME.1 | CRS_ELAPSED_TIME | DISTANCE | SEASON |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **8817** | 4 | 11 | 3 | 4 | 2787 | 4 | 1 | 1955 | 2308 | 133 | 807 | 1 |
| **12270** | 3 | 7 | 28 | 4 | 43 | 3 | 1 | 1525 | 1814 | 169 | 760 | 0 |
| **2894** | 2 | 4 | 1 | 5 | 1991 | 4 | 1 | 520 | 845 | 145 | 807 | 3 |

In [92]:
```
y_test.iloc[[0,21,912]]
```

Out[92]:

| | NDELAY |
|---|---|
| **2318** | 0.0 |
| **12270** | 4.0 |
| **10061** | 1.0 |

In [93]:
```
rf.predict(x_test.iloc[[0,21,912],:])
```

Out[93]: array([0., 4., 0.])

In [94]:
```
pd.DataFrame(dc.predict(x_test)).value_counts()
```

Out[94]:
```
0.0    1632
1.0     335
2.0     319
4.0     121
3.0      57
dtype: int64
```

## Logistic Regression

In [95]:
```
from sklearn.linear_model import LogisticRegression
lrl=LogisticRegression(solver='sag')
lrl.fit(x_train,y_train.values.ravel())
lrl.score(x_test,y_test)
```

```
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/sklearn/linear_model/_sag.py:352: ConvergenceWarning: The max_iter was reached which means the c
oef_ did not converge
  warnings.warn(
```

Out[95]: 0.6830357142857143

In [96]:
```
lrl.predict(x_test).sum()
```

Out[96]: 0.0

## SVM

In [97]:
```
from sklearn.svm import SVC
svm=SVC(kernel='sigmoid')
svm.fit(x_train,y_train.values.ravel())
svm.score(x_test,y_test)
```

Out[97]: 0.6128246753246753

In [98]:
```
pd.DataFrame(svm.predict(x_test)).value_counts()
```

Out[98]:
```
0.0    2167
2.0     230
4.0      67
dtype: int64
```

In [99]:
```
pd.DataFrame(y_test).value_counts()
```

Out[99]:
```
ADELAY
0.0       1603
1.0        388
2.0        288
4.0        150
3.0         55
dtype: int64
```

## KNearestNeighborsClassifie

In [100...
```
from sklearn.neighbors import KNeighborsClassifier
knn=KNeighborsClassifier(n_neighbors=5)
knn.fit(x_train,y_train)
knn.score(x_test,y_test)
```

```
/opt/conda/envs/Python-3.9/lib/python3.9/site-packages/sklearn/neighbors/_classification.py:198: DataConversionWarning: A column-vector y was passed wh
en a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().
  return self._fit(X, y)
```

Out[100... 0.729301948051948

In [101...
```
pd.Dataframe(knn.predict(x_test)).value_counts()
```

Out[101...
```
0.0    1942
2.0     222
1.0     197
4.0      82
3.0      21
dtype: int64
```

In [102...
```
knn.predict(x_test.iloc[[8,21,912],:])
```

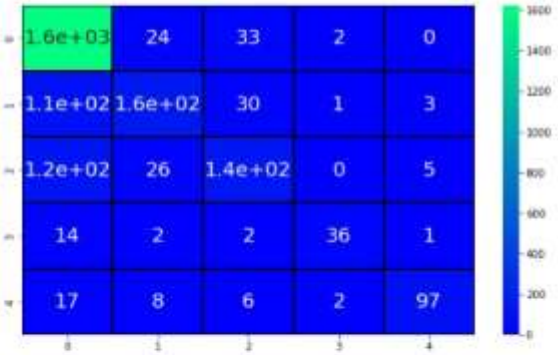
Out[102... array([0., 0., 3.])

## Evaluation of Random Forest

In [103...

```
from sklearn.metrics import confusion_matrix,accuracy_score,classification_report
pred=rf.predict(x_test)
cm=confusion_matrix(y_test, pred)
plt.figure(figsize=(10,6))
sns.heatmap(cm, annot=True,cmap='winter',linewidths=0.3, linecolor='black',annot_kws={"size": 20})
TP=cm[0][0]
TN=cm[1][1]
FN=cm[1][0]
FP=cm[0][1]
#print(round(accuracy_score(predictions,y_test)*100,2))
#print('Testing Accuracy for knn',(TP+TN)/(TP+TN+FN+FP))
print('Testing Sensitivity for Random Forest',(TP/(TP+FN)))
print('Testing Specificity for Random Forest',(TN/(TN+FP)))
print('Testing Precision for Random Forest',(TP/(TP+FP)))
print('Testing accuracy for Random Forest',accuracy_score(y_test, pred))
```

```
Testing Sensitivity for Random Forest 0.9368230547550432
Testing Specificity for Random Forest 0.9716577540106952
Testing Precision for Random Forest 0.9854368932038835
Testing accuracy for Random Forest 0.8368506493506493
```




In [104...

```
print(classification_report(y_test,pred))
```

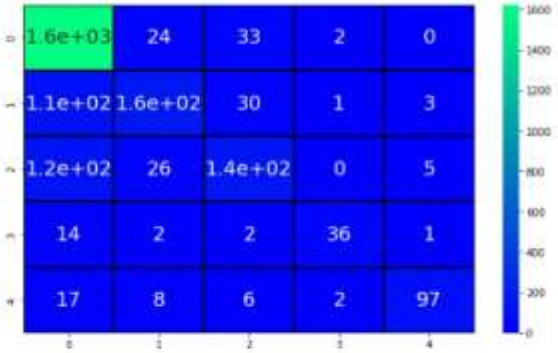
```
              precision    recall  f1-score   support

         0.0       0.86      0.96      0.91      1683
         1.0       0.72      0.53      0.61       386
         2.0       0.67      0.49      0.57       288
         3.0       0.88      0.65      0.75        55
         4.0       0.92      0.75      0.82       130

    accuracy                           0.84      2464
   macro avg       0.81      0.68      0.73      2464
weighted avg       0.83      0.84      0.83      2464
```

## Evaluation of Decision Tree

In [109...

```
from sklearn.metrics import confusion_matrix,accuracy_score,classification_report
pred1=rf.predict(x_test)
cm=confusion_matrix(y_test, pred)
plt.figure(figsize=(10,6))
sns.heatmap(cm, annot=True,cmap='winter',linewidths=0.3, linecolor='black',annot_kws={"size": 16})
TP=cm[0][0]
TN=cm[1][1]
FN=cm[1][0]
FP=cm[0][1]
#print(round(accuracy_score(prediction),y_test)*100,2))
#print('Testing Accuracy for knn',(TP+TN)/(TP+TN+FN+FP))
print('Testing Sensitivity for Random Forest',(TP/(TP+FN)))
print('Testing Specificity for Random Forest',(TN/(TN+FP)))
print('Testing Precision for Random Forest',(TP/(TP+FP)))
print('Testing accuracy for Random Forest',accuracy_score(y_test, pred1))
```

```
Testing Sensitivity for Random Forest 0.9360230547550432
Testing Specificity for Random Forest 0.8716577540106952
Testing Precision for Random Forest 0.9854368932038835
Testing accuracy for Random Forest 0.8360506493506493
```




In [111...

```
print(classification_report(y_test,pred1))
```

```
              precision    recall  f1-score   support

         0.0       0.86      0.96      0.91      1683
         1.0       0.73      0.53      0.61       300
         2.0       0.67      0.49      0.57       288
         3.0       0.98      0.65      0.78        55
         4.0       0.92      0.75      0.83       138

    accuracy                           0.84      2464
   macro avg       0.81      0.68      0.73      2464
weighted avg       0.83      0.84      0.83      2464
```

In [106]:
```
import pickle
```

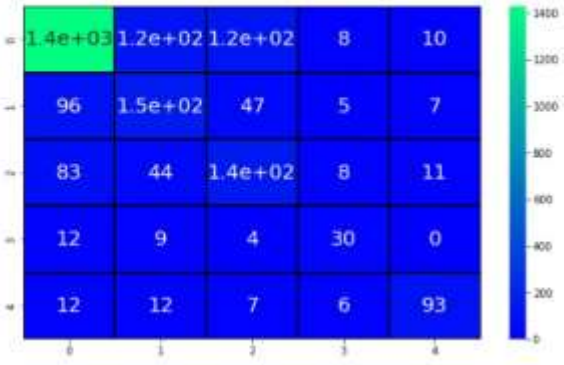
In [107]:
```
pickle.dump(rf,open("rfmodel.pkl",'wb'))
```

In [108]:
```
pwd
```

Out[108]:
```
'/home/vsuser/work'
```

In [109]:
```
pred1=dc.predict(x_test)
cm1=confusion_matrix(y_test, pred1)
plt.figure(figsize=(10,6))
sns.heatmap(cm1, annot=True,cmap='winter',linewidths=0.3, linecolor='black',annot_kws={"size": 20})
TP=cm1[0][0]
TN=cm1[1][1]
FN=cm1[1][0]
FP=cm1[0][1]
#print(round(accuracy_score(predictions3,y_test)*100,2))
print('Testing Accuracy for Decision Tree',(TP+TN)/(TP+TN+FN+FP))
print('Testing Sensitivity for Decision Tree',(TP/(TP+FN)))
print('Testing Specificity for Decision Tree',(TN/(TN+FP)))
print('Testing Precision for Decision Tree',(TP/(TP+FP)))
print('Testing accuracy for Decision Tree',accuracy_score(y_test, pred1))
```

```
Testing Accuracy for Decision Tree 0.8813370473537604
Testing Sensitivity for Decision Tree 0.9370491803278689
Testing Specificity for Decision Tree 0.5666666666666667
Testing Precision for Decision Tree 0.9243208279430789
Testing accuracy for Decision Tree 0.7495041558441559
```



In [110...

```
print(classification_report(y_test,pred))
```

```
              precision    recall  f1-score   support

         0.0       0.86      0.96      0.91      1683
         1.0       0.73      0.53      0.61       308
         2.0       0.67      0.49      0.57       288
         3.0       0.88      0.65      0.75        55
         4.0       0.92      0.75      0.82       130

    accuracy                           0.84      2464
   macro avg       0.81      0.68      0.73      2464
weighted avg       0.83      0.84      0.83      2464
```

## Evaluation of Decision Tree

In [111...

```
from sklearn.metrics import confusion_matrix,accuracy_score,classification_report
pred=rf.predict(X_test)
cm=confusion_matrix(y_test, pred)
plt.figure(figsize=(10,6))
sns.heatmap(cm, annot=True,cmap='winter',linewidths=0.3, linecolor='black',annot_kws={"size": 20})
TP=cm[0][0]
TN=cm[1][1]
FN=cm[1][0]
FP=cm[0][1]
#print(round(accuracy_score(prediction3,y_test)*100,2))
#print('Testing Accuracy for knn',(TP+TN)/(TP+TN+FN+FP))
print('Testing Sensitivity for Random Forest',(TP/(TP+FN)))
print('Testing Specificity for Random Forest',(TN/(TN+FP)))
print('Testing Precision for Random Forest',(TP/(TP+FP)))
print('Testing accuracy for Random Forest',accuracy_score(y_test, pred))
```

```
Testing Sensitivity for Random Forest 0.9360308647550481
Testing Specificity for Random Forest 0.8716577540106952
Testing Precision for Random Forest 0.9654360932038835
Testing accuracy for Random Forest 0.8368506493506493
```