Predicting Rain using weather Data of Australia

Random Forest Model

Splitting the dataset

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

df = pd.read_csv(r"C:\Users\core i5\Documents\GitHub\DataScience\
datascience\CPE 312\Logistic Regression, Decision Tree , Random
Forest\data\Logistic Regression\weatherAUS.csv")

df.head()

         Date Location  MinTemp  MaxTemp  Rainfall  Evaporation
Sunshine  \
0  2008-12-01   Albury     13.4     22.9       0.6          NaN
NaN
1  2008-12-02   Albury      7.4     25.1       0.0          NaN
NaN
2  2008-12-03   Albury     12.9     25.7       0.0          NaN
NaN
3  2008-12-04   Albury      9.2     28.0       0.0          NaN
NaN
4  2008-12-05   Albury     17.5     32.3       1.0          NaN
NaN

  WindGustDir  WindGustSpeed WindDir9am  ... Humidity9am  Humidity3pm
\
0           W           44.0          W  ...        71.0         22.0

1         WNW           44.0        NNW  ...        44.0         25.0

2         WSW           46.0          W  ...        38.0         30.0

3          NE           24.0         SE  ...        45.0         16.0

4           W           41.0        ENE  ...        82.0         33.0


   Pressure9am  Pressure3pm  Cloud9am  Cloud3pm  Temp9am  Temp3pm
RainToday  \
0       1007.7       1007.1       8.0       NaN     16.9     21.8
No
1       1010.6       1007.8       NaN       NaN     17.2     24.3
```

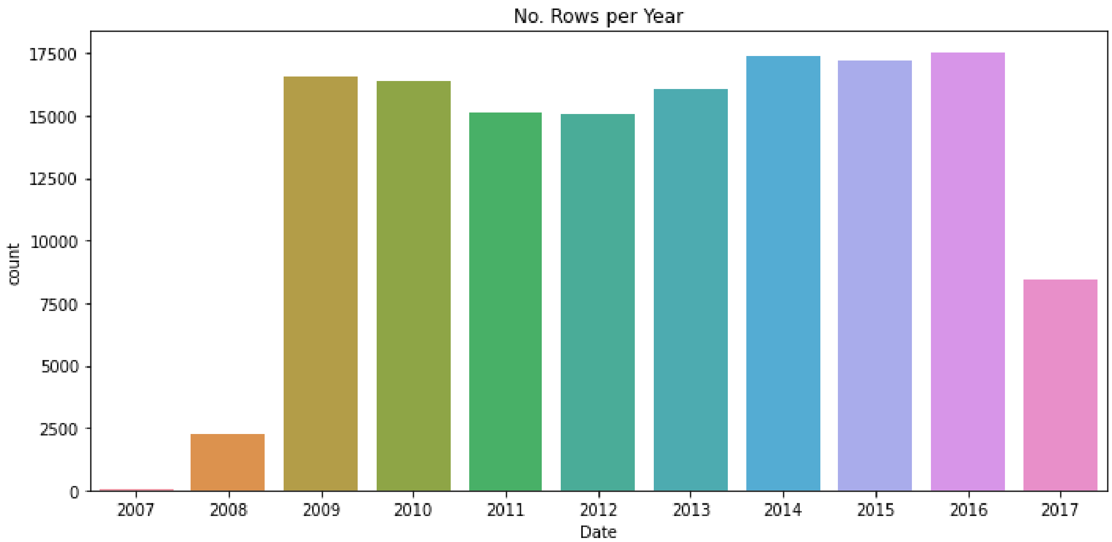
```
No
2       1007.6       1008.7       NaN       2.0     21.0     23.2
No
3       1017.6       1012.8       NaN       NaN     18.1     26.5
No
4       1010.8       1006.0       7.0       8.0     17.8     29.7
No

   RainTomorrow
0            No
1            No
2            No
3            No
4            No

[5 rows x 23 columns]
```

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 145460 entries, 0 to 145459
Data columns (total 23 columns):
 #   Column         Non-Null Count   Dtype  
---  ------         --------------   -----  
 0   Date           145460 non-null  object 
 1   Location       145460 non-null  object 
 2   MinTemp        143975 non-null  float64
 3   MaxTemp        144199 non-null  float64
 4   Rainfall       142199 non-null  float64
 5   Evaporation    82670 non-null   float64
 6   Sunshine       75625 non-null   float64
 7   WindGustDir    135134 non-null  object 
 8   WindGustSpeed  135197 non-null  float64
 9   WindDir9am     134894 non-null  object 
 10  WindDir3pm     141232 non-null  object 
 11  WindSpeed9am   143693 non-null  float64
 12  WindSpeed3pm   142398 non-null  float64
 13  Humidity9am    142806 non-null  float64
 14  Humidity3pm    140953 non-null  float64
 15  Pressure9am    130395 non-null  float64
 16  Pressure3pm    130432 non-null  float64
 17  Cloud9am       89572 non-null   float64
 18  Cloud3pm       86102 non-null   float64
 19  Temp9am        143693 non-null  float64
 20  Temp3pm        141851 non-null  float64
 21  RainToday      142199 non-null  object 
 22  RainTomorrow   142193 non-null  object 
dtypes: float64(16), object(7)
memory usage: 25.5+ MB
```

```python
df.dropna(subset = ["RainTomorrow"],inplace=True)
```

```
import seaborn as sns

plt.figure(figsize=(10,5))
plt.title('No. Rows per Year')
sns.countplot(x=pd.to_datetime(df["Date"]).dt.year)
plt.tight_layout();
plt.show()
```




```
year = pd.to_datetime(df["Date"]).dt.year
train_df = df[year < 2015]
val_df = df[year == 2015]
test_df = df[year > 2015]

print("shape of train_df is {}".format(train_df.shape))
print("shape of validity_df is {}".format(val_df.shape))
print("shape of test_df is {}".format(test_df.shape))

shape of train_df is (98988, 23)
shape of validity_df is (17231, 23)
shape of test_df is (25974, 23)

train_inputs = train_df.drop(['Date', 'RainTomorrow'], axis =1)
train_target = train_df["RainTomorrow"]

val_inputs = val_df.drop(['Date', 'RainTomorrow'], axis =1)
val_target = val_df["RainTomorrow"]
test_inputs = test_df.drop(['Date', 'RainTomorrow'], axis =1)
test_target = test_df["RainTomorrow"]
```

collect all the columns that are numerical and categorical and put them into a list

```
num_cols =
train_inputs.select_dtypes(include=np.number).columns.tolist()
```

```
cat_cols =
train_inputs.select_dtypes(include=["object"]).columns.tolist()
```

```
train_inputs[num_cols].describe()
```

```
            MinTemp      MaxTemp      Rainfall  Evaporation
Sunshine  \
count  98554.000000  98790.00000  97988.000000  61878.00000
58292.000000
mean      12.002014     23.00288      2.372935      5.28686
7.602136
std        6.345487      6.99008      8.518819      3.95104
3.788266
min       -8.500000     -4.10000      0.000000      0.00000
0.000000
25%        7.500000     17.80000      0.000000      2.60000
4.800000
50%       11.800000     22.40000      0.000000      4.60000
8.400000
75%       16.600000     27.90000      0.800000      7.20000
10.600000
max       33.900000     48.10000    371.000000     82.40000
14.300000

       WindGustSpeed  WindSpeed9am  WindSpeed3pm   Humidity9am
Humidity3pm  \
count   92086.000000  97855.000000  97848.000000  97723.000000
97802.000000
mean       40.230969     14.102192     18.770430     68.651822
51.501728
std        13.713042      8.994121      8.877497     18.995535
20.742760
min         6.000000      0.000000      0.000000      0.000000
0.000000
25%        31.000000      7.000000     13.000000     57.000000
37.000000
50%        39.000000     13.000000     19.000000     70.000000
52.000000
75%        48.000000     19.000000     24.000000     83.000000
66.000000
max       135.000000     87.000000     87.000000    100.000000
100.000000

        Pressure9am   Pressure3pm      Cloud9am      Cloud3pm
Temp9am  \
count  89643.000000  89679.000000  63224.000000  62222.000000
98205.000000
mean    1017.518046   1015.138523      4.308048      4.414451
16.827340
std        7.073083      6.997504      2.867317      2.694295
```

```
6.399855
min      980.500000    979.000000      0.000000      0.000000     -
5.900000
25%     1012.800000   1010.400000      1.000000      2.000000
12.200000
50%     1017.500000   1015.100000      5.000000      5.000000
16.500000
75%     1022.300000   1019.900000      7.000000      7.000000
21.300000
max     1041.000000   1039.600000      9.000000      9.000000
40.200000

            Temp3pm
count  98325.000000
mean      21.525622
std        6.832509
min       -5.100000
25%       16.600000
50%       20.900000
75%       26.100000
max       46.100000
```

```
train_inputs[cat_cols].nunique()
```

```
Location       49
WindGustDir    16
WindDir9am     16
WindDir3pm     16
RainToday       2
dtype: int64
```

Imputing missing data

```
from sklearn.impute import SimpleImputer

#create an imputer object
imputer = SimpleImputer(strategy="mean")

# check the columns that have nan values and how many
train_inputs[num_cols].isnull().sum()
```

```
MinTemp            434
MaxTemp            198
Rainfall          1000
Evaporation      37110
Sunshine         40696
WindGustSpeed     6902
WindSpeed9am      1133
WindSpeed3pm      1140
Humidity9am       1265
Humidity3pm       1186
Pressure9am       9345
```

```
Pressure3pm       9309
Cloud9am         35764
Cloud3pm         36766
Temp9am            783
Temp3pm            663
dtype: int64
```

```
# fit the imputer model to fill each column with missing values the
mean value for that column
imputer.fit(train_inputs[num_cols])
```

```
SimpleImputer()
```

```
# the object imputer now contains an atribute called .statistics_
which contains the mean value for each column. We can access this:
list(imputer.statistics_)
```

```
[12.002014124236458,
 23.002879846138278,
 2.37293546148508,
 5.286859627007984,
 7.602135799080491,
 40.2309688769194,
 14.102192018803331,
 18.770429645981523,
 68.6518219866357,
 51.50172798102288,
 1017.5180460270183,
 1015.1385228648849,
 4.308047576869543,
 4.414451480183858,
 16.82733974848531,
 21.525622171370454]
```

```
# we need to inject these values in the predictor variable for all our
datasets.

train_inputs[num_cols] = imputer.fit_transform(train_inputs[num_cols])
val_inputs[num_cols] = imputer.fit_transform(val_inputs[num_cols])
test_inputs[num_cols] = imputer.fit_transform(test_inputs[num_cols])
```

Normalizing our Numerical columns

```
from sklearn.preprocessing import MinMaxScaler

#create an object for MinMaxScaler
scaler = MinMaxScaler()

#scaler.transform({data fram with num cols}) will result in the
scaling of the values from (0,1)

train_inputs[num_cols] = scaler.fit_transform(train_inputs[num_cols])
```

```
val_inputs[num_cols] = scaler.fit_transform(val_inputs[num_cols])
test_inputs[num_cols] = scaler.fit_transform(test_inputs[num_cols])
```

```
# verify that the scaling worked (val_inputs is used to see the max
and min but train_inputs and test_inputs both have a max of 1 and min
of 0)
val_inputs[num_cols].describe().loc[["min","max"]]
```

```
     MinTemp  MaxTemp  Rainfall  Evaporation  Sunshine  WindGustSpeed
\
min      0.0      0.0       0.0          0.0       0.0            0.0

max      1.0      1.0       1.0          1.0       1.0            1.0


     WindSpeed9am  WindSpeed3pm  Humidity9am  Humidity3pm  Pressure9am
\
min           0.0           0.0          0.0          0.0          0.0

max           1.0           1.0          1.0          1.0          1.0


     Pressure3pm  Cloud9am  Cloud3pm  Temp9am  Temp3pm
min          0.0       0.0       0.0      0.0      0.0
max          1.0       1.0       1.0      1.0      1.0
```

Encoding Categorical Data

```
# check all of our categorical columns
train_inputs[cat_cols].nunique()
```

```
Location       49
WindGustDir    16
WindDir9am     16
WindDir3pm     16
RainToday       2
dtype: int64
```

```
train_inputs[cat_cols].isnull().sum()
```

```
Location          0
WindGustDir    6943
WindDir9am     7323
WindDir3pm     2030
RainToday      1000
dtype: int64
```

```
from sklearn.preprocessing import OneHotEncoder
```

```
# encoder object
encoder = OneHotEncoder(sparse = False, handle_unknown='ignore')
```

Try to impute missing categorical values by inputting "Unknown"

```
test_inputs.fillna("Unknown", inplace = True)
train_inputs.fillna("Unknown", inplace = True)
val_inputs.fillna("Unknown", inplace = True)

#check to see if imputation works (val_df2 is shown here but test_df2
and train_df2 also are modified)
train_inputs
```

```
       Location   MinTemp   MaxTemp  Rainfall  Evaporation  
Sunshine  \
0        Albury  0.516509  0.517241  0.001617     0.064161  0.531618

1        Albury  0.375000  0.559387  0.000000     0.064161  0.531618

2        Albury  0.504717  0.570881  0.000000     0.064161  0.531618

3        Albury  0.417453  0.614943  0.000000     0.064161  0.531618

4        Albury  0.613208  0.697318  0.002695     0.064161  0.531618

...         ...       ...       ...       ...          ...       ...

144548    Uluru  0.599057  0.714559  0.000000     0.064161  0.531618

144549    Uluru  0.556604  0.783525  0.000000     0.064161  0.531618

144550    Uluru  0.608491  0.802682  0.000000     0.064161  0.531618

144551    Uluru  0.674528  0.816092  0.000000     0.064161  0.531618

144552    Uluru  0.731132  0.837165  0.000000     0.064161  0.531618


       WindGustDir  WindGustSpeed WindDir9am WindDir3pm  ...  
WindSpeed3pm  \
0                W       0.294574          W        WNW  ...  
0.275862
1              WNW       0.294574        NNW        WSW  ...  
0.252874
2              WSW       0.310078          W        WSW  ...  
0.298851
3               NE       0.139535         SE          E  ...  
0.103448
4                W       0.271318        ENE         NW  ...  
0.229885
...            ...            ...        ...        ...  ...  
...
144548         SSE       0.286822        ESE        SSE  ...
```

```
0.298851
144549          NE       0.193798        ENE         SW  ...
0.229885
144550         ESE       0.255814        ESE        SSE  ...
0.103448
144551         ESE       0.286822        ESE        SSW  ...
0.195402
144552         WNW       0.542636        ENE        SSW  ...
0.149425

        Humidity9am  Humidity3pm  Pressure9am  Pressure3pm
Cloud9am  \
0              0.71         0.22     0.449587     0.463696  0.888889

1              0.44         0.25     0.497521     0.475248  0.478672

2              0.38         0.30     0.447934     0.490099  0.478672

3              0.45         0.16     0.613223     0.557756  0.478672

4              0.82         0.33     0.500826     0.445545  0.777778

...             ...          ...          ...          ...       ...

144548         0.22         0.13     0.555372     0.508251  0.478672

144549         0.16         0.08     0.530579     0.471947  0.478672

144550         0.15         0.08     0.519008     0.478548  0.478672

144551         0.22         0.09     0.553719     0.498350  0.478672

144552         0.16         0.09     0.522314     0.448845  0.478672


        Cloud3pm   Temp9am   Temp3pm  RainToday
0       0.490495  0.494577  0.525391         No
1       0.490495  0.501085  0.574219         No
2       0.222222  0.583514  0.552734         No
3       0.490495  0.520607  0.617188         No
4       0.888889  0.514100  0.679688         No
...          ...       ...       ...        ...
144548  0.490495  0.642082  0.720703         No
144549  0.490495  0.754881  0.779297         No
144550  0.490495  0.772234  0.796875         No
144551  0.490495  0.774403  0.826172         No
144552  0.490495  0.780911  0.830078         No

[98988 rows x 21 columns]
```

```
# We must first fit our encoder object with our dataframe so it can
recognize the categorical columns
encoder.fit(train_inputs[cat_cols])
```

```
OneHotEncoder(handle_unknown='ignore', sparse=False)
```

```
encoder.categories_
```

```
[array(['Adelaide', 'Albany', 'Albury', 'AliceSprings',
'BadgerysCreek',
        'Ballarat', 'Bendigo', 'Brisbane', 'Cairns', 'Canberra',
'Cobar',
        'CoffsHarbour', 'Dartmoor', 'Darwin', 'GoldCoast', 'Hobart',
        'Katherine', 'Launceston', 'Melbourne', 'MelbourneAirport',
        'Mildura', 'Moree', 'MountGambier', 'MountGinini',
'Newcastle',
        'Nhil', 'NorahHead', 'NorfolkIsland', 'Nuriootpa',
'PearceRAAF',
        'Penrith', 'Perth', 'PerthAirport', 'Portland', 'Richmond',
'Sale',
        'SalmonGums', 'Sydney', 'SydneyAirport', 'Townsville',
        'Tuggeranong', 'Uluru', 'WaggaWagga', 'Walpole', 'Watsonia',
        'Williamtown', 'Witchcliffe', 'Wollongong', 'Woomera'],
       dtype=object),
 array(['E', 'ENE', 'ESE', 'N', 'NE', 'NNE', 'NNW', 'NW', 'S', 'SE',
'SSE',
        'SSW', 'SW', 'Unknown', 'W', 'WNW', 'WSW'], dtype=object),
 array(['E', 'ENE', 'ESE', 'N', 'NE', 'NNE', 'NNW', 'NW', 'S', 'SE',
'SSE',
        'SSW', 'SW', 'Unknown', 'W', 'WNW', 'WSW'], dtype=object),
 array(['E', 'ENE', 'ESE', 'N', 'NE', 'NNE', 'NNW', 'NW', 'S', 'SE',
'SSE',
        'SSW', 'SW', 'Unknown', 'W', 'WNW', 'WSW'], dtype=object),
 array(['No', 'Unknown', 'Yes'], dtype=object)]
```

```
# generate columns names to label our new one-hot encoded columns
encoded_cols = list(encoder.get_feature_names(cat_cols))
```

```
print(encoded_cols)
```

```
['Location_Adelaide', 'Location_Albany', 'Location_Albury',
'Location_AliceSprings', 'Location_BadgerysCreek',
'Location_Ballarat', 'Location_Bendigo', 'Location_Brisbane',
'Location_Cairns', 'Location_Canberra', 'Location_Cobar',
'Location_CoffsHarbour', 'Location_Dartmoor', 'Location_Darwin',
'Location_GoldCoast', 'Location_Hobart', 'Location_Katherine',
'Location_Launceston', 'Location_Melbourne',
'Location_MelbourneAirport', 'Location_Mildura', 'Location_Moree',
'Location_MountGambier', 'Location_MountGinini', 'Location_Newcastle',
'Location_Nhil', 'Location_NorahHead', 'Location_NorfolkIsland',
'Location_Nuriootpa', 'Location_PearceRAAF', 'Location_Penrith',
```

```
'Location_Perth', 'Location_PerthAirport', 'Location_Portland',
'Location_Richmond', 'Location_Sale', 'Location_SalmonGums',
'Location_Sydney', 'Location_SydneyAirport', 'Location_Townsville',
'Location_Tuggeranong', 'Location_Uluru', 'Location_WaggaWagga',
'Location_Walpole', 'Location_Watsonia', 'Location_Williamtown',
'Location_Witchcliffe', 'Location_Wollongong', 'Location_Woomera',
'WindGustDir_E', 'WindGustDir_ENE', 'WindGustDir_ESE',
'WindGustDir_N', 'WindGustDir_NE', 'WindGustDir_NNE',
'WindGustDir_NNW', 'WindGustDir_NW', 'WindGustDir_S',
'WindGustDir_SE', 'WindGustDir_SSE', 'WindGustDir_SSW',
'WindGustDir_SW', 'WindGustDir_Unknown', 'WindGustDir_W',
'WindGustDir_WNW', 'WindGustDir_WSW', 'WindDir9am_E',
'WindDir9am_ENE', 'WindDir9am_ESE', 'WindDir9am_N', 'WindDir9am_NE',
'WindDir9am_NNE', 'WindDir9am_NNW', 'WindDir9am_NW', 'WindDir9am_S',
'WindDir9am_SE', 'WindDir9am_SSE', 'WindDir9am_SSW', 'WindDir9am_SW',
'WindDir9am_Unknown', 'WindDir9am_W', 'WindDir9am_WNW',
'WindDir9am_WSW', 'WindDir3pm_E', 'WindDir3pm_ENE', 'WindDir3pm_ESE',
'WindDir3pm_N', 'WindDir3pm_NE', 'WindDir3pm_NNE', 'WindDir3pm_NNW',
'WindDir3pm_NW', 'WindDir3pm_S', 'WindDir3pm_SE', 'WindDir3pm_SSE',
'WindDir3pm_SSW', 'WindDir3pm_SW', 'WindDir3pm_Unknown',
'WindDir3pm_W', 'WindDir3pm_WNW', 'WindDir3pm_WSW', 'RainToday_No',
'RainToday_Unknown', 'RainToday_Yes']
```

```python
# Now that we have generated the one-hot encoded columns, we shall
append them to our train, validation, and test datasets
train_inputs[encoded_cols] = encoder.fit_transform(train_df[cat_cols])
test_inputs[encoded_cols] = encoder.fit_transform(test_df[cat_cols])
val_inputs[encoded_cols] = encoder.fit_transform(val_df[cat_cols])

# Delete redundant columns such as the categori columns such as the
ones we used the one-encoded on
train_inputs.drop(cat_cols, axis = 1, inplace = True)
test_inputs.drop(cat_cols, axis = 1, inplace = True)
val_inputs.drop(cat_cols, axis = 1, inplace = True)

#same outputs for the train and validation datasets.
test_inputs.columns.tolist()
```

```
['MinTemp',
 'MaxTemp',
 'Rainfall',
 'Evaporation',
 'Sunshine',
 'WindGustSpeed',
 'WindSpeed9am',
 'WindSpeed3pm',
 'Humidity9am',
 'Humidity3pm',
 'Pressure9am',
 'Pressure3pm',
 'Cloud9am',
```

```
'Cloud3pm',
'Temp9am',
'Temp3pm',
'Location_Adelaide',
'Location_Albany',
'Location_Albury',
'Location_AliceSprings',
'Location_BadgerysCreek',
'Location_Ballarat',
'Location_Bendigo',
'Location_Brisbane',
'Location_Cairns',
'Location_Canberra',
'Location_Cobar',
'Location_CoffsHarbour',
'Location_Dartmoor',
'Location_Darwin',
'Location_GoldCoast',
'Location_Hobart',
'Location_Katherine',
'Location_Launceston',
'Location_Melbourne',
'Location_MelbourneAirport',
'Location_Mildura',
'Location_Moree',
'Location_MountGambier',
'Location_MountGinini',
'Location_Newcastle',
'Location_Nhil',
'Location_NorahHead',
'Location_NorfolkIsland',
'Location_Nuriootpa',
'Location_PearceRAAF',
'Location_Penrith',
'Location_Perth',
'Location_PerthAirport',
'Location_Portland',
'Location_Richmond',
'Location_Sale',
'Location_SalmonGums',
'Location_Sydney',
'Location_SydneyAirport',
'Location_Townsville',
'Location_Tuggeranong',
'Location_Uluru',
'Location_WaggaWagga',
'Location_Walpole',
'Location_Watsonia',
'Location_Williamtown',
'Location_Witchcliffe',
```

```
'Location_Wollongong',
'Location_Woomera',
'WindGustDir_E',
'WindGustDir_ENE',
'WindGustDir_ESE',
'WindGustDir_N',
'WindGustDir_NE',
'WindGustDir_NNE',
'WindGustDir_NNW',
'WindGustDir_NW',
'WindGustDir_S',
'WindGustDir_SE',
'WindGustDir_SSE',
'WindGustDir_SSW',
'WindGustDir_SW',
'WindGustDir_Unknown',
'WindGustDir_W',
'WindGustDir_WNW',
'WindGustDir_WSW',
'WindDir9am_E',
'WindDir9am_ENE',
'WindDir9am_ESE',
'WindDir9am_N',
'WindDir9am_NE',
'WindDir9am_NNE',
'WindDir9am_NNW',
'WindDir9am_NW',
'WindDir9am_S',
'WindDir9am_SE',
'WindDir9am_SSE',
'WindDir9am_SSW',
'WindDir9am_SW',
'WindDir9am_Unknown',
'WindDir9am_W',
'WindDir9am_WNW',
'WindDir9am_WSW',
'WindDir3pm_E',
'WindDir3pm_ENE',
'WindDir3pm_ESE',
'WindDir3pm_N',
'WindDir3pm_NE',
'WindDir3pm_NNE',
'WindDir3pm_NNW',
'WindDir3pm_NW',
'WindDir3pm_S',
'WindDir3pm_SE',
'WindDir3pm_SSE',
'WindDir3pm_SSW',
'WindDir3pm_SW',
'WindDir3pm_Unknown',
```

```
 'WindDir3pm_W',
 'WindDir3pm_WNW',
 'WindDir3pm_WSW',
 'RainToday_No',
 'RainToday_Unknown',
 'RainToday_Yes']
```

```
print("train_inputs shape is {}".format(train_inputs.shape))
print("train_target shape is {}".format(train_target.shape))
print("val_inputs shape is {}".format(val_inputs.shape))
print("val_target shape is {}".format(val_target.shape))
print("test_inputs shape is {}".format(test_inputs.shape))
print("test_target shape is {}".format(test_target.shape))
```

```
train_inputs shape is (98988, 119)
train_target shape is (98988,)
val_inputs shape is (17231, 119)
val_target shape is (17231,)
test_inputs shape is (25974, 119)
test_target shape is (25974,)
```

Training Random Forest Model

```
from sklearn.ensemble import RandomForestClassifier

RandomForestModel = RandomForestClassifier(n_jobs = -1, random_state = 
22)
RandomForestModel.fit(train_inputs, train_target)
```

```
RandomForestClassifier(n_jobs=-1, random_state=22)
```

Classification Metrics prior to Hypertuning

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize
import matplotlib.pyplot as plt

def accuracyscores(clf, prior_inputs, prior_target, new_inputs , 
new_target):
    print("train model score {}".format(clf.score(prior_inputs, 
prior_target)))
    print("non-train model score {}".format(clf.score(new_inputs, 
new_target)))

    y_majority = np.full(new_target.shape[0], "No")
    y_random = np.random.choice(["No", "Yes"], new_target.shape[0])

    print("random model accuracy score 
```

```
{}".format(accuracy_score(new_target, y_random)))
    print("majority model accuracy score
{}".format(accuracy_score(new_target, y_majority)))

def confusionmatrixplot(clf,inputs, target):
    prediction = clf.predict(inputs)

    data = confusion_matrix(target, prediction)
    df_cm = pd.DataFrame(data, columns=np.unique(prediction), index =
np.unique(target))
    df_cm.index.name = 'Actual'
    df_cm.columns.name = 'Predicted'
    plt.figure(figsize = (5,5))
    sns.set(font_scale=1.4)#for label size
    sns.heatmap(df_cm, cmap="Blues", fmt=
'd',annot=True,annot_kws={"size": 16});

def plot_multiclass_roc(clf, X_test, y_test, n_classes, figsize=(17,
6)):
    try:
        y_score = clf.decision_function(X_test)
        print("Using decision_function method")
    except:
        y_score = clf.predict_proba(X_test)
        print("Using predict_proba method")

    # structures
    fpr = dict()
    tpr = dict()
    roc_auc = dict()

    # calculate dummies once
    y_test_dummies = pd.get_dummies(y_test, drop_first=False).values
    for i in range(n_classes):
        fpr[i], tpr[i], _ = roc_curve(y_test_dummies[:, i], y_score[:,
i])
        roc_auc[i] = auc(fpr[i], tpr[i])

    # roc for each class
    fig, ax = plt.subplots(figsize=figsize)
    ax.plot([0, 1], [0, 1], 'k--')
    ax.set_xlim([0.0, 1.0])
    ax.set_ylim([0.0, 1.05])
    ax.set_xlabel('False Positive Rate')
    ax.set_ylabel('True Positive Rate')
    ax.set_title('Receiver operating characteristic for
RandomForest_roc_auc_cruve')
    for i in range(n_classes):
        ax.plot(fpr[i], tpr[i], label='ROC curve (area = %0.2f) for
label %i' % (roc_auc[i], i+1))
```

```
    ax.legend(loc="best")
    ax.grid(alpha=.4)
    sns.despine()
    plt.tight_layout()
    plt.show();
```

```
accuracyscores(RandomForestModel, train_inputs, train_target,
val_inputs, val_target)
```

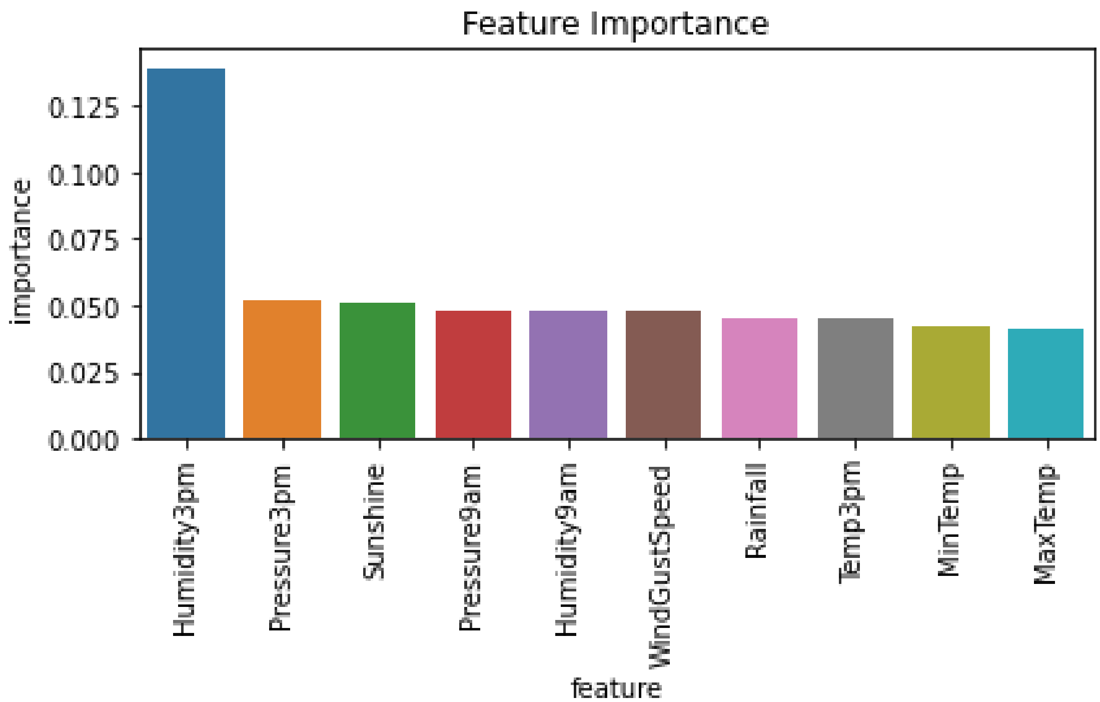
```
prior model score 0.9999696932961571
new model score 0.8549126574197667
random model accuracy score 0.4958505020022053
majority model accuracy score 0.7882885497069235
```

notice how the model works really well with the data is was trained on but not on new data. This is a clear case of overfitting.

We can benchmark our model against baseline models wherein the predicted values are either random (y_random) or contains the majority target class (y_majority). Checking their accuracies and comparing our model's own accuracy against these dumb models can give as a pretty good idea whether our model is worthwhile and better. Fortunately, our model outperformed both the dumb models using the accuracy metric.

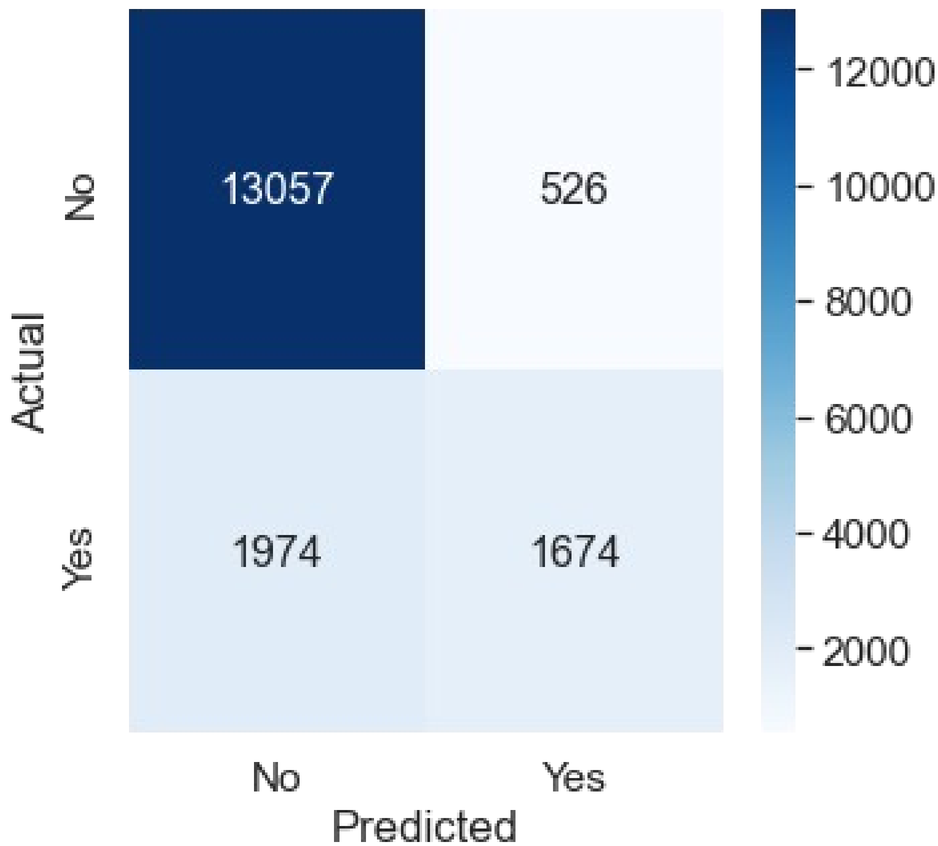
```
feature_importance_df = pd.DataFrame(
    {
        'feature': train_inputs.columns.tolist(),
        'importance': RandomForestModel.feature_importances_
    }
).sort_values(by ='importance', ascending = False)
```

```
plt.title('Feature Importance')
sns.barplot(data = feature_importance_df.head(10), x='feature',
y='importance')
plt.xticks(rotation = 90)
plt.tight_layout()
```



It seems the model gives most importance to the column Humidity3pm that is more than twice the amount than the next important feature column

```
confusionmatrixplot(RandomForestModel, val_inputs, val_target)
```



Around 54% of our Ground Truth for the class of Yes was predicted incorrectly. And this was brought upon when our model is predicting "No", instead of when the model was predicting "Yes". Our False Negatives comprise about 13% of our total number of prediction of "No"s. So we can trust our model to correctly predict a chance of no rain 86% of the time when it predicts "No". We can also trust our model to predict rain 76% of the time when it predicts "Yes".

```
print(classification_report(val_target,
RandomForestModel.predict(val_inputs)))

              precision    recall  f1-score   support

          No       0.87      0.96      0.91     13583
         Yes       0.76      0.46      0.57      3648

    accuracy                           0.85     17231
   macro avg       0.81      0.71      0.74     17231
weighted avg       0.85      0.85      0.84     17231
```

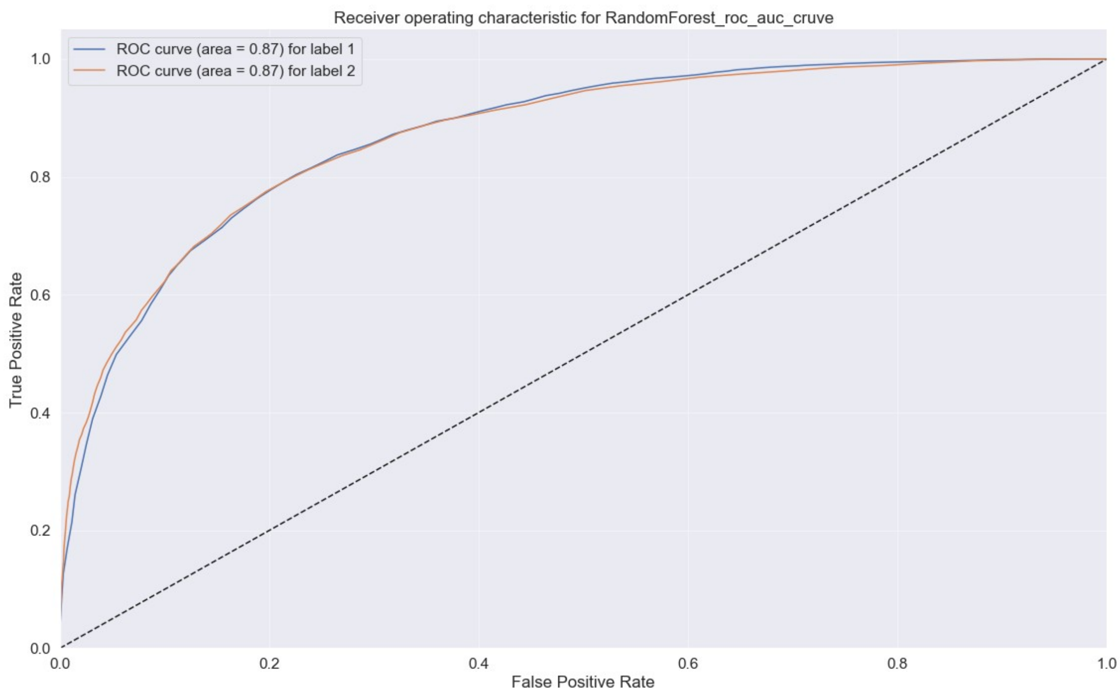
The precision for both the No and Yes class are as I described in the confusion matric explanation. However, despite this our recall score for the class "Yes" is very low compared to its precision. One factor that causes this is the fact that our dataset is imbalanced. With our target column having a majority of No values, that has caused our precision and recall for No to be higher than Yes.

```
roc_auc_score(val_target, RandomForestModel.predict_proba(val_inputs)
[:,1])
```

```
0.8717470040433668
```

```
plot_multiclass_roc(RandomForestModel, val_inputs, val_target, 2,
figsize=(16,10))
```

```
Using predict_proba method
```



ideal is 1.0, since we are at 0.87 for both classes, the model is performing well. Notice that the ROC curve and score for both of the classes are the similar (model isn't better at predicting No vs. Yes) despite having different recall and precision scores. For imbalanced datasets (like what we have) it's better to look at the ROC curve and AUC values for determining the models' performace since recall and precision scores are heavily affected by imbalanced datasets.

Hypertuning our Random Forest model

```
randomforest_random_grid = {'n_estimators': [100,200,300,400],
                            'max_depth': [4,7,10,15],
                            'min_samples_leaf': [1, 2, 4],
                            'criterion':['gini', 'entropy'],
                            }
```

```
from sklearn.model_selection import GridSearchCV
```

```
optimized_randomforest = GridSearchCV(RandomForestClassifier(n_jobs=-
1,random_state=22), randomforest_random_grid, cv=2, verbose=True,
n_jobs=-1)
```

```
best_randomforest = optimized_randomforest.fit(train_inputs,
train_target)
```

```
Fitting 2 folds for each of 96 candidates, totalling 192 fits
```

```
best_randomforest.best_params_
```

```
{'criterion': 'entropy',
 'max_depth': 15,
 'min_samples_leaf': 2,
 'n_estimators': 300,
 'n_jobs': -1}
```

```
RandomForestModel_optimized = RandomForestClassifier(criterion=
'entropy',
 max_depth= 15,
 min_samples_leaf= 2,
 n_estimators= 300,
 n_jobs=-1,
 random_state= 18)
RandomForestModel_optimized.fit(train_inputs, train_target)
```

```
RandomForestClassifier(criterion='entropy', max_depth=15,
min_samples_leaf=2,
                       n_estimators=300, n_jobs=-1, random_state=18)
```

```
y_predictions_randomforest_optimized =
RandomForestModel_optimized.predict(val_inputs)
```

Classification Metrics on Optimized Random Forest Model

```
accuracyscores(RandomForestModel_optimized, train_inputs,
train_target, val_inputs, val_target)
```

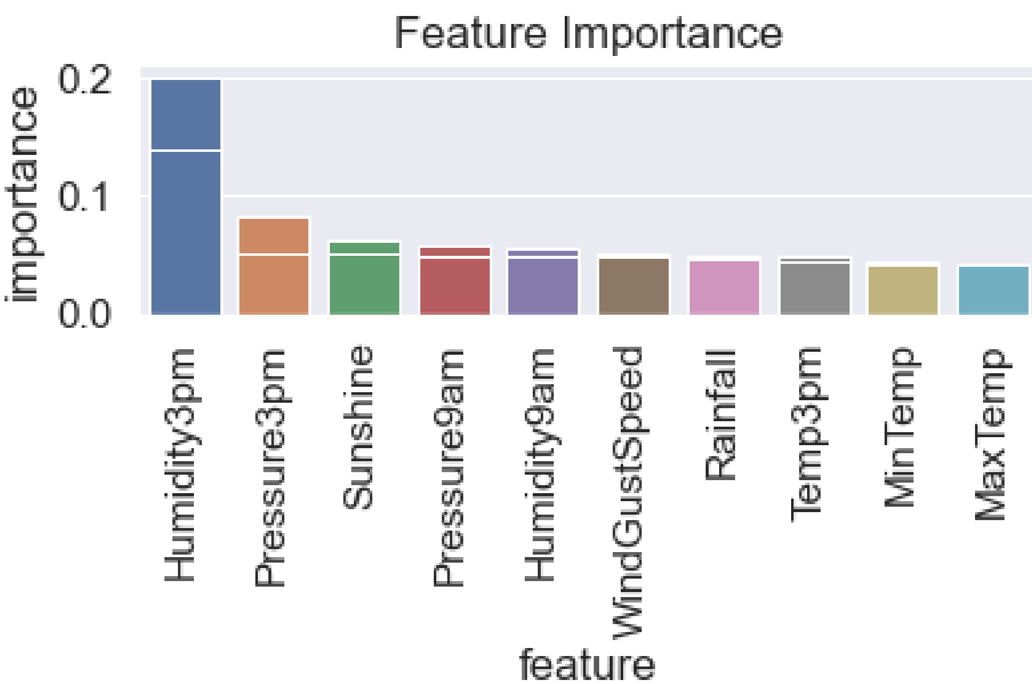
```
train model score 0.8842384935547744
non-train model score 0.8516046660089374
random model accuracy score 0.5065289304161105
majority model accuracy score 0.7882885497069235
```

```
accuracyscores(RandomForestModel, train_inputs, train_target,
val_inputs, val_target)
```

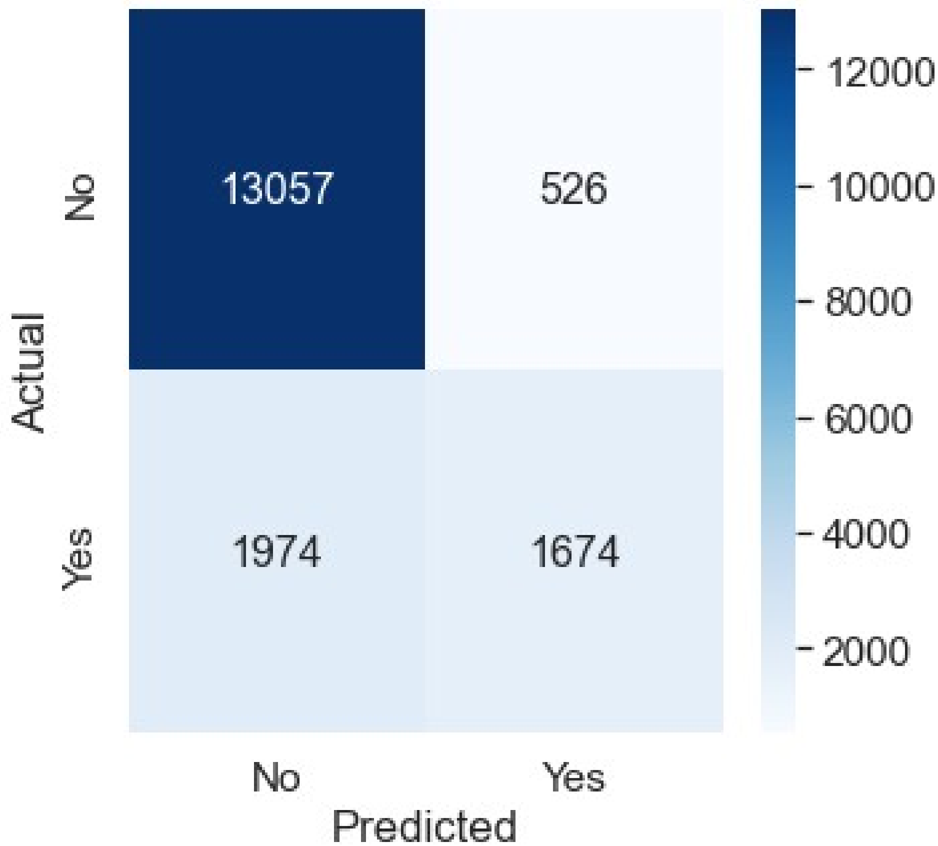
```
train model score 0.9999696932961571
non-train model score 0.8549126574197667
random model accuracy score 0.49747548023910393
majority model accuracy score 0.7882885497069235
```

```
feature_importance_optimzed = pd.DataFrame(
    {
```

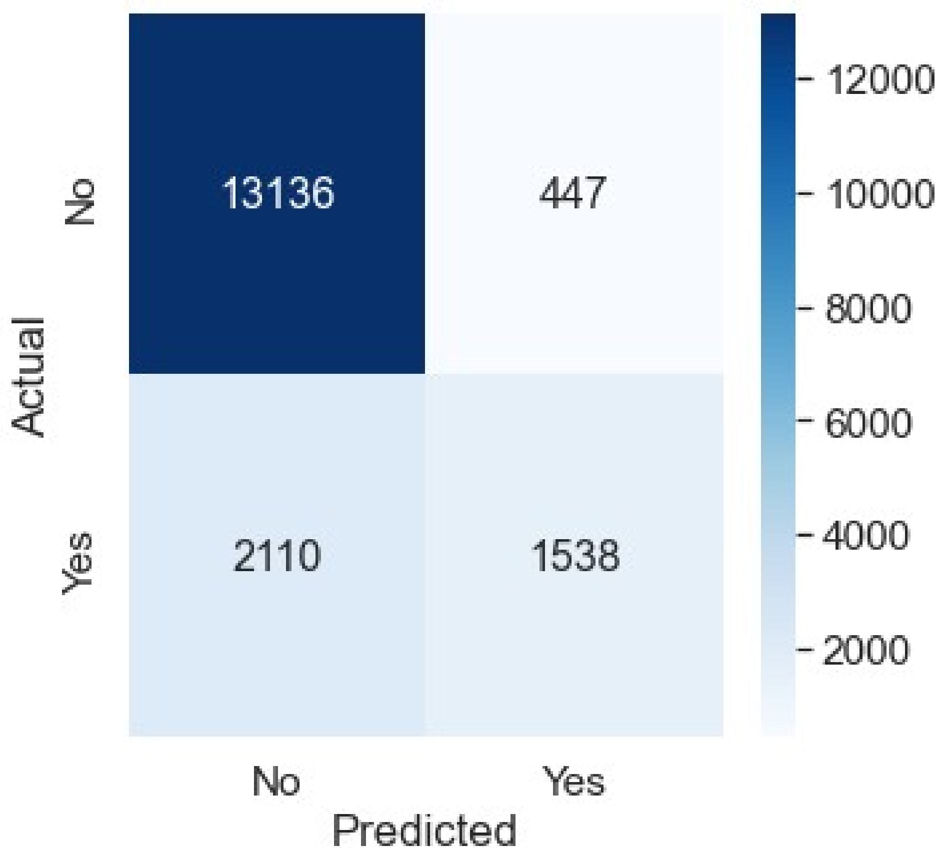
```
        'feature': train_inputs.columns.tolist(),
        'importance': RandomForestModel_optimized.feature_importances_
    }
).sort_values(by ='importance', ascending = False)

plt.title('Feature Importance')
sns.barplot(data = feature_importance_optimzed.head(10), x='feature',
y='importance')
sns.barplot(data = feature_importance_df.head(10), x='feature',
y='importance')
plt.xticks(rotation = 90)
plt.tight_layout()
```




```
confusionmatrixplot(RandomForestModel, val_inputs, val_target)
```




```
confusionmatrixplot(RandomForestModel_optimized, val_inputs,
val_target)
```




```
print(classification_report(val_target,
RandomForestModel.predict(val_inputs)))

              precision    recall  f1-score   support

          No       0.87      0.96      0.91     13583
         Yes       0.76      0.46      0.57      3648

    accuracy                           0.85     17231
   macro avg       0.81      0.71      0.74     17231
weighted avg       0.85      0.85      0.84     17231


print(classification_report(val_target,
RandomForestModel_optimized.predict(val_inputs)))

              precision    recall  f1-score   support

          No       0.86      0.97      0.91     13583
         Yes       0.77      0.42      0.55      3648

    accuracy                           0.85     17231
   macro avg       0.82      0.69      0.73     17231
```

```
weighted avg       0.84      0.85      0.83     17231
```

```
roc_auc_score(val_target, RandomForestModel.predict_proba(val_inputs)
[:,1])
```

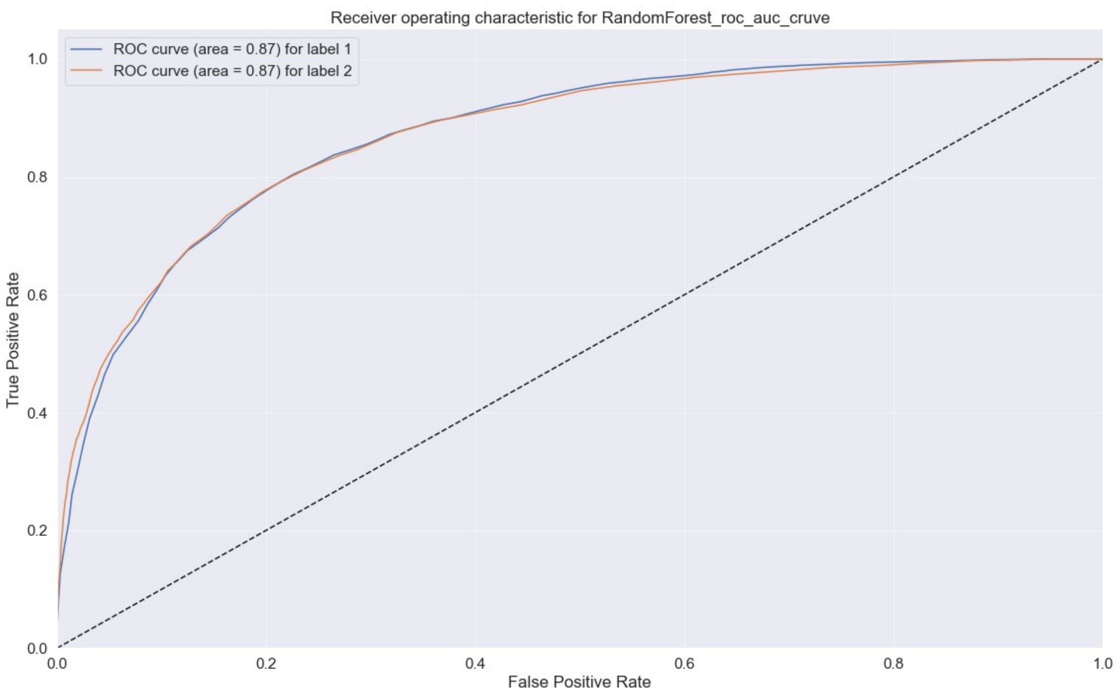
```
0.8717470040433668
```

```
roc_auc_score(val_target,
RandomForestModel_optimized.predict_proba(val_inputs)[:,1])
```

```
0.8711596773120682
```

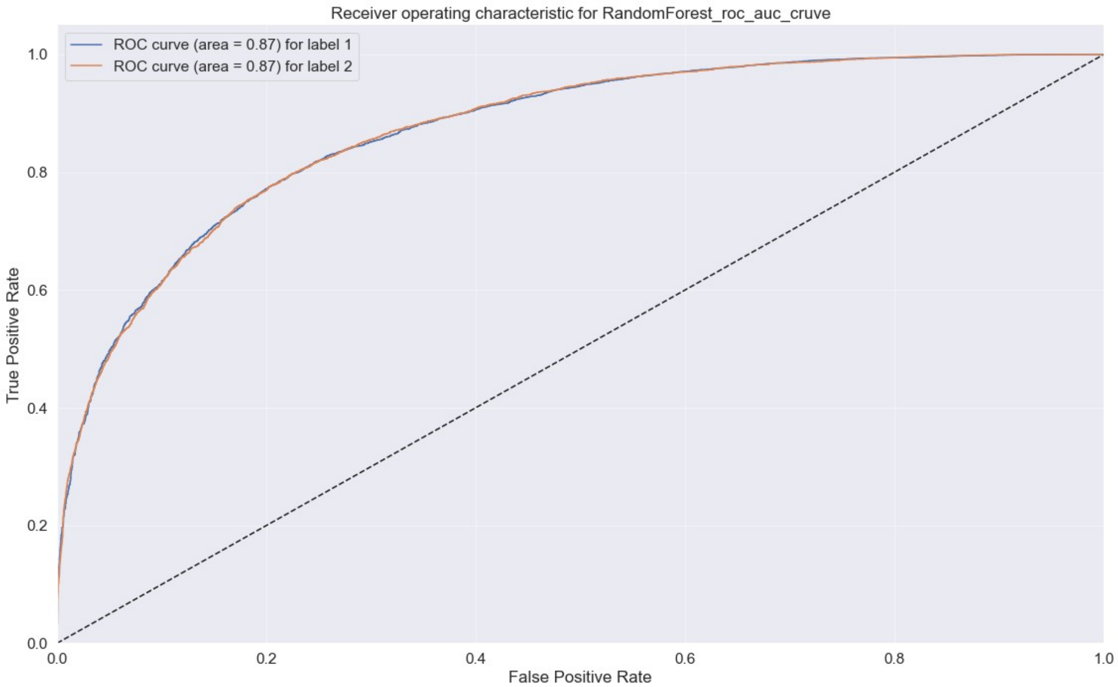
```
plot_multiclass_roc(RandomForestModel, val_inputs, val_target, 2,
figsize=(16,10))
```

```
Using predict_proba method
```




```
plot_multiclass_roc(RandomForestModel_optimized, val_inputs,
val_target, 2, figsize=(16,10))
```

```
Using predict_proba method
```



Feature Importance

- In the base model the top 1-5 and 8 had an increase in feature importance compared to the optimized model. I have not checked the other column features, but it is likely they have also expereinced a similar pattern.

Classification Report

- Optimized model is better at predicting class 0 than class 1.
- Looking at precision, the optimized model suggests that if 0 or 1 is predicted, model is correct 86% and 77% of the time, respectively. This is a decrease of 1% and an increase of 1%, respectively. Precision would not be the best metric to base our choice of model in this case.
- Looking at the recall scores, the optimized model also suggests that it was able to correctly predict all 2431 or almost 97% of the available instances of class 0 in the target column of the test dataset. However, the optimized model was only able to correctly predict 42% of the class 1 instances. There was a 4% decrese in the recall of the optimized model for class 1 and a 1% increase in the recall of the optimized model for class 0. Based on this, as well as the F1-score, the base model is clearly better.

Confusion Matrix

- Compared to the base model, the confusion matrix for the optimized model shows that the number of True Negatives increased; the number of False Positives decreased; the number of True Positives decreased; and the number of False Positives increased. Some insights we can gather is that our optimized model might not be so great to use. The model has a lot of False Negatives which is arguable worse than False Positives since adjusting for a fair weather is easier than adjusting for a rainy one. Our False Negatives increased by 6%.

`Accuracy Score`

- Inerestingly, the optimized model did not do as well as the base random forest model we had previously in terms of accuracy score for the training dataset. There was an almost 11% drop in accuracy rate for the training score. As for the validation score, the optimized model produced a lower accuracy score compared to the base model. Both models, fortunately, perfromed bettern than our "dumb" models. We should look further into other metrics before we decide that the optimized model is not favourable.

`ROC AUC Score`

- ideal is 1.0, since we are at 0.87 for both base and optimized models, I'd say they are a tie here.

The better model would probably be the base model.

Test Dataset Metric Scores

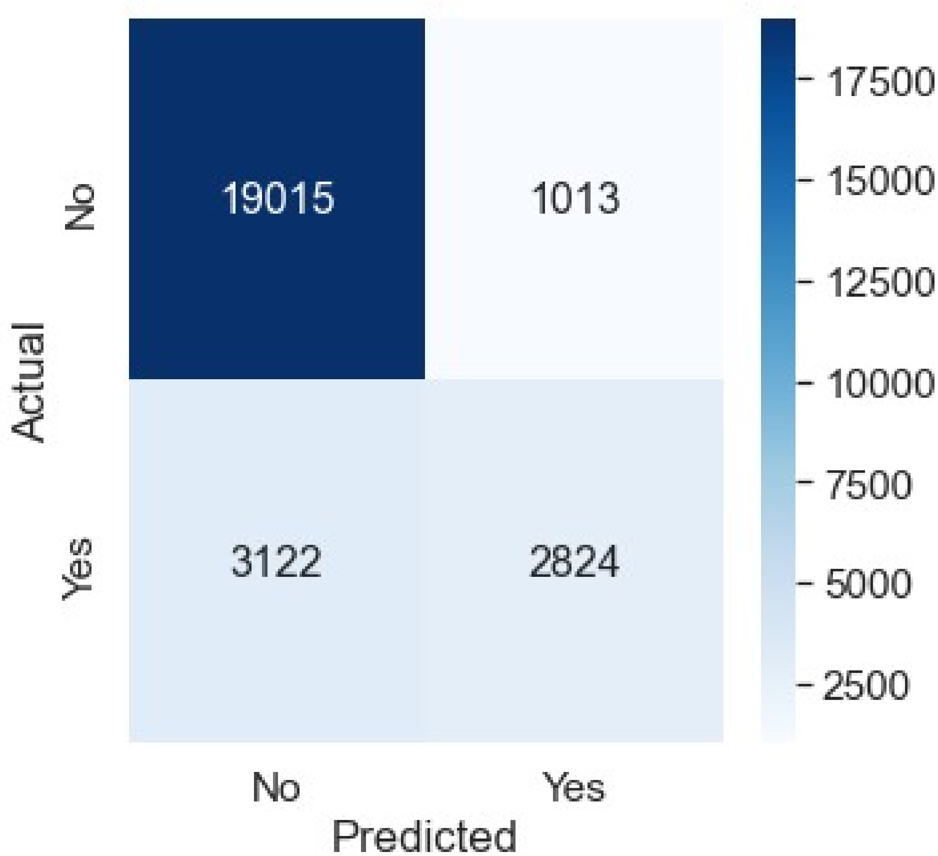
```
print(accuracyscores(RandomForestModel_optimized, train_inputs,
train_target, test_inputs, test_target))
```

```
train model score 0.8842384935547744
non-train model score 0.8379533379533379
random model accuracy score 0.5036190036190036
majority model accuracy score 0.7710787710787711
None
```

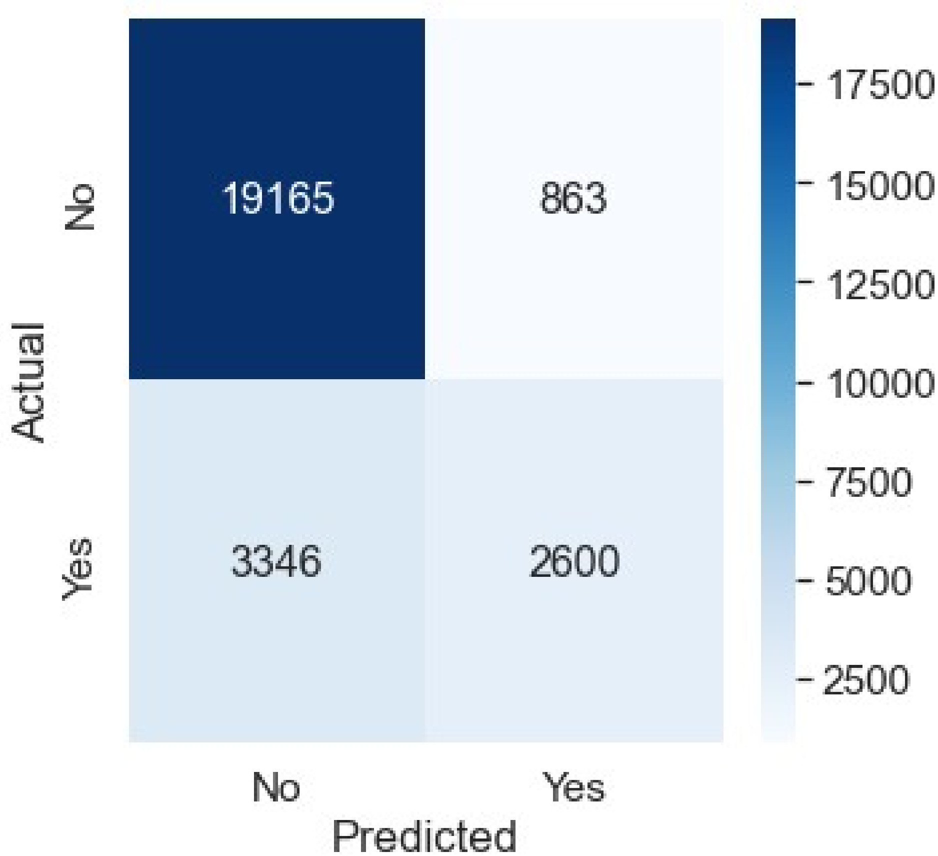
```
accuracyscores(RandomForestModel, train_inputs, train_target,
test_inputs, test_target)
```

```
train model score 0.9999696932961571
non-train model score 0.8408023408023408
random model accuracy score 0.4933009933009933
majority model accuracy score 0.7710787710787711
```

```
confusionmatrixplot(RandomForestModel, test_inputs, test_target)
```




```
confusionmatrixplot(RandomForestModel_optimized, test_inputs,
test_target)
```




```
print(classification_report(test_target,
RandomForestModel.predict(test_inputs)))
```

```
              precision    recall  f1-score   support

          No       0.86      0.95      0.90     20028
         Yes       0.74      0.47      0.58      5946

    accuracy                           0.84     25974
   macro avg       0.80      0.71      0.74     25974
weighted avg       0.83      0.84      0.83     25974
```

```
print(classification_report(test_target,
RandomForestModel_optimized.predict(test_inputs)))
```

```
              precision    recall  f1-score   support

          No       0.85      0.96      0.90     20028
         Yes       0.75      0.44      0.55      5946

    accuracy                           0.84     25974
   macro avg       0.80      0.70      0.73     25974
```

```
weighted avg       0.83      0.84      0.82     25974
```

```
roc_auc_score(test_target, 
RandomForestModel.predict_proba(test_inputs)[:,1])
```

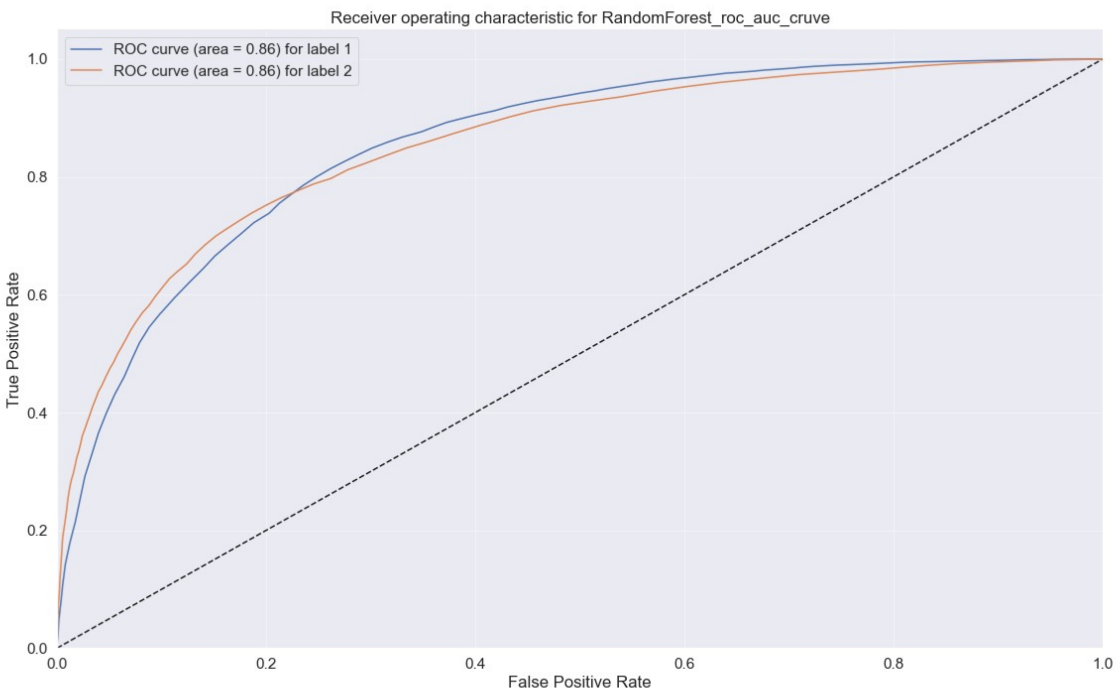
```
0.8556750913672085
```

```
roc_auc_score(test_target, 
RandomForestModel_optimized.predict_proba(test_inputs)[:,1])
```

```
0.8579382238562615
```

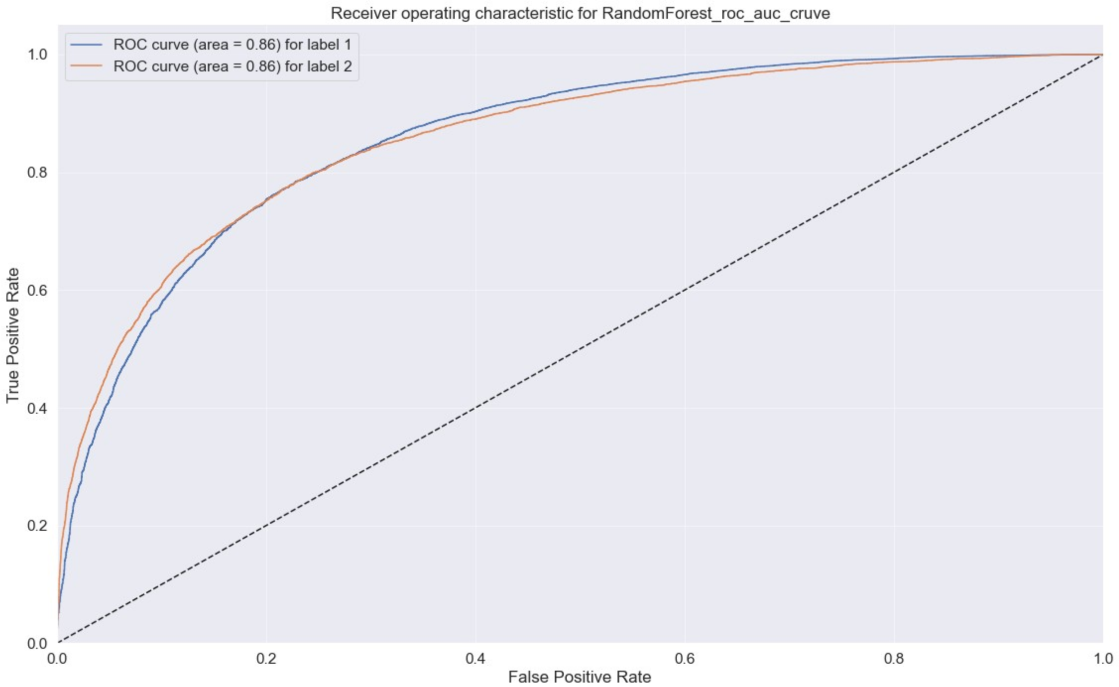
```
plot_multiclass_roc(RandomForestModel, test_inputs, test_target, 2, 
figsize=(16,10))
```

```
Using predict_proba method
```




```
plot_multiclass_roc(RandomForestModel_optimized, test_inputs, 
test_target, 2, figsize=(16,10))
```

```
Using predict_proba method
```



Conclusion

In conclusion since the base model performed better in the accuracy score, classification report, had a more favorable result for the confusion matrix, and perfromed just as well in the ROC curve and AUC score test compared to the optimized model, I would say `the base model` (**RandomForestModel**) `is the best model to use`