In [99]:

Assignment Questions

Group Number: CT1 Project Group-8

Team Members

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Problem Statement

About the data set (Rainfall Prediction data)

The dataset contains information about rainfall predictions. The aim is to find whether rainfall will occur or not based on the several parameters of the atmospheric conditions and profile.

RainTomorrow: Does tomorrow rainfall will happen or not: Yes(1) or No(0)

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
pd.options.display.max_columns = None
pd.options.display.max_rows = None
import warnings
warnings.filterwarnings('ignore')
from sklearn.impute import KNNImputer
```

1. Data Preparation

In [99]:

1.1 Read the Data

Read the dataset and print the first five observations.

In [98]:

```
df = pd.read_csv(r"C:\Users\priya\SRM PYTHON\MLSC\MP1\Rainfall_prediction_data.csv")
df.head(5)
```

Out[98]:

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	Wi
0	07-03-2012	Wollongong	16.0	20.4	8.2	NaN	NaN	S	
1	06-01-2011	PerthAirport	18.5	25.9	16.0	5.4	11.8	WSW	
2	29-06-2014	Penrith	8.7	16.5	0.0	NaN	NaN	WNW	
3	16-12-2008	Cairns	25.5	33.9	0.2	5.0	7.0	SSE	
4	21-04-2015	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	

Let us now see the number of variables and observations in the data.

```
df.shape
```

Out[99]:

```
(1040, 23)
```

INFERENCE: The given dataset contains 23 features with over 1040 rows. From the non-null count, we can understand that there are missing values for several features.

1.2 Check the Data Type

Check the data type of each variable. If the data type is not as per the data definition, change the data type.

In [101]:

```
df.dtypes
```

Out[101]:

```
Date              object
Location          object
MinTemp          float64
MaxTemp          float64
Rainfall         float64
Evaporation      float64
Sunshine         float64
WindGustDir       object
WindGustSpeed    float64
WindDir9am        object
WindDir3pm        object
WindSpeed9am     float64
WindSpeed3pm     float64
Humidity9am      float64
Humidity3pm      float64
Pressure9am      float64
Pressure3pm      float64
Cloud9am         float64
Cloud3pm         float64
Temp9am          float64
Temp3pm          float64
RainToday         object
RainTomorrow      object
dtype: object
```

INFERENCE: Out of 23 features, 7 features are of categorical datatype and 16 features are numerical in nature.

Change the data type as per the data definition.

In [102]:

```
df['Date'].dtype
```

Out[102]:

```
dtype('O')
```

INFERENCE: From the above result, we can see that feature 'Date' is in categorical datatype. Lets convert it into datetime format for further analysis.

In [103]:

```
df['Date'].head()
```

Out[103]:

```
0    07-03-2012
1    06-01-2011
2    29-06-2014
3    16-12-2008
4    21-04-2015
Name: Date, dtype: object
```

In [104]:

```
pd.to_datetime(df['Date']).head(5)
```

Out[104]:

```
0   2012-07-03
1   2011-06-01
2   2014-06-29
3   2008-12-16
4   2015-04-21
Name: Date, dtype: datetime64[ns]
```

INFERENCE: When we compare results after converting 'Date' into datetime format, we could difference in values of the data. Lets consider the first record in 'Date' feature, '07-03-2012'(7th March 2012) . After converting into datetime format,value has changed to 2012-07-03 (3rd July 2012).

Similarly, the 2nd record '06-01-2011' (6th Jan 2011) is converted to 2011-06-01 (1st June 2011). But the 3rd record '29-06-2014' (29th June 2014) has been properly converted into datetime format 2014-06-29 (29th June 2014).

In order to avoid this type of data corruption, lets extract only the month from 'Date' feature and save it in a seoarate column. Later we can convert it into datetime format and use for analysis.

In [105]:

```
df['Month']= df['Date']
```

In [106]:

```
df['Month'].head()
```

Out[106]:

```
0    07-03-2012
1    06-01-2011
2    29-06-2014
3    16-12-2008
4    21-04-2015
Name: Month, dtype: object
```

In [107]:

```
# To extract only the month number

df['Month']=df['Month'].str[3:5]
df['Month'].head()
```

Out[107]:

```
0    03
1    01
2    06
3    12
4    04
Name: Month, dtype: object
```

In [108]:

```
df['Month']=pd.to_datetime(df['Month'], format='%m').dt.month_name()
df['Month'].head()
```

Out[108]:

```
0       March
1     January
2        June
3    December
4       April
Name: Month, dtype: object
```

INFERENCE: Since we have used only the month part from 'Date' feature to convert into month name, our data is now more reliable.

In [109]:

```
# Before conversion to numerical datatype
df['RainTomorrow'].value_counts()
```

Out[109]:

```
No     829
Yes    211
Name: RainTomorrow, dtype: int64
```

In [110]:

```
for i in ['RainTomorrow']:
    df[i].replace({'Yes': 1,'No': 0},inplace=True)
```

In [111]:

```
# After conversion to numerical datatype
df['RainTomorrow'].value_counts()
```

Out[111]:

```
0    829
1    211
Name: RainTomorrow, dtype: int64
```

INFERENCE: Feature - 'RainTomorrow'is converted to numerical datatype by replacing values 'Yes' with value 1 and 'No' with value 0.

Recheck the data type after the conversion.

In [112]:

```
df['Date']=pd.to_datetime(df['Date'])
df['Date'].dtype
```

Out[112]:

```
dtype('<M8[ns]')
```

In [113]:

```
df['Month'].dtype
```

Out[113]:

```
dtype('O')
```

In [114]:

```
df['RainTomorrow'].dtype
```

Out[114]:

```
dtype('int64')
```

INFERENCE: Feature 'Date' is in datetime format and feature 'Month' is in object datatype as it stores name of the month. We will be using 'Month' feature further in our analysis. And also target variable ''RainTomorrow' is in numerical datatype.

1.3 Remove Insignificant Variables, if its applicable.

In [115]:

```
df.info()
```

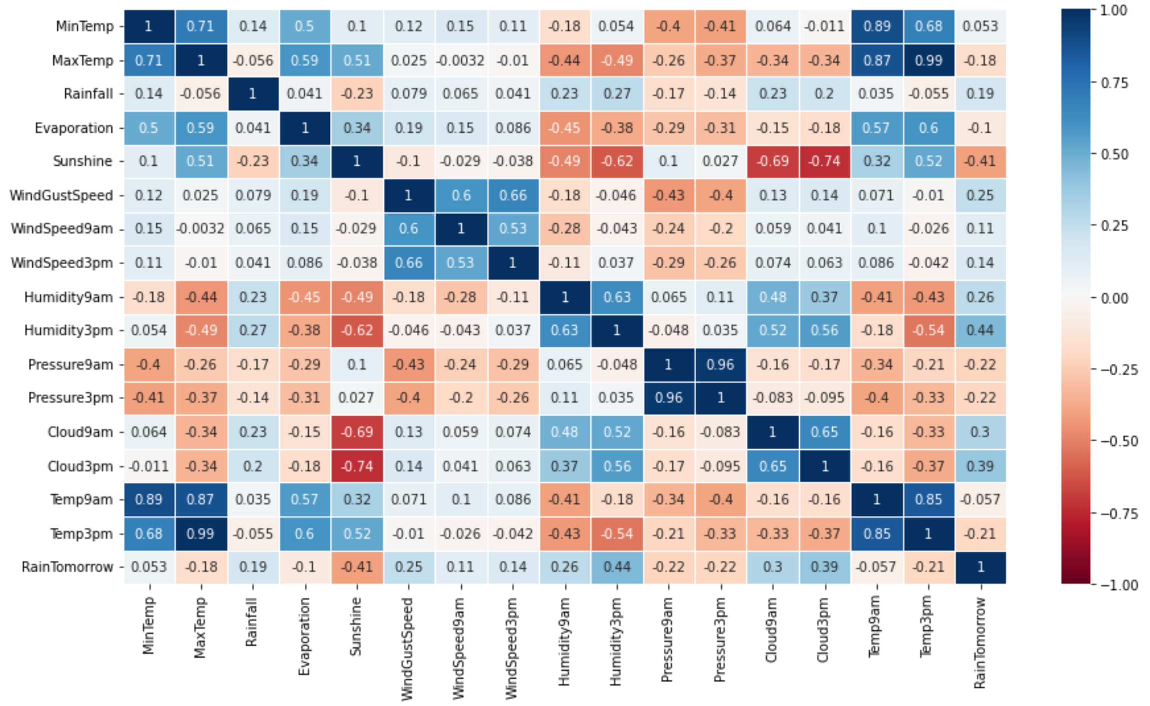
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1040 entries, 0 to 1039
Data columns (total 24 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Date           1040 non-null   datetime64[ns]
 1   Location       1040 non-null   object
 2   MinTemp        1035 non-null   float64
 3   MaxTemp        1035 non-null   float64
 4   Rainfall       1029 non-null   float64
 5   Evaporation    582 non-null    float64
 6   Sunshine       533 non-null    float64
 7   WindGustDir    969 non-null    object
 8   WindGustSpeed  969 non-null    float64
 9   WindDir9am     981 non-null    object
 10  WindDir3pm     1014 non-null   object
 11  WindSpeed9am   1032 non-null   float64
 12  WindSpeed3pm   1023 non-null   float64
 13  Humidity9am    1031 non-null   float64
 14  Humidity3pm    1016 non-null   float64
 15  Pressure9am    929 non-null    float64
 16  Pressure3pm    932 non-null    float64
 17  Cloud9am       613 non-null    float64
 18  Cloud3pm       597 non-null    float64
 19  Temp9am        1034 non-null   float64
 20  Temp3pm        1022 non-null   float64
 21  RainToday      1029 non-null   object
 22  RainTomorrow   1040 non-null   int64
 23  Month          1040 non-null   object
dtypes: datetime64[ns](1), float64(16), int64(1), object(6)
memory usage: 195.1+ KB
```

In [116]:

```
fig, ax = plt.subplots(figsize=(15,8))
sns.heatmap(df.corr(),annot = True,linewidths=.5,cmap='RdBu',vmin=-1,vmax=1)
```

Out[116]:

```
<AxesSubplot:>
```



In [117]:

```
df.drop(columns=[ 'Date','Location','WindSpeed9am','WindSpeed3pm','WindGustDir'],axis=1,i
```

INFERENCE:

Feature 'Date' can be dropped since we have extracted month and kept it in a separate column 'Month'.

Feature 'WindSpeed9am' and 'WindSpeed3pm' is dropped as they have high correlation between them. Instead of these 2 features, we can use 'WindGustSpeed' for our model .

Feature 'WindGustDir' is dropped as we have two similar other features to determine direction of wind - 'WindSpeed9am' and 'WindSpeed3pm'.

1.4 Distribution of Variables

Distribution of numeric independent variables.

In [118]:

```
num_indep = df.select_dtypes(include=np.number).columns.tolist()
print(num_indep)
print("Number of numeric var:" ,len(num_indep))
```

```
['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine', 'WindGustSpe
ed', 'Humidity9am', 'Humidity3pm', 'Pressure9am', 'Pressure3pm', 'Cloud9a
m', 'Cloud3pm', 'Temp9am', 'Temp3pm', 'RainTomorrow']
Number of numeric var: 15
```

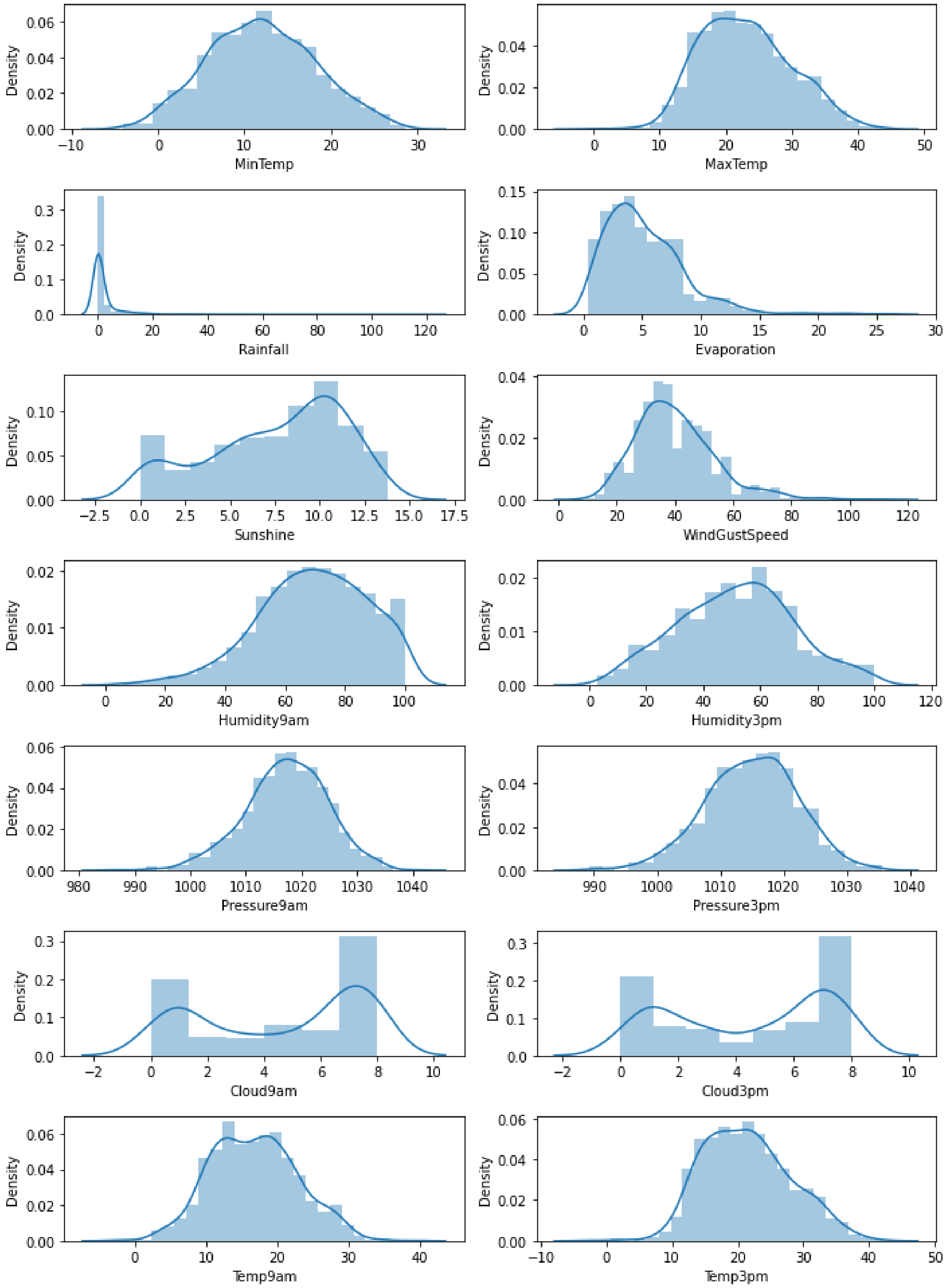
In [119]:

```
# To remove RainTomorrow which is the target/dependent variable

num_indep.pop()
print(num_indep)
print("Number of numeric var:" ,len(num_indep))
```

```
['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine', 'WindGustSpe
ed', 'Humidity9am', 'Humidity3pm', 'Pressure9am', 'Pressure3pm', 'Cloud9a
m', 'Cloud3pm', 'Temp9am', 'Temp3pm']
Number of numeric var: 14
```

In [121]:

```
plt.figure(figsize= (10,15))
for i in range(0,len(num_indep)):
    plt.subplot(8,2,int(i+1))
    sns.distplot(df[num_indep[i]])

plt.tight_layout()
plt.show()
```



In [121]:

Distribution of categoric independent variable.

```
catg_indep = df.select_dtypes(include=object).columns.tolist()
catg_indep
```

Out[121]:

```
['WindDir9am', 'WindDir3pm', 'RainToday', 'Month']
```

In [122]:

```
df_cat=df[catg_indep]
df_cat.head()
```

Out[122]:

	WindDir9am	WindDir3pm	RainToday	Month
0	SSW	SW	Yes	March
1	SSW	WSW	Yes	January
2	WNW	WNW	No	June
3	SSE	SE	No	December
4	NE	W	No	April

In [123]:

```
# Lets drop null values to plot histplot using categorical independent variables

df_cat.dropna(inplace=True)
df_cat.isnull().sum()
```

Out[123]:

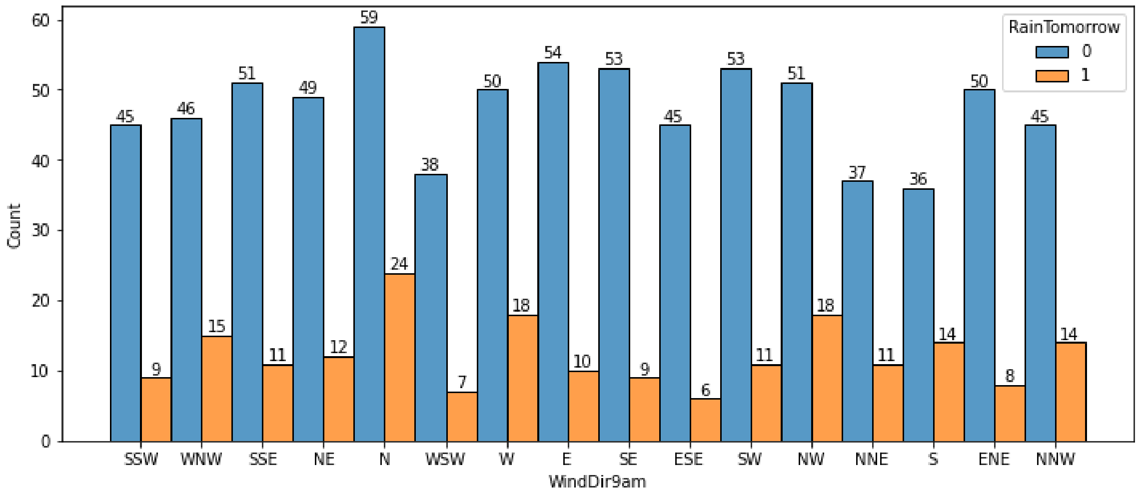
```
WindDir9am    0
WindDir3pm    0
RainToday     0
Month         0
dtype: int64
```

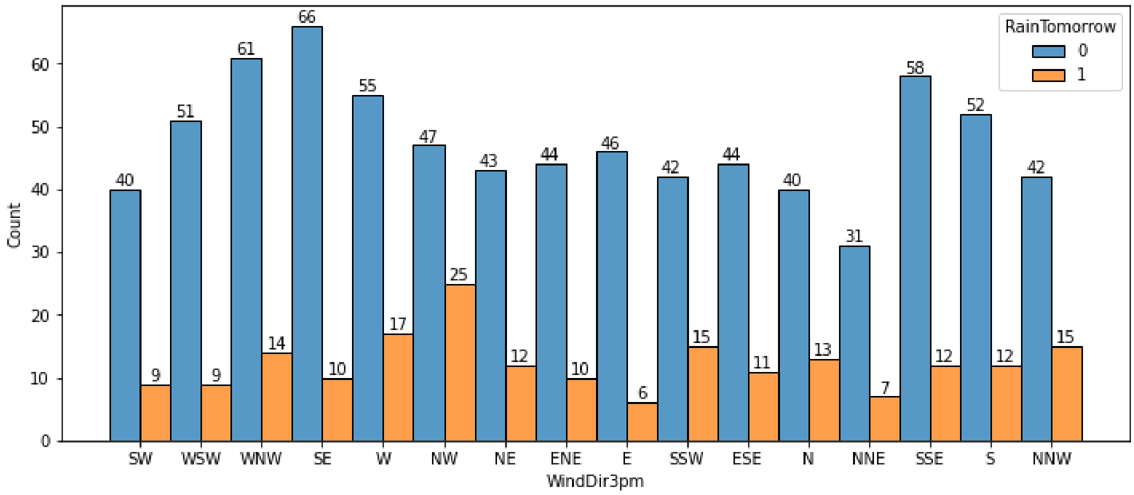
In [124]:

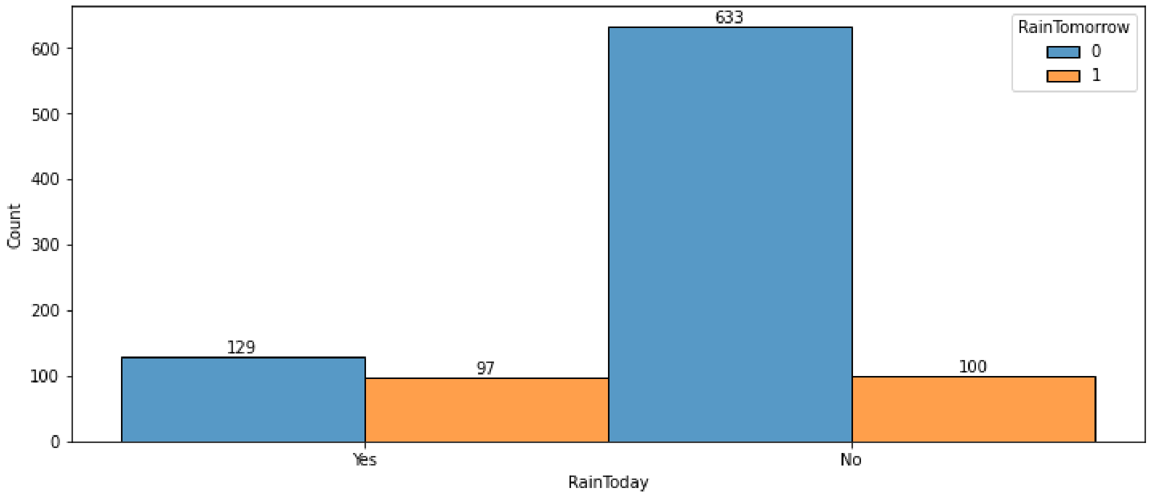
```
# pip install --user seaborn --upgrade
```

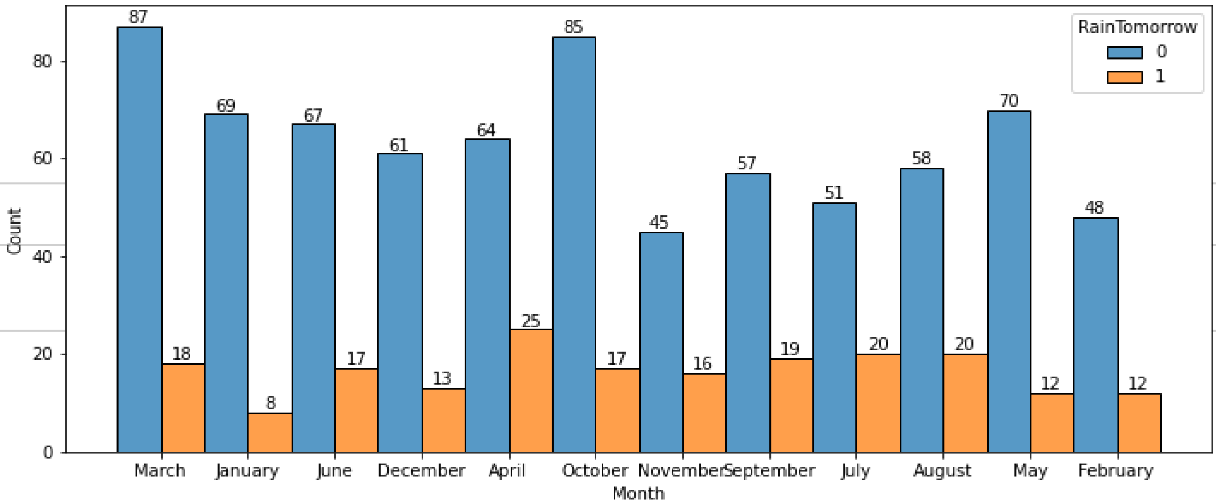
In [125]:

```
import seaborn as sns
for i in df_cat.columns:
    plt.figure(figsize= (12,5))
    y=sns.histplot(x=df_cat[i], hue=df['RainTomorrow'],multiple='dodge',stat='count')
    yes = []
    no  = []
    for i,j in zip(y.containers[0], y.containers[1]):
        yes.append(i.get_height())
        no.append(j.get_height())
    y.bar_label(y.containers[0], labels=yes)
    y.bar_label(y.containers[1], labels=no)
    plt.show()
```

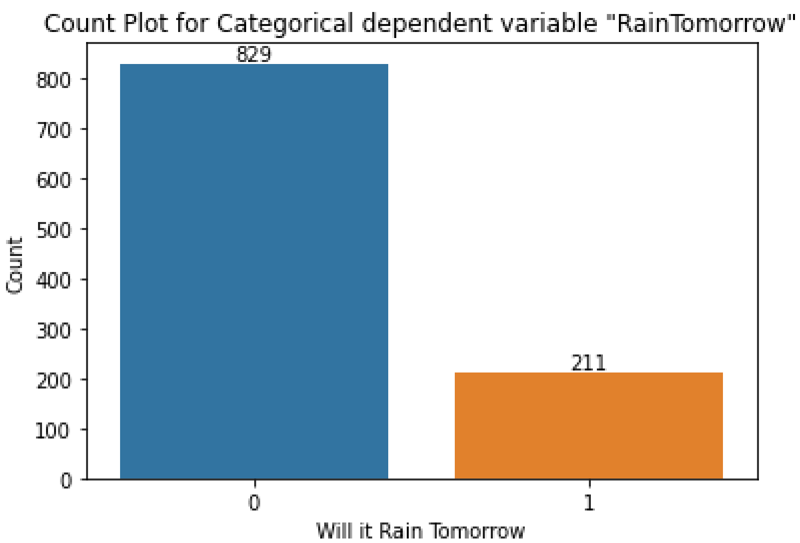








Distribution of dependent variable



1.5 Missing Value Treatment

First run a check for the presence of missing values and their percentage for each column. Then choose the right approach to treat them.

In [128]:

```
count=df.isnull().sum()
percent=(count/len(df))*100

df_missingvalues= pd.DataFrame({'Count': count, 'Percentage':percent})
df_missingvalues.sort_values(by='Percentage',ascending=False)
```

Out[128]:

	Count	Percentage
Sunshine	507	48.750000
Evaporation	458	44.038462
Cloud3pm	443	42.596154
Cloud9am	427	41.057692
Pressure9am	111	10.673077
Pressure3pm	108	10.384615
WindGustSpeed	71	6.826923
WindDir9am	59	5.673077
WindDir3pm	26	2.500000
Humidity3pm	24	2.307692
Temp3pm	18	1.730769
Rainfall	11	1.057692
RainToday	11	1.057692
Humidity9am	9	0.865385
Temp9am	6	0.576923
MinTemp	5	0.480769
MaxTemp	5	0.480769
RainTomorrow	0	0.000000
Month	0	0.000000

INFERENCE: For numerical features, lets impute using KNN imputation and for categorical features, lets impute missing values using mode.

In [129]:

```
# Function definition to impute missing values

def KNN_imp(col):
    X = df[[col]]                         # Dataframe containing column with missing valu
    imputer = KNNImputer(n_neighbors=3)   # KNN imputer object with k=3.
    X_imputed = imputer.fit_transform(X)  # Imputing missing values.
    df[col] = X_imputed                   # Replacing missing values with the imputed val

def mode_imp(col):
    for i in range(len(df)):
            mode_val=df[col].mode()
            df[col].fillna(value=mode_val[0], inplace=True)
```

In [130]:

```
# Numerical features

num_col = df.select_dtypes(include=np.number).columns.tolist()
num_col.pop() # to remove target variable "Rain Tomorrow"
print(num_col)
print("Number of numeric var:" ,len(num_col))
```

```
['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine', 'WindGustSpe
ed', 'Humidity9am', 'Humidity3pm', 'Pressure9am', 'Pressure3pm', 'Cloud9a
m', 'Cloud3pm', 'Temp9am', 'Temp3pm']
Number of numeric var: 14
```

In [131]:

```
# Categorical features

catg_col = df.select_dtypes(include='object').columns.tolist()
print(catg_col)
print("Number of numeric var:" ,len(catg_col))
```

```
['WindDir9am', 'WindDir3pm', 'RainToday', 'Month']
Number of numeric var: 4
```

In [132]:

```
# Function call to impute missing values

for i in num_col:
    KNN_imp(i)

for i in catg_col:
    mode_imp(i)
```

In [133]:

```
df.isnull().sum()
```

Out[133]:

```
MinTemp          0
MaxTemp          0
Rainfall         0
Evaporation      0
Sunshine         0
WindGustSpeed    0
WindDir9am       0
WindDir3pm       0
Humidity9am      0
Humidity3pm      0
Pressure9am      0
Pressure3pm      0
Cloud9am         0
Cloud3pm         0
Temp9am          0
Temp3pm          0
RainToday        0
RainTomorrow     0
Month            0
dtype: int64
```

INFERENCE: Now the dataset does not contain any missing values.

1.6 Dummy Encode the Categorical Variables

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1040 entries, 0 to 1039
Data columns (total 19 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   MinTemp        1040 non-null   float64
 1   MaxTemp        1040 non-null   float64
 2   Rainfall       1040 non-null   float64
 3   Evaporation    1040 non-null   float64
 4   Sunshine       1040 non-null   float64
 5   WindGustSpeed  1040 non-null   float64
 6   WindDir9am     1040 non-null   object 
 7   WindDir3pm     1040 non-null   object 
 8   Humidity9am    1040 non-null   float64
 9   Humidity3pm    1040 non-null   float64
 10  Pressure9am    1040 non-null   float64
 11  Pressure3pm    1040 non-null   float64
 12  Cloud9am       1040 non-null   float64
 13  Cloud3pm       1040 non-null   float64
 14  Temp9am        1040 non-null   float64
 15  Temp3pm        1040 non-null   float64
 16  RainToday      1040 non-null   object 
 17  RainTomorrow   1040 non-null   int64  
 18  Month          1040 non-null   object 
dtypes: float64(14), int64(1), object(4)
```

```
memory usage: 154.5+ KB
```

In [135]:

```
# Dependent variable/target - 'RainTomorrow'

df_dep = df['RainTomorrow']
df_dep.head(3)
```

Out[135]:

```
0    1
1    0
2    0
Name: RainTomorrow, dtype: int64
```

In [136]:

```
# independent variables/predictor - all features except 'RainTomorrow'

df_indep = df.drop('RainTomorrow', axis = 1)
df_indep.head(3)
```

Out[136]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindDir9am	WindD
0	16.0	20.4	8.2	5.183505	7.606379	63.0	SSW	
1	18.5	25.9	16.0	5.400000	11.800000	39.0	SSW	
2	8.7	16.5	0.0	5.183505	7.606379	56.0	WNW	

Filter numerical and categorical variables.

In [137]:

```
df_num = df_indep.select_dtypes(include = [np.number])
print(df_num.columns)
print(len(df_num.columns))
df_num.head(5)
```

```
Index(['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine',
       'WindGustSpeed', 'Humidity9am', 'Humidity3pm', 'Pressure9am',
       'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Temp9am', 'Temp3pm'],
      dtype='object')
14
```

Out[137]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	Humidity9am	Humi
0	16.0	20.4	8.2	5.183505	7.606379	63.0	69.0	
1	18.5	25.9	16.0	5.400000	11.800000	39.0	60.0	
2	8.7	16.5	0.0	5.183505	7.606379	56.0	41.0	
3	25.5	33.9	0.2	5.000000	7.000000	41.0	64.0	
4	3.8	23.0	0.0	5.183505	7.606379	28.0	56.0	

In [138]:

```
df_cat = df_indep.select_dtypes(include = [np.object])
print(df_cat.columns)
print(len(df_cat.columns))
```

```
Index(['WindDir9am', 'WindDir3pm', 'RainToday', 'Month'], dtype='object')
4
```

The logistic regression method fails in presence of categorical variables. To overcome this we use (n-1) dummy encoding.

Encode the each categorical variable and create (n-1) dummy variables for n categories of the

In [139]:

```
# To perform n-1 dummy encoding for each categorical variable - set drop_first to 'True'
# This will drop the first category of each categorical variable

df_dummy = pd.get_dummies(data=df_cat,drop_first = True)
df_dummy.head(5)
```

Out[139]:

	WindDir9am_ENE	WindDir9am_ESE	WindDir9am_N	WindDir9am_NE	WindDir9am_NNE	Wi
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	1	0	

In [140]:

```
df_dummy.shape
```

Out[140]:

```
(1040, 42)
```

INFERENCE: To perform n-1 dummy encoding for each categorical variable - set drop_first to 'True'. This will drop the first category of each categorical variable. After dummy encoding, number of categorical features has increased from 4 to 42 columns.

1.7 Scale the Data

We scale the variables to get all the variables in the same range. With this, we can avoid a problem in which some features come to dominate solely because they tend to have larger values than others.

In [141]:

```
# Min-max scaler

from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
num_scaled = scaler.fit_transform(df_num)
df_num_scaled = pd.DataFrame(num_scaled, columns = df_num.columns)
df_num_scaled.head()
```

Out[141]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	Humidity9am	Hum
0	0.614679	0.474273	0.067545	0.189822	0.551187	0.519231	0.670213	
1	0.691131	0.597315	0.131796	0.198413	0.855072	0.288462	0.574468	
2	0.391437	0.387025	0.000000	0.189822	0.551187	0.451923	0.372340	
3	0.905199	0.776286	0.001647	0.182540	0.507246	0.307692	0.617021	
4	0.241590	0.532438	0.000000	0.189822	0.551187	0.182692	0.531915	

INFERENCE: Scaling is performed only on numerical variables. We have used Min-Max scaler inorder to retain actual values of data and do not want to standardize them (i.e making mean =0 and SD=1). Since the data contains outliers , its better to use Min-Max scaler as they are robust to outliers.

Concatenate scaled numerical and dummy encoded categorical variables.

In [142]:

```
X = pd.concat([df_num_scaled,df_dummy], axis = 1)
X.head()
```

Out[142]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	Humidity9am	Hum
0	0.614679	0.474273	0.067545	0.189822	0.551187	0.519231	0.670213	
1	0.691131	0.597315	0.131796	0.198413	0.855072	0.288462	0.574468	
2	0.391437	0.387025	0.000000	0.189822	0.551187	0.451923	0.372340	
3	0.905199	0.776286	0.001647	0.182540	0.507246	0.307692	0.617021	
4	0.241590	0.532438	0.000000	0.189822	0.551187	0.182692	0.531915	

INFERENCE: After scaling numerical variables using a separate dataframe and performing dummy enoding for categorical variables in a different dataframe, lets merge them into a single input dataframe -'X'.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1040 entries, 0 to 1039
 Data columns (total 56 columns):
  #   Column            Non-Null Count  Dtype
 ---  ------            --------------  -----
  0   MinTemp           1040 non-null   float64
  1   MaxTemp           1040 non-null   float64
  2   Rainfall          1040 non-null   float64
  3   Evaporation       1040 non-null   float64
  4   Sunshine          1040 non-null   float64
  5   WindGustSpeed     1040 non-null   float64
  6   Humidity9am       1040 non-null   float64
  7   Humidity3pm       1040 non-null   float64
  8   Pressure9am       1040 non-null   float64
  9   Pressure3pm       1040 non-null   float64
  10  Cloud9am          1040 non-null   float64
  11  Cloud3pm          1040 non-null   float64
  12  Temp9am           1040 non-null   float64
  13  Temp3pm           1040 non-null   float64
  14  WindDir9am_ENE    1040 non-null   uint8
  15  WindDir9am_ESE    1040 non-null   uint8
  16  WindDir9am_N      1040 non-null   uint8
  17  WindDir9am_NE     1040 non-null   uint8
  18  WindDir9am_NNE    1040 non-null   uint8
  19  WindDir9am_NNW    1040 non-null   uint8
  20  WindDir9am_NW     1040 non-null   uint8
  21  WindDir9am_S      1040 non-null   uint8
  22  WindDir9am_SE     1040 non-null   uint8
  23  WindDir9am_SSE    1040 non-null   uint8
  24  WindDir9am_SSW    1040 non-null   uint8
  25  WindDir9am_SW     1040 non-null   uint8
  26  WindDir9am_W      1040 non-null   uint8
  27  WindDir9am_WNW    1040 non-null   uint8
  28  WindDir9am_WSW    1040 non-null   uint8
  29  WindDir3pm_ENE    1040 non-null   uint8
  30  WindDir3pm_ESE    1040 non-null   uint8
  31  WindDir3pm_N      1040 non-null   uint8
  32  WindDir3pm_NE     1040 non-null   uint8
  33  WindDir3pm_NNE    1040 non-null   uint8
  34  WindDir3pm_NNW    1040 non-null   uint8
  35  WindDir3pm_NW     1040 non-null   uint8
  36  WindDir3pm_S      1040 non-null   uint8
  37  WindDir3pm_SE     1040 non-null   uint8
  38  WindDir3pm_SSE    1040 non-null   uint8
  39  WindDir3pm_SSW    1040 non-null   uint8
  40  WindDir3pm_SW     1040 non-null   uint8
  41  WindDir3pm_W      1040 non-null   uint8
  42  WindDir3pm_WNW    1040 non-null   uint8
  43  WindDir3pm_WSW    1040 non-null   uint8
  44  RainToday_Yes     1040 non-null   uint8
  45  Month_August      1040 non-null   uint8
  46  Month_December    1040 non-null   uint8
  47  Month_February    1040 non-null   uint8
  48  Month_January     1040 non-null   uint8
  49  Month_July        1040 non-null   uint8
```

```
 50  Month_June       1040 non-null   uint8
 51  Month_March      1040 non-null   uint8
 52  Month_May        1040 non-null   uint8
 53  Month_November   1040 non-null   uint8
 54  Month_October    1040 non-null   uint8
 55  Month_September  1040 non-null   uint8
dtypes: float64(14), uint8(42)
memory usage: 156.5 KB
```

1.8 Train-Test Split

In [144]:

```
# import functions
import statsmodels
import statsmodels.api as sm

# Since intercept is not considered by default while using the 'Logit' method
# we can add it to the set of independent variables using 'add_constant()'
X = sm.add_constant(X)

# Here X = set of independent variables and df_dep = dependent variable('RainTomorrow')
X_train, X_test, Y_train, Y_test = train_test_split(X, df_dep, random_state=10, test_size

# Print dimension of train set
print('Shape of X_train', X_train.shape)
print('Shape of Y_train', Y_train.shape)

# Print dimension of test set
print('Shape of X_test', X_test.shape)
print('Shape of Y_test', Y_test.shape)
```

```
Shape of X_train (728, 57)
Shape of Y_train (728,)
Shape of X_test (312, 57)
Shape of Y_test (312,)
```

2. Logistic Regression (Full Model)

Build a full logistic model on a training dataset.

In

```
# Build the model on train data (X_train and Y_train)
logreg = sm.Logit(Y_train,X_train).fit()

# Print the summary of the model
logreg.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.302582
         Iterations 8
```

Out[145]:

Logit Regression Results

Dep. Variable:	RainTomorrow	**No. Observations:**	728
Model:	Logit	**Df Residuals:**	671
Method:	MLE	**Df Model:**	56
Date:	Sun, 07 May 2023	**Pseudo R-squ.:**	0.3868
Time:	18:04:22	**Log-Likelihood:**	-220.28
converged:	True	**LL-Null:**	-359.25
Covariance Type:	nonrobust	**LLR p-value:**	3.648e-31

INFERENCE:

Pseudo R-squ: 0.3868 - Pseudo R-squared value usually ranges from 0 to 1. Higher values indicate better fit.

Log-Likelihood: -226.89 - It measures the log-likelihood of the data. Higher value indicates better fit.

LL-Null: -359.25 - It is the log-likelihood of the data for a null model, which only includes the intercept.

LLR p-value: 3.648e-31 - LLR p-value (likelihood ratio test) is a statistical test that indicates the probability of observing the LLR statistic or a larger value under the null hypothesis. Lower p-values indicate stronger evidence against the null hypothesis. The LLR p-value less than 0.05, implies that the model is significant

A logistic regression model is set to have better fit when values are higher for LL, lower for LL-Null, and lower for LLR p-value.

Calculate the AIC (Akaike Information Criterion) value.

It is a relative measure of model evaluation. It gives a trade-off between model accuracy and model complexity.

In [146]:

```
print('AIC:', logreg.aic)
```

```
AIC: 554.5596483458571
```

INFERENCE: AIC is a measure of the trade-off between the goodness of fit of the model and the complexity of the model.It helps us choose a model that fits the data well without overfitting. This is useful when comparing multiple models fitted to the same data. Model with the lowest AIC value is usually considered to be the best model.

We can use the AIC value to compare different models created on the same dataset.

Interpret the odds for each variable

In [147]:

```
df_odds = pd.DataFrame(np.exp(logreg.params), columns= ['Odds'])
df_odds
```

Out[147]:

	Odds
const	0.000180
MinTemp	2.391608
MaxTemp	0.186897
Rainfall	0.566307
Evaporation	0.923009
Sunshine	0.201043
WindGustSpeed	1470.161649
Humidity9am	3.693517
Humidity3pm	2976.756988
Pressure9am	23765.376172
Pressure3pm	0.000005
Cloud9am	0.355462
Cloud3pm	5.083372
Temp9am	0.008614
Temp3pm	1323.878866
WindDir9am_ENE	1.567208
WindDir9am_ESE	0.473227
WindDir9am_N	2.123001
WindDir9am_NE	1.120816
WindDir9am_NNE	1.820621
WindDir9am_NNW	2.127994
WindDir9am_NW	1.924219
WindDir9am_S	2.372207
WindDir9am_SE	2.244945
WindDir9am_SSE	1.650849
WindDir9am_SSW	1.588141
WindDir9am_SW	1.514760
WindDir9am_W	1.346585
WindDir9am_WNW	2.614136
WindDir9am_WSW	0.616289
WindDir3pm_ENE	1.059003
WindDir3pm_ESE	1.464232
WindDir3pm_N	0.621669
WindDir3pm_NE	1.194824
WindDir3pm_NNE	0.450217
WindDir3pm_NNW	0.767925
WindDir3pm_NW	2.447041

INFERENCE:

Odds value of 'Humidity3pm' = 2976.7569. The odds that it will rain tomorrow increases by a factor of 3354.260 for every unit increase in 'Humidity3pm' while other variables are constant.

Odds value of 'Pressure9am' = 23765.209149. The odds that it will rain tomorrow increases by a factor of 2352.209 for every unit increase in 'Pressure9am' while other variables are constant.

Odds value of 'WindGustSpeed' = 1470.1616. The odds that it will rain tomorrow increases by a factor of 2023.649 for every unit increase in 'WindGustSpeed' while other variables are constant.

Odds value of 'Temp3pm' = 1323.8788 The odds that it will rain tomorrow increases by a factor of 220.567 for every unit increase in 'Temp3pm' while other variables are constant.

Odds constant/intercept = 0.0001797. The odds that it will Rain tomorrow by considering all other variables as zero value is 0.000118.

Do predictions on the test set.

In [148]:

```
# let 'y_pred_probability' be the predicted values of y
Y_pred_probability = logreg.predict(X_test)

# print the y_pred_probability
Y_pred_probability.head()
```

Out[148]:

```
195    0.027412
761    0.021263
109    0.201190
999    0.039386
853    0.022746
dtype: float64
```

INFERENCE: The target variable can take only two values either 0 or 1. The cut-off value to predict between 0 & 1 is 0.5. i.e. if 'y_pred_probability' is less than 0.5, consider it as 'value 0' else consider it as 'value 1'.

In [149]:

```
Y_pred = [ 0 if x < 0.5 else 1 for x in Y_pred_probability]
Y_pred[0:5]
```

Out[149]:

```
[0, 0, 0, 0, 0]
```

INFERENCE: Since the head of Y_pred_probability has values less than zero (i.e., 0.02,0.02,0.20..), Y_pred has considered value 0 for the above 5 records in Y_pred_probability.

Plot the confusion matrix.

DEFINITION: A confusion matrix is a tool for summarizing the performance of a classification algorithm. A confusion matrix will give us a clear picture of classification model performance and the types of errors produced by the model.

Four types of outcomes are possible while evaluating a classification model performance.

True Positives (TP) – True Positives occur when we predict an observation belongs to a certain class and the observation actually belongs to that class.

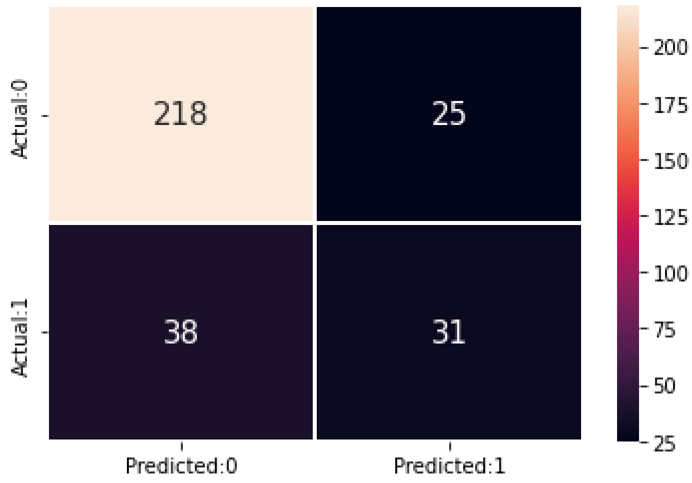
True Negatives (TN) – True Negatives occur when we predict an observation does not belong to a certain class and the observation actually does not belong to that class.

False Positives (FP) – False Positives occur when we predict an observation belongs to a certain class but the observation actually does not belong to that class. This type of error is called Type I error.

False Negatives (FN) – False Negatives occur when we predict an observation does not belong to a certain class but the observation actually belongs to that class. This is a very serious error and it is called Type II error.

In [150]:

```
from sklearn.metrics import confusion_matrix

# Confusion matrix is plotted btw the actual and predicted target values
cm = confusion_matrix(Y_test, Y_pred)

confusion_matrix = pd.DataFrame(data = cm, columns =['Predicted:0','Predicted:1'], index

sns.heatmap(confusion_matrix, annot = True, fmt = 'd',linewidths = 0.1, annot_kws = {'siz

plt.show()
```




```
# True Positives, TP = Actual '1' values predicted correctly as '1'.
TP = cm[1,1]
print('TP=',TP)

# True Negatives, TN = Actual '0' values predicted correctly as '0'.
TN = cm[0,0]
print('TN=',TN)

# False Positives FP = Actual '0' values that are falsely predicted  as '1' (Type 1 error
FP = cm[0,1]
print('FP=',FP)

# False Negatives FN = Actual '1' values that are falsely predicted  as '0' (Type 2 error
FN = cm[1,0]
print('FN=',FN)
```

```
TP= 31
TN= 218
FP= 25
FN= 38
```

INFERENCE:

True Positives (TP=31) – Actual '1' values predicted correctly as '1'.

True Negatives (TN=218) – Actual '0' values predicted correctly as '0'.

False Positives (FP=25) – Actual '0' values that are falsely predicted as '1' (Type 1 error).

False Negatives (FN=38) – Actual '1' values that are falsely predicted as '0' (Type 2 error).

Compute various performance metrics.

Precision: It is defined as the ratio of true positives to the total positive predictions.

In [152]:

```
Precision = TP / (TP+FP)
Precision
```

Out[152]:

```
0.5535714285714286
```

In [153]:

```
Precision_score = metrics.precision_score(Y_test, Y_pred)
Precision_score
```

Out[153]:

```
0.5535714285714286
```

Recall: It is the ratio of true positives to the total actual positive observations. It is also known as, `Sensitivity` or `True Positive Rate`.

In [154]:

```
Recall = TP / (TP+FN)
Recall
```

Out[154]:

```
0.4492753623188406
```

In [155]:

```
Recall_score = metrics.recall_score(Y_test, Y_pred)
Recall_score
```

Out[155]:

```
0.4492753623188406
```

Specificity: It is the ratio of true negatives to the total actual negative observations.

In [156]:

```
Specificity = TN / (TN+FP)
Specificity
```

Out[156]:

```
0.897119341563786
```

f1-score: It is defined as the harmonic mean of precision and recall.

In [157]:

```
F1_score = (2*Precision*Recall)/(Precision+Recall)
F1_score
```

Out[157]:

```
0.496
```

In [158]:

```
F1score = metrics.f1_score(Y_test, Y_pred)
F1score
```

Out[158]:

```
0.496
```

Accuracy: It is the ratio of correct predictions (i.e. TN+TP) to the total observations. According to the confusion matrix, it is the ratio of the sum of diagonal elements to the sum of all the in the matrix. It is not a very good measure if the dataset is imbalanced.

In [159]:

```
Accuracy = (TN+TP)/(TN+FP+FN+TP)
Accuracy
```

Out[159]:

```
0.7980769230769231
```

In [160]:

```
Accuracy_score = metrics.accuracy_score(Y_test, Y_pred)
Accuracy_score
```

Out[160]:

```
0.7980769230769231
```

INFERENCE:
Precision = 0.55
Recall = 0.449
Specificity= 0.897
F1_score = 0.496
Accuracy = 0.7980

INFERENCE: For a good classification model all the above performance metrics should be of higher values. This shows that model is not fit properly and it can be caused due to data imbalance issue.

In [161]:

```
from sklearn.metrics import classification_report
acc_table = classification_report(Y_test, Y_pred)
print(acc_table)
```

```
              precision    recall  f1-score   support

           0       0.85      0.90      0.87       243
           1       0.55      0.45      0.50        69

    accuracy                           0.80       312
   macro avg       0.70      0.67      0.68       312
weighted avg       0.79      0.80      0.79       312
```

INFERENCE: From the above output, we can see that recall of the positive class ('Sensitivity') is 0.45 and the recall of the negative class ('Specificity') is 0.90 .

We can see that the model with cut-off = 0.5 is not that much accurate due to imbalanced data.

INFERENCE: 'Support' is the number of observations in the corresponding class. The 'Macro average' in the output is obtained by averaging the unweighted mean per label and the 'Weighted average' is given by averaging the support-weighted mean per label.

Kappa score: It is a measure of inter-rater reliability. For logistic regression, the actual and predicted values of the target variable are the raters.

In [162]:

```
from sklearn.metrics import cohen_kappa_score
kappa = cohen_kappa_score(Y_test, Y_pred)
print('kappa value:',kappa)
```

```
kappa value: 0.37145049884881043
```

Interpretation: Write the inference based on the kappa score value and this model falls under which agreeemnet.

INFERENCE: Kappa score, also known as Cohen's kappa coefficient, is used for inter-rater agreement for categorical items. It is often used to evaluate the degree of agreement between two or more raters when classifying items into categories.Kappa score ranges from -1 to 1.

Kappa < 0: Agreement is worse than chance.

Kappa between 0 and 0.20: Slight agreement.

Kappa between 0.21 and 0.40: Fair agreement.

Kappa between 0.41 and 0.60: Moderate agreement.

Kappa between 0.61 and 0.80: Substantial agreement.

Kappa between 0.81 and 1.00: Almost perfect agreement.

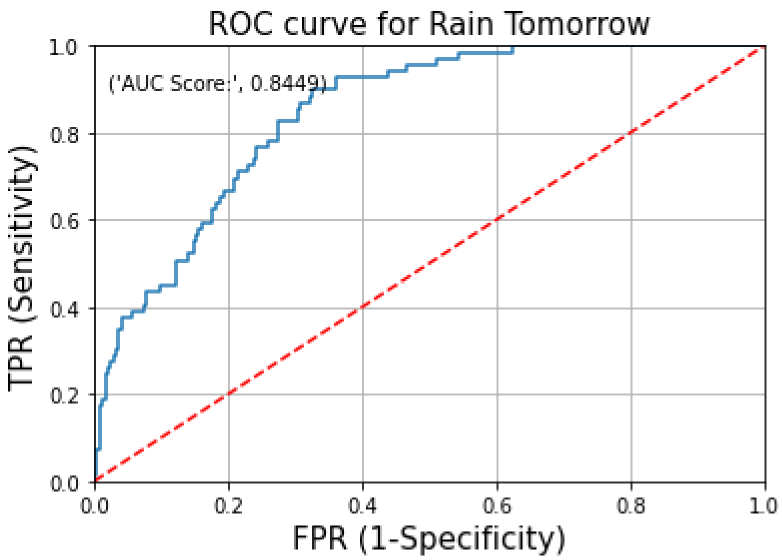
INFERENCE: Kappa score for the full model (with cut-off probability 0.5) is 0.3714. We can say that there is Fair agreement between the actual and predicted values.

Plot the ROC curve.

ROC curve is plotted with the true positive rate (tpr) on the y-axis and false positive rate (fpr) on the x-axis. The area under this curve is used as a measure of separability of the model.

In [163]:

```
from sklearn.metrics import roc_curve

FPR, TPR, thresholds = roc_curve(Y_test, Y_pred_probability)

plt.plot(FPR, TPR)

# set limits for x and y axes
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])

# plot the straight line showing worst prediction for the model
plt.plot([0, 1], [0, 1],'r--')

# add plot and axes labels
# set text size using 'fontsize'
plt.title('ROC curve for Rain Tomorrow', fontsize = 15)
plt.xlabel('FPR (1-Specificity)', fontsize = 15)
plt.ylabel('TPR (Sensitivity)', fontsize = 15)

# add the AUC score to the plot
# 'x' and 'y' gives position of the text
# 's' is the text
# use round() to round-off the AUC score upto 4 digits
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:', round(metrics.roc_auc_score(Y_test, Y_pred

# plot the grid
plt.grid(True)
```



Interpretation: Provide inference based on the obtained ROC curve and AUC score.

INFERENCE: AUC (Area Under the ROC Curve) is a metric to evaluate the performance of a binary classification model. The ROC (Receiver Operating Characteristic) curve is a plot of the true positive rate (TPR) against the false positive rate (FPR). AUC is the area under the ROC curve, which ranges between 0 and 1, where: An AUC score of 0.5 indicates a random classifier that

performs no better than chance. An AUC score between 0.5 and 1 indicates a classifier that is better than chance. In general, a higher AUC score indicates better classification performance.

If the dataset is imbalanced, i.e., the number of samples in one class is larger than other, then a high AUC score may be obtained even for a classifier that performs poorly on the minority class. In such cases, it is important to look at other metrics such as precision, recall, and F1-score to get a better understanding of the classifier's performance.

The AUC score for full model is 0.8449 and its a good performance score. Since the data is imbalanced, there could be a possibility that it correctly classifies positive cases, even if many negative cases are misclassified. Its better to look into other performance metrics value to evaluate the

Since all performance metrics state that model performance is poor, lets us balance the data through SMOTE and again build logistc regression model.

BALANCING DATA USING SMOTE -Synthetic Minority Over-sampling Technique.

In [164]:

```
# Number of values in 'RainTomorrow' for each class before SMOTE

df_dep.value_counts()
```

Out[164]:

```
0    829
1    211
Name: RainTomorrow, dtype: int64
```

In [165]:

```
from imblearn.over_sampling import SMOTE

smote = SMOTE(sampling_strategy='minority')

X_sm, Y_sm = smote.fit_resample(X, df_dep)

# Number of values in 'RainTomorrow' for each class after SMOTE
Y_sm.value_counts()
```

Out[165]:

```
1    829
0    829
Name: RainTomorrow, dtype: int64
```

In [166]:

```
X_smtrain, X_smtest, Y_smtrain, Y_smtest = train_test_split(X_sm, Y_sm, test_size=0.3, ra
print('Shape of X_train', X_smtrain.shape)
print('Shape of Y_train', Y_smtrain.shape)

# Print dimension of test set
print('Shape of X_smtest', X_smtest.shape)
print('Shape of Y_smtest', Y_smtest.shape)
```

```
Shape of X_train (1160, 57)
Shape of Y_train (1160,)
Shape of X_smtest (498, 57)
Shape of Y_smtest (498,)
```

In [167]:

```
# Build the model on train data (X_train and Y_train)
sm_logreg = sm.Logit(Y_smtrain,X_smtrain).fit()

# Print the summary of the model
sm_logreg.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.252950
         Iterations 8
```

Out[167]:

Logit Regression Results

Dep. Variable:	RainTomorrow	**No. Observations:**	1160
Model:	Logit	**Df Residuals:**	1103
Method:	MLE	**Df Model:**	56
Date:	Sun, 07 May 2023	**Pseudo R-squ.:**	0.6350
Time:	18:04:25	**Log-Likelihood:**	-293.42
converged:	True	**LL-Null:**	-803.91
Covariance Type:	nonrobust	**LLR p-value:**	2.509e-177

INFERENCE:

Pseudo R-squ: 0.6277 - Pseudo R-squared value usually ranges from 0 to 1. Higher values indicate better fit. Value has improved from 0.3868 to 0.6277 for balanced data.

Log-Likelihood: -299.99 - It measures the log-likelihood of the data. Higher value indicates better fit. Value has improved from -226.89 to -299.99 for balanced data.

LL-Null: -803.91 - It is the log-likelihood of the data for a null model, which only includes the intercept.Value has further reduced from -359.25 to -803.91 for

balanced data.

LLR p-value: 6.641e-175 - LLR p-value (likelihood ratio test) is a statistical test that indicates the probability of observing the LLR statistic or a larger value under the null hypothesis. Lower p-values indicate stronger evidence against the null hypothesis. The LLR p-value less than 0.05, implies that the model is significant.

In [168]:

```
print('AIC:', sm_logreg.aic)
```

```
AIC: 700.8431732353822
```

In [169]

```
sm_df_odds = pd.DataFrame(np.exp(sm_logreg.params), columns= ['Odds'])
sm_df_odds
```

Out[169]:

	Odds
const	3.286865
MinTemp	3.863197
MaxTemp	0.003292
Rainfall	0.883990
Evaporation	0.972654
Sunshine	0.111382
WindGustSpeed	4282.861179
Humidity9am	0.644102
Humidity3pm	40809.134559
Pressure9am	50.638373
Pressure3pm	0.000071
Cloud9am	0.496597
Cloud3pm	3.844736
Temp9am	0.000420
Temp3pm	73052.372720
WindDir9am_ENE	0.099860
WindDir9am_ESE	0.048454
WindDir9am_N	0.103578
WindDir9am_NE	0.119612
WindDir9am_NNE	0.135251
WindDir9am_NNW	0.070698
WindDir9am_NW	0.107802
WindDir9am_S	0.326052
WindDir9am_SE	0.174577

WindDir9am_SSE	0.144665
WindDir9am_SSW	0.112938
WindDir9am_SW	0.084195
WindDir9am_W	0.059933
WindDir9am_WNW	0.140676
WindDir9am_WSW	0.016058
WindDir3pm_ENE	0.089913
WindDir3pm_ESE	0.042105
WindDir3pm_N	0.074502
WindDir3pm_NE	0.065001
WindDir3pm_NNE	0.018913
WindDir3pm_NNW	0.061746
WindDir3pm_NW	0.105192

	Odds
WindDir3pm_S	0.111313
WindDir3pm_SE	0.059194
WindDir3pm_SSE	0.033517
WindDir3pm_SSW	0.130360
WindDir3pm_SW	0.036962
WindDir3pm_W	0.043519
WindDir3pm_WNW	0.024668
WindDir3pm_WSW	0.048548
RainToday_Yes	0.888265
Month_August	0.480208
Month_December	0.123317
Month_February	0.084112
Month_January	0.078962
Month_July	0.168490
Month_June	0.094946
Month_March	0.049564
Month_May	0.026322
Month_November	0.121446
Month_October	0.073820
Month_September	0.153072

In [170]:

```
Y_smpred_prob = sm_logreg.predict(X_smtest)

# print the y_pred_probability
Y_smpred_prob.head()
```

Out[170]:

```
486     0.341469
1442    0.699630
1181    0.983067
123     0.937996
36      0.011933
dtype: float64
```

In [171]:

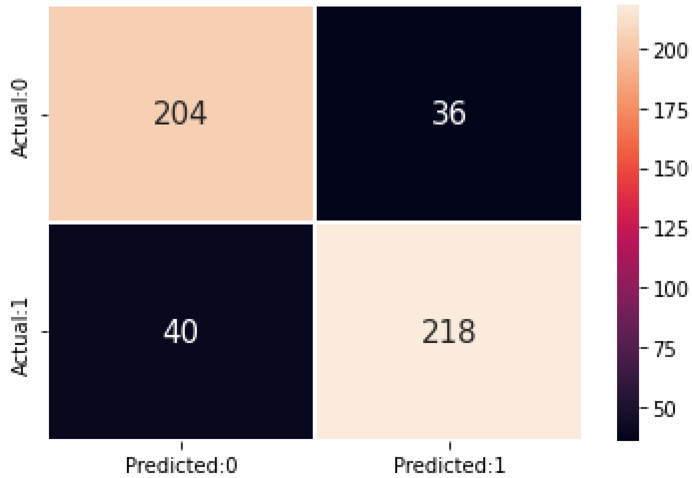
```
Y_smpred = [ 0 if x < 0.5 else 1 for x in Y_smpred_prob]
Y_smpred[0:5]
```

Out[171]:

```
[0, 1, 1, 1, 0]
```

In [172]:

```
from sklearn.metrics import confusion_matrix

# Confusion matrix is plotted btw the actual and predicted target values
cm_sm = confusion_matrix(Y_smtest, Y_smpred)

confusion_matrix = pd.DataFrame(data = cm_sm, columns =['Predicted:0','Predicted:1'], in

sns.heatmap(confusion_matrix, annot = True, fmt = 'd',linewidths = 0.1, annot_kws = {'si

plt.show()
```



In [173]:

```
# True Positives, TP = Actual '1' values predicted correctly as '1'.
TP = cm_sm[1,1]
print('TP=',TP)

# True Negatives, TN = Actual '0' values predicted correctly as '0'.
TN = cm_sm[0,0]
print('TN=',TN)

# False Positives FP = Actual '0' values that are falsely predicted  as '1' (Type 1 error
FP = cm_sm[0,1]
print('FP=',FP)

# False Negatives FN = Actual '1' values that are falsely predicted  as '0' (Type 2 error
FN = cm_sm[1,0]
print('FN=',FN)
```

```
TP= 218
TN= 204
FP= 36
FN= 40
```

INFERENCE:

True Positives (TP=216) – Actual '1' values predicted correctly as '1'.

True Negatives (TN=204) – Actual '0' values predicted correctly as '0'.

False Positives (FP=36) – Actual '0' values that are falsely predicted as '1' (Type 1 error).

False Negatives (FN=42) – Actual '1' values that are falsely predicted as '0' (Type 2 error).

In [174]:

```
print('Precision_score = ', metrics.precision_score(Y_smtest, Y_smpred))
print('Recall_score = ', metrics.recall_score(Y_smtest, Y_smpred))
print('F1score = ',  metrics.f1_score(Y_smtest, Y_smpred) )
print('Accuracy_score = ', metrics.accuracy_score(Y_smtest, Y_smpred))
```

```
Precision_score =  0.8582677165354331
Recall_score =  0.8449612403100775
F1score =  0.8515625
Accuracy_score =  0.8473895582329317
```

In [175]:

```
Specificity = TN / (TN+FP)
print('Specificity= ',Specificity)
```

```
Specificity=  0.85
```

INFERENCE:
Precision = 0.857
Recall = 0.837
Specificity= 0.85
F1_score = 0.847
Accuracy = 0.8433

INFERENCE: From the above values we can conclude that the performance evaluation metrics are good and the classification model is fit properly.

In [176]:

```
from sklearn.metrics import classification_report
acc_table_sm = classification_report(Y_smtest, Y_smpred)
print(acc_table_sm)
```

```
              precision    recall  f1-score   support

           0       0.84      0.85      0.84       240
           1       0.86      0.84      0.85       258

    accuracy                           0.85       498
   macro avg       0.85      0.85      0.85       498
weighted avg       0.85      0.85      0.85       498
```

INFERENCE: For a balanced model, we can infer from the above output that the recall of the positive class ('Sensitivity') is 0.84 and the recall of the negative class ('Specificity') is 0.85. The precision value for positive class is 0.86 and negative class is 0.84 which is relatively close to each other.

We can see that the model with cut-off = 0.5 is 84% accurate.

INFERENCE: 'Support' is the number of observations in the corresponding class. The 'Macro average' in the output is obtained by averaging the unweighted mean per label and the 'Weighted average' is given by averaging the support-weighted mean per label.

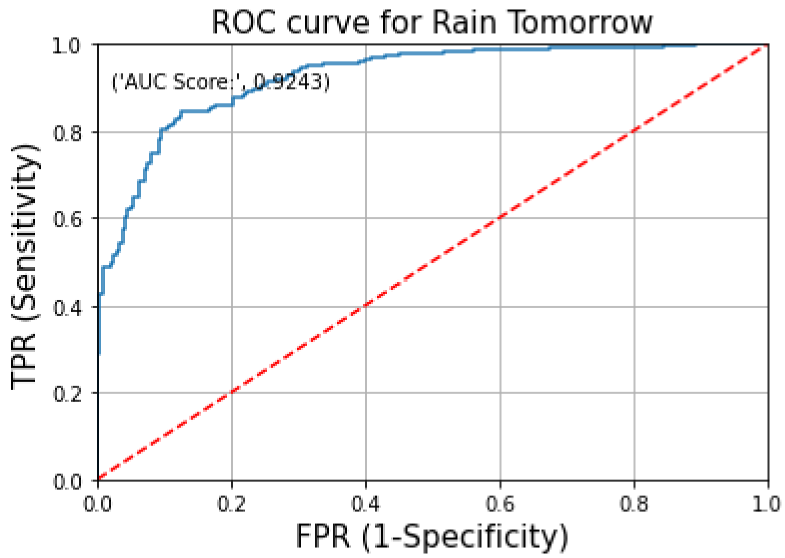
In [177]:

```
from sklearn.metrics import cohen_kappa_score
sm_kappa = cohen_kappa_score(Y_smtest, Y_smpred)
print('kappa value:',sm_kappa)
```

```
kappa value: 0.694557427852024
```

In [178]:

```
from sklearn.metrics import roc_curve

FPR_s, TPR_s, thresholds_s = roc_curve(Y_smtest, Y_smpred_prob)

plt.plot(FPR_s, TPR_s)

# set limits for x and y axes
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])

# plot the straight line showing worst prediction for the model
plt.plot([0, 1], [0, 1],'r--')

# add plot and axes labels
# set text size using 'fontsize'
plt.title('ROC curve for Rain Tomorrow', fontsize = 15)
plt.xlabel('FPR (1-Specificity)', fontsize = 15)
plt.ylabel('TPR (Sensitivity)', fontsize = 15)

# add the AUC score to the plot
# 'x' and 'y' gives position of the text
# 's' is the text
# use round() to round-off the AUC score upto 4 digits
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:', round(metrics.roc_auc_score(Y_smtest, Y_sm

# plot the grid
plt.grid(True)
```



INFERENCE: AUC (Area Under the ROC Curve) is a metric to evaluate the performance of a binary classification model.

The AUC score for a classification model created using balanced data is 0.9243 and its a very good performance score.

Identify the Best Cut-off value using Youden's Index

In [179]:

```
sm_youdens_table = pd.DataFrame({'TPR_s': TPR_s,
                                 'FPR_s': FPR_s,
                                 'Threshold_s': thresholds_s})

# calculate the difference between TPR and FPR for each threshold and store the values ir
sm_youdens_table['Difference'] = sm_youdens_table.TPR_s - sm_youdens_table.FPR_s

# sort the dataframe based on the values of difference
# 'ascending = False' sorts the data in descending order
# 'reset_index' resets the index of the dataframe
# 'drop = True' drops the previous index
sm_youdens_table = sm_youdens_table.sort_values('Difference', ascending = False).reset_ir

# print the first five observations
sm_youdens_table.head()
```

Out[179]:

	TPR_s	FPR_s	Threshold_s	Difference
0	0.844961	0.125000	0.535761	0.719961
1	0.825581	0.116667	0.579426	0.708915
2	0.829457	0.120833	0.569925	0.708624
3	0.802326	0.095833	0.651314	0.706492
4	0.810078	0.104167	0.623133	0.705911

In [186]:

```
Y_smpred_youden = [ 0 if x < 0.53 else 1 for x in Y_smpred_prob]
Y_smpred_youden[0:5]
```

Out[186]:

```
[0, 1, 1, 1, 0]
```

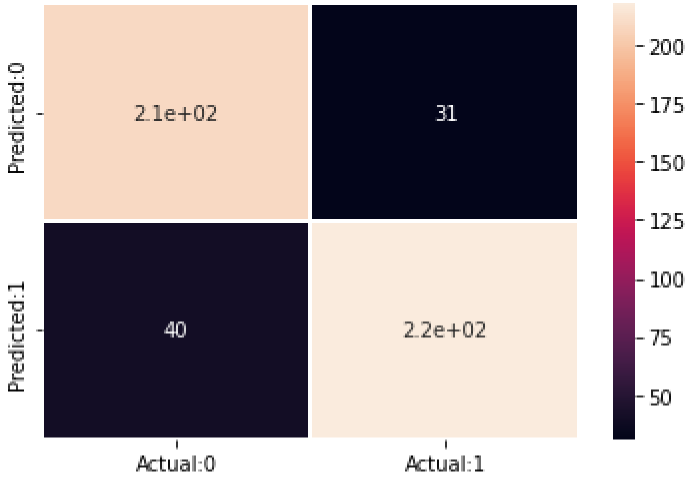
INFERENCE: Youden's index, also known as Youden's J statistic or simply J statistic, is a measure of the overall performance of a binary classifier. It is defined as the difference between the true positive rate (sensitivity) and the false positive rate (1-specificity), and it ranges from 0 to 1. The formula for Youden's index is: J = sensitivity + specificity - 1

INFERENCE: Sensitivity is the proportion of true positive results (TP) out of all actual positives (TP + FN). Specificity is the proportion of true negative results (TN) out of all actual negatives (TN + FP). The interpretation of Youden's index is that it represents the ability of a classifier to correctly identify both positive and negative samples. A value of 0 indicates that the classifier performs no better than chance, while a value of 1 indicates perfect classification.

The threshold value for maximum difference(0.719961) is 0.535761 and is fairly a good score.

In [187]:

```
from sklearn.metrics import confusion_matrix

sm_cm_you = confusion_matrix(Y_smtest, Y_smpred_youden)

conf_matrix_you = pd.DataFrame(data = sm_cm_you,columns = ['Actual:0','Actual:1'], index

sns.heatmap(conf_matrix_you, annot = True, linewidths = 0.1, annot_kws = {'size':10})

plt.show()
```



In [188]:

```
# True Positives, TP = Actual '1' values predicted correctly as '1'.
TP = sm_cm_you[1,1]
print('TP=',TP)

# True Negatives, TN = Actual '0' values predicted correctly as '0'.
TN = sm_cm_you[0,0]
print('TN=',TN)

# False Positives FP = Actual '0' values that are falsely predicted  as '1' (Type 1 error
FP = sm_cm_you[0,1]
print('FP=',FP)

# False Negatives FN = Actual '1' values that are falsely predicted  as '0' (Type 2 error
FN = sm_cm_you[1,0]
print('FN=',FN)
```

```
TP= 218
TN= 209
FP= 31
FN= 40
```

INFERENCE:

True Positives (TP=218) – Actual '1' values predicted correctly as '1'.

True Negatives (TN=209) – Actual '0' values predicted correctly as '0'.

False Positives (FP=31) – Actual '0' values that are falsely predicted as '1' (Type 1 error).This value has reduced compared to previous confusion matrix.

False Negatives (FN=40) – Actual '1' values that are falsely predicted as '0' (Type 2 error).

In [189]:

```
sm_acc_table_youden = classification_report(Y_smtest, Y_smpred_youden)
print(sm_acc_table_youden)
```

```
              precision    recall  f1-score   support

           0       0.84      0.87      0.85       240
           1       0.88      0.84      0.86       258

    accuracy                           0.86       498
   macro avg       0.86      0.86      0.86       498
weighted avg       0.86      0.86      0.86       498
```

INFERENCE: For a balanced model with youden's cut off value, we can infer from the above output that the values have improved. The recall of the positive class ('Sensitivity') is 0.84 and the recall of the negative class ('Specificity') is 0.87 . The precision value for positive class is 0.88 and negative class is 0.84 which is relatively close to each other.

We can see that the model with youden's cut-off value 0.53 is 86% accurate.

INFERENCE: 'Support' is the number of observations in the corresponding class. The 'Macro average' in the output is obtained by averaging the unweighted mean per label and the 'Weighted average' is given by averaging

In [190]:

```
kappa = cohen_kappa_score(Y_smtest, Y_smpred_youden)
print('kappa value:',kappa)
```

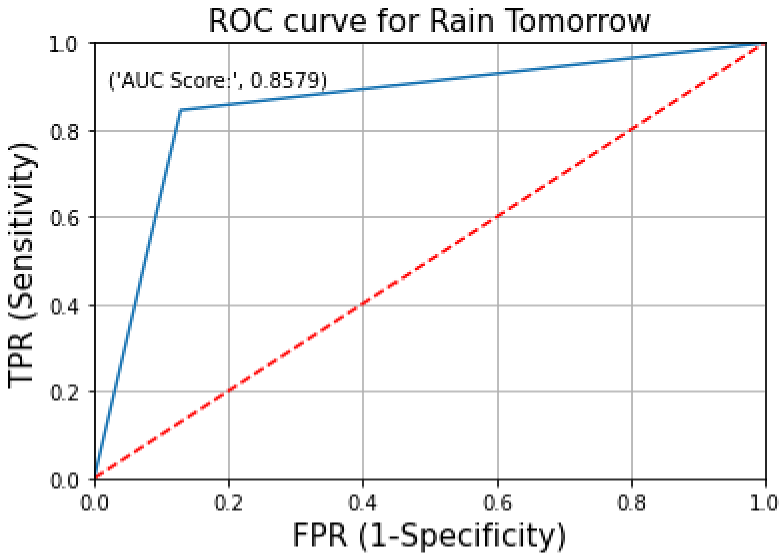
```
kappa value: 0.714859437751004
```

INFERENCE: Kappa score, also known as Cohen's kappa coefficient, is used for inter-rater agreement for categorical items. Kappa score ranges from -1 to 1.

INFERENCE: Kappa score for the balanced model (with cut-off probability 0.53) is 0.7148 which is almost 0.70. We can say that there is Substantial agreement between the actual and predicted values.

In [191]:

```
FPR_s, TPR_s, thresholds_s = roc_curve(Y_smtest, Y_smpred_youden)

plt.plot(FPR_s, TPR_s)

# set limits for x and y axes
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])

# plot the straight line showing worst prediction for the model
plt.plot([0, 1], [0, 1],'r--')

# add plot and axes labels
# set text size using 'fontsize'
plt.title('ROC curve for Rain Tomorrow', fontsize = 15)
plt.xlabel('FPR (1-Specificity)', fontsize = 15)
plt.ylabel('TPR (Sensitivity)', fontsize = 15)

# add the AUC score to the plot
# 'x' and 'y' gives position of the text
# 's' is the text
# use round() to round-off the AUC score upto 4 digits
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:', round(metrics.roc_auc_score(Y_smtest, Y_sm

# plot the grid
plt.grid(True)
```



INFERENCE: AUC (Area Under the ROC Curve) is a metric to evaluate the performance of a binary classification model.

The AUC score for creating model using balanced data and after optimizing it with youden's index is 0.8579 and its a very good performance score.