In [1]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, confusion_matrix, roc_curve, roc_au
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import pickle



import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
data = pd.read_csv('https://raw.githubusercontent.com/dsrscientist/dataset3/mai

data.head()
```

Out[2]:

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

5 rows × 23 columns

Data Directory

- Date - The date of observation
- Location -The common name of the location of the weather station
- MinTemp -The minimum temperature in degrees celsius
- MaxTemp -The maximum temperature in degrees celsius
- Rainfall -The amount of rainfall recorded for the day in mm
- Evaporation -The so-called Class A pan evaporation (mm) in the 24 hours to 9am
- Sunshine -The number of hours of bright sunshine in the day.
- WindGustDi r- The direction of the strongest wind gust in the 24 hours to midnight
- WindGustSpeed -The speed (km/h) of the strongest wind gust in the 24 hours to midnight
- WindDir9am -Direction of the wind at 9am
- WindDir3pm -Direction of the wind at 3pm
- WindSpeed9am -Wind speed (km/hr) averaged over 10 minutes prior to 9am
- WindSpeed3pm -Wind speed (km/hr) averaged over 10 minutes prior to 3pm

- Humidity9am -Humidity (percent) at 9am
- Humidity3pm -Humidity (percent) at 3pm
- Pressure9am -Atmospheric pressure (hpa) reduced to mean sea level at 9am
- Pressure3pm -Atmospheric pressure (hpa) reduced to mean sea level at 3pm
- Cloud9am - Fraction of sky obscured by cloud at 9am.
- Cloud3pm -Fraction of sky obscured by cloud
- Temp9am-Temperature (degrees C) at 9am
- Temp3pm -Temperature (degrees C) at 3pm
- RainToday -Boolean: 1 if precipitation (mm) in the 24 hours to 9am exceeds 1mm, otherwise 0
- RainTomorrow -The amount of next day rain in mm. Used to create response variable . A kind of measure of the "risk".

In [3]:
```
data.columns
```

Out[3]:
```
Index(['Date', 'Location', 'MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation',
       'Sunshine', 'WindGustDir', 'WindGustSpeed', 'WindDir9am', 'WindDir3p
m',
       'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humidity3pm',
       'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Temp9am',
       'Temp3pm', 'RainToday', 'RainTomorrow'],
      dtype='object')
```

In [4]:
```
data.shape
```

Out[4]:
```
(8425, 23)
```

In [5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8425 entries, 0 to 8424
Data columns (total 23 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Date           8425 non-null   object 
 1   Location       8425 non-null   object 
 2   MinTemp        8350 non-null   float64
 3   MaxTemp        8365 non-null   float64
 4   Rainfall       8185 non-null   float64
 5   Evaporation    4913 non-null   float64
 6   Sunshine       4431 non-null   float64
 7   WindGustDir    7434 non-null   object 
 8   WindGustSpeed  7434 non-null   float64
 9   WindDir9am     7596 non-null   object 
 10  WindDir3pm     8117 non-null   object 
 11  WindSpeed9am   8349 non-null   float64
 12  WindSpeed3pm   8318 non-null   float64
 13  Humidity9am    8366 non-null   float64
 14  Humidity3pm    8323 non-null   float64
 15  Pressure9am    7116 non-null   float64
 16  Pressure3pm    7113 non-null   float64
 17  Cloud9am       6004 non-null   float64
 18  Cloud3pm       5970 non-null   float64
 19  Temp9am        8369 non-null   float64
 20  Temp3pm        8329 non-null   float64
 21  RainToday      8185 non-null   object 
 22  RainTomorrow   8186 non-null   object 
dtypes: float64(16), object(7)
memory usage: 1.5+ MB
```

In [6]:
```
data.isnull().sum()
```

Out[6]:
```
Date               0
Location           0
MinTemp           75
MaxTemp           60
Rainfall         240
Evaporation     3512
Sunshine        3994
WindGustDir      991
WindGustSpeed    991
WindDir9am       829
WindDir3pm       308
WindSpeed9am      76
WindSpeed3pm     107
Humidity9am       59
Humidity3pm      102
Pressure9am     1309
Pressure3pm     1312
Cloud9am        2421
Cloud3pm        2455
Temp9am           56
Temp3pm           96
RainToday        240
RainTomorrow     239
dtype: int64
```

In [7]:
```
elements = data.select_dtypes(include=['object']).columns

print(elements)

for i in elements:
    data[i] = data[i].fillna(data[i].mode()[0])
```

```
Index(['Date', 'Location', 'WindGustDir', 'WindDir9am', 'WindDir3pm',
       'RainToday', 'RainTomorrow'],
      dtype='object')
```

In [8]:
```
cont = data.select_dtypes(include=['float']).columns

print(cont)

for i in cont:
    data[i] = data[i].fillna(data[i].mean())
```

```
Index(['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine',
       'WindGustSpeed', 'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am',
       'Humidity3pm', 'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm',
       'Temp9am', 'Temp3pm'],
      dtype='object')
```

In [9]:
```
data.isnull().sum()
```

Out[9]:
```
Date             0
Location         0
MinTemp          0
MaxTemp          0
Rainfall         0
Evaporation      0
Sunshine         0
WindGustDir      0
WindGustSpeed    0
WindDir9am       0
WindDir3pm       0
WindSpeed9am     0
WindSpeed3pm     0
Humidity9am      0
Humidity3pm      0
Pressure9am      0
Pressure3pm      0
Cloud9am         0
Cloud3pm         0
Temp9am          0
Temp3pm          0
RainToday        0
RainTomorrow     0
dtype: int64
```

In [10]:
```
data.head()
```

Out[10]:

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGust
0	2008-12-01	Albury	13.4	22.9	0.6	5.389395	7.632205	W	
1	2008-12-02	Albury	7.4	25.1	0.0	5.389395	7.632205	WNW	
2	2008-12-03	Albury	12.9	25.7	0.0	5.389395	7.632205	WSW	
3	2008-12-04	Albury	9.2	28.0	0.0	5.389395	7.632205	NE	
4	2008-12-05	Albury	17.5	32.3	1.0	5.389395	7.632205	W	

5 rows × 23 columns

In [11]:
```
# Extract the Day and Month from Date column.

data['Day']= data['Date'].str.split('-').str[2]
data['Month']= data['Date'].str.split('-').str[1]
data['Year'] = data['Date'].str.split('-').str[0]

data.head()
```

Out[11]:

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGust
0	2008-12-01	Albury	13.4	22.9	0.6	5.389395	7.632205	W	
1	2008-12-02	Albury	7.4	25.1	0.0	5.389395	7.632205	WNW	
2	2008-12-03	Albury	12.9	25.7	0.0	5.389395	7.632205	WSW	
3	2008-12-04	Albury	9.2	28.0	0.0	5.389395	7.632205	NE	
4	2008-12-05	Albury	17.5	32.3	1.0	5.389395	7.632205	W	

5 rows × 26 columns

In [12]:
```
data['Month'].unique()
```

Out[12]:
```
array(['12', '01', '02', '03', '04', '05', '06', '07', '08', '09', '10',
       '11'], dtype=object)
```

In [13]:
```
data['Year'].unique()
```

Out[13]:
```
array(['2008', '2009', '2010', '2011', '2013', '2014', '2015', '2016',
       '2017', '2012'], dtype=object)
```

In [14]:
```
data['Day'].unique()
```

Out[14]:
```
array(['01', '02', '03', '04', '05', '06', '07', '08', '09', '10', '11',
       '12', '13', '14', '15', '16', '17', '18', '19', '20', '21', '22',
       '23', '24', '25', '26', '27', '28', '29', '30', '31'], dtype=object)
```

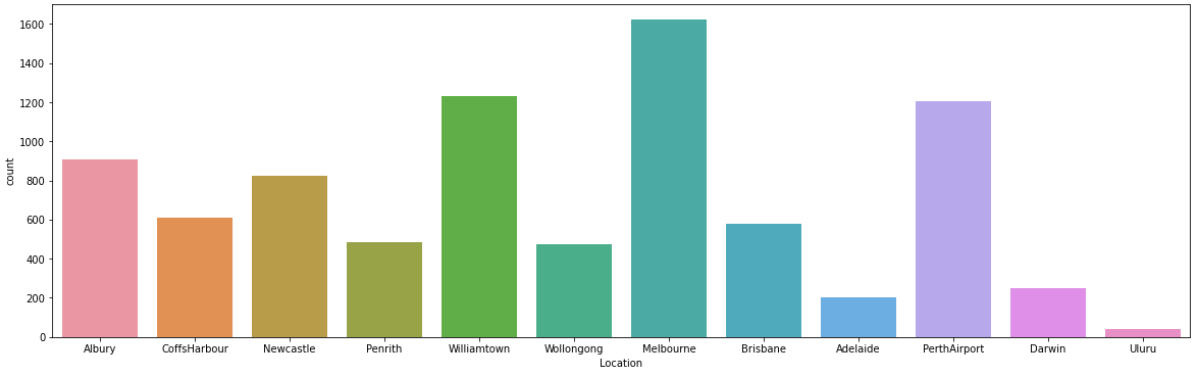
In [15]:
```
#Converting the datatype for newly created features

data['Day'] = data['Day'].astype(int)
data['Month'] = data['Month'].astype(int)
data['Year'] = data['Year'].astype(int)
```

In [16]:
```
data['Location'].unique()
```

Out[16]:
```
array(['Albury', 'CoffsHarbour', 'Newcastle', 'Penrith', 'Williamtown',
       'Wollongong', 'Melbourne', 'Brisbane', 'Adelaide', 'PerthAirport',
       'Darwin', 'Uluru'], dtype=object)
```

In [17]:
```
plt.figure(figsize=(20,6))
sns.countplot(data['Location'])
print(data['Location'].value_counts())
```

```
Melbourne       1622
Williamtown     1230
PerthAirport    1204
Albury           907
Newcastle        822
CoffsHarbour     611
Brisbane         579
Penrith          482
Wollongong       474
Darwin           250
Adelaide         205
Uluru             39
Name: Location, dtype: int64
```

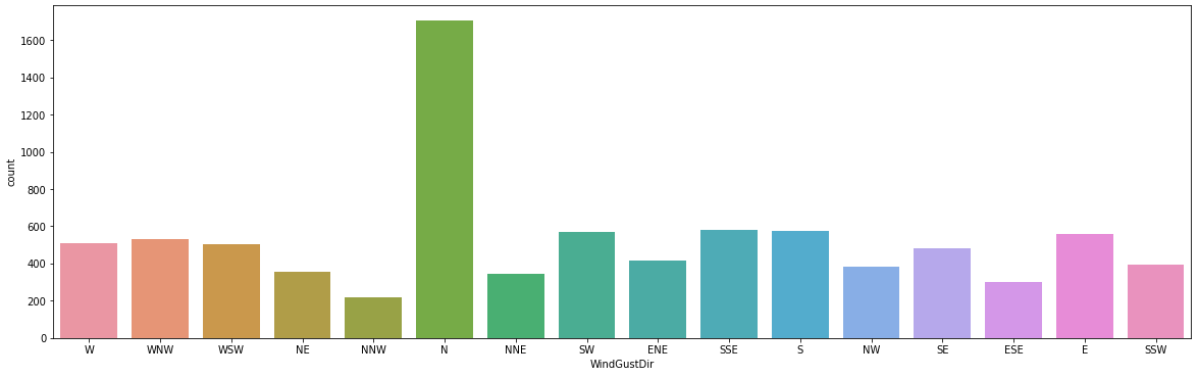


In [18]:
```
data['WindGustDir'].unique()
```

Out[18]:
```
array(['W', 'WNW', 'WSW', 'NE', 'NNW', 'N', 'NNE', 'SW', 'ENE', 'SSE',
       'S', 'NW', 'SE', 'ESE', 'E', 'SSW'], dtype=object)
```

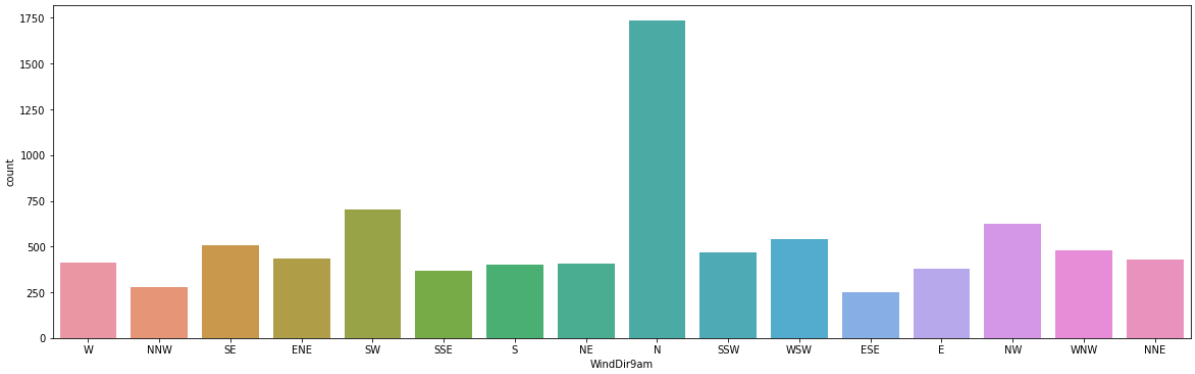
In [19]:
```
plt.figure(figsize=(20,6))
sns.countplot(data['WindGustDir'])
print(data['WindGustDir'].value_counts())
```

```
N      1704
SSE     578
S       577
SW      572
E       557
WNW     531
W       507
WSW     504
SE      484
ENE     415
SSW     396
NW      383
NE      353
NNE     343
ESE     302
NNW     219
Name: WindGustDir, dtype: int64
```



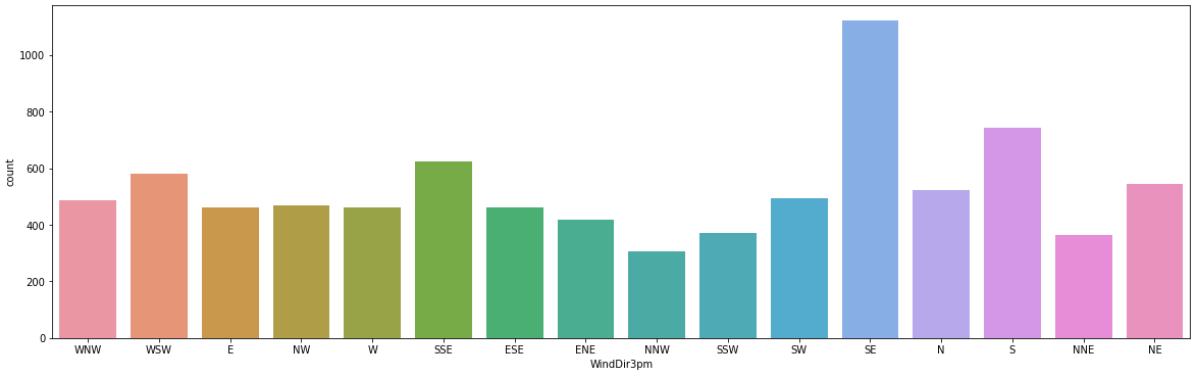
In [20]:
```
plt.figure(figsize=(20,6))
sns.countplot(data['WindDir9am'])
print(data['WindDir9am'].value_counts())
```

```
N      1735
SW      704
NW      625
WSW     543
SE      505
WNW     480
SSW     467
ENE     433
NNE     430
W       414
NE      409
S       402
E       380
SSE     365
NNW     280
ESE     253
Name: WindDir9am, dtype: int64
```



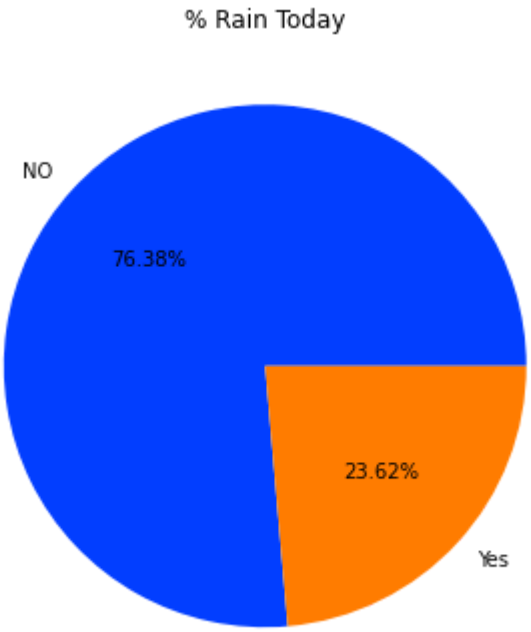
In [21]:
```
plt.figure(figsize=(20,6))
sns.countplot(data['WindDir3pm'])
print(data['WindDir3pm'].value_counts())
```

```
SE     1121
S       742
SSE     623
WSW     580
NE      544
N       524
SW      494
WNW     487
NW      468
W       462
ESE     462
E       460
ENE     417
SSW     370
NNE     365
NNW     306
Name: WindDir3pm, dtype: int64
```

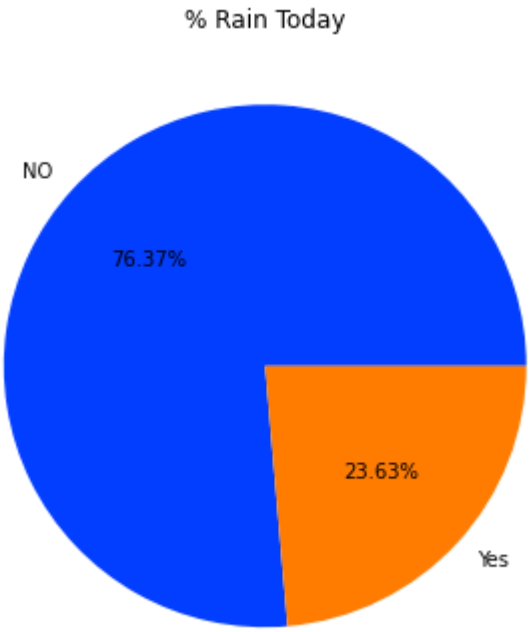


We can see the difference between wind Direction at 9am and 3pm. At 9am Major wind direction was from N, whereas at 3PM it was from SE.

In [22]:
```
plt.figure(figsize=(10,6))

# define Seaborn color palette to use
palette_color = sns.color_palette('bright')

# plotting data on chart
plt.pie(data['RainToday'].value_counts()*100.0 /len(data),
        labels=['NO', 'Yes'],
        colors=palette_color,
        autopct='%.2f%%')

# displaying chart
plt.title('% Rain Today')
plt.show()
```

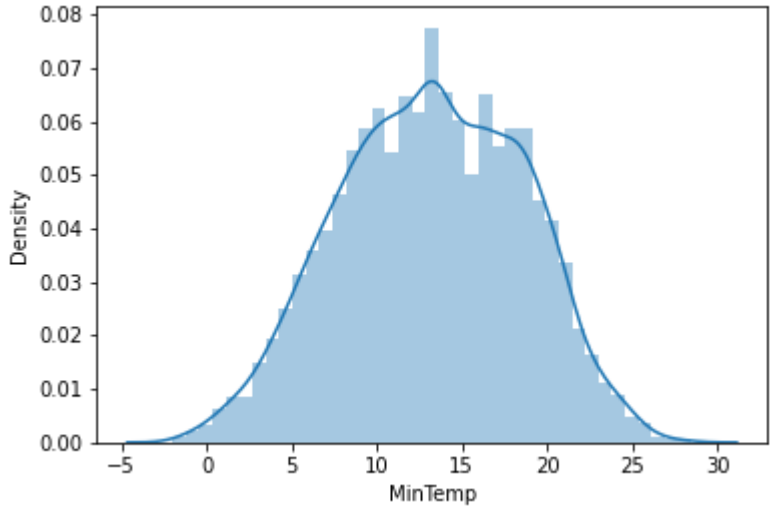


In [23]:
```
plt.figure(figsize=(10,6))

# define Seaborn color palette to use
palette_color = sns.color_palette('bright')

# plotting data on chart
plt.pie(data['RainTomorrow'].value_counts()*100.0 /len(data),
        labels=['NO', 'Yes'],
        colors=palette_color,
        autopct='%.2f%%')

# displaying chart
plt.title('% Rain Today')
plt.show()
```



In [24]:
```
sns.distplot(data['MinTemp'])
```

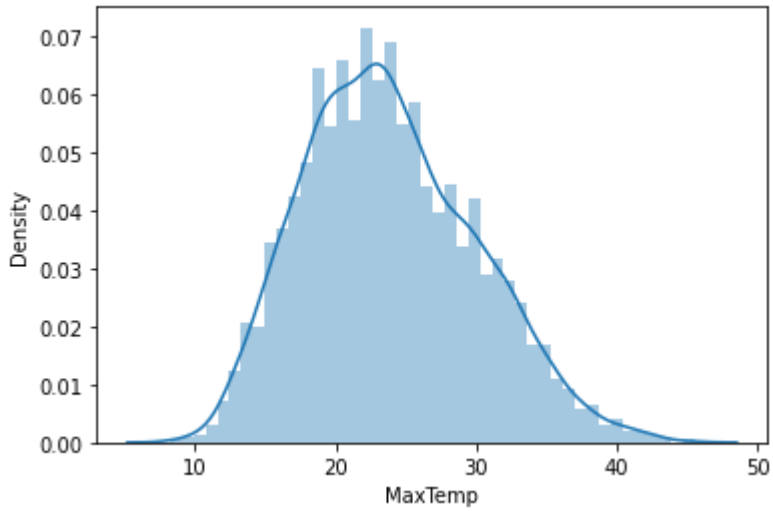
Out[24]:
```
<AxesSubplot:xlabel='MinTemp', ylabel='Density'>
```



Min Temp curve looks like a perfect normal curve with most of the values lies in the range of 10 to 20.

In [25]:
```
sns.distplot(data['MaxTemp'])
```

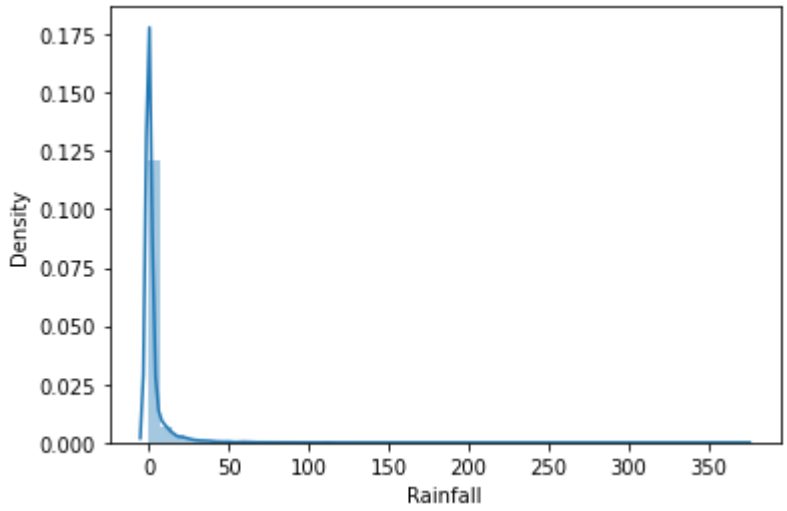
Out[25]:
```
<AxesSubplot:xlabel='MaxTemp', ylabel='Density'>
```



Max Temp curve also looks like a perfect normal curve with most of the values lies in the range of 20 to 30.

In [26]:
```
sns.distplot(data['Rainfall'])
```

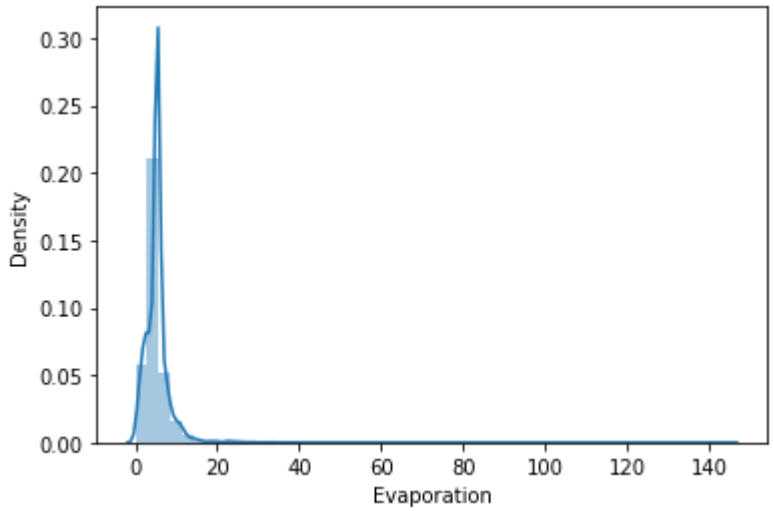
Out[26]:
```
<AxesSubplot:xlabel='Rainfall', ylabel='Density'>
```



It seems like majority of the values lies near to zero. Which seems like there is skewness in the data.

In [27]:
```
sns.distplot(data['Evaporation'])
```

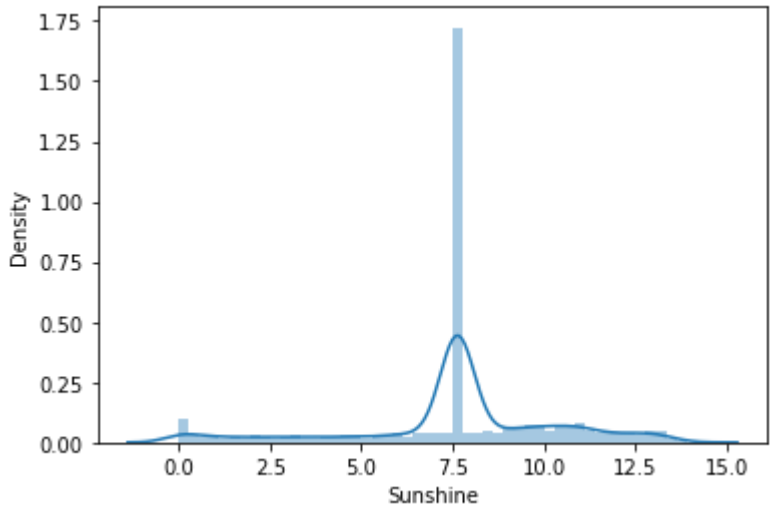
Out[27]:
```
<AxesSubplot:xlabel='Evaporation', ylabel='Density'>
```



Majority of the values lies near to zero. Which seems like there is skewness in the data.

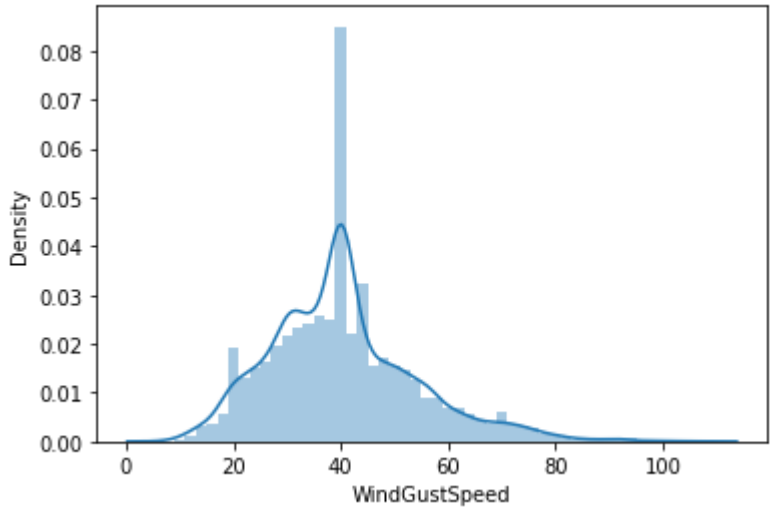
In [28]:
```
sns.distplot(data['Sunshine'])
```

Out[28]: <AxesSubplot:xlabel='Sunshine', ylabel='Density'>



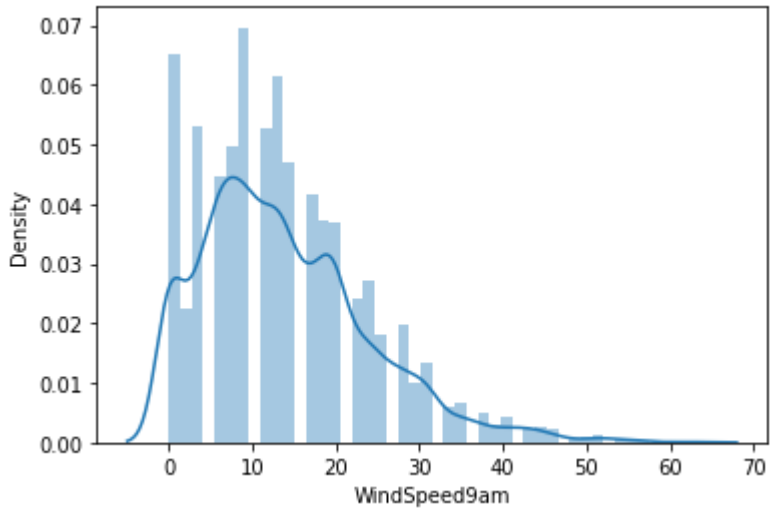
In [29]:
```
sns.distplot(data['WindGustSpeed'])
```

Out[29]: <AxesSubplot:xlabel='WindGustSpeed', ylabel='Density'>



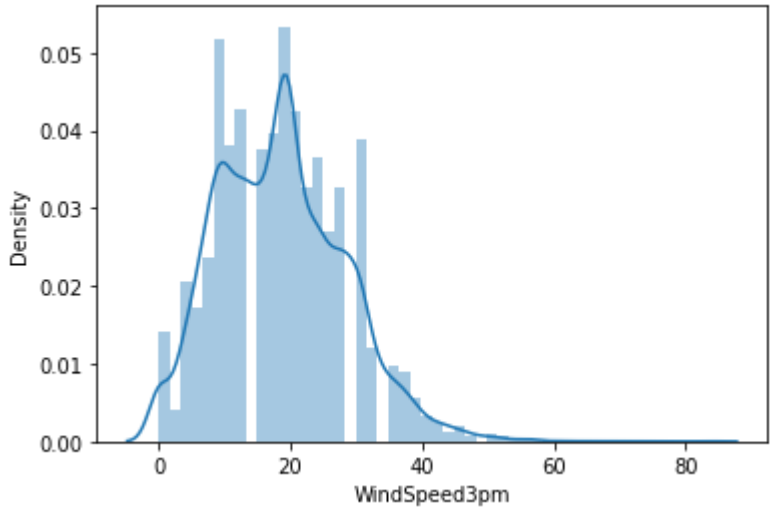
In [30]:
```
sns.distplot(data['WindSpeed9am'])
```

Out[30]:
```
<AxesSubplot:xlabel='WindSpeed9am', ylabel='Density'>
```



In [31]:
```
sns.distplot(data['WindSpeed3pm'])
```

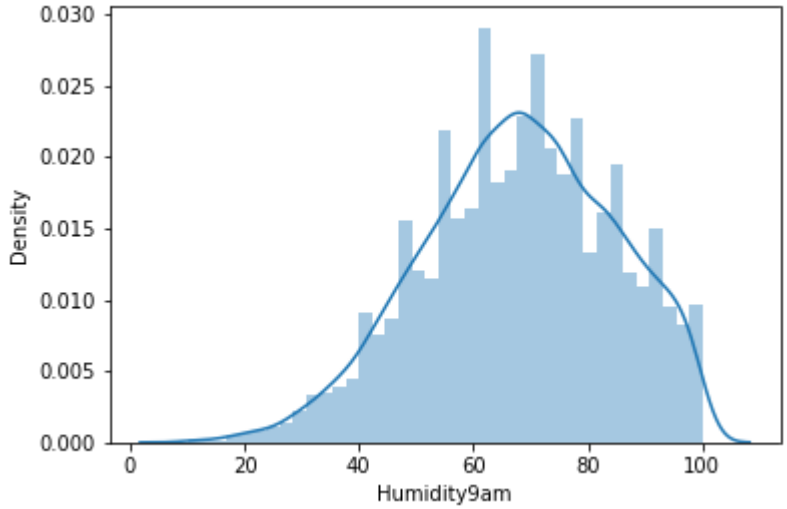
Out[31]:
```
<AxesSubplot:xlabel='WindSpeed3pm', ylabel='Density'>
```



Both WindSpeed 9am and 3pm has the same trend. We will create a new Column for Avg Windspeed by concating the two columns.

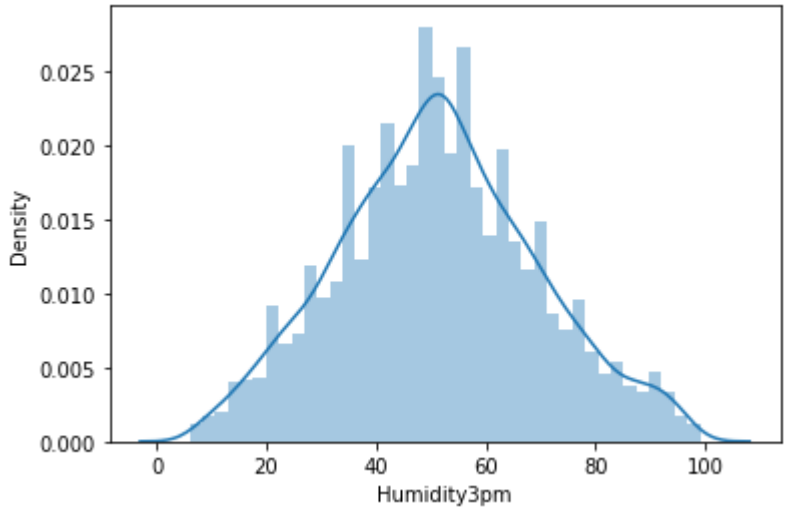
In [32]:
```
sns.distplot(data['Humidity9am'])
```

Out[32]:
```
<AxesSubplot:xlabel='Humidity9am', ylabel='Density'>
```



In [33]:
```
sns.distplot(data['Humidity3pm'])
```

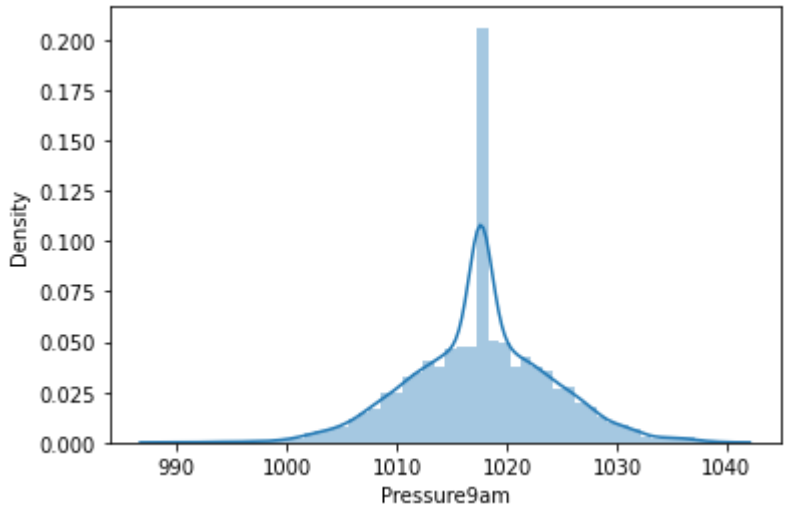
Out[33]:
```
<AxesSubplot:xlabel='Humidity3pm', ylabel='Density'>
```



Both Humidity 9am and 3pm has the same trend. We will create a new Column for Avg Humidity by concating the two columns.

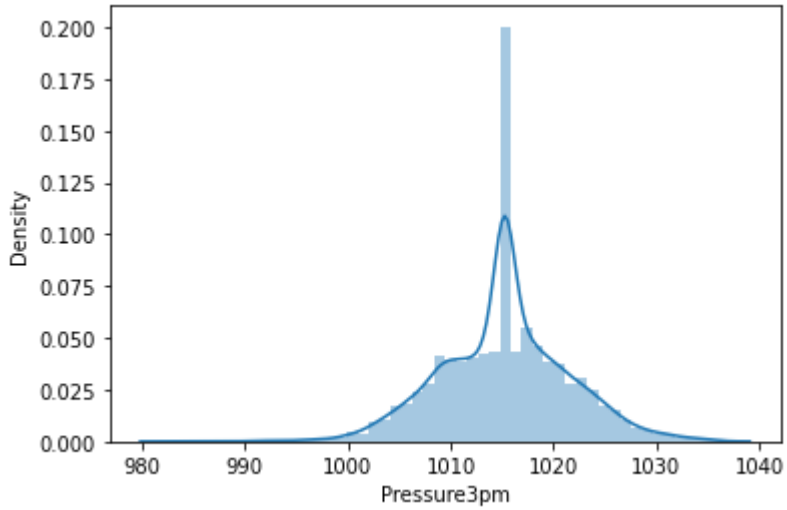
In [34]:
```
sns.distplot(data['Pressure9am'])
```

Out[34]:
```
<AxesSubplot:xlabel='Pressure9am', ylabel='Density'>
```



In [35]:
```
sns.distplot(data['Pressure3pm'])
```

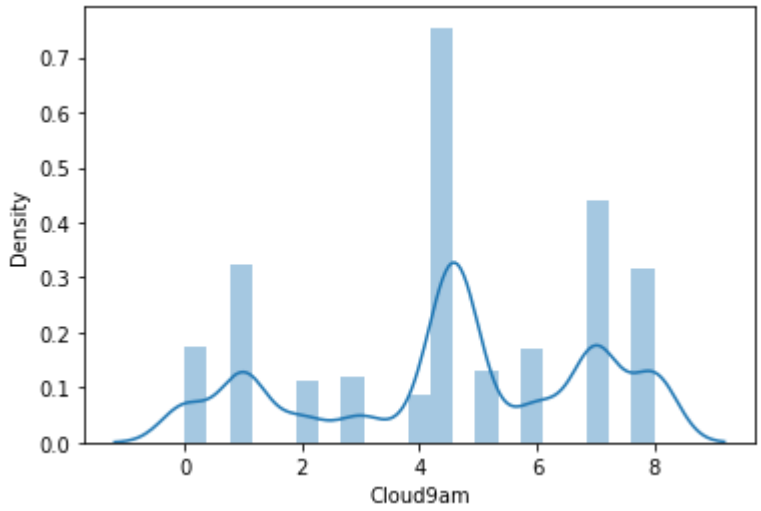
Out[35]:
```
<AxesSubplot:xlabel='Pressure3pm', ylabel='Density'>
```



Both Pressure 9am and 3pm has the same trend. We will create a new Column for Avg Pressure by concating the two columns.

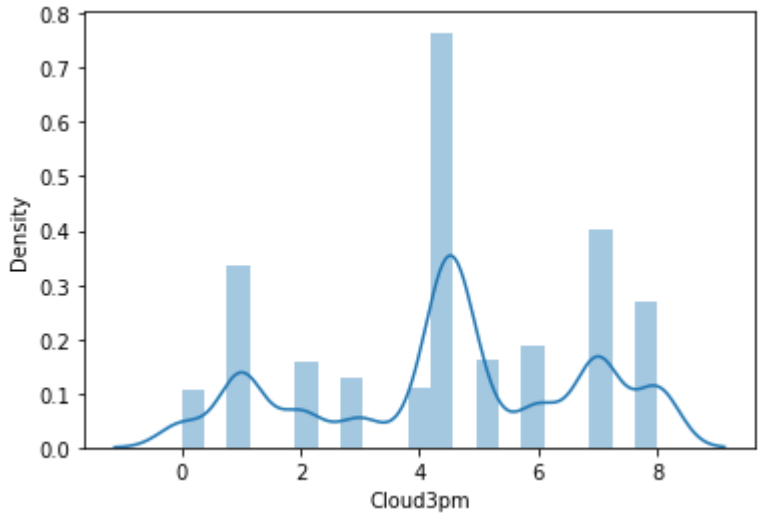
In [36]:
```
sns.distplot(data['Cloud9am'])
```

Out[36]:
```
<AxesSubplot:xlabel='Cloud9am', ylabel='Density'>
```



In [37]:
```
sns.distplot(data['Cloud3pm'])
```

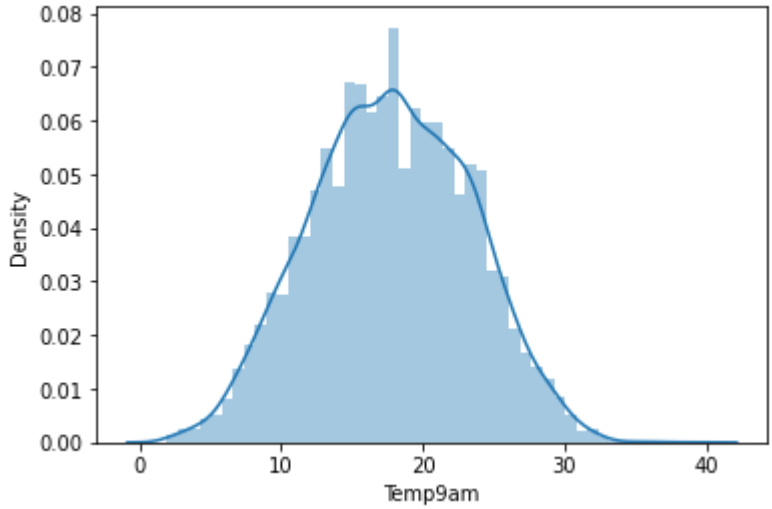
Out[37]:
```
<AxesSubplot:xlabel='Cloud3pm', ylabel='Density'>
```



Both Cloud 9am and 3pm has the same trend. We will create a new Column for Avg Cloud by concating the two columns.

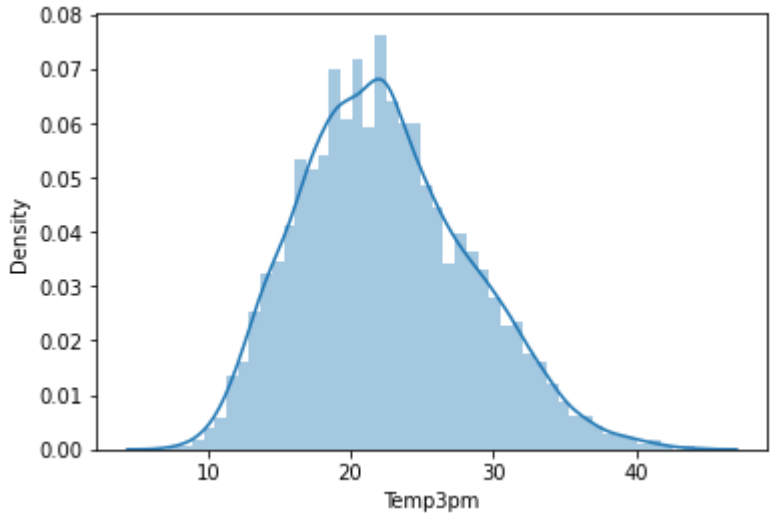
In [38]:
```
sns.distplot(data['Temp9am'])
```

Out[38]:
```
<AxesSubplot:xlabel='Temp9am', ylabel='Density'>
```



In [39]:
```
sns.distplot(data['Temp3pm'])
```

Out[39]:
```
<AxesSubplot:xlabel='Temp3pm', ylabel='Density'>
```



Both Temp 9am and 3pm has the same trend. We will create a new Column for Avg Temp by concating the two columns.

In [40]:
```
data['Avg_WindSpeed']=(data['WindSpeed9am']+data['WindSpeed3pm'])/2

data['Avg_Humidity']=(data['Humidity9am']+data['Humidity3pm'])/2

data['Avg_Cloud']=(data['Cloud9am']+data['Cloud3pm'])/2

data['Avg_Temp'] = (data['Temp9am']+data['Temp3pm'])/2

data['Avg_Pressure']=(data['Pressure9am']+data['Pressure3pm'])/2
```

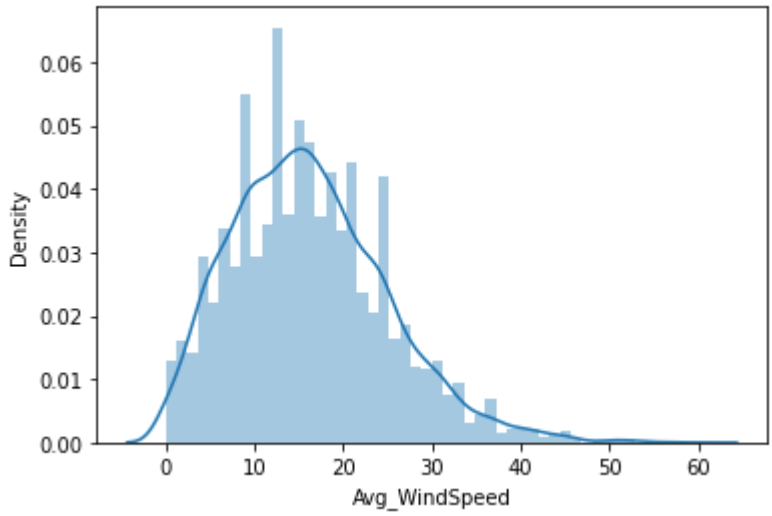
In [41]:
```
data = data.drop(columns = ['Date', 'WindSpeed9am', 'WindSpeed3pm', 'Humidity9a

data.head()
```

Out[41]:

	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSpeed
0	Albury	13.4	22.9	0.6	5.389395	7.632205	W	44.0
1	Albury	7.4	25.1	0.0	5.389395	7.632205	WNW	44.0
2	Albury	12.9	25.7	0.0	5.389395	7.632205	WSW	46.0
3	Albury	9.2	28.0	0.0	5.389395	7.632205	NE	24.0
4	Albury	17.5	32.3	1.0	5.389395	7.632205	W	41.0

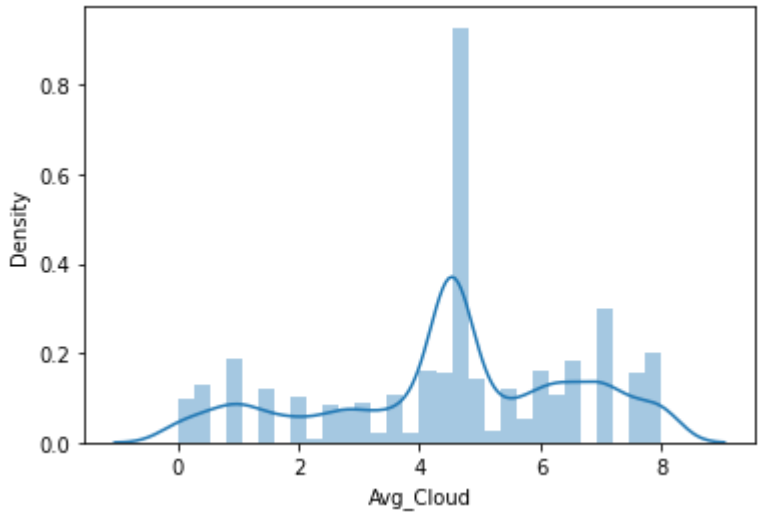
In [42]:
```
sns.distplot(data['Avg_WindSpeed'])
```

Out[42]:
```
<AxesSubplot:xlabel='Avg_WindSpeed', ylabel='Density'>
```



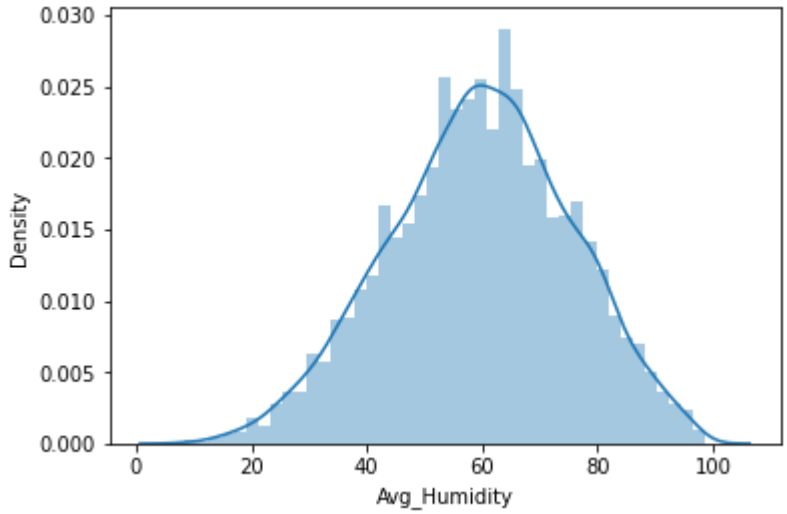
In [43]:
```
sns.distplot(data['Avg_Cloud'])
```

Out[43]: <AxesSubplot:xlabel='Avg_Cloud', ylabel='Density'>



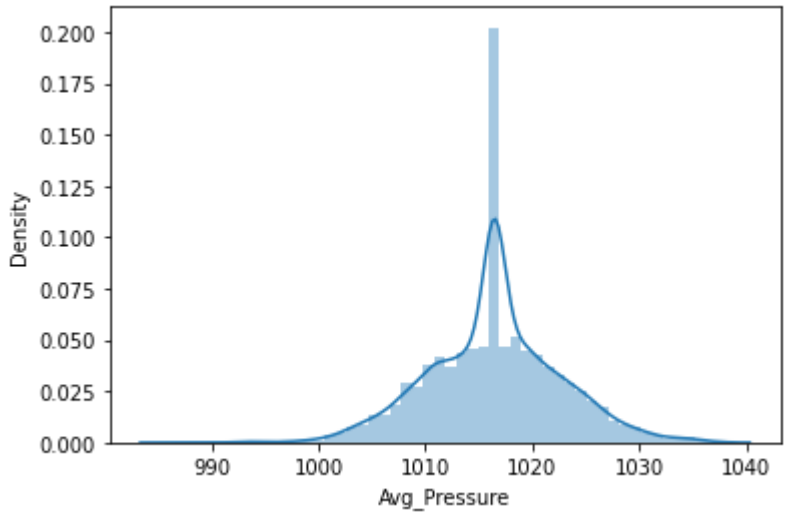
In [44]:
```
sns.distplot(data['Avg_Humidity'])
```

Out[44]: <AxesSubplot:xlabel='Avg_Humidity', ylabel='Density'>



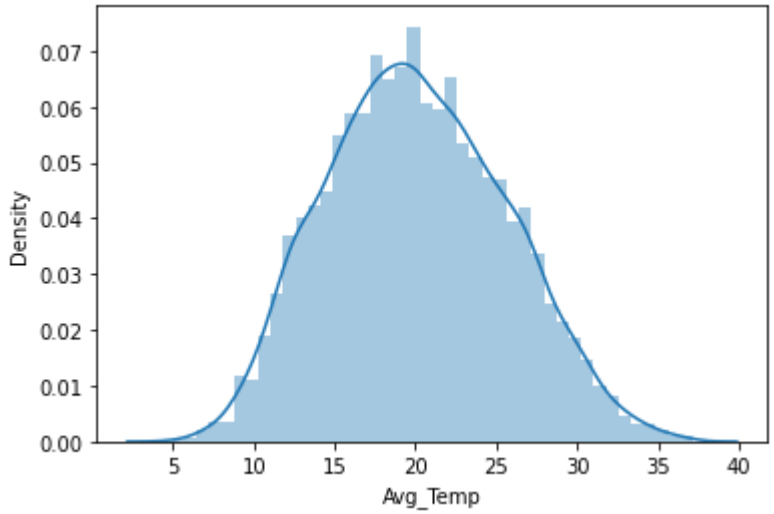
In [45]:
```
sns.distplot(data['Avg_Pressure'])
```

Out[45]:
```
<AxesSubplot:xlabel='Avg_Pressure', ylabel='Density'>
```



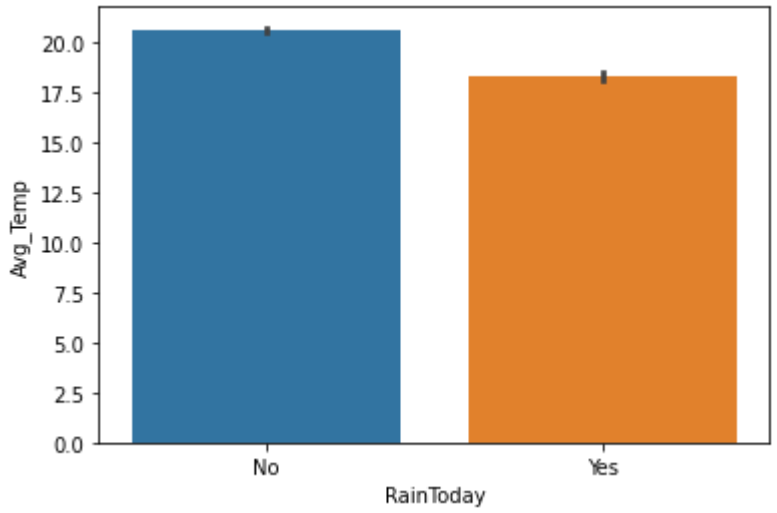
In [46]:
```
sns.distplot(data['Avg_Temp'])
```

Out[46]:
```
<AxesSubplot:xlabel='Avg_Temp', ylabel='Density'>
```



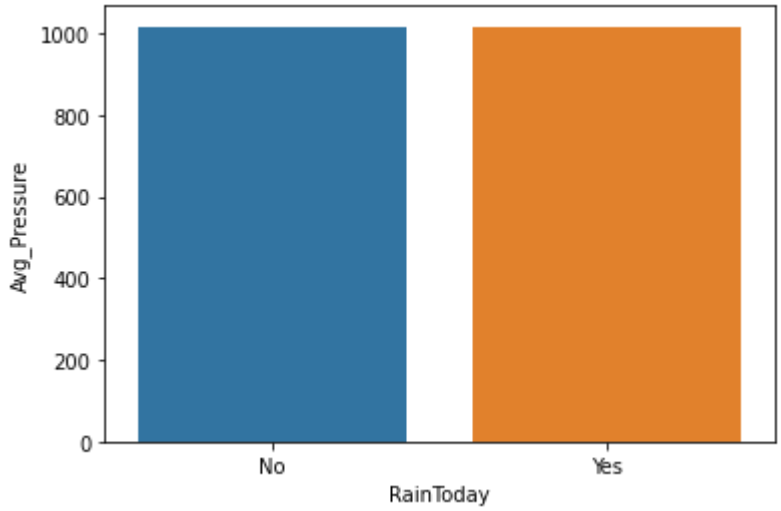
In [47]:
```
sns.barplot(y='Avg_Temp', x='RainToday', data = data)
```

Out[47]: <AxesSubplot:xlabel='RainToday', ylabel='Avg_Temp'>



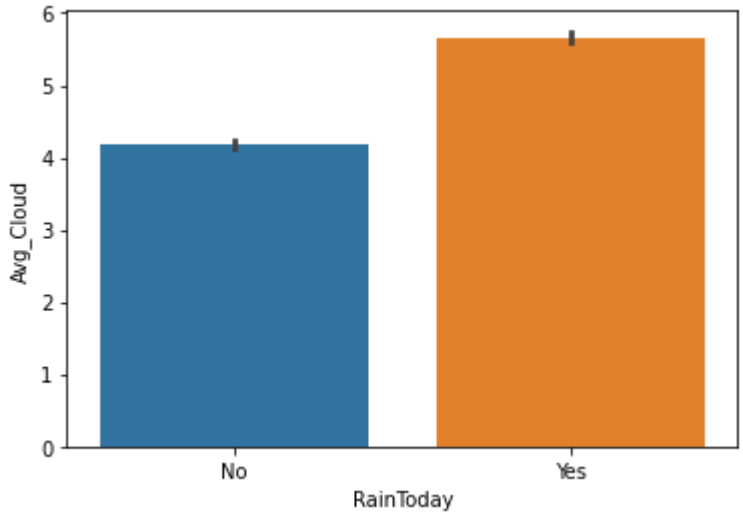
In [48]:
```
sns.barplot(y='Avg_Pressure', x='RainToday', data = data)
```

Out[48]: <AxesSubplot:xlabel='RainToday', ylabel='Avg_Pressure'>



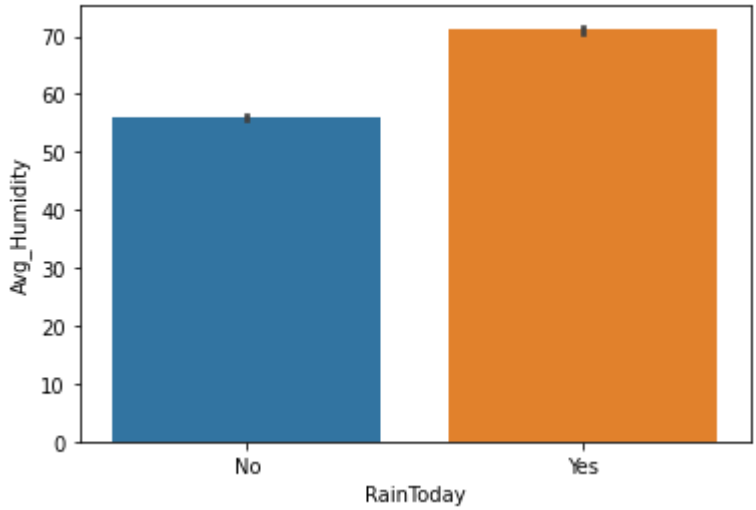
In [49]:
```
sns.barplot(y='Avg_Cloud', x='RainToday', data = data)
```

Out[49]:
```
<AxesSubplot:xlabel='RainToday', ylabel='Avg_Cloud'>
```



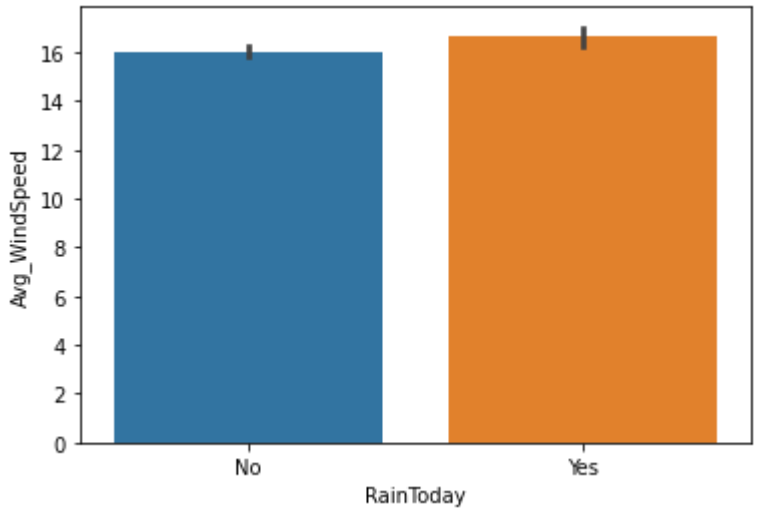
In [50]:
```
sns.barplot(y='Avg_Humidity', x='RainToday', data = data)
```

Out[50]:
```
<AxesSubplot:xlabel='RainToday', ylabel='Avg_Humidity'>
```



In [51]:
```
sns.barplot(y='Avg_WindSpeed', x='RainToday', data = data)
```

Out[51]:
```
<AxesSubplot:xlabel='RainToday', ylabel='Avg_WindSpeed'>
```



Data Encoding

In [52]:
```
# Encoding Dataset

from sklearn.preprocessing import LabelEncoder

enc = LabelEncoder()

catg = data.select_dtypes(include=['object']).columns

catg
```

Out[52]:
```
Index(['Location', 'WindGustDir', 'WindDir9am', 'WindDir3pm', 'RainToday',
       'RainTomorrow'],
      dtype='object')
```

In [53]:
```
for i in catg:
    data[i] = enc.fit_transform(data[i])
```

In [54]:
```
data.head()
```

Out[54]:

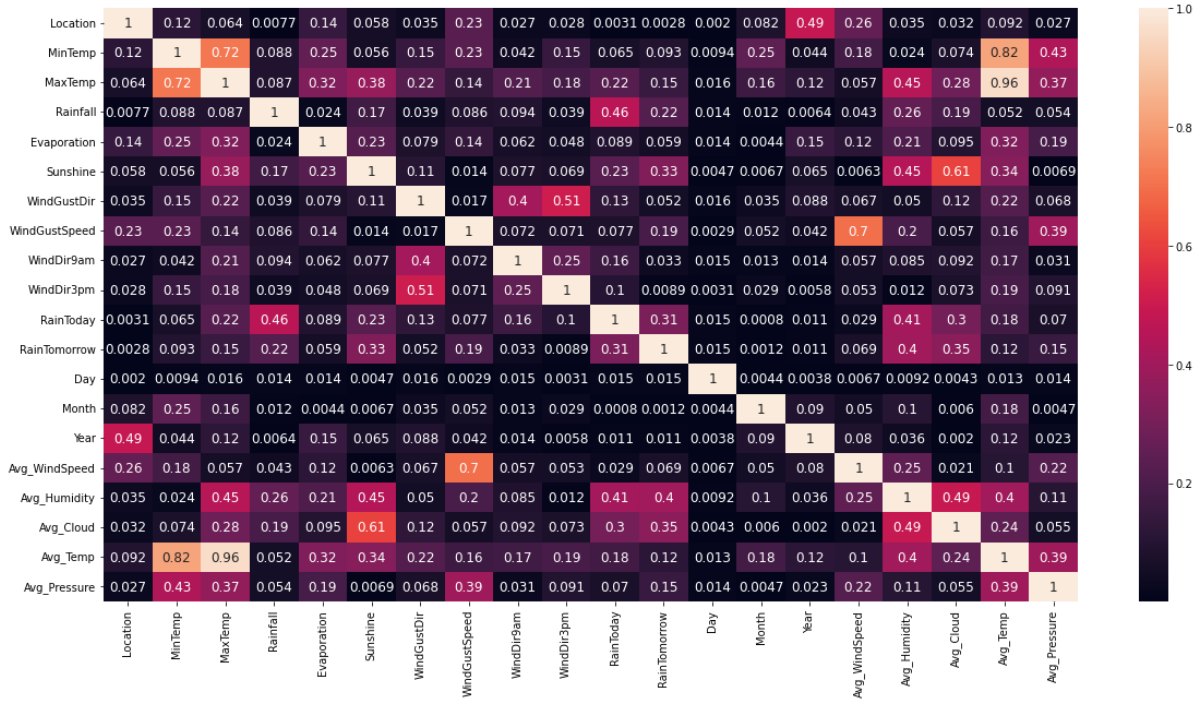
	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSpeed
0	1	13.4	22.9	0.6	5.389395	7.632205	13	44.0
1	1	7.4	25.1	0.0	5.389395	7.632205	14	44.0
2	1	12.9	25.7	0.0	5.389395	7.632205	15	46.0
3	1	9.2	28.0	0.0	5.389395	7.632205	4	24.0
4	1	17.5	32.3	1.0	5.389395	7.632205	13	41.0

In [55]:
```
data.describe().T
```

Out[55]:

	count	mean	std	min	25%	50%	75%
Location	8425.0	5.793591	3.162654	0.00	3.000000	6.000000	8.000000
MinTemp	8425.0	13.193305	5.379488	-2.00	9.300000	13.200000	17.300000
MaxTemp	8425.0	23.859976	6.114516	8.20	19.300000	23.300000	28.000000
Rainfall	8425.0	2.805913	10.309308	0.00	0.000000	0.000000	1.400000
Evaporation	8425.0	5.389395	3.852004	0.00	4.000000	5.389395	5.389395
Sunshine	8425.0	7.632205	2.825451	0.00	7.632205	7.632205	8.900000
WindGustDir	8425.0	7.217804	4.702616	0.00	3.000000	7.000000	12.000000
WindGustSpeed	8425.0	40.174469	13.776101	7.00	31.000000	40.174469	48.000000
WindDir9am	8425.0	7.267418	4.588045	0.00	3.000000	7.000000	12.000000
WindDir3pm	8425.0	7.810445	4.430162	0.00	4.000000	8.000000	11.000000
RainToday	8425.0	0.236202	0.424773	0.00	0.000000	0.000000	0.000000
RainTomorrow	8425.0	0.236320	0.424846	0.00	0.000000	0.000000	0.000000
Day	8425.0	15.741958	8.787354	1.00	8.000000	16.000000	23.000000
Month	8425.0	6.442136	3.437994	1.00	3.000000	6.000000	9.000000
Year	8425.0	2012.102433	2.473137	2008.00	2010.000000	2011.000000	2014.000000
Avg_WindSpeed	8425.0	16.190654	8.760580	0.00	9.500000	15.500000	21.500000
Avg_Humidity	8425.0	59.536143	15.856811	8.50	49.000000	60.000000	70.500000
Avg_Cloud	8425.0	4.534902	2.098294	0.00	3.500000	4.534902	6.251591
Avg_Temp	8425.0	20.102474	5.532595	4.90	16.050000	19.850000	24.000000
Avg_Pressure	8425.0	1016.438154	6.186076	986.35	1012.700000	1016.438154	1020.050000

In [56]:
```
data_corr = data.corr().abs()

plt.figure(figsize = (20,10))
sns.heatmap(data_corr, annot = True, annot_kws={'size':12})
plt.show()
```



The highest value for correlation matrix is 0.96 between Avg_Temp and Max_Temp, which shows a strong correlation between the two columns. Apart from that there is no such column with high correlation value. We will also check for multicollinearity using VIF.

Checking Skewness and Outliers

In [57]:
```
x = data.drop(['RainTomorrow'], axis=1)
y = data['RainTomorrow']
```

In [58]:
```
print(x.shape)
print(y.shape)
```

```
(8425, 19)
(8425,)
```

In [59]:
```
x.skew().sort_values(ascending = False)
```

Out[59]:
```
Evaporation      14.023948
Rainfall         13.218403
RainToday         1.242362
WindGustSpeed     0.757000
Avg_WindSpeed     0.644306
Year              0.418663
MaxTemp           0.380654
WindDir9am        0.172792
Avg_Temp          0.170653
WindGustDir       0.119640
Month             0.039388
Avg_Pressure      0.005032
Day               0.004260
Location         -0.050456
MinTemp          -0.089989
WindDir3pm       -0.119847
Avg_Humidity     -0.151055
Avg_Cloud        -0.374727
Sunshine         -0.716525
dtype: float64
```

Keeping +/- 0.5 as the range for skewness, here are the columns which are beyond the range.

- Evaporation - Continuous
- Rainfall - Categorical
- RainToday - Categorical
- WindGustSpeed - Continuous
- Avg_WindSpeed - Continuous
- Sunshine - Continuous

Multiple columns are having continuous data and has skewness beyond the range. Therefore we will treat the skewness.

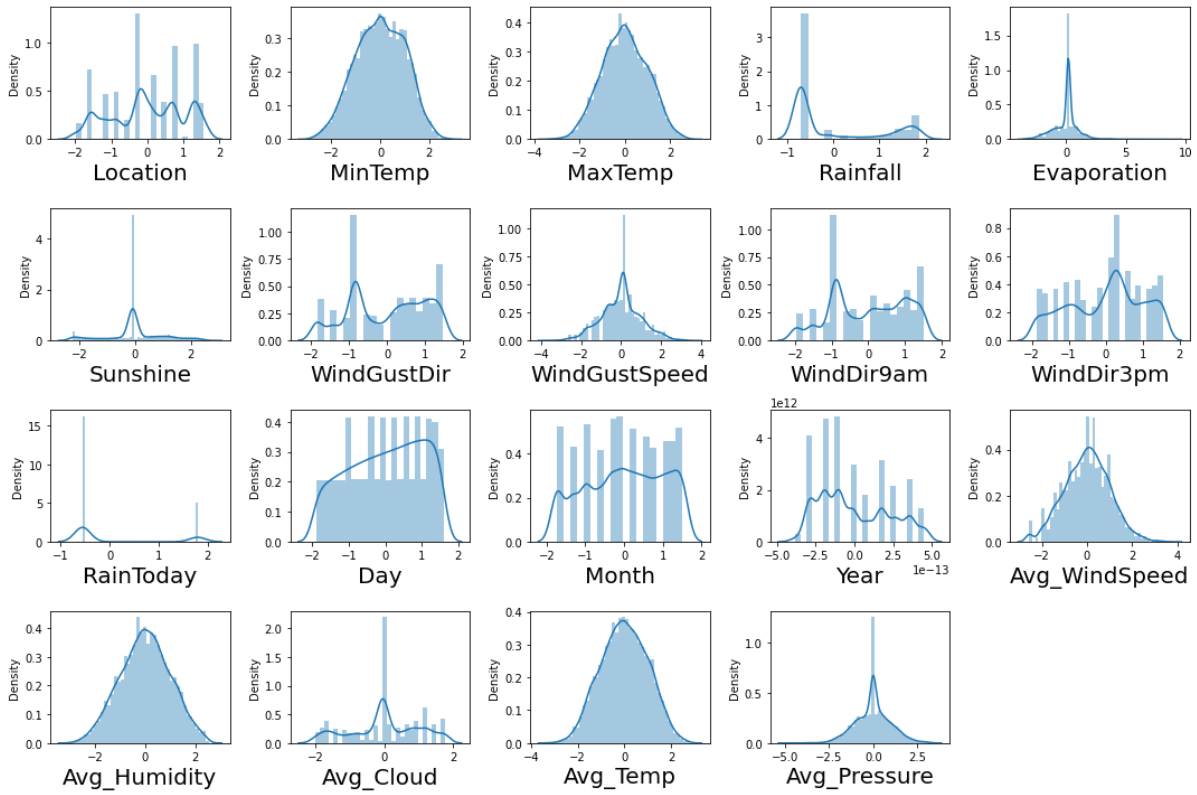
In [60]:
```
from sklearn.preprocessing import power_transform
x_new = power_transform(x)
```

In [61]:
```
pd.DataFrame(x_new, columns = x.columns).skew().sort_values(ascending = False)
```

Out[61]:
```
RainToday        1.242362
Rainfall         0.904387
Evaporation      0.080305
WindGustSpeed    0.010481
Avg_Pressure     0.000947
Year             0.000000
MaxTemp         -0.010591
Avg_WindSpeed   -0.023574
Avg_Temp        -0.029065
Avg_Humidity    -0.047725
Sunshine        -0.075544
MinTemp         -0.102983
WindDir9am      -0.155025
Month           -0.155749
Location        -0.186657
WindGustDir     -0.187177
Avg_Cloud       -0.192919
Day             -0.211250
WindDir3pm      -0.248689
dtype: float64
```

In [62]:
```
x = pd.DataFrame(x_new, columns = x.columns)
```

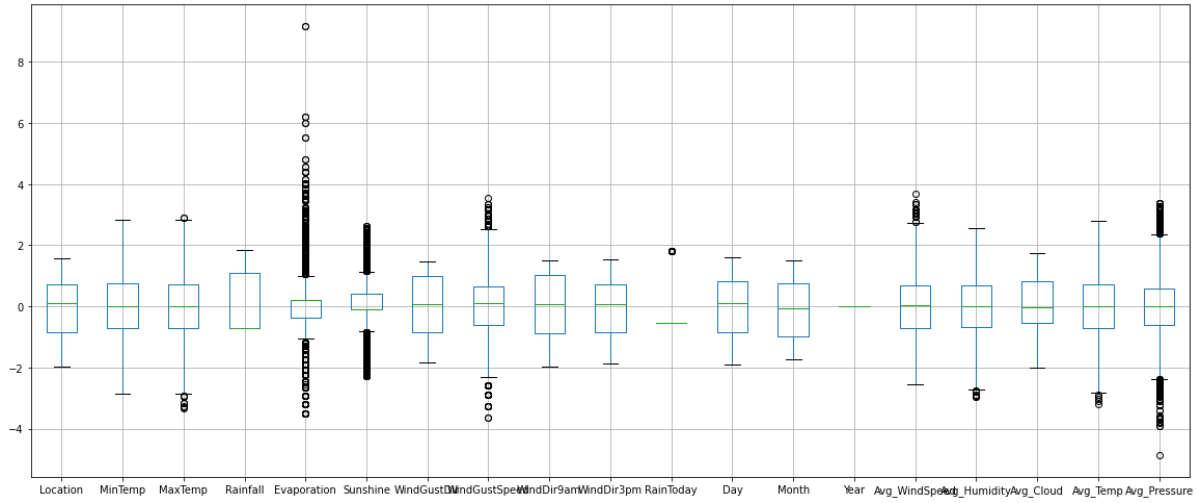
In [63]:
```
plt.figure(figsize = (15,10))
plotnumber = 1

for column in x:
    if plotnumber <= 20:
        ax = plt.subplot(4,5,plotnumber)
        sns.distplot(x[column])
        plt.xlabel(column, fontsize = 20)
    plotnumber +=1
plt.tight_layout()
```



Now the skewness is removed from the data. We can proceed ahead for Data Cleaning.

Checking Outliers

In [64]:
```
x.iloc[:,:].boxplot(figsize = (20,10))
plt.subplots_adjust(bottom=0.25)
plt.show()
```



In [65]:
```
from scipy.stats import zscore

print('High Side Outliers present')
print((zscore(x)<3).all())

print('**************************************')

print('Low Side Outliers Present')
print((zscore(x)>-3).all())
```

```
High Side Outliers present
Location          True
MinTemp           True
MaxTemp           True
Rainfall          True
Evaporation      False
Sunshine          True
WindGustDir       True
WindGustSpeed    False
WindDir9am        True
WindDir3pm        True
RainToday         True
Day               True
Month             True
Year              True
Avg_WindSpeed    False
Avg_Humidity      True
Avg_Cloud         True
Avg_Temp          True
Avg_Pressure     False
dtype: bool
**************************************
Low Side Outliers Present
Location          True
MinTemp           True
MaxTemp          False
Rainfall          True
Evaporation      False
Sunshine          True
WindGustDir       True
WindGustSpeed    False
WindDir9am        True
WindDir3pm        True
RainToday         True
Day               True
Month             True
Year              True
Avg_WindSpeed     True
Avg_Humidity      True
Avg_Cloud         True
Avg_Temp         False
Avg_Pressure     False
dtype: bool
```

Features having outliers in High Side are: 1. Evaporation, 2.WindGustSpeed, 3. Avg_WindSpeed, 4. Avg_Pressure

Features having outliers in Low side are: 1.MaxTemp, 2. Evaporation, 3.WindGustSpeed, 4. Avg_Temp, 5. Avg_Pressure

In [66]:
```
# Validating OUtliers

#1st Quantile
q1 = x.quantile(0.25)

#3rd quantile
q3 = x.quantile(0.75)

#IQR
iqr = q3 - q1
```

In [67]:
```
Evaporation_high = q3.Evaporation + (1.5 * iqr.Evaporation)

# Check the Indexes which have higher values

index1 = np.where(x['Evaporation']> Evaporation_high)

x = x.drop(x['Evaporation'].index[index1])

y = y.drop(y.index[index1])

print(x.shape)
print(y.shape)
```

```
(7674, 19)
(7674,)
```

In [68]:
```
WindGustSpeed_high = q3.WindGustSpeed + (1.5 * iqr.WindGustSpeed)

# Check the Indexes which have higher values

index1 = np.where(x['WindGustSpeed']> WindGustSpeed_high)

x = x.drop(x['WindGustSpeed'].index[index1])

y = y.drop(y.index[index1])

print(x.shape)
print(y.shape)
```

```
(7622, 19)
(7622,)
```

In [69]:
```
Avg_WindSpeed_high = q3.Avg_WindSpeed + (1.5 * iqr.Avg_WindSpeed)

# Check the Indexes which have higher values

index1 = np.where(x['Avg_WindSpeed']>Avg_WindSpeed_high )

x = x.drop(x['Avg_WindSpeed'].index[index1])

y = y.drop(y.index[index1])

print(x.shape)
print(y.shape)
```

```
(7616, 19)
(7616,)
```

In [70]:
```
Avg_Pressure_high = q3.Avg_Pressure + (1.5 * iqr.Avg_Pressure)

# Check the Indexes which have higher values

index1 = np.where(x['Avg_Pressure']>Avg_Pressure_high )

x = x.drop(x['Avg_Pressure'].index[index1])

y = y.drop(y.index[index1])

print(x.shape)
print(y.shape)
```

```
(7509, 19)
(7509,)
```

In [71]:
```
MaxTemp_low = q1.MaxTemp - (1.5 * iqr.MaxTemp)

# Check the Indexes which have higher values

index1 = np.where(x['MaxTemp']< MaxTemp_low  )

x = x.drop(x['MaxTemp'].index[index1])

y = y.drop(y.index[index1])

print(x.shape)
print(y.shape)
```

```
(7501, 19)
(7501,)
```

In [72]:
```
Evaporation_low = q1.Evaporation- (1.5 * iqr.Evaporation)

# Check the Indexes which have higher values

index1 = np.where(x['Evaporation']< Evaporation_low )

x = x.drop(x['Evaporation'].index[index1])

y = y.drop(y.index[index1])

print(x.shape)
print(y.shape)
```

```
(6443, 19)
(6443,)
```

In [73]:
```
WindGustSpeed_low = q1.WindGustSpeed- (1.5 * iqr.WindGustSpeed)

# Check the Indexes which have higher values

index1 = np.where(x['WindGustSpeed']< WindGustSpeed_low  )

x = x.drop(x['WindGustSpeed'].index[index1])

y = y.drop(y.index[index1])

print(x.shape)
print(y.shape)
```

```
(6362, 19)
(6362,)
```

In [74]:
```
Avg_Temp_low = q1.Avg_Temp- (1.5 * iqr.Avg_Temp)

# Check the Indexes which have higher values

index1 = np.where(x['Avg_Temp']< Avg_Temp_low  )

x = x.drop(x['Avg_Temp'].index[index1])

y = y.drop(y.index[index1])

print(x.shape)
print(y.shape)
```

```
(6361, 19)
(6361,)
```

In [75]:
```
Avg_Pressure_low = q1. Avg_Pressure- (1.5 * iqr.Avg_Pressure)

# Check the Indexes which have higher values

index1 = np.where(x['Avg_Pressure']<  Avg_Pressure_low  )

x = x.drop(x['Avg_Pressure'].index[index1])

y = y.drop(y.index[index1])

print(x.shape)
print(y.shape)
```

```
(6300, 19)
(6300,)
```

In [76]:
```
from scipy.stats import zscore

print('High Side Outliers present')
print((zscore(x)<3).all())

print('**************************************')

print('Low Side Outliers Present')
print((zscore(x)>-3).all())
```

```
High Side Outliers present
Location          True
MinTemp           True
MaxTemp          False
Rainfall          True
Evaporation       True
Sunshine          True
WindGustDir       True
WindGustSpeed     True
WindDir9am        True
WindDir3pm        True
RainToday         True
Day               True
Month             True
Year              True
Avg_WindSpeed     True
Avg_Humidity      True
Avg_Cloud         True
Avg_Temp          True
Avg_Pressure      True
dtype: bool
**************************************
Low Side Outliers Present
Location          True
MinTemp           True
MaxTemp          False
Rainfall          True
Evaporation       True
Sunshine          True
WindGustDir       True
WindGustSpeed     True
WindDir9am        True
WindDir3pm        True
RainToday         True
Day               True
Month             True
Year              True
Avg_WindSpeed     True
Avg_Humidity     False
Avg_Cloud         True
Avg_Temp         False
Avg_Pressure      True
dtype: bool
```

There is still some outliers present in the dataset. We will remove them before proceeding

In [77]:
```
# Validating OUtliers

#1st Quantile
q1 = x.quantile(0.25)

#3rd quantile
q3 = x.quantile(0.75)

#IQR
iqr = q3 - q1
```

In [78]:
```
MaxTemp_high = q3.MaxTemp + (1.5 * iqr.MaxTemp)

# Check the Indexes which have higher values

index1 = np.where(x['MaxTemp']> MaxTemp_high)

x = x.drop(x['MaxTemp'].index[index1])

y = y.drop(y.index[index1])

print(x.shape)
print(y.shape)
```

```
(6296, 19)
(6296,)
```

In [79]:
```
MaxTemp_low = q1.MaxTemp - (1.5 * iqr.MaxTemp)

# Check the Indexes which have higher values

index1 = np.where(x['MaxTemp']< MaxTemp_low  )

x = x.drop(x['MaxTemp'].index[index1])

y = y.drop(y.index[index1])

print(x.shape)
print(y.shape)
```

```
(6278, 19)
(6278,)
```

In [80]:
```
Avg_Temp_low = q1.Avg_Temp - (1.5 * iqr.Avg_Temp)

# Check the Indexes which have higher values

index1 = np.where(x['Avg_Temp']< Avg_Temp_low)

x = x.drop(x['Avg_Temp'].index[index1])

y = y.drop(y.index[index1])

print(x.shape)
print(y.shape)
```

```
(6265, 19)
(6265,)
```

In [81]:
```
Avg_Humidity_low = q1.Avg_Humidity- (1.5 * iqr.Avg_Humidity)

# Check the Indexes which have higher values

index1 = np.where(x['Avg_Humidity']< Avg_Humidity_low )

x = x.drop(x['Avg_Humidity'].index[index1])

y = y.drop(y.index[index1])

print(x.shape)
print(y.shape)
```

```
(6260, 19)
(6260,)
```

In [82]:
```
from scipy.stats import zscore

print('High Side Outliers present')
print((zscore(x)<3).all())

print('**************************************')

print('Low Side Outliers Present')
print((zscore(x)>-3).all())
```

```
High Side Outliers present
Location          True
MinTemp           True
MaxTemp           True
Rainfall          True
Evaporation       True
Sunshine          True
WindGustDir       True
WindGustSpeed     True
WindDir9am        True
WindDir3pm        True
RainToday         True
Day               True
Month             True
Year              True
Avg_WindSpeed     True
Avg_Humidity      True
Avg_Cloud         True
Avg_Temp         False
Avg_Pressure      True
dtype: bool
**************************************
Low Side Outliers Present
Location         True
MinTemp          True
MaxTemp          True
Rainfall         True
Evaporation      True
Sunshine         True
WindGustDir      True
WindGustSpeed    True
WindDir9am       True
WindDir3pm       True
RainToday        True
Day              True
Month            True
Year             True
Avg_WindSpeed    True
Avg_Humidity     True
Avg_Cloud        True
Avg_Temp         True
Avg_Pressure     True
dtype: bool
```

In [83]:
```
Avg_Temp_high = q3.Avg_Temp + (1.5 * iqr.Avg_Temp)

# Check the Indexes which have higher values

index1 = np.where(x['Avg_Temp']> Avg_Temp_high)

x = x.drop(x['Avg_Temp'].index[index1])

y = y.drop(y.index[index1])

print(x.shape)
print(y.shape)
```

```
(6255, 19)
(6255,)
```

In [84]:
```
from scipy.stats import zscore

print('High Side Outliers present')
print((zscore(x)<3).all())

print('**************************************')

print('Low Side Outliers Present')
print((zscore(x)>-3).all())
```

```
High Side Outliers present
Location         True
MinTemp          True
MaxTemp          True
Rainfall         True
Evaporation      True
Sunshine         True
WindGustDir      True
WindGustSpeed    True
WindDir9am       True
WindDir3pm       True
RainToday        True
Day              True
Month            True
Year             True
Avg_WindSpeed    True
Avg_Humidity     True
Avg_Cloud        True
Avg_Temp         True
Avg_Pressure     True
dtype: bool
**************************************
Low Side Outliers Present
Location         True
MinTemp          True
MaxTemp          True
Rainfall         True
Evaporation      True
Sunshine         True
WindGustDir      True
WindGustSpeed    True
WindDir9am       True
WindDir3pm       True
RainToday        True
Day              True
Month            True
Year             True
Avg_WindSpeed    True
Avg_Humidity     True
Avg_Cloud        True
Avg_Temp         True
Avg_Pressure     True
dtype: bool
```

In [85]:
```
# Percentage Data Loss

Data_loss = ((8425-6255)/8425)*100

Data_loss
```

Out[85]: 25.7566765578635

Now the outliers are treated. We can proceed furthur.

In [86]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

x_scaled = scaler.fit_transform(x)
```

In [87]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor

vif = pd.DataFrame()

vif['vif'] = [variance_inflation_factor(x_scaled, i) for i in range (x_scaled.s

vif['features'] = x.columns


# Lets check the values
vif
```

Out[87]:

	vif	features
0	1.593531	Location
1	6.989521	MinTemp
2	14.633397	MaxTemp
3	5.109942	Rainfall
4	1.193588	Evaporation
5	1.642327	Sunshine
6	1.546501	WindGustDir
7	1.960328	WindGustSpeed
8	1.278026	WindDir9am
9	1.443167	WindDir3pm
10	4.767002	RainToday
11	1.002824	Day
12	1.152514	Month
13	1.526477	Year
14	2.012627	Avg_WindSpeed
15	2.381139	Avg_Humidity
16	1.822565	Avg_Cloud
17	24.403893	Avg_Temp
18	1.365915	Avg_Pressure

As we have seen in the correlation matrix, The column Max_Temp and Avg_Temp are having strong correlation between them. Therefore we reed to remove one column in order to reduce mulitcollinearity.

In [88]:
```
x = x.drop(['Avg_Temp'], axis=1)

x.head()
```

Out[88]:

	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSpeed
0	-1.57287	0.041124	-0.077141	0.534236	0.195503	-0.082709	1.160646	0.380260
1	-1.57287	-1.076281	0.280346	-0.698529	0.195503	-0.082709	1.319872	0.380260
2	-1.57287	-0.051713	0.374368	-0.698529	0.195503	-0.082709	1.474872	0.515695
3	-1.57287	-0.740202	0.722385	-0.698529	0.195503	-0.082709	-0.578373	-1.265782
4	-1.57287	0.800894	1.327005	0.888946	0.195503	-0.082709	1.160646	0.169468

In [89]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

x_scaled = scaler.fit_transform(x)
```

In [90]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor

vif = pd.DataFrame()

vif['vif'] = [variance_inflation_factor(x_scaled, i) for i in range (x_scaled.s

vif['features'] = x.columns


# Lets check the values
vif
```

Out[90]:

	vif	features
0	1.591532	Location
1	3.669213	MinTemp
2	3.977359	MaxTemp
3	5.099294	Rainfall
4	1.191640	Evaporation
5	1.637798	Sunshine
6	1.545461	WindGustDir
7	1.933966	WindGustSpeed
8	1.276851	WindDir9am
9	1.441555	WindDir3pm
10	4.762022	RainToday
11	1.002804	Day
12	1.148889	Month
13	1.514214	Year
14	2.006025	Avg_WindSpeed
15	2.241931	Avg_Humidity
16	1.796431	Avg_Cloud
17	1.365245	Avg_Pressure

We can clearly observe that, the VIF values have reduced significantly. And as the max VIF value for the dataset is below 10. we are certain that there is no multicollinearity present in the dataset.

Model Building

In [91]:
```
from sklearn.metrics import accuracy_score, confusion_matrix, roc_curve, roc_au
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
import xgboost as xgb
from sklearn.svm import SVC
```

In [92]:
```
maxAccu = 0
maxRS = 0

model = [LogisticRegression(),
         RandomForestClassifier(),
         DecisionTreeClassifier(),
         KNeighborsClassifier(),
         xgb.XGBClassifier(),
         SVC()]

for rs in range(1,200):
    x_train, x_test, y_train, y_test = train_test_split(x_scaled, y, test_size
    for i in model:
        i.fit(x_train, y_train)
        y_pred = i.predict(x_test)
        acc = accuracy_score(y_test,y_pred)
        print('Accuracy score', acc, 'random_state', rs, 'Model', i)
        if acc > maxAccu:
            maxAccu = acc
            maxRS = rs
            final_model = i


print('Max Accuracy score is', maxAccu, 'at random_state', rs, 'for Model:', i)
```

```
Accuracy score 0.8241687979539642 random_state 1 Model LogisticRegression()
Accuracy score 0.8804347826086957 random_state 1 Model RandomForestClassifi
er()
Accuracy score 0.8356777493606138 random_state 1 Model DecisionTreeClassifi
er()
Accuracy score 0.8190537084398977 random_state 1 Model KNeighborsClassifier
()
Accuracy score 0.8823529411764706 random_state 1 Model XGBClassifier(base_s
core=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwis
e',
              importance_type=None, interaction_constraints='',
              learning_rate=0.300000012, max_bin=256, max_cat_to_onehot=4,
              max_delta_step=0, max_depth=6, max_leaves=0, min_child_weight
=1,
              missing=nan, monotone_constraints='()', n_estimators=100,
              n_jobs=0, num_parallel_tree=1, predictor='auto', random_state
```

In [93]:
```
print('Max Accuracy score is', maxAccu, 'at random_state', rs, 'for Model:', i)
```

```
Max Accuracy score is 0.9008951406649617 at random_state 199 for Model: SVC()
```

In [94]:
```
from sklearn.model_selection import cross_val_score

x_train, x_test, y_train, y_test = train_test_split(x_scaled, y, test_size = 0.

svc = SVC()

svc.fit(x_train, y_train)

y_pred = svc.predict(x_test)

print('Accuracy Score: ', accuracy_score(y_test, y_pred))

for i in range (2,11):
    cvscore = cross_val_score(svc, x_scaled, y, cv = i)
    cvs = cvscore.mean()
    print("At CV:", i)
    print("Cross Validation Score is: ", cvs*100)
    print("Accuracy_Score is : ", accuracy_score(y_test, y_pred))
```

```
Accuracy Score:  0.8356777493606138
At CV: 2
Cross Validation Score is:  82.44597626317112
Accuracy_Score is :  0.8356777493606138
At CV: 3
Cross Validation Score is:  79.69624300559553
Accuracy_Score is :  0.8356777493606138
At CV: 4
Cross Validation Score is:  82.70196503870679
Accuracy_Score is :  0.8356777493606138
At CV: 5
Cross Validation Score is:  79.24860111910472
Accuracy_Score is :  0.8356777493606138
At CV: 6
Cross Validation Score is:  81.80688795117682
Accuracy_Score is :  0.8356777493606138
At CV: 7
Cross Validation Score is:  82.89422685658884
Accuracy_Score is :  0.8356777493606138
At CV: 8
Cross Validation Score is:  83.00571272321208
Accuracy_Score is :  0.8356777493606138
At CV: 9
Cross Validation Score is:  82.81374900079936
Accuracy_Score is :  0.8356777493606138
At CV: 10
Cross Validation Score is:  83.2142875399361
Accuracy_Score is :  0.8356777493606138
```

In [95]:
```
cvscore_selected = cross_val_score(svc, x_scaled, y, cv = 10).mean()
print("The CV Score is: ", cvscore_selected, "\nThe Accuracy_Score is: ", accur
```

```
The CV Score is:  0.8321428753993609
The Accuracy_Score is:  0.8356777493606138
```

Parameter Tuning using GridSearchCV

In [96]:
```
# HyperParameter Tuning

param_grid = {'C': [0.1, 1, 10, 100, 1000],
              'gamma': [1, 0.1, 0.01, 0.001, 0.0001],
              'kernel': ['rbf']}

grd = GridSearchCV(svc, param_grid = param_grid)
grd.fit(x_train, y_train)

print('Best Param ==>', grd.best_params_)

clf = grd.best_estimator_      # reinstiating with best parameters

clf.fit(x_train, y_train)
y_pred = clf.predict(x_test)

svc_conf_mat = confusion_matrix(y_test, y_pred)

print('\nconf_mat ==>', '\n', svc_conf_mat)

print('\nAccuracy rf Normal ==>', '\n', accuracy_score(y_test, y_pred))
```

```
Best Param ==> {'C': 10, 'gamma': 0.1, 'kernel': 'rbf'}

conf_mat ==>
 [[1135   67]
 [ 148  214]]

Accuracy rf Normal ==>
 0.862531969309463
```

Final Accuracy is: 86% and the Best Model is SVC.

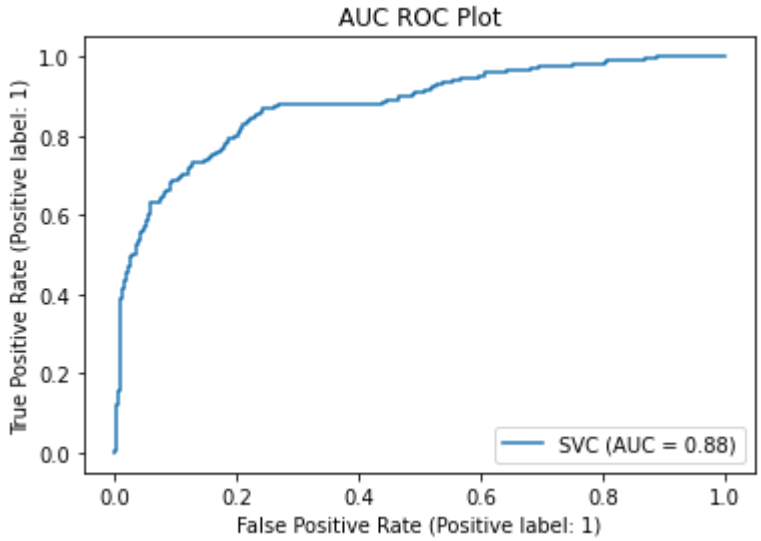
In [97]:
```
# auc roc plot
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.metrics import plot_roc_curve

print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.88      0.94      0.91      1202
           1       0.76      0.59      0.67       362

    accuracy                           0.86      1564
   macro avg       0.82      0.77      0.79      1564
weighted avg       0.86      0.86      0.86      1564
```

In [98]:
```
fpr, tpr, thresholds = roc_curve(y_test, y_pred, pos_label = True)

print(fpr)
print('*******')
print(tpr)
print('*******')
print(thresholds)
```

```
[0.         0.05574043 1.        ]
*******
[0.         0.59116022 1.        ]
*******
[2 1 0]
```

In [99]:
```
plot_roc_curve(clf, x_test, y_test)
plt.title("AUC ROC Plot")
plt.show()
```



Final Accuracy is 86% and AUC score is 88%, which is very good.

In [100]:
```
# Saving the Model

import joblib
joblib.dump(clf, "Rainfall_Prediction_Classifier.pkl")
```

Out[100]:
```
['Rainfall_Prediction_Classifier.pkl']
```

Prediction for Rainfall

In [101]:
```
data.head()
```

Out[101]:

	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSpeed
0	1	13.4	22.9	0.6	5.389395	7.632205	13	44.0
1	1	7.4	25.1	0.0	5.389395	7.632205	14	44.0
2	1	12.9	25.7	0.0	5.389395	7.632205	15	46.0
3	1	9.2	28.0	0.0	5.389395	7.632205	4	24.0
4	1	17.5	32.3	1.0	5.389395	7.632205	13	41.0

In [102]:
```
x_r = pd.concat([x,y],axis=1)
```

In [103]:
```
x_r.head()
```

Out[103]:

	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSpeed
0	-1.57287	0.041124	-0.077141	0.534236	0.195503	-0.082709	1.160646	0.380260
1	-1.57287	-1.076281	0.280346	-0.698529	0.195503	-0.082709	1.319872	0.380260
2	-1.57287	-0.051713	0.374368	-0.698529	0.195503	-0.082709	1.474872	0.515699
3	-1.57287	-0.740202	0.722385	-0.698529	0.195503	-0.082709	-0.578373	-1.265782
4	-1.57287	0.800894	1.327005	0.888946	0.195503	-0.082709	1.160646	0.169468

In [104]:
```
x_r.columns
```

Out[104]:
```
Index(['Location', 'MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine',
       'WindGustDir', 'WindGustSpeed', 'WindDir9am', 'WindDir3pm', 'RainToday',
       'Day', 'Month', 'Year', 'Avg_WindSpeed', 'Avg_Humidity', 'Avg_Cloud',
       'Avg_Pressure', 'RainTomorrow'],
      dtype='object')
```

In [105]:
```
x_r = x.drop(['Rainfall'], axis=1)
y_r = x['Rainfall']

print(x_r.shape)
print(y_r.shape)
```

```
(6255, 17)
(6255,)
```

In [106]:
```
from scipy.stats import zscore

print('High Side Outliers present')
print((zscore(x)<3).all())

print('**************************************')

print('Low Side Outliers Present')
print((zscore(x)>-3).all())
```

```
High Side Outliers present
Location         True
MinTemp          True
MaxTemp          True
Rainfall         True
Evaporation      True
Sunshine         True
WindGustDir      True
WindGustSpeed    True
WindDir9am       True
WindDir3pm       True
RainToday        True
Day              True
Month            True
Year             True
Avg_WindSpeed    True
Avg_Humidity     True
Avg_Cloud        True
Avg_Pressure     True
dtype: bool
**************************************
Low Side Outliers Present
Location         True
MinTemp          True
MaxTemp          True
Rainfall         True
Evaporation      True
Sunshine         True
WindGustDir      True
WindGustSpeed    True
WindDir9am       True
WindDir3pm       True
RainToday        True
Day              True
Month            True
Year             True
Avg_WindSpeed    True
Avg_Humidity     True
Avg_Cloud        True
Avg_Pressure     True
dtype: bool
```

In [107]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

xr_scaled = scaler.fit_transform(x_r)
```

In [108]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor

vif = pd.DataFrame()

vif['vif'] = [variance_inflation_factor(xr_scaled, i) for i in range (xr_scaled

vif['features'] = x_r.columns


# Lets check the values
vif
```

Out[108]:

	vif	features
0	1.591126	Location
1	3.644337	MinTemp
2	3.968600	MaxTemp
3	1.186778	Evaporation
4	1.637787	Sunshine
5	1.544190	WindGustDir
6	1.927823	WindGustSpeed
7	1.276512	WindDir9am
8	1.440392	WindDir3pm
9	1.322082	RainToday
10	1.002228	Day
11	1.140060	Month
12	1.502118	Year
13	2.006008	Avg_WindSpeed
14	2.211998	Avg_Humidity
15	1.793007	Avg_Cloud
16	1.362709	Avg_Pressure

There is no multicollinearity in the dataset.

In [109]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from sklearn.ensemble import RandomForestRegressor
import xgboost as xgb
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR
```

In [110]:
```
max_r2_score = 0
maxRS = 0
model = [LinearRegression(),
         DecisionTreeRegressor(),
         KNeighborsRegressor(),
         RandomForestRegressor(),
         xgb.XGBRegressor(),
         SVR()]

for rs in range(1,200):
    xr_train, xr_test, yr_train, yr_test = train_test_split(xr_scaled, y_r, tes
    for ir in model:
        ir.fit(xr_train, yr_train)
        yr_pred = ir.predict(xr_test)
        r2score = r2_score( yr_test,yr_pred)
        print('r2_score', r2score*100,'%', 'random_state', rs, 'Model', ir)
        if r2score > max_r2_score:
            max_r2_score = r2score
            maxRS = rs
            final_model = ir


print("max R2 score corresponds to random state: ", maxRS, 'is', max_r2_score,
```

```
r2_score 80.72804564227182 % random_state 1 Model LinearRegression()
r2_score 77.28007838016502 % random_state 1 Model DecisionTreeRegressor()
r2_score 79.28297086285211 % random_state 1 Model KNeighborsRegressor()
r2_score 87.04468551549682 % random_state 1 Model RandomForestRegressor()
r2_score 86.58829154185173 % random_state 1 Model XGBRegressor(base_score=
0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
             importance_type=None, interaction_constraints='',
             learning_rate=0.300000012, max_bin=256, max_cat_to_onehot=4,
             max_delta_step=0, max_depth=6, max_leaves=0, min_child_weight=
1,
             missing=nan, monotone_constraints='()', n_estimators=100, n_jo
bs=0,
             num_parallel_tree=1, predictor='auto', random_state=0, reg_alp
ha=0,
             reg_lambda=1, ...)
r2_score 81.74609242841294 % random_state 1 Model SVR()
```

In [111]:
```
print("max R2 score corresponds to random state: ", maxRS, 'is', max_r2_score,
```

```
max R2 score corresponds to random state:  23 is 0.9134539944044737 and Model
is:  RandomForestRegressor()
```

In [112]:
```
from sklearn import metrics

print('MAE:', metrics.mean_absolute_error(yr_test, yr_pred))
print('MSE:', metrics.mean_squared_error(yr_test, yr_pred))
print('RMSE:', np.sqrt(metrics.mean_squared_error(yr_test, yr_pred)))
```

```
MAE: 0.2265338386090994
MSE: 0.16643856673807222
RMSE: 0.4079688305962506
```

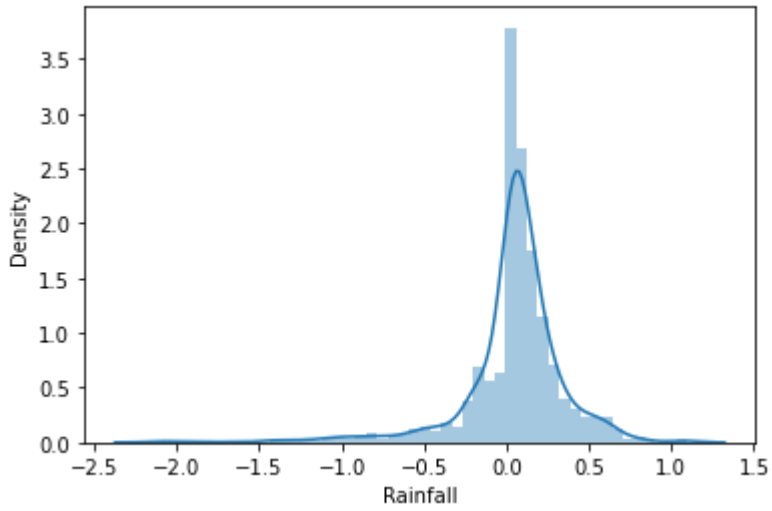
Parameter Tuning using GridSearchCV

In [113]:
```
from sklearn.model_selection import GridSearchCV

param_grid = {"max_depth": np.arange(1,100, 10),
              "n_estimators": np.arange(1,200, 10)}

rf = RandomForestRegressor()

grd = GridSearchCV(rf, param_grid = param_grid)
grd.fit(xr_train, yr_train)

print('Best Param ==>', grd.best_params_)

rf = grd.best_estimator_

rf.fit(xr_train, yr_train)
yr_pred = rf.predict(xr_test)


print('R2 Score: ', rf.score(xr_test, yr_test))

print('Mean Squared Error: ', mean_squared_error(yr_test, yr_pred))
```

```
Best Param ==> {'max_depth': 41, 'n_estimators': 191}
R2 Score:  0.8880814819338959
Mean Squared Error:  0.10602574225719207
```

In [114]:
```
#checking distribution on the test dataset
sns.distplot(rf.predict(xr_test) - yr_test)
```

Out[114]:
```
<AxesSubplot:xlabel='Rainfall', ylabel='Density'>
```



we are getting a normal distribution curve which means that our model Random Forest Regressor is performing correctly.

In [116]:
```
# # Saving the Model

# import joblib
# joblib.dump(rf, "Rainfall_Prediction_Regression.pkl")
```

Out[116]:
```
['Rainfall_Prediction_Regression.pkl']
```

In [ ]: