```
import pandas as pd
import numpy as np

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

from imblearn.over_sampling import SMOTE
from sklearn.linear_model import LogisticRegression
from imblearn.over_sampling import SMOTE
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
from sklearn.model_selection import train_test_split, GridSearchCV

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


# Setting the default styling attributes for seaborn
sns.set_theme(style='darkgrid')


df = pd.read_csv('/content/weatherAUS.csv')



df.shape
```

```
(145460, 23)
```

```
##Exploratory data analysis


##Data Preview
df.head()
```

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSpeed	WindDir9am	...	Humidity9am	Humidity
0	2008-12-01	Albury	13.4	22.9	0.6	NaN	NaN	W	44.0	W	...	71.0	2
1	2008-12-02	Albury	7.4	25.1	0.0	NaN	NaN	WNW	44.0	NNW	...	44.0	2
2	2008-12-03	Albury	12.9	25.7	0.0	NaN	NaN	WSW	46.0	W	...	38.0	3
3	2008-12-04	Albury	9.2	28.0	0.0	NaN	NaN	NE	24.0	SE	...	45.0	1
4	2008-12-05	Albury	17.5	32.3	1.0	NaN	NaN	W	41.0	ENE	...	82.0	3

5 rows × 23 columns

```
df.columns
```

```
Index(['Date', 'Location', 'MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation',
       'Sunshine', 'WindGustDir', 'WindGustSpeed', 'WindDir9am', 'WindDir3pm',
       'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humidity3pm',
       'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Temp9am',
       'Temp3pm', 'RainToday', 'RainTomorrow'],
      dtype='object')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 145460 entries, 0 to 145459
Data columns (total 23 columns):
 #   Column         Non-Null Count   Dtype
```

```
 ---  ------         --------------   -----
  0   Date           145460 non-null  object
  1   Location       145460 non-null  object
  2   MinTemp        143975 non-null  float64
  3   MaxTemp        144199 non-null  float64
  4   Rainfall       142199 non-null  float64
  5   Evaporation    82670 non-null   float64
  6   Sunshine       75625 non-null   float64
  7   WindGustDir    135134 non-null  object
  8   WindGustSpeed  135197 non-null  float64
  9   WindDir9am     134894 non-null  object
  10  WindDir3pm     141232 non-null  object
  11  WindSpeed9am   143693 non-null  float64
  12  WindSpeed3pm   142398 non-null  float64
  13  Humidity9am    142806 non-null  float64
  14  Humidity3pm    140953 non-null  float64
  15  Pressure9am    130395 non-null  float64
  16  Pressure3pm    130432 non-null  float64
  17  Cloud9am       89572 non-null   float64
  18  Cloud3pm       86102 non-null   float64
  19  Temp9am        143693 non-null  float64
  20  Temp3pm        141851 non-null  float64
  21  RainToday      142199 non-null  object
  22  RainTomorrow   142193 non-null  object
dtypes: float64(16), object(7)
memory usage: 25.5+ MB
```

Observations:

The Date column needs converted to a datetime datatype The datatypes for all other columns look good as is There appears to be a large number of missing values across multiple columns Looking into the number of missing values per column as a percentage:

```
round(df.isnull().sum() / len(df),3)
```

	0
Date	0.000
Location	0.000
MinTemp	0.010
MaxTemp	0.009
Rainfall	0.022
Evaporation	0.432
Sunshine	0.480
WindGustDir	0.071
WindGustSpeed	0.071
WindDir9am	0.073
WindDir3pm	0.029
WindSpeed9am	0.012
WindSpeed3pm	0.021
Humidity9am	0.018
Humidity3pm	0.031
Pressure9am	0.104
Pressure3pm	0.103
Cloud9am	0.384
Cloud3pm	0.408
Temp9am	0.012
Temp3pm	0.025
RainToday	0.022
RainTomorrow	0.022

Observations:

Evaporation, Sunshine, Cloud9am, and Cloud3pm are all missing more than 35% of their values Aside from Date and Location, all columns are missing at least some values These missing values can be handled by either dropping certain columns/rows, imputing the values, or a mix of both Next, taking a look at some summary statistics:

```
df.describe()
```

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am	WindSpeed3pm	Humidity9am
count	143975.000000	144199.000000	142199.000000	82670.000000	75625.000000	135197.000000	143693.000000	142398.000000	142806.000000
mean	12.194034	23.221348	2.360918	5.468232	7.611178	40.035230	14.043426	18.662657	68.880831
std	6.398495	7.119049	8.478060	4.193704	3.785483	13.607062	8.915375	8.809800	19.029164
min	-8.500000	-4.800000	0.000000	0.000000	0.000000	6.000000	0.000000	0.000000	0.000000
25%	7.600000	17.900000	0.000000	2.600000	4.800000	31.000000	7.000000	13.000000	57.000000
50%	12.000000	22.600000	0.000000	4.800000	8.400000	39.000000	13.000000	19.000000	70.000000
75%	16.900000	28.200000	0.800000	7.400000	10.600000	48.000000	19.000000	24.000000	83.000000
max	33.900000	48.100000	371.000000	145.000000	14.500000	135.000000	130.000000	87.000000	100.000000

Observations:

Multiple columns have clear outliers (e.g., the max Rainfall value is 371.0 despite the 75th percentile being 0.8) Not seeing any values that are immediate cause for concern (such as a negative value for minimum Rainfall)

In order to get a better feel for the data and catch any placeholder values that may not have shown up in the summary statistics, I also want to check the top five most frequent values for each column.

```
for col in df.columns:
    print('\n')
    print(col)
    print('-'*15)
    print(df[col].value_counts(normalize=True).head())
```

```
Date
---------------
Date
2013-11-12    0.000337
2014-09-01    0.000337
2014-08-23    0.000337
2014-08-24    0.000337
2014-08-25    0.000337
Name: proportion, dtype: float64


Location
---------------
Location
Canberra     0.023622
Sydney       0.022989
Darwin       0.021951
Melbourne    0.021951
Brisbane     0.021951
Name: proportion, dtype: float64


MinTemp
---------------
MinTemp
11.0    0.006244
10.2    0.006237
9.6     0.006223
10.5    0.006140
9.0     0.006057
Name: proportion, dtype: float64


MaxTemp
---------------
MaxTemp
```

```
20.0    0.006137
19.0    0.005846
19.8    0.005825
20.4    0.005784
19.9    0.005707
Name: proportion, dtype: float64


Rainfall
---------------
Rainfall
0.0    0.640511
0.2    0.061611
0.4    0.026597
0.6    0.018228
0.8    0.014459
Name: proportion, dtype: float64


Evaporation
```

Observations:

The value counts of the Date column need further explored on a non-normalized basis There's a disconnect between the Rainfall value counts and the RainToday / RainTomorrow value counts. While roughly 64% of observations had a value of 0 for Rainfall, about 77.5% of days did not have rainfall according to the latter two columns. This discrepency is likely due to differences in the number of missing values for each column

The RainToday and RainTomorrow columns should be converted to 0s and 1s for easier manipulation Further exploring the Date column:

```
df.Date.value_counts()
```

Show hidden output

```
df.Location.nunique()
```

```
49
```

The maximum number of observations for a given date aligns with the number of unique locations within the dataset. This intuitively makes sense because each weather station at the different locations would be reporting their own data for a given day.

Adjusting the RainToday and RainTomorrow columns:

```
df.RainToday = df.RainToday.map({'No': 0, 'Yes': 1})
df.RainToday.value_counts(normalize=True)
```

RainToday	proportion
0.0	0.775807
1.0	0.224193

```
df.RainTomorrow = df.RainTomorrow.map({'No': 0, 'Yes': 1})
df.RainTomorrow.value_counts(normalize=True)
```

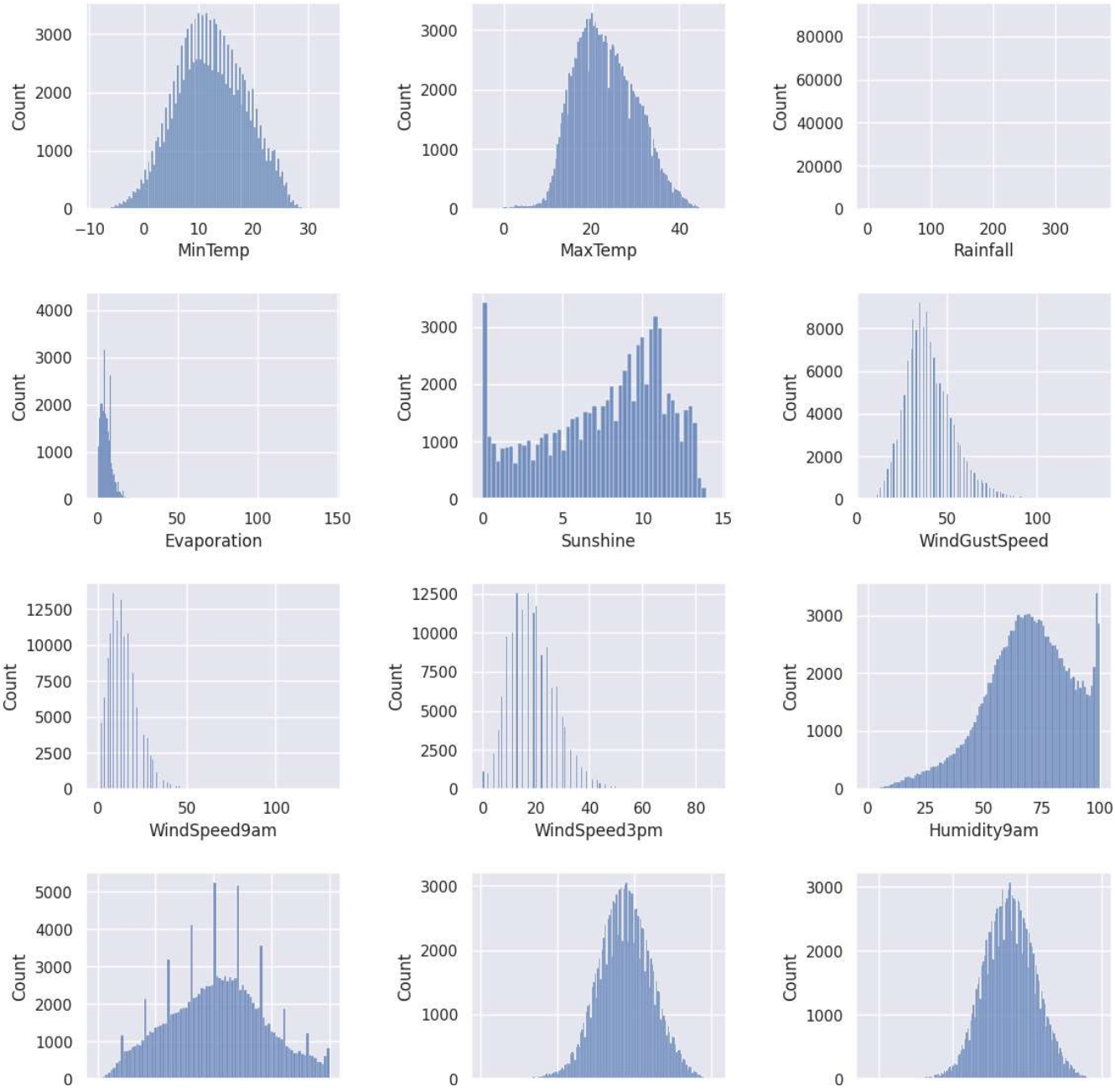
RainTomorrow	proportion
0.0	0.775819
1.0	0.224181

```
fig, axes = plt.subplots(nrows=6, ncols=3, figsize=(12, 18))
axes = axes.reshape(-1)

continuous = [col for col in df.columns if df[col].dtype != object]
for i, col in enumerate(continuous):
    sns.histplot(df[col], ax=axes[i])

fig.tight_layout(pad=2.0)
plt.title('Histograms of Columns')
```

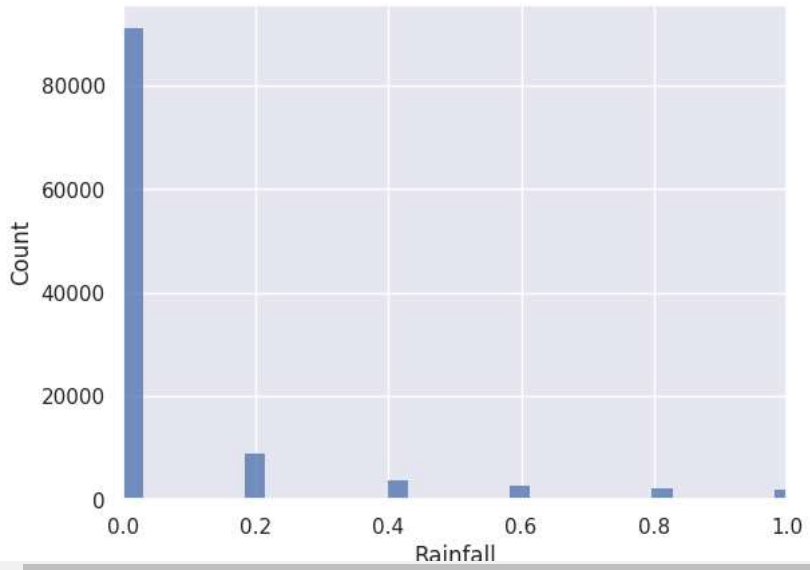
```
Text(0.5, 1.0, 'Histograms of Columns')
```



Observations:

Most features are normally distributed as expected The Rainfall distribution needs further investigation as the large outlier is likely affecting the ability to plot the data The Sunshine distribution is interesting but largely explainable: The high frequency of 0 values represents days where it is overcast all day The abrupt decline in frequency after around 11 hours is a reflection of the limited number of days of the year where it is light out for that many hours or longer The Humidity9am distribution is particularly interesting due to the large spike in frequencies near 100% Since the summary statistics section showed that the 75th percentile for the Rainfall feature is only 0.8, the following plot shows the distribution of values betwen 0 and 1.

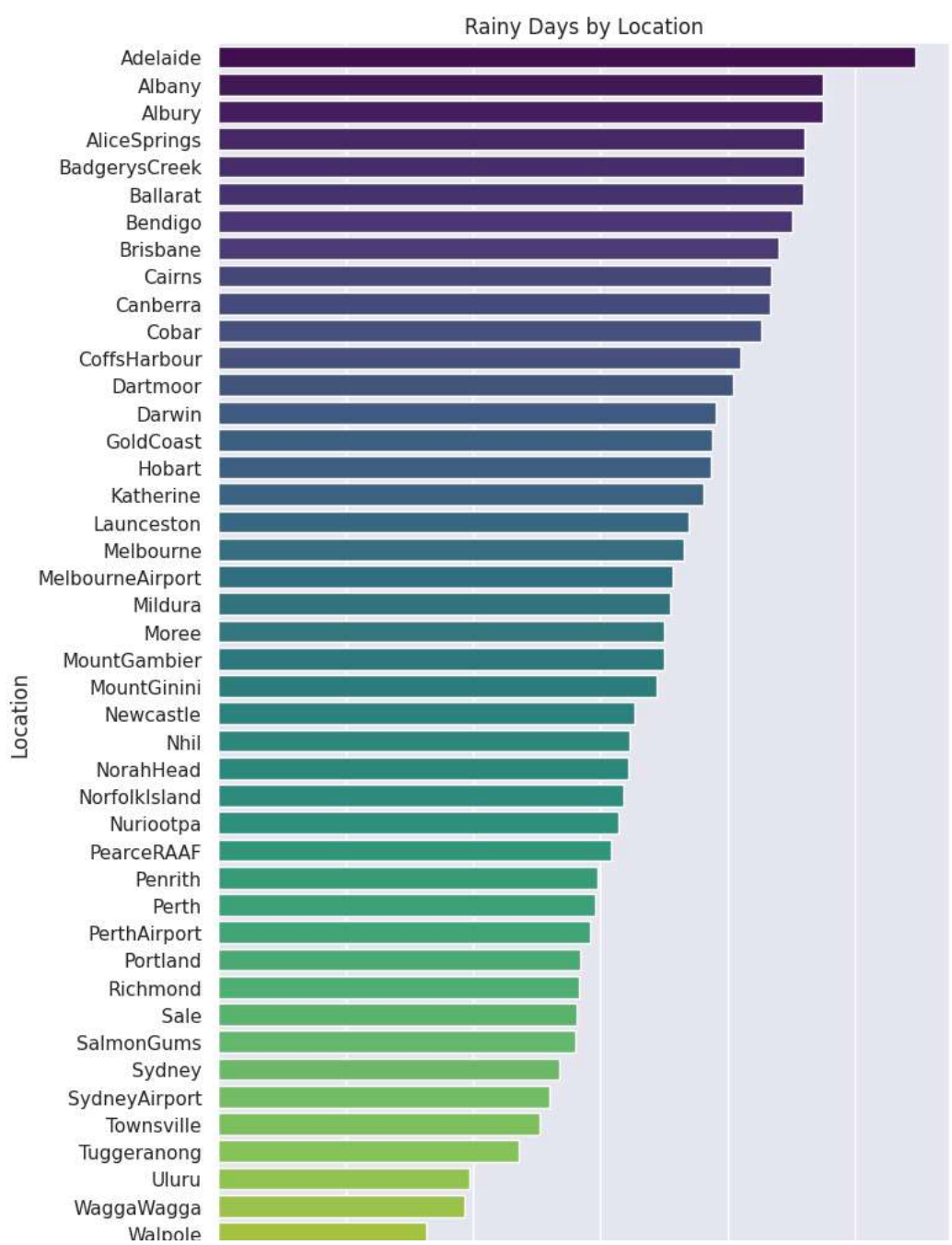
```
sns.histplot(df.Rainfall)
plt.xlim(0, 1);
```




```
df_rain_by_loc = df.groupby(by='Location').sum()
df_rain_by_loc = df_rain_by_loc[['RainToday']]
df_rain_by_loc.head()
```

Location	RainToday
Adelaide	689.0
Albany	902.0
Albury	617.0
AliceSprings	244.0
BadgerysCreek	583.0

```
plt.figure(figsize=(8, 12))
sns.barplot(x='RainToday',
            y=df_rain_by_loc.index,
            data=df_rain_by_loc.sort_values('RainToday', ascending=False),
            orient='h',
            palette='viridis'
           )
plt.xlabel('Number of Days')
plt.title('Rainy Days by Location')
plt.tight_layout()
```



The above chart is useful for a quick check on the differences between locations with regard to the number of rainy days but suffers from one key issue: the number of observations from each location is not exactly the same. Checking the value counts for each location (below) reveals that the locations of Katherine, Nhil, and Uluru should be ignored when analyzing the above plot. The remaining locations have value counts that are close enough to be properly comparabl

```
df.Location.value_counts()
```

Location	count
Canberra	3436
Sydney	3344
Darwin	3193
Melbourne	3193
Brisbane	3193
Adelaide	3193
Perth	3193
Hobart	3193
Albany	3040
MountGambier	3040
Ballarat	3040
Townsville	3040
GoldCoast	3040
Cairns	3040
Launceston	3040
AliceSprings	3040
Bendigo	3040
Albury	3040
MountGinini	3040
Wollongong	3040
Newcastle	3039
Tuggeranong	3039
Penrith	3039
Woomera	3009
Nuriootpa	3009
Cobar	3009
CoffsHarbour	3009
Moree	3009
Sale	3009
PerthAirport	3009

Rainfall exhibits seasonality in many areas of the world. Through grouping the data by month of the year, the percentage of days that it rains in a given month can be easily calculated. Any sort of trend would indicate that the month of the year is a valuable piece of information for modeling purposes.

```
df_seasonality = df.copy()
df_seasonality['month'] = df_seasonality.Date.apply(lambda x: int(str(x)[5:7]))
df_seasonality[['Date', 'month']].head()
```

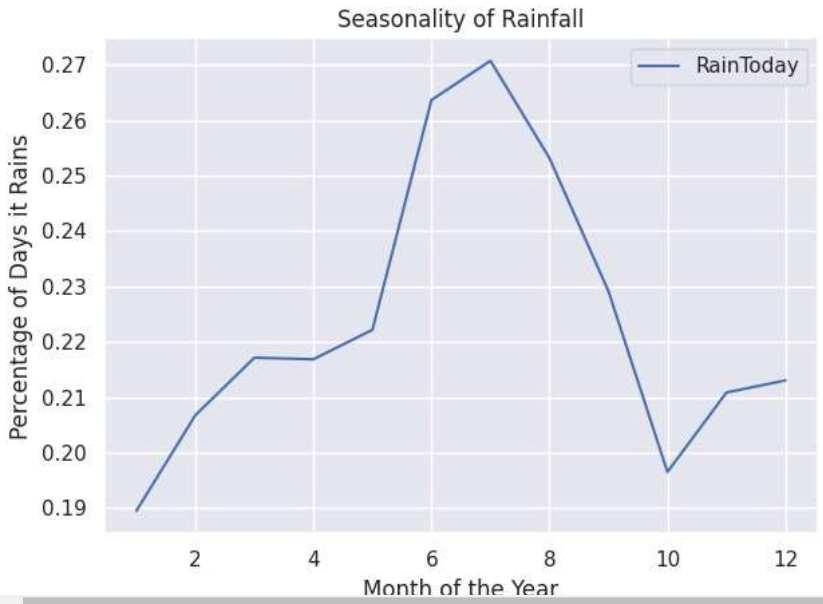
	Date	month
0	2008-12-01	12
1	2008-12-02	12
2	2008-12-03	12
3	2008-12-04	12
4	2008-12-05	12

```
df_seasonality_grouped = df_seasonality.groupby('month')['RainToday'].mean()
df_seasonality_grouped
```

month	RainToday
1	0.189484
2	0.206746
3	0.217135
4	0.216845
5	0.222163
6	0.263638
7	0.270736
8	0.253167
9	0.229135
10	0.196512
11	0.210843
12	0.213037

```
# Convert the pandas Series to a DataFrame
df_seasonality_grouped = df_seasonality_grouped.to_frame()

# Create the line plot
sns.lineplot(data=df_seasonality_grouped)
plt.title('Seasonality of Rainfall')
plt.xlabel('Month of the Year')
plt.ylabel('Percentage of Days it Rains')
plt.tight_layout()
plt.show()
```



Rainfall in Australia clearly has a degree of seasonality.

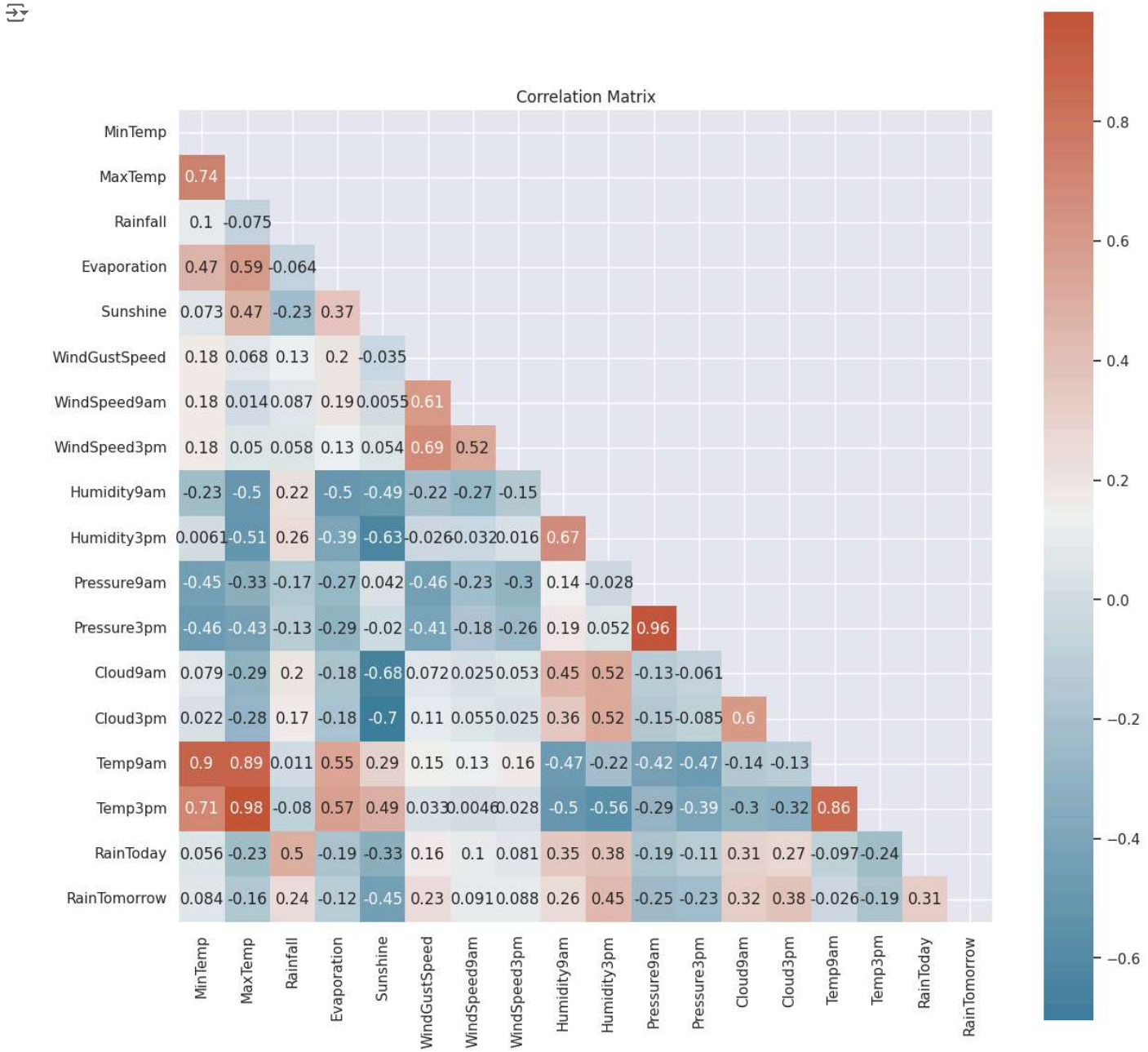
```
# Select only the numerical columns
numerical_columns = df.select_dtypes(include=['int64', 'float64']).columns

# Create the correlation matrix
corr_matrix = df[numerical_columns].corr()

# Creating a mask to block the top right half of the heatmap (redundant information)
mask = np.triu(np.ones_like(corr_matrix))

# Custom color map
cmap = sns.diverging_palette(230, 20, as_cmap=True)

# Create the heatmap
plt.figure(figsize=(14, 14))
sns.heatmap(corr_matrix, mask=mask, cmap=cmap, annot=True, square=True)
plt.title('Correlation Matrix')
plt.show()
```



Observations:

Nothing in this correlation heatmap is surprising Features with strong correlations (either positive or negative) have intuitive reasons for being so

Data Preprocessing Missing Values The primary preprocessing need for this dataset is handling the missing values. Given the strong correlations between certain features, using a multivariate feature imputation method makes sense. While still experimental, the IterativeImputer module from sklearn is perfect for this use case and appears stable enough. This module...

"...models each feature with missing values as a function of other features, and uses that estimate for imputation. It does so in an iterated round-robin fashion: at each step, a feature column is designated as output y and the other feature columns are treated as inputs X. A regressor is fit on (X, y) for known y. Then, the regressor is used to predict the missing values of y. This is done for each feature in an iterative fashion, and then is repeated for max_iter imputation rounds. The results of the final imputation round are returned."

Source: 6.4.3. Multivariate feature imputation

I do not want to impute values for the target variable (RainTomorrow) since this will detract from the ground truth and have potential negative effects on the model. To start, I'll drop rows in which the RainTomorrow value is missing.

```
df_imputed = df.dropna(axis=0, subset=['RainTomorrow'])
df_imputed.isna().sum()
```

	0
Date	0
Location	0
MinTemp	637
MaxTemp	322
Rainfall	1406
Evaporation	60843
Sunshine	67816
WindGustDir	9330
WindGustSpeed	9270
WindDir9am	10013
WindDir3pm	3778
WindSpeed9am	1348
WindSpeed3pm	2630
Humidity9am	1774
Humidity3pm	3610
Pressure9am	14014
Pressure3pm	13981
Cloud9am	53657
Cloud3pm	57094
Temp9am	904
Temp3pm	2726
RainToday	1406
RainTomorrow	0

Continuous Features For the continuous features, I'll apply the IterativeImputer.

```
cont_feats = [col for col in df_imputed.columns if df_imputed[col].dtype != object]
cont_feats.remove('RainTomorrow')
cont_feats
```

```
['MinTemp',
 'MaxTemp',
 'Rainfall',
 'Evaporation',
 'Sunshine',
 'WindGustSpeed',
 'WindSpeed9am',
 'WindSpeed3pm',
```

```
        'Humidity9am',
        'Humidity3pm',
        'Pressure9am',
        'Pressure3pm',
        'Cloud9am',
        'Cloud3pm',
        'Temp9am',
        'Temp3pm',
        'RainToday']
```

```
imputer = IterativeImputer(random_state=42)
df_imputed_cont = imputer.fit_transform(df_imputed[cont_feats])
df_imputed_cont = pd.DataFrame(df_imputed_cont, columns=cont_feats)
df_imputed_cont.head()
```

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am	WindSpeed3pm	Humidity9am	Humidity3pm	Pressure9am
0	13.4	22.9	0.6	6.497888	7.048211	44.0	20.0	24.0	71.0	22.0	1007.7
1	7.4	25.1	0.0	6.270412	10.863393	44.0	4.0	22.0	44.0	25.0	1010.6
2	12.9	25.7	0.0	8.659380	11.812408	46.0	19.0	26.0	38.0	30.0	1007.6
3	9.2	28.0	0.0	6.764941	11.542532	24.0	11.0	9.0	45.0	16.0	1017.6
4	17.5	32.3	1.0	7.455971	5.520080	41.0	7.0	20.0	82.0	33.0	1010.8

```
df_imputed_cont.isna().sum()
```

```
MinTemp          0
MaxTemp          0
Rainfall         0
Evaporation      0
Sunshine         0
WindGustSpeed    0
WindSpeed9am     0
WindSpeed3pm     0
Humidity9am      0
Humidity3pm      0
Pressure9am      0
Pressure3pm      0
Cloud9am         0
Cloud3pm         0
Temp9am          0
Temp3pm          0
RainToday        0
dtype: int64
```

Categorical Features For the categorical features, I'll be replacing the missing values with a randomly chosen option from the unique values of each feature according to their probability distribution.

```
cat_feats = [col for col in df_imputed.columns if col not in cont_feats]
cat_feats.remove('RainTomorrow')

# Also removing Date and Location since no values are missing
cat_feats.remove('Date')
cat_feats.remove('Location')
cat_feats
```

```
['WindGustDir', 'WindDir9am', 'WindDir3pm']
```

```
df_imputed_cat = df_imputed[cat_feats]

for col in df_imputed_cat.columns:
    # Get values and probabilities without renaming the index
    value_counts = df_imputed_cat.WindDir3pm.value_counts()
    values = value_counts.index.values
    probs = value_counts.values / value_counts.sum()  # Normalize probabilities

    df_imputed_cat[col].replace(np.nan, np.random.choice(a=values, p=probs), inplace=True)

df_imputed_cat.head()
```

	WindGustDir	WindDir9am	WindDir3pm
0	W	W	WNW
1	WNW	NNW	WSW
2	WSW	W	WSW
3	NE	SE	E
4	W	ENE	NW

```
df_imputed_cat.isna().sum()
```

```
WindGustDir    0
WindDir9am     0
WindDir3pm     0
dtype: int64
```

```
df_date_loc = df_imputed[['Date', 'Location']]
df_target = df_imputed.RainTomorrow

print(df_date_loc.shape)
print(df_imputed_cont.shape)
print(df_imputed_cat.shape)
print(df_target.shape)
```

```
(142193, 2)
(142193, 17)
(142193, 3)
(142193,)
```

```
df_imputed_final = pd.concat(objs=[df_date_loc.reset_index(drop=True),
                                   df_imputed_cont.reset_index(drop=True),
                                   df_imputed_cat.reset_index(drop=True),
                                   df_target.reset_index(drop=True)
                                  ],
                             axis=1
                            )
df_imputed_final.shape
```

```
(142193, 23)
```

```
df_imputed_final.head()
```

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am	WindSpeed3pm	...	Pressure3pm	Clou
0	2008-12-01	Albury	13.4	22.9	0.6	6.497888	7.048211	44.0	20.0	24.0	...	1007.1	8.00
1	2008-12-02	Albury	7.4	25.1	0.0	6.270412	10.863393	44.0	4.0	22.0	...	1007.8	1.91
2	2008-12-03	Albury	12.9	25.7	0.0	8.659380	11.812408	46.0	19.0	26.0	...	1008.7	2.01
3	2008-12-04	Albury	9.2	28.0	0.0	6.764941	11.542532	24.0	11.0	9.0	...	1012.8	1.20
4	2008-12-05	Albury	17.5	32.3	1.0	7.455971	5.520080	41.0	7.0	20.0	...	1006.0	7.00

5 rows × 23 columns

```
df_imputed_final.isna().sum()
```

```
Date             0
Location         0
MinTemp          0
MaxTemp          0
Rainfall         0
Evaporation      0
Sunshine         0
WindGustSpeed    0
WindSpeed9am     0
WindSpeed3pm     0
Humidity9am      0
```

```
Humidity3pm      0
Pressure9am      0
Pressure3pm      0
Cloud9am         0
Cloud3pm         0
Temp9am          0
Temp3pm          0
RainToday        0
WindGustDir      0
WindDir9am       0
WindDir3pm       0
RainTomorrow     0
dtype: int64
```

Double-click (or enter) to edit

Extracting the Month As seen in the EDA section, rainfall in Australia exhibits seasonality. Instead of using the full date from the Date column, extracting just the month is much more valuable

```
df_month = df_imputed_final.copy()
df_month.insert(1, 'Month', df_month.Date.apply(lambda x: int(str(x)[5:7])))
df_month.drop(columns='Date', inplace=True)
df_month.head()
```

	Month	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am	WindSpeed3pm	...	Pressure3pm	Clou
0	12	Albury	13.4	22.9	0.6	6.497888	7.048211	44.0	20.0	24.0	...	1007.1	8.00
1	12	Albury	7.4	25.1	0.0	6.270412	10.863393	44.0	4.0	22.0	...	1007.8	1.91
2	12	Albury	12.9	25.7	0.0	8.659380	11.812408	46.0	19.0	26.0	...	1008.7	2.01
3	12	Albury	9.2	28.0	0.0	6.764941	11.542532	24.0	11.0	9.0	...	1012.8	1.20
4	12	Albury	17.5	32.3	1.0	7.455971	5.520080	41.0	7.0	20.0	...	1006.0	7.00

5 rows × 23 columns

```
rain_today_counts = df_month['RainToday'].value_counts()
print("RainToday counts:")
print(rain_today_counts)

# Count occurrences of 0 and 1 in 'RainTomorrow'
rain_tomorrow_counts = df_month['RainTomorrow'].value_counts()
print("\nRainTomorrow counts:")
print(rain_tomorrow_counts)
```

```
RainToday counts:
RainToday
 0.000000    109332
 1.000000     31455
 0.223905         5
-0.212430         1
 0.059504         1
              ...
 0.821150         1
 0.543710         1
 0.661142         1
 0.480625         1
-0.123669         1
Name: count, Length: 1404, dtype: int64

RainTomorrow counts:
RainTomorrow
0.0    110316
1.0     31877
Name: count, dtype: int64
```

Dummy Variables All categorical features now need transformed into dummy variables in order to be useable in the modeling section.

```
categoricals = ['Month', 'Location', 'WindGustDir', 'WindDir9am', 'WindDir3pm']
df_dummies = pd.get_dummies(df_month, columns=categoricals ,  dtype=int)
df_dummies.head()
```

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am	WindSpeed3pm	Humidity9am	Humidity3pm	...	WindDir3
0	13.4	22.9	0.6	6.497888	7.048211	44.0	20.0	24.0	71.0	22.0	...	
1	7.4	25.1	0.0	6.270412	10.863393	44.0	4.0	22.0	44.0	25.0	...	
2	12.9	25.7	0.0	8.659380	11.812408	46.0	19.0	26.0	38.0	30.0	...	
3	9.2	28.0	0.0	6.764941	11.542532	24.0	11.0	9.0	45.0	16.0	...	
4	17.5	32.3	1.0	7.455971	5.520080	41.0	7.0	20.0	82.0	33.0	...	

5 rows × 127 columns

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MODELING

```
df_final = df_dummies.copy()
X = df_final.drop(columns='RainTomorrow')
y = df_final.RainTomorrow

X_train, X_test, y_train, y_test = train_test_split(X, y,test_size=0.3, random_state=42)

print('Train size:', X_train.shape[0])
print('Test size: ', X_test.shape[0])
```

```
Train size: 99535
Test size:  42658
```

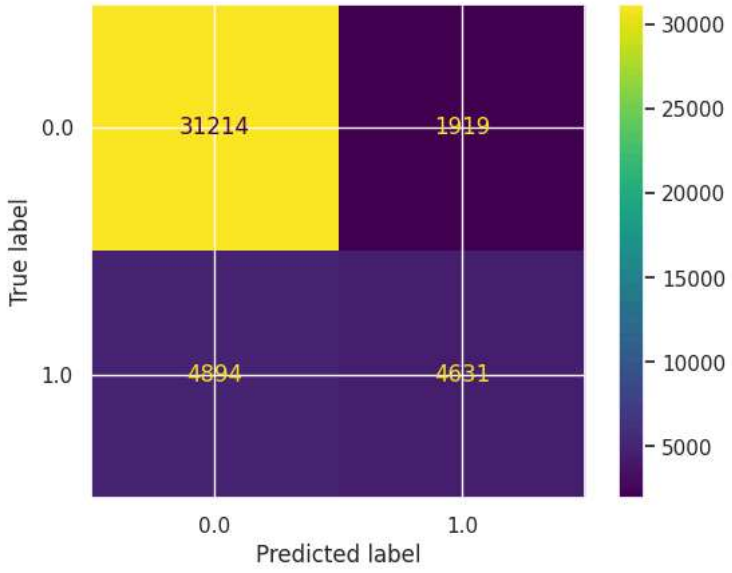
LOGISTIC

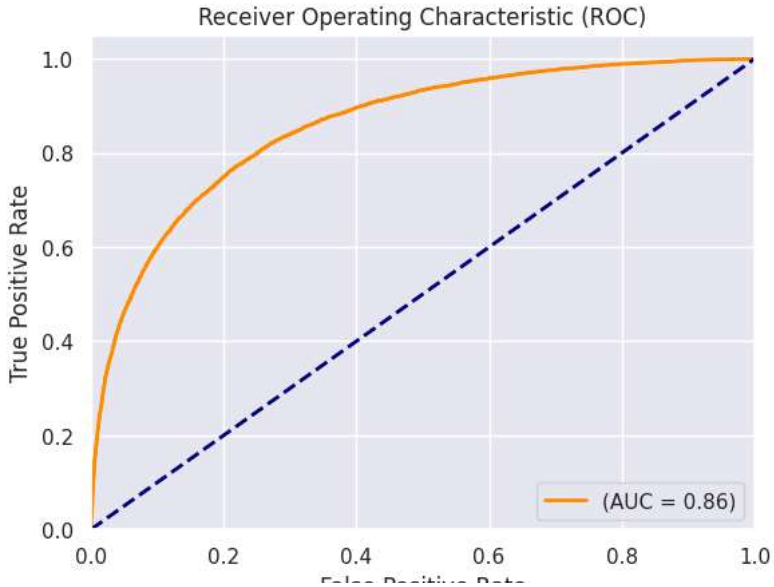
```
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
y_pred = logreg.predict(X_test)
y_pred
```

```
array([1., 0., 0., ..., 0., 1., 0.])
```

```
from sklearn.metrics import (accuracy_score, precision_score, recall_score,
                             f1_score, confusion_matrix, ConfusionMatrixDisplay,
                             roc_curve, auc)
import matplotlib.pyplot as plt

def evaluate_model(model, X_train, y_train, X_test, y_test):
    # Make predictions
    y_pred = model.predict(X_test)
    y_proba = model.predict_proba(X_test)[:, 1]  # For ROC AUC curve

    # Calculate metrics
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    f1_sc = f1_score(y_test, y_pred)
    conf_matrix = confusion_matrix(y_test, y_pred)

    # Training and testing scores
    train_score = model.score(X_train, y_train)
    test_score = model.score(X_test, y_test)

    # ROC AUC curve
    fpr, tpr, _ = roc_curve(y_test, y_proba)
    roc_auc = auc(fpr, tpr)

    # Print metrics
    print(f"Accuracy: {accuracy:.4f}")
    print(f"Precision: {precision:.4f}")
    print(f"Recall: {recall:.4f}")
    print(f"F1 Score: {f1_sc:.4f}")
    print(f"Training Score: {train_score:.4f}")
    print(f"Testing Score: {test_score:.4f}")
    print(f"ROC AUC: {roc_auc:.4f}")

    # Display confusion matrix
    disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix, display_labels=model.classes_)
    disp.plot()

    # Plot ROC curve
    plt.figure()
    plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'(AUC = {roc_auc:.2f})')
    plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC)')
    plt.legend(loc='lower right')
    plt.show()

    return accuracy, precision, recall, f1_sc, train_score, test_score, roc_auc



evaluate_model(logreg, X_train, y_train, X_test, y_test)
```

```
Accuracy: 0.8403
Precision: 0.7070
Recall: 0.4862
F1 Score: 0.5762
Training Score: 0.8420
Testing Score: 0.8403
ROC AUC: 0.8580
```





Observations:

Decent performance for a baseline model

Recall is the weakest point, particularly for days where it does rain tomorrow

The model is well fit, with both the train and test scores approximately the same

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Correcting Class Imbalance A class imbalance currently exists for the target variable. Correcting for this may help improve model performance. To do so, I will resample the training data using SMOTE.

```
X_train_resampled, y_train_resampled = SMOTE().fit_resample(X_train, y_train)

print('Original')
print('-'*20)
print(y_train.value_counts())
print('\n')
print('SMOTE')
print('-'*20)
print(pd.Series(y_train_resampled).value_counts())
```

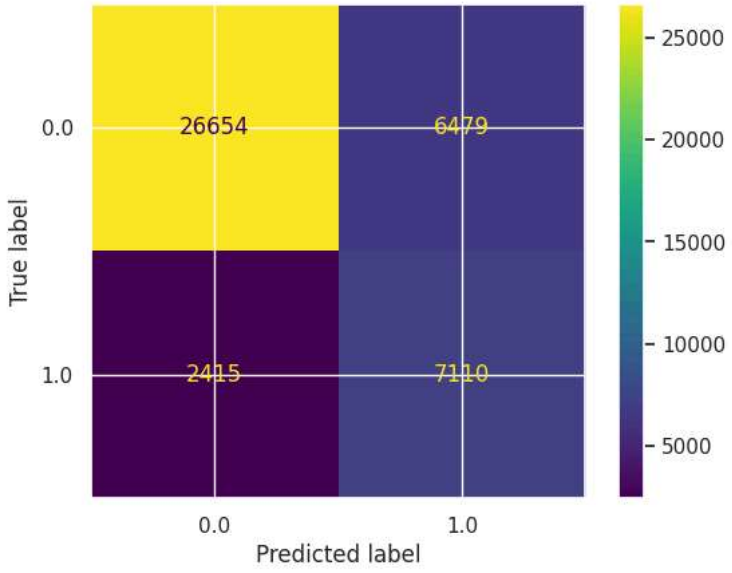
```
Original
--------------------
RainTomorrow
0.0    77183
1.0    22352
Name: count, dtype: int64


SMOTE
--------------------
RainTomorrow
0.0    77183
1.0    77183
Name: count, dtype: int64
```

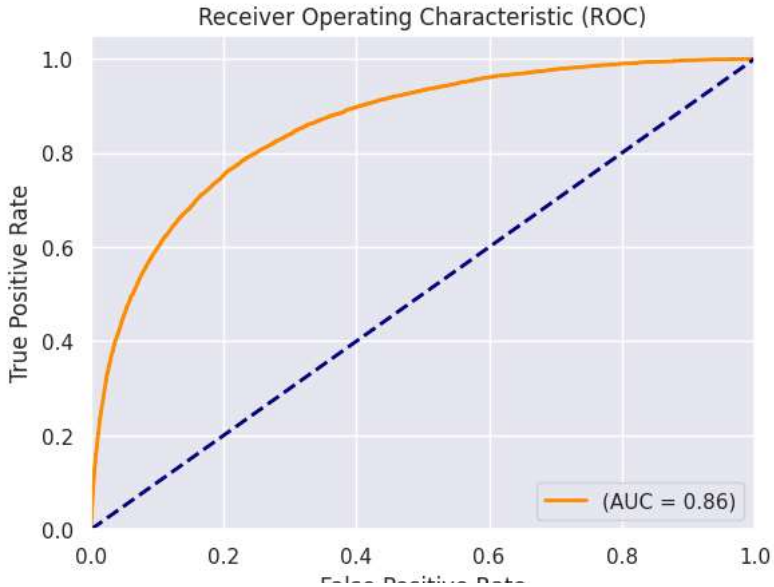
```
logreg_smote = LogisticRegression(random_state=42)
logreg_smote.fit(X_train_resampled, y_train_resampled)
y_pred_smote = logreg_smote.predict(X_test)
y_pred_smote
```

```
array([1., 1., 0., ..., 0., 1., 0.])
```

```
evaluate_model(logreg_smote, X_train_resampled,y_train_resampled, X_test, y_test)
```

```
Accuracy: 0.7915
Precision: 0.5232
Recall: 0.7465
F1 Score: 0.6152
Training Score: 0.7910
Testing Score: 0.7915
ROC AUC: 0.8582
```





Observations:

Despite a slight increase in the positive F1 score, the accuracy of this model sharply decreased This model remains well fit but scores for both the train and test sets decreased Contrary to my initial thoughts, using SMOTE actually had worse performance and will not be utilized in subsequent iterations

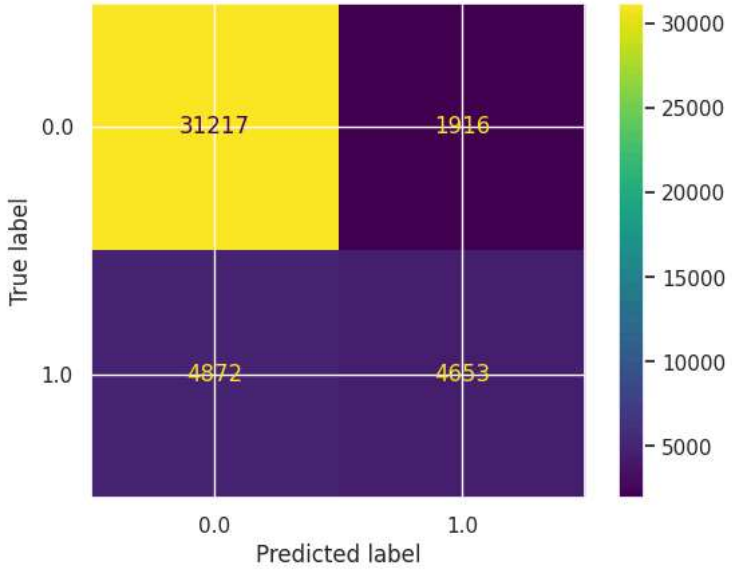
Hyperparameter Tuning

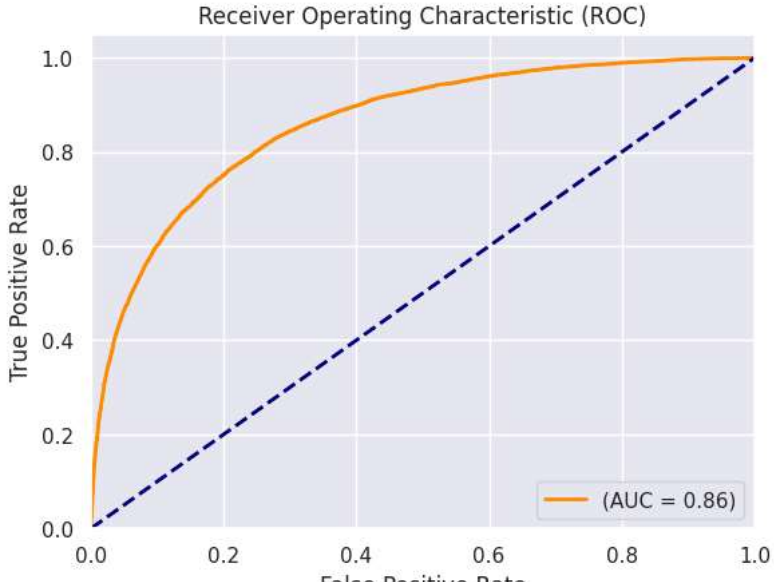
```
'''logreg_params = {
    'C': [1, 1e8, 1e16],
    'fit_intercept': [True, False],
    'max_iter': [50, 100, 150],
    'random_state': [42]
}

logreg_gs = GridSearchCV(logreg_smote, logreg_params, scoring='f1', cv=3)
logreg_gs.fit(X_train, y_train)'''
```

```
GridSearchCV
estimator: LogisticRegression
LogisticRegression
```

```
'''evaluate_model(logreg_gs, X_train_resampled, y_train_resampled, X_test, y_test)'''
```

```
Accuracy: 0.8409
Precision: 0.7083
Recall: 0.4885
F1 Score: 0.5782
Training Score: 0.6355
Testing Score: 0.5782
ROC AUC: 0.8597
```





Observations:

Slight improvements in precision and model fitness Overall, not much improvement over the baseline logreg model

```
0.5782279110227414,
```

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```
0.8596598153326691)
```

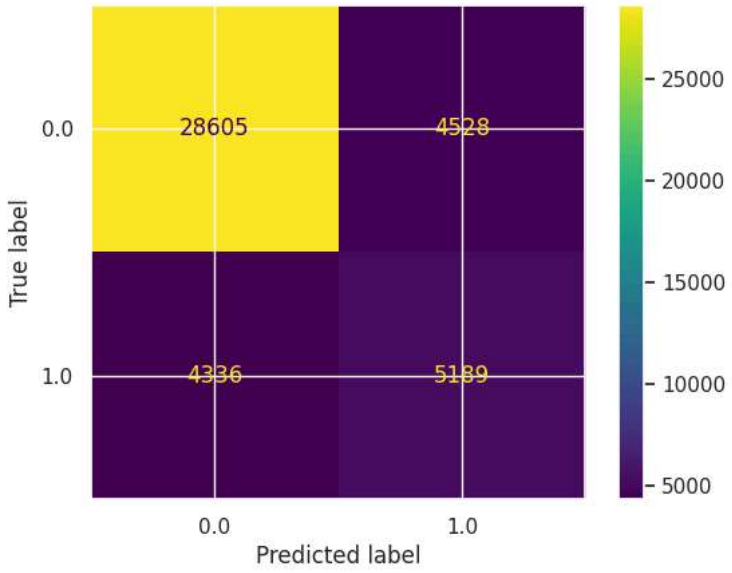
Decision Tree

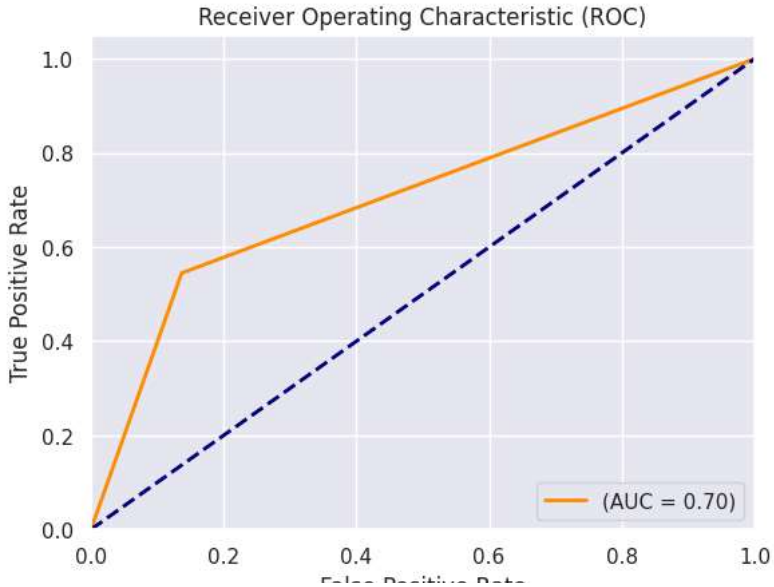
```
clf = DecisionTreeClassifier()
clf.fit(X_train, y_train)
y_pred_tree = clf.predict(X_test)
y_pred_tree
```

```
array([1., 0., 0., ..., 0., 1., 0.])
```

```
evaluate_model(clf, X_train, y_train, X_test, y_test)
```

```
Accuracy: 0.7922
Precision: 0.5340
Recall: 0.5448
F1 Score: 0.5393
Training Score: 1.0000
Testing Score: 0.7922
ROC AUC: 0.7041
```





Observations:

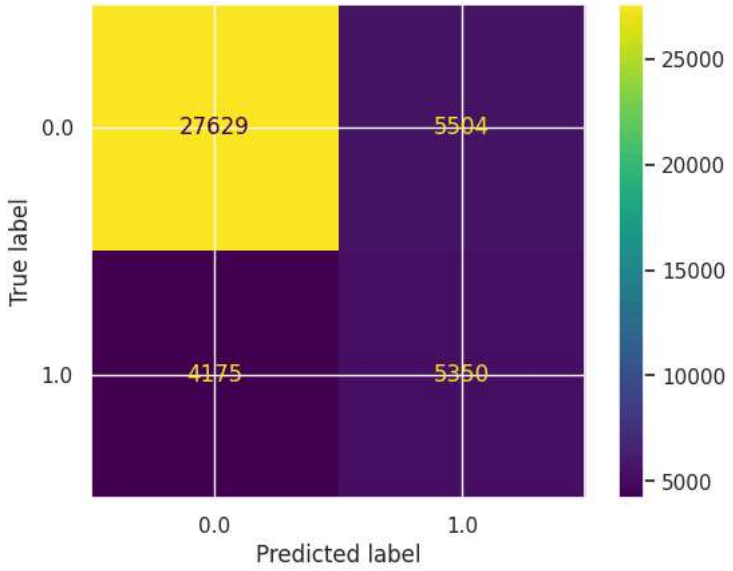
The accuracy is lower than the tuned logisitic regression model The model is overfit, given by the much higher score for the train data versus the test data

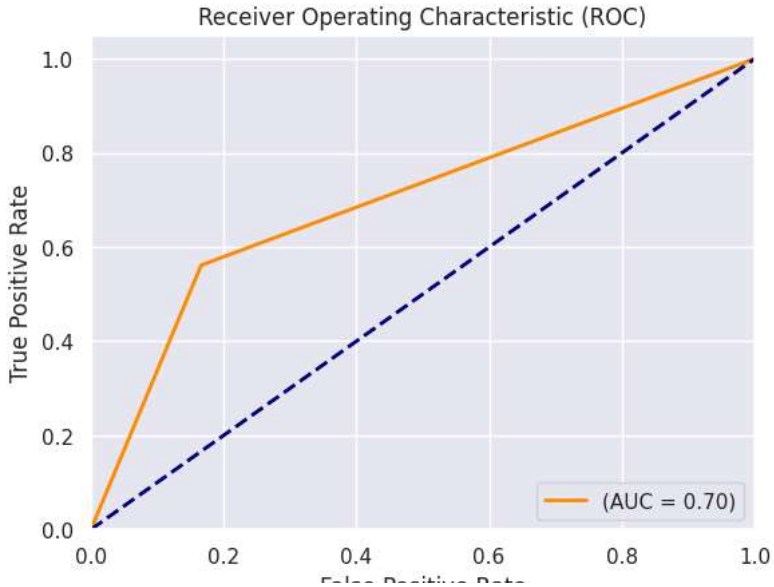
```
clf_smote = DecisionTreeClassifier()
clf_smote.fit(X_train_resampled, y_train_resampled)
y_pred_smote = clf_smote.predict(X_test)
y_pred_smote
```

```
array([0., 0., 0., ..., 0., 1., 1.])
```

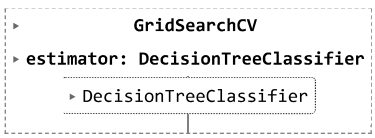
```
evaluate_model(clf_smote, X_train_resampled, y_train_resampled, X_test, y_test)
```

```
Accuracy: 0.7731
Precision: 0.4929
Recall: 0.5617
F1 Score: 0.5251
Training Score: 1.0000
Testing Score: 0.7731
ROC AUC: 0.6978
```



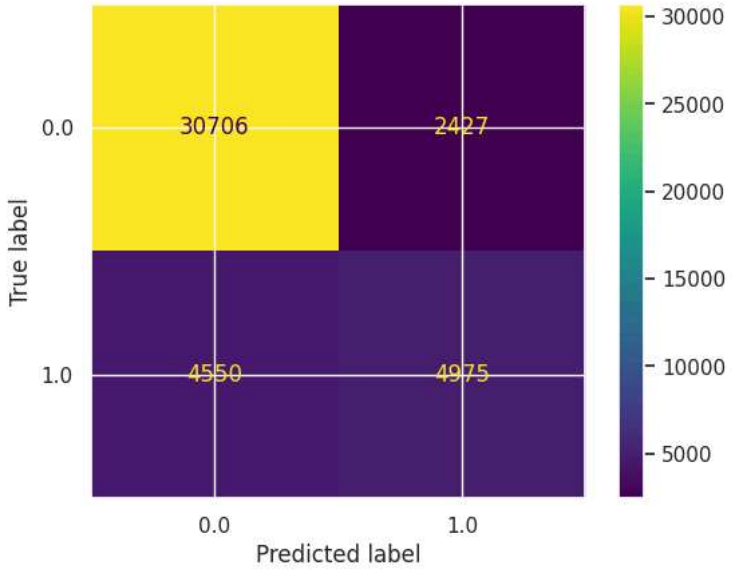


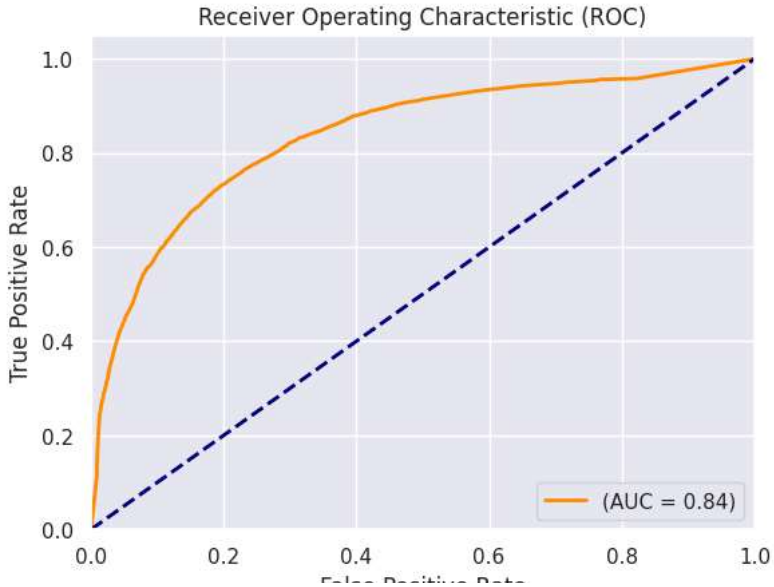

```
'''params = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [3, 7, 11],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 3, 5],
    'random_state': [42]
}

clf_gs = GridSearchCV(clf_smote, param_grid=params, scoring='f1', cv=3)
clf_gs.fit(X_train, y_train)'''
```




```
evaluate_model(clf_gs, X_train_resampled, y_train_resampled, X_test, y_test)
```

```
Accuracy: 0.8364
Precision: 0.6721
Recall: 0.5223
F1 Score: 0.5878
Training Score: 0.7018
Testing Score: 0.5878
ROC AUC: 0.8373
```





Observations:

Solid increases in the evaluation metrics The tuned model is much better fit than the baseline model which showed overfitness

```
0.5878182784899865,
```

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```
0.8373462763175188)
```

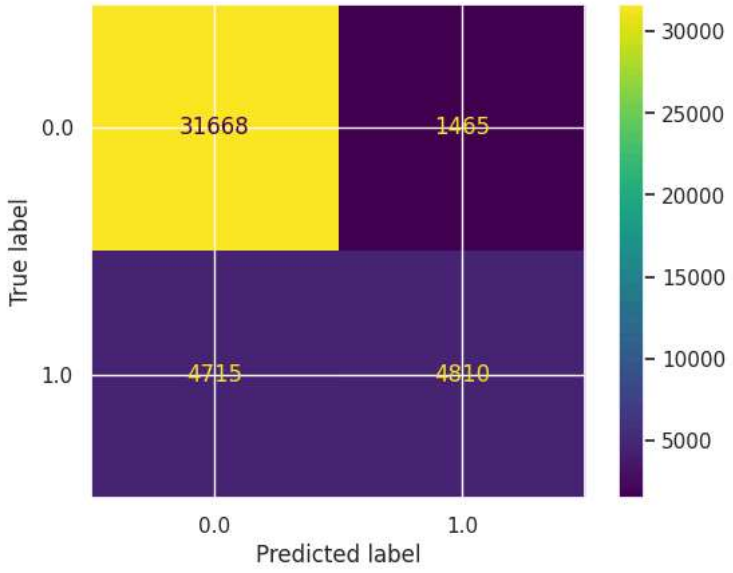
Random Forest

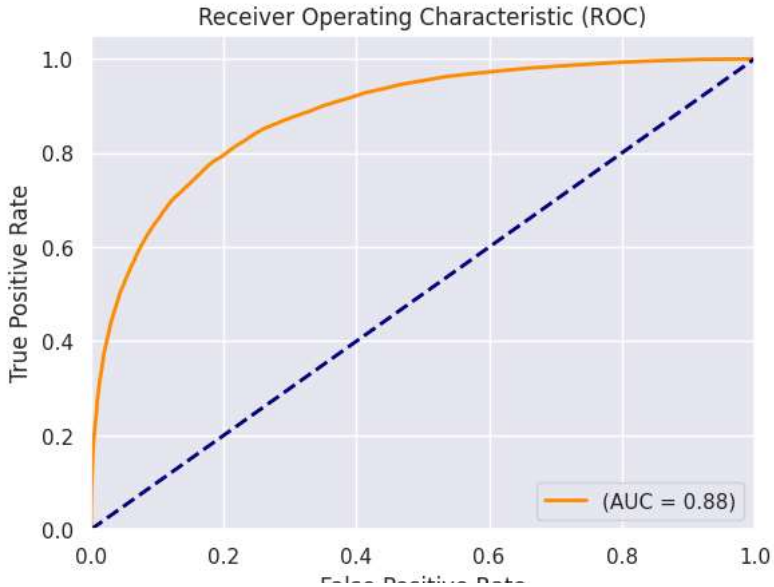
```
rf = RandomForestClassifier()
rf.fit(X_train, y_train)
y_pred_rf = rf.predict(X_test)
y_pred_rf
```

```
array([1., 0., 0., ..., 0., 1., 0.])
```

```
evaluate_model(rf, X_train, y_train, X_test, y_test)
```

```
Accuracy: 0.8551
Precision: 0.7665
Recall: 0.5050
F1 Score: 0.6089
Training Score: 1.0000
Testing Score: 0.8551
ROC AUC: 0.8827
```





Observations:

Good scores on the evaluation metrics The model is a bit overfit

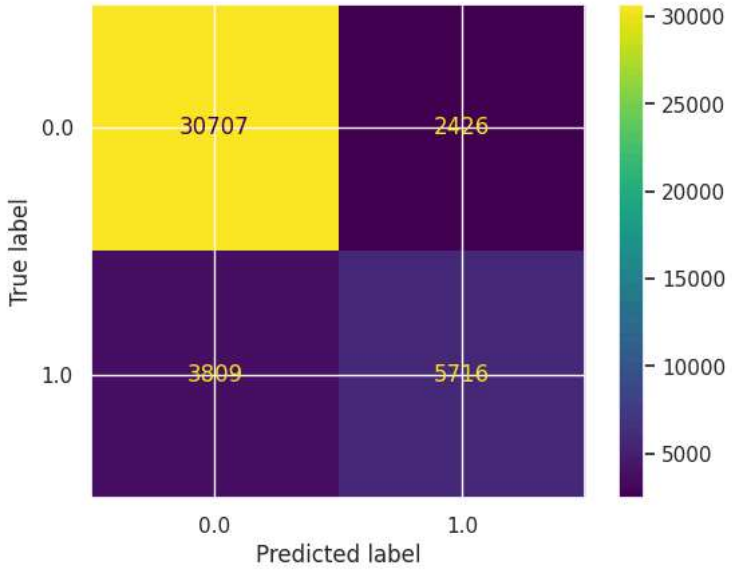
```
0.6088607594936709,
```

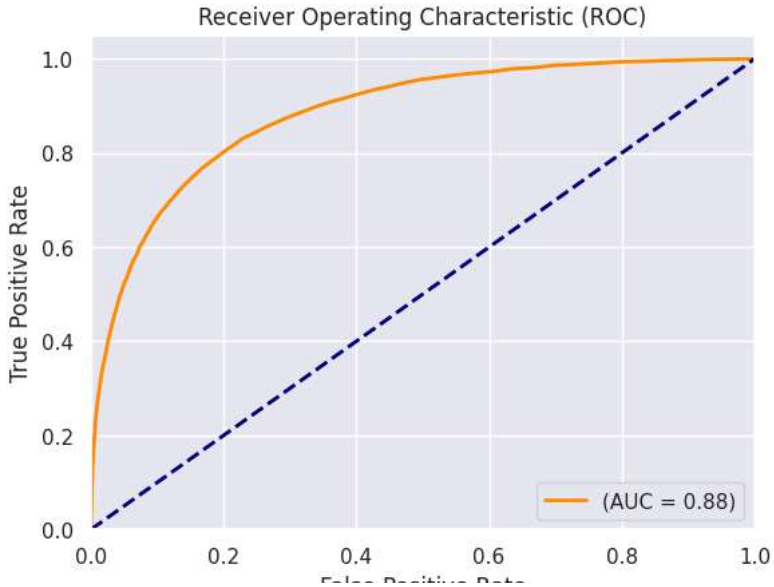
```
rf_smote = RandomForestClassifier()
rf_smote.fit(X_train_resampled, y_train_resampled)
y_pred_smote = rf_smote.predict(X_test)
y_pred_smote
```

```
array([1., 0., 0., ..., 0., 0., 0.])
```

```
evaluate_model(rf_smote, X_train_resampled, y_train_resampled, X_test, y_test)
```

```
Accuracy: 0.8538
Precision: 0.7020
Recall: 0.6001
F1 Score: 0.6471
Training Score: 1.0000
Testing Score: 0.8538
ROC AUC: 0.8842
```






```
from sklearn.utils import shuffle

# Shuffle and sample 20% of the data
X_train_sample, y_train_sample = shuffle(X_train_resampled, y_train_resampled, random_state=42)
X_train_sample = X_train_sample[:int(0.2 * len(X_train))]
y_train_sample = y_train_sample[:int(0.2 * len(y_train))]

rf_params = {
    'n_estimators': [10, 35, 100],
    'criterion': ['gini', 'entropy'],
    'max_depth': [3, 7, 11],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 3, 5],
    'random_state': [42]
}

rf_gs = GridSearchCV(rf_smote, param_grid=rf_params, scoring='f1', cv=3)
rf_gs.fit(X_train_sample, y_train_sample)
```

```
GridSearchCV
estimator: RandomForestClassifier
RandomForestClassifier
```

```
best_params = rf_gs.best_params_
rf_best = RandomForestClassifier(**best_params)
rf_best.fit(X_train_resampled, y_train_resampled)
y_pred_best = rf_best.predict(X_test)
y_pred_best
```

```
array([1., 0., 0., ..., 0., 1., 0.])
```

```
rf_params = {
    'n_estimators': [10, 35, 100],
    'criterion': ['gini', 'entropy'],
    'max_depth': [3, 7, 11],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 3, 5],
    'random_state': [42]
}

rf_gs = GridSearchCV(rf_smote, param_grid=rf_params, scoring='accuracy', cv=3)
rf_gs.fit(X_train, y_train)
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
<ipython-input-58-fe420f2b86cb> in <cell line: 11>()
      9
     10 rf_gs = GridSearchCV(rf_smote, param_grid=rf_params, scoring='accuracy', cv=3)
---> 11 rf_gs.fit(X_train, y_train)

18 frames
/usr/local/lib/python3.10/dist-packages/sklearn/tree/_classes.py in _fit(self, X, y, sample_weight, check_input,
missing_values_in_feature_mask)
    441             )
    442
--> 443         builder.build(self.tree_, X, y, sample_weight, missing_values_in_feature_mask)
    444
    445         if self.n_outputs_ == 1 and is_classifier(self):
```

```
rf_gs.best_params_
```

```
{'criterion': 'gini',
 'max_depth': 11,
 'min_samples_leaf': 1,
 'min_samples_split': 10,
 'n_estimators': 100,
 'random_state': 42}
```

```
round(rf_gs.best_score_, 4)
```

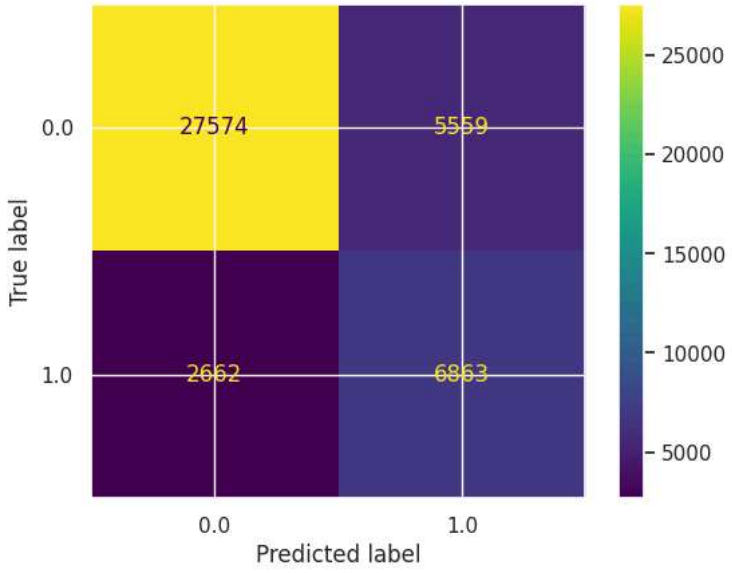
```
0.8309
```

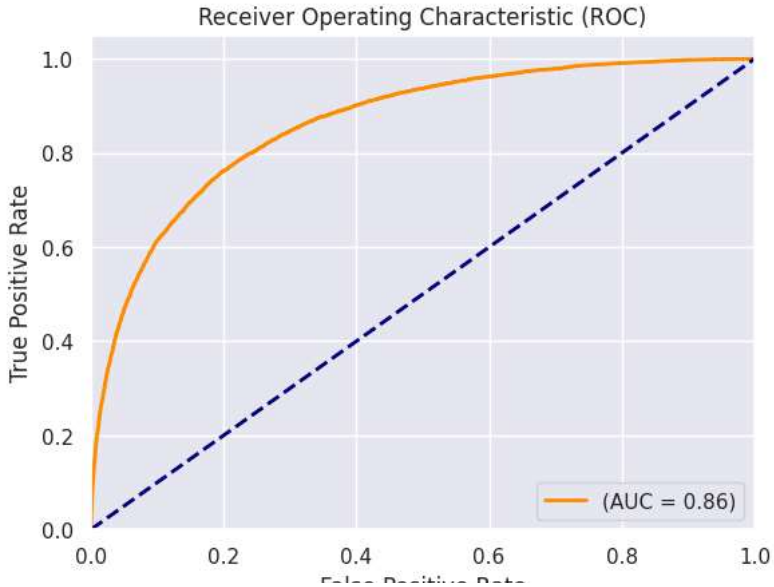
```
y_pred_rf_gs = rf_gs.predict(X_test)
y_pred_rf_gs
```

```
array([1., 1., 0., ..., 0., 1., 0.])
```

```
evaluate_model(rf_gs,  X_train_resampled, y_train_resampled, X_test, y_test)
```

```
Accuracy: 0.8073
Precision: 0.5525
Recall: 0.7205
F1 Score: 0.6254
Training Score: 0.8379
Testing Score: 0.6254
ROC AUC: 0.8628
```





Observations:

The accuracy score remained roughly the same while the F1 score decreased Small increase in the AUC of the ROC curve Furthermore, the tuned model has a much better fit than the baseline model

Start coding or generate with AI.

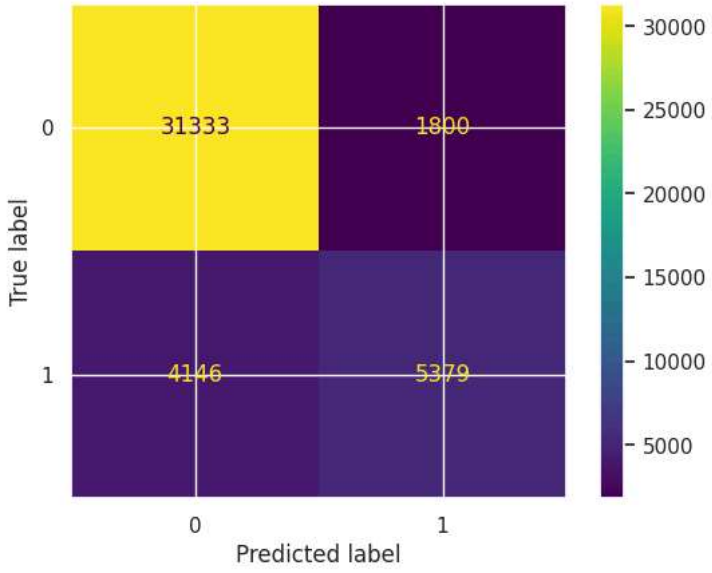
XGBoost

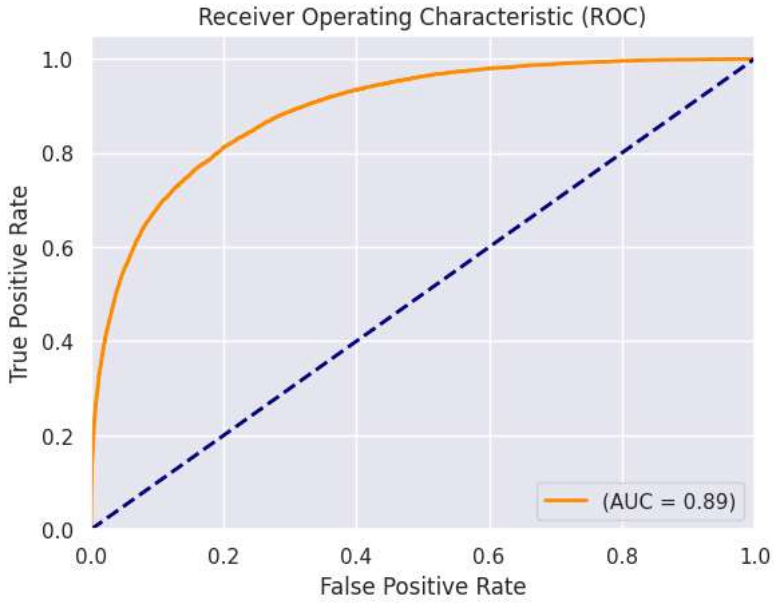
```
xgb = XGBClassifier()
xgb.fit(X_train, y_train)
y_pred_xgb = xgb.predict(X_test)
y_pred_xgb
```

```
array([1, 0, 0, ..., 0, 0, 0])
```

```
evaluate_model(xgb, X_train, y_train, X_test, y_test)
```

```
Accuracy: 0.8606
Precision: 0.7493
Recall: 0.5647
F1 Score: 0.6440
Training Score: 0.8937
Testing Score: 0.8606
ROC AUC: 0.8926
```






```
(0.8606123118758497,
 0.7492687003760969,
 0.5647244094488189,
 0.644037356321839,
 0.893655498066007,
 0.8606123118758497,
 0.892612848891127)
```

Observations:

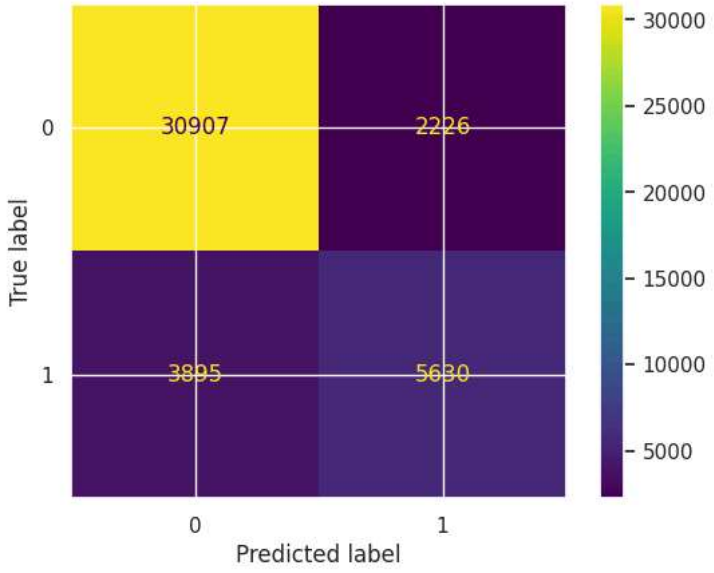
Highest accuracy score yet Highest AUC yet The model is decently fit

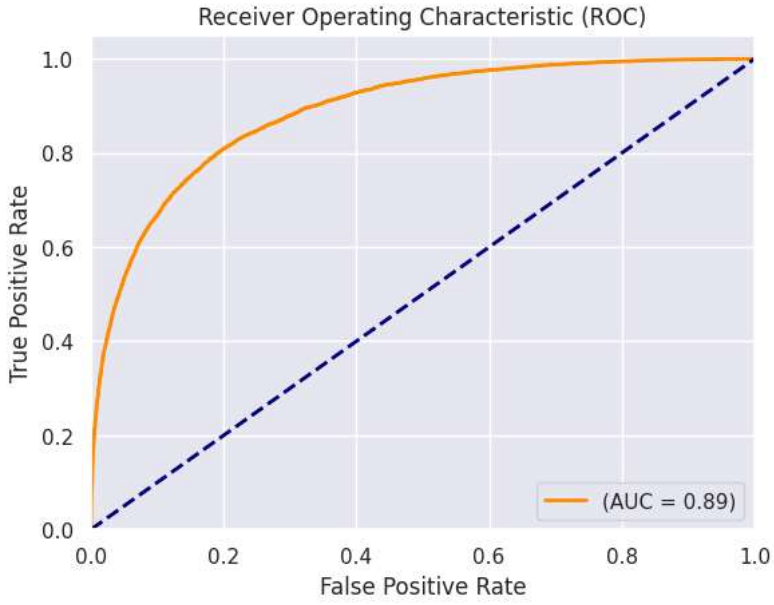
```
xgb_smote = XGBClassifier()
xgb_smote.fit(X_train_resampled, y_train_resampled)
y_pred_smote = xgb_smote.predict(X_test)
y_pred_smote
```

```
array([1, 0, 0, ..., 0, 0, 0])
```

```
evaluate_model(xgb_smote,X_train_resampled, y_train_resampled, X_test, y_test)
```

```
Accuracy: 0.8565
Precision: 0.7166
Recall: 0.5911
F1 Score: 0.6478
Training Score: 0.9267
Testing Score: 0.8565
ROC AUC: 0.8879
```






```
(0.8565099160767031,
 0.7166496945010183,
 0.5910761154855643,
 0.647833841551119,
 0.9267131363124004,
 0.8565099160767031,
 0.8878547265918564)
```

```
xgb_params = {
    'n_estimators': [10, 35, 100],
    'max_depth': [5, 10, 15],
    'learning_rate': [0.01, 0.1, 0.25],
}

xgb_gs = GridSearchCV(xgb_smote, xgb_params, scoring='accuracy', cv=10)
xgb_gs.fit(X_train_resampled, y_train_resampled)
```

```
GridSearchCV
estimator: XGBClassifier
XGBClassifier
```

```
xgb_gs.best_params_
```

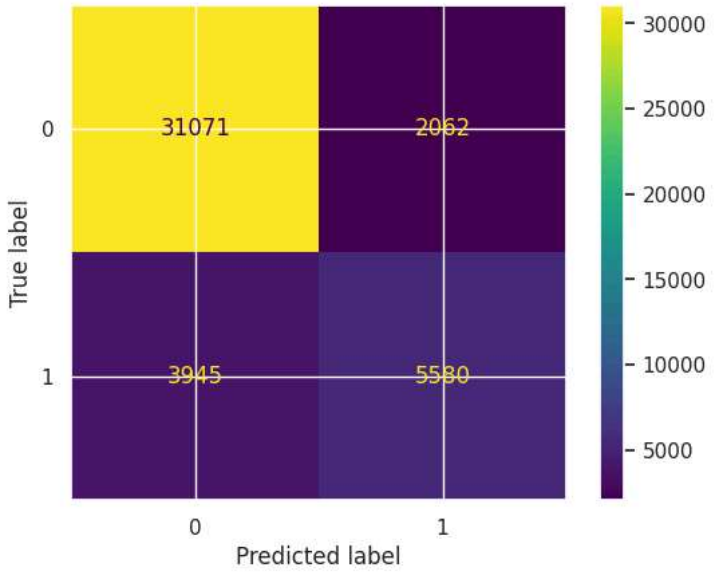
```
{'learning_rate': 0.1, 'max_depth': 15, 'n_estimators': 100}
```

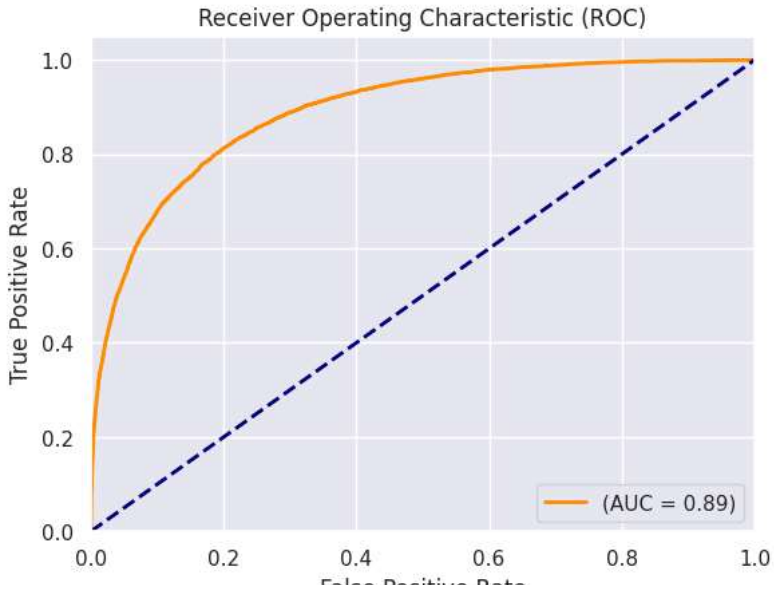
```
round(xgb_gs.best_score_, 4)
```

```
0.9053
```

```
evaluate_model(xgb_gs,X_train_resampled, y_train_resampled, X_test, y_test)
```

```
Accuracy: 0.8592
Precision: 0.7302
Recall: 0.5858
F1 Score: 0.6501
Training Score: 0.9947
Testing Score: 0.8592
ROC AUC: 0.8916
```





Observations:

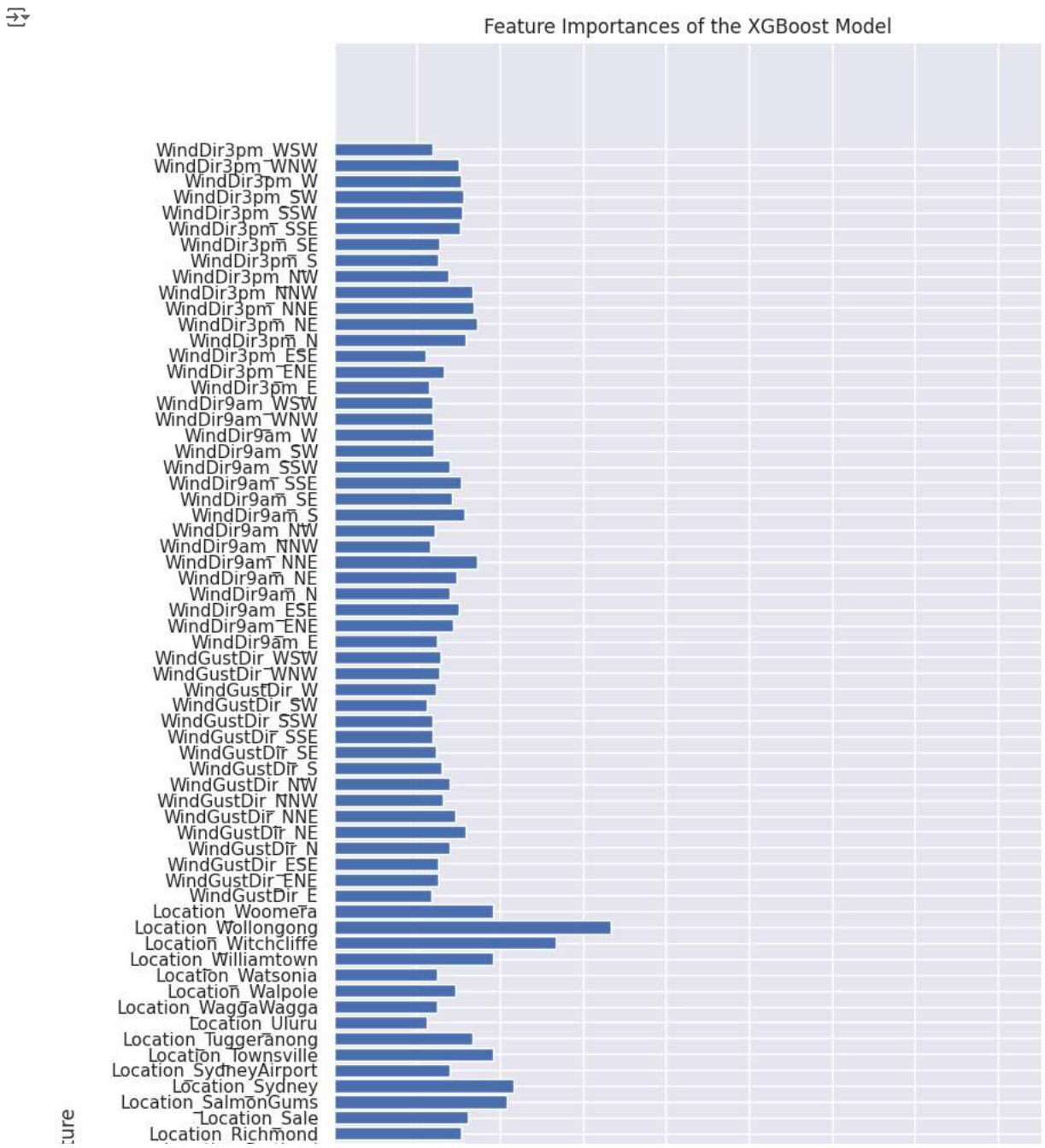
Slight improvement in some metrics but largely the same AUC remains the same Model fitness slightly decreased Overall, not much of an impact

Start coding or generate with AI.

Feature Importances Since this model achieved the best results, I want to explore the feature importances a bit more in depth.

```
best_xgb = xgb_gs.best_estimator_

plt.figure(figsize=(8, 25))
plt.barh(range(best_xgb.n_features_in_), best_xgb.feature_importances_)
plt.yticks(np.arange(best_xgb.n_features_in_), X_train.columns.values)
plt.xlabel('Feature Importance')
plt.ylabel('Feature')
plt.title('Feature Importances of the XGBoost Model');
```



Although the dummy variables were necessary for modeling the data, they are not conducive to analyzing the feature importances. As a result, I need to regroup the data into their primary categories to aggregate their category-level importances.

```
feat_imp_df = pd.DataFrame(data={'Feature': df_final.columns.drop('RainTomorrow'),
                                 'Importance': best_xgb.feature_importances_
                                }
                           )
feat_imp_df['Group'] = feat_imp_df.Feature.apply(lambda x: x.split('_')[0])
feat_imp_df
```

	Feature	Importance	Group
0	MinTemp	0.005734	MinTemp
1	MaxTemp	0.005767	MaxTemp
2	Rainfall	0.009005	Rainfall
3	Evaporation	0.005389	Evaporation
4	Sunshine	0.012969	Sunshine
...	...	...	...
121	WindDir3pm_SSW	0.007768	WindDir3pm
122	WindDir3pm_SW	0.007832	WindDir3pm
123	WindDir3pm_W	0.007702	WindDir3pm
124	WindDir3pm_WNW	0.007541	WindDir3pm
125	WindDir3pm_WSW	0.005957	WindDir3pm

126 rows × 3 columns

Pressure9am

```
feat_imp_df.Group.value_counts()
```

Group	count
Location	49
WindDir3pm	16
WindDir9am	16
WindGustDir	16
Month	12
MaxTemp	1
RainToday	1
Temp3pm	1
Temp9am	1
Cloud3pm	1
Cloud9am	1
MinTemp	1
Pressure9am	1
Humidity3pm	1
Humidity9am	1
WindSpeed3pm	1
WindSpeed9am	1
WindGustSpeed	1
Sunshine	1
Evaporation	1
Rainfall	1
Pressure3pm	1

dtype: int64

These value counts align with the number of unique values for the categorical columns in the original dataframe (excluding Month which was engineered later), meaning the lambda function worked as expected.

```
feat_imp_df_grouped = feat_imp_df.groupby(by='Group').sum()
feat_imp_df_grouped.sort_values('Importance', ascending=False, inplace=True)
feat_imp_df_grouped
```

Group	Feature	Importance
Location	Location_AdelaideLocation_AlbanyLocation_Albur...	0.428995
WindDir3pm	WindDir3pm_EWindDir3pm_ENEWindDir3pm_ESEWindDi...	0.115179
WindDir9am	WindDir9am_EWindDir9am_ENEWindDir9am_ESEWindDi...	0.109501
WindGustDir	WindGustDir_EWindGustDir_ENEWindGustDir_ESEWin...	0.103443
Month	Month_1Month_2Month_3Month_4Month_5Month_6Mont...	0.081561
Humidity3pm	Humidity3pm	0.040610
Sunshine	Sunshine	0.012969
RainToday	RainToday	0.012557
Pressure3pm	Pressure3pm	0.011413
WindGustSpeed	WindGustSpeed	0.009836
Rainfall	Rainfall	0.009005
Cloud3pm	Cloud3pm	0.008432
Pressure9am	Pressure9am	0.005917
Temp9am	Temp9am	0.005901
Temp3pm	Temp3pm	0.005828
MaxTemp	MaxTemp	0.005767
MinTemp	MinTemp	0.005734
Humidity9am	Humidity9am	0.005559
WindSpeed3pm	WindSpeed3pm	0.005558
Cloud9am	Cloud9am	0.005527
Evaporation	Evaporation	0.005389
WindSpeed9am	WindSpeed9am	0.005319

```
plt.figure(figsize=(7, 8))
sns.barplot(y=feat_imp_df_grouped.index,
            x=feat_imp_df_grouped.Importance,
            orient='h',
            color=sns.color_palette()[0]
           )
plt.title('Feature Importances for the XGBoost Model')
plt.ylabel('Feature Group')
plt.xlabel('Importance')
plt.tight_layout()
```