NEXT DAY RAIN PREDICTION

Import Libraries

```
# Data wrangling, analysis, and visualization
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

# Pre-modeling stage
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

# Modeling stage
from sklearn.model_selection import GridSearchCV

from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

# Evaluation stage
from sklearn.metrics import classification_report, roc_auc_score, confusion_matrix, ConfusionMatrixDisplay
```

LOAD AND UNDERSTAND THE DATASET

```
df = pd.read_csv('Weather_Data.csv')
```

```
df.head()
```

	Date	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSpeed	WindDir9am	WindDir3pm	...	Humidity9am
0	2/1/2008	19.5	22.4	15.6	6.2	0.0	W	41	S	SSW	...	92
1	2/2/2008	19.5	25.6	6.0	3.4	2.7	W	41	W	E	...	83
2	2/3/2008	21.6	24.5	6.6	2.4	0.1	W	41	ESE	ESE	...	88
3	2/4/2008	20.2	22.8	18.8	2.2	0.0	W	41	NNE	E	...	83
4	2/5/2008	19.7	25.7	77.4	4.8	0.0	W	41	NNE	W	...	88

5 rows × 22 columns

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3271 entries, 0 to 3270
Data columns (total 22 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Date           3271 non-null   object
 1   MinTemp        3271 non-null   float64
 2   MaxTemp        3271 non-null   float64
 3   Rainfall       3271 non-null   float64
 4   Evaporation    3271 non-null   float64
 5   Sunshine       3271 non-null   float64
 6   WindGustDir    3271 non-null   object
 7   WindGustSpeed  3271 non-null   int64
 8   WindDir9am     3271 non-null   object
 9   WindDir3pm     3271 non-null   object
 10  WindSpeed9am   3271 non-null   int64
 11  WindSpeed3pm   3271 non-null   int64
 12  Humidity9am    3271 non-null   int64
 13  Humidity3pm    3271 non-null   int64
 14  Pressure9am    3271 non-null   float64
 15  Pressure3pm    3271 non-null   float64
 16  Cloud9am       3271 non-null   int64
 17  Cloud3pm       3271 non-null   int64
 18  Temp9am        3271 non-null   float64
 19  Temp3pm        3271 non-null   float64
```

```
 20  RainToday      3271 non-null   object
 21  RainTomorrow   3271 non-null   object
dtypes: float64(9), int64(7), object(6)
memory usage: 562.3+ KB
```

```
# Check for rows with null values

condition_null = df.isnull().any(axis=1)
df[condition_null]
```

Date	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSpeed

0 rows × 22 columns

```
# Check for duplicated rows

condition_dupl = df.duplicated()
df[condition_dupl]
```

Date	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSpeed

0 rows × 22 columns

Sidenote on **RainToday**

```
# Create dataframe for only RainToday and Rainfall columns
df_RToday_RF = df[['RainToday','Rainfall']]

# Show the least RainFall value for records of RainToday = 1
condition = df['RainToday'] == 'Yes'
df_RToday_RF[condition].sort_values(by='Rainfall', ascending=True)
```

	RainToday	Rainfall
403	Yes	1.2
104	Yes	1.2
1677	Yes	1.2
2544	Yes	1.2
1823	Yes	1.2
...	...	...
1707	Yes	95.2
1104	Yes	99.4
2484	Yes	105.8
1425	Yes	109.4
2483	Yes	119.4

849 rows × 2 columns

Comment: The dataset **confirms** a rain for the day if the amount of rainfall (in millimeters) is at least 1.2 mm.

Balanced or imbalanced dataset?

```
# Compute distribution of our target variable

df['RainTomorrow'].value_counts()
```

```
No     2422
Yes     849
Name: RainTomorrow, dtype: int64
```

Comment: The positive class (raining tomorrow) accounts for 35% of the dataset. This means we have a moderately imbalanced dataset.

DATA PRE-PROCESSING

Replace categorical 'Yes' and 'No' with 1 and 0

```
df = df.replace(['Yes', 'No'], [1, 0])
```

```
# Check transformed values for RainToday

df['RainToday'].value_counts()
```

```
0    2422
1     849
Name: RainToday, dtype: int64
```

```
# Check transformed values for RainTomorrow

df['RainTomorrow'].value_counts()
```

```
0    2422
1     849
Name: RainTomorrow, dtype: int64
```

NOTE: Although both RainToday and RainTomorrow have the same distributions of 1s and 0s, they are not equal for every row of the dataset.

Add a new column called 'Month'

Why add a Month column?

Answer: Because climate depends on months. Certain months are more susceptible to rainfall than other months.

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

```
df.insert(1, 'Month', df['Date'].dt.month)
df.tail()
```

	Date	Month	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	Wi
3266	2017-06-21	6	8.6	19.6	0.0	2.0	7.8	SSE	
3267	2017-06-22	6	9.3	19.2	0.0	2.0	9.2	W	
3268	2017-06-23	6	9.4	17.7	0.0	2.4	2.7	W	
3269	2017-06-24	6	10.1	19.3	0.0	1.4	9.3	W	
3270	2017-06-25	6	7.6	19.3	0.0	3.4	9.4	W	

5 rows × 23 columns

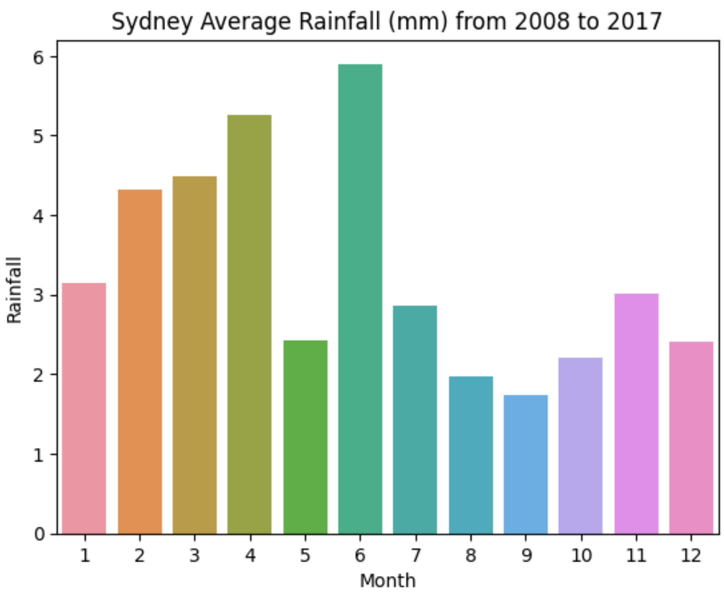
Sidenote: When is the rainy season in Sydney?

```
df_monthlyrain = df[['Month', 'Rainfall']].groupby('Month').mean().reset_index()
df_monthlyrain
```

	Month	Rainfall
0	1	3.150181

```
# Visualize rainfall vs. month

sns.barplot(data=df_monthlyrain, x='Month', y='Rainfall')
plt.title('Sydney Average Rainfall (mm) from 2008 to 2017')
plt.show()
```



Comment: Our dataset is aligned with the fact that Sydney's wettest months are from March to June.

We can now delete the Date column as we no longer need it for modeling later.

```
df = df.drop('Date', axis=1)
```

Convert categorical columns (with more than 2 values) into dummy variables

```
# Print column names for easy copy-pasting
df.columns
```

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

```
cat_columns = ['Month', 'WindGustDir', 'WindDir9am', 'WindDir3pm']

df = pd.get_dummies(df, columns=cat_columns, dtype=int)
```

```
df.info()
```

```
 39  WindGustDir_SE   3271 non-null   int64
 40  WindGustDir_SSE  3271 non-null   int64
 41  WindGustDir_SSW  3271 non-null   int64
 42  WindGustDir_SW   3271 non-null   int64
 43  WindGustDir_W    3271 non-null   int64
 44  WindGustDir_WNW  3271 non-null   int64
 45  WindGustDir_WSW  3271 non-null   int64
 46  WindDir9am_E     3271 non-null   int64
 47  WindDir9am_ENE   3271 non-null   int64
 48  WindDir9am_ESE   3271 non-null   int64
 49  WindDir9am_N     3271 non-null   int64
 50  WindDir9am_NE    3271 non-null   int64
 51  WindDir9am_NNE   3271 non-null   int64
 52  WindDir9am_NNW   3271 non-null   int64
 53  WindDir9am_NW    3271 non-null   int64
 54  WindDir9am_S     3271 non-null   int64
 55  WindDir9am_SE    3271 non-null   int64
 56  WindDir9am_SSE   3271 non-null   int64
 57  WindDir9am_SSW   3271 non-null   int64
 58  WindDir9am_SW    3271 non-null   int64
 59  WindDir9am_W     3271 non-null   int64
 60  WindDir9am_WNW   3271 non-null   int64
 61  WindDir9am_WSW   3271 non-null   int64
 62  WindDir3pm_E     3271 non-null   int64
 63  WindDir3pm_ENE   3271 non-null   int64
 64  WindDir3pm_ESE   3271 non-null   int64
 65  WindDir3pm_N     3271 non-null   int64
 66  WindDir3pm_NE    3271 non-null   int64
 67  WindDir3pm_NNE   3271 non-null   int64
 68  WindDir3pm_NNW   3271 non-null   int64
 69  WindDir3pm_NW    3271 non-null   int64
 70  WindDir3pm_S     3271 non-null   int64
 71  WindDir3pm_SE    3271 non-null   int64
 72  WindDir3pm_SSE   3271 non-null   int64
 73  WindDir3pm_SSW   3271 non-null   int64
 74  WindDir3pm_SW    3271 non-null   int64
 75  WindDir3pm_W     3271 non-null   int64
 76  WindDir3pm_WNW   3271 non-null   int64
 77  WindDir3pm_WSW   3271 non-null   int64
dtypes: float64(9), int64(69)
memory usage: 1.9 MB
```

Comment: We now have 77 features that are ready for modeling.

MACHINE LEARNING MODELING

Separate Features and the Target

```
features = df.drop('RainTomorrow', axis=1)
y = df['RainTomorrow']
```

Create training and testing sets

```
X_train, X_test, y_train, y_test = train_test_split(features, y, test_size=0.2, random_state=8)

print(len(X_train), ':', len(y_train))
print(len(X_test), ':', len(y_test))
```

```
2616 : 2616
655 : 655
```

TRAINING MODELS

I have to scale the continuous variables using the StandardScaler **without** affecting the categorical columns. Thus, I need to separate continous and categorical from our training set.

Separate continuous and categorical features sub-dataframes

```
X_train.columns
```

```
Index(['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine',
       'WindGustSpeed', 'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am',
       'Humidity3pm', 'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm',
       'Temp9am', 'Temp3pm', 'RainToday', 'Month_1', 'Month_2', 'Month_3',
       'Month_4', 'Month_5', 'Month_6', 'Month_7', 'Month_8', 'Month_9',
```

```
       'Month_10', 'Month_11', 'Month_12', 'WindGustDir_E', 'WindGustDir_ENE',
       'WindGustDir_ESE', 'WindGustDir_N', 'WindGustDir_NE', 'WindGustDir_NNE',
       'WindGustDir_NNW', 'WindGustDir_NW', 'WindGustDir_S', 'WindGustDir_SE',
       'WindGustDir_SSE', 'WindGustDir_SSW', 'WindGustDir_SW', 'WindGustDir_W',
       'WindGustDir_WNW', 'WindGustDir_WSW', 'WindDir9am_E', 'WindDir9am_ENE',
       'WindDir9am_ESE', 'WindDir9am_N', 'WindDir9am_NE', 'WindDir9am_NNE',
       'WindDir9am_NNW', 'WindDir9am_NW', 'WindDir9am_S', 'WindDir9am_SE',
       'WindDir9am_SSE', 'WindDir9am_SSW', 'WindDir9am_SW', 'WindDir9am_W',
       'WindDir9am_WNW', 'WindDir9am_WSW', 'WindDir3pm_E', 'WindDir3pm_ENE',
       'WindDir3pm_ESE', 'WindDir3pm_N', 'WindDir3pm_NE', 'WindDir3pm_NNE',
       'WindDir3pm_NNW', 'WindDir3pm_NW', 'WindDir3pm_S', 'WindDir3pm_SE',
       'WindDir3pm_SSE', 'WindDir3pm_SSW', 'WindDir3pm_SW', 'WindDir3pm_W',
       'WindDir3pm_WNW', 'WindDir3pm_WSW'],
      dtype='object')
```

```
# Categorical features dataframe

X_train_categorical = X_train[['RainToday', 'Month_1', 'Month_2',
       'Month_3', 'Month_4', 'Month_5', 'Month_6', 'Month_7', 'Month_8',
       'Month_9', 'Month_10', 'Month_11', 'Month_12', 'WindGustDir_E',
       'WindGustDir_ENE', 'WindGustDir_ESE', 'WindGustDir_N', 'WindGustDir_NE',
       'WindGustDir_NNE', 'WindGustDir_NNW', 'WindGustDir_NW', 'WindGustDir_S',
       'WindGustDir_SE', 'WindGustDir_SSE', 'WindGustDir_SSW',
       'WindGustDir_SW', 'WindGustDir_W', 'WindGustDir_WNW', 'WindGustDir_WSW',
       'WindDir9am_E', 'WindDir9am_ENE', 'WindDir9am_ESE', 'WindDir9am_N',
       'WindDir9am_NE', 'WindDir9am_NNE', 'WindDir9am_NNW', 'WindDir9am_NW',
       'WindDir9am_S', 'WindDir9am_SE', 'WindDir9am_SSE', 'WindDir9am_SSW',
       'WindDir9am_SW', 'WindDir9am_W', 'WindDir9am_WNW', 'WindDir9am_WSW',
       'WindDir3pm_E', 'WindDir3pm_ENE', 'WindDir3pm_ESE', 'WindDir3pm_N',
       'WindDir3pm_NE', 'WindDir3pm_NNE', 'WindDir3pm_NNW', 'WindDir3pm_NW',
       'WindDir3pm_S', 'WindDir3pm_SE', 'WindDir3pm_SSE', 'WindDir3pm_SSW',
       'WindDir3pm_SW', 'WindDir3pm_W', 'WindDir3pm_WNW', 'WindDir3pm_WSW']]

X_train_categorical.tail()
```

	RainToday	Month_1	Month_2	Month_3	Month_4	Month_5	Month_6	Month_7	Month_
2181	0	0	0	0	0	0	1	0	
2409	0	0	1	0	0	0	0	0	
2033	0	1	0	0	0	0	0	0	
1364	0	1	0	0	0	0	0	0	
451	1	0	0	0	1	0	0	0	

5 rows × 61 columns

NOTE: The indices are retained after the train test split, which randomly selected 80% of the dataset for training.

```
# Numerical features dataframe

X_train_numerical = X_train[['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine',
                 'WindGustSpeed', 'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am',
                 'Humidity3pm', 'Pressure9am', 'Pressure3pm', 'Cloud9am',
                 'Cloud3pm', 'Temp9am', 'Temp3pm']]

X_train_numerical.tail()
```

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am
2181	10.3	17.2	0.2	2.6	1.2	54	13
2409	17.6	25.6	0.2	4.2	7.8	31	9
2033	19.3	28.7	0.0	10.6	13.1	52	7
1364	18.5	22.4	0.8	6.6	3.4	56	24
451	11.0	17.4	6.2	2.4	2.7	41	17

Standardization of numerical features from the training set

```
scaler = StandardScaler()
```

```
# NOTE: It is important that we retain the indices because each index corresponds to a date from our original dataset
# Each row must preserve the information for each day (although some features for that row will be scaled)

orig_indices = X_train_numerical.index
orig_indices
```

```
Int64Index([1450,  512, 2744, 2473, 2183, 1649, 1278,  257,  147, 1914,
            ...
            2096, 1384, 2899, 2184,  986, 2181, 2409, 2033, 1364,  451],
           dtype='int64', length=2616)
```

```
scaled_array = scaler.fit_transform(X_train_numerical)
X_nums_scaled = pd.DataFrame(scaled_array, columns=X_train_numerical.columns, index=orig_indices)

X_nums_scaled.tail()
```

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9
2181	-0.996134	-1.285959	-0.318300	-0.943062	-1.568282	1.139407	-0.2920
2409	0.608557	0.586696	-0.318300	-0.359240	0.154271	-0.966763	-0.8602
2033	0.982253	1.277795	-0.337697	1.976049	1.537534	0.956262	-1.1442
1364	0.806396	-0.126696	-0.260112	0.516493	-0.994098	1.322552	1.2703
451	-0.842260	-1.241372	0.263582	-1.016040	-1.176793	-0.051037	0.2760

Combine X_nums_scaled to X_train_categorical to finalize our training features dataframe

```
X_train_scaled = pd.concat([X_nums_scaled, X_train_categorical], axis=1, join='inner')
```

```
X_train_scaled.tail()
```

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9
2181	-0.996134	-1.285959	-0.318300	-0.943062	-1.568282	1.139407	-0.2920
2409	0.608557	0.586696	-0.318300	-0.359240	0.154271	-0.966763	-0.8602
2033	0.982253	1.277795	-0.337697	1.976049	1.537534	0.956262	-1.1442
1364	0.806396	-0.126696	-0.260112	0.516493	-0.994098	1.322552	1.2703
451	-0.842260	-1.241372	0.263582	-1.016040	-1.176793	-0.051037	0.2760

5 rows × 77 columns

```
# Print number of rows for our finalized training set (it must be 2616)

len(X_train_scaled)
```

```
2616
```

Train 5 ML Classifiers

1. K-Nearest Neighbors (KNN)

```
# Create our KNN model

knn = KNeighborsClassifier()

# Find the best n_neighbors parameter using GridSearchCV

param_grid_knn = {'n_neighbors': list(range(1,51))}

grid_search_knn = GridSearchCV(knn, param_grid_knn, cv=5)

grid_search_knn.fit(X_train_scaled, y_train)

# Print the best parameter and accuracy score
print("Best k:", grid_search_knn.best_params_['n_neighbors'])
print("Best score:", grid_search_knn.best_score_)

# Assign the best KNN model
knn_final = grid_search_knn.best_estimator_
knn_final
```

```
Best k: 35
Best score: 0.8344846963350021
▾ KNeighborsClassifier
KNeighborsClassifier(n_neighbors=35)
```

2. Logistic Regression (LR)

```
# Create our Logistic Regression model

log_reg = LogisticRegression(solver='liblinear')

# Find the best C parameter using GridSearchCV

param_grid_LR = {'C': [0.001, 0.01, 0.1, 1, 10, 100]}

grid_search_LR = GridSearchCV(log_reg, param_grid_LR, cv=5)

grid_search_LR.fit(X_train_scaled, y_train)

# Print the best parameter and accuracy score

print("Best C:", grid_search_LR.best_params_['C'])
print("Best score:", grid_search_LR.best_score_)

# Assign the best Logistic Regression model

log_reg_final = grid_search_LR.best_estimator_
log_reg_final
```

```
Best C: 0.1
Best score: 0.8383080583246976
▾ LogisticRegression
LogisticRegression(C=0.1, solver='liblinear')
```

3. Support Vector Machine (SVM)

```
# Create our SVM model

svm = SVC(probability=True)

# Find the best C parameter using GridSearchCV

param_grid_svm = {'C': [0.001, 0.01, 0.1, 1, 10, 100]}

grid_search_svm = GridSearchCV(svm, param_grid_svm, cv=5)

grid_search_svm.fit(X_train_scaled, y_train)

# Print the best parameter and accuracy score

print('Best C:', grid_search_svm.best_params_['C'])
print('Best score:', grid_search_svm.best_score_)

# Assign the best SVM model

svm_final = grid_search_svm.best_estimator_
svm_final
```

```
Best C: 1
Best score: 0.8405981346605753
▾ SVC
SVC(C=1, probability=True)
```

4. Decision Tree Classifier (DTC)

```
# Create our DTC model

dtc = DecisionTreeClassifier()

# Find the best max_depth parameter using GridSearchCV

param_grid_dtc = {'max_depth': list(range(3, 31))}

grid_search_dtc = GridSearchCV(dtc, param_grid_dtc, cv=5)

grid_search_dtc.fit(X_train_scaled, y_train)

# Print the best parameter and accuracy score

print('Best max_depth:', grid_search_dtc.best_params_['max_depth'])
print('Best score:', grid_search_dtc.best_score_)

# Assign our best DTC model

dtc_final = grid_search_dtc.best_estimator_
dtc_final
```

```
Best max_depth: 3
Best score: 0.8253083356443301
▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=3)
```

5. Random Forest Classifier (RFC)

```
# Create our RFC model

rfc = RandomForestClassifier(random_state=8)

# Find the best max_depth parameter using GridSearchCV

param_grid_rfc = {'max_depth': list(range(3,31))}

grid_search_rfc = GridSearchCV(rfc, param_grid_rfc, cv=5)

grid_search_rfc.fit(X_train_scaled, y_train)

# Print the best parameter and accuracy score

print('Best max_depth:', grid_search_rfc.best_params_['max_depth'])
print('Best score:', grid_search_rfc.best_score_)

# Assign our best rf model

rfc_final = grid_search_rfc.best_estimator_
rfc_final
```

```
Best max_depth: 12
Best score: 0.8459533227270738
```

```
RandomForestClassifier
RandomForestClassifier(max_depth=12, random_state=8)
```

EVALUATING OUR MODELS

Just like what we did for the training set, we need to scale our features of the testing set first, before evaluating our models to it.

Make a properly scaled test set

```
# Categorical features dataframe

X_test_categorical = X_test[['RainToday', 'Month_1', 'Month_2',
       'Month_3', 'Month_4', 'Month_5', 'Month_6', 'Month_7', 'Month_8',
       'Month_9', 'Month_10', 'Month_11', 'Month_12', 'WindGustDir_E',
       'WindGustDir_ENE', 'WindGustDir_ESE', 'WindGustDir_N', 'WindGustDir_NE',
       'WindGustDir_NNE', 'WindGustDir_NNW', 'WindGustDir_NW', 'WindGustDir_S',
       'WindGustDir_SE', 'WindGustDir_SSE', 'WindGustDir_SSW',
       'WindGustDir_SW', 'WindGustDir_W', 'WindGustDir_WNW', 'WindGustDir_WSW',
       'WindDir9am_E', 'WindDir9am_ENE', 'WindDir9am_ESE', 'WindDir9am_N',
       'WindDir9am_NE', 'WindDir9am_NNE', 'WindDir9am_NNW', 'WindDir9am_NW',
       'WindDir9am_S', 'WindDir9am_SE', 'WindDir9am_SSE', 'WindDir9am_SSW',
       'WindDir9am_SW', 'WindDir9am_W', 'WindDir9am_WNW', 'WindDir9am_WSW',
       'WindDir3pm_E', 'WindDir3pm_ENE', 'WindDir3pm_ESE', 'WindDir3pm_N',
       'WindDir3pm_NE', 'WindDir3pm_NNE', 'WindDir3pm_NNW', 'WindDir3pm_NW',
       'WindDir3pm_S', 'WindDir3pm_SE', 'WindDir3pm_SSE', 'WindDir3pm_SSW',
       'WindDir3pm_SW', 'WindDir3pm_W', 'WindDir3pm_WNW', 'WindDir3pm_WSW']]

X_test_categorical.tail()
```

	RainToday	Month_1	Month_2	Month_3	Month_4	Month_5	Month_6	Month_7	Month_
3001	0	0	0	0	0	0	0	0	
1671	0	0	0	0	0	0	0	0	
702	0	1	0	0	0	0	0	0	
1288	0	0	0	0	0	0	0	0	
1552	0	0	0	0	0	0	0	1	

5 rows × 61 columns

```
# Numerical features dataframe

X_test_numerical = X_test[['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine',
                  'WindGustSpeed', 'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am',
                  'Humidity3pm', 'Pressure9am', 'Pressure3pm', 'Cloud9am',
                  'Cloud3pm', 'Temp9am', 'Temp3pm']]

X_test_numerical.tail()
```

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am
3001	10.9	23.2	0.0	6.2	9.7	61	20
1671	15.7	22.0	0.0	5.4	5.2	30	13
702	22.1	25.8	0.0	8.6	7.8	41	11
1288	13.5	23.5	0.0	8.0	12.4	48	6
1552	9.0	18.2	0.0	5.0	10.0	46	9

```
def make_scaled_test_set(df_num, df_cat):
  '''A function that recycles the codes we did for training set, to scale our testing set'''

  # Get the index for each row of numerical dataframe
  orig_indices = df_num.index

  # Scale our numerical dataframe
  scaler = StandardScaler()
  scaled_array = scaler.fit_transform(df_num)
  X_nums_scaled = pd.DataFrame(scaled_array, columns=df_num.columns, index=orig_indices)

  # Combine the scaled numerical df and the categorical df
  X_test_scaled = pd.concat([X_nums_scaled, df_cat], axis=1, join='inner')

  return X_test_scaled
```

```
X_test_scaled = make_scaled_test_set(df_num=X_test_numerical, df_cat=X_test_categorical)
X_test_scaled.tail()
```

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9
3001	-0.910285	0.010213	-0.342537	0.375201	0.718244	1.921901	0.6863
1671	0.140314	-0.258256	-0.342537	0.091785	-0.483041	-1.079960	-0.3063
702	1.541112	0.591894	-0.342537	1.225447	0.211035	-0.014784	-0.5899
1288	-0.341211	0.077330	-0.342537	1.012886	1.439015	0.663056	-1.2989
1552	-1.326147	-1.108405	-0.342537	-0.049922	0.798330	0.469387	-0.8735

5 rows × 77 columns

Evaluate our KNN model

```
y_pred_knn = knn_final.predict(X_test_scaled)

report = classification_report(y_test, y_pred_knn)

print(report)
```

```
              precision    recall  f1-score   support

           0       0.83      0.97      0.89       477
           1       0.84      0.46      0.59       178

    accuracy                           0.83       655
   macro avg       0.83      0.71      0.74       655
weighted avg       0.83      0.83      0.81       655
```

Evaluate our LR model

```
y_pred_lr = log_reg_final.predict(X_test_scaled)

report = classification_report(y_test, y_pred_lr)

print(report)
```

```
              precision    recall  f1-score   support

           0       0.86      0.93      0.89       477
           1       0.76      0.59      0.66       178

    accuracy                           0.84       655
   macro avg       0.81      0.76      0.78       655
```

```
weighted avg       0.83      0.84      0.83       655
```

Evaluate our SVM model

```
y_pred_svm = svm_final.predict(X_test_scaled)

report = classification_report(y_test, y_pred_svm)

print(report)
```

```
              precision    recall  f1-score   support

           0       0.85      0.95      0.90       477
           1       0.82      0.54      0.65       178

    accuracy                           0.84       655
   macro avg       0.83      0.75      0.78       655
weighted avg       0.84      0.84      0.83       655
```

Evaluate our DTC model

```
y_pred_dtc = dtc_final.predict(X_test_scaled)

report = classification_report(y_test, y_pred_dtc)

print(report)
```

```
              precision    recall  f1-score   support

           0       0.83      0.93      0.88       477
           1       0.72      0.50      0.59       178

    accuracy                           0.81       655
   macro avg       0.78      0.71      0.73       655
weighted avg       0.80      0.81      0.80       655
```

Evaluate our RFC model

```
y_pred_rfc = rfc_final.predict(X_test_scaled)

report = classification_report(y_test, y_pred_rfc)

print(report)
```

```
              precision    recall  f1-score   support

           0       0.84      0.96      0.89       477
           1       0.82      0.51      0.63       178

    accuracy                           0.84       655
   macro avg       0.83      0.73      0.76       655
weighted avg       0.83      0.84      0.82       655
```

COMPARING OUR MODELS

Since we have an imbalanced dataset we need to use weighted f1-score as basis of performance comparison (instead of accuracy). In case of a tie, we will use weighted recall. Why use recall? Because in rain prediction, it is important to minimize false negative rate. If we forecast NOT raining tomorrow, people won't bring umbrellas, so we better be confident for a negative forecast.

```
data = {'LR': [0.83, 0.84],
    'SVM': [0.83, 0.84],
    'RFC': [0.82, 0.84],
    'KNN': [0.81, 0.83],
    'DTC': [0.80, 0.81]
}
```

Comment: LR and SVM are tied in our primary metrics. They are also tied in terms of accuracy.

Let's check if they are still tied at ROC-AUC metric, which is also used for comparing models for binary classfication task with imbalanced dataset.

LR	SVM	RFC	KNN	DTC

```
# ROC-AUC for our LR model

y_pred_lr_proba = log_reg_final.predict_proba(X_test_scaled)[:, 1]

roc_auc = roc_auc_score(y_test, y_pred_lr_proba)

print('ROC-AUC score:', roc_auc)
```

```
ROC-AUC score: 0.8659694250111888
```

```
# ROC-AUC for our SVM model

y_pred_svm_proba = svm_final.predict_proba(X_test_scaled)[:, 1]

roc_auc = roc_auc_score(y_test, y_pred_svm_proba)

print('ROC-AUC score:', roc_auc)
```

```
ROC-AUC score: 0.8601394483310957
```