Rainfall Prediction using Machine Learning – Python

Today there are no certain methods by using which we can predict whether there will be rainfall today or not. Even the meteorological department's prediction fails sometimes. In this article, we will learn how to build a machine-learning model which can predict whether there will be rainfall today or not based on some atmospheric factors. This problem is related to *Rainfall Prediction using Machine Learning* because machine learning models tend to perform better on the previously known task which needed highly skilled individuals to do so.

Importing Libraries and Dataset

Python libraries make it easy for us to handle the data and perform typical and complex tasks with a single line of code.

- **Pandas** – This library helps to load the data frame in a 2D array format and has multiple functions to perform analysis tasks in one go.
- **Numpy** – Numpy arrays are very fast and can perform large computations in a very short time.
- **Matplotlib**/**Seaborn** – This library is used to draw visualizations.
- Sklearn – This module contains multiple libraries are having pre-implemented functions to perform tasks from data preprocessing to model development and evaluation.
- **XGBoost** – This contains the eXtreme Gradient Boosting machine learning algorithm which is one of the algorithms which helps us to achieve high accuracy on predictions.

Python3

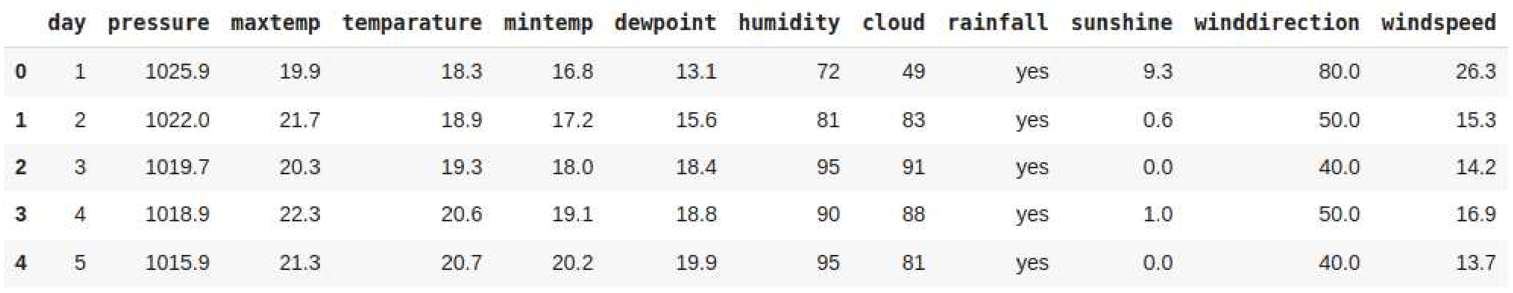
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn import metrics
from sklearn.svm import SVC
from xgboost import XGBClassifier
from sklearn.linear_model import LogisticRegression
from imblearn.over_sampling import RandomOverSampler

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

Now let's load the dataset into the panda's data frame and print its first five rows.

Python3

```
df = pd.read_csv('Rainfall.csv')
df.head()
```

Output:



	day	pressure	maxtemp	temparature	mintemp	dewpoint	humidity	cloud	rainfall	sunshine	winddirection	windspeed
0	1	1025.9	19.9	18.3	16.8	13.1	72	49	yes	9.3	80.0	26.3
1	2	1022.0	21.7	18.9	17.2	15.6	81	83	yes	0.6	50.0	15.3
2	3	1019.7	20.3	19.3	18.0	18.4	95	91	yes	0.0	40.0	14.2
3	4	1018.9	22.3	20.6	19.1	18.8	90	88	yes	1.0	50.0	16.9
4	5	1015.9	21.3	20.7	20.2	19.9	95	81	yes	0.0	40.0	13.7

First Five rows of the dataset

Now let's check the size of the dataset.

Python3

```
df.shape
```

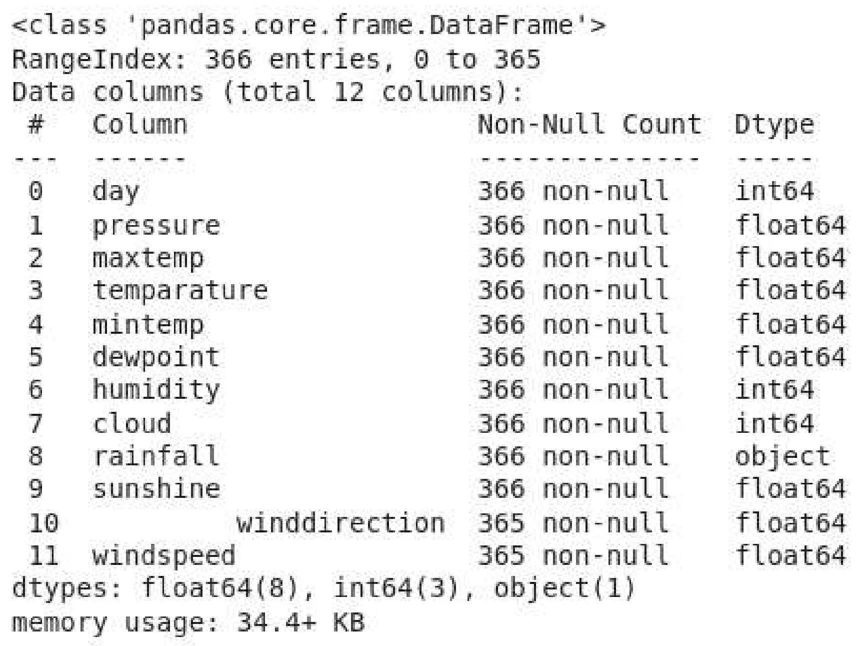
Output:

```
(366, 12)
```

Let's check which column of the dataset contains which type of data.

Python3

Output:



```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 366 entries, 0 to 365
Data columns (total 12 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   day                    366 non-null    int64
 1   pressure               366 non-null    float64
 2   maxtemp                366 non-null    float64
 3   temparature            366 non-null    float64
 4   mintemp                366 non-null    float64
 5   dewpoint               366 non-null    float64
 6   humidity               366 non-null    int64
 7   cloud                  366 non-null    int64
 8   rainfall               366 non-null    object
 9   sunshine               366 non-null    float64
 10           winddirection 365 non-null    float64
 11  windspeed              365 non-null    float64
dtypes: float64(8), int64(3), object(1)
memory usage: 34.4+ KB
```

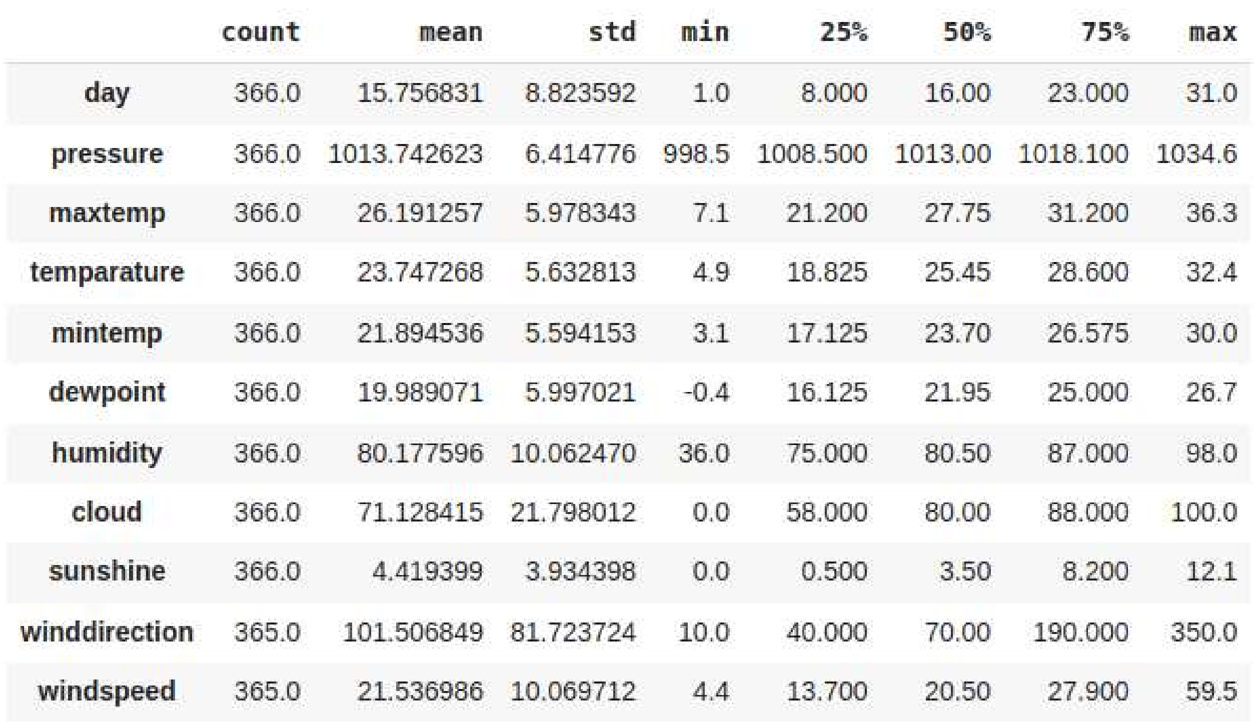
Information regarding data in the columns

As per the above information regarding the data in each column, we can observe that there are no null values.

Python3

```
df.describe().T
```

Output:



	count	mean	std	min	25%	50%	75%	max
day	366.0	15.756831	8.823592	1.0	8.000	16.00	23.000	31.0
pressure	366.0	1013.742623	6.414776	998.5	1008.500	1013.00	1018.100	1034.6
maxtemp	366.0	26.191257	5.978343	7.1	21.200	27.75	31.200	36.3
temparature	366.0	23.747268	5.632813	4.9	18.825	25.45	28.600	32.4
mintemp	366.0	21.894536	5.594153	3.1	17.125	23.70	26.575	30.0
dewpoint	366.0	19.989071	5.997021	-0.4	16.125	21.95	25.000	26.7
humidity	366.0	80.177596	10.062470	36.0	75.000	80.50	87.000	98.0
cloud	366.0	71.128415	21.798012	0.0	58.000	80.00	88.000	100.0
sunshine	366.0	4.419399	3.934398	0.0	0.500	3.50	8.200	12.1
winddirection	365.0	101.506849	81.723724	10.0	40.000	70.00	190.000	350.0
windspeed	365.0	21.536986	10.069712	4.4	13.700	20.50	27.900	59.5

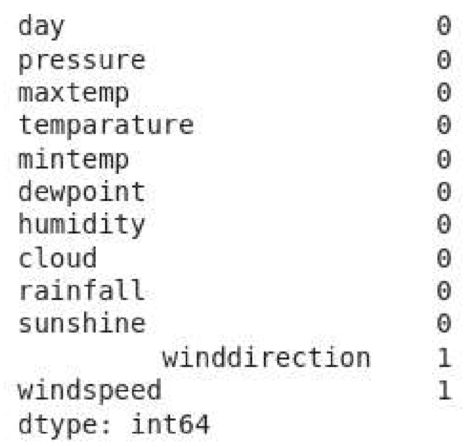
Descriptive statistical measures of the dataset

Data Cleaning

The data which is obtained from the primary sources is termed the raw data and required a lot of preprocessing before we can derive any conclusions from it or do some modeling on it. Those preprocessing steps are known as data cleaning and it includes, outliers removal, null value imputation, and removing discrepancies of any sort in the data inputs.

Python3

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



```
day                         0
pressure                    0
maxtemp                     0
temparature                 0
mintemp                     0
dewpoint                    0
humidity                    0
cloud                       0
rainfall                    0
sunshine                    0
         winddirection      1
windspeed                   1
dtype: int64
```

Sum of null values present in each column

So there is one null value in the **'winddirection'** as well as the **'windspeed'** column. But what's up with the column name wind direction?

Python3

```
df.columns
```

Output:

```
Index(['day', 'pressure ', 'maxtemp', 'temperature', 'mintemp', 'dewpoint',
       'humidity ', 'cloud ', 'rainfall', 'sunshine', '         winddirection',
       'windspeed'],
      dtype='object')
```

Here we can observe that there are unnecessary spaces in the names of the columns let's remove that.

```
df.rename(str.strip,
          axis='columns',
          inplace=True)

df.columns
```

Output:

```
Index(['day', 'pressure', 'maxtemp', 'temperature', 'mintemp', 'dewpoint',
       'humidity', 'cloud', 'rainfall', 'sunshine', 'winddirection',
       'windspeed'],
      dtype='object')
```

Now it’s time for null value imputation.

Python3

```
for col in df.columns:

  # Checking if the column contains
  # any null values
  if df[col].isnull().sum() > 0:
    val = df[col].mean()
    df[col] = df[col].fillna(val)

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

Output:

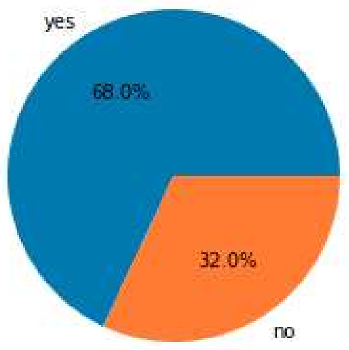
Exploratory Data Analysis

EDA is an approach to analyzing the data using visual techniques. It is used to discover trends, and patterns, or to check assumptions with the help of statistical summaries and graphical representations. Here we will see how to check the data imbalance and skewness of the data.

Python3

```
plt.pie(df['rainfall'].value_counts().values,
        labels = df['rainfall'].value_counts().index,
        autopct='%1.1f%%')
plt.show()
```

Output:



Pie chart for the number of data for each target

Python3

```
df.groupby('rainfall').mean()
```

Output:

Here we can clearly draw some observations:

- **maxtemp** is relatively lower on days of rainfall.
- **dewpoint** value is higher on days of rainfall.
- **humidity** is high on the days when rainfall is expected.
- Obviously, clouds must be there for rainfall.
- **sunshine** is also less on days of rainfall.
- **windspeed** is higher on days of rainfall.

The observations we have drawn from the above dataset are very much similar to what is observed in real life as well.

Python3

```
features = list(df.select_dtypes(include = np.number).columns)
features.remove('day')
print(features)
```

Output:

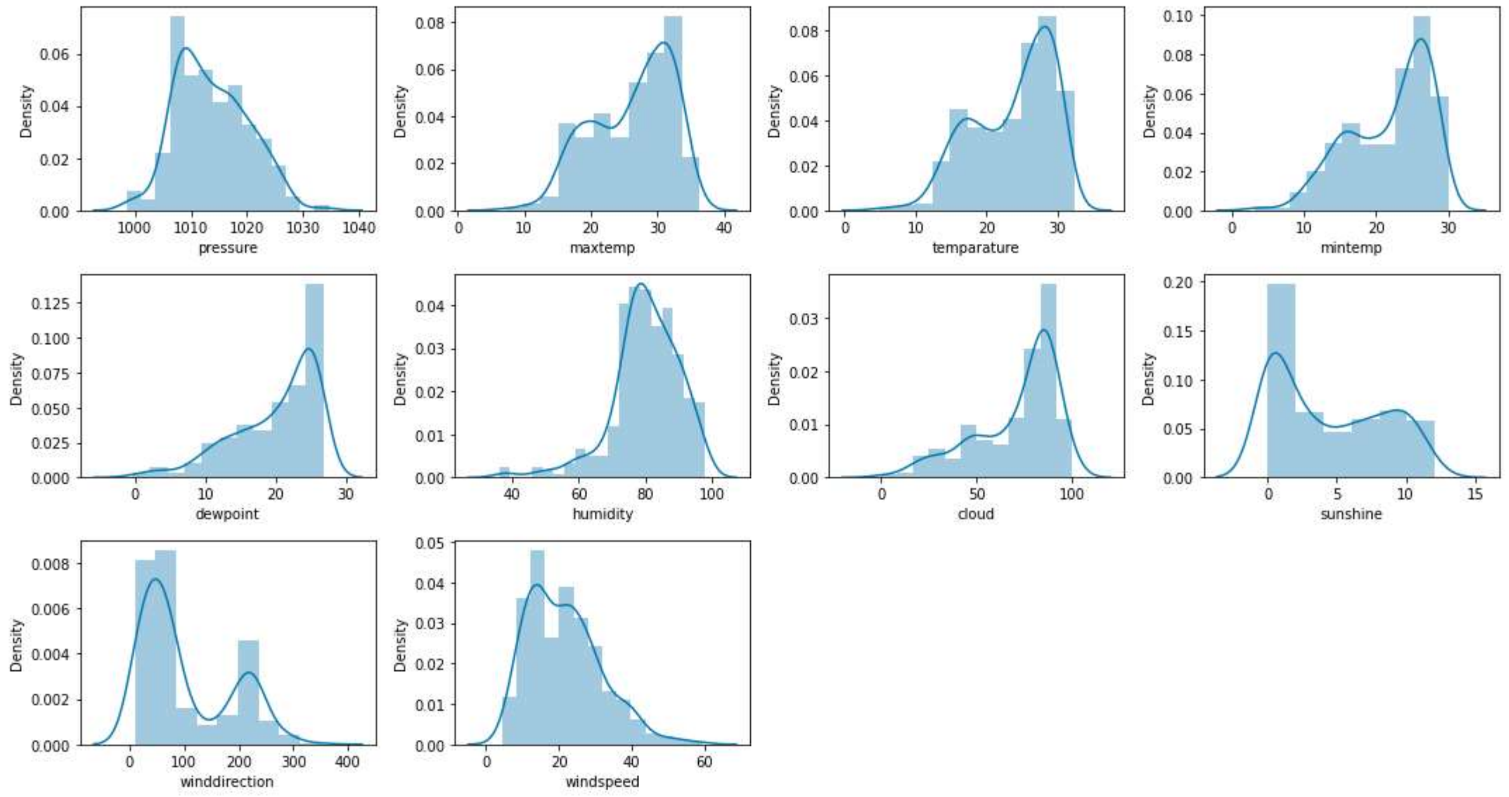
```
['pressure', 'maxtemp', 'temperature', 'mintemp', 'dewpoint', 'humidity', 'cloud',
'sunshine', 'winddirection', 'windspeed']
```

Let's check the distribution of the continuous features given in the dataset.

Python3

```
for i, col in enumerate(features):
  plt.subplot(3,4, i + 1)
  sb.distplot(df[col])
plt.tight_layout()
plt.show()
```

Output:



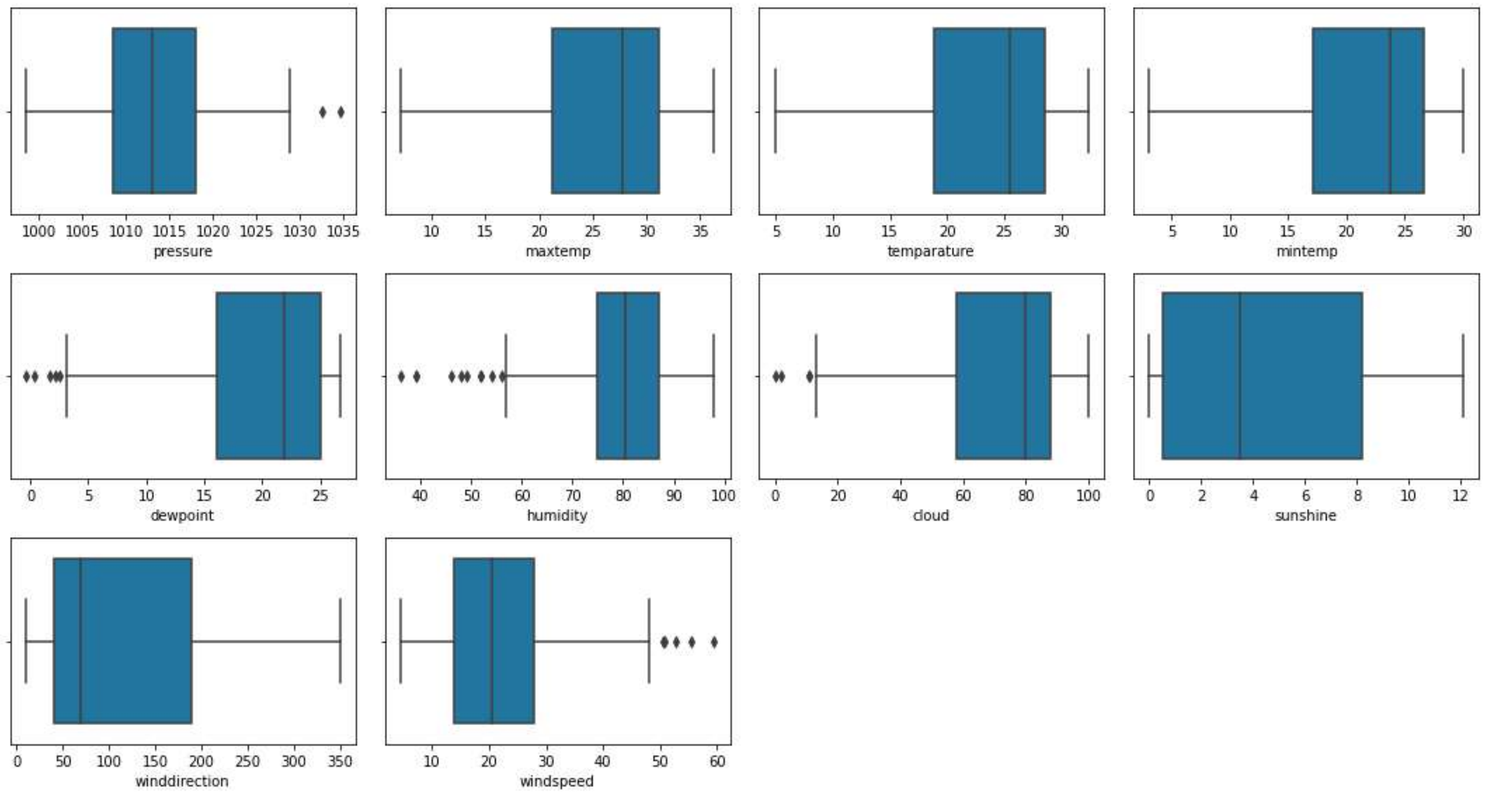
Distribution plot for the columns with continuous data

Let’s draw boxplots for the continuous variable to detect the outliers present in the data.

Python3

```
for i, col in enumerate(features):
  plt.subplot(3,4, i + 1)
  sb.boxplot(df[col])
plt.tight_layout()
plt.show()
```

Output:



Box plots for the columns with continuous data

There are outliers in the data but sadly we do not have much data so, we cannot remove this.

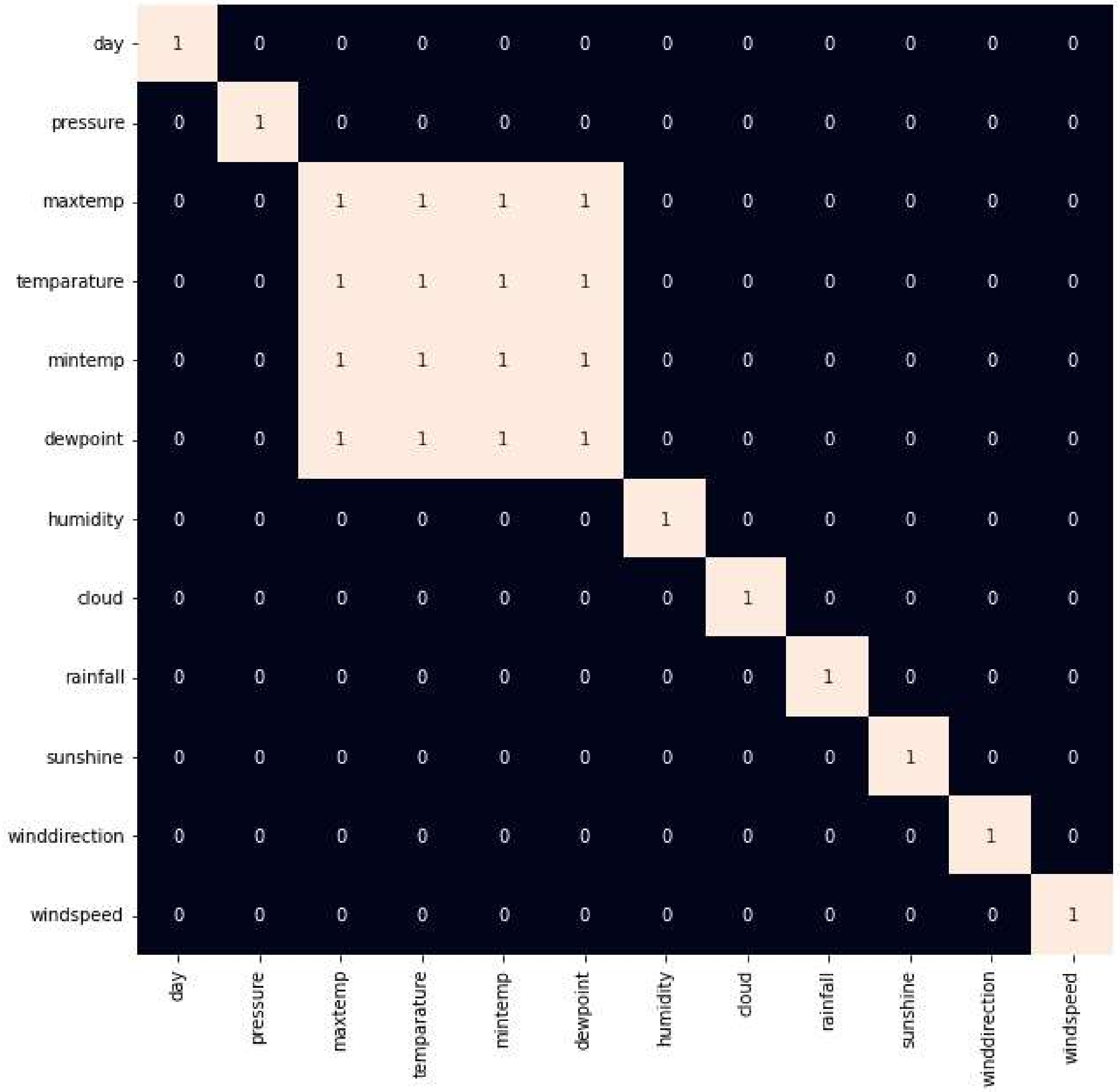
Python3

Sometimes there are highly correlated features that just increase the dimensionality of the feature space and do not good for the model's performance. So we must check whether there are highly correlated features in this dataset or not.

Python3

```
plt.figure(figsize=(10,10))
sb.heatmap(df.corr() > 0.8,
           annot=True,
           cbar=False)
plt.show()
```

Output:



Heat map to detect highly correlated features

Now we will remove the highly correlated features ‘maxtemp’ and ‘mintemp’. But why not temp or dewpoint? This is because temp and dewpoint provide distinct information regarding the weather and atmospheric

Python3

```python
df.drop(['maxtemp', 'mintemp'], axis=1, inplace=True)
```

Model Training

Now we will separate the features and target variables and split them into training and testing data by using which we will select the model which is performing best on the validation data.

Python3

```python
features = df.drop(['day', 'rainfall'], axis=1)
target = df.rainfall
```

As we found earlier that the dataset we were using was imbalanced so, we will have to balance the training data before feeding it to the model.

Python3

```python
X_train, X_val, \
    Y_train, Y_val = train_test_split(features,
                                      target,
                                      test_size=0.2,
                                      stratify=target,
                                      random_state=2)

# As the data was highly imbalanced we will
# balance it by adding repetitive rows of minority class.
ros = RandomOverSampler(sampling_strategy='minority',
```

The features of the dataset were at different scales so, normalizing it before training will help us to obtain optimum results faster along with stable training.

Python3

```
# Normalizing the features for stable and fast training.
scaler = StandardScaler()
X = scaler.fit_transform(X)
X_val = scaler.transform(X_val)
```

Now let's train some state-of-the-art models for classification and train them on our training data.

- LogisticRegression
- XGBClassifier
- SVC

Python3

```
models = [LogisticRegression(), XGBClassifier(), SVC(kernel='rbf', probability=True)]

for i in range(3):
  models[i].fit(X, Y)

  print(f'{models[i]} : ')

  train_preds = models[i].predict_proba(X)
  print('Training Accuracy : ', metrics.roc_auc_score(Y, train_preds[:,1]))

  val_preds = models[i].predict_proba(X_val)
  print('Validation Accuracy : ', metrics.roc_auc_score(Y_val, val_preds[:,1]))
  print()
```

```
LogisticRegression() :
Training Accuracy :  0.8893967324057472
Validation Accuracy :  0.8966666666666667

XGBClassifier() :
Training Accuracy :  0.9903285270573975
Validation Accuracy :  0.8408333333333333

SVC(probability=True) :
Training Accuracy :  0.9026413474407211
Validation Accuracy :  0.8858333333333333
```

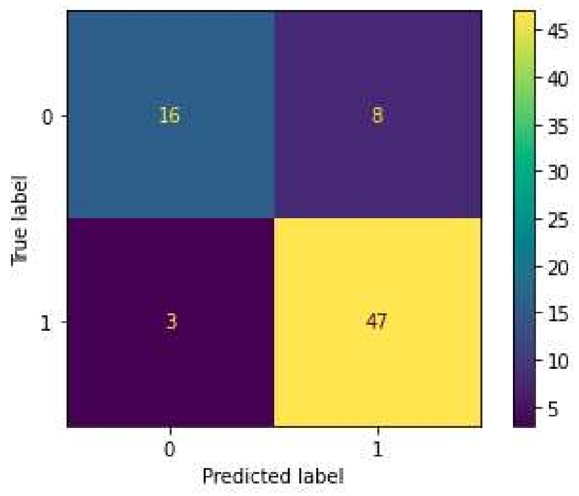
Model Evaluation

From the above accuracies, we can say that Logistic Regression and support vector classifier are satisfactory as the gap between the training and the validation accuracy is low. Let's plot the confusion matrix as well for the validation data using the SVC model.

Python3

```
metrics.plot_confusion_matrix(models[2], X_val, Y_val)
plt.show()
```

Output:



Confusion matrix for the validation data

Let's plot the classification report as well for the validation data using the SVC model.

Python3

```
print(metrics.classification_report(Y_val,
                                    models[2].predict(X_val)))
```

Output:

```
              precision    recall  f1-score   support

           0       0.84      0.67      0.74        24
           1       0.85      0.94      0.90        50

    accuracy                           0.85        74
   macro avg       0.85      0.80      0.82        74
```