Link to the OneDrive : https://colab.research.google.com/drive/125BZV0eG7l3ZF6wg2acbRiXU1bvB8a_P?usp=sharing

1. Importing Basic Libraries

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

2. Reading the Dataset

```
data = pd.read_csv("/content/Rainfall.csv")
```

3. Basic checks on the data

```
data.shape
```

```
(366, 12)
```

```
data.head()
```

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

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```
data.info()
```

```
<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
```

```
data.describe()
```

	day	pressure	maxtemp	temparature	mintemp	dewpoint	humidity	cloud	
count	366.000000	366.000000	366.000000	366.000000	366.000000	366.000000	366.000000	366.000000	3
mean	15.756831	1013.742623	26.191257	23.747268	21.894536	19.989071	80.177596	71.128415	
std	8.823592	6.414776	5.978343	5.632813	5.594153	5.997021	10.062470	21.798012	
min	1.000000	998.500000	7.100000	4.900000	3.100000	-0.400000	36.000000	0.000000	
25%	8.000000	1008.500000	21.200000	18.825000	17.125000	16.125000	75.000000	58.000000	
50%	16.000000	1013.000000	27.750000	25.450000	23.700000	21.950000	80.500000	80.000000	
75%	23.000000	1018.100000	31.200000	28.600000	26.575000	25.000000	87.000000	88.000000	
max	31.000000	1034.600000	36.300000	32.400000	30.000000	26.700000	98.000000	100.000000	

```
# Display count of unique values in each column
for column in data.columns:
    unique_values = data[column].nunique()
    print(f"Unique values in {column}: {unique_values}")
```

```
Unique values in day: 31
Unique values in pressure : 188
Unique values in maxtemp: 174
Unique values in temparature: 158
Unique values in mintemp: 157
Unique values in dewpoint: 158
Unique values in humidity : 49
Unique values in cloud : 79
Unique values in rainfall: 2
Unique values in sunshine: 104
Unique values in          winddirection: 31
Unique values in windspeed: 223
```

```
data.columns
```

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

4. Correcting the space in winddirection column

```
data.columns = data.columns.str.strip()
```

```
data.columns
```

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

5. Dropping irrelevent columns for prediction

```
data.drop(columns=['day'], inplace = True)
```

```
data.tail()
```

	pressure	maxtemp	temparature	mintemp	dewpoint	humidity	cloud	rainfall	sunshine	winddirecti
361	1022.7	18.8	17.7	16.9	15.0	84	90	yes	0.0	3
362	1026.6	18.6	17.3	16.3	12.8	75	85	yes	1.0	2
363	1025.9	18.9	17.7	16.4	13.3	75	78	yes	4.6	7
364	1025.3	19.2	17.3	15.2	13.3	78	86	yes	1.2	2
365	1026.4	20.5	17.8	15.5	13.0	74	66	no	5.7	2

6. Checking Null Value

```
data.isnull().sum()
```

	0
pressure	0
maxtemp	0
temparature	0
mintemp	0
dewpoint	0
humidity	0
cloud	0
rainfall	0
sunshine	0
winddirection	1
windspeed	1

```
data['winddirection'].unique()
```

```
array([ 80.,  50.,  40.,  20.,  30.,  60.,  70.,  10., 200., 220., 120.,
       190., 210., 300., 240., 180., 230.,  90., 170., 150., 100., 130.,
        nan, 160., 270., 280., 250., 260., 290., 350., 110., 140.])
```

```
data['windspeed'].unique()
```

```
array([26.3, 15.3, 14.2, 16.9, 13.7, 14.5, 21.5, 14.3, 39.3, 37.7, 23.3,
       23.9, 24.4, 33.2, 37.5, 40. , 23.4, 28.4, 38. , 50.6, 26.2, 35.3,
       55.5, 59.5, 28.7, 21.3, 29.6, 28.8, 25. , 21.2, 43.1, 31.9, 27.3,
        9.1, 44.7, 20.5, 16.7, 17.2, 22. , 15.8, 13.9, 10.2, 33.5, 23.5,
       19.2, 18.6, 22.2, 19.3, 28. , 20.4, 15.2,  9.2, 34.2, 27.1, 14.7,
       15.4, 13.3,  6.6, 13.8, 15.1, 39.7, 36. , 22.8, 26.7, 26.5, 13.1,
       12.5, 38.3, 42. , 19.4, 13.4, 14.6, 26.9, 14.8,  4.5,  8.3,  8. ,
       20. , 10. , 17.3, 31.8, 29.8, 11.2, 16. , 19.6, 20.9,  7.3, 11.1,
       13. ,  8.5, 24.2, 20.2, 30.5, 27. , 23.7, 11.8, 15.5, 12.1,  9.5,
       16.3, 12. , 26. , 28.6, 24.9, 28.3, 15.7, 21.9, 39.5, 30.3, 26.4,
       22.3, 25.9, 11.3,  7.9,  7.4, 16.2, 34.8, 32.5, 24. , 19. , 25.2,
       31.7, 27.4, 20.8,  9.8, 12.6,  nan, 24.3, 30. , 29.3, 23.2, 12.8,
       19.8, 12.4, 10.9,  9.6,  9. , 11.9, 26.1, 25.1, 33. , 22.5, 24.8,
       18.8, 22.4, 22.6, 12.3, 21.6, 17.5, 16.1, 14.1,  5.5,  4.4,  8.7,
        6.1, 22.9, 12.9, 18. , 18.1, 16.6,  6.9, 13.6, 11.7, 11. , 10.7,
       16.4,  8.9,  5.9,  5.7,  8.6, 16.5, 18.2, 29. , 24.5, 21.4, 39.9,
       41.3, 32.2,  8.1, 14. , 12.7, 30.6, 52.8, 50.7, 37. , 30.4, 30.2,
```

```
       28.2, 32.4,  9.9, 13.2, 19.7, 28.9, 10.3, 40.8, 32.9, 46.3, 43.8,
       41.4, 29.7, 35.8, 25.5, 22.1, 40.4, 29.2, 31.2, 34.3, 34. , 15.9,
       27.9, 37.9, 21.8, 28.5, 35.1, 20.7, 20.3, 26.8, 48. , 35.6, 15. ,
        9.4, 27.6, 18.4, 33.4])
```

7. Handling Missing Values

```
data['winddirection'] = data['winddirection'].fillna(data['winddirection'].mode()[0])
data['windspeed'] = data['windspeed'].fillna(data['windspeed'].median())
```

```
data.isnull().sum()
```

	0
pressure	0
maxtemp	0
temparature	0
mintemp	0
dewpoint	0
humidity	0
cloud	0
rainfall	0
sunshine	0
winddirection	0
windspeed	0

```
data['rainfall'].unique()
```

```
array(['yes', 'no'], dtype=object)
```

```
# Converting yes and no to 1 and 0 respectively
data['rainfall'] = data['rainfall'].map({'yes': 1, 'no': 0})
data.head()
```

	pressure	maxtemp	temparature	mintemp	dewpoint	humidity	cloud	rainfall	sunshine	winddirectio
0	1025.9	19.9	18.3	16.8	13.1	72	49	1	9.3	80.(
1	1022.0	21.7	18.9	17.2	15.6	81	83	1	0.6	50.(
2	1019.7	20.3	19.3	18.0	18.4	95	91	1	0.0	40.(
3	1018.9	22.3	20.6	19.1	18.8	90	88	1	1.0	50.(
4	1015.9	21.3	20.7	20.2	19.9	95	81	1	0.0	40.(

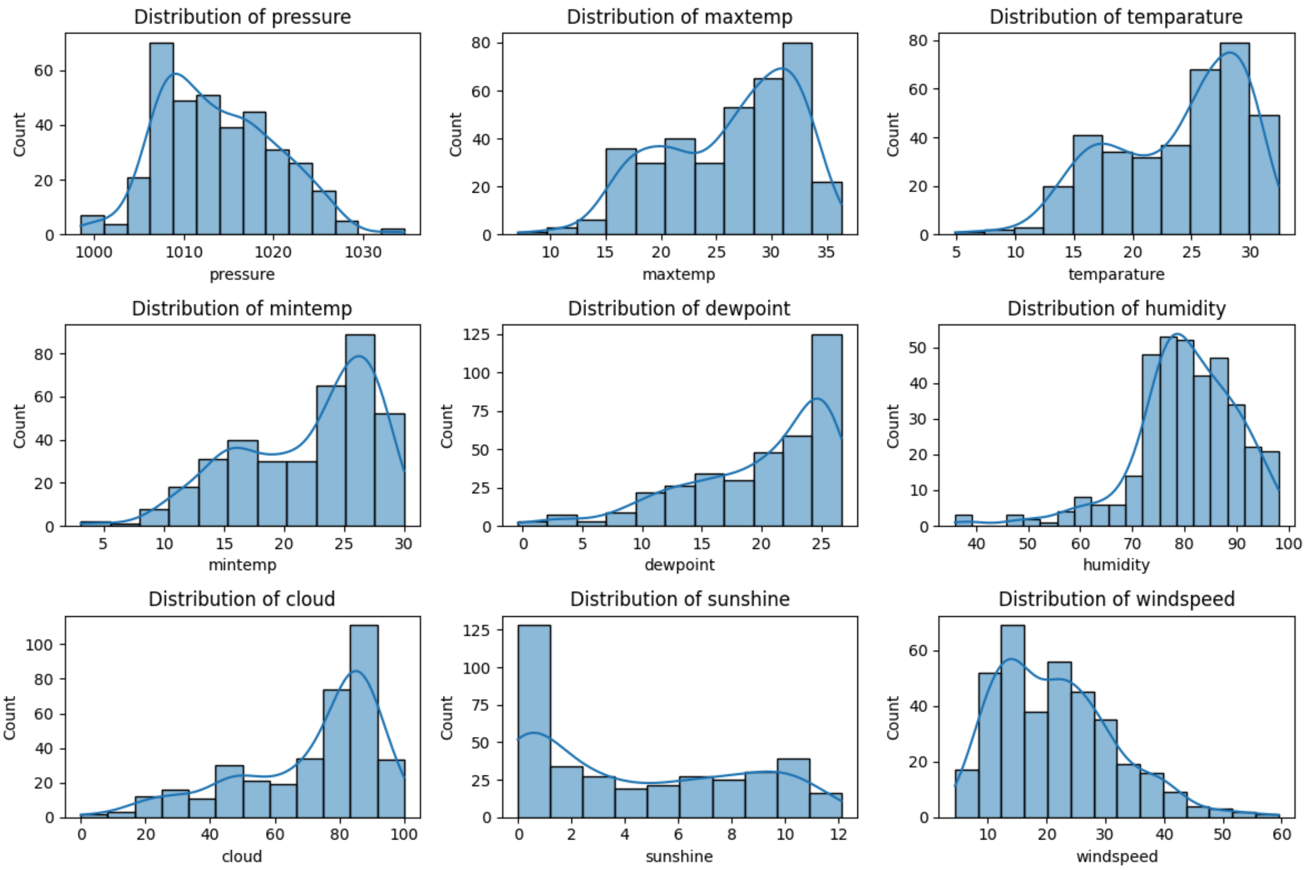
Next steps: Generate code with `data` View recommended plots New interactive sheet

8. Explore Data Analysis

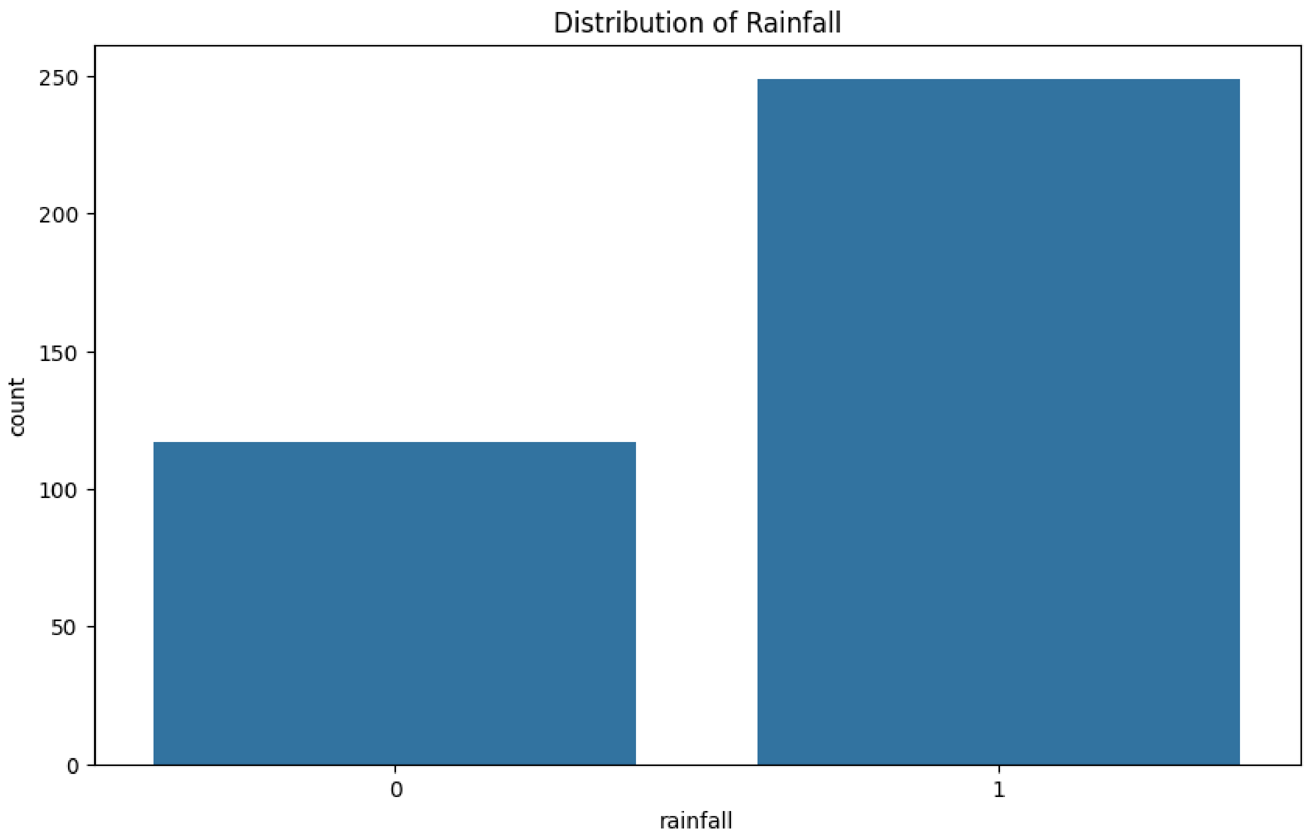
```
data.columns
```

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

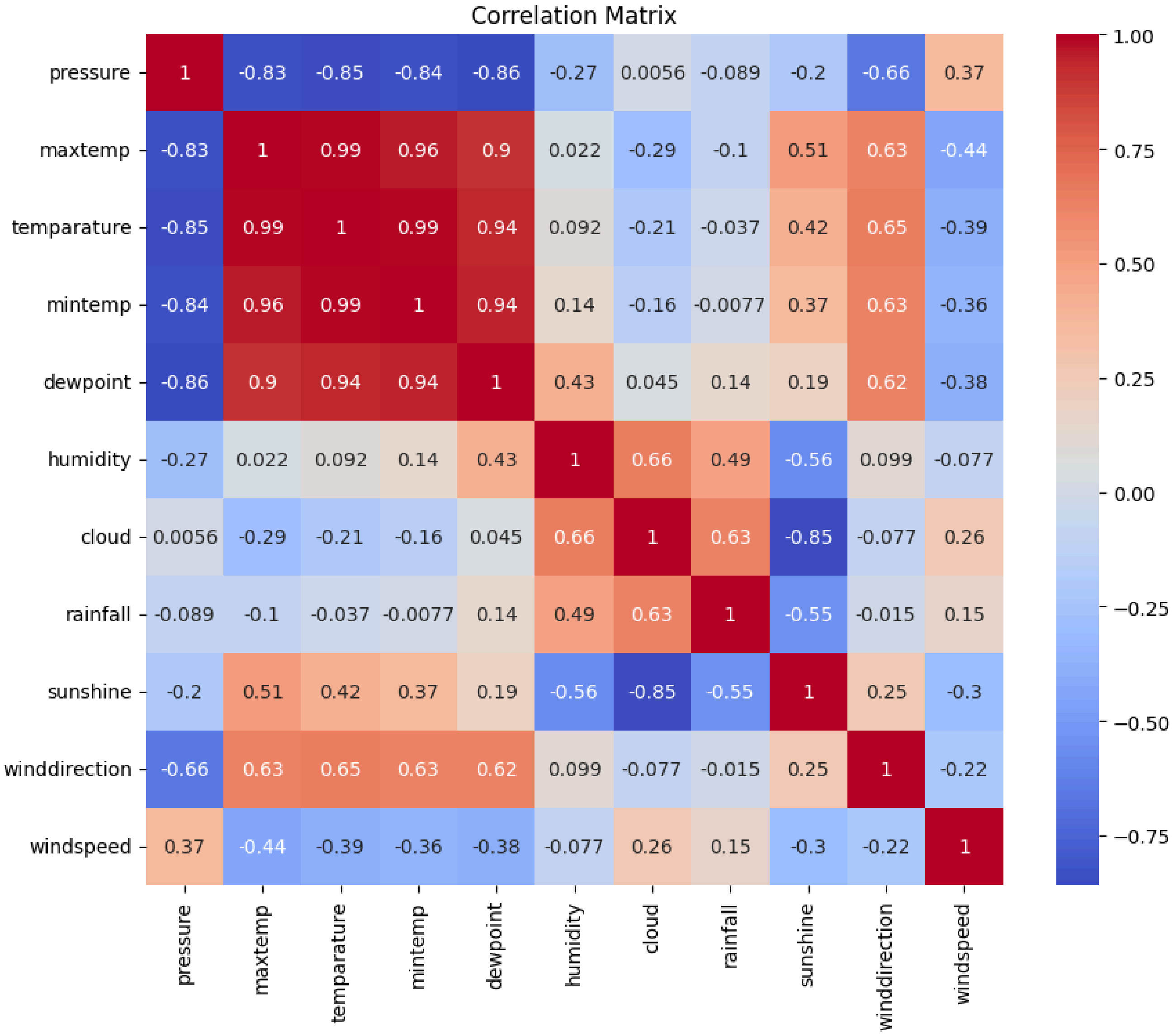
```
plt.figure(figsize=(12,8))

for i, column in enumerate(['pressure', 'maxtemp', 'temparature', 'mintemp', 'dewpoint', 'humidity',
       'cloud', 'sunshine', 'windspeed'], 1):
  plt.subplot(3,3,i)
  sns.histplot(data[column], kde=True)
  plt.title(f"Distribution of {column}")
plt.tight_layout()
plt.show()
```




```
plt.figure(figsize=(10,6))
sns.countplot(x='rainfall', data = data)
plt.title("Distribution of Rainfall")
plt.show()
```

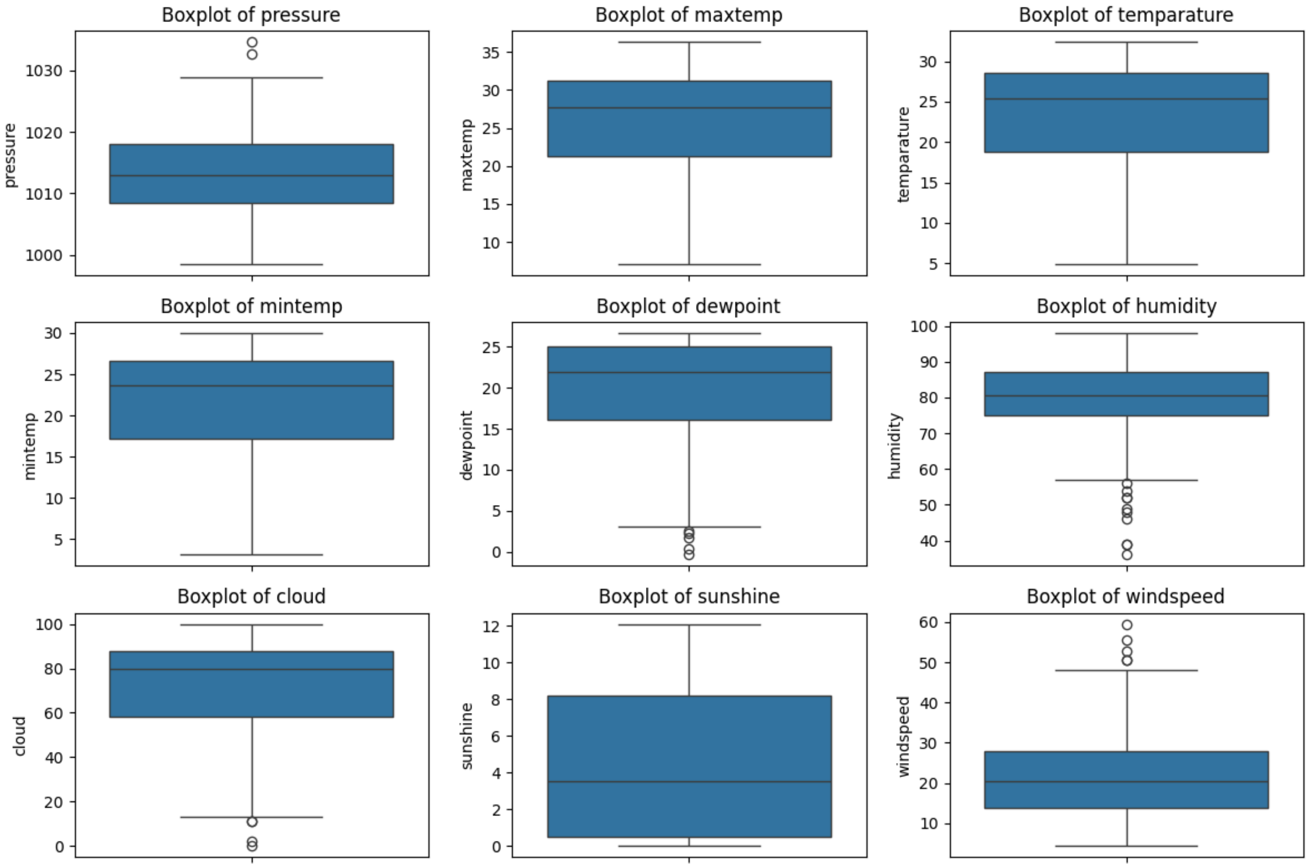



```
#Correlation matrix

corr_matrix = data.corr()
plt.figure(figsize=(10,8))
sns.heatmap(data.corr(), annot=True, cmap='coolwarm')
plt.title("Correlation Matrix")
plt.show()
```



	pressure	maxtemp	temparature	mintemp	dewpoint	humidity	cloud	rainfall	sunshine	winddirection	windspeed
pressure	1	-0.83	-0.85	-0.84	-0.86	-0.27	0.0056	-0.089	-0.2	-0.66	0.37
maxtemp	-0.83	1	0.99	0.96	0.9	0.022	-0.29	-0.1	0.51	0.63	-0.44
temparature	-0.85	0.99	1	0.99	0.94	0.092	-0.21	-0.037	0.42	0.65	-0.39
mintemp	-0.84	0.96	0.99	1	0.94	0.14	-0.16	-0.0077	0.37	0.63	-0.36
dewpoint	-0.86	0.9	0.94	0.94	1	0.43	0.045	0.14	0.19	0.62	-0.38
humidity	-0.27	0.022	0.092	0.14	0.43	1	0.66	0.49	-0.56	0.099	-0.077
cloud	0.0056	-0.29	-0.21	-0.16	0.045	0.66	1	0.63	-0.85	-0.077	0.26
rainfall	-0.089	-0.1	-0.037	-0.0077	0.14	0.49	0.63	1	-0.55	-0.015	0.15
sunshine	-0.2	0.51	0.42	0.37	0.19	-0.56	-0.85	-0.55	1	0.25	-0.3
winddirection	-0.66	0.63	0.65	0.63	0.62	0.099	-0.077	-0.015	0.25	1	-0.22
windspeed	0.37	-0.44	-0.39	-0.36	-0.38	-0.077	0.26	0.15	-0.3	-0.22	1

```
plt.figure(figsize=(12,8))

for i, column in enumerate(['pressure', 'maxtemp', 'temparature', 'mintemp', 'dewpoint', 'humidity',
       'cloud', 'sunshine', 'windspeed'], 1):
  plt.subplot(3,3,i)
  sns.boxplot(data[column])
  plt.title(f"Boxplot of {column}")
plt.tight_layout()
plt.show()
```



9. Data Preprocessing

```
#Dropping highly correlated columns
data = data.drop(['maxtemp', 'mintemp', 'dewpoint'], axis = 1)
data.head()
```

	pressure	temparature	humidity	cloud	rainfall	sunshine	winddirection	windspeed
0	1025.9	18.3	72	49	1	9.3	80.0	26.3
1	1022.0	18.9	81	83	1	0.6	50.0	15.3
2	1019.7	19.3	95	91	1	0.0	40.0	14.2
3	1018.9	20.6	90	88	1	1.0	50.0	16.9
4	1015.9	20.7	95	81	1	0.0	40.0	13.7

Next steps: Generate code with data View recommended plots New interactive sheet

10. Checking the Balance of Target variable and Handling imbalance

```
data['rainfall'].value_counts()
```

rainfall	count
1	249
0	117

```
rainfall_1 = data[data['rainfall'] == 1]
rainfall_0 = data[data['rainfall'] == 0]
```

```
# Downsampling the data for rainfall_1
from sklearn.utils import resample
rainfall_1_downsample = resample(rainfall_1, replace = False, n_samples = len(rainfall_0), random_state = 42
rainfall_1_downsample
```

	pressure	temparature	humidity	cloud	rainfall	sunshine	winddirection	windspeed
188	1005.9	30.2	77	53	1	10.5	270.0	11.3
9	1017.5	18.0	85	91	1	0.0	70.0	37.7
137	1012.3	23.7	80	86	1	0.3	80.0	39.5
89	1018.3	20.0	79	89	1	2.4	40.0	14.8
157	1008.8	26.2	91	80	1	2.2	20.0	11.2
...	...	...	...	...	...	...	...	...
252	1012.0	28.2	74	44	1	10.1	70.0	26.2
349	1019.0	18.4	69	70	1	2.2	10.0	26.8
187	1008.4	27.3	93	88	1	0.5	130.0	24.8
0	1025.9	18.3	72	49	1	9.3	80.0	26.3
2	1019.7	19.3	95	91	1	0.0	40.0	14.2

117 rows × 8 columns

Next steps: Generate code with rainfall_1_downsample | View recommended plots | New interactive sheet

```
# merging rainfall column values 0 and 1
rainfall_downsample = pd.concat([rainfall_1_downsample, rainfall_0])
rainfall_downsample
```

	pressure	temparature	humidity	cloud	rainfall	sunshine	winddirection	windspeed
188	1005.9	30.2	77	53	1	10.5	270.0	11.3
9	1017.5	18.0	85	91	1	0.0	70.0	37.7
137	1012.3	23.7	80	86	1	0.3	80.0	39.5
89	1018.3	20.0	79	89	1	2.4	40.0	14.8
157	1008.8	26.2	91	80	1	2.2	20.0	11.2
...	...	...	...	...	...	...	...	...
351	1025.9	13.2	39	25	0	9.1	20.0	35.6
352	1026.4	13.9	48	11	0	9.5	40.0	25.2
353	1025.4	16.2	62	71	0	2.1	30.0	29.0
360	1020.6	17.9	74	87	0	0.6	30.0	21.6
365	1026.4	17.8	74	66	0	5.7	20.0	23.3

234 rows × 8 columns

Next steps: Generate code with rainfall_downsample | View recommended plots | New interactive sheet

```
# Shuffling the data
rainfall_downsample = rainfall_downsample.sample(frac = 1, random_state = 42).reset_index(drop = True)
rainfall_downsample.head()
```

	pressure	temparature	humidity	cloud	rainfall	sunshine	winddirection	windspeed
0	1022.2	18.0	78	90	1	0.0	30.0	28.5
1	1013.4	26.2	69	17	0	10.5	70.0	12.4
2	1006.1	29.6	74	27	0	10.8	220.0	8.7
3	1007.6	27.6	85	84	1	1.8	70.0	34.8
4	1021.2	14.8	66	18	0	10.1	20.0	24.4

Next steps: Generate code with rainfall_downsample | View recommended plots | New interactive sheet

```
rainfall_downsample['rainfall'].value_counts()
```

rainfall	count
1	117
0	117

11. Data split into Training and Testing data

```
# Splitting features as X and target variable as Y
X = rainfall_downsample.drop(columns = ['rainfall'])
y = rainfall_downsample['rainfall']
print(X)
```

```
     pressure  temparature  humidity  cloud  sunshine  winddirection  \
0      1022.2         18.0        78     90       0.0           30.0
1      1013.4         26.2        69     17      10.5           70.0
2      1006.1         29.6        74     27      10.8          220.0
3      1007.6         27.6        85     84       1.8           70.0
4      1021.2         14.8        66     18      10.1           20.0
..        ...          ...       ...    ...       ...            ...
229    1008.1         28.1        86     75       5.7           20.0
230    1010.1         21.5        91     89       0.0           70.0
231    1020.6         16.1        91     88       0.3           50.0
232    1008.3         29.4        74     29       5.7           10.0
233    1005.0         28.6        87     82       2.2          160.0

     windspeed
0         28.5
1         12.4
2          8.7
3         34.8
4         24.4
..         ...
229        9.5
230       31.8
231       24.4
232        4.4
233       12.6

[234 rows x 7 columns]
```

```
print(y)
```

```
0      1
1      0
2      0
3      1
4      0
      ..
229    1
230    1
231    1
232    0
233    1
Name: rainfall, Length: 234, dtype: int64
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 42, test_size = 0.2)
```

12. Model Training using Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier()

params = {
    "n_estimators" : [50, 100, 200],
    "max_features" : ["sqrt", "log2"],
    "max_depth" : [None, 5, 10, 15],
    "min_samples_split" : [2, 5, 10],
    "min_samples_leaf" : [1, 2, 4]
}
```

```
# Hyper Parameter Tuning
from sklearn.model_selection import GridSearchCV

gridsearch = GridSearchCV(estimator=rf, param_grid=params, cv=5, n_jobs=-1, verbose=2)
gridsearch.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 216 candidates, totalling 1080 fits
▸ GridSearchCV
▸ best_estimator_:
  RandomForestClassifier
  ▸ RandomForestClassifier
```

```
best_rf = gridsearch.best_estimator_
print("Best Parameter for the RF model is :", gridsearch.best_params_)
best_rf
```

```
Best Parameter for the RF model is : {'max_depth': 15, 'max_features': 'log2', 'min_samples_leaf': 1, '
▾ RandomForestClassifier
RandomForestClassifier(max_depth=15, max_features='log2', min_samples_split=5)
```

12.1. Model Validation on Test Data

```
from sklearn.model_selection import cross_val_score

cv_scores = cross_val_score(best_rf, X_train, y_train, cv=5)
print("Cross Validation Score : ", cv_scores)
print("Mean Cross Validation Score : ", cv_scores.mean())
```

```
Cross Validation Score :  [0.68421053 0.84210526 0.86486486 0.81081081 0.86486486]
Mean Cross Validation Score :  0.813371266002845
```

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix, clas

y_pred1 = best_rf.predict(X_test)
print("Test set Accuracy : ", accuracy_score(y_test, y_pred1))
print("Test set Confusion Matrix : \n", confusion_matrix(y_test, y_pred1))
print("Recall Score : ", classification_report(y_test, y_pred1))
```

```
Test set Accuracy :  0.7872340425531915
Test set Confusion Matrix :
 [[18  6]
 [ 4 19]]
Recall Score :                precision    recall  f1-score   support

           0       0.82      0.75      0.78        24
           1       0.76      0.83      0.79        23

    accuracy                           0.79        47
   macro avg       0.79      0.79      0.79        47
weighted avg       0.79      0.79      0.79        47
```

13. Model Training using Gradient Boosting Classifier

```
from sklearn.ensemble import GradientBoostingClassifier

# Define the model
gb = GradientBoostingClassifier()

# Define the parameter grid
params = {
    "n_estimators" : [50, 100, 150, 200, 300],
    "learning_rate" : [0.01, 0.1, 0.2, 0.3],
    "max_depth" : [3, 5, 7, 9],
    "min_samples_split" : [2, 5, 10],
    "min_samples_leaf" : [1, 2, 4]
}


# Hyperparameter Tuning
gridsearch = GridSearchCV(estimator=gb, param_grid=params, cv=5, n_jobs=-1, verbose=2)
gridsearch.fit(X_train, y_train)
best_gb = gridsearch.best_estimator_
print("Best Parameters for the Gradient Boosting model are:", gridsearch.best_params_)
```

```
Fitting 5 folds for each of 720 candidates, totalling 3600 fits
Best Parameters for the Gradient Boosting model are: {'learning_rate': 0.1, 'max_depth': 5, 'min_sample
```

13. Model Evaluation

```
cv_scores = cross_val_score(best_gb, X_train, y_train, cv=5)
print("Cross-Validation Scores:", cv_scores)
print("Mean Cross-Validation Score:", cv_scores.mean())
```

```
Cross-Validation Scores: [0.71052632 0.81578947 0.75675676 0.81081081 0.81081081]
Mean Cross-Validation Score: 0.7809388335704126
```

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix, clas

# Make predictions
y_pred2 = best_gb.predict(X_test)

# Print evaluation metrics
print("Test Set Accuracy:", accuracy_score(y_test, y_pred2))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred2))
print("Classification Report:\n", classification_report(y_test, y_pred2))
```

```
Test Set Accuracy: 0.7446808510638298
Confusion Matrix:
 [[18  6]
 [ 6 17]]
Classification Report:
               precision    recall  f1-score   support

           0       0.75      0.75      0.75        24
           1       0.74      0.74      0.74        23

    accuracy                           0.74        47
```