Performing EDA & Implementing Logistic Regression on Algerian forest fires dataset

1. Date : (DD/MM/YYYY) Day, month ('june' to 'september'), year (2012) Weather data observations
2. Temp : temperature noon (temperature max) in Celsius degrees: 22 to 42
3. RH : Relative Humidity in %: 21 to 90
4. Ws :Wind speed in km/h: 6 to 29
5. Rain: total day in mm: 0 to 16.8 FWI Components
6. Fine Fuel Moisture Code (FFMC) index from the FWI system: 28.6 to 92.5
7. Duff Moisture Code (DMC) index from the FWI system: 1.1 to 65.9
8. Drought Code (DC) index from the FWI system: 7 to 220.4
9. Initial Spread Index (ISI) index from the FWI system: 0 to 18.5
10. Buildup Index (BUI) index from the FWI system: 1.1 to 68
11. Fire Weather Index (FWI) Index: 0 to 31.1
12. Classes: two classes, namely â€œFireâ€ and â€œnot Fireâ€

In [1]:

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model  import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
import scikitplot as skl
sns.set()
```

In [2]:

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

Out[2]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
0	1	6	2012	29	57	18	0	65.7	3.4	7.6	1.3	3.4	0.5	not fire
1	2	6	2012	29	61	13	1.3	64.4	4.1	7.6	1	3.9	0.4	not fire
2	3	6	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	not fire
3	4	6	2012	25	89	13	2.5	28.6	1.3	6.9	0	1.7	0	not fire
4	5	6	2012	27	77	16	0	64.8	3	14.2	1.2	3.9	0.5	not fire

Data Cleaning & Label Encoding

In [3]:

```
df.drop([122,123,124], inplace = True)
df.reset_index(inplace=True)
df.drop('index',axis=1,inplace=True)
```

In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 14 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   day          244 non-null    object
 1   month        244 non-null    object
 2   year         244 non-null    object
 3   Temperature  244 non-null    object
 4    RH          244 non-null    object
 5    Ws          244 non-null    object
 6   Rain         244 non-null    object
 7   FFMC         244 non-null    object
 8   DMC          244 non-null    object
 9   DC           244 non-null    object
 10  ISI          244 non-null    object
 11  BUI          244 non-null    object
 12  FWI          244 non-null    object
 13  Classes      243 non-null    object
dtypes: object(14)
memory usage: 26.8+ KB
```

In [5]:

```
df.columns
```

Out[5]:

```
Index(['day', 'month', 'year', 'Temperature', ' RH', ' Ws', 'Rain ', 'FFMC',
       'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes'],
      dtype='object')
```

In [6]:

```
df.columns = [co.strip() for co in df.columns]
df.columns
```

Out[6]:

```
Index(['day', 'month', 'year', 'Temperature', 'RH', 'Ws', 'Rain', 'FFMC',
       'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes'],
      dtype='object')
```

In [7]:

```
# we adding a new column Region to dataset
# rows 1 = Bejaia Region and 0 = Sidi Bel-abbes Region
df['Region'] = 1
for i in range(len(df)):
    if i >= 122:
        df['Region'][i] = 0
```

```
C:\Users\Thanmai\AppData\Local\Temp/ipykernel_14092/3918257608.py:6: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pand
as.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-v
ersus-a-copy)
  df['Region'][i] = 0
```

In [8]:

```
df['Classes'].unique()
```

Out[8]:

```
array(['not fire   ', 'fire   ', 'fire', 'fire ', 'not fire', 'not fire ',
       'not fire     ', nan, 'not fire    '], dtype=object)
```

In [9]:

```
df['Classes'] = df['Classes'].str.strip()
df['Classes'].unique()
```

Out[9]:

```
array(['not fire', 'fire', nan], dtype=object)
```

In [10]:

```
df[df['Classes'].isnull()]
```

Out[10]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Clas
165	14	7	2012	37	37	18	0.2	88.9	12.9	14.6 9	12.5	10.4	fire	N

In [11]:

```
df['FWI'] = df.FWI.apply(lambda x: x.replace('fire', ''))# For replce the string fire with
df[df['Classes'].isnull()]
```

Out[11]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Clas
165	14	7	2012	37	37	18	0.2	88.9	12.9	14.6 9	12.5	10.4		N

In [12]:

```
df['FWI'] = df.FWI.replace(r'^\s*$', np.nan, regex=True) # replacing null value with NAN
```

In [13]:

```
 #Let's relpace the class value with mode
modeValueRating = df['Classes'].mode()
df['Classes'].fillna(value=modeValueRating[0], inplace = True)
#Now, let's relpace the FWI value with Median
df['FWI'].fillna(df['FWI'].median(), inplace = True)
#relpace the blank space in DC
df['DC'] = df.DC.apply(lambda x: x.replace(' ', ''))
```

In [14]:

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

Out[14]:

0

In [15]:

```
# Statistical summary of data
df.describe().T
```

Out[15]:

	count	mean	std	min	25%	50%	75%	max
Region	244.0	0.5	0.501028	0.0	0.0	0.5	1.0	1.0

In [16]:

```
#Let's check the datatypes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 15 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   day          244 non-null    object
 1   month        244 non-null    object
 2   year         244 non-null    object
 3   Temperature  244 non-null    object
 4   RH           244 non-null    object
 5   Ws           244 non-null    object
 6   Rain         244 non-null    object
 7   FFMC         244 non-null    object
 8   DMC          244 non-null    object
 9   DC           244 non-null    object
 10  ISI          244 non-null    object
 11  BUI          244 non-null    object
 12  FWI          244 non-null    object
 13  Classes      244 non-null    object
 14  Region       244 non-null    int64 
dtypes: int64(1), object(14)
memory usage: 28.7+ KB
```

Changing dtypes to numerical

In [17]:

```
df = df.astype({'RH':np.int64, 'Temperature':np.int64, 'Ws':np.int64, 'Rain':np.float64, 'F
               ,'DMC':np.float64, 'DC':np.float64, 'ISI':np.float64, 'BUI':np.float64,
               'FWI':np.float64})
```

In [18]:

```
# Printing all the categorical columns
categorical_col = [fea for fea in df.columns if df[fea].dtype == 'O']
print('Categorical columns--',categorical_col)

# Printing all the numerical columns
numerical_col = [fea for fea in df.columns if df[fea].dtype != 'O']
print('Numerical columns--',numerical_col)
```

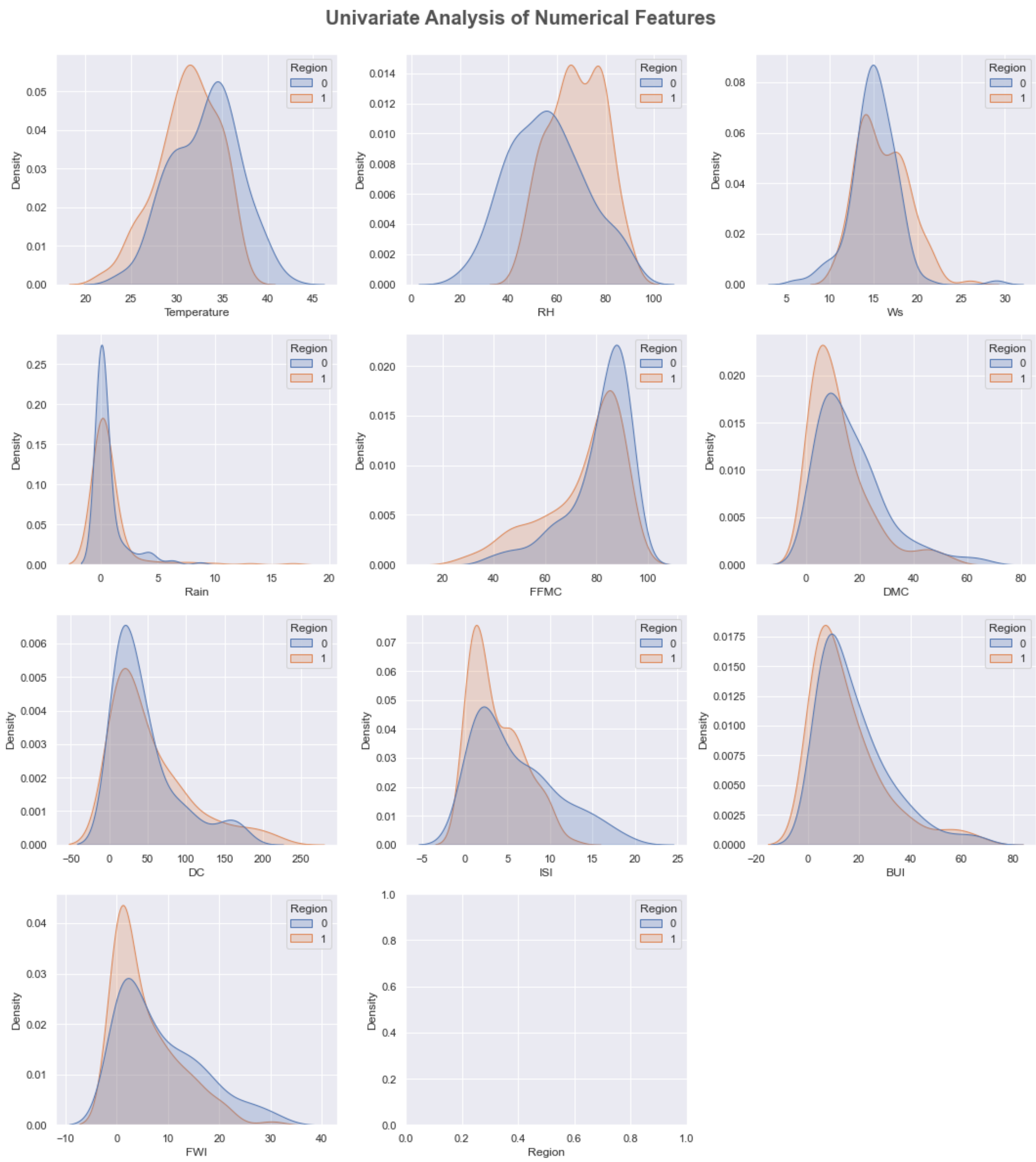
```
Categorical columns-- ['day', 'month', 'year', 'Classes']
Numerical columns-- ['Temperature', 'RH', 'Ws', 'Rain', 'FFMC', 'DMC', 'DC',
'ISI', 'BUI', 'FWI', 'Region']
```

Distribution Numerical Features of our Dataset

In [19]:

```
plt.figure(figsize=(15, 20))
plt.suptitle('Univariate Analysis of Numerical Features', fontsize=20, fontweight='bold', a

for i in range(0, len(numerical_col)):
    plt.subplot(5, 3, i+1)
    sns.kdeplot(x=df[numerical_col[i]],shade=True, color='b',hue='Region',data=df)
    plt.xlabel(numerical_col[i])
    plt.tight_layout()
```

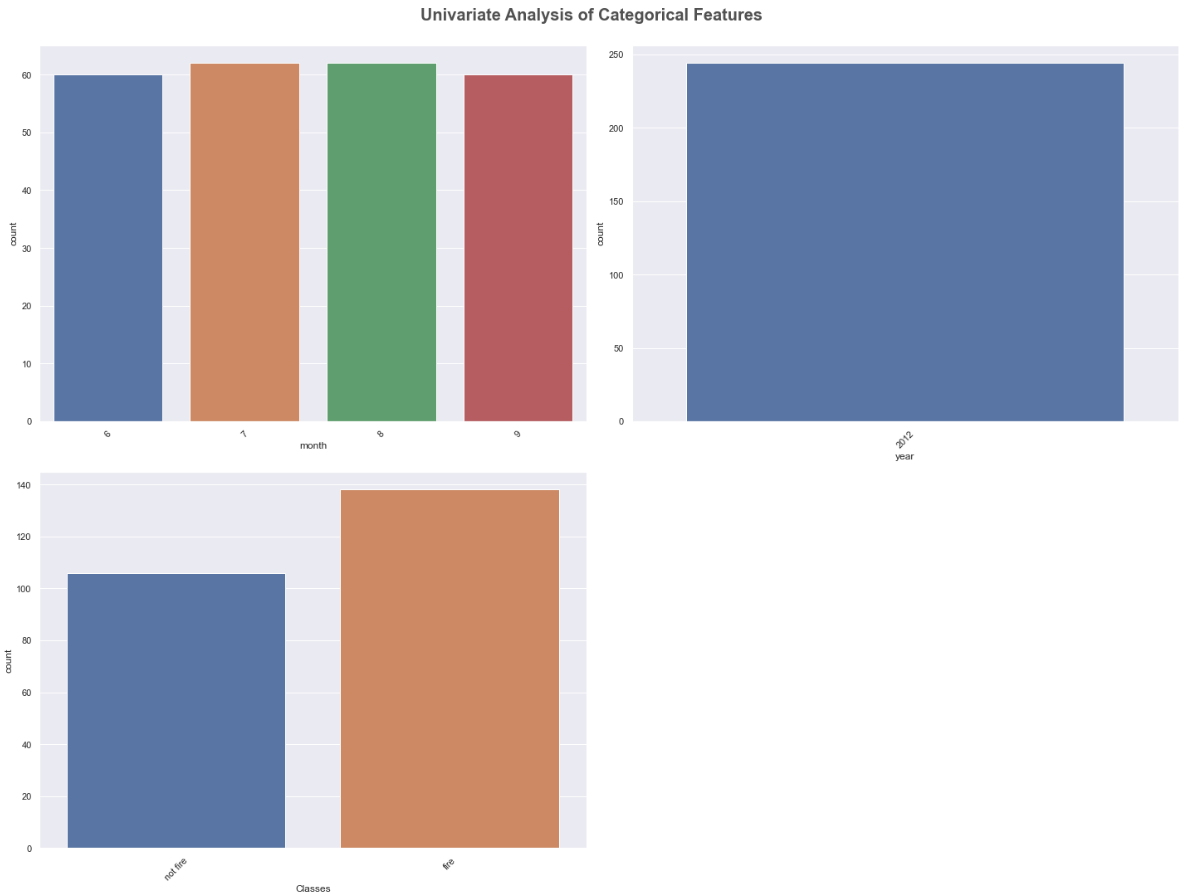
```
C:\Users\Thanmai\anaconda3\lib\site-packages\seaborn\distributions.py:316: U
serWarning: Dataset has 0 variance; skipping density estimate. Pass `warn_si
ngular=False` to disable this warning.
  warnings.warn(msg, UserWarning)
```



Distribution Categorical Features of our Dataset

In [20]:

```
# categorical columns
plt.figure(figsize=(20, 15))
plt.suptitle('Univariate Analysis of Categorical Features', fontsize=20, fontweight='bold',
cat1 = ['month', 'year', 'Classes']
for i in range(0, len(cat1)):
    plt.subplot(2, 2, i+1)
    sns.countplot(x=df[cat1[i]])
    plt.xlabel(cat1[i])
    plt.xticks(rotation=45)
    plt.tight_layout()
```



Checking for Correlation

In [21]:

```
df[numerical_col].corr()
```

Out[21]:

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	
Temperature	1.000000	-0.654443	-0.278132	-0.326786	0.677491	0.483105	0.370511	0.6
RH	-0.654443	1.000000	0.236084	0.222968	-0.645658	-0.405133	-0.220344	-0.6
Ws	-0.278132	0.236084	1.000000	0.170169	-0.163255	-0.001246	0.076253	0.0
Rain	-0.326786	0.222968	0.170169	1.000000	-0.544045	-0.288548	-0.296808	-0.3
FFMC	0.677491	-0.645658	-0.163255	-0.544045	1.000000	0.602391	0.503919	0.7
DMC	0.483105	-0.405133	-0.001246	-0.288548	0.602391	1.000000	0.875362	0.6
DC	0.370511	-0.220344	0.076253	-0.296808	0.503919	0.875362	1.000000	0.4
ISI	0.607551	-0.690637	0.015248	-0.347105	0.739730	0.674499	0.498926	1.0
BUI	0.455504	-0.348587	0.029756	-0.299171	0.589652	0.982073	0.941906	0.6
FWI	0.562344	-0.574773	0.030910	-0.323831	0.688876	0.875791	0.739634	0.9
Region	-0.273496	0.406424	0.176829	0.041080	-0.224680	-0.191094	0.081482	-0.2

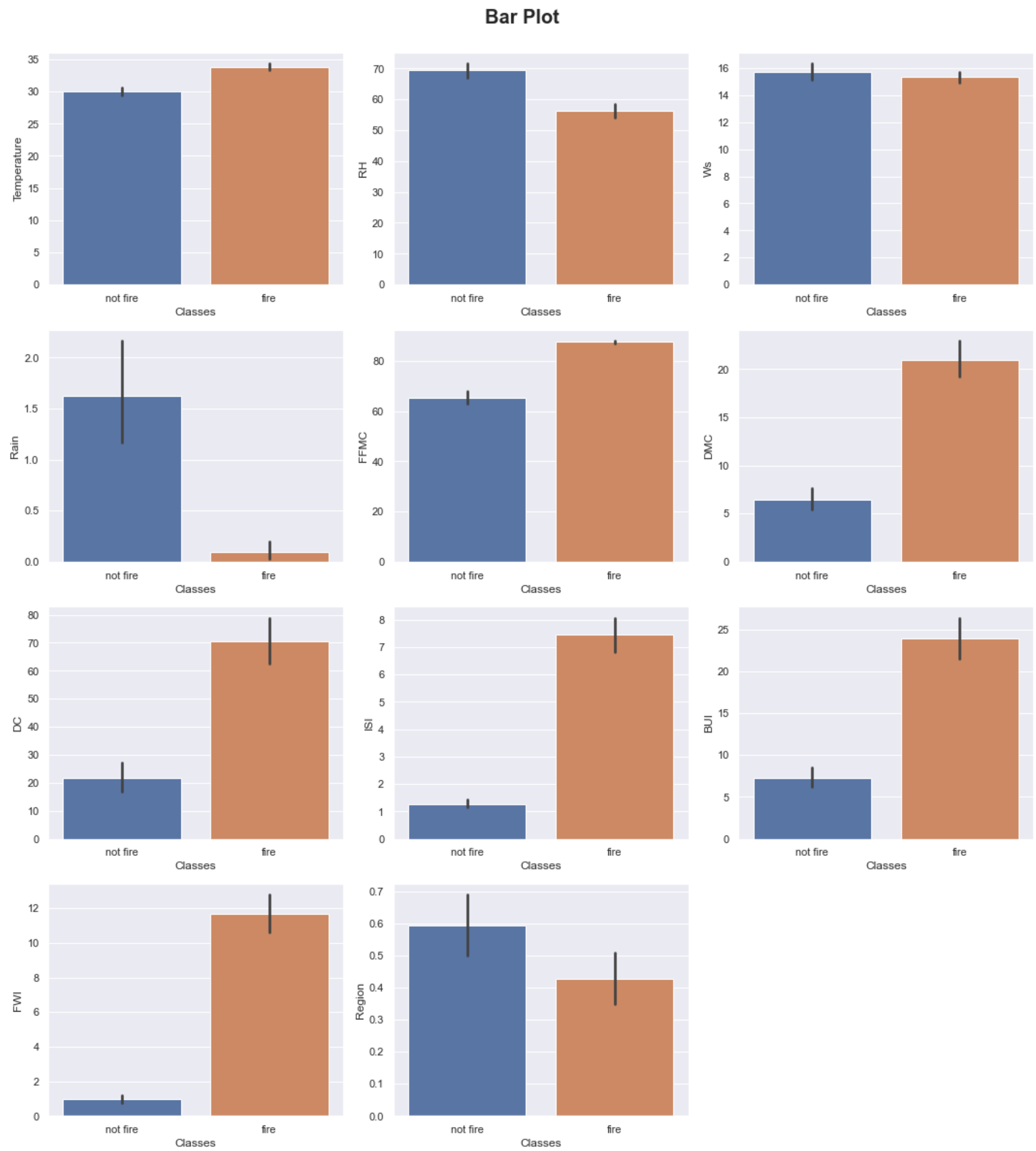
In [22]:

```
plt.figure(figsize = (15,10))
sns.heatmap(df[numerical_col].corr(), cmap="CMRmap", annot=True)
plt.show()
```

Plotting Relationship Between Independent & Target Variables

In [23]:

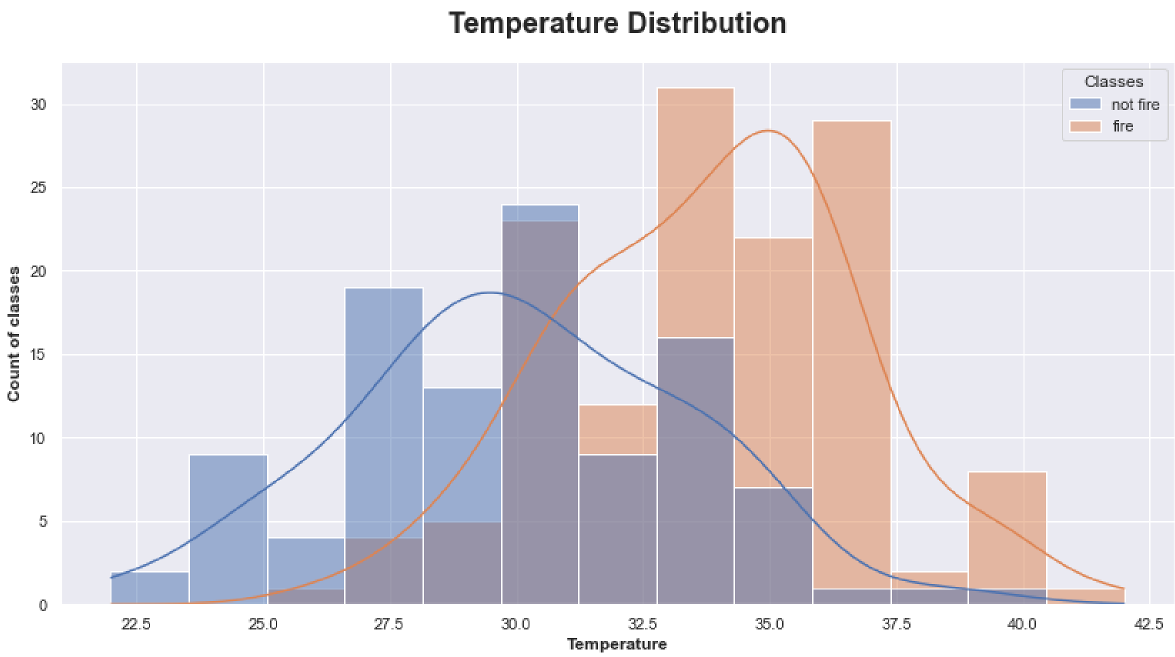
```
plt.figure(figsize=(15, 20))
plt.suptitle('Bar Plot', fontsize=20, fontweight='bold', alpha=1, y=1)

for i in range(0, len(numerical_col)):
    plt.subplot(5, 3, i+1)
    sns.barplot(y=numerical_col[i], x='Classes', data=df)
    plt.tight_layout()
```



Plotting Relation Between Temperature & Fire

In [24]:

```
features = ['Temperature', 'Classes']
Temperature_df = df[features]
plt.subplots(figsize=(14,7))
sns.histplot( data=Temperature_df,x=Temperature_df['Temperature'], hue='Classes', color = '
#sns.histplot(Temperature_df.Temperature, color='g', kde=True)
plt.title("Temperature Distribution", weight="bold",fontsize=20, pad=20)
plt.ylabel("Count of classes", weight="bold", fontsize=12)
plt.xlabel("Temperature", weight="bold", fontsize=12)
plt.show()
```



Most of the time fire occurred in between 32 to 42.5 degree

In [25]:

```
df['Temperature'].describe()
```

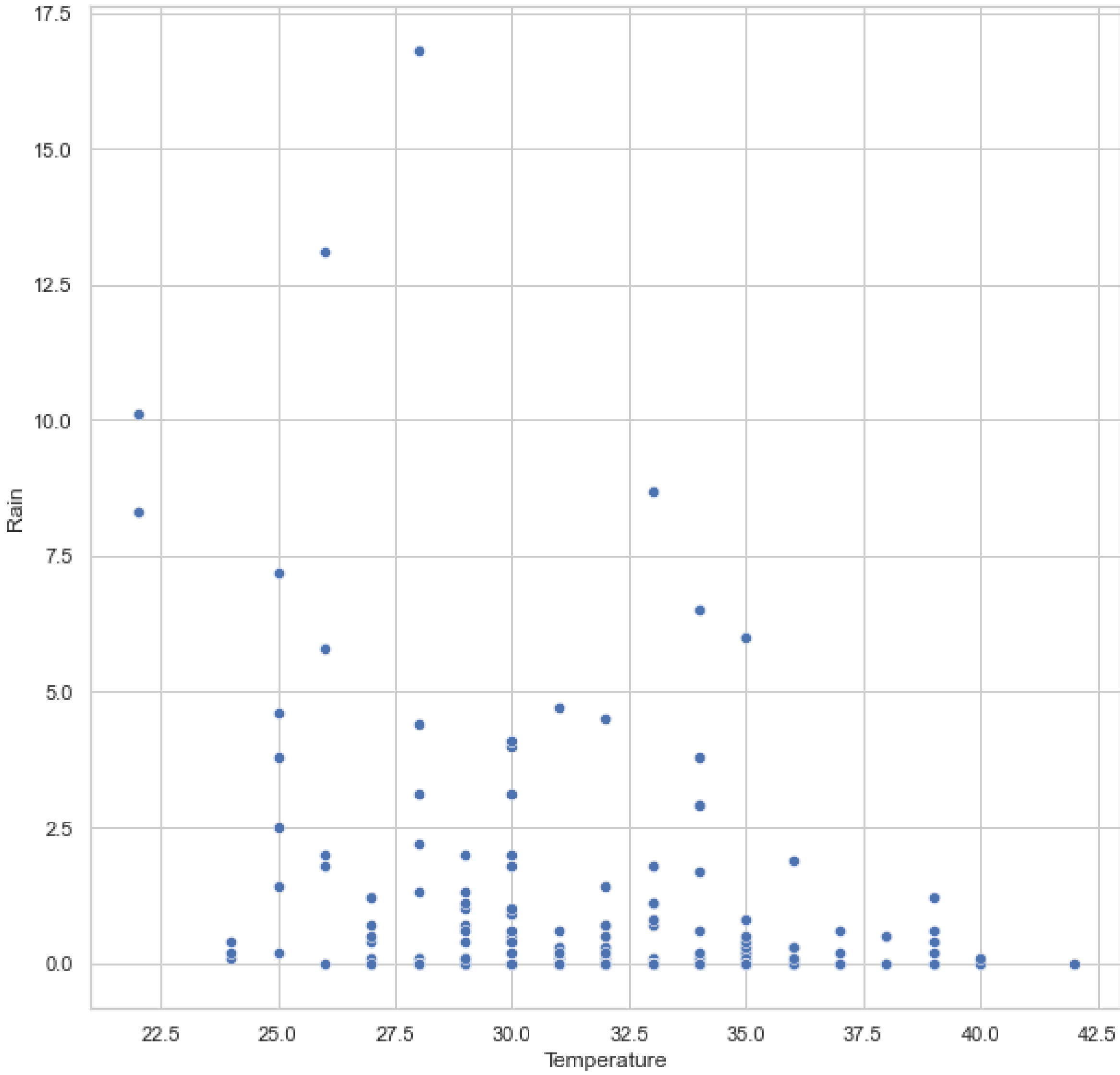
Out[25]:

```
count    244.000000
mean      32.172131
std        3.633843
min       22.000000
25%       30.000000
50%       32.000000
75%       35.000000
max       42.000000
Name: Temperature, dtype: float64
```

Plotting correlation between Temperature & Rain features

In [33]:

```
sns.set_style('whitegrid')
plt.figure(figsize=(10,10))
sns.scatterplot(x=df['Temperature'],y=df['Rain'],data=df)
df['Temperature'].corr(df['Rain'])
#print("Correlation value is",df['DMC'].df['DC'])
plt.show()
```



Train Test Split

In [36]:

```
X = df.iloc[:, 3:13]
y = df['Classes']
X
```

Out[36]:

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI
0	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5
1	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4
2	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1
3	25	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0
4	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5
...	...	...	...	...	...	...	...	...	...	...
239	30	65	14	0.0	85.4	16.0	44.5	4.5	16.9	6.5
240	28	87	15	4.4	41.1	6.5	8.0	0.1	6.2	0.0
241	27	87	29	0.5	45.9	3.5	7.9	0.4	3.4	0.2
242	24	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7
243	24	64	15	0.2	67.3	3.8	16.5	1.2	4.8	0.5

244 rows × 10 columns

In [37]:

```
y
```

Out[37]:

```
0      not fire
1      not fire
2      not fire
3      not fire
4      not fire
         ...
239        fire
240    not fire
241    not fire
242    not fire
243    not fire
Name: Classes, Length: 244, dtype: object
```

In [38]:

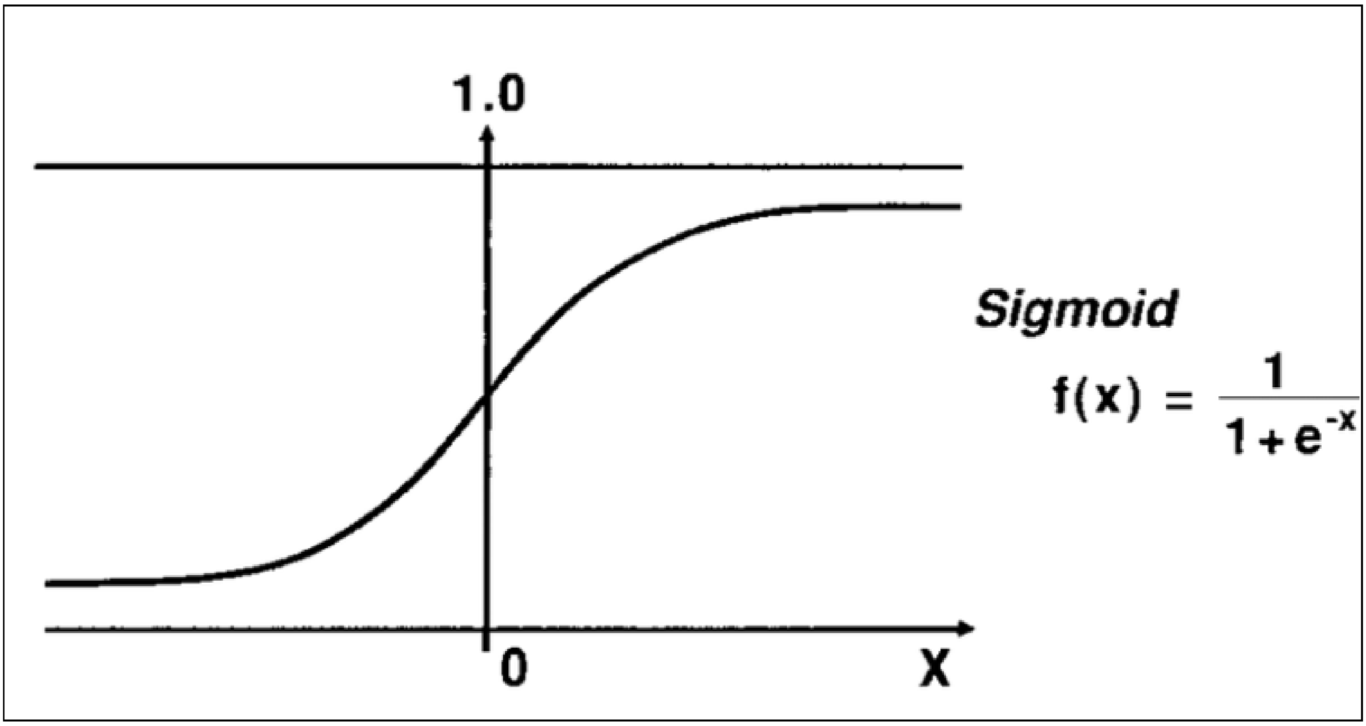
```
# separate dataset into train and test
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,random_state=0)
print(X_train.shape, X_test.shape)
print(y_train.shape, y_test.shape)
```

```
(170, 10) (74, 10)
(170,) (74,)
```

Logistic Regression

Logistic Regression is the extension of ‘Linear regression’. Target variable in linear regression model will be continuous. Whereas in this algorithm the target variable will be discrete. So if our prediction needs to be discrete, we can use Logistic regression. We need not get carried away from the name as it is holding “regression”. This algorithm is built for classification problems.

Classification problems are also called as binary problems, where the output will be between 2 classes. It is either 0 or 1/Yes or No. Function used in this algorithm is “Sigmoid” or “Logistic” which is represented as



In [40]:

```
log_reg = LogisticRegression()

log_reg.fit(X_train,y_train)
```

```
C:\Users\Thanmai\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.
py:763: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scik
it-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regre
ssion (https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression)
  n_iter_i = _check_optimize_result(
```

Out[40]:

```
LogisticRegression()
```

In [41]:

```
print(log_reg.coef_)
print(log_reg.intercept_)
```

```
[[ 0.34518088  0.01648984  0.2947388  -0.52687827 -0.11698837  0.17015191
  -0.02407884 -1.38469931  0.16852135 -1.87257507]]
[0.12822092]
```

In [49]:

```
y_pred = log_reg.predict(X_test)

dataset = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
dataset.head(30)
```

Out[49]:

	Actual	Predicted
64	fire	fire
63	not fire	not fire
55	fire	fire
111	fire	fire
225	fire	fire
92	not fire	not fire
76	fire	not fire
181	fire	fire
188	not fire	not fire
180	fire	fire
73	fire	fire
107	not fire	not fire
150	fire	fire
198	fire	fire
224	not fire	not fire
44	not fire	not fire
145	fire	fire
110	fire	fire
243	not fire	not fire
189	not fire	not fire
210	not fire	not fire
104	not fire	not fire
138	not fire	not fire
8	not fire	not fire
199	fire	fire
203	fire	fire
220	fire	fire
125	not fire	not fire
5	fire	fire
22	fire	fire

We can see from the above comparision between actual and predicted value that the accuracy of the model is good. Now let's calculate the performance metrics.

Performance Metrics

These are some frequently used metrics in industry for classification problems to measure accuracy percentages and error levels they are as follows:

a. Confusion Matrix, b. Classification Report, c. ROC Curve & d. Accuracy Score

Confusion Matrix

Confusion Matrix below is used to find the amount of values which are predicted correctly & wrongly.

		Predicted	
Actual		Positive	Negative
	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

In [51]:

```
# Confusion Matrix
conf_mat = confusion_matrix(y_test,y_pred)
conf_mat
```

Out[51]:

```
array([[38,  2],
       [ 0, 34]], dtype=int64)
```

In [52]:

```
true_positive = conf_mat[0][0]
false_positive = conf_mat[0][1]
false_negative = conf_mat[1][0]
true_negative = conf_mat[1][1]
```

Accuracy

Accuracy is defined as the number of correct predictions over the total predictions: accuracy = correct_predictions / total_predictions

However, we can further expand on this using these:

- True Positive (TP) - you predicted positive and it’s actually positive

- True Negative (TN) - you predicted negative and it's actually negative
- False Positive (FP) - you predicted positive and it's actually negative
- False Negative (FN) - you predicted negative and it's actually positive So we can say the true predictions are TN+TP, while the false prediction is FP+FN. The equation can now be redefined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

In [45]:

```
accuracy = accuracy_score(y_test,y_pred)
accuracy
```

Out[45]:

```
0.972972972972973
```

Precision and Recall

If we want to further test the "accuracy" in different classes where we want to ensure that when the model predicts positive, it is in fact true positive - we use precision. We can also call this Positive Prediction Value which can be defined as:

$$Precision = \frac{TP}{TP + FP}$$

In [53]:

```
# Precison
Precision = true_positive/(true_positive+false_positive)
Precision
```

Out[53]:

```
0.95
```

In [54]:

```
# Recall
Recall = true_positive/(true_positive+false_negative)
Recall
```

Out[54]:

```
1.0
```

F1 Score

This is defined as Harmonic mean between Precision and Recall values

$$F_{beta} = (\beta^2 + 1)\frac{Precision \cdot Recall}{\beta^2 Precision + Recall} = (\beta^2 + 1)\frac{TP}{\beta^2(FN + FP) + (1 - \beta^2)TP}$$

In [55]:

```
F1_Score = 2*(Recall * Precision) / (Recall + Precision)
F1_Score
```

Out[55]:

```
0.9743589743589743
```