In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
dataset_forest=pd.read_csv("Algerian_forest_fires_dataset_UPDATE.csv",header=1)
```

Exploratory data analysis

Data preprocessing and clearning Opertaion

In [3]:

```
dataset_forest.head()
```

Out[3]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
0	01	06	2012	29	57	18	0	65.7	3.4	7.6	1.3	3.4	0.5	not fire
1	02	06	2012	29	61	13	1.3	64.4	4.1	7.6	1	3.9	0.4	not fire
2	03	06	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	not fire
3	04	06	2012	25	89	13	2.5	28.6	1.3	6.9	0	1.7	0	not fire
4	05	06	2012	27	77	16	0	64.8	3	14.2	1.2	3.9	0.5	not fire

In [4]:

```
dataset_forest.drop([122,123],inplace=True,axis=0)
dataset_forest.reset_index(inplace=True)
dataset_forest.drop('index',axis=1,inplace=True)
```

In [5]:

```
dataset_forest.shape
```

Out[5]:

(244, 14)

In [6]:

```
dataset_forest.columns
```

Out[6]:

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

In [7]:

```
dataset_forest.rename(columns={' RH':'RH',' Ws':'Ws','Rain ':'Rain','Classes  ':'Classes'},
```

In [8]:

```
dataset_forest['Classes']=dataset_forest['Classes'].str.strip()
```

In [9]:

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

Out[9]:

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

In [10]:

```
dataset_forest.loc[:122,'region']='bejaia'
dataset_forest.loc[122:,'region']='Sidi-Bel Abbes'
```

In [11]:

```
dataset_forest.isnull().sum()
```

Out[11]:

```
day            0
month          0
year           0
Temperature    0
RH             0
Ws             0
Rain           0
FFMC           0
DMC            0
DC             0
ISI            0
BUI            0
FWI            0
Classes        1
region         0
dtype: int64
```

In [12]:

```
dataset_forest.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      243 non-null    object
 14  region       244 non-null    object
dtypes: object(15)
memory usage: 28.7+ KB
```

In [13]:

```
dataset_forest.describe()
```

Out[13]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Cl
count	244	244	244	244	244	244	244	244	244	244	244	244	244	
unique	31	4	1	19	62	18	39	173	166	198	106	174	127	
top	01	07	2012	35	64	14	0	88.9	7.9	8	1.1	3	0.4	
freq	8	62	244	29	10	43	133	8	5	5	8	5	12	

In [14]:

```
dataset_forest.index[dataset_forest['DC']=='14.6 9']
```

Out[14]:

```
Int64Index([165], dtype='int64')
```

In [15]:

```
dataset_forest.loc[165,'DC']=14.6
```

In [16]:

```
dataset_forest.loc[165,'FWI']=dataset_forest['FWI'].mode()[0]
```

In [17]:

```
dataset_forest.fillna(method='bfill', inplace=True)
```

In [18]:

```
dataset_forest=dataset_forest.astype({'day':int,'month':int,'year':int,'Temperature':int,'R
```

In [19]:

```
dataset_forest=dataset_forest.astype({'Rain':float,'FFMC':float,'DMC':float,'DC':float,'ISI
```

In [20]:

```
dataset_forest
```

Out[20]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Class
0	1	6	2012	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	not f
1	2	6	2012	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	not f
2	3	6	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	not f
3	4	6	2012	25	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0	not f
4	5	6	2012	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	not f
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
239	26	9	2012	30	65	14	0.0	85.4	16.0	44.5	4.5	16.9	6.5	f
240	27	9	2012	28	87	15	4.4	41.1	6.5	8.0	0.1	6.2	0.0	not f
241	28	9	2012	27	87	29	0.5	45.9	3.5	7.9	0.4	3.4	0.2	not f
242	29	9	2012	24	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7	not f
243	30	9	2012	24	64	15	0.2	67.3	3.8	16.5	1.2	4.8	0.5	not f

244 rows × 15 columns

Statistical Information of the Dataset

In [21]:

```
dataset_forest.describe().T
```

Out[21]:

	count	mean	std	min	25%	50%	75%	max
day	244.0	15.754098	8.825059	1.0	8.000	16.00	23.000	31.0
month	244.0	7.500000	1.112961	6.0	7.000	7.50	8.000	9.0
year	244.0	2012.000000	0.000000	2012.0	2012.000	2012.00	2012.000	2012.0
Temperature	244.0	32.172131	3.633843	22.0	30.000	32.00	35.000	42.0
RH	244.0	61.938525	14.884200	21.0	52.000	63.00	73.250	90.0
Ws	244.0	15.504098	2.810178	6.0	14.000	15.00	17.000	29.0
Rain	244.0	0.760656	1.999406	0.0	0.000	0.00	0.500	16.8
FFMC	244.0	77.887705	14.337571	28.6	72.075	83.50	88.300	96.0
DMC	244.0	14.673361	12.368039	0.7	5.800	11.30	20.750	65.9
DC	244.0	49.288115	47.619662	6.9	13.275	33.10	68.150	220.4
ISI	244.0	4.774180	4.175318	0.0	1.400	3.50	7.300	19.0
BUI	244.0	16.664754	14.204824	1.1	6.000	12.25	22.525	68.0
FWI	244.0	7.008197	7.437383	0.0	0.700	4.20	11.375	31.1

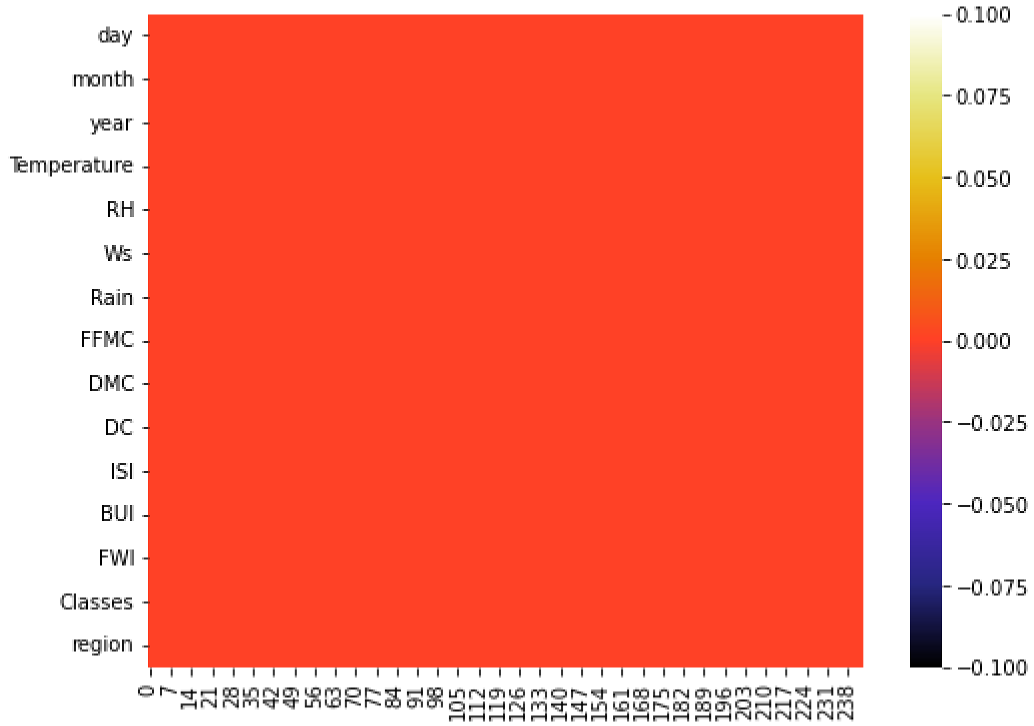
Chcek the NaN or Null value

In [22]:

```
plt.figure(figsize=(8,6))
sns.heatmap(dataset_forest.isna().transpose(),
            cmap='CMRmap')
```

Out[22]:

<AxesSubplot:>



In [23]:

```
numeric_features = [i for i in dataset_forest.columns if dataset_forest[i].dtype!='O']
categorical_features = [i for i in dataset_forest.columns if dataset_forest[i].dtype=='O']
```

In [24]:

```
numeric_features
```

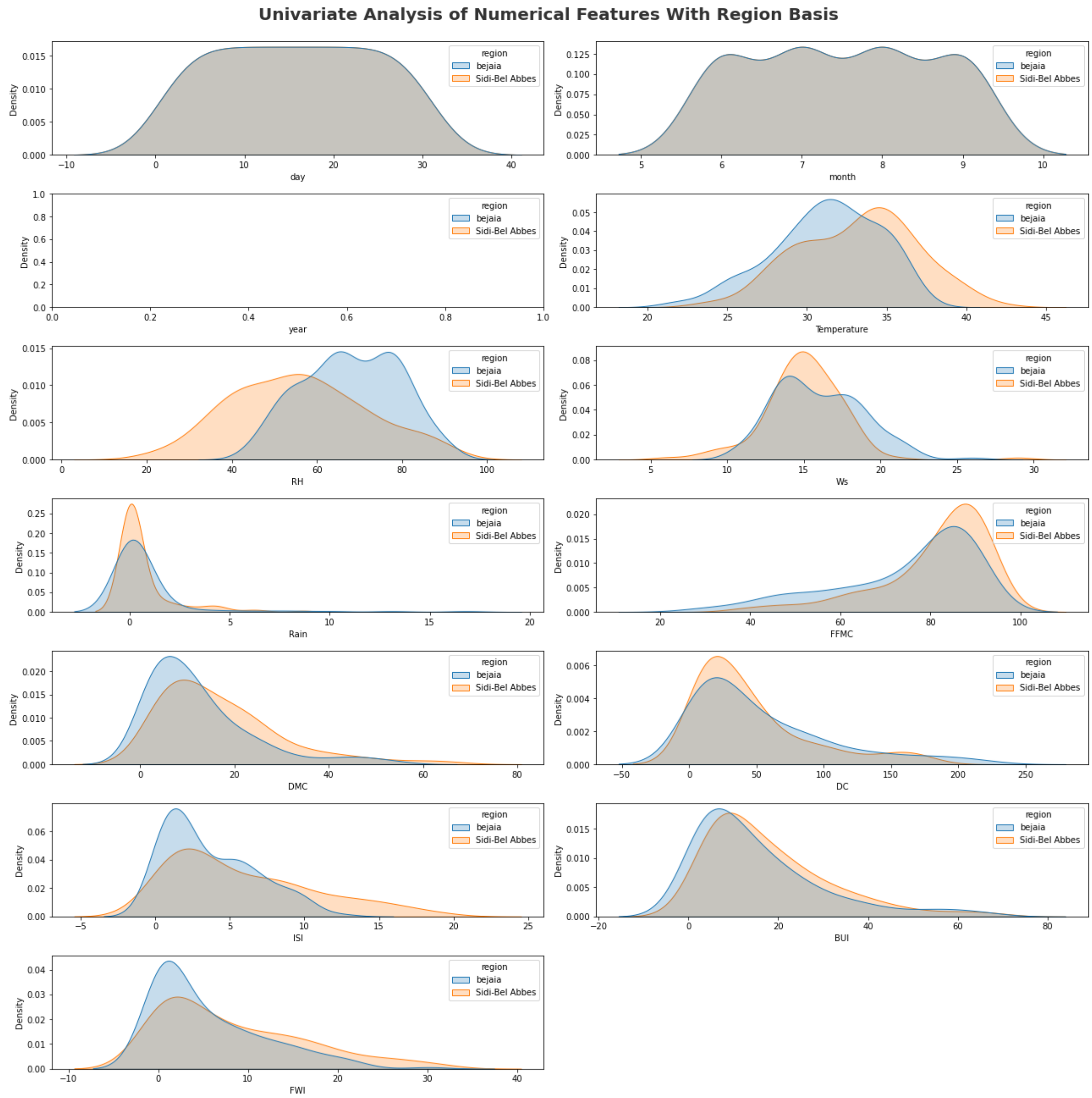
Out[24]:

```
['day',
 'month',
 'year',
 'Temperature',
 'RH',
 'Ws',
 'Rain',
 'FFMC',
 'DMC',
 'DC',
 'ISI',
 'BUI',
 'FWI']
```

Univariate Analysis

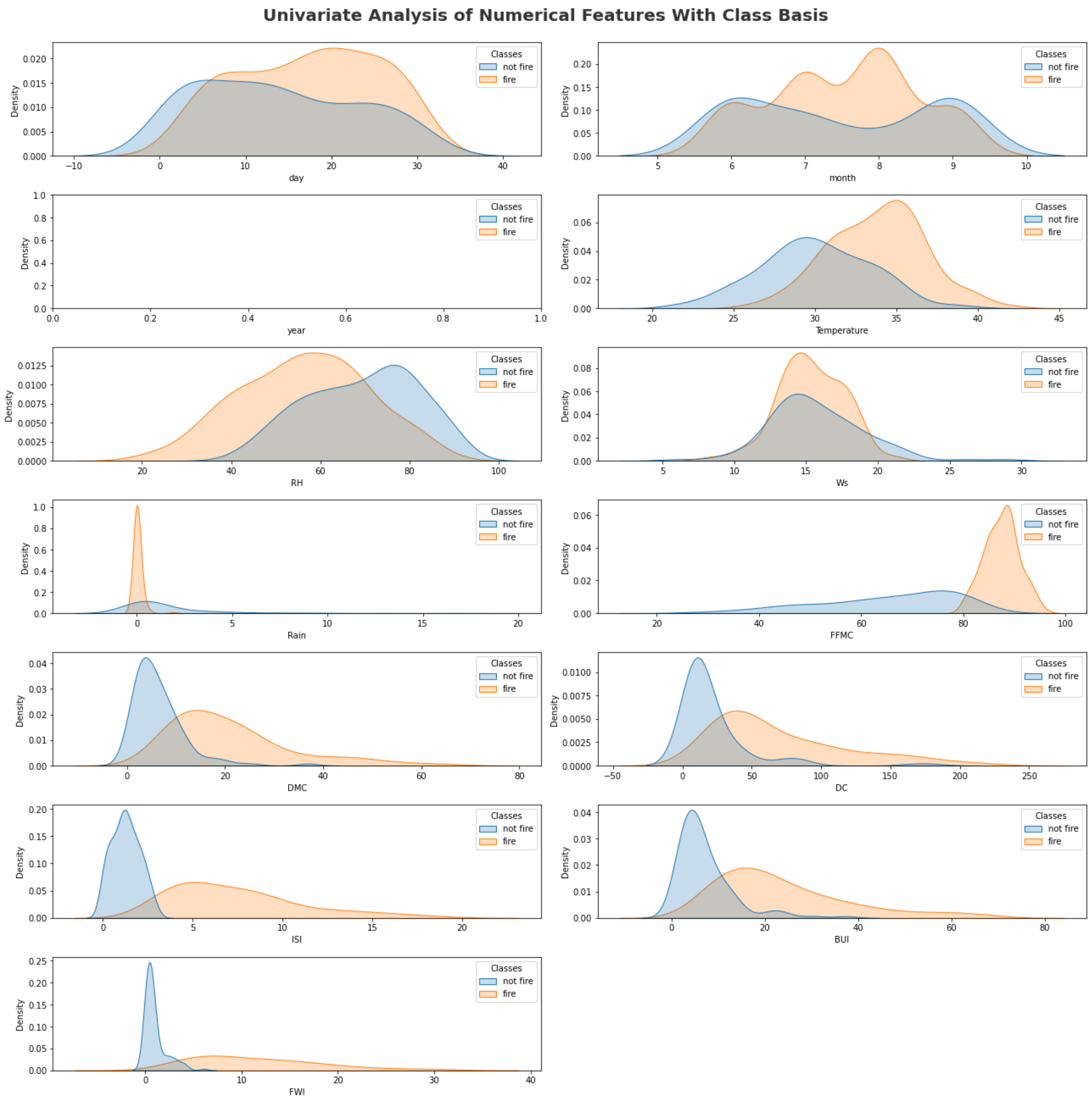
In [25]:

```
plt.figure(figsize=(18,18))
plt.suptitle('Univariate Analysis of Numerical Features With Region Basis', fontsize=20, fo
 
for i in range(0, len(numeric_features)):
    plt.subplot(7, 2, i+1)
    sns.kdeplot(x=dataset_forest[numeric_features[i]],shade=True,hue='region',data=dataset_
    plt.xlabel(numeric_features[i])
    plt.tight_layout()
```



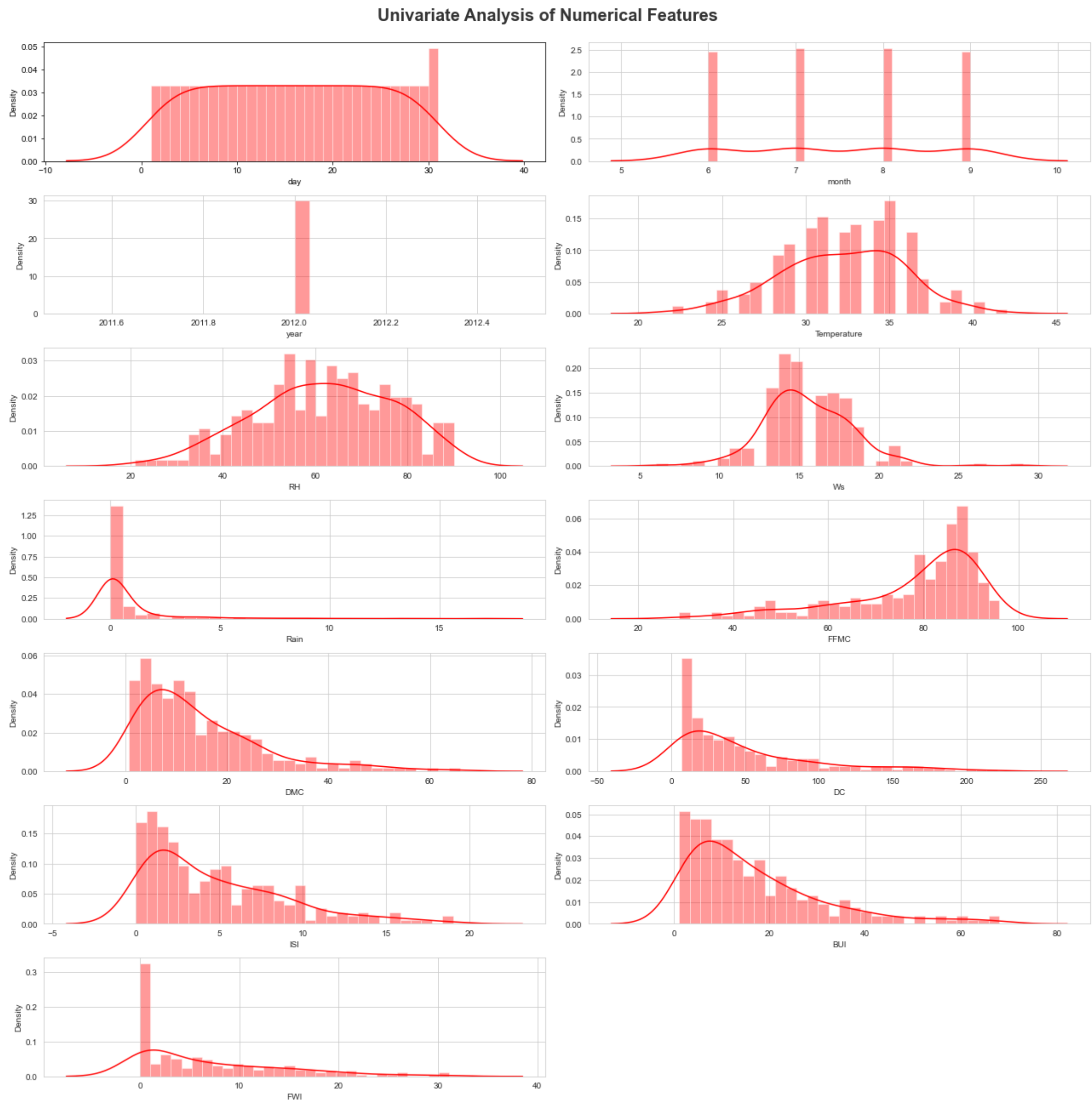
In [26]:

```
plt.figure(figsize=(18,18))
plt.suptitle('Univariate Analysis of Numerical Features With Class Basis', fontsize=20, fon

for i in range(0, len(numeric_features)):
    plt.subplot(7, 2, i+1)
    sns.kdeplot(x=dataset_forest[numeric_features[i]],shade=True,hue='Classes',data=dataset
    plt.xlabel(numeric_features[i])
    plt.tight_layout()
```



In [27]:

```
plt.figure(figsize=(18,18))
plt.suptitle('Univariate Analysis of Numerical Features', fontsize=20, fontweight='bold', a

for i in range(0, len(numeric_features)):
    plt.subplot(7, 2, i+1)
    sns.set_style('whitegrid')
    sns.distplot(dataset_forest[numeric_features[i]], kde = True, color ='red', bins = 30)
    plt.xlabel(numeric_features[i])
    plt.tight_layout()
```



Observations:

Attribute Information:

- Temp : temperature noon (temperature max) in Celsius degrees: 22 to 42
- RH : Relative Humidity in %: 21 to 90
- Ws :Wind speed in km/h: 6 to 29
- Rain: total day in mm: 0 to 16.8

- FWI Components
- Fine Fuel Moisture Code (FFMC) index from the FWI system: 28.6 to 92.5
- Duff Moisture Code (DMC) index from the FWI system: 1.1 to 65.9
- Drought Code (DC) index from the FWI system: 7 to 220.4
- Initial Spread Index (ISI) index from the FWI system: 0 to 18.5
- Buildup Index (BUI) index from the FWI system: 1.1 to 68
- Fire Weather Index (FWI) Index: 0 to 31.1

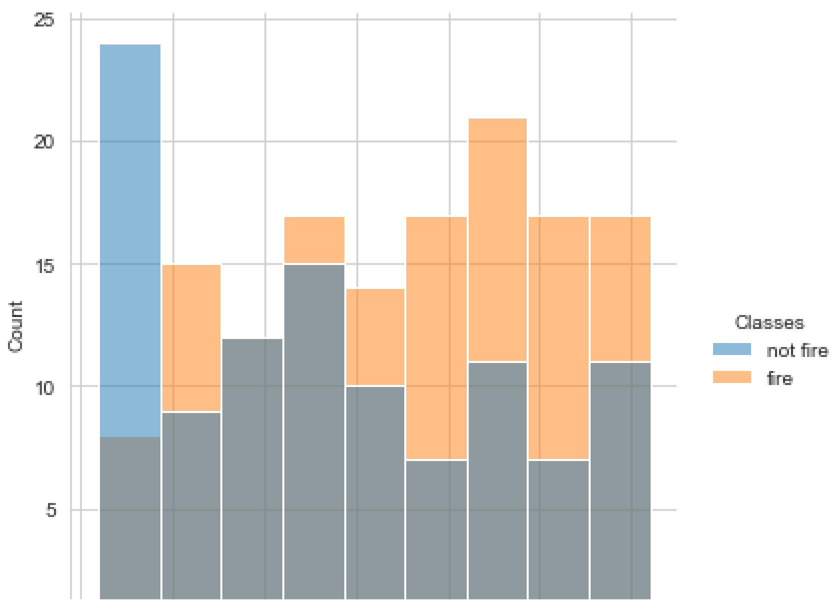
Distribution Information:

- Temperature,RH,Ws is likely normal distribution but not fully normal distribution
- FFMC data is left skewed distribution
- DC,ISI,BUI,FWI,DMC data is right skewed distribution
- Rain is likely log Normal distribution

In [28]:

```
for i in dataset_forest.columns:
    plt.figure(figsize=(14,6))
    sns.displot(data=dataset_forest,x=i,hue='Classes',kind='hist')
```

```
&lt;Figure size 1008x432 with 0 Axes&gt;
```

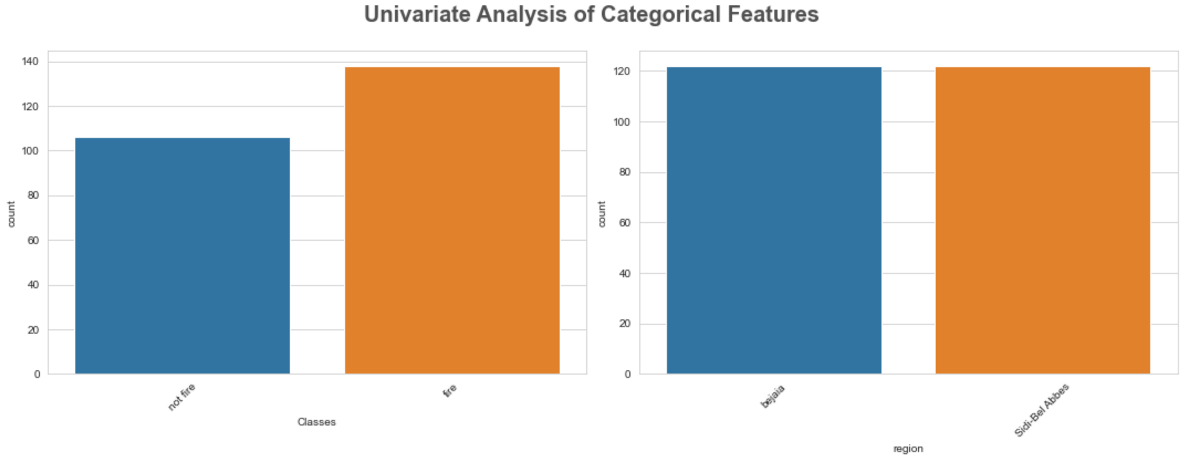


Observations::

- Most of the Fire happened in the month of August
- As per the plot, we can see that when the temperature is more than 35 then most of the Fires happened
- Most Fire cases occurred when the Relative Humidity is around 20% to 70%
- Most Fire cases occurred when the Wind speed is between 13 km/h to 20 km/h
- Rapidly increasing Fine Fuel Moisture (FFMC) is one of the most important causes of Fire cases
- When Initial Spread Index (ISI) is more than 5.0 then we can see most of the Fire cases
- When Buildup Index (BUI) is more than 10 then we can see most of the Fire cases
- When Fire Weather Index (FWI) is more than 10 then we can see most of the Fire cases
- The highest number of Fire cases occurred in the Sidi-Bel Abbes region

In [29]:

```
plt.figure(figsize=(15,10))
plt.suptitle('Univariate Analysis of Categorical Features', fontsize=20, fontweight='bold',
for i in range(0, len(categorical_features)):
    plt.subplot(2, 2, i+1)
    sns.countplot(x=dataset_forest[categorical_features[i]])
    plt.xlabel(categorical_features[i])
    plt.xticks(rotation=45)
    plt.tight_layout()
```



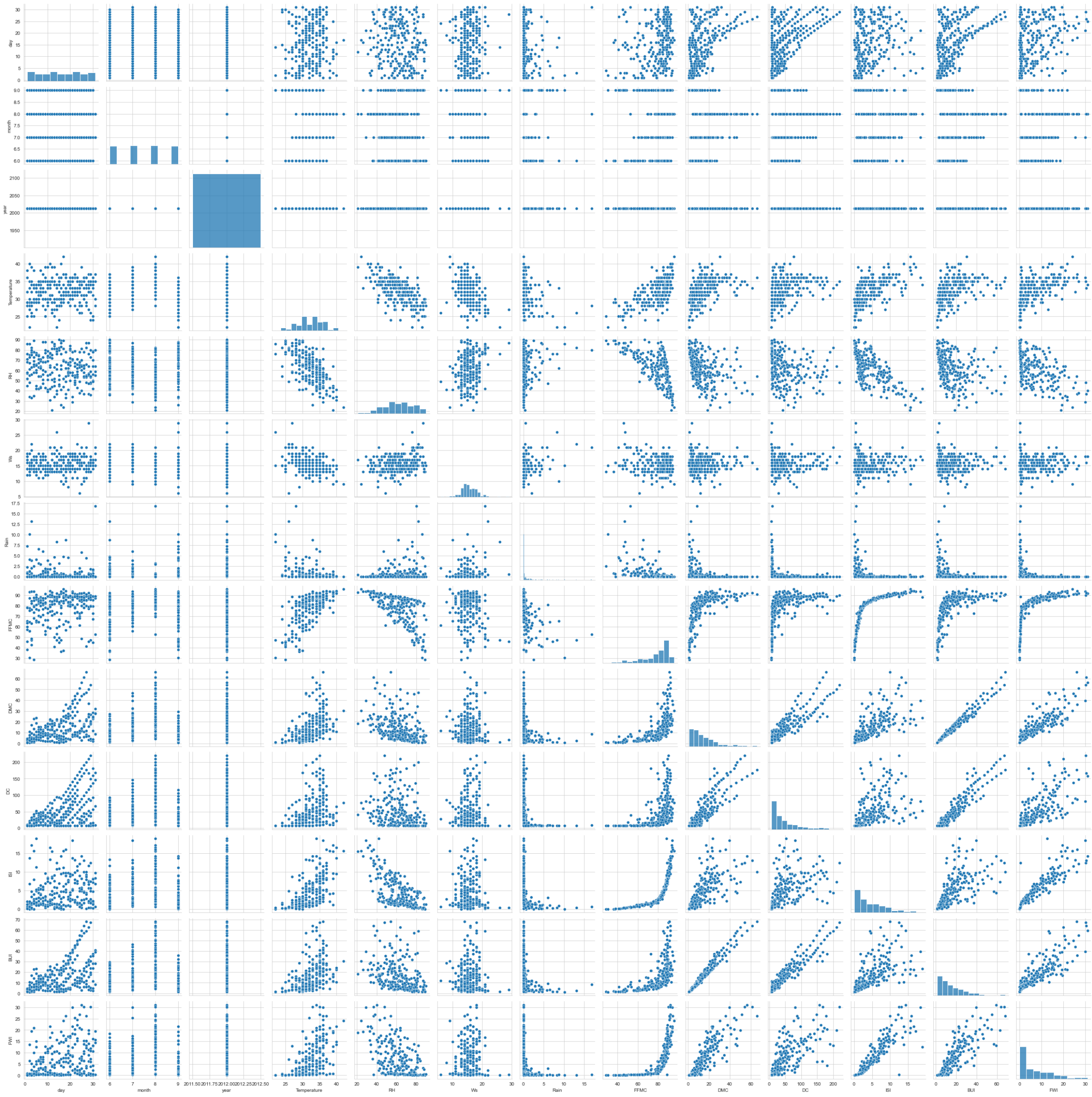
Multivariate Analysis

In [30]:

```
sns.pairplot(dataset_forest)
```

Out[30]:

```
<seaborn.axisgrid.PairGrid at 0x1d8347edaf0>
```

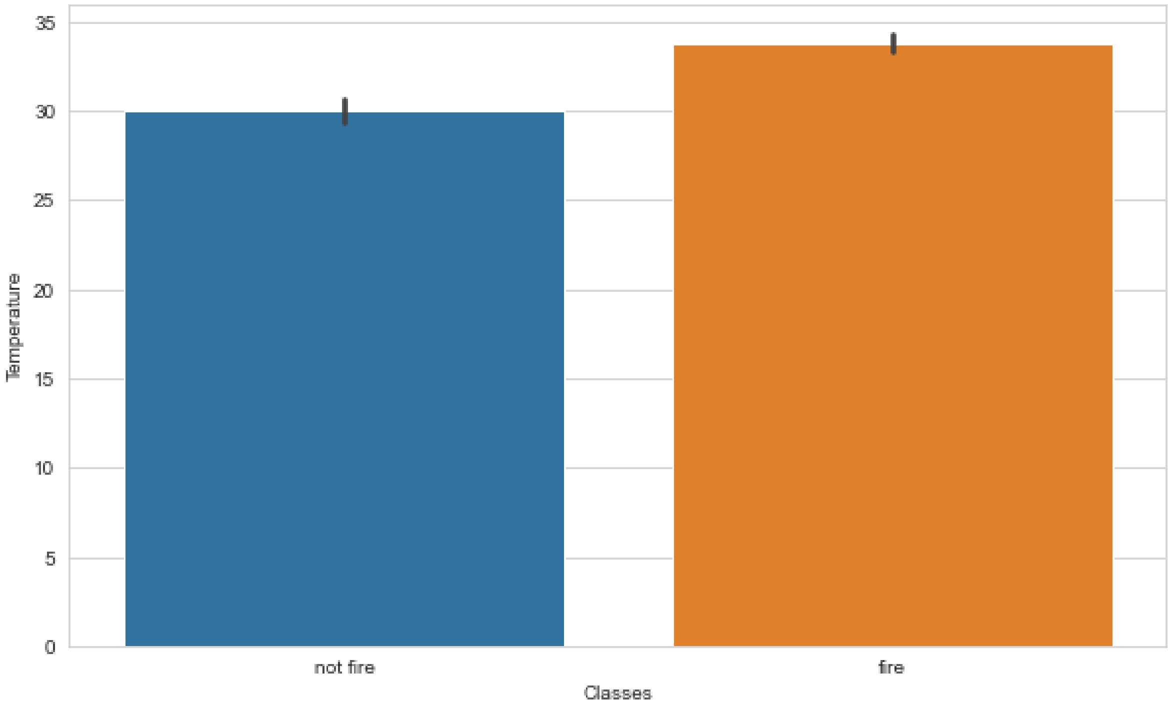


In [31]:

```
plt.figure(figsize=(10,6))
sns.barplot(x='Classes',y='Temperature',data=dataset_forest)
```

Out[31]:

```
<AxesSubplot:xlabel='Classes', ylabel='Temperature'>
```

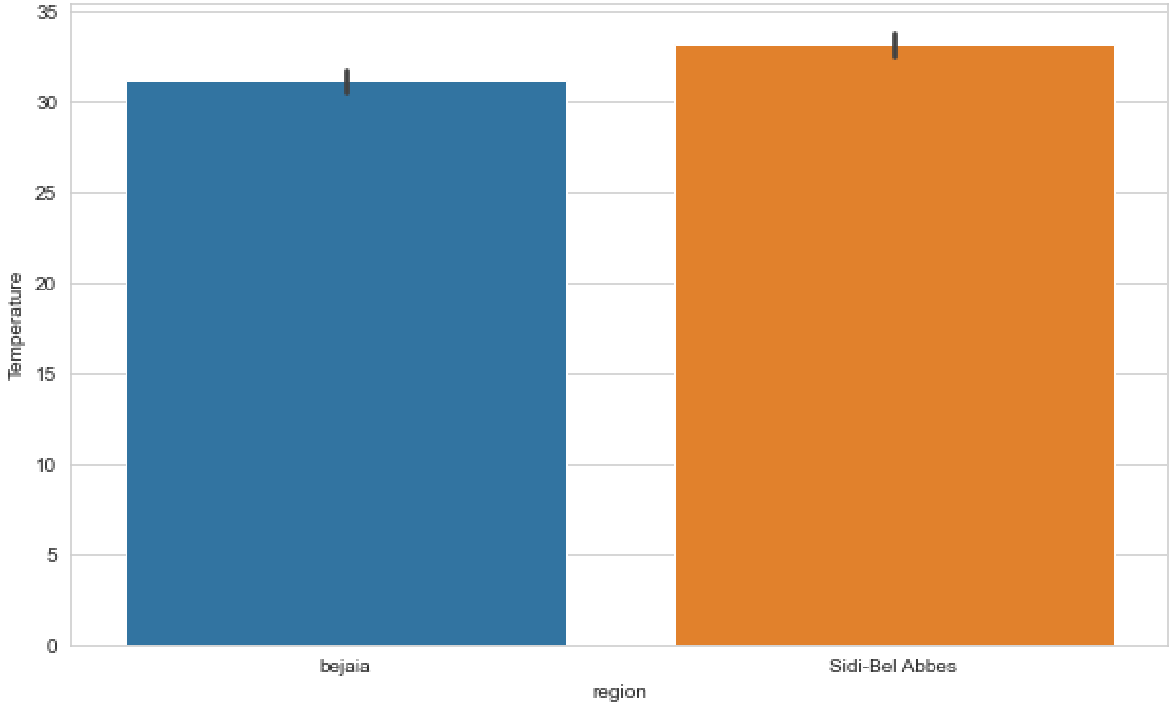


In [32]:

```
plt.figure(figsize=(10,6))
sns.barplot(x='region',y='Temperature',data=dataset_forest)
```

Out[32]:

```
<AxesSubplot:xlabel='region', ylabel='Temperature'>
```

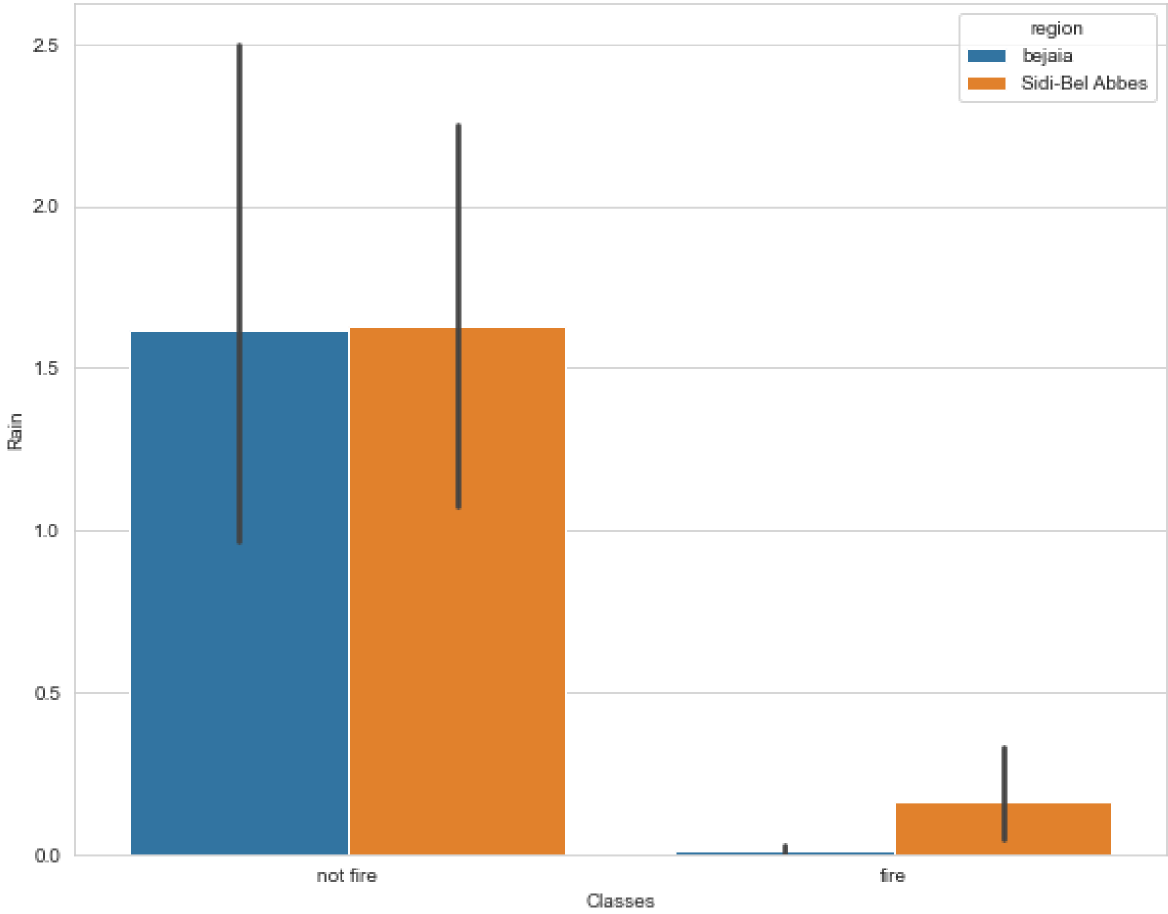


In [33]:

```
plt.figure(figsize=(10,8))
sns.barplot(x='Classes',y='Rain',hue='region',data=dataset_forest)
```

Out[33]:

<AxesSubplot:xlabel='Classes', ylabel='Rain'>

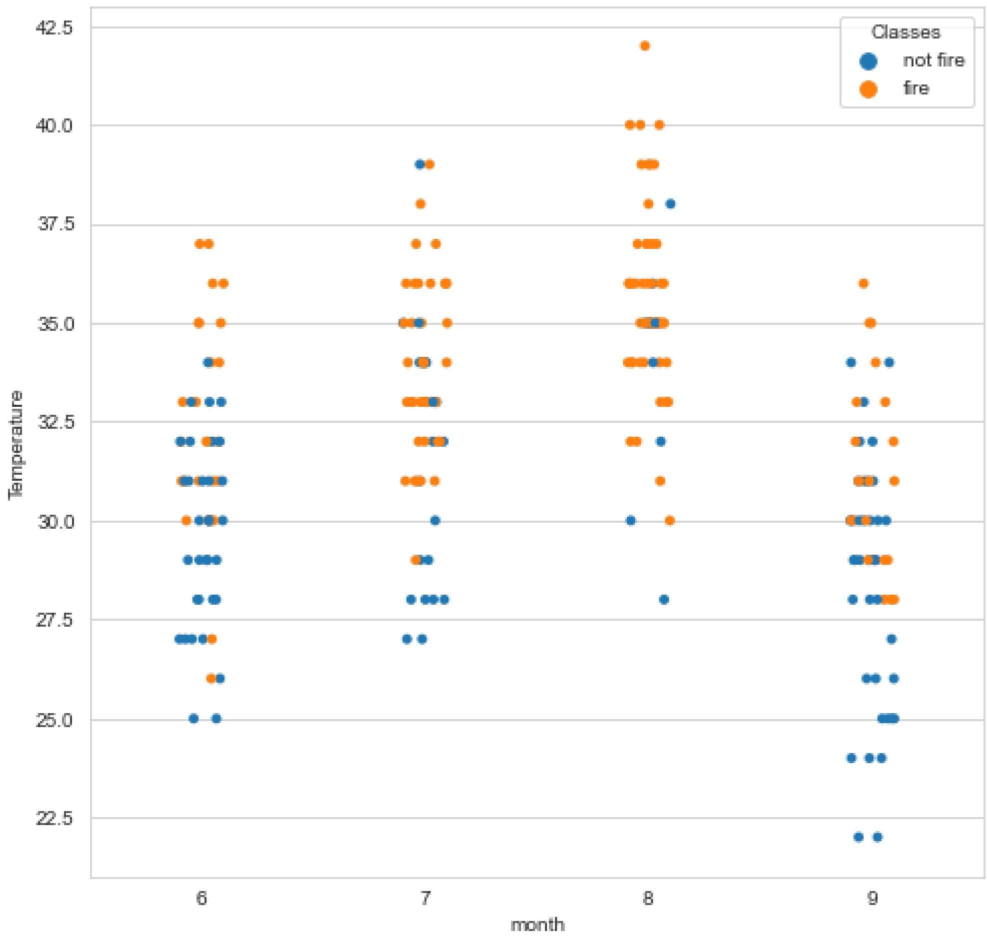


In [34]:

```
plt.figure(figsize=(8,8))
sns.stripplot(x='month',
    y='Temperature',
    hue='Classes',data=dataset_forest)
```

Out[34]:

<AxesSubplot:xlabel='month', ylabel='Temperature'>



Observations:

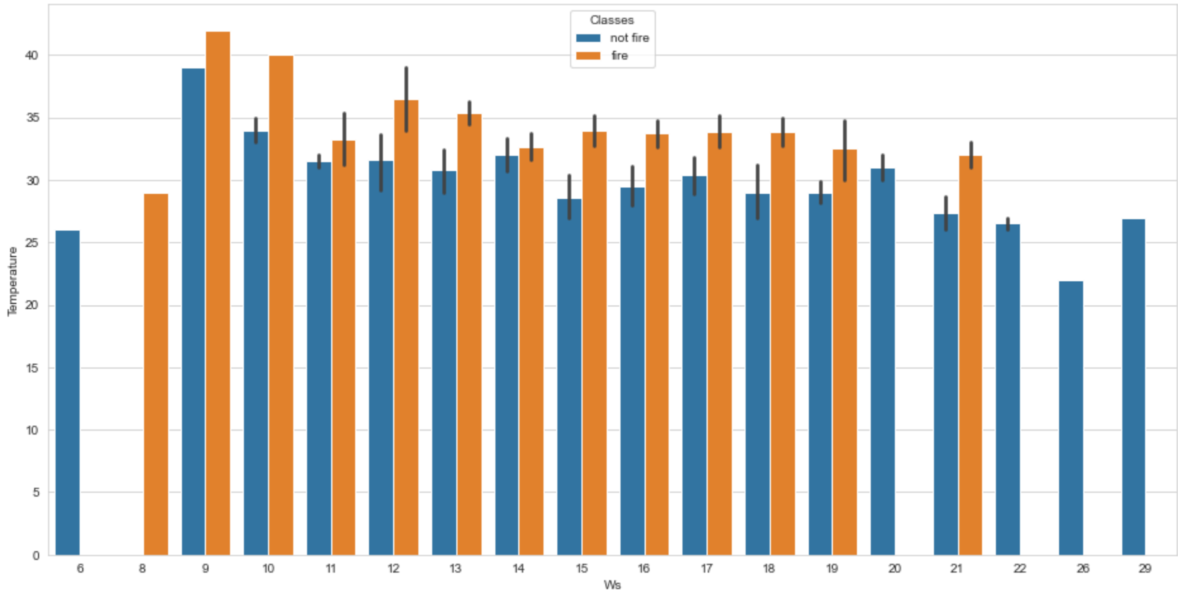
- The Temperature is high in the month of August, that's why fire cases also occurred
- The Temperature is falling in the month of September, so not many fire cases in the month of September

In [35]:

```
plt.figure(figsize=(16,8))
sns.barplot(x="Ws",
    y="Temperature",
    hue="Classes",
    data=dataset_forest)
```

Out[35]:

<AxesSubplot:xlabel='Ws', ylabel='Temperature'>



Observations:

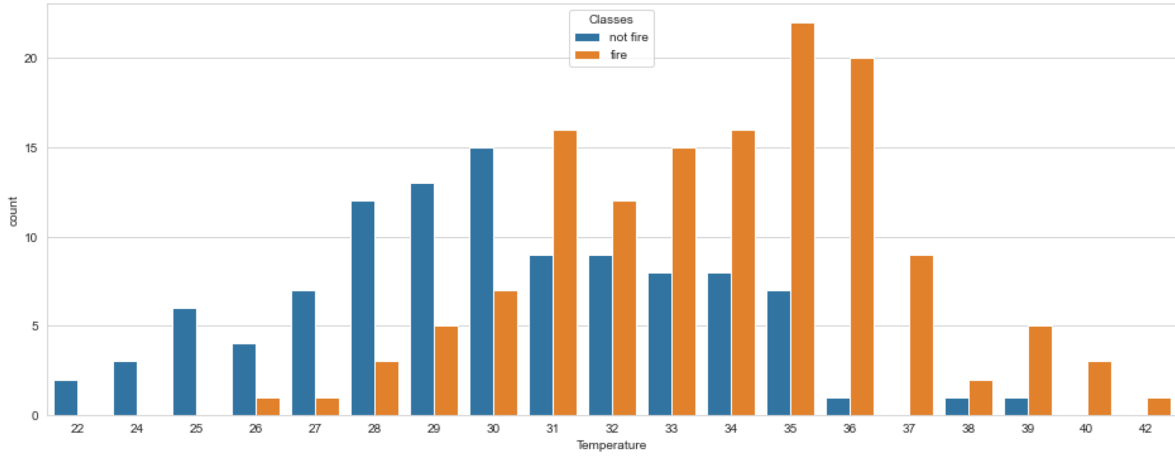
- Fire cases started happening whenever wind speed is increased

In [36]:

```
plt.figure(figsize=(16,6))
sns.countplot(x="Temperature",hue="Classes",data=dataset_forest)
```

Out[36]:

```
<AxesSubplot:xlabel='Temperature', ylabel='count'>
```

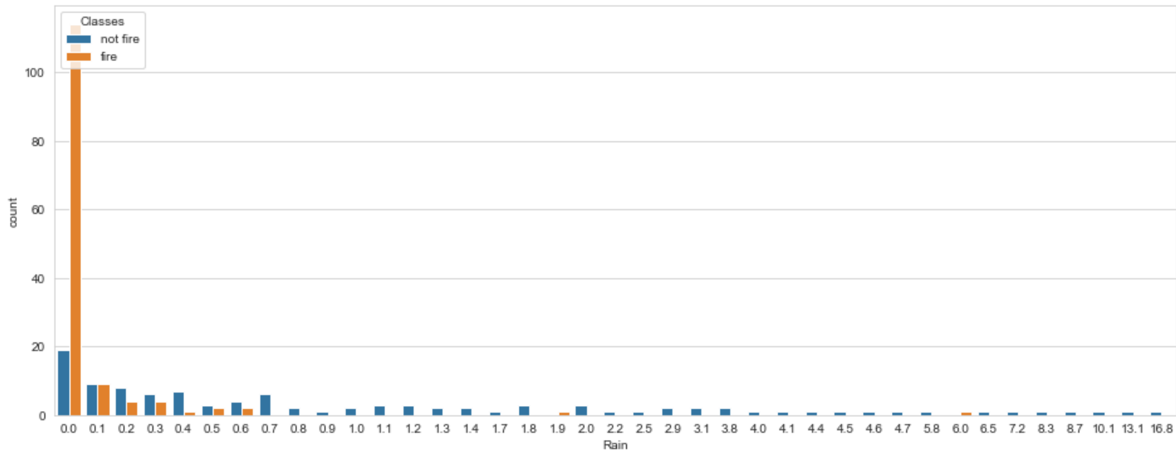


In [37]:

```
plt.figure(figsize=(16,6))
sns.countplot(x="Rain",hue="Classes",data=dataset_forest)
```

Out[37]:

```
<AxesSubplot:xlabel='Rain', ylabel='count'>
```

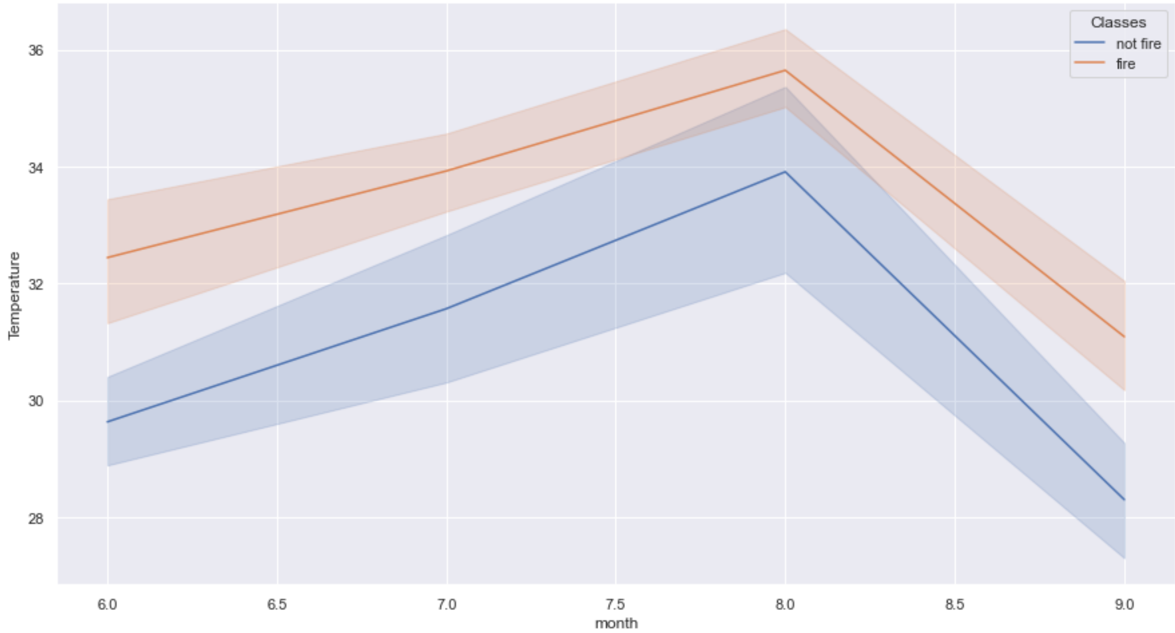


In [38]:

```
plt.figure(figsize=(15,8))
sns.set_theme(style="darkgrid")
sns.lineplot(x='month', y="Temperature",
             hue="Classes",
             data=dataset_forest)
```

Out[38]:

```
<AxesSubplot:xlabel='month', ylabel='Temperature'>
```



Observations:

- The number of fire cases increased when the temperature was above 32 degree during Auguest and the temperature decreased in The September

In [39]:

```
plt.figure(figsize=(25,25))
plt.suptitle('Monthly Wises Multivariate Analysis  All of The Numerical Features', fontsize
              
for i in range(0, len(numeric_features)):
    plt.subplot(7, 2, i+1)
    sns.set_style('whitegrid')
    #sns.distplot(dataset_forest[numeric_features[i]], kde = True, color ='red', bins = 30)
    sns.stripplot(x='month',y=numeric_features[i],data=dataset_forest)
    plt.xlabel(numeric_features[i])
    plt.tight_layout()
```

Observations:

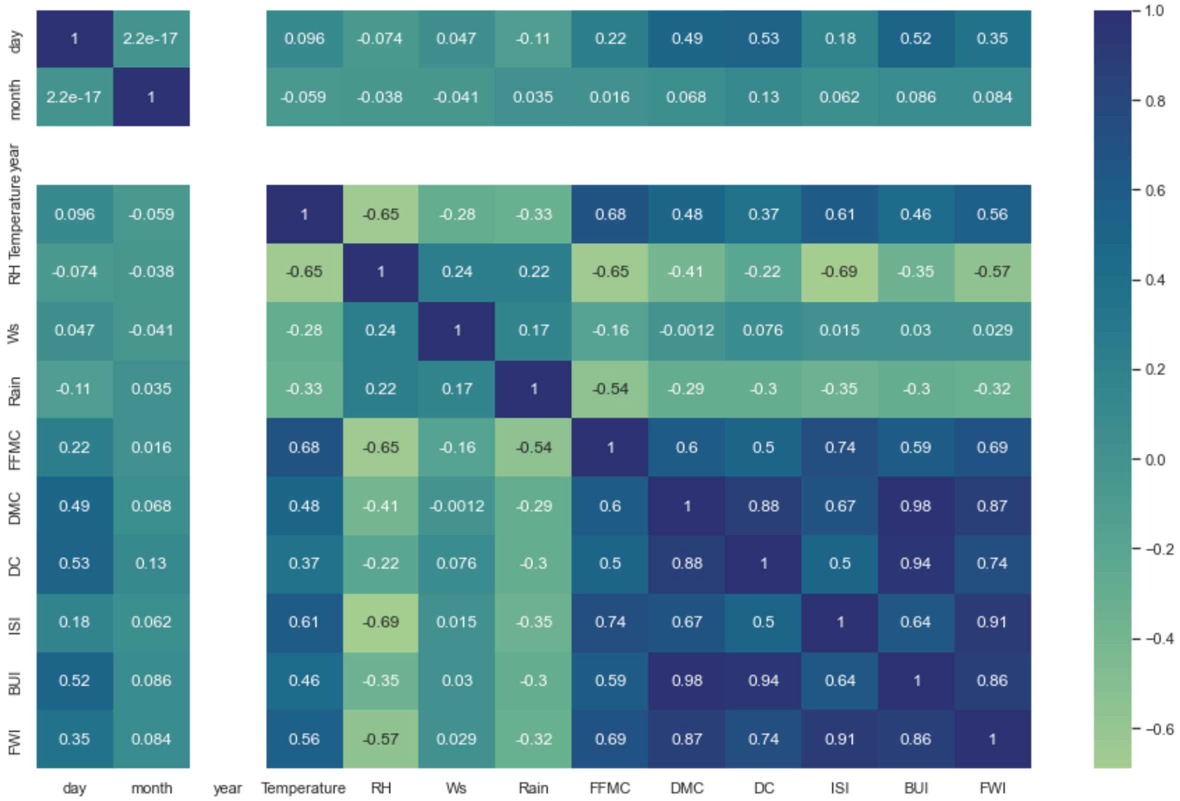
- In the Month of August Temperature was high and FWI Components were also high(FFMC, DMC,DC,ISI, BUI,FWI)
- Relative Humidity was high in the Month of june and September

In [40]:

```
plt.figure(figsize = (16,10))
sns.heatmap(dataset_forest.corr(),cmap="crest", annot=True)
```

Out[40]:

```
<AxesSubplot:>
```



Observations:

- DMC and BUI is highly +Ve Correlation
- DC and BUI also +Ve Correlation
- ISI and FWI also +Ve Correlation
- RH and DC is -Ve Correlation

In [41]:

```
dataset_forest['Date']=pd.to_datetime(dataset_forest[['day','month','year']])
dataset_forest.drop(['day','month','year'],axis=1,inplace=True)
```

Handling Categorical Features

In [42]:

```
dataset_forest['Classes']=dataset_forest['Classes'].map({'not fire':0,'fire':1})
```

In [43]:

```
dataset_forest['region'].replace('bejaia',1,inplace=True)
dataset_forest['region'].replace('Sidi-Bel Abbes',0,inplace=True)
```

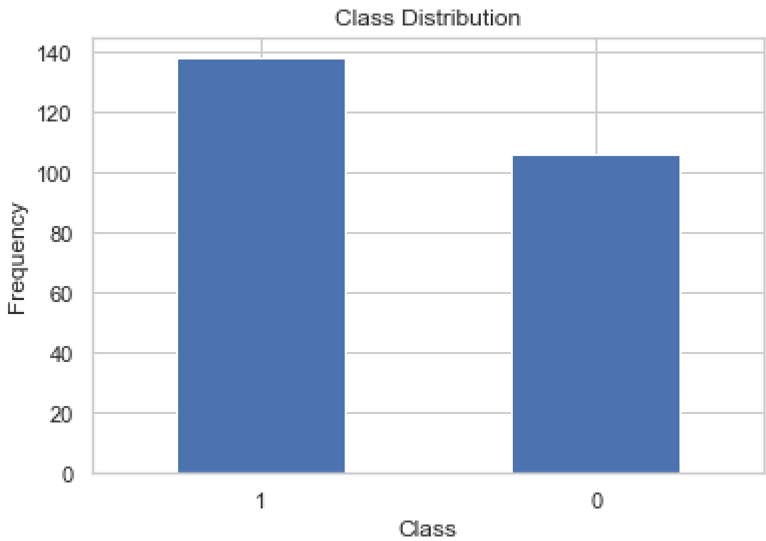
Chceking the dataset is Balance or Imbalanced Data

In [44]:

```
count_class = pd.value_counts(dataset_forest['Classes'],sort=True)
count_class.plot(kind='bar',rot=0)
plt.title("Class Distribution")
plt.xlabel("Class")
plt.ylabel("Frequency")
```

Out[44]:

```
Text(0, 0.5, 'Frequency')
```



Observations:

- As per the Frequency of the target variable, it is a normal dataset with 1 class around 130 and 0 class around 110

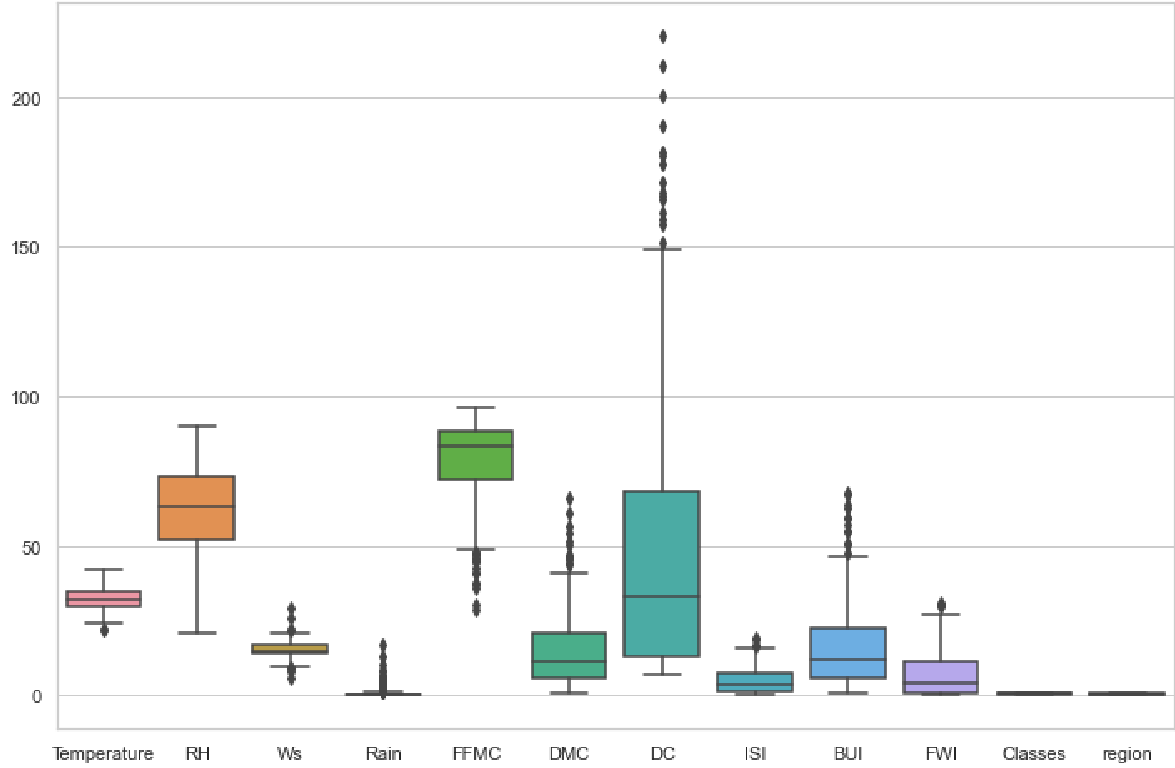
Outlier Check

In [45]:

```
plt.figure(figsize=(12,8))
sns.boxplot(data=dataset_forest)
```

Out[45]:

<AxesSubplot:>



Separating Outcome or Target Variable

In [46]:

```
y=dataset_forest["Classes"]
```

Dropping unnecessary columns

In [47]:

```
dataset_forest=dataset_forest.drop(['Classes','Date'],axis=1)
```

In [48]:

```
dataset_forest.columns
```

Out[48]:

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

Handleing the Outlier

In [49]:

```
def Handle_outliers(dataset,column):
    IQR=dataset[column].quantile(0.75)-dataset[column].quantile(0.25)
    lower_fence=dataset[column].quantile(0.25)-(IQR*1.5)
    upper_fence=dataset[column].quantile(0.75)+(IQR*1.5)
    print("IQR:",IQR)
    print(f"Lower Fence {column}:",lower_fence)
    print(f"Upper Fence {column}:",upper_fence)
    print("____________________________________________")
    dataset_forest.loc[dataset[column]<=lower_fence,column]=lower_fence
    dataset_forest.loc[dataset[column]>=upper_fence,column]=upper_fence
```

In [50]:

```
columns=dataset_forest.columns
```

In [51]:

```
for col in columns:
    Handle_outliers(dataset_forest,col)
```

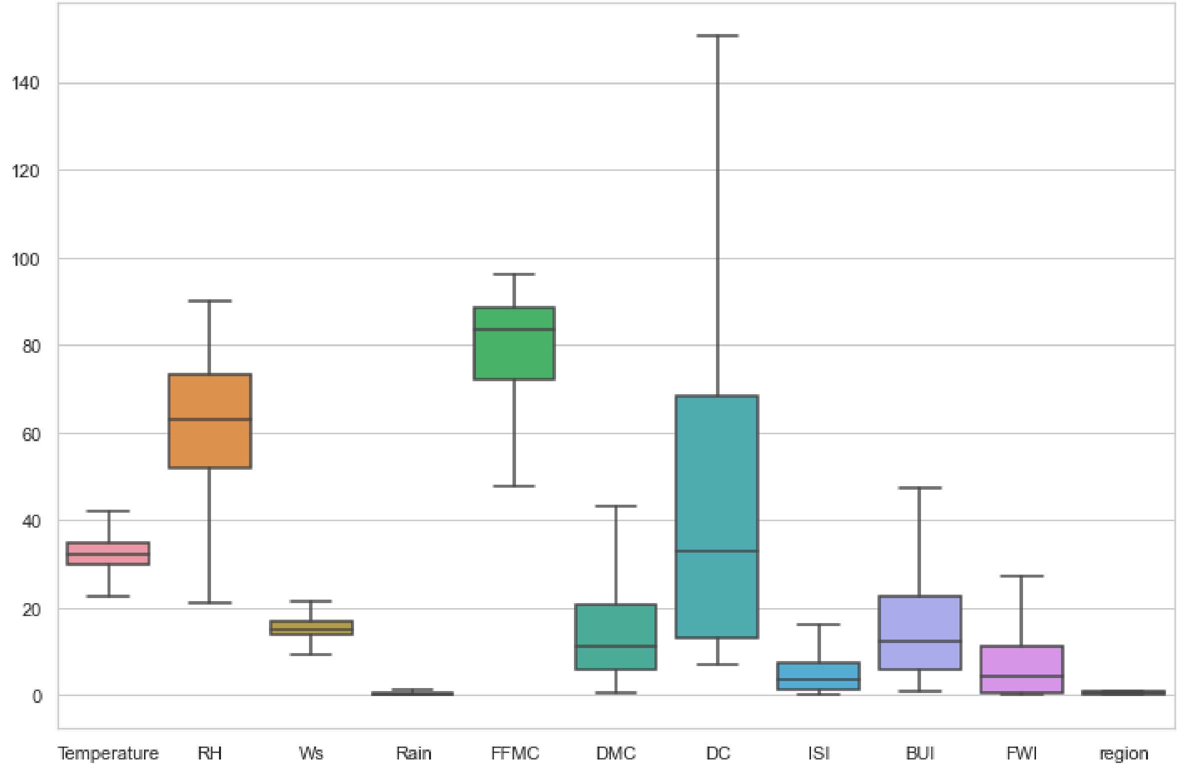
```
IQR: 5.0
Lower Fence Temperature: 22.5
Upper Fence Temperature: 42.5
________________________________________________
IQR: 21.25
Lower Fence RH: 20.125
Upper Fence RH: 105.125
________________________________________________
IQR: 3.0
Lower Fence Ws: 9.5
Upper Fence Ws: 21.5
________________________________________________
IQR: 0.5
Lower Fence Rain: -0.75
Upper Fence Rain: 1.25
________________________________________________
IQR: 16.224999999999994
Lower Fence FFMC: 47.73750000000001
Upper Fence FFMC: 112.63749999999999
________________________________________________
IQR: 14.95
Lower Fence DMC: -16.624999999999996
Upper Fence DMC: 43.175
________________________________________________
IQR: 54.87500000000001
Lower Fence DC: -69.03750000000002
Upper Fence DC: 150.46250000000003
________________________________________________
IQR: 5.9
Lower Fence ISI: -7.450000000000001
Upper Fence ISI: 16.150000000000002
________________________________________________
IQR: 16.525
Lower Fence BUI: -18.787499999999998
Upper Fence BUI: 47.3125
________________________________________________
IQR: 10.675
Lower Fence FWI: -15.312500000000004
Upper Fence FWI: 27.387500000000003
________________________________________________
IQR: 1.0
Lower Fence region: -1.5
Upper Fence region: 2.5
________________________________________________
```

In [52]:

```
plt.figure(figsize=(12,8))
sns.boxplot(data=dataset_forest)
```

Out[52]:

<AxesSubplot:>



In [53]:

```
y.shape
```

Out[53]:

(244,)

In [54]:

```
X=dataset_forest
```

In [55]:

```
X.shape
```

Out[55]:

```
(244, 11)
```

In [56]:

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
```

In [57]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=200)
```

In [58]:

```
X_train.shape
```

Out[58]:

```
(170, 11)
```

In [59]:

```
X_test.shape
```

Out[59]:

```
(74, 11)
```

In [60]:

```
y_train.shape
```

Out[60]:

```
(170,)
```

In [61]:

```
y_test.shape
```

Out[61]:

```
(74,)
```

Standardize features

In [62]:

```
from sklearn.preprocessing import StandardScaler
```

In [63]:

```
scaler=StandardScaler()
```

In [64]:

```
X_train=scaler.fit_transform(X_train)
```

In [65]:

```
X_test=scaler.transform(X_test)
```

In [66]:

```
X_train
```

Out[66]:

```
array([[-1.87139667,  1.62190181,  2.15570343, ..., -1.11716349,
        -0.9508287 ,  0.94280904],
       [-0.5600305 ,  1.09821082,  1.76790493, ..., -0.914993  ,
        -0.89832019,  0.94280904],
       [-1.08457697,  1.22913357,  2.15570343, ..., -0.61173726,
        -0.91144732,  0.94280904],
       ...,
       [-0.5600305 ,  1.81828593,  0.21671093, ..., -1.13271507,
        -0.9508287 ,  0.94280904],
       [-2.52707976,  0.96728807,  2.34960268, ..., -1.13271507,
        -0.93770158,  0.94280904],
       [ 0.48906244, -0.53832354,  0.99230793, ...,  0.74902567,
         1.01824036,  0.94280904]])
```

In [67]:

```
X_test
```

Out[67]:

```
array([[ 0.75133568, -1.78208964,  0.60450943, -0.6878656 ,  1.01507283,
         0.81352099,  1.16943313,  2.0517225 ,  1.02895404,  1.88463075,
        -1.06066017],
       [-0.5600305 ,  1.22913357,  1.38010643,  0.13418819, -1.24691026,
        -0.80779352, -0.70022726, -0.89197027, -0.79835618, -0.88519307,
         0.94280904],
       [-0.29775726,  0.05082883, -0.17108757, -0.6878656 ,  0.37597285,
        -0.75492457, -0.68392885, -0.26614582, -0.75947724, -0.53076064,
        -1.06066017],
       [ 1.01360891, -0.47286216, -0.55888608, -0.6878656 ,  0.92890205,
         2.53837053,  2.40723912,  1.17093254,  2.42179209,  2.47535147,
        -1.06066017],
       [-1.87139667,  0.96728807,  0.60450943,  1.88105251, -2.17773426,
        -1.1514417 , -0.92141996, -1.10057842, -1.11716349, -0.93770158,
         0.94280904],
       [-0.5600305 ,  0.31267433, -0.17108757, -0.27683871, -0.32775523,
        -0.90471993, -0.47670622, -0.79925553, -0.79058039, -0.85893881,
        -1.06066017],
```

In [68]:

```
y_train
```

Out[68]:

```
104    0
13     0
91     0
190    1
170    1
      ..
42     0
68     0
16     0
105    0
26     1
Name: Classes, Length: 170, dtype: int64
```

In [69]:

```
y_test
```

Out[69]:

```
234    1
44     0
220    1
209    1
92     0
      ..
166    1
164    1
63     0
153    1
33     0
Name: Classes, Length: 74, dtype: int64
```

In [70]:

```
log_reg=LogisticRegression()
```

In [71]:

```
log_reg.fit(X_train,y_train)
```

Out[71]:

```
LogisticRegression()
```

In [72]:

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

```
[[ 0.31556568  0.36701972  0.06643531 -0.15846261  2.27420466  0.02276405
   0.04608258  2.17916419 -0.0092186   1.64441524 -0.17467832]]
```

In [73]:

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

```
[1.35152071]
```

In [74]:

```
log_reg_pred=log_reg.predict(X_test)
```

Confusion Matrix

In [75]:

```
confusion_mat=confusion_matrix(y_test,log_reg_pred)
```

In [76]:

```
print(confusion_mat)
```

```
[[31  1]
 [ 0 42]]
```

In [77]:

```
print("Accuracy :",accuracy_score(y_test,log_reg_pred))
```

```
Accuracy : 0.9864864864864865
```

Accuracy : 0.9864

In [78]:

```
TP=confusion_mat[0][0]
FP=confusion_mat[0][1]
FN=confusion_mat[1][0]
TN=confusion_mat[1][1]
```

Precision

In [79]:

```
Precision=TP/(TP+FP)
```

In [80]:

```
print(Precision)
```

```
0.96875
```

Precision : 0.968

Recall

In [81]:

```
Recall = TP/(TP+FN)
```

In [82]:

```
print(Recall)
```

```
1.0
```

Recall : 1.0

F1 Score

In [83]:

```
F1_score = 2*(Recall * Precision)/(Recall+Precision)
```

In [84]:

```
print(F1_score)
```

```
0.9841269841269841
```

F1 Score : 0.9841

Actual and Prediction Dataset

In [85]:

```
DF=pd.DataFrame({'Actual':y_test,'Predicted':log_reg_pred})
```

In [86]:

```
DF.head(15)
```

Out[86]:

	Actual	Predicted
234	1	1
44	0	0
220	1	1
209	1	1
92	0	0
217	0	0
232	1	1
75	1	1
142	1	1
132	1	1
98	0	0
9	0	0
58	1	1
66	1	1
213	1	1

Thank You

Type *Markdown* and LaTeX: α^2