Algerian Forest Fire Dataset

In [1]:
```
# importing Necessary Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import classification_report
```

In [2]:
```
# Reading the dataset
dataset = pd.read_csv('Algerian_forest_fires_dataset.csv')
dataset.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

In [3]:
```
# finding the shape of the dataset
dataset.shape
```

Out[3]:
```
(247, 14)
```

OBSERVATIONS: It seems like it is a very small dataset with 247 rows and 14 columns.

In this dataset we have 2 regions namely Bejaia has 122 records and Sidi Bel-abbes has 122 records

Exploratory Data Analysis

In [4]:
```
dataset.isnull().sum()
```

Out[4]:
```
day            1
month          2
year           2
Temperature    2
 RH            2
 Ws            2
Rain           2
FFMC           2
DMC            2
DC             2
ISI            2
BUI            2
FWI            2
Classes        3
dtype: int64
```

In [5]:
```
dataset[dataset.isnull().any(axis=1)]
```

Out[5]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
122	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
123	Sidi-Bel Abbes Region Dataset	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
168	14	7	2012	37	37	18	0.2	88.9	12.9	14.6 9	12.5	10.4	fire	NaN

In [6]:
```
dataset[dataset.isnull().all(axis='columns')]
```

Out[6]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
122	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

OBSERVATIONS: here we have the data for sidi-Bel Abbes Region from row 123 so we can create a new column region

In [7]:
```
# creating a new column for region
dataset.loc[:122 ,'Region'] = 0
dataset.loc[123: ,'Region'] = 1

# droping NAN rows
dataset = dataset.dropna().reset_index(drop = True)
```

OBSERVATIONS : Now we have replaced Bejaia = 0 and sidi-Bel Abbes Region = 1

In [8]:
```
dataset.shape
```

Out[8]:
```
(244, 15)
```

In [9]:
```
dataset.loc[[122]]
```

Out[9]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region
122	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	1.0

In [10]:
```
# dropping index 122
dataset = dataset.drop(122).reset_index(drop = True)
```

In [11]:
```
dataset.shape
```
Out[11]:
```
(243, 15)
```

OBSERVATIONS : Now we have 243 rows and 15 columns

In [12]:
```
# Copying the dataset
df = dataset.copy()
```

In [13]:
```
df.head()
```
Out[13]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region
0	1	6	2012	29	57	18	0	65.7	3.4	7.6	1.3	3.4	0.5	not fire	0.0
1	2	6	2012	29	61	13	1.3	64.4	4.1	7.6	1	3.9	0.4	not fire	0.0
2	3	6	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	not fire	0.0
3	4	6	2012	25	89	13	2.5	28.6	1.3	6.9	0	1.7	0	not fire	0.0
4	5	6	2012	27	77	16	0	64.8	3	14.2	1.2	3.9	0.5	not fire	0.0

In [14]:
```
#checking null values
df.isnull().sum()
```
Out[14]:
```
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        0
Region         0
dtype: int64
```

OBSERVATIONS : There is no Null values

In [15]:
```
# checking datatypes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 243 entries, 0 to 242
Data columns (total 15 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   day          243 non-null    object 
 1   month        243 non-null    object 
 2   year         243 non-null    object 
 3   Temperature  243 non-null    object 
 4    RH          243 non-null    object 
 5    Ws          243 non-null    object 
 6   Rain         243 non-null    object 
 7   FFMC         243 non-null    object 
 8   DMC          243 non-null    object 
 9   DC           243 non-null    object 
 10  ISI          243 non-null    object 
 11  BUI          243 non-null    object 
 12  FWI          243 non-null    object 
 13  Classes      243 non-null    object 
 14  Region       243 non-null    float64
dtypes: float64(1), object(14)
memory usage: 28.6+ KB
```

OBSERVATIONS : There are 14 categorical and 1 numerical features

In [16]:
```
df.columns
```

Out[16]:
```
Index(['day', 'month', 'year', 'Temperature', ' RH', ' Ws', 'Rain ', 'FFMC',
       'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes  ', 'Region'],
      dtype='object')
```

OBSERVATIONS : As we have spaces in column names we can strip it

In [17]:
```
df.columns = df.columns.str.strip()
```

In [18]:
```
df.columns
```

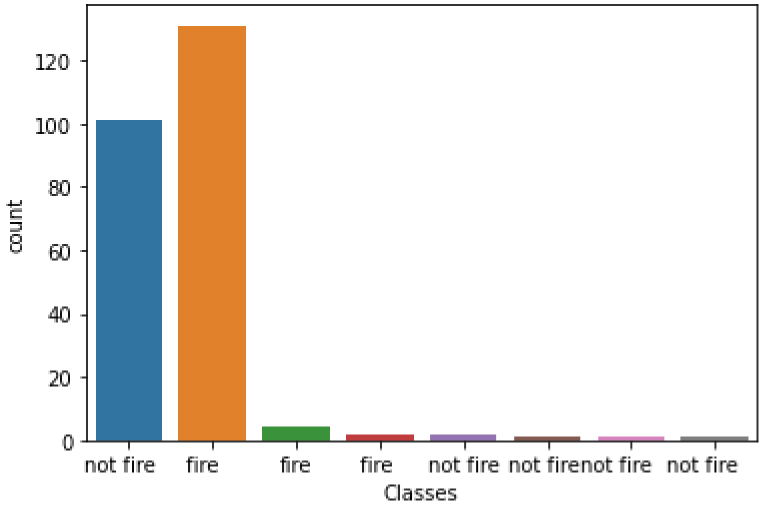
Out[18]:
```
Index(['day', 'month', 'year', 'Temperature', 'RH', 'Ws', 'Rain', 'FFMC',
       'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes', 'Region'],
      dtype='object')
```

In [19]:
```
df['Classes'].unique()
```

Out[19]:
```
array(['not fire   ', 'fire   ', 'fire', 'fire ', 'not fire', 'not fire ',
       'not fire     ', 'not fire    '], dtype=object)
```

In [20]:
```
# Univariate Analysis
sns.countplot(data = df, x = 'Classes')
```

Out[20]:
```
<AxesSubplot:xlabel='Classes', ylabel='count'>
```



OBSERVATIONS : we have to strip the target column as well

In [21]:
```
df['Classes'] = df['Classes'].str.strip()
```

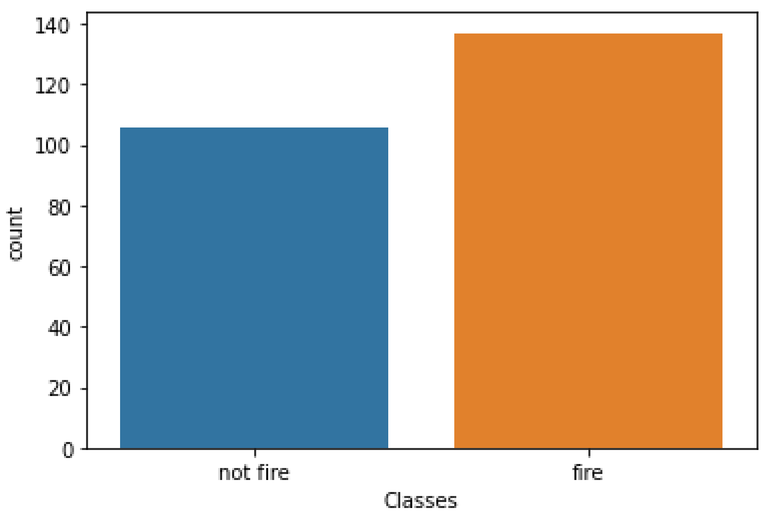
In [22]:
```
df['Classes'].unique()
```

Out[22]:
```
array(['not fire', 'fire'], dtype=object)
```

OBSERVATIONS : Now we got 2 unique values in the Target Feature, 'Fire' and 'Not Fire'

In [23]:
```
# Univariate Analysis
sns.countplot(data = df, x = 'Classes')
```

Out[23]:
```
<AxesSubplot:xlabel='Classes', ylabel='count'>
```



OBSERVATIONS : We can clearly see that the area fired is larger than the area not fired

In [24]:
```
sns.countplot(data = df, x = 'Region', hue = 'Classes')
```

Out[24]:
```
<AxesSubplot:xlabel='Region', ylabel='count'>
```

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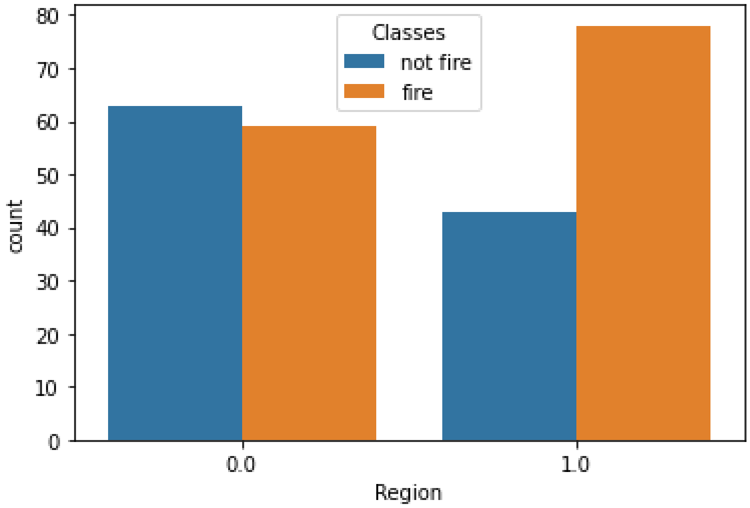
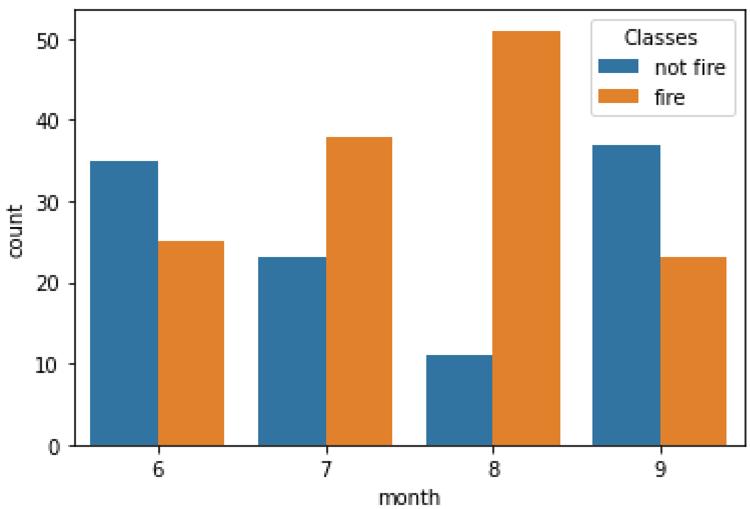


OBSERVATIONS : We can clearly see that the area fired in sidi-Bel Abbes Region is very high

In [25]:
```
sns.countplot(data = df, x = 'month', hue = 'Classes')
```

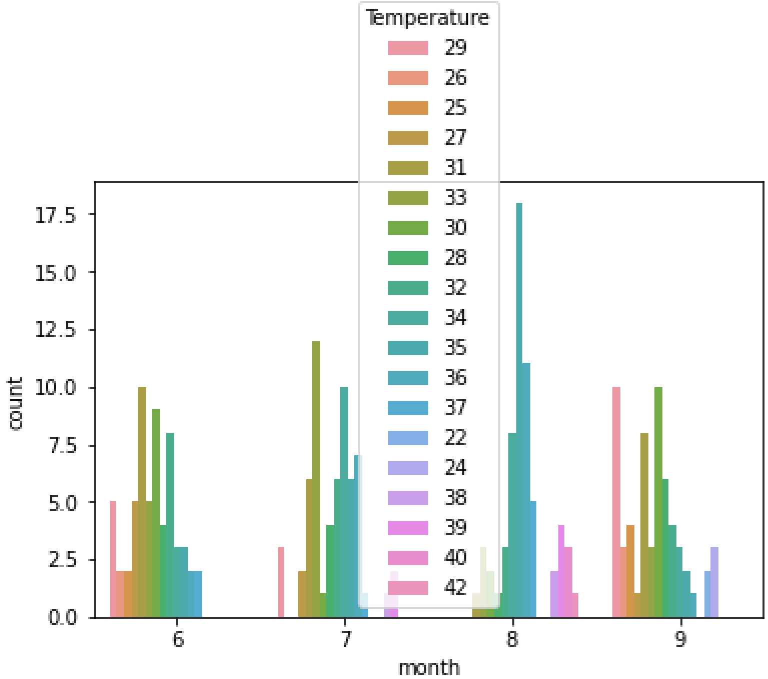
Out[25]:
```
<AxesSubplot:xlabel='month', ylabel='count'>
```



OBSERVATIONS : We can see that the fire got spread high in the month of August

In [26]:
```
sns.countplot(data = df, x = 'month', hue = 'Temperature')
```

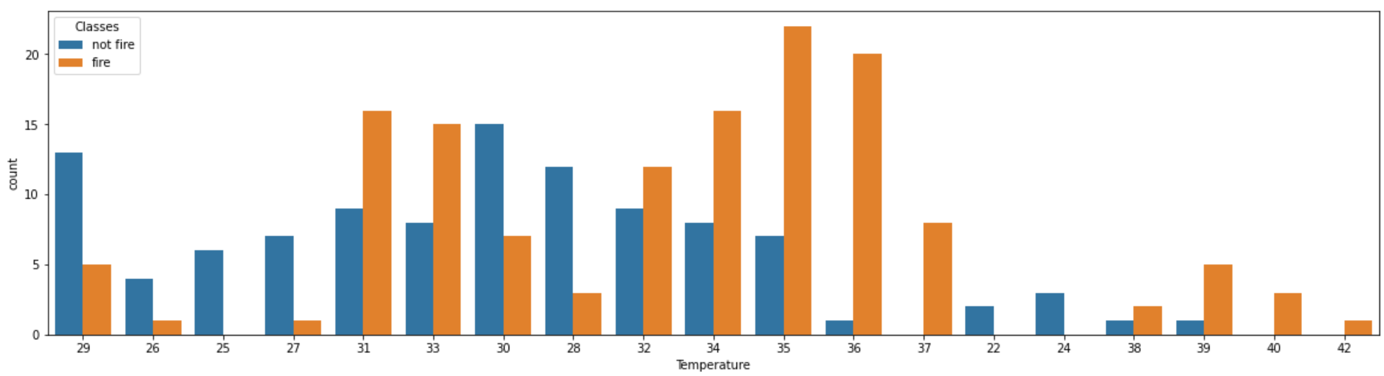
Out[26]:
```
<AxesSubplot:xlabel='month', ylabel='count'>
```



OBSERVATIONS : The Highest number of times the hot temperature sustained in the month of August

In [27]:
```python
# Visualizing whether the temperature could also be a reason for fire or not
plt.figure(figsize=(20,5))
sns.countplot(x = 'Temperature',data = df,hue = 'Classes')
```

Out[27]: <AxesSubplot:xlabel='Temperature', ylabel='count'>



OBSERVATIONS : It seems that the fire got increased when the temperature raised

In [28]:
```python
df['year'].unique()
```

Out[28]: array(['2012'], dtype=object)

In [29]:
```python
df.shape
```

Out[29]: (243, 15)

In [30]:
```python
#Encoding Target feature
df['Classes'] = np.where(df['Classes'] == 'not fire' ,0,1)
```

OBERVATIONS : Encoding 'not fire' = 0 and 'fire' = 1

In [31]:
```python
# checking Data is balanced or not
df['Classes'].value_counts()
```

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Out[31]:
```
1    137
0    106
Name: Classes, dtype: int64
```

Splitting data into train and test

In [32]:
```
X = df.drop(columns = ['Classes'])
y = df['Classes']
```

In [33]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=5, test_size=0.3)
```

In [34]:
```
X_train.shape
```

Out[34]:
```
(170, 14)
```

In [35]:
```
y_train.shape
```

Out[35]:
```
(170,)
```

In [36]:
```
X_test.shape
```

Out[36]:
```
(73, 14)
```

In [37]:
```
y_test.shape
```

Out[37]:
```
(73,)
```

Data Preprocessing on Train and Test data

In [38]:
```
X_train.isnull().sum()
```

Out[38]:
```
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
Region         0
dtype: int64
```

In [39]:
```
X_test.isnull().sum()
```

```
Out[39]: 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
         Region         0
         dtype: int64
```

OBSERVATIONS : There is no null values in train and test data

```
In [40]: df.dtypes
```

```
Out[40]: day             object
         month           object
         year            object
         Temperature     object
         RH              object
         Ws              object
         Rain            object
         FFMC            object
         DMC             object
         DC              object
         ISI             object
         BUI             object
         FWI             object
         Classes          int32
         Region         float64
         dtype: object
```

```
In [41]: # Converting the dtypes
         X_train = X_train.astype({'day' : int,'month' : int, 'year' : int,'Temperature' : int,'R
         X_train = X_train.astype({'Rain' : float,'FFMC' : float,'DMC' : float,'DC' : float,'ISI'
         X_test = X_test.astype({'day' : int,'month' : int, 'year' : int,'Temperature' : int,'RH'
         X_test = X_test.astype({'Rain' : float,'FFMC' : float,'DMC' : float,'DC' : float,'ISI' :
```

```
In [42]: X_train.dtypes
```

```
Out[42]: day              int32
         month            int32
         year             int32
         Temperature      int32
         RH               int32
         Ws               int32
         Rain           float64
         FFMC           float64
         DMC            float64
         DC             float64
         ISI            float64
         BUI            float64
         FWI            float64
         Region           int32
         dtype: object
```

```
In [43]: X_test.dtypes
```

Out[43]:
```
day                int32
month              int32
year               int32
Temperature        int32
RH                 int32
Ws                 int32
Rain             float64
FFMC             float64
DMC              float64
DC               float64
ISI              float64
BUI              float64
FWI              float64
Region             int32
dtype: object
```

In [44]:
```
y_train.unique()
```

Out[44]:
```
array([0, 1])
```

In [45]:
```
y_train.value_counts()
```

Out[45]:
```
1    100
0     70
Name: Classes, dtype: int64
```

In [46]:
```
y_test.value_counts()
```

Out[46]:
```
1    37
0    36
Name: Classes, dtype: int64
```

In [47]:
```
# Finding Coorelation
X_train.corr()
```

Out[47]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	
day	1.000000	0.062996	NaN	0.070720	-0.075157	0.022991	-0.033666	0.186148	0.452093	0.4
month	0.062996	1.000000	NaN	-0.029865	-0.056639	-0.074480	0.039739	0.022951	0.090696	0.1
year	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
Temperature	0.070720	-0.029865	NaN	1.000000	-0.650623	-0.318634	-0.331731	0.676161	0.484817	0.3
RH	-0.075157	-0.056639	NaN	-0.650623	1.000000	0.267859	0.216749	-0.658829	-0.448995	-0.2
Ws	0.022991	-0.074480	NaN	-0.318634	0.267859	1.000000	0.304219	-0.247078	-0.072303	0.0
Rain	-0.033666	0.039739	NaN	-0.331731	0.216749	0.304219	1.000000	-0.493266	-0.259379	-0.2
FFMC	0.186148	0.022951	NaN	0.676161	-0.658829	-0.247078	-0.493266	1.000000	0.619200	0.5
DMC	0.452093	0.090696	NaN	0.484817	-0.448995	-0.072303	-0.259379	0.619200	1.000000	0.8
DC	0.467876	0.162674	NaN	0.377729	-0.285920	0.000246	-0.282252	0.543761	0.877566	1.0
ISI	0.182816	0.083054	NaN	0.627675	-0.695484	-0.069566	-0.326489	0.760974	0.715397	0.5
BUI	0.471813	0.113536	NaN	0.461702	-0.404365	-0.049457	-0.272397	0.613633	0.985142	0.9
FWI	0.327793	0.109309	NaN	0.572181	-0.597090	-0.038416	-0.298655	0.699432	0.895125	0.7
Region	0.084592	-0.047086	NaN	0.321939	-0.434017	-0.162755	-0.124946	0.268313	0.281624	0.0

In [48]:
```
plt.figure(figsize = (20,15))
sns.heatmap(X_train.corr(), annot=True)
```

<AxesSubplot:>

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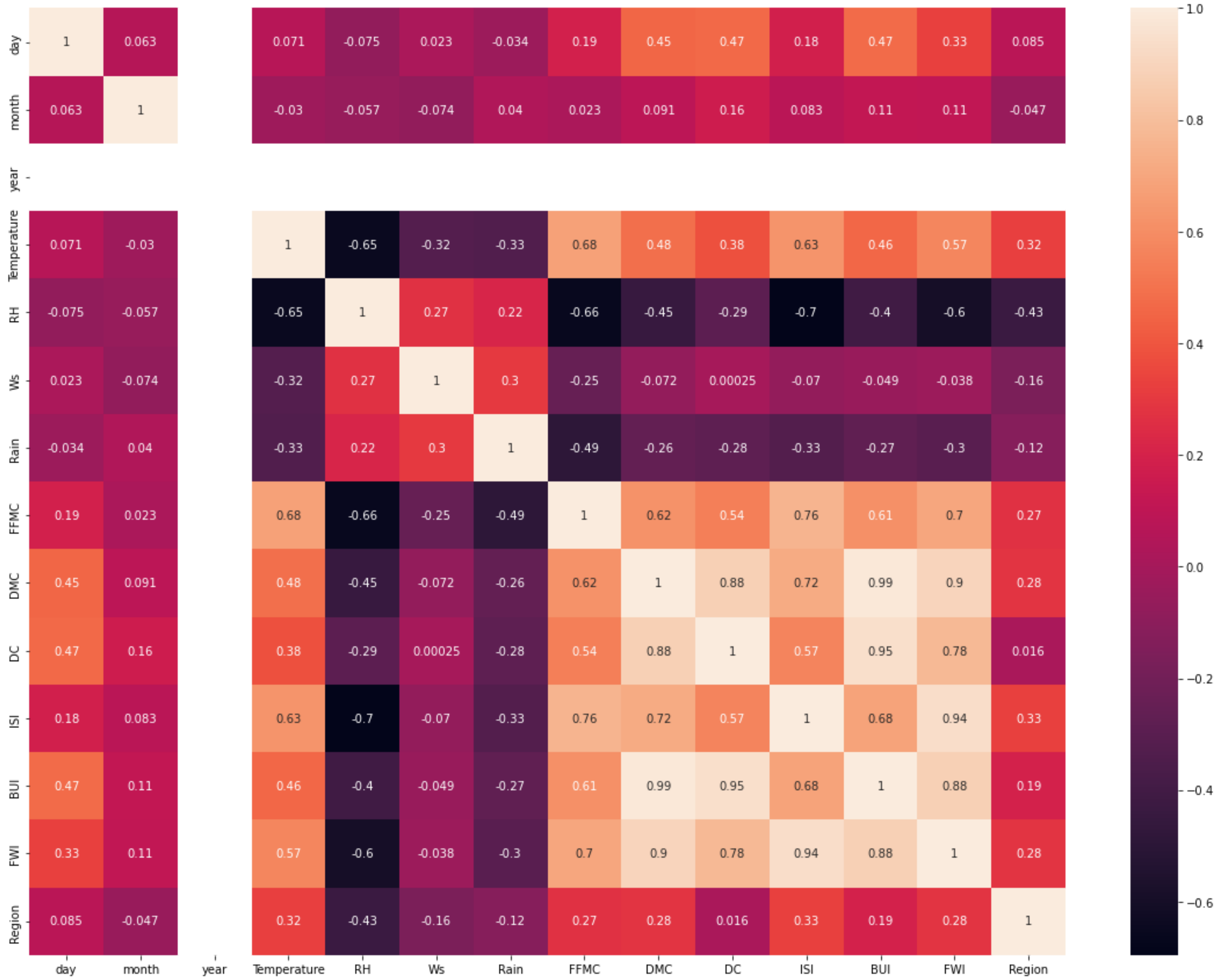


OBSERVATIONS :

Temperature is highly correlated with RH, FFMC, ISI, FWI

RH is highly correlated with Temperature, FFMC, ISI, FWI

FFMC is highly correlated with RH, DMC, DC, ISI, BUI, FWI

DMC is highly correlated with FFMC, DC, ISI, BUI, FWI

DC is highly Correlated with FFMC, DMC, ISI, BUI, FWI

ISI is highly correlated with Temperature, RH, FFMC, DMC, DC, BUI, FWI

BUI is highly correlated with FFMC, DMC, DC, ISI, FWI

FWI is highly correlated with Temperature, RH, FFMC, DMC, DC, ISI, BUI

In [49]:

```
# finding features that are more than 80% correlated
def correlation(datas, threshold):
    col_corr = set()
    corr_matrix = datas.corr()
    for i in range(len(corr_matrix.columns)):
        for j in range(i):
            if abs(corr_matrix.iloc[i, j]) > threshold:
                colname = corr_matrix.columns[i]
                col_corr.add(colname)
    return col_corr
```

In [50]:

```
correlated_features = correlation(X_train,0.8)
correlated_features
```

Out[50]: {'BUI', 'DC', 'FWI'}

so here BUI, DC, FWI are more than 80% correlated and so we can drop it and also we can drop day, month, year features

In [51]:
```
# droping features
X_train.drop(columns=['BUI','DC','FWI','day','month','year'],axis=1,inplace=True)
X_test.drop(columns=['BUI','DC','FWI','day','month','year'],axis=1,inplace=True)
```

In [52]:
```
X_train.reset_index(inplace=True)
```

In [53]:
```
X_test.reset_index(inplace=True)
```

In [54]:
```
X_train.drop(columns='index',axis=1,inplace=True)
X_test.drop(columns='index',axis=1,inplace=True)
```

In [55]:
```
X_train.head()
```

Out[55]:

	Temperature	RH	Ws	Rain	FFMC	DMC	ISI	Region
0	33	73	12	1.8	59.9	2.2	0.7	0
1	31	64	15	0.0	86.7	14.2	5.7	0
2	31	65	18	0.0	84.3	12.5	4.8	0
3	30	77	21	1.8	58.5	1.9	1.1	0
4	33	70	17	0.0	85.4	18.5	5.2	0

In [56]:
```
X_test.head()
```

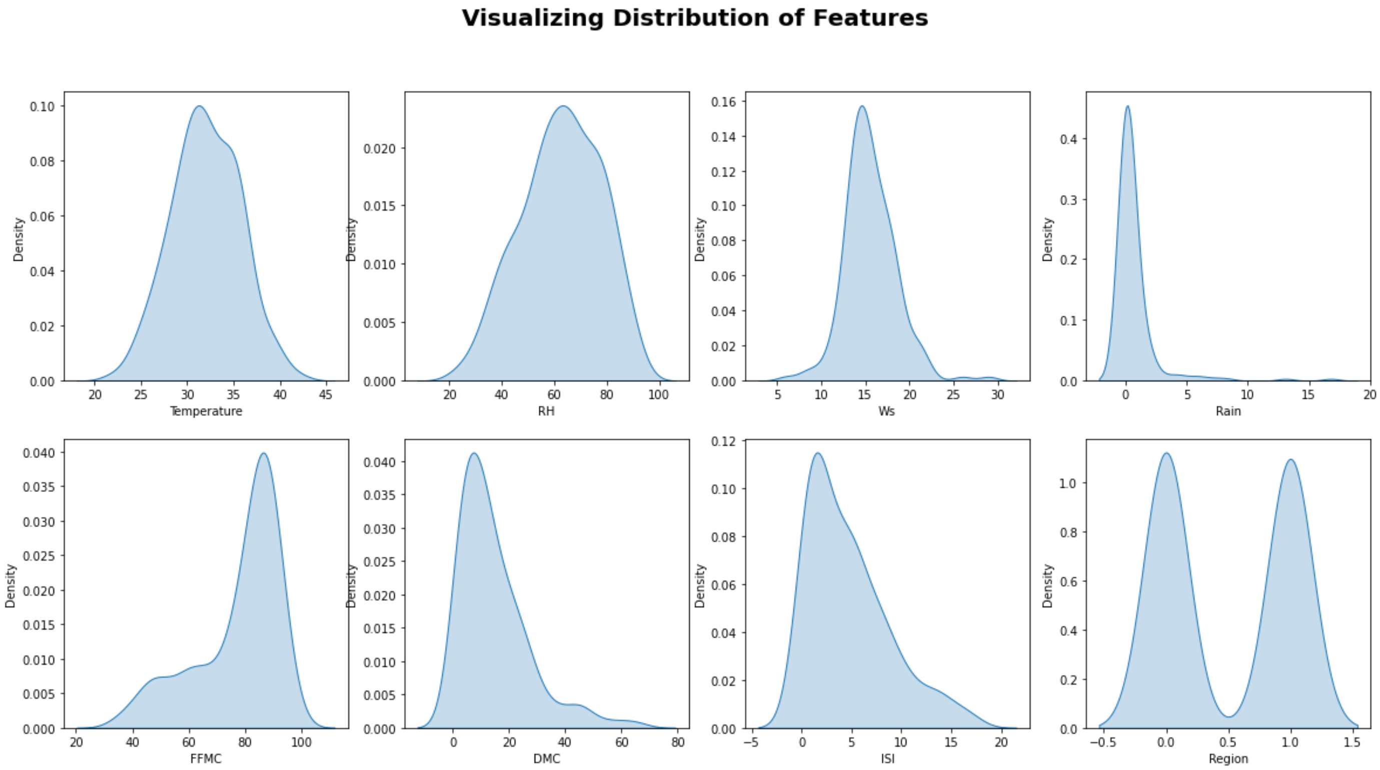
Out[56]:

	Temperature	RH	Ws	Rain	FFMC	DMC	ISI	Region
0	36	53	19	0.0	89.2	17.1	10.0	0
1	34	71	14	6.5	64.5	3.3	1.0	1
2	32	51	13	0.0	88.7	16.0	6.9	1
3	29	73	17	0.1	68.4	1.9	1.4	0
4	34	56	15	2.9	74.8	7.1	1.6	1

In [57]:
```
# Visualizing the Distribution

plt.figure(figsize=(20,10))
plt.suptitle('Visualizing Distribution of Features',fontsize = 20, fontweight = 'bold')

for i in range(0,len(X_train.columns)):
    plt.subplot(2,4,i+1)
    sns.kdeplot(x = X_train[X_train.columns[i]], shade=True)
```

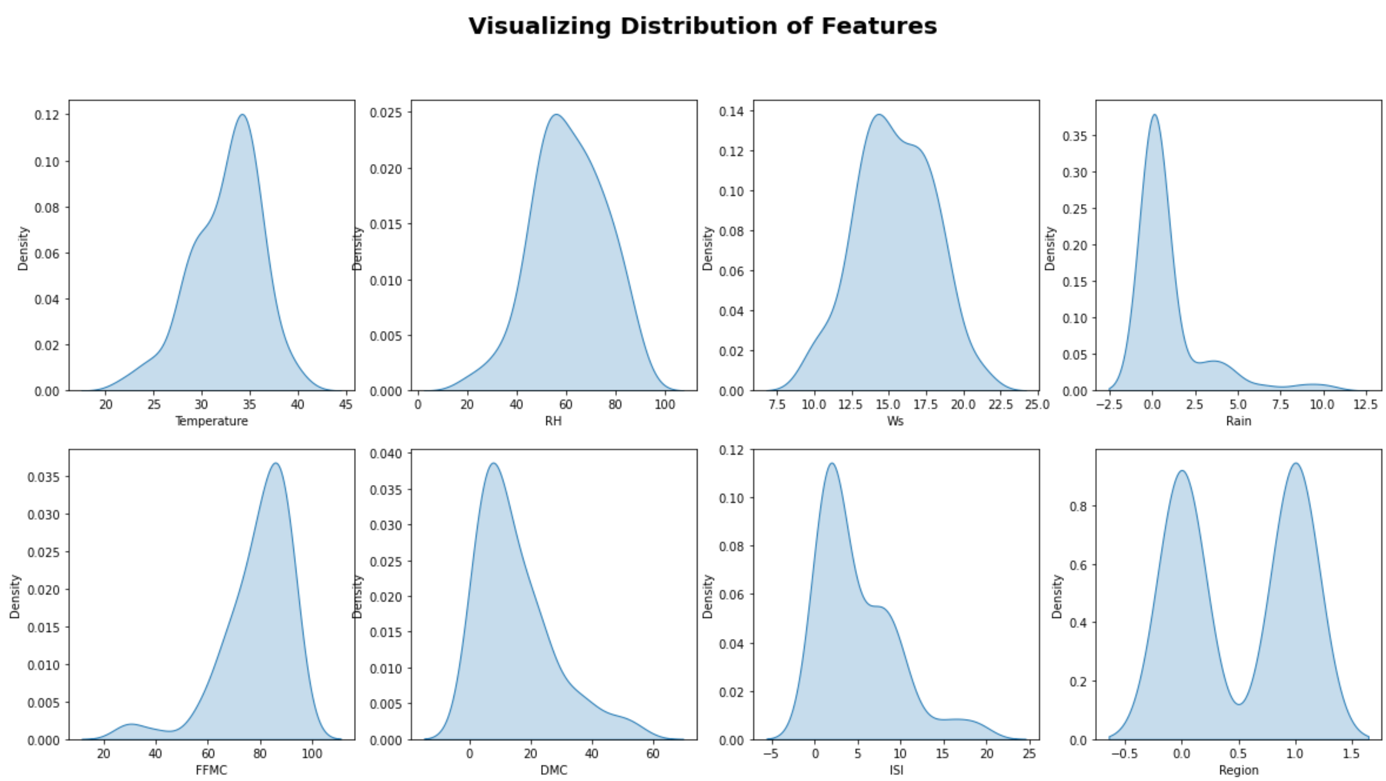


In [58]:

```python
# Visualizing the Distribution

plt.figure(figsize=(20,10))
plt.suptitle('Visualizing Distribution of Features',fontsize = 20, fontweight = 'bold')

for i in range(0,len(X_test.columns)):
    plt.subplot(2,4,i+1)
    sns.kdeplot(x = X_test[X_test.columns[i]], shade=True)
```



Feature Scaling

In [59]:
```
scalar = StandardScaler()
X_train_scaled = scalar.fit_transform(X_train)
X_test_scaled = scalar.transform(X_test)
```

In [60]:
```
X_train_scaled
```

Out[60]:
```
array([[ 0.2768811 ,  0.70529363, -1.21076039, ..., -0.99829831,
        -0.98570585, -0.98830369],
       [-0.270442  ,  0.10445886, -0.18503315, ..., -0.03197397,
         0.25206926, -0.98830369],
       [-0.270442  ,  0.17121827,  0.84069409, ..., -0.16886992,
         0.02926974, -0.98830369],
       ...,
       [-1.09142665,  1.6399255 , -0.18503315, ..., -0.65203209,
        -1.13423887,  1.01183473],
       [ 0.55054265, -1.4977672 ,  0.84069409, ...,  3.35821393,
         2.38104246,  1.01183473],
       [-0.54410355,  0.70529363,  0.49878501, ..., -0.9660875 ,
        -0.88668385, -0.98830369]])
```

In [61]:
```
X_test_scaled
```

```
Out[61]: array([[ 1.09786575e+00, -6.29894755e-01,  1.18260317e+00,
                 -3.51344403e-01,  7.94125580e-01,  2.01554415e-01,
                  1.31655586e+00, -9.88303691e-01],
                [ 5.50542648e-01,  5.71774790e-01, -5.26942228e-01,
                  2.89748878e+00, -8.81350911e-01, -9.09718576e-01,
                 -9.11439348e-01,  1.01183473e+00],
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```

Model Building

In [62]:

```
#Logistic Regression
Logistic = LogisticRegression()
Logistic.fit(X_train_scaled,y_train)
```

Out[62]:

```
▼ LogisticRegression
LogisticRegression()
```

In [63]:

```
print('intercept value',Logistic.intercept_)
print('slope value',Logistic.coef_)
```

```
intercept value [1.24236416]
slope value [[0.28937305 0.41153979 0.02255954 0.14680038 2.56456001 0.93944141
  2.72338307 0.12505735]]
```

Evaluating the model

In [64]:

```
print('Training_score',Logistic.score(X_train_scaled,y_train))
print('Testing_score',Logistic.score(X_test_scaled,y_test))
```

```
Training_score 0.9705882352941176
Testing_score 0.9315068493150684
```

In [65]:

```
# Predicting the y_test data
Logistic.predict = Logistic.predict(X_test_scaled)
Logistic.predict
```

Out[65]:
```
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```

In [66]:
```
accuracy_score = accuracy_score(y_test,Logistic.predict)
Classification_Report = classification_report(y_test,Logistic.predict)

print('Logistic Regression')
print(accuracy_score)
print(Classification_Report)
```

```
Logistic Regression
0.9315068493150684
              precision    recall  f1-score   support

           0       0.97      0.89      0.93        36
           1       0.90      0.97      0.94        37

    accuracy                           0.93        73
   macro avg       0.93      0.93      0.93        73
weighted avg       0.93      0.93      0.93        73
```

In [ ]:

In [ ]: