# **Algerian Forest Fires Dataset**

#### **Data Set Information:**

The dataset includes 244 instances that regroup a data of two regions of Algeria,namely the Bejaia region located in the northwest of Algeria and the Sidi Bel-abbes region located in the northwest of Algeria.

122 instances for each region.

The period from June 2012 to September 2012. The dataset includes 11 attribues and 1 output attribue (class) The 244 instances have been classified into fire(138 classes) and not fire (106 classes) classes.

#### **Attribute Information:**

- 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 Fire and not Fire

## **Importing Libraries**

```
In [1]:
```

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

## Load the dataset

```
In [2]:
```

```
dataset=pd.read_csv('Algerian_forest_fires_dataset_UPDATE.csv' ,header=1)
```

## Top 5 rows

```
In [3]:
```

```
dataset.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

```
In [83]:
## Shape
df.shape
Out[83]:
(243, 12)
```

## **Check data types**

```
In [84]:
```

```
df.dtypes
Out[84]:
Temperature
                int64
               int64
                int64
Rain
             float64
FFMC
             float64
             float64
DMC
DC
             float64
ISI
              float64
BUI
              float64
FWI
              float64
Classes
                int32
Region
                int64
dtype: object
```

## **Summary of dataset**

```
In [4]:
```

```
dataset.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 246 entries, 0 to 245
Data columns (total 14 columns):
# Column Non-Null Count Dtype
              -----
0 day
              246 non-null
                            object
1 month
              245 non-null
                           object
2 year
              245 non-null
                            object
3 Temperature 245 non-null
                            object
   RH
              245 non-null
4
                            object
    Ws
              245 non-null
5
                            object
  Rain
              245 non-null
6
                            object
              245 non-null
7
   FFMC
                            object
  DMC
                           object
8
              245 non-null
9
   DC
              245 non-null object
10 ISI
              245 non-null object
11 BUI
              245 non-null object
```

245 non-null object

244 non-null object

# **Data Cleaning**

dtypes: object(14)
memory usage: 27.0+ KB

## **Check missing values**

In [ ]:

12 FWI

13 Classes

```
## missing values
dataset[dataset.isnull().any(axis=1)]
```

The dataset is converted into two sets based on Region from 122th index, we can make a new column based on the Region

1: "Bejaia Region Dataset"

2: "Sidi-Bel Abbes Region Dataset"

Add new column with region

```
In [5]:
```

```
dataset.loc[:122, "Region"]=0
dataset.loc[122:, "Region"]=1
df=dataset
```

## In [6]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 246 entries, 0 to 245
Data columns (total 15 columns):
          Non-Null Count Dtype
# Column
___
               -----
              246 non-null
                           object
0
   day
1 month 245 non-null object
2 year 245 non-null object
3
  Temperature 245 non-null object
4
   RH 245 non-null object
5
    Ws
              245 non-null object
6 Rain
              245 non-null object
7 FFMC
              245 non-null object
8 DMC
              245 non-null object
9 DC
              245 non-null object
10 ISI
              245 non-null
                            object
11 BUI
              245 non-null
                            object
```

245 non-null

244 non-null

246 non-null dtypes: float64(1), object(14)

memory usage: 29.0+ KB

#### In [7]:

```
df.head()
```

12 FWI

14 Region

13 Classes

### Out[7]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region
(	01	06	2012	29	57	18	0	65.7	3.4	7.6	1.3	3.4	0.5	not fire	0.0
1	02	06	2012	29	61	13	1.3	64.4	4.1	7.6	1	3.9	0.4	not fire	0.0
2	03	06	2012	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	not fire	0.0
3	04	06	2012	25	89	13	2.5	28.6	1.3	6.9	0	1.7	0	not fire	0.0
4	05	06	2012	27	77	16	0	64.8	3	14.2	1.2	3.9	0.5	not fire	0.0

object

object

float64

## In [9]:

```
df[['Region']]=df[['Region']].astype(int)
```

```
In [10]:
```

```
df.head()
```

A 1 [1 A 1

```
Out[IU]:
```

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

## In [11]:

df.tail()

Out[11]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region
241	26	09	2012	30	65	14	0	85.4	16	44.5	4.5	16.9	6.5	fire	1
242	27	09	2012	28	87	15	4.4	41.1	6.5	8	0.1	6.2	0	not fire	1
243	28	09	2012	27	87	29	0.5	45.9	3.5	7.9	0.4	3.4	0.2	not fire	1
244	29	09	2012	24	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7	not fire	1
245	30	09	2012	24	64	15	0.2	67.3	3.8	16.5	1.2	4.8	0.5	not fire	1

## In [12]:

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

## Out[12]:

day 0 month 1 1 year Temperature RH Ws Rain FFMC 1 DMC 1 DC 1 ISI 1 BUI 1 FWI 1 Classes 2 Region dtype: int64

## In [13]:

```
## Removing the null values
df=df.dropna().reset_index(drop=True)
```

## In [14]:

df.head()

## Out[14]:

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

```
day month year Temperature RH wis Rain FFMe DMC 100 181 But FW Classes Region
In [15]:
df.isnull().sum()
Out[15]:
day
               0
               0
month
               0
year
Temperature
RH
Ws
               0
Rain
FFMC
               0
DMC
               0
DC
               0
               0
TST
               0
BUI
FWI
               0
Classes
               0
Region
dtype: int64
In [16]:
df.iloc[[122]]
Out[16]:
    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
In [17]:
##remove the 122nd row
df=df.drop(122).reset index(drop=True)
In [18]:
df.iloc[[122]]
Out[18]:
    day month year Temperature RH Ws Rain FFMC DMC DC ISI BUI FWI Classes Region
122 01
           06 2012
                          32 71 12
                                      0.7
                                                2.5 8.2 0.6 2.8 0.2 not fire
                                          57.1
Check column names
In [21]:
df.columns
Out[21]:
Index(['day', 'month', 'year', 'Temperature', 'RH', 'Ws', 'Rain', 'FFMC',
       'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes', 'Region'],
      dtype='object')
In [22]:
## fix spaces in columns names
df.columns=df.columns.str.strip()
df.columns
Out[22]:
```

```
dtype='object')
In [23]:
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 243 entries, 0 to 242
Data columns (total 15 columns):
   Column Non-Null Count Dtype
___
0
               243 non-null object
   day
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
              243 non-null object
243 non-null object
243 non-null object
243 non-null object
 9 DC
10 ISI
11 BUI
12 FWI
13 Classes
               243 non-null
                             object
14 Region 243 non-null
                             int32
dtypes: int32(1), object(14)
memory usage: 27.7+ KB
Changes the required columns as integer data type
In [24]:
df.columns
Out[24]:
dtype='object')
In [25]:
df[['month','day','year','Temperature','RH','Ws']]=df[['month','day','year','Temperature
', 'RH', 'Ws']].astype(int)
In [26]:
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
                             int32
1 month
               243 non-null
                             int32
2 year 243 non-null
                             int32
3 Temperature 243 non-null
                             int32
  RH
               243 non-null
                             int32
 4
                             int32
   Ws
 5
               243 non-null
                           int32
object
object
object
   Rain
               243 non-null
 6
 7
               243 non-null
    FFMC
               243 non-null
8
    DMC
 9
    DC
               243 non-null object
              243 non-null object
10 ISI
11 BUI
               243 non-null object
12 FWI
              243 non-null object
```

13 Classes

243 non-null object

010

```
In [27]:
df.head()
Out[27]:
  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
1
    2
          6 2012
                         29
                            61
                                13
                                    1.3
                                         64.4
                                               4.1
                                                   7.6
                                                        1
                                                          3.9
                                                              0.4
                                                                  not fire
                                                                             0
    3
          6 2012
                                         47.1
                                                   7.1 0.3
                                                          2.7
                                                                  not fire
2
                         26
                            82
                                22
                                   13.1
                                               2.5
                                                              0.1
                                                                             0
3
    4
          6 2012
                         25
                            89
                                13
                                    2.5
                                         28.6
                                               1.3
                                                   6.9
                                                        0
                                                          1.7
                                                                0
                                                                  not fire
                                                                             0
    5
          6 2012
                         27
                            77
                                16
                                     0
                                         64.8
                                                3 14.2 1.2 3.9
                                                              0.5
                                                                  not fire
                                                                             0
Changing the other columns to float data datatype
In [28]:
objects=[features for features in df.columns if df[features].dtypes=='0']
In [29]:
objects
Out [29]:
['Rain', 'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes']
In [30]:
for i in objects:
    if i!='Classes':
        df[i]=df[i].astype(float)
In [31]:
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 243 entries, 0 to 242
Data columns (total 15 columns):
 # Column
                 Non-Null Count Dtype
                   -----
___
 0
                   243 non-null
                                   int32
   day
                  243 non-null
 1 month
                                   int32
 2
                  243 non-null
                                   int32
   year
 3 Temperature 243 non-null
                                   int32
                  243 non-null
 5
   Ws
                   243 non-null
                                   int32
 6
   Rain
                  243 non-null
                                   float64
 7
                  243 non-null
                                   float64
   FFMC
 8
   DMC
                  243 non-null
                                   float64
 9
    DC
                   243 non-null
                                   float64
 10 ISI
                   243 non-null
                                    float64
 11
     BUI
                   243 non-null
                                    float64
 12
    FWI
                   243 non-null
                                    float64
                   243 non-null
 13
    Classes
                                    object
 14 Region
                  243 non-null
                                    int32
dtypes: float64(7), int32(7), object(1)
memory usage: 22.0+ KB
In [32]:
```

14 Kegion

objects

dtypes: int32(7), object(8)
memory usage: 22.0+ KB

∠43 non-null

1nt32

```
Out[32]:
['Rain', 'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'Classes']
In [33]:
df.describe()
Out[33]:
day month vear Temperature RH Ws Rain FFMC DMC DC
```

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC
count	243.000000	243.000000	243.0	243.000000	243.000000	243.000000	243.000000	243.000000	243.000000	243.000000
mean	15.761317	7.502058	2012.0	32.152263	62.041152	15.493827	0.762963	77.842387	14.680658	49.430864
std	8.842552	1.114793	0.0	3.628039	14.828160	2.811385	2.003207	14.349641	12.393040	47.665606
min	1.000000	6.000000	2012.0	22.000000	21.000000	6.000000	0.000000	28.600000	0.700000	6.900000
25%	8.000000	7.000000	2012.0	30.000000	52.500000	14.000000	0.000000	71.850000	5.800000	12.350000
50%	16.000000	8.000000	2012.0	32.000000	63.000000	15.000000	0.000000	83.300000	11.300000	33.100000
75%	23.000000	8.000000	2012.0	35.000000	73.500000	17.000000	0.500000	88.300000	20.800000	69.100000
max	31.000000	9.000000	2012.0	42.000000	90.000000	29.000000	16.800000	96.000000	65.900000	220.400000
4										<u> </u>

```
In [34]:
```

```
df.head()
```

#### Out[34]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region
0	1	6	2012	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	not fire	0
1	2	6	2012	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	not fire	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
3	4	6	2012	25	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0	not fire	0
4	5	6	2012	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	not fire	0

```
In [35]:
```

```
## Let ave the cleaned dataset
df.to_csv('Algerian_forest_fires_cleaned_dataset.csv',index=False)
```

# **Exploratory Data Analysis**

```
In [36]:
```

```
## drop day, month and year
df_copy=df.drop(['day', 'month', 'year'], axis=1)
```

## In [37]:

```
df_copy.head()
```

Out[37]:

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region
0	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	not fire	0
1	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	not fire	0
2	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	not fire	0
3	25	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0	not fire	0

## 4 Temperature RH We Rain FFMC DMC 122 ISL BUY FWY Classes Region

```
In [38]:
```

fire 2
not fire 2
not fire 1
not fire 1
not fire 1

Name: Classes, dtype: int64

### In [39]:

```
## Encoding of the categories in classes
df_copy['Classes']=np.where(df_copy['Classes'].str.contains('not fire'),0,1)
```

## In [40]:

```
df_copy.head()
```

#### Out[40]:

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region
0	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	0	0
1	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	0	0
2	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	0	0
3	25	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0	0	0
4	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	0	0

### In [41]:

```
df_copy.tail()
```

## Out[41]:

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region
238	30	65	14	0.0	85.4	16.0	44.5	4.5	16.9	6.5	1	1
239	28	87	15	4.4	41.1	6.5	8.0	0.1	6.2	0.0	0	1
240	27	87	29	0.5	45.9	3.5	7.9	0.4	3.4	0.2	0	1
241	24	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7	0	1
242	24	64	15	0.2	67.3	3.8	16.5	1.2	4.8	0.5	0	1

### In [42]:

```
df_copy['Classes'].value_counts()
```

## Out[42]:

1 137 0 106

Name: Classes, dtype: int64

#### In [43]:

```
## Plot desnity plot for all features
```

```
df_copy.hist(bins=50, figsize=(20,15))
plt.show()
                      Temperature
 30
                                                            15.0
                                                            12.5
 20
                                                            10.0
                                                             5.0
                                                                                     FFMC
                                                                                                                                                 DMC
175
                                                              25
 150
 125
                                                              20
                                                              15
 75
                                                              10
 50
 25
                        7.5
                          DC
 60
 50
 40
                                                              10
 30
 20
 10
                                                                 0.0
                                                                                             12.5
                         FWI
                                                                                    Classes
                                                                                                                                                Region
 50
                                                             120
                                                                                                                         100
                                                             100
 40
                                                                                                                         80
                                                             80
 30
                                                                                                                         60
                                                             60
                                                                                                                         40
                                                             40
  10
                                                             20
```

## In [44]:

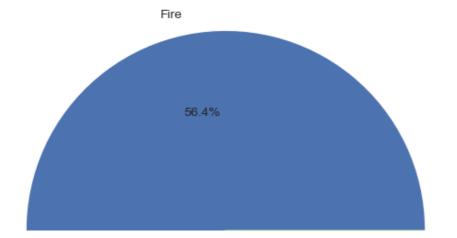
plt.style.use('seaborn')

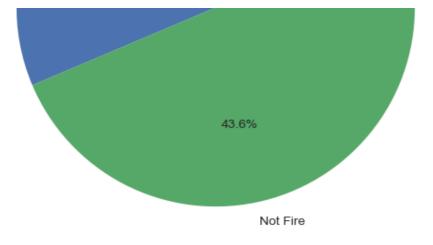
```
## Percentage for Pie Chart
percentage=df_copy['Classes'].value_counts(normalize=True)*100
```

## In [45]:

```
# plotting piechart
classlabels=["Fire","Not Fire"]
plt.figure(figsize=(12,7))
plt.pie(percentage, labels=classlabels, autopct='%1.1f%%')
plt.title("Pie Chart of Classes")
plt.show()
```

## Pie Chart of Classes





# **Correlation**

In [46]:

df\_copy.corr()

Out[46]:

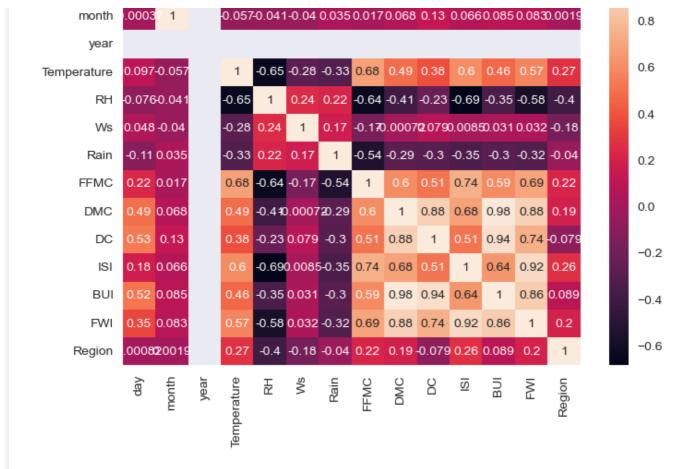
	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classe
Temperature	1.000000	- 0.651400	- 0.284510	0.326492	0.676568	0.485687	0.376284	0.603871	0.459789	0.566670	0.51601
RH	-0.651400	1.000000	0.244048	0.222356	- 0.644873	- 0.408519	- 0.226941	- 0.686667	- 0.353841	- 0.580957	0.43216
Ws	-0.284510	0.244048	1.000000	0.171506	- 0.166548	0.000721	0.079135	0.008532	0.031438	0.032368	0.06996
Rain	-0.326492	0.222356	0.171506	1.000000	0.543906	- 0.288773	0.298023	- 0.347484	- 0.299852	0.324422	0.37909
FFMC	0.676568	- 0.644873	- 0.166548	0.543906	1.000000	0.603608	0.507397	0.740007	0.592011	0.691132	0.76949
DMC	0.485687	- 0.408519	0.000721	0.288773	0.603608	1.000000	0.875925	0.680454	0.982248	0.875864	0.58565
DC	0.376284	0.226941	0.079135	0.298023	0.507397	0.875925	1.000000	0.508643	0.941988	0.739521	0.51112
ISI	0.603871	0.686667	0.008532	- 0.347484	0.740007	0.680454	0.508643	1.000000	0.644093	0.922895	0.73519
BUI	0.459789	0.353841	0.031438	- 0.299852	0.592011	0.982248	0.941988	0.644093	1.000000	0.857973	0.58663
FWI	0.566670	- 0.580957	0.032368	0.324422	0.691132	0.875864	0.739521	0.922895	0.857973	1.000000	0.71921
Classes	0.516015	- 0.432161	0.069964	0.379097	0.769492	0.585658	0.511123	0.735197	0.586639	0.719216	1.00000
Region	0.269555	0.402682	- 0.181160	0.040013	0.222241	0.192089	- 0.078734	0.263197	0.089408	0.197102	0.16234
4											····· Þ

In [47]:

sns.heatmap(df.corr(),annot=True)

Out[47]:

<AxesSubplot:>

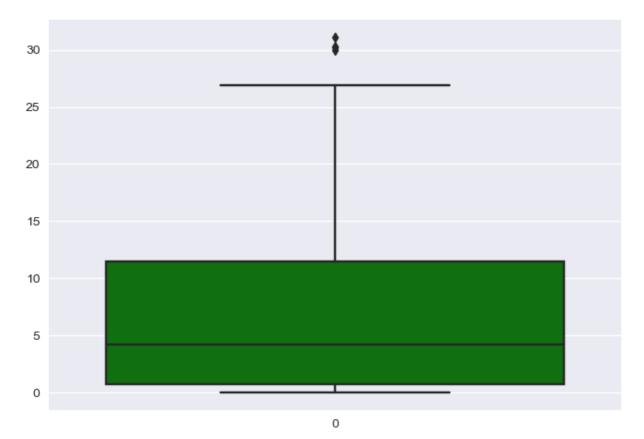


### In [48]:

```
## Box Plots
sns.boxplot(df['FWI'],color='green')
```

#### Out[48]:

<AxesSubplot:>



## In [49]:

```
df.head()
```

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region
0	1	6	2012	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	not fire	0
1	2	6	2012	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	not fire	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
3	4	6	2012	25	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0	not fire	0
4	5	6	2012	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	not fire	0

#### In [50]:

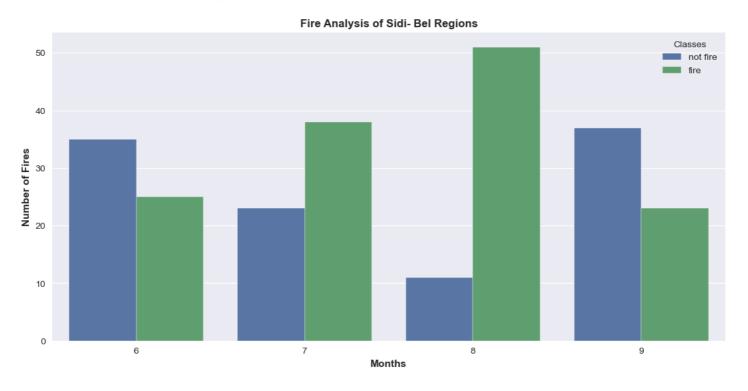
```
df['Classes']=np.where(df['Classes'].str.contains('not fire'), 'not fire', 'fire')
```

#### In [51]:

```
## Monthly Fire Analysis
dftemp=df.loc[df['Region']==1]
plt.subplots(figsize=(13,6))
sns.set_style('whitegrid')
sns.countplot(x='month', hue='Classes', data=df)
plt.ylabel('Number of Fires', weight='bold')
plt.xlabel('Months', weight='bold')
plt.title("Fire Analysis of Sidi- Bel Regions", weight='bold')
```

#### Out[51]:

Text(0.5, 1.0, 'Fire Analysis of Sidi- Bel Regions')

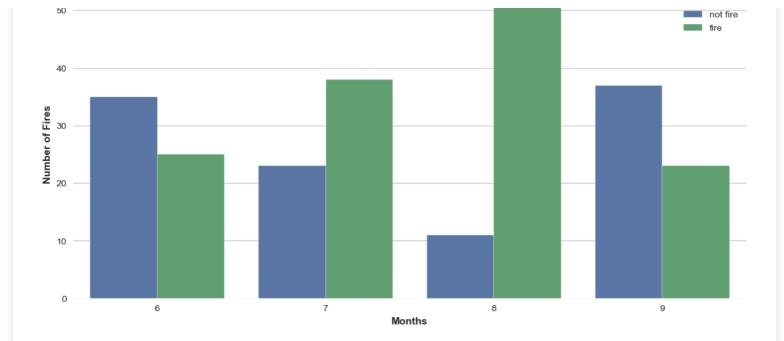


## In [52]:

```
## Monthly Fire Analysis
dftemp=df.loc[df['Region']==0]
plt.subplots(figsize=(13,6))
sns.set_style('whitegrid')
sns.countplot(x='month', hue='Classes', data=df)
plt.ylabel('Number of Fires', weight='bold')
plt.xlabel('Months', weight='bold')
plt.title("Fire Analysis of Brjaia Regions", weight='bold')
```

#### Out[52]:

Text(0.5, 1.0, 'Fire Analysis of Brjaia Regions')



Its observed that August and September had the most number of forest fires for both regions. And from the above plot of months, we can understand few things

Most of the fires happened in August and very high Fires happened in only 3 months - June, July and August.

## Less Fires was on September

```
In [53]:
```

```
df=pd.read_csv('Algerian_forest_fires_cleaned_dataset.csv')
```

### In [54]:

```
df.head()
```

Out[54]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region
0	1	6	2012	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	not fire	0
1	2	6	2012	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	not fire	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
3	4	6	2012	25	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0	not fire	0
4	5	6	2012	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	not fire	0

## In [55]:

```
df.columns
```

#### Out[55]:

## In [56]:

```
##drop month, day and yyear
df.drop(['day','month','year'],axis=1,inplace=True)
```

## In [57]:

```
df.head()
```

Out[57]:

```
Temperature RH Ws Rain FFMC DMC DC ISI BUI FWI Classes Region
0
                57
                    18
                         0.0
                               65.7
                                      3.4 7.6 1.3 3.4
                                                        0.5 not fire
                                                                         0
            29
1
                61
                    13
                         1.3
                               64.4
                                          7.6 1.0 3.9
                                                        0.4 not fire
                                                                         0
            29
                                      4.1
2
            26
               82
                    22
                        13.1
                               47.1
                                      2.5
                                          7.1 0.3
                                                   2.7
                                                        0.1
                                                            not fire
                                                                         0
3
            25 89
                    13
                         2.5
                               28.6
                                          6.9 0.0
                                                   1.7
                                                        0.0 not fire
                                                                         0
                                      1.3
            27 77 16
                         0.0
                               64.8
                                      3.0 14.2 1.2
                                                   3.9
                                                        0.5
                                                            not fire
                                                                         0
In [58]:
```

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

## Out[58]:

fire 131
not fire 101
fire 4
fire 2
not fire 2
not fire 1
not fire 1
not fire 1

Name: Classes, dtype: int64

## In [59]:

```
## Encoding
df['Classes']=np.where(df['Classes'].str.contains("not fire"),0,1)
```

#### In [60]:

df.tail()

Out[60]:

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	Region
238	30	65	14	0.0	85.4	16.0	44.5	4.5	16.9	6.5	1	1
239	28	87	15	4.4	41.1	6.5	8.0	0.1	6.2	0.0	0	1
240	27	87	29	0.5	45.9	3.5	7.9	0.4	3.4	0.2	0	1
241	24	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7	0	1
242	24	64	15	0.2	67.3	3.8	16.5	1.2	4.8	0.5	0	1

#### In [61]:

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

## Out[61]:

1 137 0 106

Name: Classes, dtype: int64

#### In [62]:

```
## Independent And dependent features
X=df.drop('FWI',axis=1)
y=df['FWI']
```

## In [63]:

X.head()

Out[63]:

```
RJ/
                   Wa Rain Franc DMC
                                          P.G ISI BUIL Classes Region
0 Temperatuge
1
           29
               61
                    13
                         1.3
                               64.4
                                          7.6 1.0
                                                  3.9
                                                                     0
2
                    22
                        13.1
                               47.1
                                          7.1 0.3 2.7
                                                             0
                                                                     0
           26
               82
                                      2.5
3
           25
               89
                    13
                         2.5
                               28.6
                                      1.3
                                          6.9 0.0 1.7
                                                             0
                                                                     0
           27
               77 16
                         0.0
                               64.8
                                      3.0 14.2 1.2 3.9
                                                             0
                                                                     0
```

## In [64]:

```
У
Out[64]:
       0.5
1
       0.4
2
       0.1
3
       0.0
4
       0.5
       6.5
238
239
       0.0
240
       0.2
       0.7
241
242
       0.5
Name: FWI, Length: 243, dtype: float64
```

# In [65]:

```
#Train Test Split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test=train_test_split(X, y, test_size=0.25, random_state=42)
```

### In [66]:

```
X_train.shape, X_test.shape
Out[66]:
```

((182, 11), (61, 11))

## In [67]:

```
## Feature Selection based on correlattion
X_train.corr()
```

### Out[67]:

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	Classes	Regio
Temperature	1.000000	0.656095	0.305977	- 0.317512	0.694768	0.498173	0.390684	0.629848	0.473609	0.542141	0.25454
RH	-0.656095	1.000000	0.225736	0.241656	0.653023	- 0.414601	0.236078	- 0.717804	0.362317	- 0.456876	0.39466
Ws	-0.305977	0.225736	1.000000	0.251932	0.190076	0.000379	0.096576	0.023558	0.035633	0.082570	0.19996
Rain	-0.317512	0.241656	0.251932	1.000000	- 0.545491	- 0.289754	0.302341	0.345707	0.300964	0.369357	0.05902
FFMC	0.694768	0.653023	0.190076	- 0.545491	1.000000	0.620807	0.524101	0.750799	0.607210	0.781259	0.2495
DMC	0.498173	- 0.414601	0.000379	- 0.289754	0.620807	1.000000	0.868647	0.685656	0.983175	0.617273	0.21258
DC	0.390684	0.236078	0.096576	0.302341	0.524101	0.868647	1.000000	0.513701	0.942414	0.543581	0.06083
ISI	0.629848	- 0.717804	0.023558	0.345707	0.750799	0.685656	0.513701	1.000000	0.643818	0.742977	0.29644
B	0.470000	-	0.005000	-	0.007040	0 000475	0.040444	0.040040	1 000000	0.040000	0.44406

	ROI	0.473609 Temperature	0.362 <b>347</b>	บ.บ35633 <b>Ws</b>	0.30	0.607210 <b>FFMC</b>	0.983175 <b>DMC</b>	U.942414 DC	บ.643818 <b>ISI</b>	1.000000 <b>BUI</b>	U.612239 Classes	0.11489 <b>Regio</b>
	Classes	0.542141	- 0.456876	- 0.082570	0.369357	0.781259	0.617273	0.543581	0.742977	0.612239	1.000000	0.18883
	Region	0.254549	0.394665	0.199969	0.059022	0.249514	0.212582	0.060838	0.296441	0.114897	0.188837	1.00000
4												·

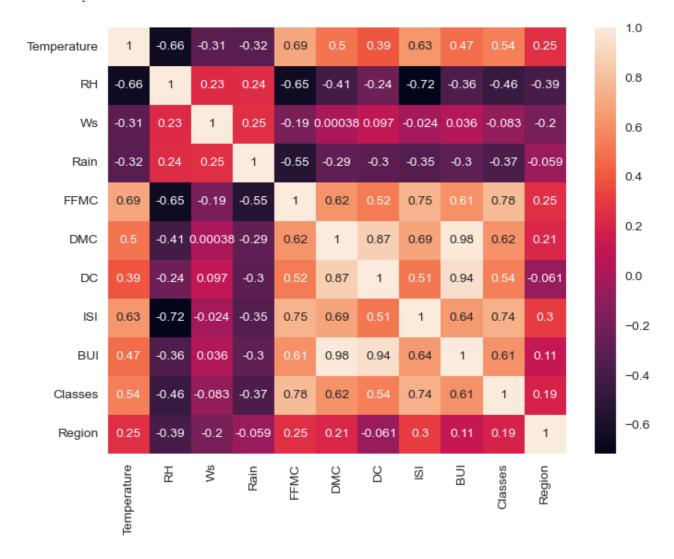
# **Feature Selection**

```
In [70]:
```

```
## Check for multicollinearity
plt.figure(figsize=(8,6))
corr=X_train.corr()
sns.heatmap(corr,annot=True)
```

## Out[70]:

<AxesSubplot:>



## In [71]:

X train.corr()

## Out[71]:

	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	Classes	Regio
Temperature	1.000000	0.656095	0.305977	0.317512	0.694768	0.498173	0.390684	0.629848	0.473609	0.542141	0.25454
RH	-0.656095	1.000000	0.225736	0.241656	0.653023	- 0.414601	0.236078	- 0.717804	- 0.362317	- 0.456876	0.39466
14/-	0.005077	0.005706	4 000000	0.054000	-	0.00070	0.000576	-	0.005600	-	

```
-U.3U39// U.223/30
                                 1.000000 0.251932
                                                          U.UUU3/9 U.U905/0
                                                                                    ひ.ひろつろう
                                                 0.199976
                                                                          0.023558
                                                                                            %32529
            Temperature
                            RH
                                     Ws
                                            Rain
                                                             DMC
                                                                                        BUI
               -0.317512 0.241656 0.251932 1.000000
       Rain
                                                 0.545491 0.289754 0.302341 0.345707 0.300964 0.369357 0.05902
                        0.653023 0.190076 0.545491 1.000000 0.620807 0.524101 0.750799 0.607210 0.781259 0.24951
               0.694768
      FFMC
                        0.414601 0.000379 0.289754 0.620807 1.000000 0.868647 0.685656 0.983175 0.617273 0.21258
      DMC
               0.498173
                        \begin{smallmatrix} & & & & & \\ 0.236078 & & & & \\ 0.302341 & & 0.524101 & 0.868647 & 1.000000 & 0.513701 & 0.942414 & 0.543581 \\ \end{smallmatrix}
        DC
               0.390684
                        ISI
               0.629848
                        0.362317 0.035633 0.300964 0.607210 0.983175 0.942414 0.643818 1.000000 0.612239 0.11489
       BUI
                        0.456876 0.082570 0.369357 0.781259 0.617273 0.543581 0.742977 0.612239 1.000000 0.18883
    Classes
               0.542141
                        0.394665 0.199969 0.059022 0.249514 0.212582 0.060838 0.296441 0.114897 0.188837 1.00000
     Region
In [72]:
def correlation(dataset, threshold):
    col_corr = set()
    corr matrix = dataset.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 [73]:
## threshold--Domain expertise
```

```
corr features=correlation(X train, 0.85)
```

```
In [74]:
corr features
Out[74]:
{ 'BUI', 'DC' }
In [75]:
## drop features when correlation is more than 0.85
X train.drop(corr features,axis=1,inplace=True)
X test.drop(corr features,axis=1,inplace=True)
X train.shape, X test.shape
Out [75]:
```

# Feature Scaling Or Standardization

```
In [76]:
```

((182, 9), (61, 9))

```
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
X train scaled=scaler.fit transform(X train)
X test scaled=scaler.transform(X test)
```

In [77]:

## **Box Plots To understand Effect Of Standard Scaler**

```
In [78]:
```

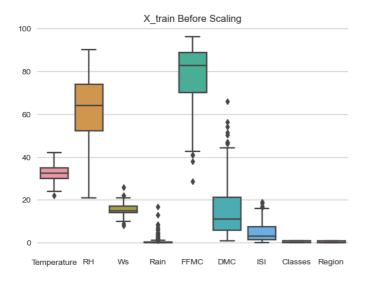
X\_train\_scaled

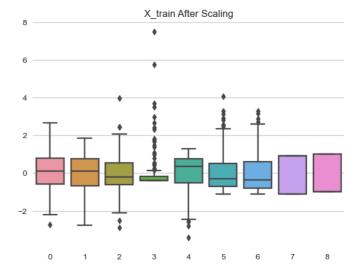
```
plt.subplots(figsize=(15, 5))
plt.subplot(1, 2, 1)
sns.boxplot(data=X_train)
plt.title('X_train Before Scaling')
plt.subplot(1, 2, 2)
sns.boxplot(data=X_train_scaled)
plt.title('X_train After Scaling')
```

#### Out[78]:

Text(0.5, 1.0, 'X\_train After Scaling')

-1.10431526, -0.98907071]])





# **Linear Regression Model**

Linear regression is a statistical approach used to model the relationship between a dependent variable and one or more independent variables, by fitting a linear equation to the observed data.

#### In [79]:

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score
linreg=LinearRegression()
linreg.fit(X_train_scaled,y_train)
y_pred=linreg.predict(X_test_scaled)
mae=mean_absolute_error(y_test,y_pred)
score=r2_score(y_test,y_pred)
print("Mean absolute error", mae)
```

```
print("R2 Score", score)
```

Mean absolute error 0.5468236465249986 R2 Score 0.9847657384266951

# **Lasso Regression**

#### **Feature Selection**

```
In [80]:
```

```
from sklearn.linear_model import Lasso
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score
lasso=Lasso()
lasso.fit(X_train_scaled,y_train)
y_pred=lasso.predict(X_test_scaled)
mae=mean_absolute_error(y_test,y_pred)
score=r2_score(y_test,y_pred)
print("Mean absolute error", mae)
print("R2 Score", score)
```

Mean absolute error 1.1331759949144087 R2 Score 0.9492020263112388

# **Ridge Regression model**

## Reducing Overfitting thats why we use Ridge Regression

```
In [81]:
```

```
from sklearn.linear_model import Ridge
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score
ridge=Ridge()
ridge.fit(X_train_scaled,y_train)
y_pred=ridge.predict(X_test_scaled)
mae=mean_absolute_error(y_test,y_pred)
score=r2_score(y_test,y_pred)
print("Mean absolute error", mae)
print("R2 Score", score)
```

Mean absolute error 0.5642305340105719 R2 Score 0.9842993364555512

# **Elasticnet Regression Model**

```
In [82]:
```

```
from sklearn.linear_model import ElasticNet
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score
elastic=ElasticNet()
elastic.fit(X_train_scaled,y_train)
y_pred=elastic.predict(X_test_scaled)
mae=mean_absolute_error(y_test,y_pred)
score=r2_score(y_test,y_pred)
print("Mean absolute error", mae)
print("R2 Score", score)
```

Mean absolute error 1.8822353634896 R2 Score 0.8753460589519703

# **Import Pickle**

```
import pickle
pickle.dump(scaler,open('scaler.pkl','wb'))
pickle.dump(ridge,open('ridge.pkl','wb'))
```