Algerian forest fire Logiscic regression for forest fire prediction

Life cycle of Machine learning Project

- Understanding the Problem Statement
- Data Collection
- Exploratory data analysis
- Data Cleaning
- Data Pre-Processing
- Model Training
- Choose best model

1) Problem statement.

Check for Data Balance

1. If data set is not imbalanced create a model with accuracy greater than 90% and observe Precission, or recall or f1 score.

If data is imbalanced

1. If data is imbalanced then,handel imbalanced data and create a model with accuracy greater than 90% and observe Precission, or recall or f1 score.

Reading the data

In [1]:
```
### 2.1 Import Data and Required Packages
```

In [106]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import warnings
from six.moves import urllib

warnings.filterwarnings("ignore")

%matplotlib inline
```

In [182]:
```
df = pd.read_csv('Algerian_forest_fires_dataset_UPDATE.csv',header=1,skiprow
df.head()
```

Out[182]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
0	1	6	2012	29	57	18	0.0	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	1.0	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	0.0	1.7	0.0	not fire
4	5	6	2012	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	not fire

In [277]:
```
#Out of topic experiment (Just for fun)
#!pip install colorama
from colorama import Fore
print(Fore.RED +"Fire! Fire! Fire!")
print(Fore.CYAN +"Fire! Fire! Fire!")
print(Fore.GREEN +"Fire! Fire! Fire!")
print(Fore.MAGENTA +"Fire! Fire! Fire!")
print(Fore.YELLOW +"Fire! Fire! Fire!")
print(Fore.BLUE +"Fire! Fire! Fire!")
print(Fore.RED +"Fire! Fire! Fire!")
print(Fore.GREEN +"Fire! Fire! Fire!")
```

```
Fire! Fire! Fire!
Fire! Fire! Fire!
Fire! Fire! Fire!
Fire! Fire! Fire!
Fire! Fire! Fire!
Fire! Fire! Fire!
Fire! Fire! Fire!
Fire! Fire! Fire!
```

In [183]:
```
df
```

Out[183]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
0	1	6	2012	29	57	18	0.0	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	1.0	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	0.0	1.7	0.0	not fire
4	5	6	2012	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	not fire
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
239	26	9	2012	30	65	14	0.0	85.4	16.0	44.5	4.5	16.9	6.5	fire
240	27	9	2012	28	87	15	4.4	41.1	6.5	8.0	0.1	6.2	0.0	not fire
241	28	9	2012	27	87	29	0.5	45.9	3.5	7.9	0.4	3.4	0.2	not fire
242	29	9	2012	24	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7	not fire
243	30	9	2012	24	64	15	0.2	67.3	3.8	16.5	1.2	4.8	0.5	not fire

244 rows × 14 columns

In [184]:
```
df.iloc[:126]
```

Out[184]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
0	1	6	2012	29	57	18	0.0	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	1.0	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	0.0	1.7	0.0	not fire
4	5	6	2012	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	not fire
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
121	30	9	2012	25	78	14	1.4	45.0	1.9	7.5	0.2	2.4	0.1	not fire
122	1	6	2012	32	71	12	0.7	57.1	2.5	8.2	0.6	2.8	0.2	not fire
123	2	6	2012	30	73	13	4.0	55.7	2.7	7.8	0.6	2.9	0.2	not fire
124	3	6	2012	29	80	14	2.0	48.7	2.2	7.6	0.3	2.6	0.1	not fire
125	4	6	2012	30	64	14	0.0	79.4	5.2	15.4	2.2	5.6	1.0	not fire

126 rows × 14 columns

Remove extra Rows and Add a new column for region

In [ ]:
```

```

In [165]:
```
#df.drop(df.index[[122,123,124]], inplace=True)
```

In [185]:
```
for index in range(df.shape[0]):
    if index < 122:
        df.loc[index,'region'] = 0
    else:
        df.loc[index,'region'] = 1
```

In [186]:
```
df.iloc[:125]
```

Out[186]:

	day	month	year	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes
0	1	6	2012	29	57	18	0.0	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	1.0	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	0.0	1.7	0.0	not fire
4	5	6	2012	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	not fire
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
120	29	9	2012	26	80	16	1.8	47.4	2.9	7.7	0.3	3.0	0.1	not fire
121	30	9	2012	25	78	14	1.4	45.0	1.9	7.5	0.2	2.4	0.1	not fire
122	1	6	2012	32	71	12	0.7	57.1	2.5	8.2	0.6	2.8	0.2	not fire
123	2	6	2012	30	73	13	4.0	55.7	2.7	7.8	0.6	2.9	0.2	not fire
124	3	6	2012	29	80	14	2.0	48.7	2.2	7.6	0.3	2.6	0.1	not fire

125 rows × 15 columns

In [187]:
```
df.drop(['year'], axis=1, inplace=True)
```

In [188]:
```
df.columns
```

Out[188]:
```
Index(['day', 'month', 'Temperature', ' RH', ' Ws', 'Rain ', 'FFMC', 'DMC',
       'DC', 'ISI', 'BUI', 'FWI', 'Classes  ', 'region'],
      dtype='object')
```

In [189]:
```
col = [x.strip() for x in df.columns]
print(col)
```

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

In [190]:
```
df.columns = col
```

In [191]:
```
1 df
```

Out[191]:

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

244 rows × 14 columns

In [192]:
```
1 df.shape
```

Out[192]:
```
(244, 14)
```

In [158]:
```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 244 entries, 0 to 124
Data columns (total 14 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   day          241 non-null    object 
 1   month        241 non-null    object 
 2   Temperature  241 non-null    object 
 3   RH           241 non-null    object 
 4   Ws           241 non-null    object 
 5   Rain         241 non-null    object 
 6   FFMC         241 non-null    object 
 7   DMC          241 non-null    object 
 8   DC           241 non-null    object 
 9   ISI          241 non-null    object 
 10  BUI          241 non-null    object 
 11  FWI          241 non-null    object 
 12  Classes      241 non-null    object 
 13  region       241 non-null    float64
dtypes: float64(1), object(13)
memory usage: 28.6+ KB
```

In [193]:
```
#Checking for Unique data in Classes
df['Classes'].unique()
```

Out[193]:
```
array(['not fire   ', 'fire   ', 'fire', 'fire ', 'not fire', 'not fire ',
       'not fire     ', 'not fire    '], dtype=object)
```

In [194]:
```
df['Classes'] = df['Classes'].map(lambda x: x.strip())
```

In [196]:
```
#Checking for Unique data in Classes
df['Classes'].unique()
```

Out[196]:
```
array(['not fire', 'fire'], dtype=object)
```

In [197]:
```
#Adding a column fire to indicate 0 for no fire and 1 for fire
df['fire'] = pd.factorize(df.Classes)[0]
```

In [198]:
```
#Cleaned Data Frame
df
```

Out[198]:

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

244 rows × 15 columns

Basic Details About Data Set

Show top 5 records

In [199]:
```
1 df.head()
```

Out[199]:

	day	month	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	region	f
0	1	6	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	not fire	0.0	
1	2	6	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	not fire	0.0	
2	3	6	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	not fire	0.0	
3	4	6	25	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0	not fire	0.0	
4	5	6	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	not fire	0.0	

Shape of the dataset

In [200]:
```
1 df.tail()
```

Out[200]:

	day	month	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	Classes	region
239	26	9	30	65	14	0.0	85.4	16.0	44.5	4.5	16.9	6.5	fire	1.0
240	27	9	28	87	15	4.4	41.1	6.5	8.0	0.1	6.2	0.0	not fire	1.0
241	28	9	27	87	29	0.5	45.9	3.5	7.9	0.4	3.4	0.2	not fire	1.0
242	29	9	24	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7	not fire	1.0
243	30	9	24	64	15	0.2	67.3	3.8	16.5	1.2	4.8	0.5	not fire	1.0

In [15]:
```
1 df.shape
```

Out[15]: (244, 16)

In [ ]:
```
1
```

Summery of the dataset

In [201]:
```
1 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    int64  
 1   month        244 non-null    int64  
 2   Temperature  244 non-null    int64  
 3   RH           244 non-null    int64  
 4   Ws           244 non-null    int64  
 5   Rain         244 non-null    float64
 6   FFMC         244 non-null    float64
 7   DMC          244 non-null    float64
 8   DC           244 non-null    float64
 9   ISI          244 non-null    float64
 10  BUI          244 non-null    float64
 11  FWI          244 non-null    float64
 12  Classes      244 non-null    object 
 13  region       244 non-null    float64
 14  fire         244 non-null    int64  
dtypes: float64(8), int64(6), object(1)
memory usage: 28.7+ KB
```

Observation: As a lot of relevant columns are in Object type, we need to convert the type to do basic opearation.

Action:Converting desired columns into float

In [204]:
```
1 df.columns
```

Out[204]:
```
Index(['day', 'month', 'Temperature', 'RH', 'Ws', 'Rain', 'FFMC', 'DMC', 'DC',
       'ISI', 'BUI', 'FWI', 'Classes', 'region', 'fire'],
      dtype='object')
```

In [206]:
```
1 df = df.astype({'day':'int','month':'int','Temperature':'int','RH':'int','Ws
```

In [207]:
```
1 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    int32  
 1   month        244 non-null    int32  
 2   Temperature  244 non-null    int32  
 3   RH           244 non-null    int32  
 4   Ws           244 non-null    int32  
 5   Rain         244 non-null    float64
 6   FFMC         244 non-null    float64
 7   DMC          244 non-null    float64
 8   DC           244 non-null    float64
 9   ISI          244 non-null    float64
 10  BUI          244 non-null    float64
 11  FWI          244 non-null    float64
 12  Classes      244 non-null    object 
 13  region       244 non-null    float64
 14  fire         244 non-null    int64  
dtypes: float64(8), int32(5), int64(1), object(1)
memory usage: 24.0+ KB
```

In [208]:
```
1 # Dropping Classes as it is a Object type variable
2 df.drop(['Classes'], axis=1, inplace=True)
```

In [209]:
```
1 df.describe()
```

Out[209]:

	day	month	Temperature	RH	Ws	Rain	FFMC	
count	244.000000	244.000000	244.000000	244.000000	244.000000	244.000000	244.000000	244.0
mean	15.754098	7.500000	32.172131	61.938525	15.504098	0.760656	77.887705	14.6
std	8.825059	1.112961	3.633843	14.884200	2.810178	1.999406	14.337571	12.3
min	1.000000	6.000000	22.000000	21.000000	6.000000	0.000000	28.600000	0.7
25%	8.000000	7.000000	30.000000	52.000000	14.000000	0.000000	72.075000	5.8
50%	16.000000	7.500000	32.000000	63.000000	15.000000	0.000000	83.500000	11.3
75%	23.000000	8.000000	35.000000	73.250000	17.000000	0.500000	88.300000	20.7
max	31.000000	9.000000	42.000000	90.000000	29.000000	16.800000	96.000000	65.9

In [210]:
```
df.head()
```

Out[210]:

	day	month	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	region	fire
0	1	6	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	0.0	0
1	2	6	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	0.0	0
2	3	6	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	0.0	0
3	4	6	25	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0	0.0	0
4	5	6	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	0.0	0

Exploring Data

In [211]:
```
# define numerical & categorical columns
numeric_features = [feature for feature in df.columns if df[feature].dtype !
categorical_features = [feature for feature in df.columns if df[feature].dty

# print columns
print('We have {} numerical features : {}'.format(len(numeric_features), num
print('\nWe have {} categorical features : {}'.format(len(categorical_featur
```

```
We have 14 numerical features : ['day', 'month', 'Temperature', 'RH', 'Ws', 'Ra
in', 'FFMC', 'DMC', 'DC', 'ISI', 'BUI', 'FWI', 'region', 'fire']

We have 0 categorical features : []
```

Attribute Information

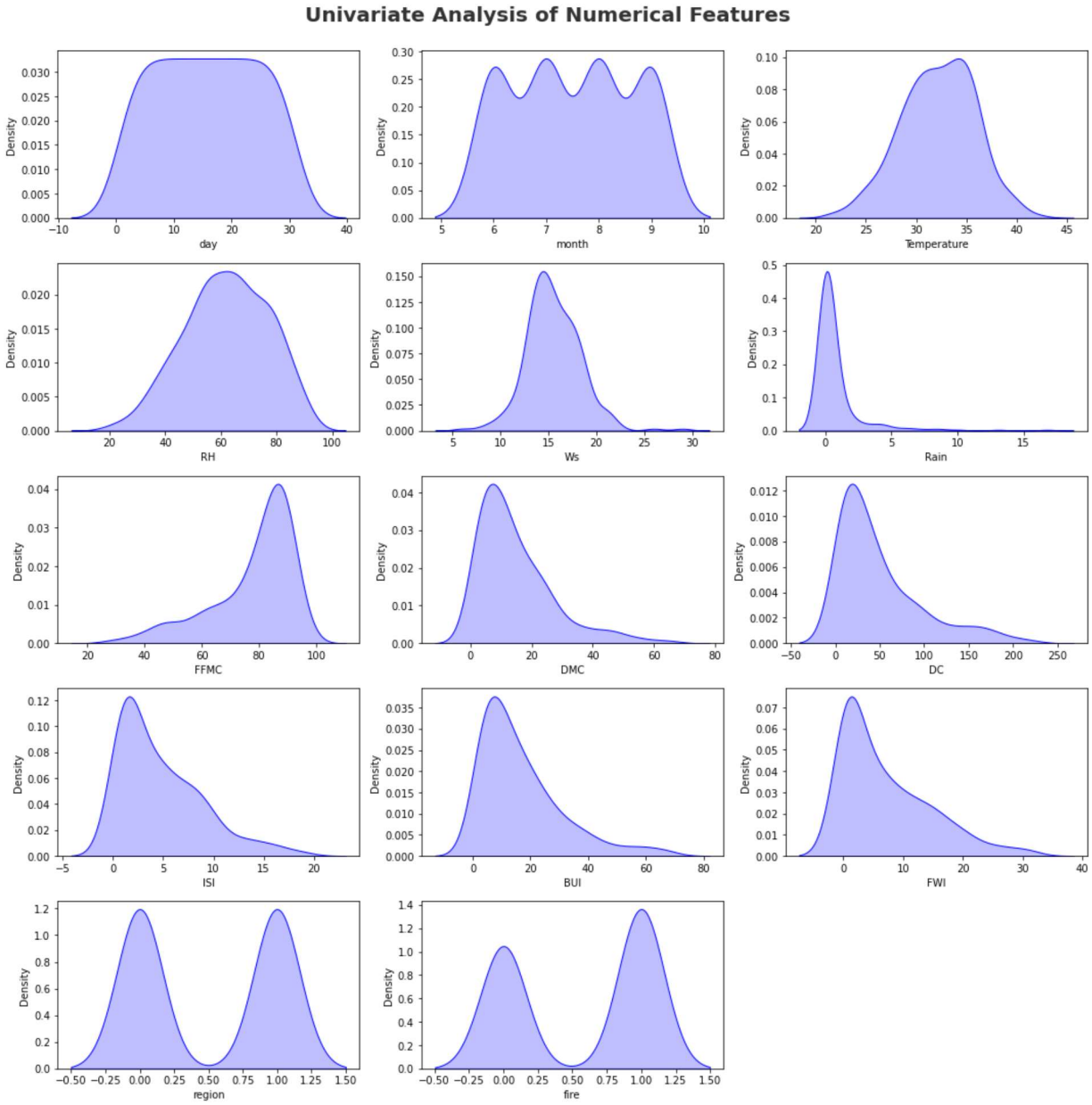
1. Date : (DD/MM/YYYY) Day, month ('june' to 'september'), year (2012) Weather data observations
2. Temp : temperature noon (temperature max) in Celsius degrees: 22 to 42
3. RH : Relative Humidity in %: 21 to 90
4. Ws :Wind speed in km/h: 6 to 29
5. Rain: total day in mm: 0 to 16.8 FWI Components
6. 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
13. Region: 0 Signifies Bejaia region and 1 signifies Sidi Bel-abbes region
14. Fire: 0 indicstes fire and 1 indicates no fire

Univariate Analysis

- The term univariate analysis refers to the analysis of one variable prefix “uni” means “one.” The purpose of univariate analysis is to understand the distribution of values for a single variable.

In [212]:
```
plt.figure(figsize=(15, 15))
plt.suptitle('Univariate Analysis of Numerical Features', fontsize=20, fontw

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



Report

- Rain, DMC, BUI, ISI are right skewed and postively skewed.
- FFMC is left skewed
- Outliers in BUI and DMC power.

Multivariate Analysis

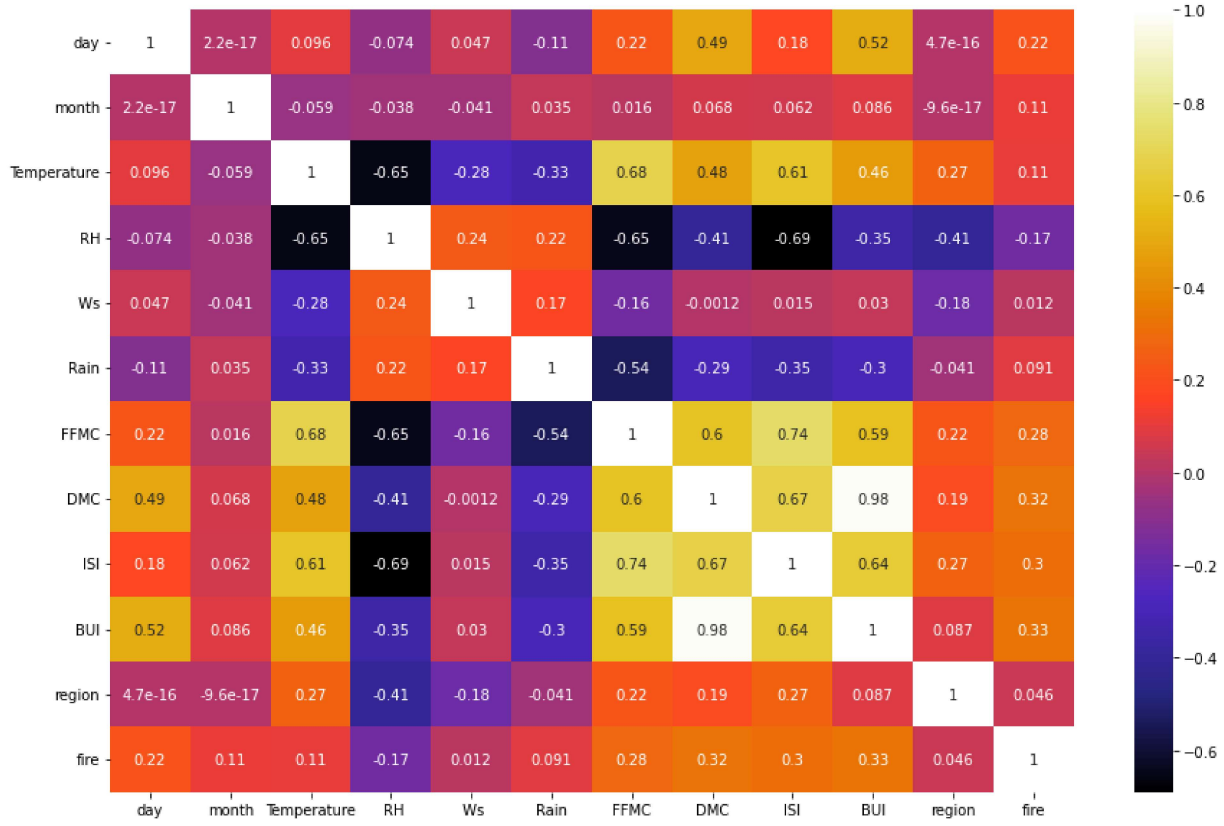
Check Multicollinearity in Numerical features

In [213]:
```
1 df[(list(df.columns)[1:])].corr()
```

Out[213]:

	month	Temperature	RH	Ws	Rain	FFMC	DMC	
month	1.000000e+00	-0.059017	-0.037884	-0.041447	0.035322	0.015577	0.068178	0.1
Temperature	-5.901677e-02	1.000000	-0.654443	-0.278132	-0.326786	0.677491	0.483105	0.3
RH	-3.788419e-02	-0.654443	1.000000	0.236084	0.222968	-0.645658	-0.405133	-0.2
Ws	-4.144673e-02	-0.278132	0.236084	1.000000	0.170169	-0.163255	-0.001246	0.0
Rain	3.532207e-02	-0.326786	0.222968	0.170169	1.000000	-0.544045	-0.288548	-0.2
FFMC	1.557668e-02	0.677491	-0.645658	-0.163255	-0.544045	1.000000	0.602391	0.5
DMC	6.817778e-02	0.483105	-0.405133	-0.001246	-0.288548	0.602391	1.000000	0.8
DC	1.276719e-01	0.370498	-0.220330	0.076245	-0.296804	0.503910	0.875358	1.0
ISI	6.354476e-02	0.605971	-0.688268	0.012245	-0.347862	0.740751	0.678355	0.5
BUI	8.556743e-02	0.456415	-0.349685	0.030303	-0.299409	0.590251	0.982206	0.9
FWI	8.173226e-02	0.566839	-0.580457	0.033957	-0.324755	0.691430	0.875191	0.7
region	-9.586232e-17	0.273496	-0.406424	-0.176829	-0.041080	0.224680	0.191094	-0.0
fire	2.233266e-02	0.518119	-0.435023	-0.066529	-0.379449	0.770114	0.584188	0.5

In [26]:
```
plt.figure(figsize = (15,10))
sns.heatmap(df.corr(), cmap="CMRmap", annot=True)
plt.show()
```



Report

- RH is negatively corelated with Temperature, FFMC and ISI
- Rain is negatively correlated with Temperature and FFMC,DMC, ISI and BUI

Checking Null Values

In [214]:
```
df.isnull().sum()
```

Out[214]:
```
day            0
month          0
Temperature    0
RH             0
Ws             0
Rain           0
FFMC           0
DMC            0
DC             0
ISI            0
BUI            0
FWI            0
region         0
fire           0
dtype: int64
```

Report: There are no null values

In [215]:
```
continues_features=[feature for feature in numeric_features if len(df[featur
print('Num of continues features :',continues_features)
```

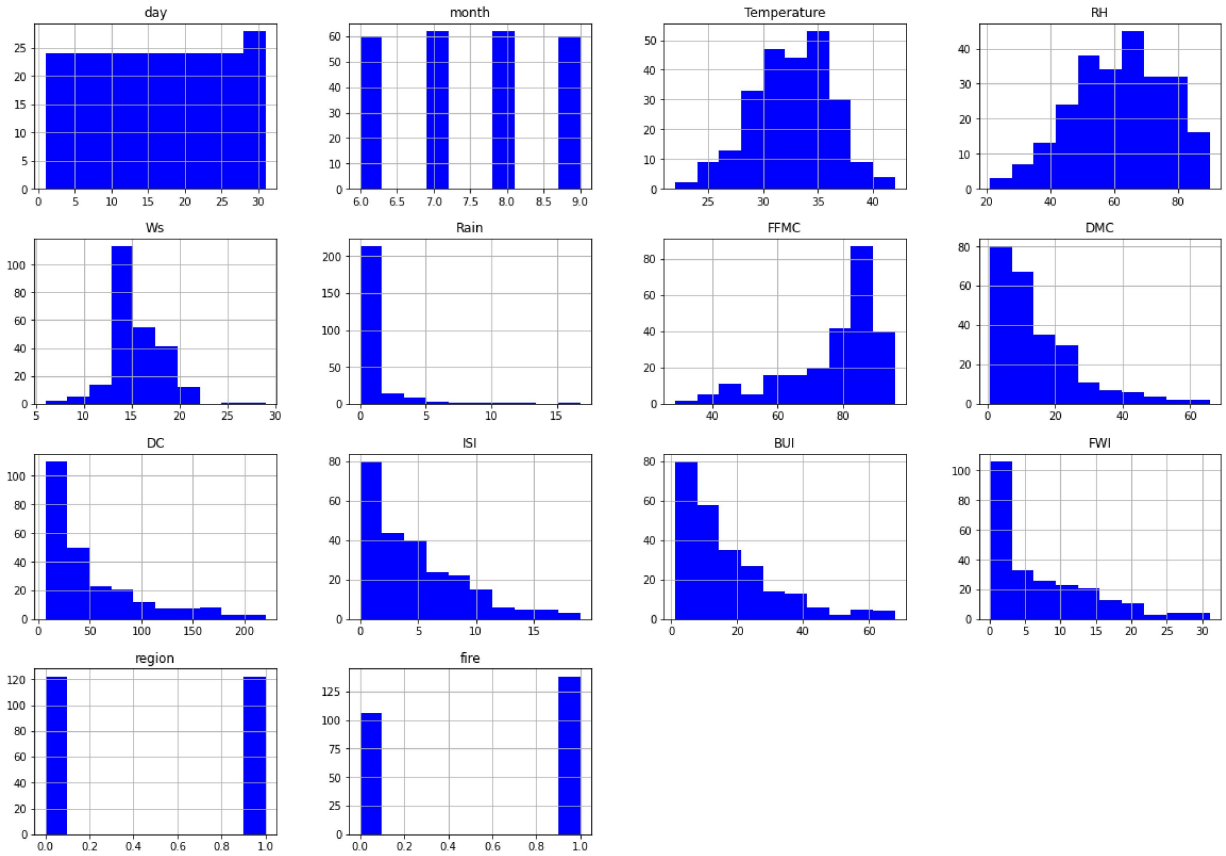
```
Num of continues features : ['day', 'Temperature', 'RH', 'Ws', 'Rain', 'FFMC',
'DMC', 'DC', 'ISI', 'BUI', 'FWI']
```

In [216]:
```
continues_features=[feature for feature in numeric_features if len(df[featur
print('Num of catagorical features :',continues_features)
```

```
Num of catagorical features : ['region', 'fire']
```

In [217]:
```
#Histograms
df.hist(figsize=(20,14),color='b')
```

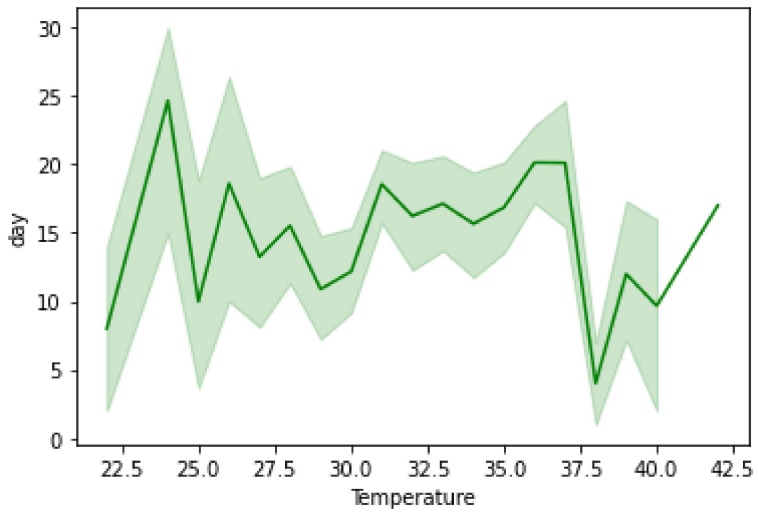
Out[217]:
```
array([[<AxesSubplot:title={'center':'day'}>,
        <AxesSubplot:title={'center':'month'}>,
        <AxesSubplot:title={'center':'Temperature'}>,
        <AxesSubplot:title={'center':'RH'}>],
       [<AxesSubplot:title={'center':'Ws'}>,
        <AxesSubplot:title={'center':'Rain'}>,
        <AxesSubplot:title={'center':'FFMC'}>,
        <AxesSubplot:title={'center':'DMC'}>],
       [<AxesSubplot:title={'center':'DC'}>,
        <AxesSubplot:title={'center':'ISI'}>,
        <AxesSubplot:title={'center':'BUI'}>,
        <AxesSubplot:title={'center':'FWI'}>],
       [<AxesSubplot:title={'center':'region'}>,
        <AxesSubplot:title={'center':'fire'}>, <AxesSubplot:>,
        <AxesSubplot:>]], dtype=object)
```



Report:

In [218]:
```
#Line Plot
sns.lineplot(x='Temperature',y='day', data=df,color='g')
```

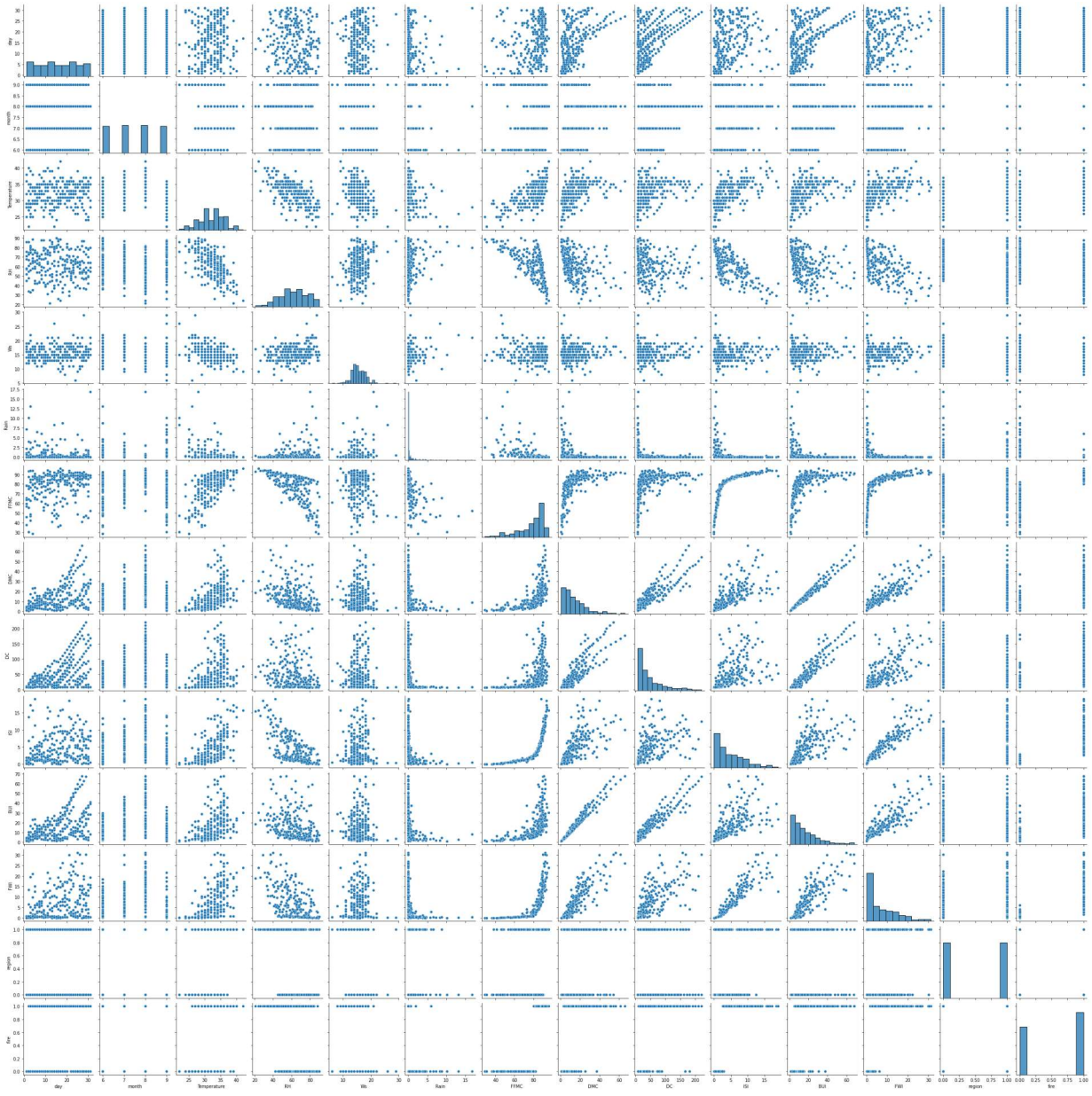
Out[218]: <AxesSubplot:xlabel='Temperature', ylabel='day'>



Report:

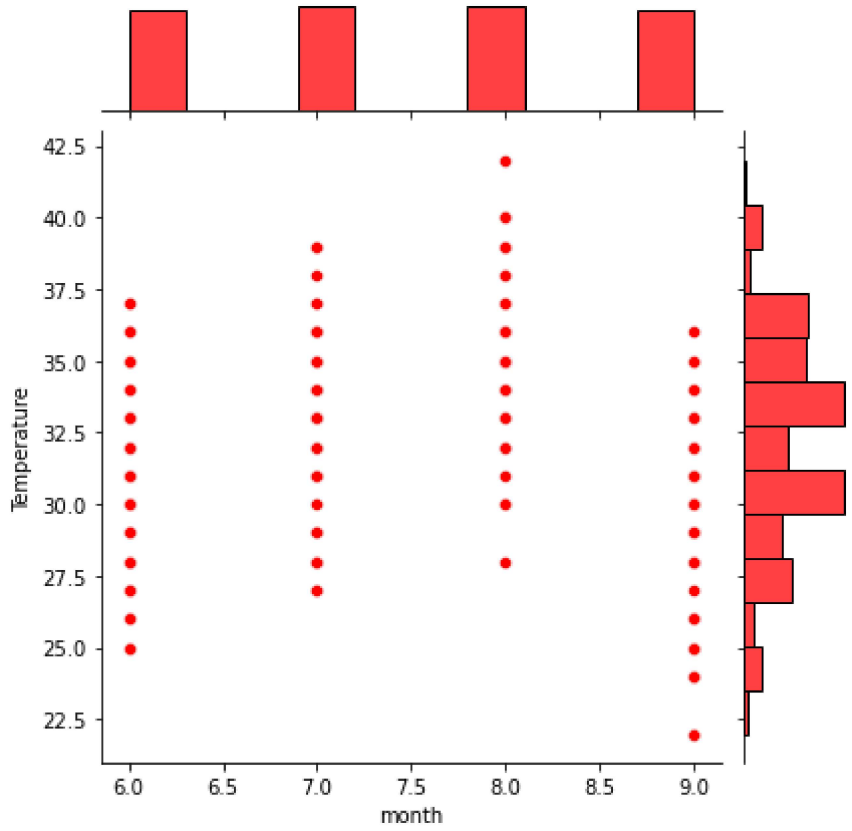
In [219]:
```
#Pairplot
sns.pairplot(df)
```

Out[219]: <seaborn.axisgrid.PairGrid at 0x1fd7ac6dd90>

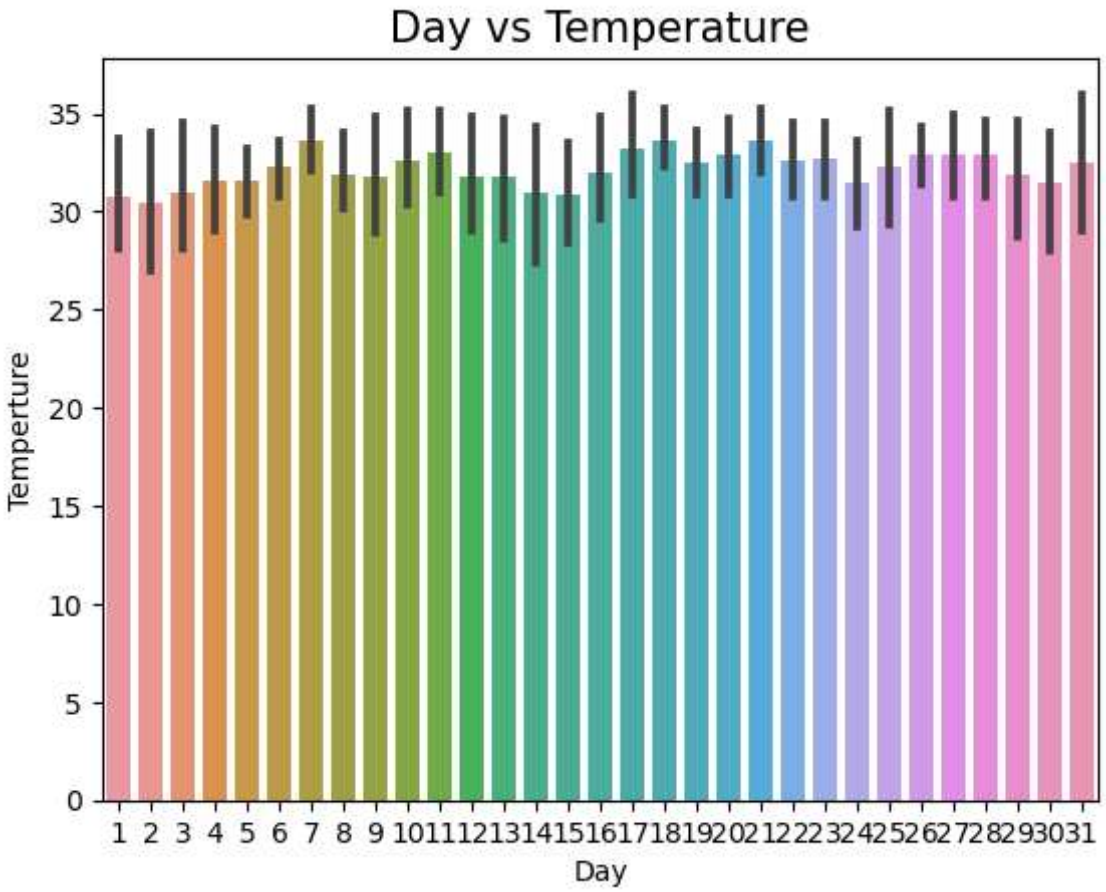


In [220]:
```
#Jointplot
sns.jointplot(x='month',y='Temperature',data=df,color='r')
```

Out[220]: <seaborn.axisgrid.JointGrid at 0x1fd7a289460>



In [221]:
```
#Barplot
plt.style.use('default')
sns.barplot(x='day',y='Temperature',data=df)
plt.title('Day vs Temperature',fontsize=15)
plt.xlabel('Day')
plt.ylabel('Temperture')
plt.show()
```



Basic analysis of data

In [222]:
```
#The highest temperature in the dataset
df.Temperature.max()
```

Out[222]: 42

In [223]:
```
#The lowest temperature in the dataset
df.Temperature.min()
```

Out[223]: 22

In [224]:
```
#When did it rain the most
highest_rain = df.sort_values(by='Rain',ascending=False)[['Rain','day','mont
highest_rain
```

Out[224]:

	Rain	day	month
91	16.8	31	8

Report: On August 31st it rain the most

In [225]:
```
#When did it rain the least
lowest_rain = df.sort_values(by='Rain',ascending=True)[['Rain','day','month'
lowest_rain
```

Out[225]:

	Rain	day	month
0	0.0	1	6

Report: On June 1st it rain the lowest

In [226]:
```
#hotest month
hotest_month = df.sort_values(by='Temperature',ascending=False)[['month']].h
hotest_month
```

Out[226]:

	month
199	8

Report: June is the hotest month

In [227]:
```
#collest month
coolest_month = df.sort_values(by='Temperature',ascending=True)[['month']].h
coolest_month
```

Out[227]:

	month
105	9

Report: September is the collest month

In [228]:
```
#The day which was coolest , id it rain or not , from which region it belong
coolest_temperature = df.sort_values(by='Temperature',ascending=True)[['Temp
coolest_temperature
```

Out[228]:

	Temperature	day	month	Rain
105	22	14	9	8.3

Report: The day was coolest on 14th September, it rain on that day and there was no forest fire on that day.

Checking if our predicted value 'Fire' is balanced or not

In [230]:
```
df['fire'].unique()
```

Out[230]:
```
array([0, 1], dtype=int64)
```

In [231]:
```
df['fire'].value_counts()
```

Out[231]:
```
1    138
0    106
Name: fire, dtype: int64
```

In [232]:
```
#Percentage calculation
df['fire'].value_counts()/len(df['fire'])*100
```

Out[232]:
```
1    56.557377
0    43.442623
Name: fire, dtype: float64
```

As from above observation we can conclude that our predictated feature is not imbalanced

Splitting Training and Testing data

In [233]:
```
## Independent And Dependent Features
X=df.loc[: , df.columns != 'fire']
y=df.iloc[:,-1]
```

In [234]:
```
X
```

Out[234]:

	day	month	Temperature	RH	Ws	Rain	FFMC	DMC	DC	ISI	BUI	FWI	region
0	1	6	29	57	18	0.0	65.7	3.4	7.6	1.3	3.4	0.5	0.0
1	2	6	29	61	13	1.3	64.4	4.1	7.6	1.0	3.9	0.4	0.0
2	3	6	26	82	22	13.1	47.1	2.5	7.1	0.3	2.7	0.1	0.0
3	4	6	25	89	13	2.5	28.6	1.3	6.9	0.0	1.7	0.0	0.0
4	5	6	27	77	16	0.0	64.8	3.0	14.2	1.2	3.9	0.5	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
239	26	9	30	65	14	0.0	85.4	16.0	44.5	4.5	16.9	6.5	1.0
240	27	9	28	87	15	4.4	41.1	6.5	8.0	0.1	6.2	0.0	1.0
241	28	9	27	87	29	0.5	45.9	3.5	7.9	0.4	3.4	0.2	1.0
242	29	9	24	54	18	0.1	79.7	4.3	15.2	1.7	5.1	0.7	1.0
243	30	9	24	64	15	0.2	67.3	3.8	16.5	1.2	4.8	0.5	1.0

244 rows × 13 columns

In [250]:
```
1 X.corr()
```

Out[250]:

	day	month	Temperature	RH	Ws	Rain	FFMC	D
day	1.000000e+00	2.232788e-17	0.095772	-0.074209	0.047001	-0.112265	0.224032	0.491
month	2.232788e-17	1.000000e+00	-0.059017	-0.037884	-0.041447	0.035322	0.015577	0.068
perature	9.577222e-02	-5.901677e-02	1.000000	-0.654443	-0.278132	-0.326786	0.677491	0.483
RH	-7.420934e-02	-3.788419e-02	-0.654443	1.000000	0.236084	0.222968	-0.645658	-0.405
Ws	4.700086e-02	-4.144673e-02	-0.278132	0.236084	1.000000	0.170169	-0.163255	-0.001
Rain	-1.122654e-01	3.532207e-02	-0.326786	0.222968	0.170169	1.000000	-0.544045	-0.288
FFMC	2.240321e-01	1.557668e-02	0.677491	-0.645658	-0.163255	-0.544045	1.000000	0.602
DMC	4.915710e-01	6.817778e-02	0.483105	-0.405133	-0.001246	-0.288548	0.602391	1.000
DC	5.279285e-01	1.276719e-01	0.370498	-0.220330	0.076245	-0.296804	0.503910	0.875
ISI	1.793008e-01	6.354476e-02	0.605971	-0.688268	0.012245	-0.347862	0.740751	0.678
BUI	5.172239e-01	8.556743e-02	0.456415	-0.349685	0.030303	-0.299409	0.590251	0.982
FWI	3.502343e-01	8.173226e-02	0.566839	-0.580457	0.033957	-0.324755	0.691430	0.875
region	4.662229e-16	-9.586232e-17	0.273496	-0.406424	-0.176829	-0.041080	0.224680	0.191

In [251]:
```
1 y
```

Out[251]:
```
0      0
1      0
2      0
3      0
4      0
      ..
239    1
240    0
241    0
242    0
243    0
Name: fire, Length: 244, dtype: int64
```

In [236]:
```
1 from sklearn.model_selection import train_test_split
```

In [237]:
```
1 X_train, X_test, y_train, y_test = train_test_split(
2     X, y, test_size=0.33, random_state=10)
```

In [238]:
```
## Standardize or feature scaling the datasets
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
```

In [239]:
```
scaler
```

Out[239]:
```
StandardScaler()
```

In [240]:
```
X_train = scaler.fit_transform(X_train)
```

In [241]:
```
X_train
```

Out[241]:
```
array([[ 1.0627621 ,  1.33562856, -1.77085211, ..., -0.32636097,
        -0.86597829,  0.98176139],
       [ 0.34495731,  0.44338489,  1.09557186, ...,  0.76499972,
         1.21371864, -1.01857744],
       [ 1.30203036, -1.34110244, -0.33764012, ...,  0.35224151,
         0.48516239, -1.01857744],
       ...,
       [-0.01394508,  1.33562856, -0.05099773, ...,  0.08639724,
         0.37919057,  0.98176139],
       [-1.32992053, -1.34110244, -0.62428252, ..., -0.76710278,
        -0.78649943,  0.98176139],
       [-0.61211574, -1.34110244, -1.19756732, ..., -0.27738965,
        -0.7997459 , -1.01857744]])
```

In [242]:
```
X_test=scaler.transform(X_test)
```

In [243]:
```
X_test
```

Out[243]:
```
array([[-0.49248161, -0.44885878,  0.52228707, ..., -0.68315196,
        -0.81299238,  0.98176139],
       [ 1.90020102, -0.44885878,  0.80892946, ...,  1.72343828,
         1.16073273, -1.01857744],
       [-1.68882292,  0.44338489,  1.09557186, ..., -0.8300659 ,
        -0.7997459 , -1.01857744],
       ...,
       [ 0.94312797, -1.34110244,  0.23564467, ..., -0.69014786,
        -0.81299238,  0.98176139],
       [ 1.30203036,  0.44338489,  0.23564467, ...,  3.3185039 ,
         3.0947184 ,  0.98176139],
       [-0.13357921,  1.33562856, -2.9174217 , ..., -1.04693886,
        -0.90571772, -1.01857744]])
```

Model Training

Logistic Regression

In [252]:
```
from sklearn.linear_model import LogisticRegression
```

In [253]:
```
regression=LogisticRegression()
```

In [254]:
```
regression
```

Out[254]:
```
LogisticRegression()
```

In [255]:
```
regression.fit(X_train,y_train)
```

Out[255]:
```
LogisticRegression()
```

In [256]:
```
## print the coefficients and the intercept
print(regression.coef_)
```

```
[[-0.23249353  0.25370753  0.19141307  0.14861084  0.15768003 -0.18306069
   2.12253196 -0.01312533 -0.25073368  2.46959371  0.25751442  1.9479519
   0.25213316]]
```

In [257]:
```
print(regression.intercept_)
```

```
[1.06223645]
```

In [258]:
```
## PRediction for the test data
reg_pred=regression.predict(X_test)
```

In [259]:
```
reg_pred
```

Out[259]:
```
array([0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1,
       1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1,
       1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1,
       0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0], dtype=int64)
```

Assumptions of Logistic Regression

In [262]:
```
from sklearn.metrics import confusion_matrix
```

In [269]:
```
cm = confusion_matrix(y_test,reg_pred)
cm
```

Out[269]:
```
array([[30,  0],
       [ 7, 44]], dtype=int64)
```

In [279]:
```
tp = cm[0][0]
fp = cm[0][1]
fn = cm[1][0]
tn = cm[1][1]
print(tp,fp,fn,tn)
```

```
30 0 7 44
```

In [275]:
```
accuracy = (tp+tn)/(tp+fp+fn+tn)
accuracy
```

Out[275]: 0.9135802469135802

Model prediction is 91 % accurate

This is as per the task requirement

In [ ]:
```
```