Support Vector Machines Assignment

Data Set - Forest_fires

1. Import Necessary libraries

In [1]:

```
import pandas as pd
import numpy as np

from matplotlib import pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

2. Import Data

In [2]:

```
forest_data = pd.read_csv('forestfires.csv')
forest_data
```

Out[2]:

	month	day	FFMC	DMC	DC	ISI	temp	RH	wind	rain	...	monthfeb	monthjan	monthjul	monthjun	monthmar	monthmay	monthnov	monthoct	monthsep	size_category
0	mar	fri	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	...	0	0	0	0	1	0	0	0	0	small
1	oct	tue	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	...	0	0	0	0	0	0	0	1	0	small
2	oct	sat	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	...	0	0	0	0	0	0	0	1	0	small
3	mar	fri	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	...	0	0	0	0	1	0	0	0	0	small
4	mar	sun	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	...	0	0	0	0	1	0	0	0	0	small
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
512	aug	sun	81.6	56.7	665.6	1.9	27.8	32	2.7	0.0	...	0	0	0	0	0	0	0	0	0	large
513	aug	sun	81.6	56.7	665.6	1.9	21.9	71	5.8	0.0	...	0	0	0	0	0	0	0	0	0	large
514	aug	sun	81.6	56.7	665.6	1.9	21.2	70	6.7	0.0	...	0	0	0	0	0	0	0	0	0	large
515	aug	sat	94.4	146.0	614.7	11.3	25.6	42	4.0	0.0	...	0	0	0	0	0	0	0	0	0	small
516	nov	tue	79.5	3.0	106.7	1.1	11.8	31	4.5	0.0	...	0	0	0	0	0	0	1	0	0	small

517 rows × 31 columns

3. Data Understanding

3.1 Initial Analysis :

In [3]:

```
forest_data.head()
```

Out[3]:

	month	day	FFMC	DMC	DC	ISI	temp	RH	wind	rain	...	monthfeb	monthjan	monthjul	monthjun	monthmar	monthmay	monthnov	monthoct	monthsep	size_category
0	mar	fri	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	...	0	0	0	0	1	0	0	0	0	small
1	oct	tue	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	...	0	0	0	0	0	0	0	1	0	small
2	oct	sat	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	...	0	0	0	0	0	0	0	1	0	small
3	mar	fri	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	...	0	0	0	0	1	0	0	0	0	small
4	mar	sun	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	...	0	0	0	0	1	0	0	0	0	small

5 rows × 31 columns

In [4]:

```
forest_data.shape
```

Out[4]:

```
(517, 31)
```

In [5]:

```
forest_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 517 entries, 0 to 516
Data columns (total 31 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   month          517 non-null    object 
 1   day            517 non-null    object 
 2   FFMC           517 non-null    float64
 3   DMC            517 non-null    float64
 4   DC             517 non-null    float64
 5   ISI            517 non-null    float64
 6   temp           517 non-null    float64
 7   RH             517 non-null    int64  
 8   wind           517 non-null    float64
 9   rain           517 non-null    float64
 10  area           517 non-null    float64
 11  dayfri         517 non-null    int64  
 12  daymon         517 non-null    int64  
 13  daysat         517 non-null    int64  
 14  daysun         517 non-null    int64  
 15  daythu         517 non-null    int64  
 16  daytue         517 non-null    int64  
 17  daywed         517 non-null    int64  
 18  monthapr       517 non-null    int64  
 19  monthaug       517 non-null    int64  
 20  monthdec       517 non-null    int64  
 21  monthfeb       517 non-null    int64  
 22  monthjan       517 non-null    int64  
 23  monthjul       517 non-null    int64  
 24  monthjun       517 non-null    int64  
 25  monthmar       517 non-null    int64  
 26  monthmay       517 non-null    int64  
 27  monthnov       517 non-null    int64  
 28  monthoct       517 non-null    int64  
 29  monthsep       517 non-null    int64  
 30  size_category  517 non-null    object 
dtypes: float64(8), int64(20), object(3)
memory usage: 125.3+ KB
```

In [6]:

```
forest_data.isna().sum()
```

Out[6]:

```
month            0
day              0
FFMC             0
DMC              0
DC               0
ISI              0
temp             0
RH               0
wind             0
rain             0
area             0
dayfri           0
daymon           0
daysat           0
daysun           0
daythu           0
daytue           0
daywed           0
monthapr         0
monthaug         0
monthdec         0
monthfeb         0
monthjan         0
monthjul         0
monthjun         0
monthmar         0
monthmay         0
monthnov         0
monthoct         0
monthsep         0
size_category    0
dtype: int64
```

In [7]:

```
forest_data.describe()
```

Out[7]:

	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area	dayfri	...	monthdec	monthfeb	monthjan	monthjul	monthjun	monthmar	monthmay	month
count	517.000000	517.000000	517.000000	517.000000	517.000000	517.000000	517.000000	517.000000	517.000000	517.000000	...	517.000000	517.000000	517.000000	517.000000	517.000000	517.000000	517.000000	517.000
mean	90.644681	110.872340	547.940039	9.021663	18.889168	44.288201	4.017602	0.021663	12.847292	0.164410	...	0.017408	0.038685	0.003868	0.061896	0.032882	0.104449	0.003868	0.001
std	5.520111	64.046482	248.066192	4.559477	5.806625	16.317469	1.791653	0.295959	63.655818	0.371006	...	0.130913	0.193029	0.062137	0.241199	0.178500	0.306138	0.062137	0.043
min	18.700000	1.100000	7.900000	0.000000	2.200000	15.000000	0.400000	0.000000	0.000000	0.000000	...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
25%	90.200000	68.600000	437.700000	6.500000	15.500000	33.000000	2.700000	0.000000	0.000000	0.000000	...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
50%	91.600000	108.300000	664.200000	8.400000	19.300000	42.000000	4.000000	0.000000	0.520000	0.000000	...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
75%	92.900000	142.400000	713.900000	10.800000	22.800000	53.000000	4.900000	0.000000	6.570000	0.000000	...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
max	96.200000	291.300000	860.600000	56.100000	33.300000	100.000000	9.400000	6.400000	1090.840000	1.000000	...	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000

8 rows × 28 columns

In [8]:

```
forest_data.dtypes
```

Out[8]:

```
month             object
day               object
FFMC             float64
DMC              float64
DC               float64
ISI              float64
temp             float64
RH                 int64
wind             float64
rain             float64
area             float64
dayfri             int64
daymon             int64
daysat             int64
daysun             int64
daythu             int64
daytue             int64
daywed             int64
monthapr           int64
monthaug           int64
monthdec           int64
monthfeb           int64
monthjan           int64
monthjul           int64
monthjun           int64
monthmar           int64
monthmay           int64
monthnov           int64
monthoct           int64
monthsep           int64
size_category     object
dtype: object
```

In [9]:

```
forest_data.columns
```

Out[9]:

```
Index(['month', 'day', 'FFMC', 'DMC', 'DC', 'ISI', 'temp', 'RH', 'wind',
       'rain', 'area', 'dayfri', 'daymon', 'daysat', 'daysun', 'daythu',
       'daytue', 'daywed', 'monthapr', 'monthaug', 'monthdec', 'monthfeb',
       'monthjan', 'monthjul', 'monthjun', 'monthmar', 'monthmay', 'monthnov',
       'monthoct', 'monthsep', 'size_category'],
      dtype='object')
```

In [10]:

```
forest_data_1 = forest_data.drop(['month','day'],axis = 1)
forest_data_1
```

Out[10]:

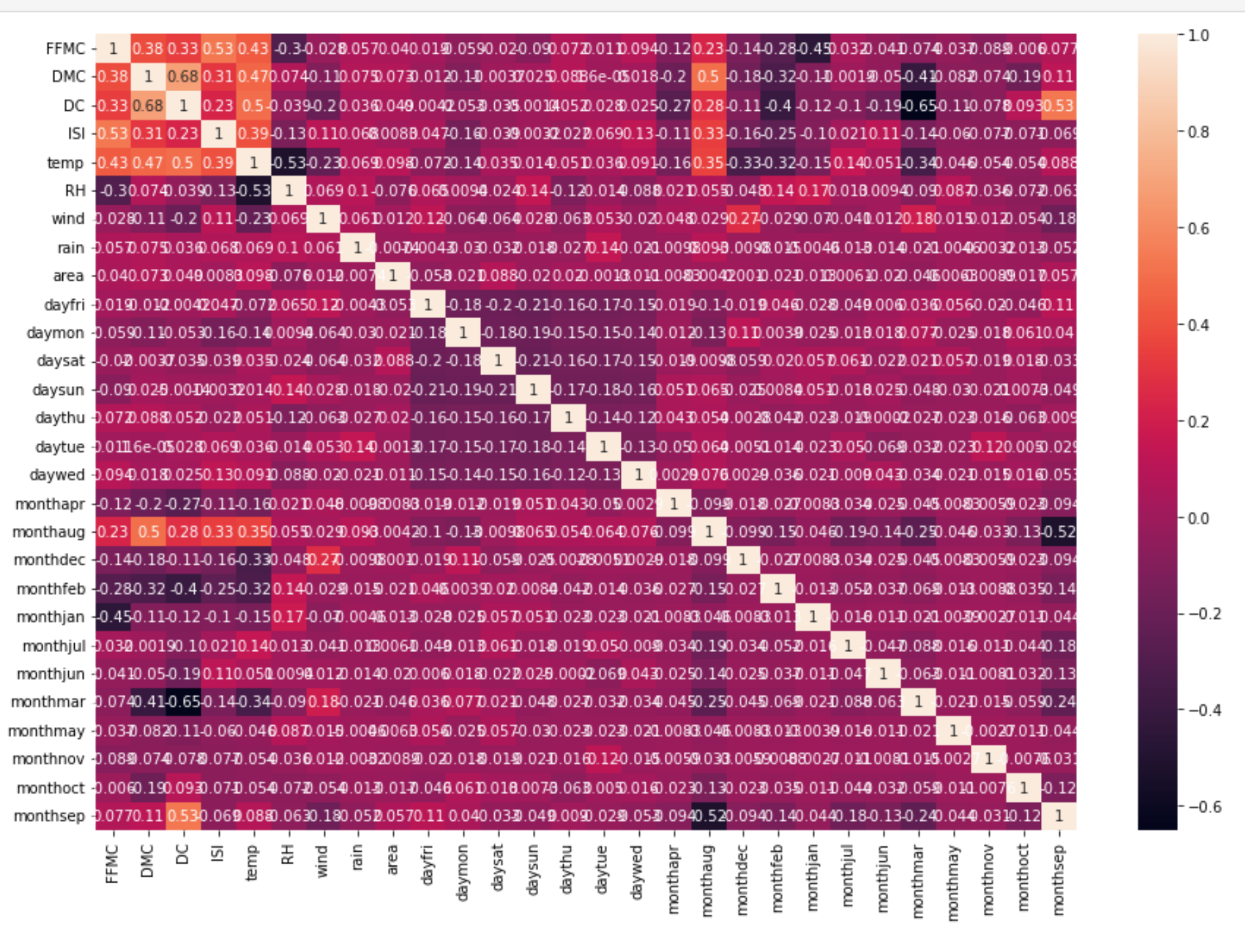
	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area	dayfri	...	monthfeb	monthjan	monthjul	monthjun	monthmar	monthmay	monthnov	monthoct	monthsep	size_category
0	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	0.00	1	...	0	0	0	0	1	0	0	0	0	small
1	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	0.00	0	...	0	0	0	0	0	0	0	1	0	small
2	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	0.00	0	...	0	0	0	0	0	0	0	1	0	small
3	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	0.00	1	...	0	0	0	0	1	0	0	0	0	small
4	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	0.00	0	...	0	0	0	0	1	0	0	0	0	small
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
512	81.6	56.7	665.6	1.9	27.8	32	2.7	0.0	6.44	0	...	0	0	0	0	0	0	0	0	0	large
513	81.6	56.7	665.6	1.9	21.9	71	5.8	0.0	54.29	0	...	0	0	0	0	0	0	0	0	0	large
514	81.6	56.7	665.6	1.9	21.2	70	6.7	0.0	11.16	0	...	0	0	0	0	0	0	0	0	0	large
515	94.4	146.0	614.7	11.3	25.6	42	4.0	0.0	0.00	0	...	0	0	0	0	0	0	0	0	0	small
516	79.5	3.0	106.7	1.1	11.8	31	4.5	0.0	0.00	0	...	0	0	0	0	0	0	1	0	0	small

517 rows × 29 columns

3.2 Correlation Matrix :

In [11]:

```
plt.figure(figsize = (15,10))
sns.heatmap(forest_data_1.corr(),annot = True)
plt.show()
```



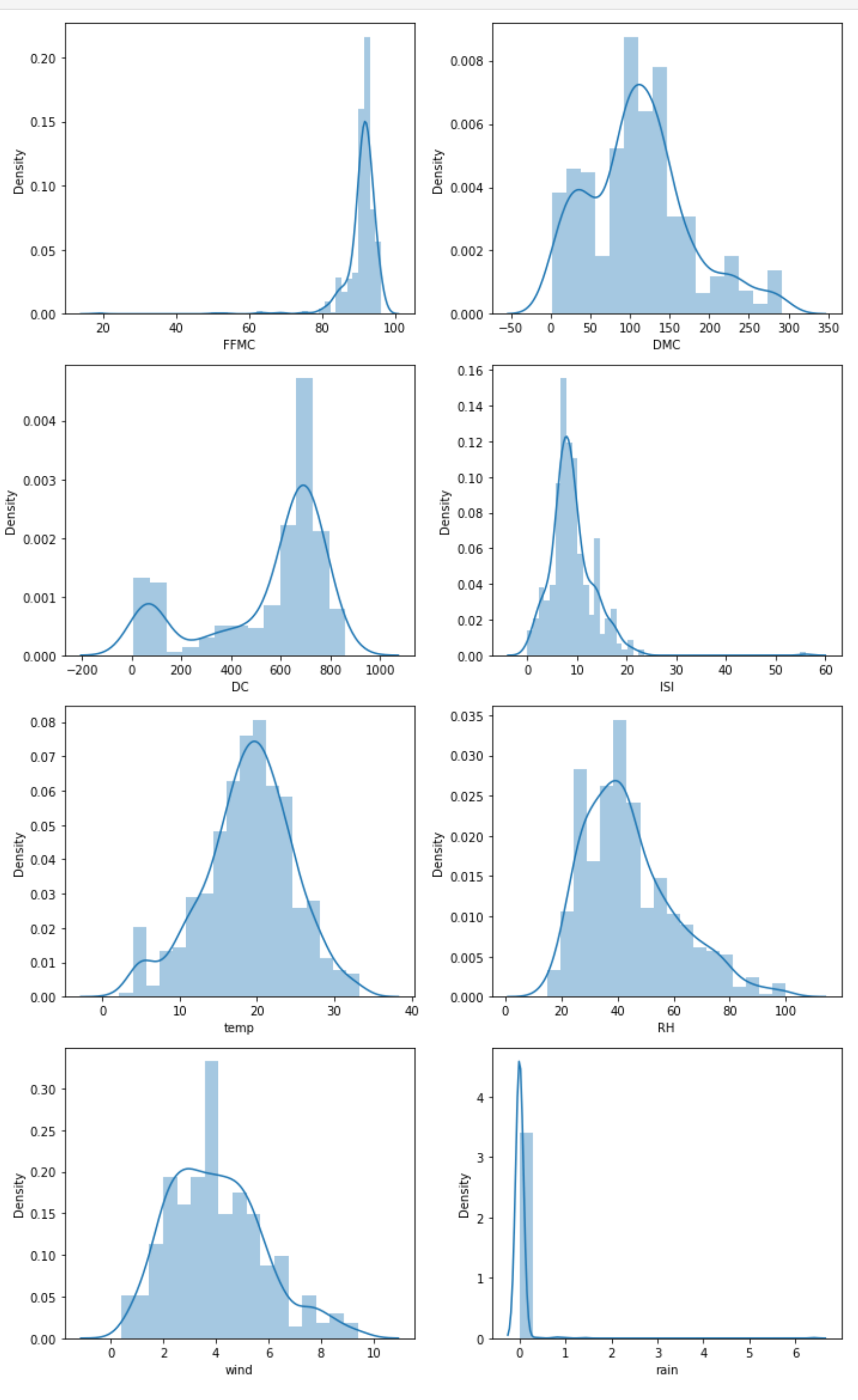
3.3 Visualization using distplot :

In [12]:

```
fig, ax = plt.subplots(4,2, figsize = (10,16))

sns.distplot(forest_data_1.FFMC, ax = ax[0,0])
sns.distplot(forest_data_1.DMC, ax = ax[0,1])
sns.distplot(forest_data_1.DC, ax = ax[1,0])
sns.distplot(forest_data_1.ISI, ax = ax[1,1])
sns.distplot(forest_data_1.temp, ax = ax[2,0])
sns.distplot(forest_data_1.RH, ax = ax[2,1])
sns.distplot(forest_data_1.wind, ax = ax[3,0])
sns.distplot(forest_data_1.rain, ax = ax[3,1])

plt.tight_layout()
plt.show()
```



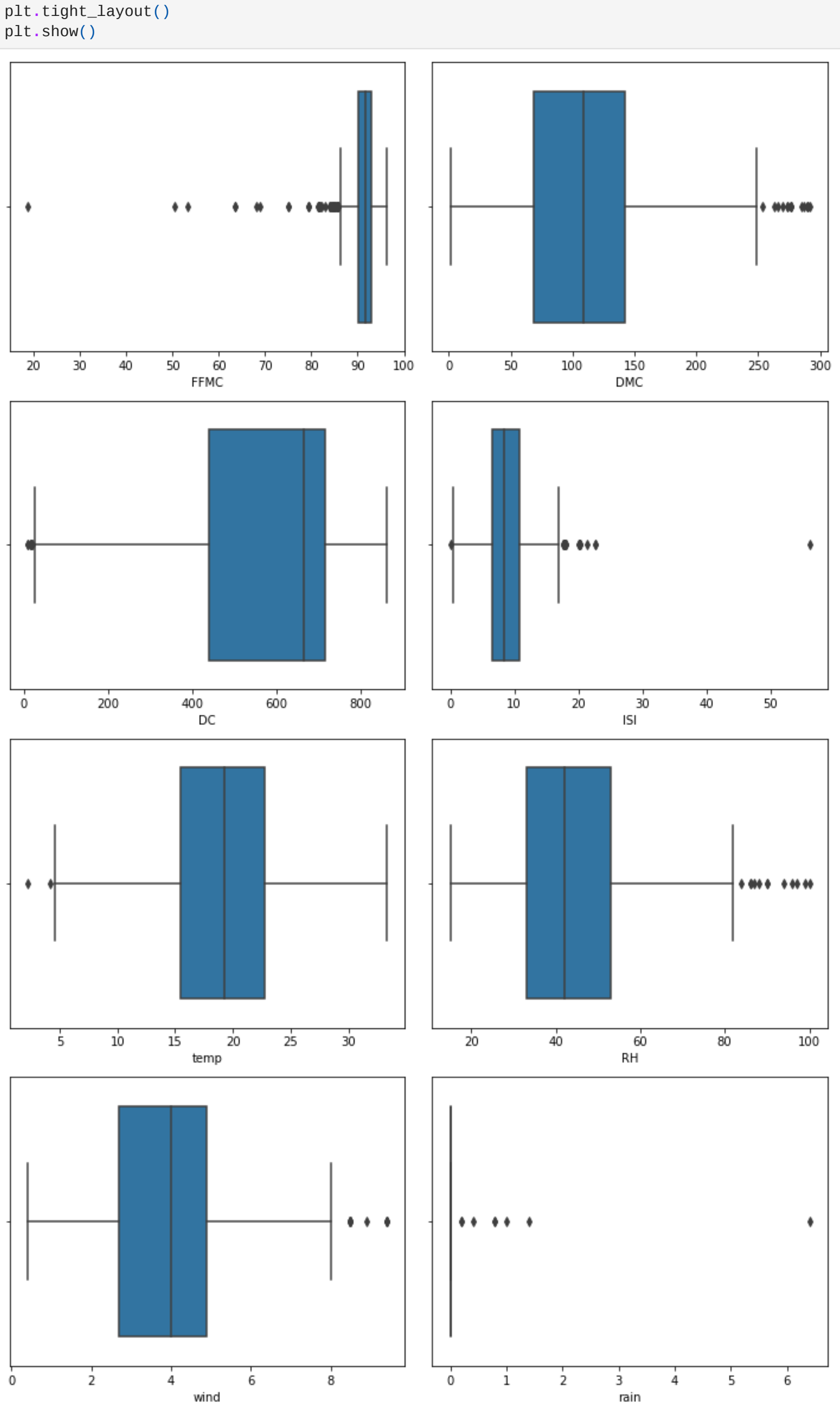
3.4 Checking of the outlier :

In [13]:

```
fig, ax = plt.subplots(4,2, figsize = (10,16))

sns.boxplot(forest_data_1.FFMC, ax = ax[0,0])
sns.boxplot(forest_data_1.DMC, ax = ax[0,1])
sns.boxplot(forest_data_1.DC, ax = ax[1,0])
sns.boxplot(forest_data_1.ISI, ax = ax[1,1])
sns.boxplot(forest_data_1.temp, ax = ax[2,0])
sns.boxplot(forest_data_1.RH, ax = ax[2,1])
sns.boxplot(forest_data_1.wind, ax = ax[3,0])
sns.boxplot(forest_data_1.rain, ax = ax[3,1])

plt.tight_layout()
plt.show()
```



4. Extrating the independent and dependent variables

In [14]:

```
x = forest_data_1.iloc[:,0:28]
x
```

Out[14]:

	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area	dayfri	...	monthdec	monthfeb	monthjan	monthjul	monthjun	monthmar	monthmay	monthnov	monthoct	monthsep
0	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	0.00	1	...	0	0	0	0	0	1	0	0	0	0
1	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	0.00	0	...	0	0	0	0	0	0	0	0	1	0
2	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	0.00	0	...	0	0	0	0	0	0	0	0	1	0
3	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	0.00	1	...	0	0	0	0	0	1	0	0	0	0
4	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	0.00	0	...	0	0	0	0	0	1	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
512	81.6	56.7	665.6	1.9	27.8	32	2.7	0.0	6.44	0	...	0	0	0	0	0	0	0	0	0	0
513	81.6	56.7	665.6	1.9	21.9	71	5.8	0.0	54.29	0	...	0	0	0	0	0	0	0	0	0	0
514	81.6	56.7	665.6	1.9	21.2	70	6.7	0.0	11.16	0	...	0	0	0	0	0	0	0	0	0	0
515	94.4	146.0	614.7	11.3	25.6	42	4.0	0.0	0.00	0	...	0	0	0	0	0	0	0	0	0	0
516	79.5	3.0	106.7	1.1	11.8	31	4.5	0.0	0.00	0	...	0	0	0	0	0	0	0	1	0	0

517 rows × 28 columns

In [15]:

```
y = forest_data_1['size_category']
y
```

Out[15]:

```
0      small
1      small
2      small
3      small
4      small
       ...  
512    large
513    large
514    large
515    small
516    small
Name: size_category, Length: 517, dtype: object
```

4.1 Data Splitting :

In [16]:

```
from sklearn.model_selection import train_test_split
```

In [17]:

```
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size = 0.3)
```

5. Appling Grid search for best 'C' or 'Gamma' value

In [18]:

```
from sklearn.preprocessing import StandardScaler
from sklearn import svm
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
```

In [19]:

```
clf = SVC()
```

In [20]:

```
param_grid = [{'kernel':['rbf'],'gamma':[10,0.5,0.1],'C':[10,0.1,0.001] }]

gsv = GridSearchCV(clf,param_grid,cv = 10)
gsv.fit(x_train,y_train)
```

Out[20]:

```
GridSearchCV(cv=10, estimator=SVC(),
             param_grid=[{'C': [10, 0.1, 0.001], 'gamma': [10, 0.5, 0.1],
                          'kernel': ['rbf']}])
```

In [21]:

```
gsv.best_params_ , gsv.best_score_
```

Out[21]:

```
({'C': 10, 'gamma': 0.5, 'kernel': 'rbf'}, 0.7340840840840841)
```

6. SVM with Kernel rbf

In [22]:

```
from sklearn.metrics import accuracy_score, confusion_matrix,classification_report
```

In [23]:

```
clf = SVC(kernel = 'rbf',C = 10, gamma = 0.1)
clf.fit(x_train , y_train)

y_pred = clf.predict(x_test)
```

In [24]:

```
acc = accuracy_score(y_test, y_pred) * 100
print('Accuracy For Kernal rbf :', acc)
```

```
Accuracy For Kernal rbf : 75.0
```

In [25]:

```
confusion_matrix(y_test, y_pred)
```

Out[25]:

```
array([[  0,  39],
       [  0, 117]], dtype=int64)
```

7. SVM with Kernel linear

In [26]:

```
clf = SVC(kernel = 'linear',C = 10, gamma = 0.1)
clf.fit(x_train , y_train)

y_pred = clf.predict(x_test)
```

In [27]:

```
acc = accuracy_score(y_test, y_pred) * 100
print('Accuracy For Kernal Linear :', acc)
```

```
Accuracy For Kernal Linear : 99.35897435897436
```

In [28]:

```
confusion_matrix(y_test, y_pred)
```

Out[28]:

```
array([[ 39,   0],
       [  1, 116]], dtype=int64)
```

8. SVM with Kernel poly

In [29]:

```
clf = SVC(kernel = 'poly',C = 10, gamma = 0.1)
clf.fit(x_train , y_train)

y_pred = clf.predict(x_test)
```

In [30]:

```
acc = accuracy_score(y_test, y_pred) * 100
print('Accuracy For Kernal Poly :', acc)
```

```
Accuracy For Kernal Poly : 98.07692307692307
```

In [31]:

```
confusion_matrix(y_test, y_pred)
```

Out[31]:

```
array([[ 37,   2],
       [  1, 116]], dtype=int64)
```

9. SVM with Kernel sigmoid

In [32]:

```
clf = SVC(kernel = 'sigmoid',C = 10, gamma = 0.1)
clf.fit(x_train , y_train)

y_pred = clf.predict(x_test)
```

In [33]:

```
acc = accuracy_score(y_test, y_pred) * 100
print('Accuracy For Kernal Sigmoid :', acc)
```

```
Accuracy For Kernal Sigmoid : 75.0
```

In [34]:

```
confusion_matrix(y_test, y_pred)
```

Out[34]:

```
array([[  0,  39],
       [  0, 117]], dtype=int64)
```

Conclusion :

```
The Accuracy Model For Kernal rbf     : 75%
The Accuracy Model For Kernal Linear  : 99.35%
The Accuracy Model For Kernal Poly    : 98.07%
The Accuracy Model For Kernal Sigmoid : 75.0%
```

SVM with Kernel Linear have the Best Model Accuracy with 99.3%