SVC on Wine Dataset with

The Dataset source : Kaggle (: https://raw.githubusercontent.com/aniruddhachoudhury/Red-Wine-Quality/master/winequality-red.csv (https://raw.githubusercontent.com/aniruddhachoudhury/Red-Wine-Quality/master/winequality-red.csv)).

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Content :

- 1. EDA and FE for both dataset
- 2. SVC Model
- 3. Performance metrics for above model
- 4. Performance improvement using GridSearchCV

Import required libraries

In [1]:

```
### Pandas and Numpy
import pandas as pd
import numpy as np
### Visualisation libraries
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
### For Q-Q Plot
import scipy.stats as stats
### To ignore warnings
import warnings
warnings.filterwarnings('ignore')
### Machine Learning libraries
import sklearn
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.svm import SVR
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report, r2
### To be able to see maximum columns on screen
pd.set_option('display.max_columns', 500)
### To save the model
import pickle
```

Support Vector Classifier for Wine Dataset

In [15]:

```
# upload dataset
pd.read_csv("https://raw.githubusercontent.com/aniruddhachoudhury/Red-Wine-Quality/mast
```

Out[15]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	al
0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	
1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99680	3.20	0.68	
2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99700	3.26	0.65	
3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99800	3.16	0.58	
4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	
...	...	...	...	...	...	...	...	...	...	...	
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	

1599 rows × 12 columns

In [16]:

```
from IPython import display
display.Image("wine.jpg")

```

Out[16]:

In [17]:

```
data=pd.read_csv("https://raw.githubusercontent.com/aniruddhachoudhury/Red-Wine-Quality
```

In [18]:

```
data.columns

```

Out[18]:

```
Index(['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'densit
y',
       'pH', 'sulphates', 'alcohol', 'quality'],
      dtype='object')
```

In [19]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   fixed acidity         1599 non-null   float64
 1   volatile acidity      1599 non-null   float64
 2   citric acid           1599 non-null   float64
 3   residual sugar        1599 non-null   float64
 4   chlorides             1599 non-null   float64
 5   free sulfur dioxide   1599 non-null   float64
 6   total sulfur dioxide  1599 non-null   float64
 7   density               1599 non-null   float64
 8   pH                    1599 non-null   float64
 9   sulphates             1599 non-null   float64
 10  alcohol               1599 non-null   float64
 11  quality               1599 non-null   int64  
dtypes: float64(11), int64(1)
memory usage: 150.0 KB
```

Observation

No null values in the data set from info

In [20]:

```
data.head()
```

Out[20]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcoh
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9

In [21]:

```
data.describe().T

```

Out[21]:

	count	mean	std	min	25%	50%	75%	max
fixed acidity	1599.0	8.319637	1.741096	4.60000	7.1000	7.90000	9.200000	15.90000
volatile acidity	1599.0	0.527821	0.179060	0.12000	0.3900	0.52000	0.640000	1.58000
citric acid	1599.0	0.270976	0.194801	0.00000	0.0900	0.26000	0.420000	1.00000
residual sugar	1599.0	2.538806	1.409928	0.90000	1.9000	2.20000	2.600000	15.50000
chlorides	1599.0	0.087467	0.047065	0.01200	0.0700	0.07900	0.090000	0.61100
free sulfur dioxide	1599.0	15.874922	10.460157	1.00000	7.0000	14.00000	21.000000	72.00000
total sulfur dioxide	1599.0	46.467792	32.895324	6.00000	22.0000	38.00000	62.000000	289.00000
density	1599.0	0.996747	0.001887	0.99007	0.9956	0.99675	0.997835	1.00369
pH	1599.0	3.311113	0.154386	2.74000	3.2100	3.31000	3.400000	4.01000
sulphates	1599.0	0.658149	0.169507	0.33000	0.5500	0.62000	0.730000	2.00000
alcohol	1599.0	10.422983	1.065668	8.40000	9.5000	10.20000	11.100000	14.90000
quality	1599.0	5.636023	0.807569	3.00000	5.0000	6.00000	6.000000	8.00000

In [22]:

```
data.quality
```

Out[22]:

```
0       5
1       5
2       5
3       6
4       5
       ..
1594    5
1595    6
1596    6
1597    5
1598    6
Name: quality, Length: 1599, dtype: int64
```

- getting unique values for quality feature

In [23]:

```
data.quality.unique()
```

Out[23]:

```
array([5, 6, 7, 4, 8, 3], dtype=int64)
```

- getting count of record for each unique value in quality

In [24]:

```
data["quality"].value_counts()
```

Out[24]:

```
5    681
6    638
7    199
4     53
8     18
3     10
Name: quality, dtype: int64
```

In [25]:

```
### getting null values in each feature
data.isnull().sum()
```

Out[25]:

```
fixed acidity           0
volatile acidity        0
citric acid             0
residual sugar          0
chlorides               0
free sulfur dioxide     0
total sulfur dioxide    0
density                 0
pH                      0
sulphates               0
alcohol                 0
quality                 0
dtype: int64
```

Visualising Numerical data

In [26]:

```
numerical_features = [fea for fea in data.columns if data[fea].dtypes !="O"]
numerical_features
```

Out[26]:

```
['fixed acidity',
 'volatile acidity',
 'citric acid',
 'residual sugar',
 'chlorides',
 'free sulfur dioxide',
 'total sulfur dioxide',
 'density',
 'pH',
 'sulphates',
 'alcohol',
 'quality']
```

In [30]:

```
### getting  numerical features
numerical_features=[feature for feature in data.columns if data[feature].dtypes!='O']
print(numerical_features)

```

```
['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar', 'chlo
rides', 'free sulfur dioxide', 'total sulfur dioxide', 'density', 'pH', 'sul
phates', 'alcohol', 'quality']
```

In [31]:

```
### getting count of unique value in each feature
for feature in numerical_features:
 print("'{}', = '{}' No. of unique values".format(feature, data[feature].nunique()))

```

```
'fixed acidity', = '96' No. of unique values
'volatile acidity', = '143' No. of unique values
'citric acid', = '80' No. of unique values
'residual sugar', = '91' No. of unique values
'chlorides', = '153' No. of unique values
'free sulfur dioxide', = '60' No. of unique values
'total sulfur dioxide', = '144' No. of unique values
'density', = '436' No. of unique values
'pH', = '89' No. of unique values
'sulphates', = '96' No. of unique values
'alcohol', = '65' No. of unique values
'quality', = '6' No. of unique values
```

In [32]:

```
continuous_features=[fea for fea in numerical_features if data[fea].nunique()>6]
print(continuous_features)
```

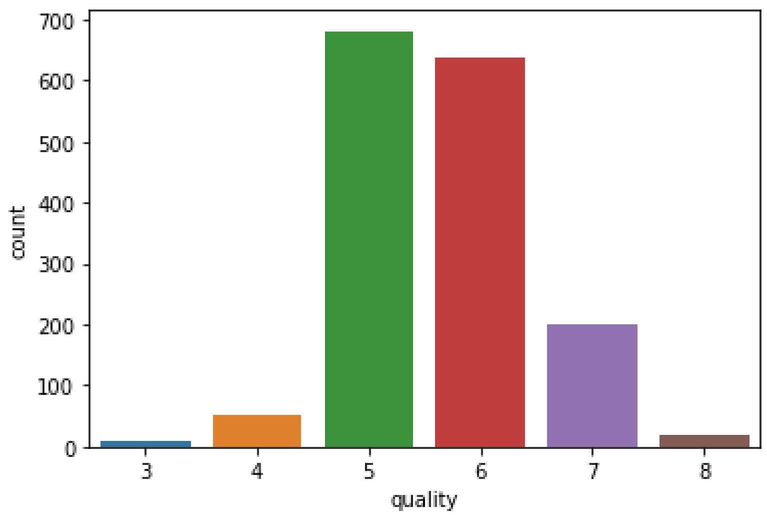
```
['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar', 'chlo
rides', 'free sulfur dioxide', 'total sulfur dioxide', 'density', 'pH', 'sul
phates', 'alcohol']
```

In [33]:

```
#visualising count of quality feature
sns.countplot(data=data,x='quality' )
```

Out[33]:

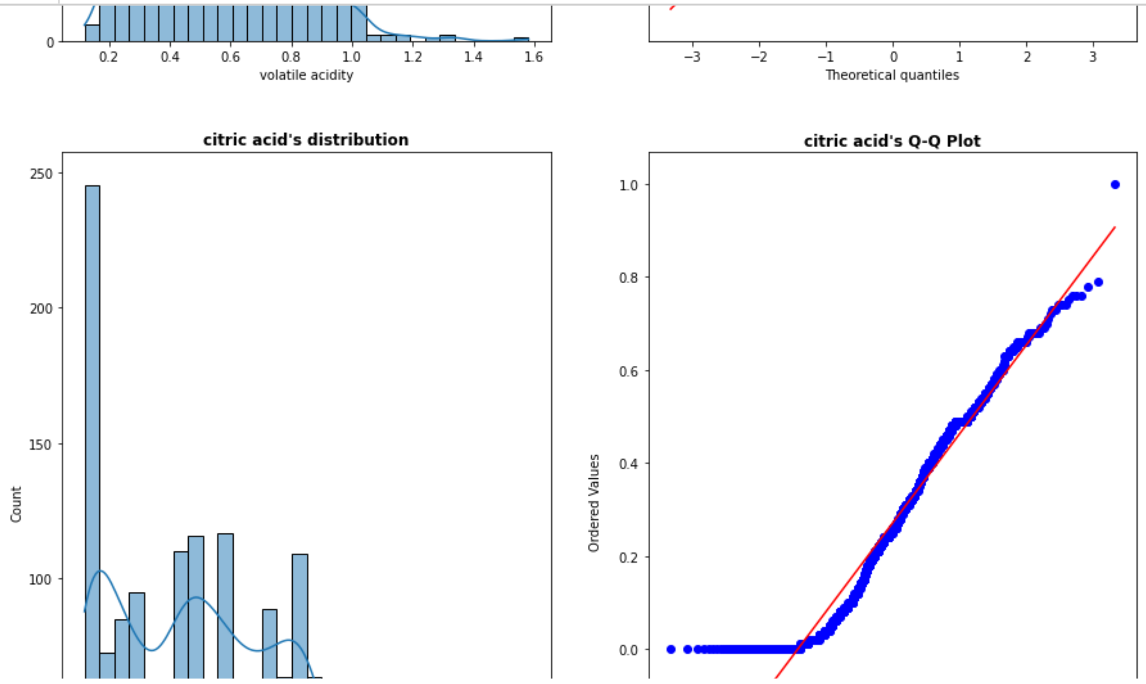
```
<AxesSubplot:xlabel='quality', ylabel='count'>
```



In [35]:

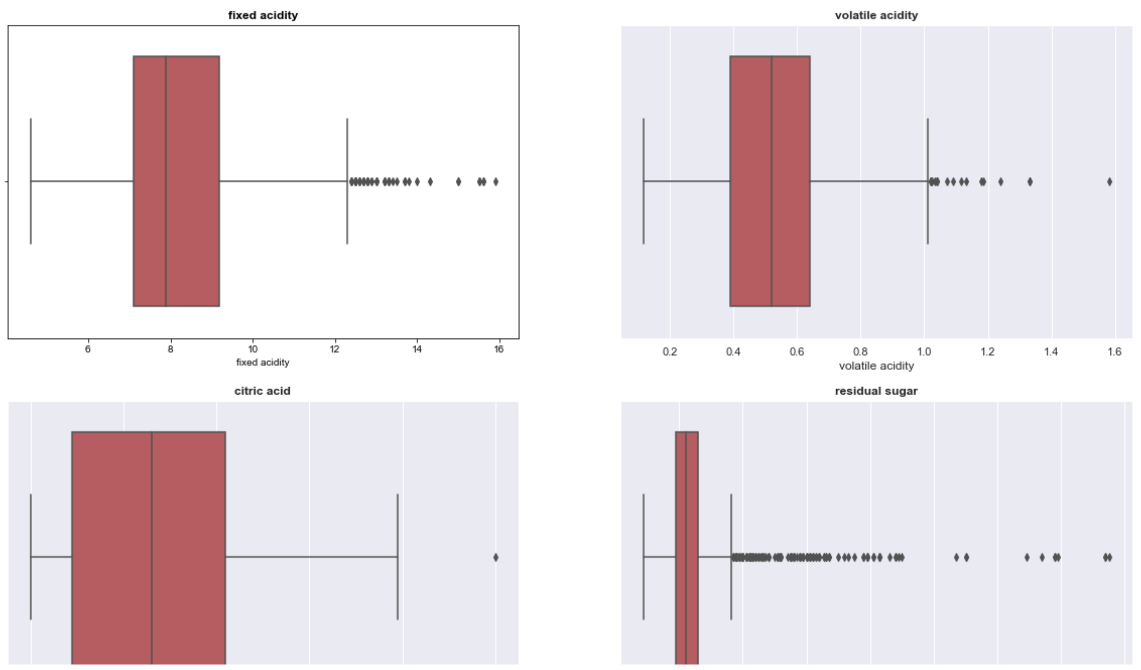
```
# Checking distribution of Continuous numerical features
for i in continuous_features:
 plt.figure(figsize=(15,10))
 plt.subplot(121)
 sns.histplot(data=data, x=i, kde=True, bins=30)
 plt.title("{}'s distribution".format(i),fontweight="bold")

 plt.subplot(122)
 stats.probplot(data[i], dist='norm', plot=plt)
 plt.title("{}'s Q-Q Plot".format(i),fontweight="bold")
 plt.show();
```



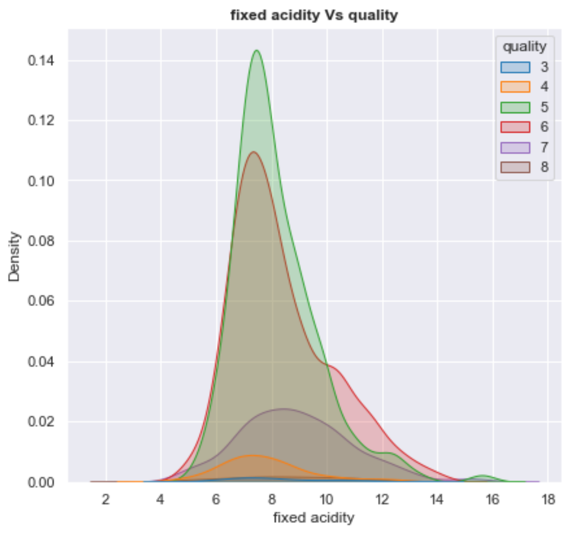
In [36]:

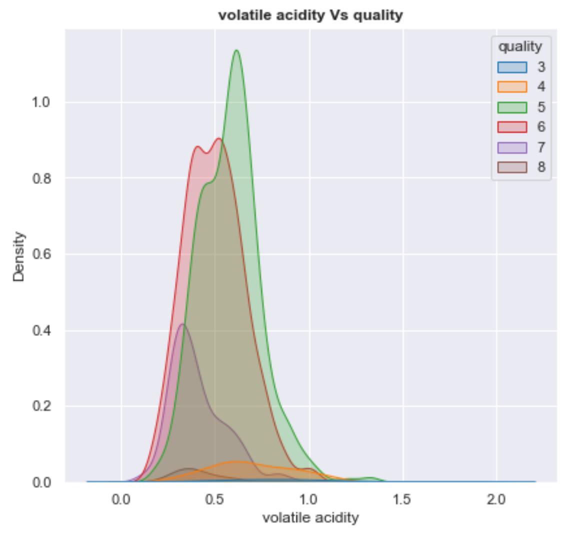
```
# Checking outliers in numerical features
plt.figure(figsize=(20,40))
for i in enumerate(continuous_features):
 plt.subplot(6, 2, i[0]+1)
 sns.set(rc={'figure.figsize':(10,10)})
 sns.boxplot(data=data, x=i[1], color='r')
 plt.title("{}".format(i[1]), fontweight="bold")
```

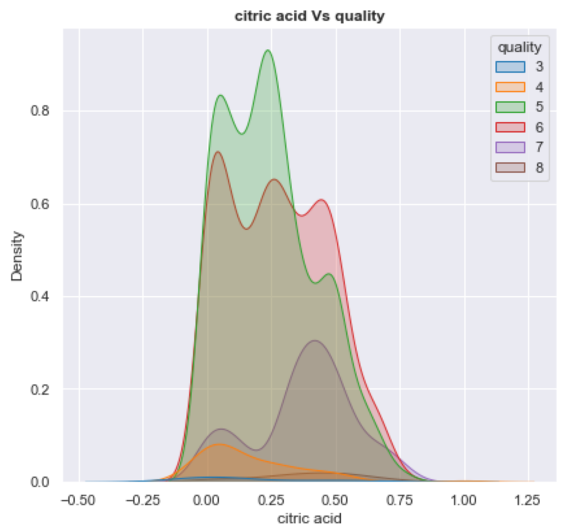


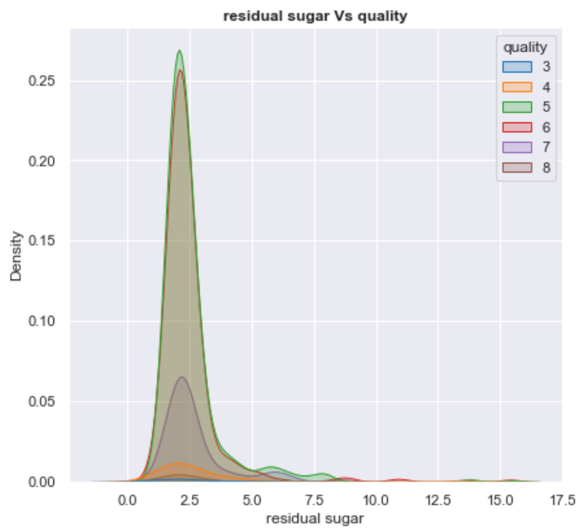
In [37]:

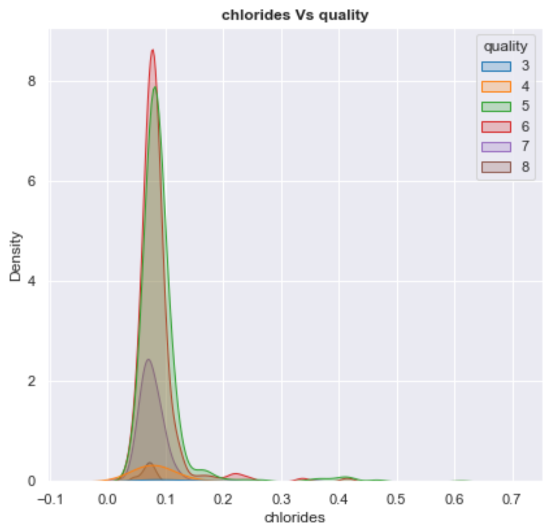
```
### Comparing Continuous numerical features with quality feature
palette1=sns.color_palette("tab10", 6)
plt.figure(figsize=(15,45))
for i in enumerate(continuous_features):
    plt.subplot(6, 2, i[0]+1)
    sns.set(rc={'figure.figsize':(7,7)})
    sns.kdeplot(data=data, x=i[1], hue='quality', palette=palette1, fill=True)
    plt.title("{} Vs quality".format(i[1]),fontweight="bold")
```

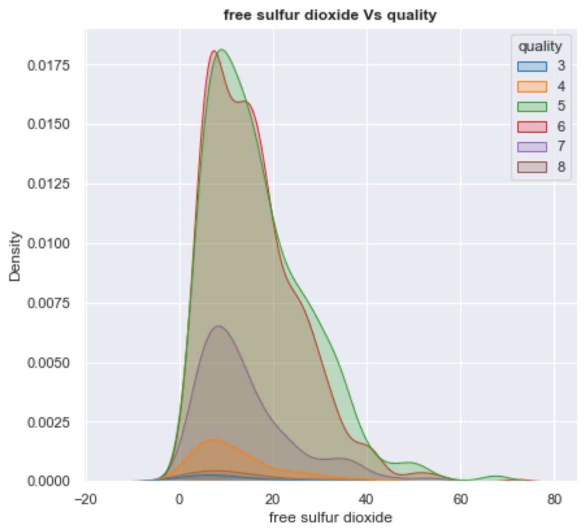


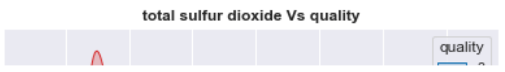


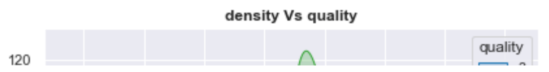


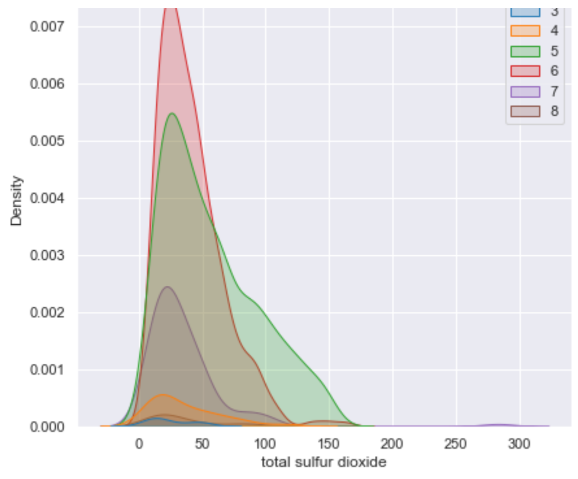


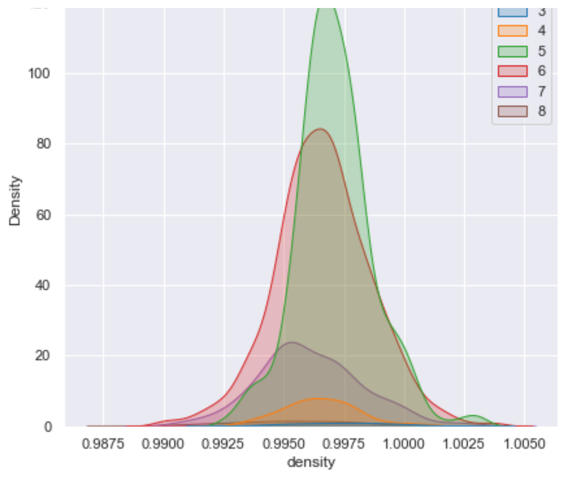


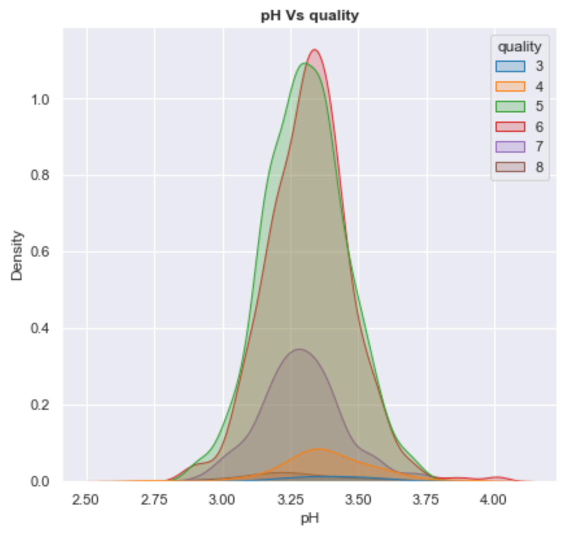


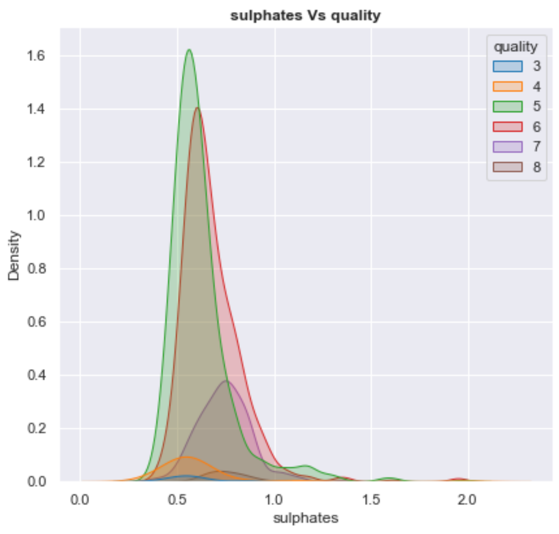


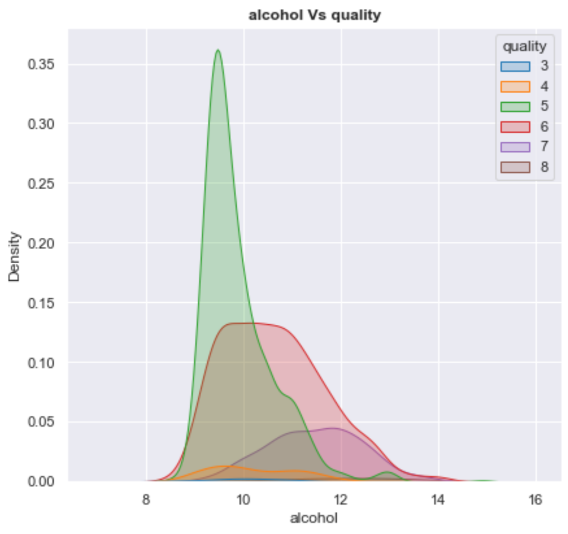












In [ ]:

```python
# getting outliers in features for each unique value in quality feature
plt.figure(figsize=(20,40))
for i in enumerate(continuous_features):
 plt.subplot(6, 2, i[0]+1)
 sns.set(rc={'figure.figsize':(10,6)})
 sns.boxplot(data=data, y=i[1], x='quality')
 plt.title("{} vs quality".format(i[1]),fontsize=15, fontweight="bold")
```

In [40]:

```
#getting correlation for all the features
corr=data.corr()
corr

```

Out[40]:

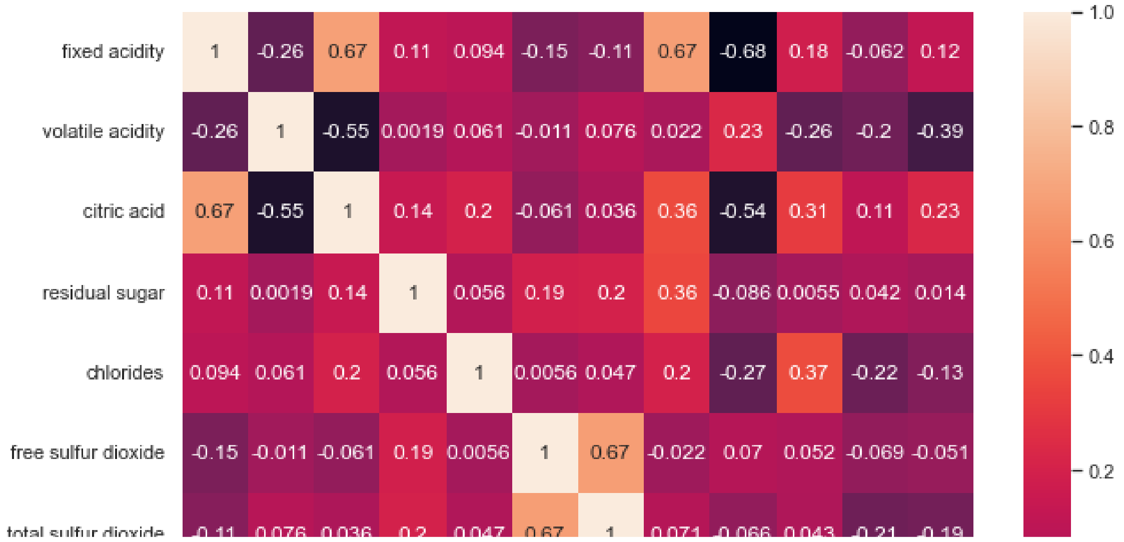
	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density
fixed acidity	1.000000	-0.256131	0.671703	0.114777	0.093705	-0.153794	-0.113181	0.668047
volatile acidity	-0.256131	1.000000	-0.552496	0.001918	0.061298	-0.010504	0.076470	0.022026
citric acid	0.671703	-0.552496	1.000000	0.143577	0.203823	-0.060978	0.035533	0.364947
residual sugar	0.114777	0.001918	0.143577	1.000000	0.055610	0.187049	0.203028	0.355283
chlorides	0.093705	0.061298	0.203823	0.055610	1.000000	0.005562	0.047400	0.200632
free sulfur dioxide	-0.153794	-0.010504	-0.060978	0.187049	0.005562	1.000000	0.667666	-0.021946
total sulfur dioxide	-0.113181	0.076470	0.035533	0.203028	0.047400	0.667666	1.000000	0.071269
density	0.668047	0.022026	0.364947	0.355283	0.200632	-0.021946	0.071269	1.000000
pH	-0.682978	0.234937	-0.541904	-0.085652	-0.265026	0.070377	-0.066495	-0.341699
sulphates	0.183006	-0.260987	0.312770	0.005527	0.371260	0.051658	0.042947	0.148506
alcohol	-0.061668	-0.202288	0.109903	0.042075	-0.221141	-0.069408	-0.205654	-0.496180
quality	0.124052	-0.390558	0.226373	0.013732	-0.128907	-0.050656	-0.185100	-0.174919

In [45]:

```python
# Plotting heatmap for visualising the correlation between features
sns.set(rc={'figure.figsize':(10,10)})
sns.heatmap(data=corr, annot=True)
```

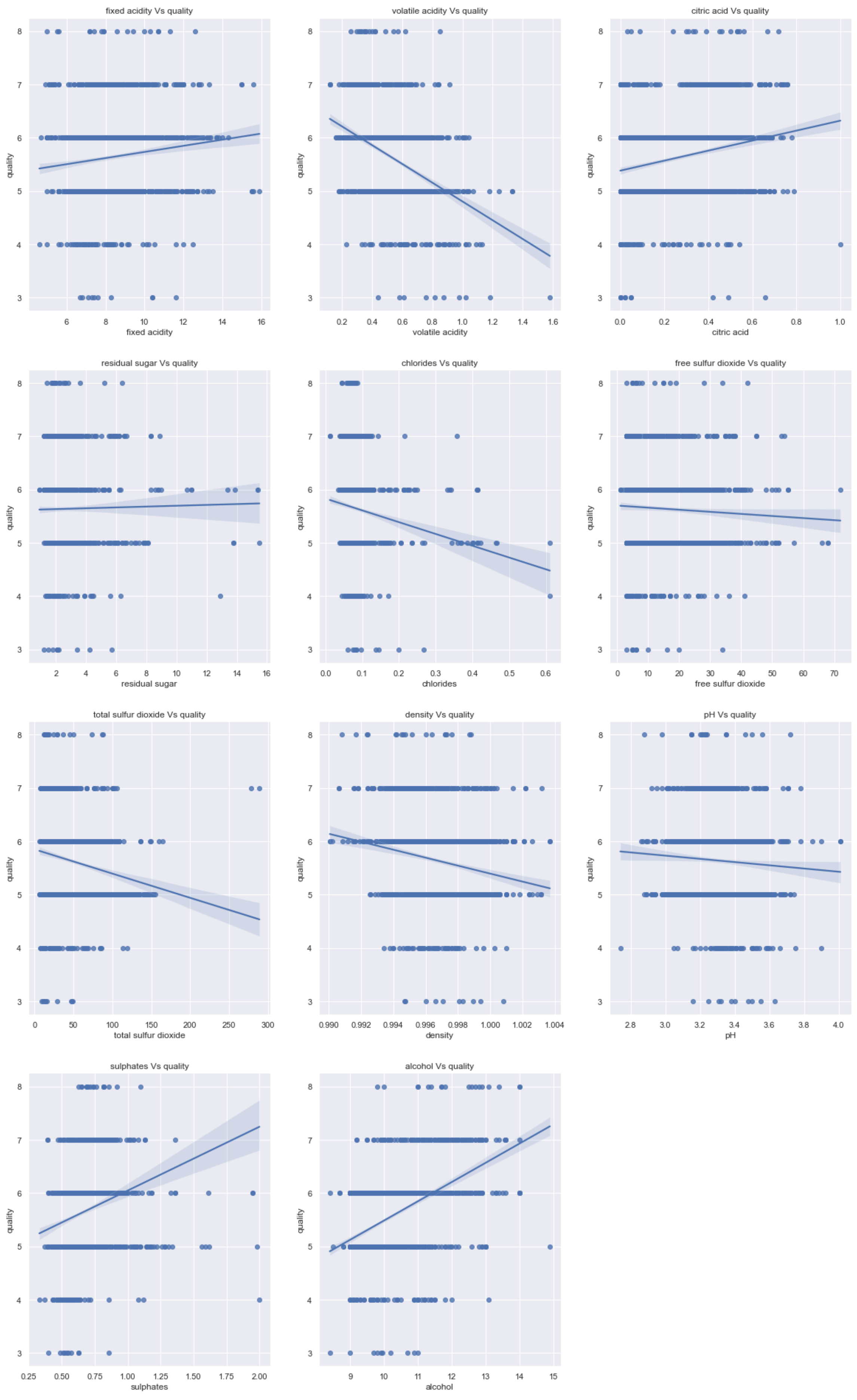
Out[45]:

```
<AxesSubplot:>
```



In [51]:

```
### plotting regplot for all the features wrt. quality
plt.figure(figsize=(20,60))
for i in enumerate(continuous_features):
 plt.subplot(7, 3, i[0]+1)
 sns.set(rc={'figure.figsize':(8,10)})
 sns.regplot(data=data, x=i[1], y='quality')
 plt.xlabel(i[1])
 plt.ylabel("quality")
 plt.title("{} Vs quality".format(i[1]))
```



Splitting data into independent and dependent features

In [52]:

```
X=data.iloc[:,:-1]
y=data.iloc[:,-1]
X.head()
```

Out[52]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcoh
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9

In [53]:

```
y.head()
```

Out[53]:

```
0    5
1    5
2    5
3    6
4    5
Name: quality, dtype: int64
```

In [55]:

```
# if we select random_state=10 then all have same data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=

```

In [63]:

```
# check the shapes as both test and train set need to have same shape
print("X_train shape is : ",X_train.shape )
print("y_train shape is : ",y_train.shape )
print("X_test shape is : ",X_test.shape )
print("y_test shape is : ",y_test.shape )
```

```
X_train shape is :  (1199, 11)
y_train shape is :  (1199,)
X_test shape is :  (400, 11)
y_test shape is :  (400,)
```

Feature Scaling or Standardization

In [66]:

```
scaler=StandardScaler()
print ("scaler",scaler)
print("-----------******----------------")
#### apply scaler on X train data
scaler.fit_transform(X_train)

```

```
scaler StandardScaler()
-----------******----------------
```

Out[66]:

```
array([[ 0.36628211,  0.9252263 , -1.41559084, ...,  0.2800327 ,
        -0.34099149, -1.03579592],
       [ 0.99530488, -1.38052243,  0.95277345, ..., -1.75526948,
         0.71993818, -0.17938734],
       [ 0.65220155,  1.88126845, -0.07695015, ..., -0.37651639,
        -0.22931468, -0.36970036],
       ...,
       [-0.77739563, -0.8181447 ,  1.10723199, ...,  0.54265233,
         0.60826138,  0.96249075],
       [ 0.93812099, -0.98685802,  1.00425963, ..., -0.50782621,
        -0.78769872,  1.5334298 ],
       [-0.77739563,  0.41908633,  0.12899457, ..., -0.04824185,
         2.84179753, -0.17938734]])
```

In [67]:

```
## after transfor store the data into variable called X_train or any new variable
X_train=scaler.fit_transform(X_train)
X_train
```

Out[67]:

```
array([[ 0.36628211,  0.9252263 , -1.41559084, ...,  0.2800327 ,
        -0.34099149, -1.03579592],
       [ 0.99530488, -1.38052243,  0.95277345, ..., -1.75526948,
         0.71993818, -0.17938734],
       [ 0.65220155,  1.88126845, -0.07695015, ..., -0.37651639,
        -0.22931468, -0.36970036],
       ...,
       [-0.77739563, -0.8181447 ,  1.10723199, ...,  0.54265233,
         0.60826138,  0.96249075],
       [ 0.93812099, -0.98685802,  1.00425963, ..., -0.50782621,
        -0.78769872,  1.5334298 ],
       [-0.77739563,  0.41908633,  0.12899457, ..., -0.04824185,
         2.84179753, -0.17938734]])
```

In [69]:

```
## to avoide leakage use transform only
X_test=scaler.transform(X_test)
X_test
```

Out[69]:

```
array([[ -5.09401291,  -4.70982525,   3.48987574, ..., -21.16897975,
         -4.65995954,  -9.78440705],
       [ -5.09401291,   3.82943022,  -6.84834865, ..., -29.79011384,
         -9.33685053, -10.2371451 ],
       [ -2.837715  ,  -9.77012479,  10.91219068, ..., -40.99758817,
          0.32872419, -11.68590685],
       ...,
       [ -5.06131294,  -5.97490014,  -0.75144709, ..., -15.99629929,
         -1.85382494,  -8.87893095],
       [ -4.93051306,  -3.76101909,   0.04380094, ..., -26.3416602 ,
         -7.1543014 , -10.68988315],
       [ -4.995913  , -11.3514684 ,  -1.8117778 , ..., -28.49694373,
          0.32872419,  -9.42221661]])
```

Building SVC Model

In [100]:

```
from sklearn.svm import SVC

svc=SVC()
svc
```

Out[100]:

```
SVC()
```

In [71]:

```
svc.fit(X_train,y_train)  # y_train - dependent feature and  X_train- independent featu
```

Out[71]:

```
SVC()
```

In [72]:

```python
svc_pred=svc.predict(X_test)
svc_pred

```

Out[72]:

```
array([5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5], dtype=int64)
```

In [77]:

```python
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, classifi
confusion_mat=confusion_matrix(y_test, svc_pred)
confusion_mat
```

Out[77]:

```
array([[  0,   0,   2,   0,   0,   0],
       [  0,   0,  15,   0,   0,   0],
       [  0,   0, 172,   0,   0,   0],
       [  0,   0, 152,   0,   0,   0],
       [  0,   0,  50,   0,   0,   0],
       [  0,   0,   9,   0,   0,   0]], dtype=int64)
```

In [92]:

```python
# check the accuracy of model
acc=accuracy_score(y_test, svc_pred)
print ("accuracy of model=",acc*100)

```

```
accuracy of model= 43.0
```

In [86]:

```
report=classification_report(y_test, svc_pred, zero_division=False)
print("Model Output : ")
print(report)

```

```
Model Output :
              precision    recall  f1-score   support

           3       0.00      0.00      0.00         2
           4       0.00      0.00      0.00        15
           5       0.43      1.00      0.60       172
           6       0.00      0.00      0.00       152
           7       0.00      0.00      0.00        50
           8       0.00      0.00      0.00         9

    accuracy                           0.43       400
   macro avg       0.07      0.17      0.10       400
weighted avg       0.18      0.43      0.26       400
```

In [88]:

```
from sklearn.linear_model import LogisticRegression
log_reg=LogisticRegression()
log_reg

```

Out[88]:

```
LogisticRegression()
```

In [90]:

```
log_reg.fit(X_train,y_train)

```

Out[90]:

```
LogisticRegression()
```

In [91]:

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

```

Out[91]:

```
array([4, 4, 5, 4, 4, 4, 4, 4, 5, 4, 4, 4, 4, 4, 4, 4, 4, 4, 5, 3, 4, 4,
       4, 4, 4, 4, 3, 4, 8, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 5,
       4, 4, 5, 4, 4, 8, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 5, 4, 4, 4, 4, 4, 4, 4, 5, 4, 4, 4, 4, 4, 5, 4, 4, 4, 4,
       4, 8, 4, 4, 4, 4, 4, 4, 4, 4, 5, 4, 4, 4, 5, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 3, 4, 4, 4, 4, 4, 4, 5, 4, 4, 4, 4, 4, 4, 4, 4, 8, 4, 3, 4,
       4, 4, 4, 4, 4, 5, 4, 5, 4, 4, 4, 4, 4, 4, 4, 3, 4, 4, 4, 5, 4, 5,
       3, 4, 3, 4, 4, 4, 4, 4, 4, 5, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 5, 3,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 8, 4, 3, 8, 4, 5,
       4, 4, 4, 4, 4, 5, 3, 4, 4, 4, 3, 4, 4, 3, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 3, 4, 4, 4, 4, 4, 4, 4, 3, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 3, 8, 4, 5, 4, 8, 4, 4, 4, 4, 4, 4, 4, 5, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 5, 4, 4, 4, 4, 4, 4, 4, 4, 5, 4, 4, 4, 4, 4, 4, 4,
       5, 8, 5, 5, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 8, 4, 8, 4, 8, 4, 4,
       4, 4, 4, 3, 4, 4, 4, 4, 4, 4, 4, 3, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 5, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4], dtype=int64)
```

In [93]:

```
report_log=classification_report(y_test, log_pred, zero_division=False)
print(report_log)

```

```
              precision    recall  f1-score   support

           3       0.06      0.50      0.11         2
           4       0.04      0.93      0.08        15
           5       0.44      0.07      0.12       172
           6       0.00      0.00      0.00       152
           7       0.00      0.00      0.00        50
           8       0.08      0.11      0.10         9

    accuracy                           0.07       400
   macro avg       0.10      0.27      0.07       400
weighted avg       0.19      0.07      0.06       400
```

Increasing performance of model (Hyper-parameter Tuning)

In [97]:

```
### using different kernels to guage performanc of model for constant hyper-parameter C
kernels=['linear', 'rbf', 'poly', 'sigmoid']
for kernel in kernels:
 model=SVC(kernel=kernel, C=1.0)
 model.fit(X_train, y_train)
 print("For kernel {} modal accuracy is :  {}".format(kernel, model.score(X_test, y_tes

```

```
For kernel linear modal accuracy is :  0.36
For kernel rbf modal accuracy is :  0.43
For kernel poly modal accuracy is :  0.0275
For kernel sigmoid modal accuracy is :  0.3475
```

In [99]:

```
### for polynomial kernel with different degree of polynomial with constant hyper-param
for degree in range(1,11):
 model=SVC(kernel='poly', degree=degree, C=100)
 model.fit(X_train, y_train)
 print("For degree {} modal accuracy is : {}".format(degree, model.score(X_test, y_test
```

```
For degree 1 modal accuracy is : 0.35
For degree 2 modal accuracy is : 0.0825
For degree 3 modal accuracy is : 0.0675
For degree 4 modal accuracy is : 0.0225
For degree 5 modal accuracy is : 0.3325
For degree 6 modal accuracy is : 0.015
For degree 7 modal accuracy is : 0.17
For degree 8 modal accuracy is : 0.0125
For degree 9 modal accuracy is : 0.0225
For degree 10 modal accuracy is : 0.0125
```

gridsearchcv

gridsearchcv is used to increase the model efficiency

In [103]:

```
from sklearn.model_selection import GridSearchCV
```

In [116]:

```
param_grid={'C':[i for i in range(1,100,10)], 'kernel':['linear', 'rbf', 'poly', 'sigmo
grid=GridSearchCV(SVC(), param_grid=param_grid)
grid.fit(X_train, y_train)
```

Out[116]:

```
GridSearchCV(estimator=SVC(),
             param_grid={'C': [1, 11, 21, 31, 41, 51, 61, 71, 81, 91],
                         'degree': [1, 2, 3, 4, 5, 6, 7],
                         'kernel': ['linear', 'rbf', 'poly', 'sigmoid']})
```

In [118]:

```
### getting best parameters after gridsearchCV
print("Best parameters are {} for optimal accuracy.".format(grid.best_params_))



print("-------------****------------------")

### getting best accuracy after gridsearchCV
print("Best accuracy is {}".format(grid.score(X_test, y_test)))
```

```
Best parameters are {'C': 11, 'degree': 1, 'kernel': 'rbf'} for optimal accu
racy.
-------------****------------------
Best accuracy is 0.43
```

In [119]:

```
print("Accuracy of SVC without Hyperparameter Tuning is : ",acc)
print("Accuracy of SVC with Hyperparameter Tuning is {}".format(grid.score(X_test, y_te
```

```
Accuracy of SVC without Hyperparameter Tuning is :  0.43
Accuracy of SVC with Hyperparameter Tuning is 0.43
```

In [120]:

```
# Why I am not getteing improve accuracy if I apply gridsearchcv
```

In [ ]:

```
*Github link:
*Linkdin link :
```

In [ ]:

```
# END
```

In [ ]:

```

```

In [ ]:

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In [ ]:

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In [ ]:

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