```
#Importing required packages.
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.linear_model import SGDClassifier
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
%matplotlib inline
```

```
#Loading dataset
wine = pd.read_csv('/content/archive (1).zip')
```

```
#Let's check how the data is distributed
wine.head()
```

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

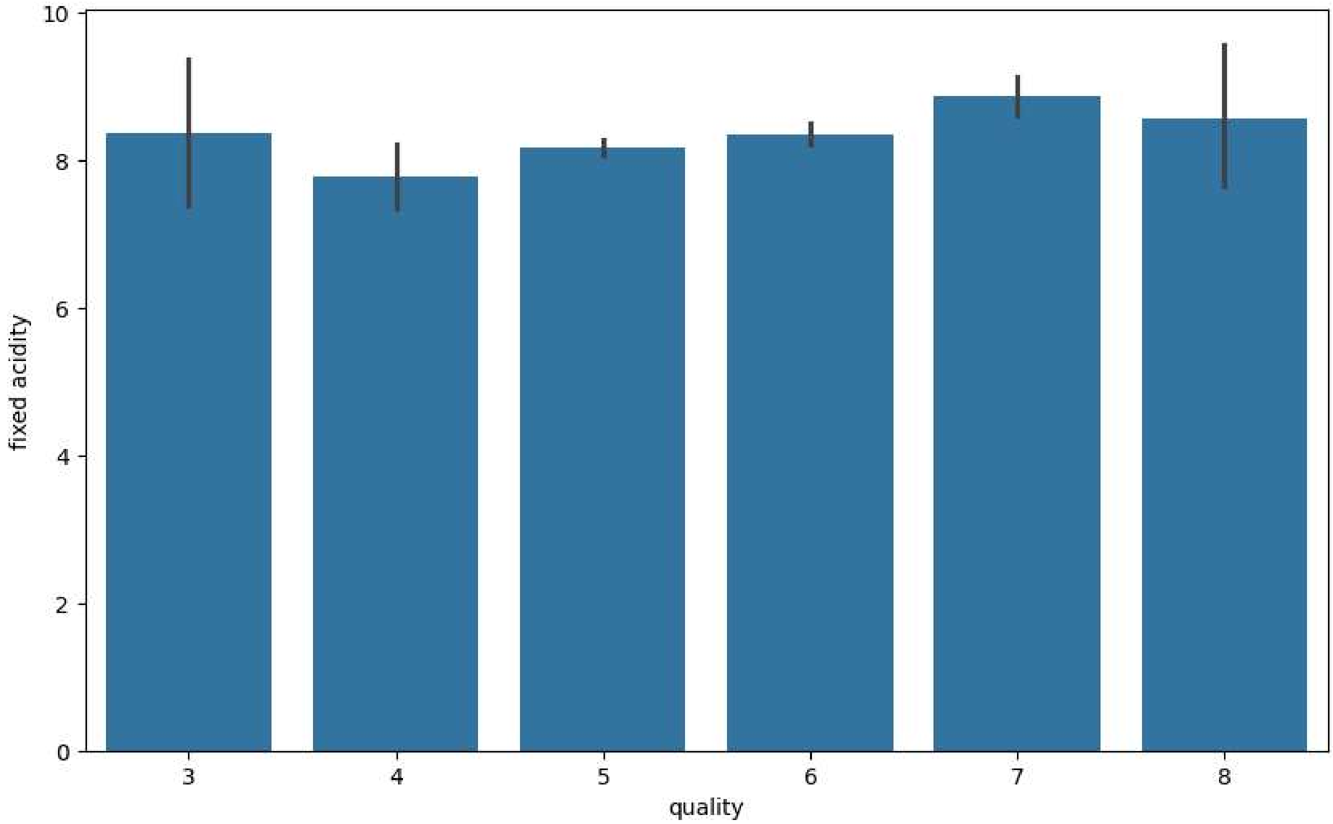
```
#Information about the data columns
wine.info()
```

```
<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
```

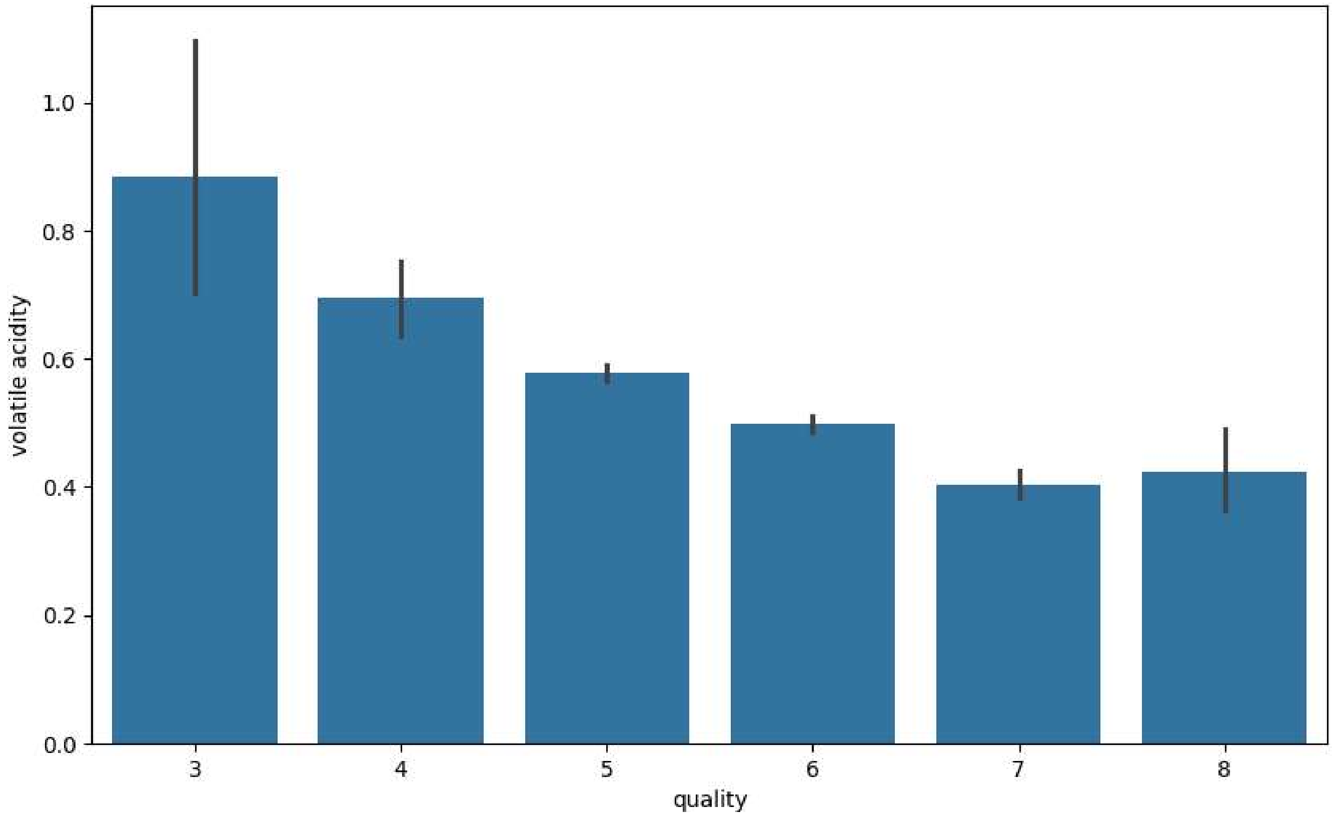
```
#Here we see that fixed acidity does not give any specification to classify the quality.
fig = plt.figure(figsize = (10,6))
sns.barplot(x = 'quality', y = 'fixed acidity', data = wine)
```

```
<Axes: xlabel='quality', ylabel='fixed acidity'>
```



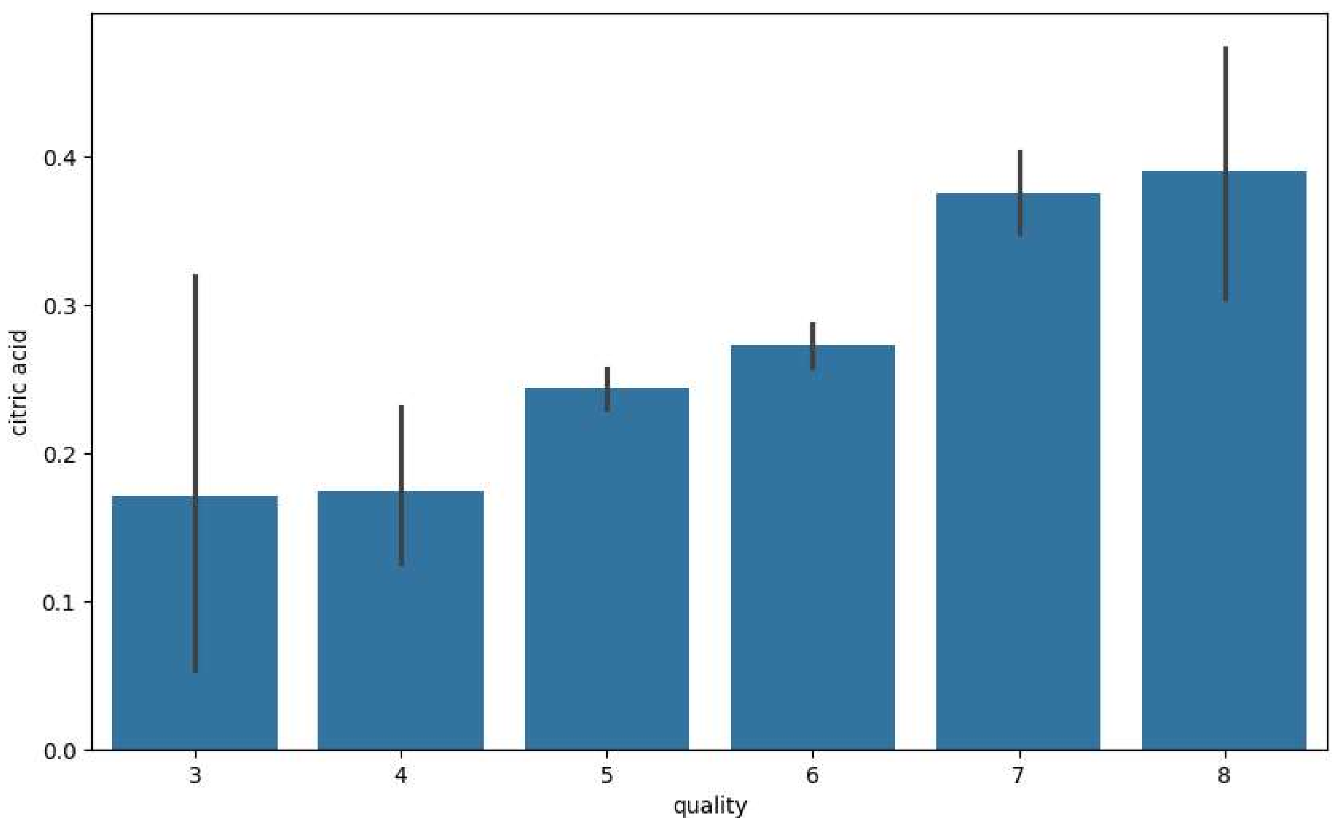

```
#Here we see that its quite a downing trend in the volatile acidity as we go higher the qual
fig = plt.figure(figsize = (10,6))
sns.barplot(x = 'quality', y = 'volatile acidity', data = wine)
```

```
<Axes: xlabel='quality', ylabel='volatile acidity'>
```



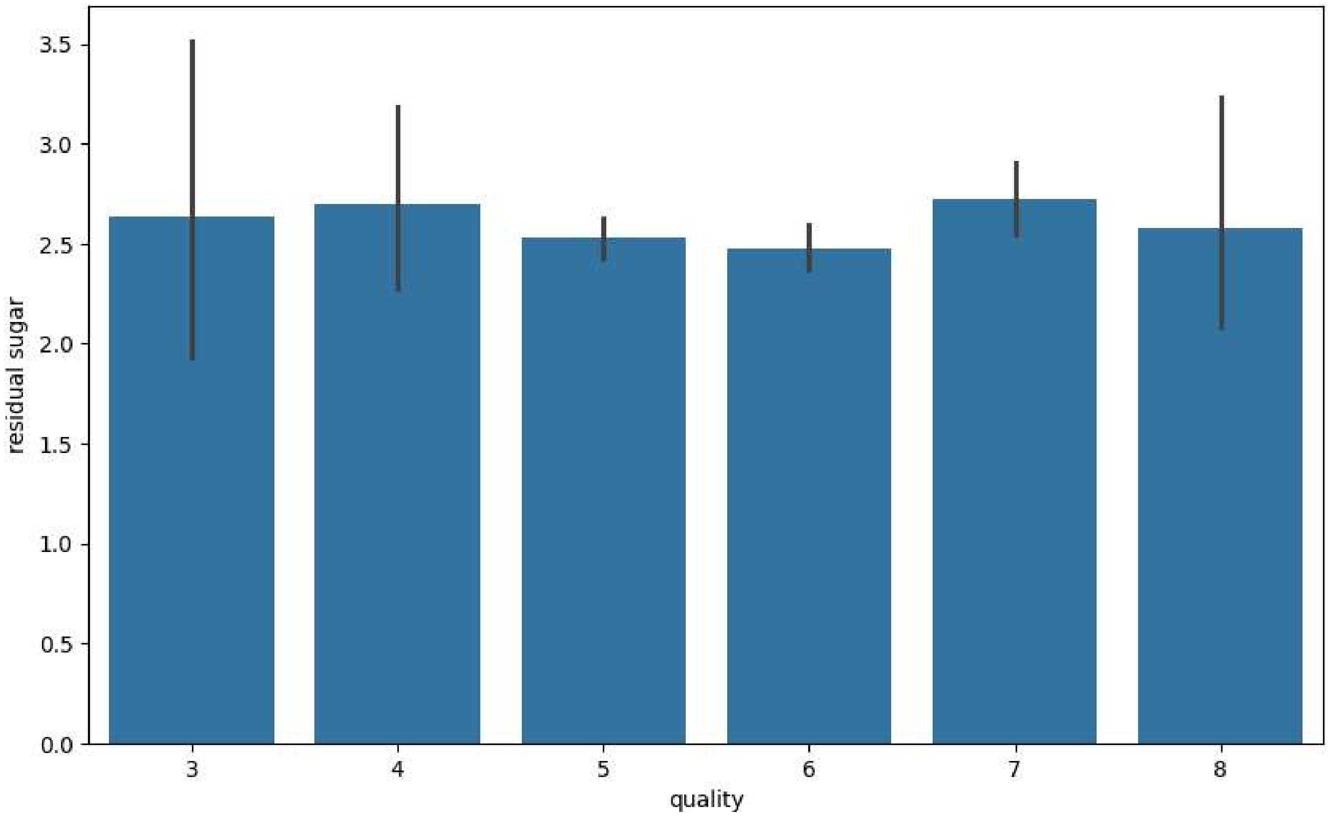

```
#Composition of citric acid go higher as we go higher in the quality of the wine
fig = plt.figure(figsize = (10,6))
sns.barplot(x = 'quality', y = 'citric acid', data = wine)
```

```
<Axes: xlabel='quality', ylabel='citric acid'>
```



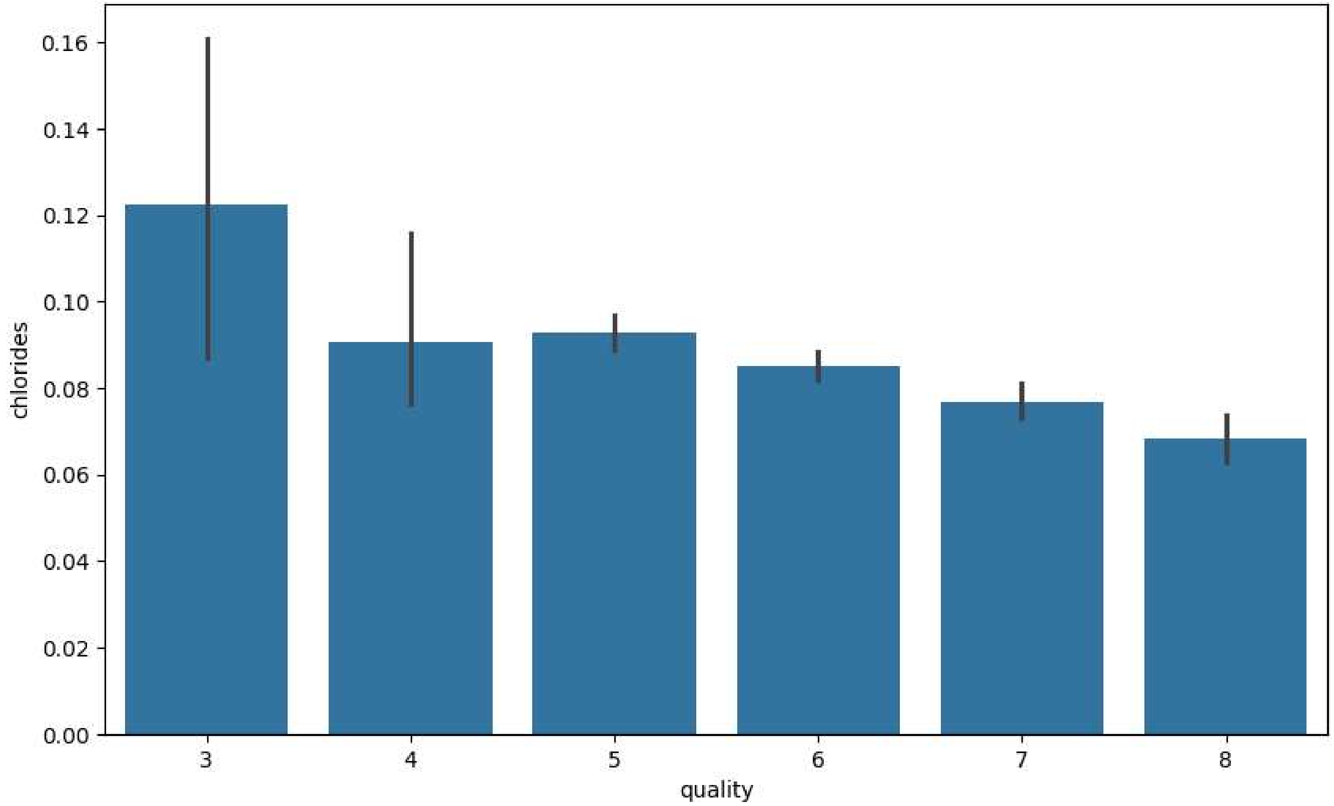
```
fig = plt.figure(figsize = (10,6))
sns.barplot(x = 'quality', y = 'residual sugar', data = wine)
```

```
<Axes: xlabel='quality', ylabel='residual sugar'>
```



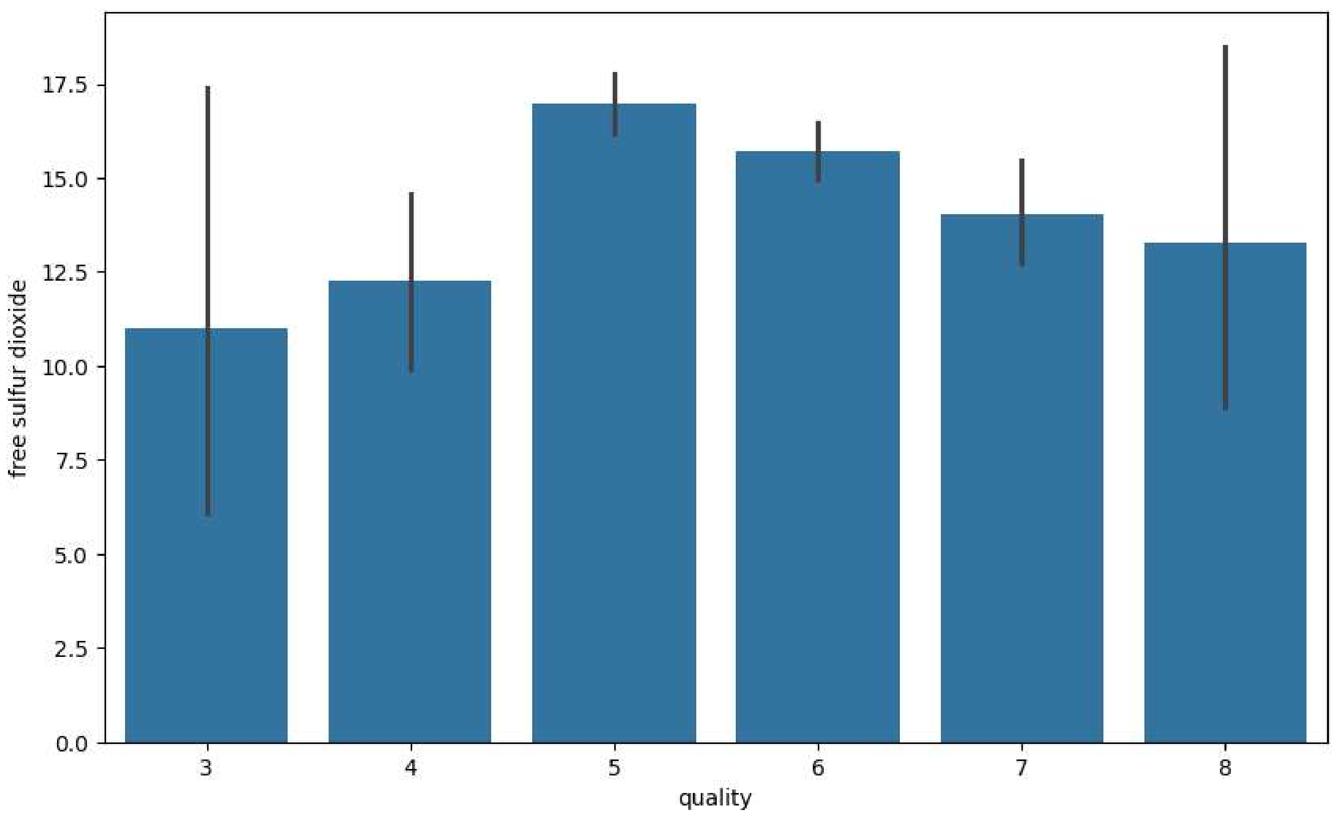

```
#Composition of chloride also go down as we go higher in the quality of the wine
fig = plt.figure(figsize = (10,6))
sns.barplot(x = 'quality', y = 'chlorides', data = wine)
```

```
<Axes: xlabel='quality', ylabel='chlorides'>
```



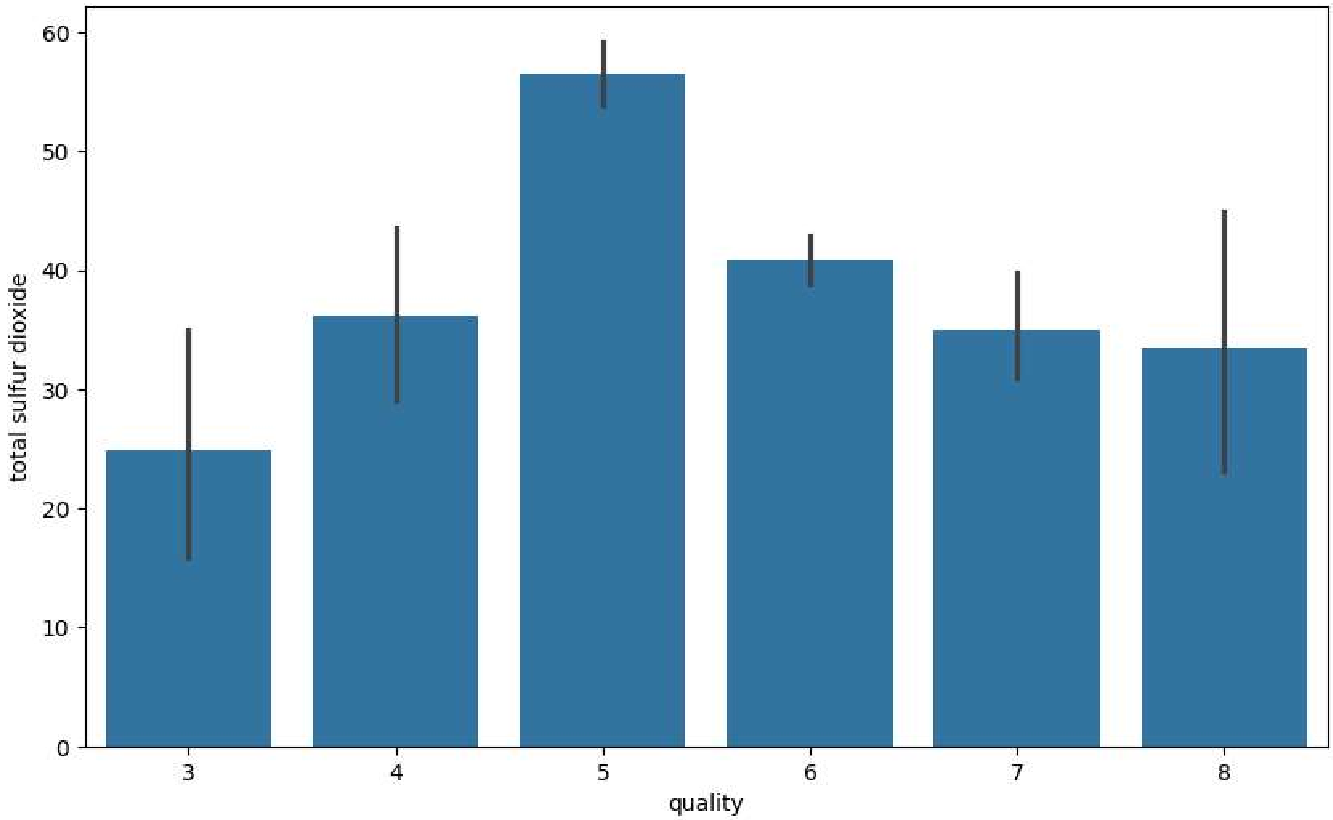

```
fig = plt.figure(figsize = (10,6))
sns.barplot(x = 'quality', y = 'free sulfur dioxide', data = wine)
```

```
<Axes: xlabel='quality', ylabel='free sulfur dioxide'>
```



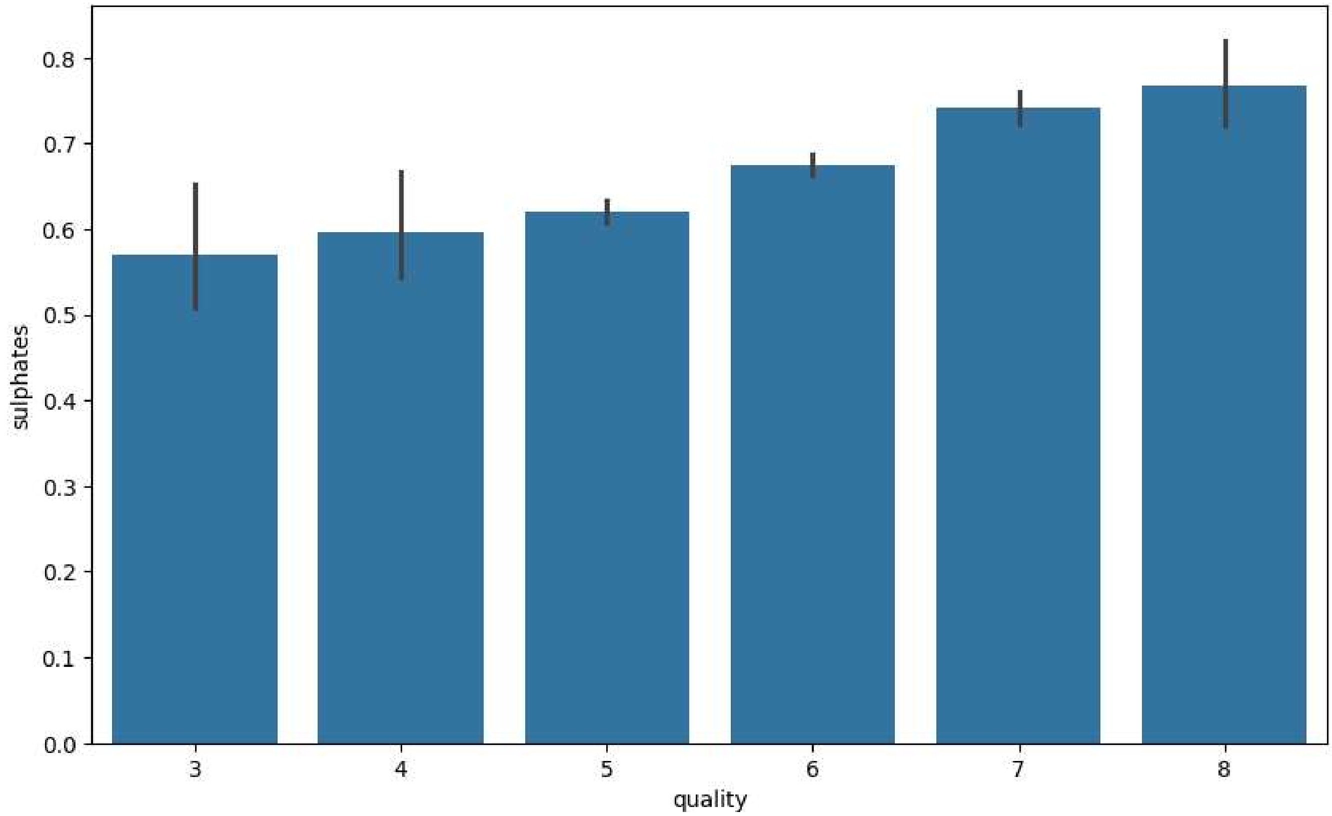
```
fig = plt.figure(figsize = (10,6))
sns.barplot(x = 'quality', y = 'total sulfur dioxide', data = wine)
```

```
<Axes: xlabel='quality', ylabel='total sulfur dioxide'>
```



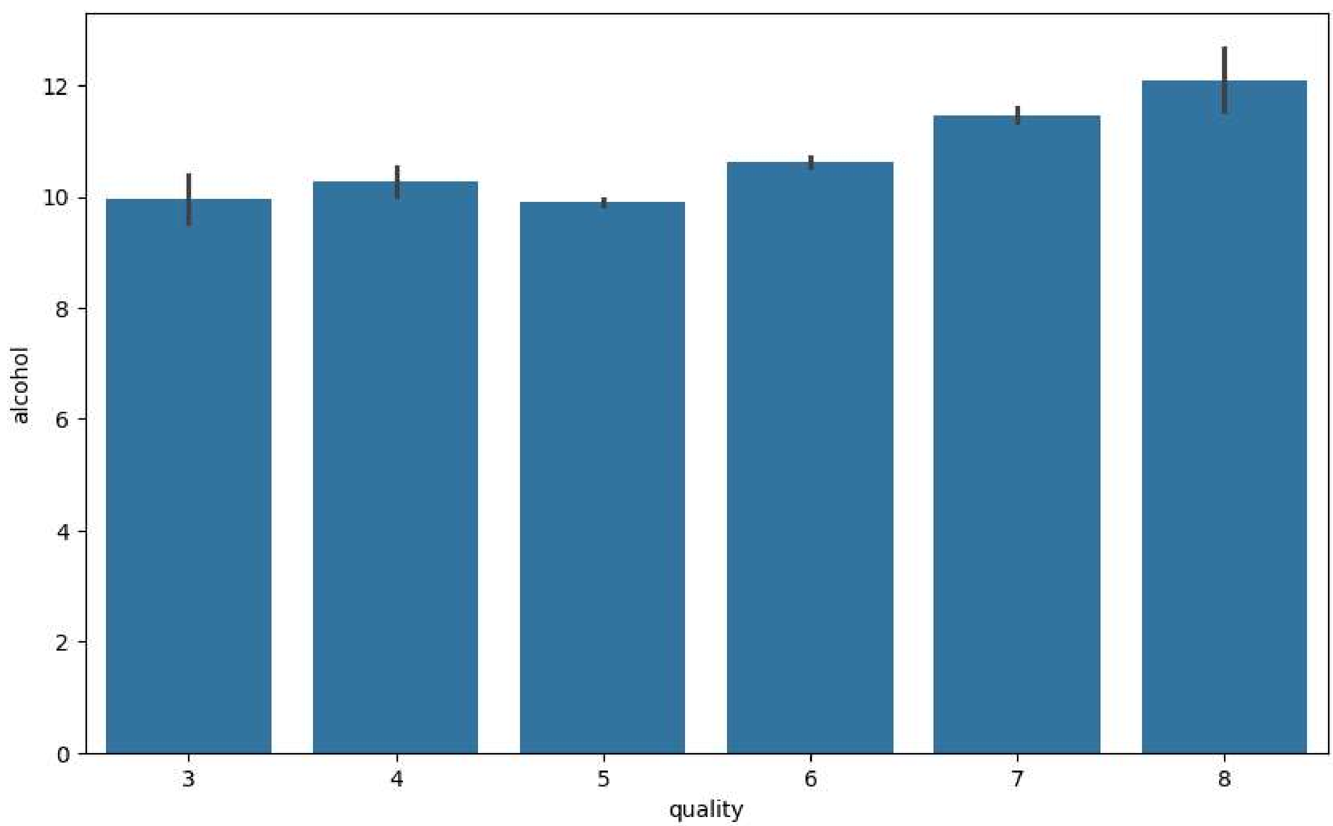

```
fig = plt.figure(figsize = (10,6))
sns.barplot(x = 'quality', y = 'sulphates', data = wine)
```

```
<Axes: xlabel='quality', ylabel='sulphates'>
```




```
fig = plt.figure(figsize = (10,6))
sns.barplot(x = 'quality', y = 'alcohol', data = wine)
```

```
<Axes: xlabel='quality', ylabel='alcohol'>
```



```
#Making binary classificaion for the response variable.
#Dividing wine as good and bad by giving the limit for the quality
bins = (2, 6.5, 8)
group_names = ['bad', 'good']
wine['quality'] = pd.cut(wine['quality'], bins = bins, labels = group_names)
```

```
#Now lets assign a labels to our quality variable
label_quality = LabelEncoder()
```

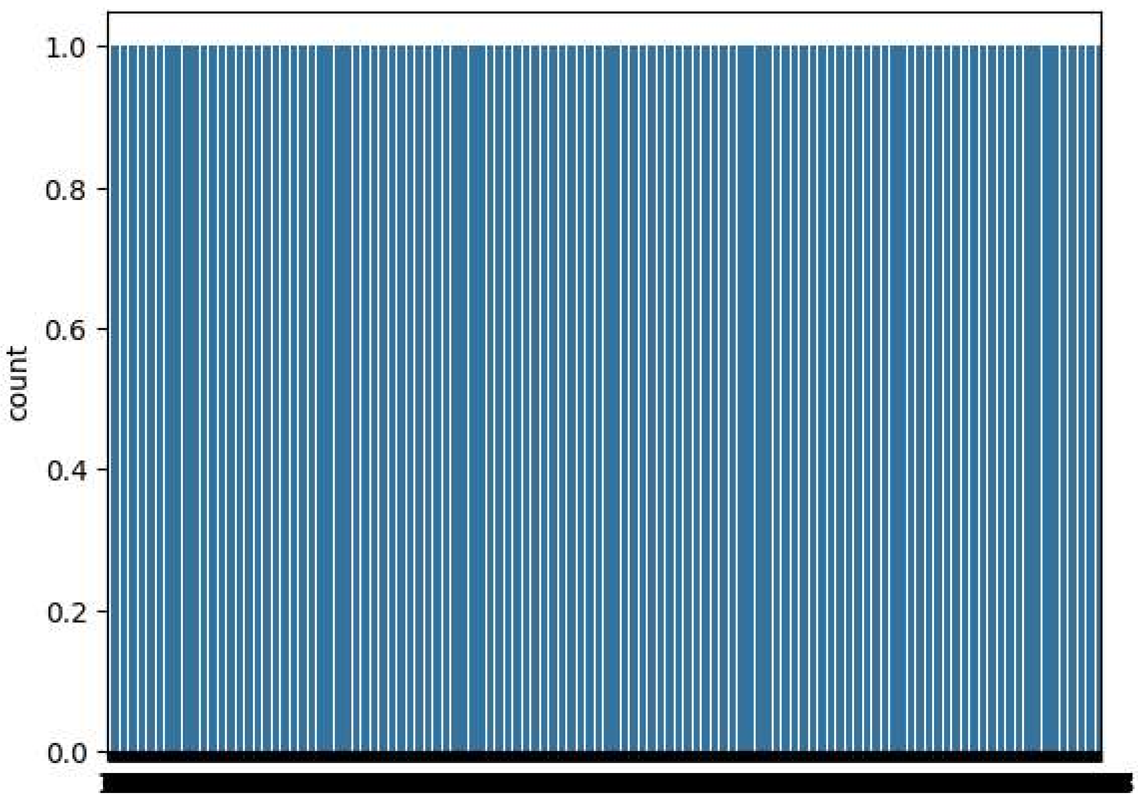
```
#Bad becomes 0 and good becomes 1
wine['quality'] = label_quality.fit_transform(wine['quality'])
```

```
wine['quality'].value_counts()
```

```
quality
0    1382
1     217
Name: count, dtype: int64
```

```
sns.countplot(wine['quality'])
```

```
<Axes: ylabel='count'>
```




```
#Now seperate the dataset as response variable and feature variabes
X = wine.drop('quality', axis = 1)
y = wine['quality']
```

```
#Train and Test splitting of data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 42

#Applying Standard scaling to get optimized result
sc = StandardScaler()

X_train = sc.fit_transform(X_train)
X_test = sc.fit_transform(X_test)

rfc = RandomForestClassifier(n_estimators=200)
rfc.fit(X_train, y_train)
pred_rfc = rfc.predict(X_test)

#Let's see how our model performed
print(classification_report(y_test, pred_rfc))
```

```
              precision    recall  f1-score   support

           0       0.90      0.96      0.93       273
           1       0.64      0.38      0.48        47

    accuracy                           0.88       320
   macro avg       0.77      0.67      0.71       320
weighted avg       0.86      0.88      0.86       320
```

```
#Confusion matrix for the random forest classification
print(confusion_matrix(y_test, pred_rfc))
```

```
[[263  10]
 [ 29  18]]
```

```
#Stochastic Gradient Decent Classifier
sgd = SGDClassifier(penalty=None)
sgd.fit(X_train, y_train)
pred_sgd = sgd.predict(X_test)

print(classification_report(y_test, pred_sgd))
```

```
              precision    recall  f1-score   support

           0       0.89      0.97      0.93       273
           1       0.62      0.32      0.42        47

    accuracy                           0.87       320
   macro avg       0.76      0.64      0.68       320
weighted avg       0.85      0.87      0.85       320
```

```
print(confusion_matrix(y_test, pred_sgd))
```

```
[[264   9]
 [ 32  15]]
```

```
#Support vector classifier
svc = SVC()
svc.fit(X_train, y_train)
pred_svc = svc.predict(X_test)
```

```
print(classification_report(y_test, pred_svc))
```

```
              precision    recall  f1-score   support

           0       0.88      0.98      0.93       273
           1       0.71      0.26      0.37        47

    accuracy                           0.88       320
   macro avg       0.80      0.62      0.65       320
weighted avg       0.86      0.88      0.85       320
```

```
#grid search CV
#Finding best parameters for our SVC model
param = {
    'C': [0.1,0.8,0.9,1,1.1,1.2,1.3,1.4],
    'kernel':['linear', 'rbf'],
    'gamma' :[0.1,0.8,0.9,1,1.1,1.2,1.3,1.4]
}
```