Red Wine Quality Prediction

```
  #importing required packages
   import pandas as pd import
       numpy as np import
matplotlib.pyplot as plt import
        seaborn as sns
from sklearn.model_selection import train_test_split,GridSearchCV,
cross_val_score
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score from
sklearn.tree import DecisionTreeClassifier

#loading dataset
data=pd.read_csv("C:\\Users\\mathi\\Downloads\\winequality-red.csv")
data
```

```
      fixed acidity   volatile acidity   citric acid   residual sugar
chlorides  \
0               7.4              0.700         0.00              1.9
0.076
1               7.8              0.880         0.00              2.6
0.098
2               7.8              0.760         0.04              2.3
0.092
3              11.2               0.280         0.56              1.9
0.075
4               7.4              0.700         0.00              1.9
0.076
...              ...                 ...           ...               ...
...
1594            6.2              0.600         0.08              2.0
0.090
1595            5.9              0.550         0.10              2.2
0.062
1596            6.3              0.510         0.13              2.3
0.076
1597            5.9              0.645         0.12              2.0
0.075
1598            6.0              0.310         0.47              3.6
0.067

      free sulfur dioxide  total sulfur dioxide  density   pH  sulphates
\
0                    11.0                  34.0  0.99780  3.51
0.56
```

1	25.0	67.0	0.99680	3.20	0.68
2	15.0	54.0	0.99700	3.26	0.65

```
3     17.0                  60.0  0.99800  3.16
0.58
4     11.0                  34.0  0.99780  3.51       0.56
...                    ...                   ...      ...   ...
...
1594                  32.0                  44.0  0.99490  3.45
0.58
1595                  39.0                  51.0  0.99512  3.52
0.76
1596                  29.0                  40.0  0.99574  3.42
0.75
1597                  32.0                  44.0  0.99547  3.57
0.71
1598                  18.0                  42.0  0.99549  3.39
0.66
      alcohol
quality
0          9.4
           5
1          9.8
           5
2          9.8
           5
3          9.8
           6
4          9.4
           5
...        ...
...
1594      10.5
          5
1595      11.2
          6
1596      11.0
          6
1597      10.2
          5
1598      11.0
          6
[1599   rows   x   12
columns]
data.head()
   fixed acidity  volatile acidity  citric acid  residual sugar
chlorides  \

0            7.4              0.70         0.00             1.9
0.076
1            7.8              0.88         0.00             2.6
```

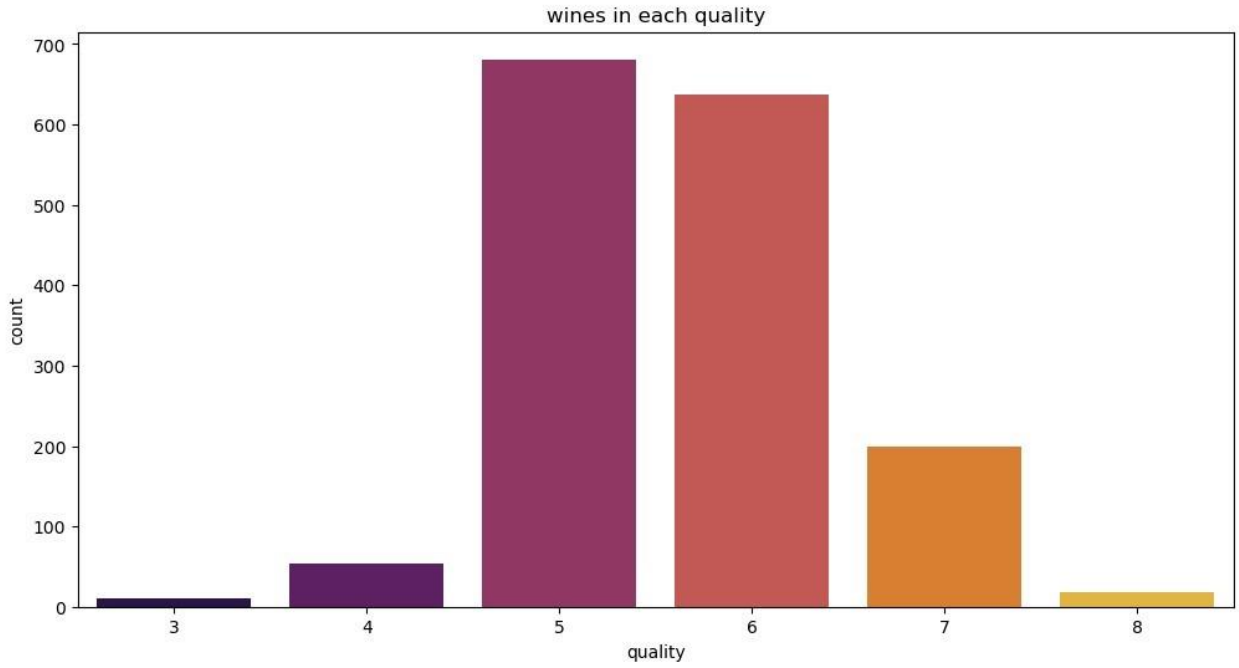
```
   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates
                                                                       
                  11.0                  34.0   0.9978  3.51       0.56
0.098
2             7.8               0.76         0.04              2.3
0.092
3            11.2               0.28         0.56              1.9
0.075
4             7.4               0.70         0.00              1.9
0.076
\
0
```

```
1                  25.0                  67.0   0.9968  3.20       0.68

2                  15.0                  54.0   0.9970  3.26       0.65

3                  17.0                  60.0   0.9980  3.16       0.58

4                  11.0                  34.0   0.9978  3.51       0.56


   alcohol  quality  0
9.4        5
1      9.8        5
2      9.8        5
3      9.8        6  4      9.4        5

data.shape (1599,

12) data.describe()

       fixed acidity  volatile acidity  citric acid  residual sugar  \
count     1599.000000       1599.000000  1599.000000     1599.000000
mean         8.319637          0.527821     0.270976        2.538806
std          1.741096          0.179060     0.194801        1.409928
min          4.600000          0.120000     0.000000        0.900000
25%          7.100000          0.390000     0.090000        1.900000
50%          7.900000          0.520000     0.260000        2.200000
75%          9.200000          0.640000     0.420000        2.600000
max         15.900000          1.580000     1.000000       15.500000

         chlorides    free  sulfur  dioxide    total  sulfur  dioxide
density  \
count  1599.000000          1599.000000           1599.000000
1599.000000
mean      0.087467            15.874922             46.467792
0.996747
std       0.047065            10.460157             32.895324
0.001887
min       0.012000             1.000000              6.000000
0.990070
25%       0.070000             7.000000             22.000000
0.995600
50%       0.079000            14.000000             38.000000
0.996750
75%       0.090000            21.000000             62.000000
0.997835
max       0.611000           72.000000           289.000000    1.003690
                pH    sulphates      alcohol      quality
count  1599.000000  1599.000000  1599.000000  1599.000000
mean      3.311113     0.658149    10.422983     5.636023  std
0.154386     0.169507     1.065668     0.807569  min
```

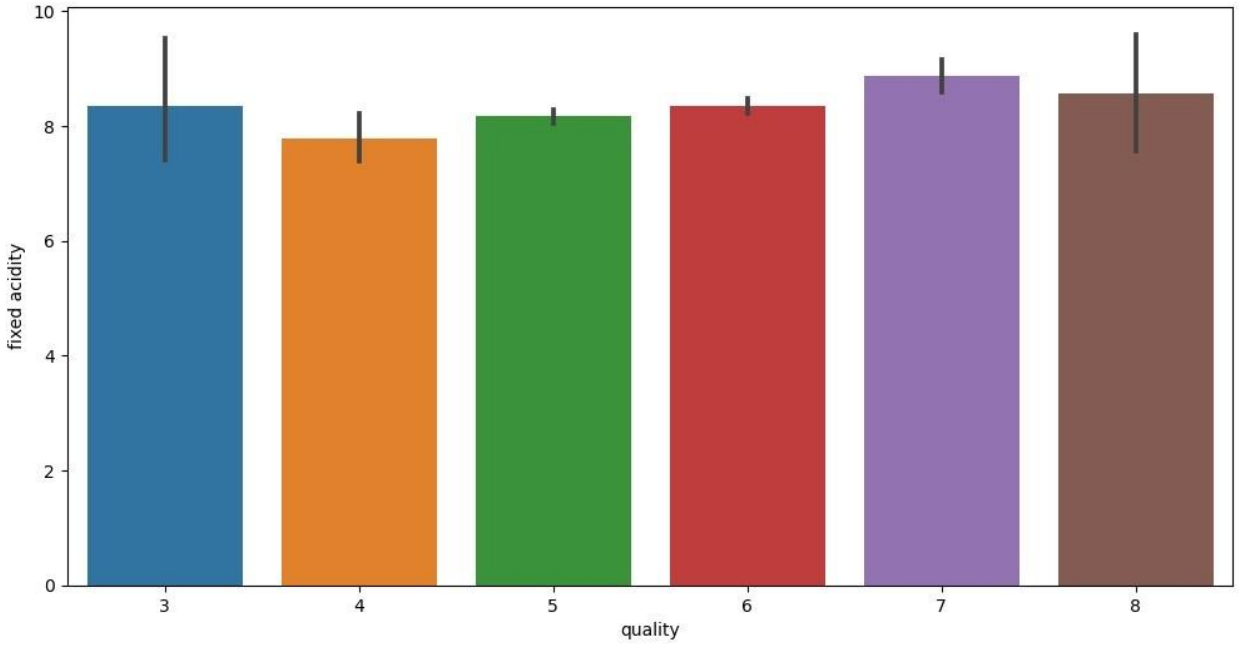
```
2.740000     0.330000     8.400000     3.000000  25%
3.210000     0.550000     9.500000     5.000000
50%       3.310000     0.620000    10.200000     6.000000  75%
3.400000     0.730000    11.100000     6.000000  max
4.010000     2.000000    14.900000     8.000000  data.info()

<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
```

```
plt.figure(figsize=(12,6))
sns.countplot(x='quality',data=data,palette='inferno')
plt.title('wines in each quality')
```

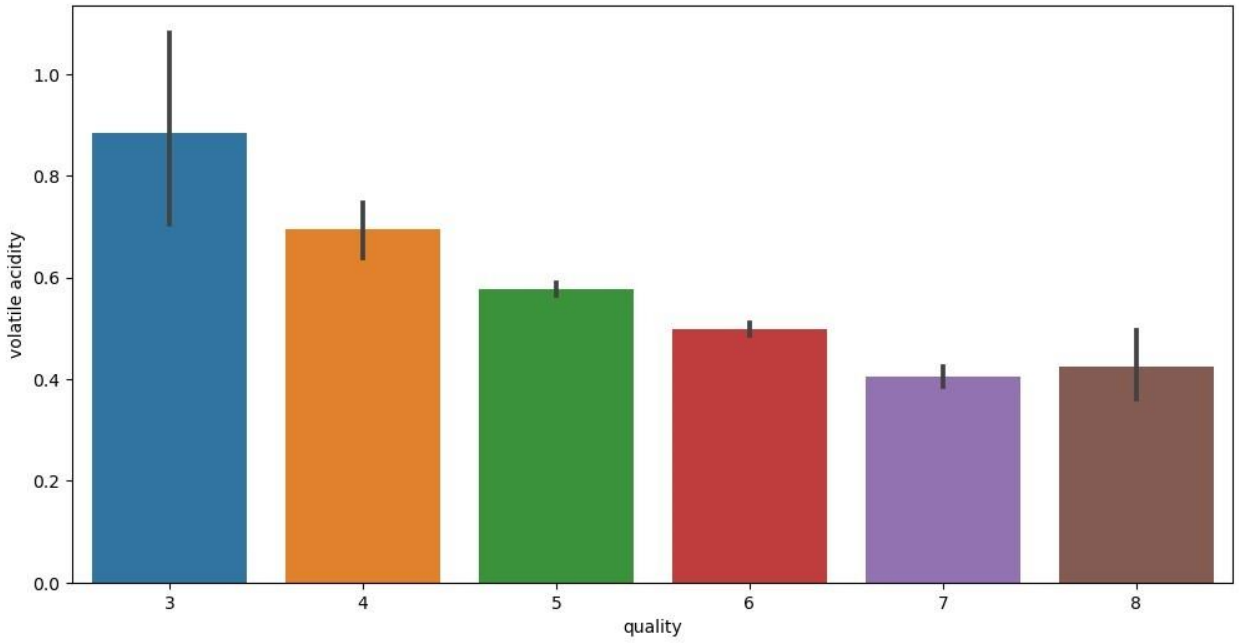
```
Text(0.5, 1.0, 'wines in each quality')
```



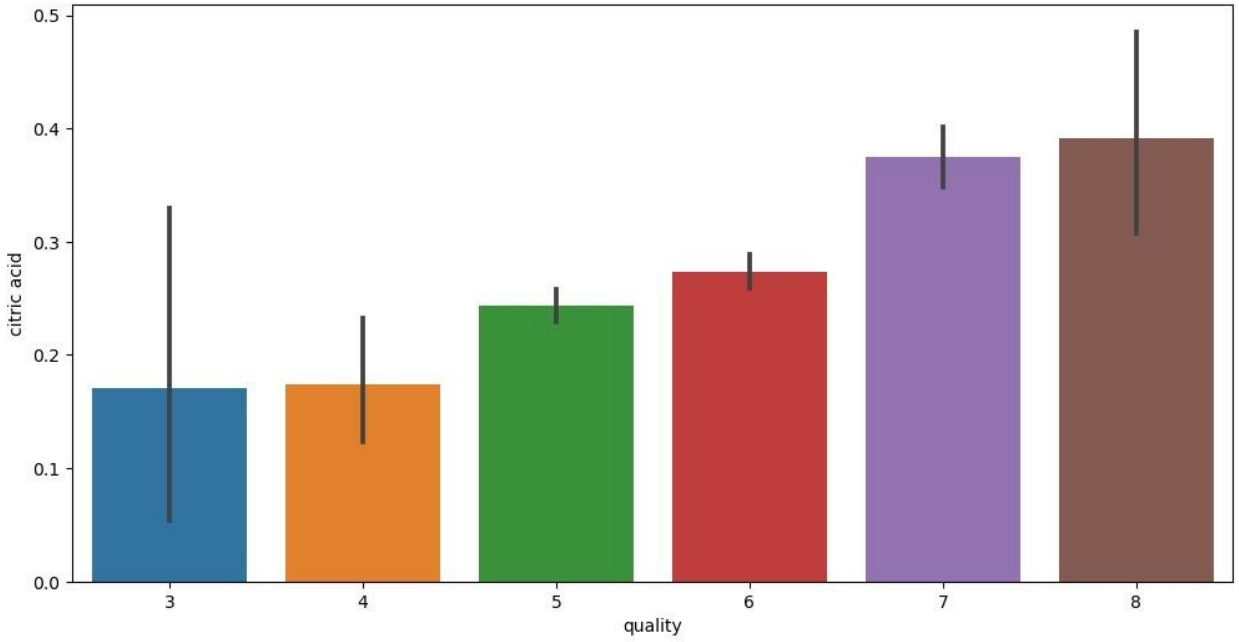

```
plt.figure(figsize=(12,6))
sns.barplot(x='quality',y='fixed acidity',data=data)
plt.show()
```



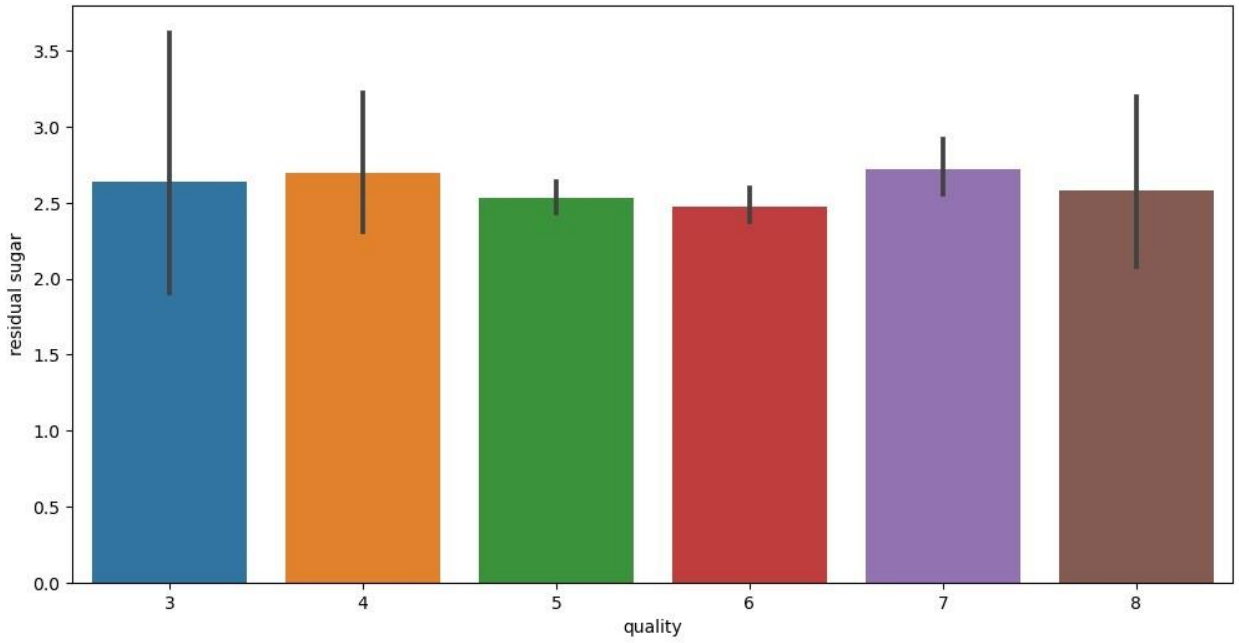

```
plt.figure(figsize=(12,6))
sns.barplot(x='quality',y='volatile acidity',data=data)
plt.show()
```



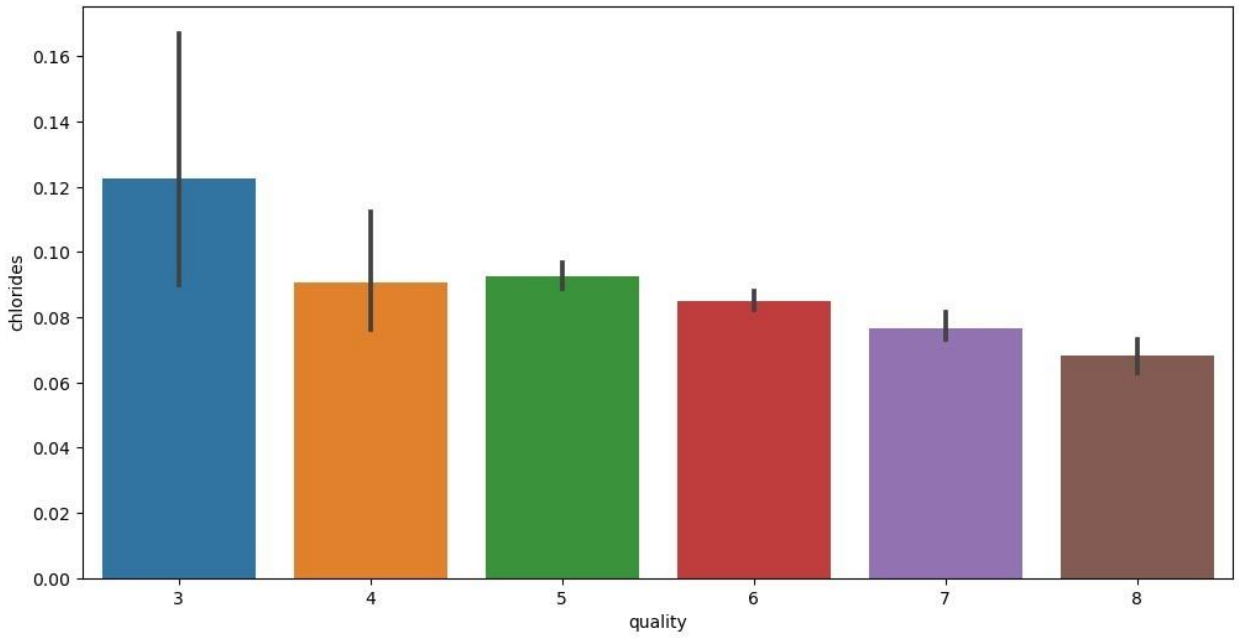

```
plt.figure(figsize=(12,6))
sns.barplot(x='quality',y='citric acid',data=data)
plt.show()
```



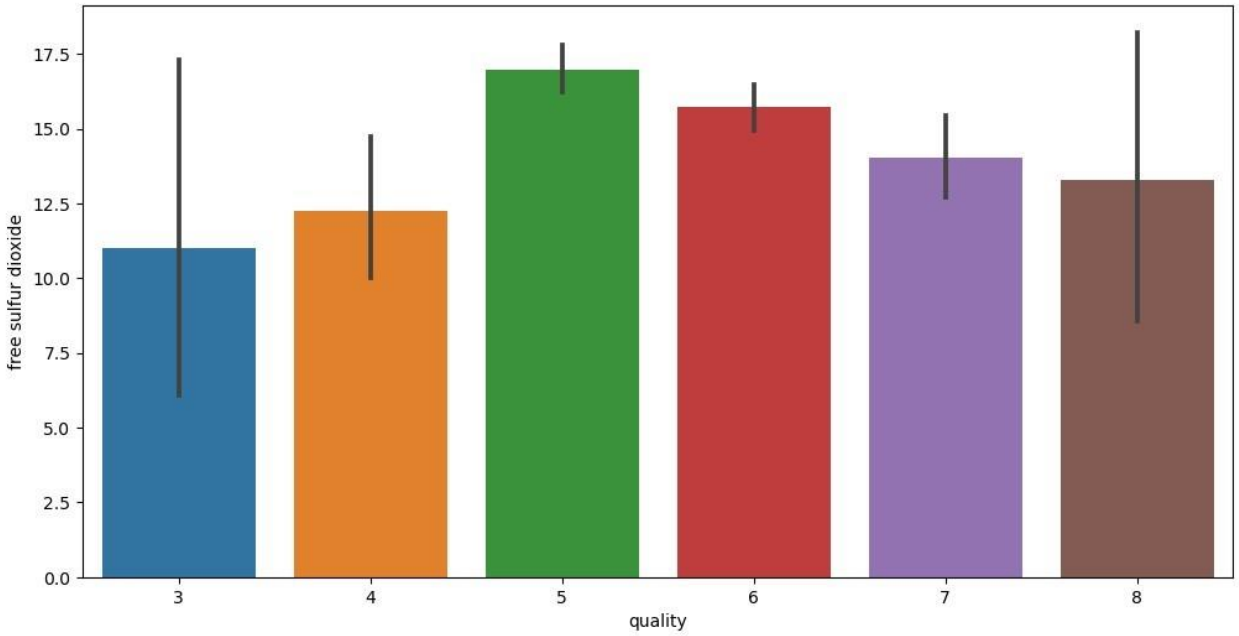

```
plt.figure(figsize=(12,6))
sns.barplot(x='quality',y='residual sugar',data=data)
plt.show()
```



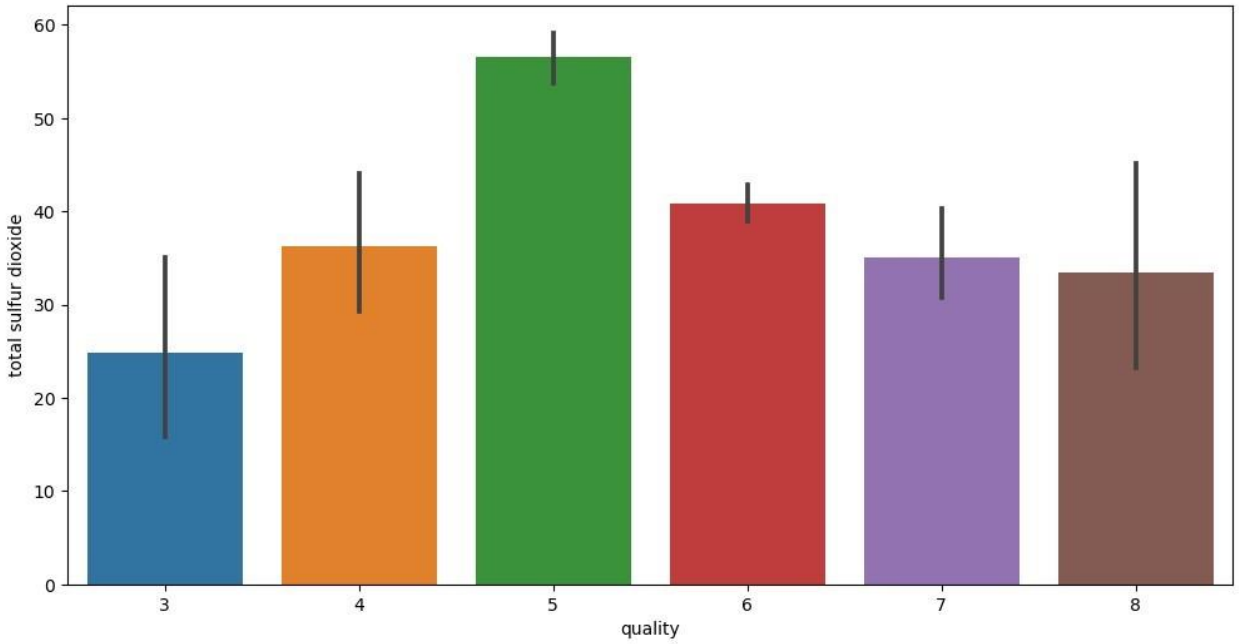

```
plt.figure(figsize=(12,6))
sns.barplot(x='quality',y='chlorides',data=data)
plt.show()
```



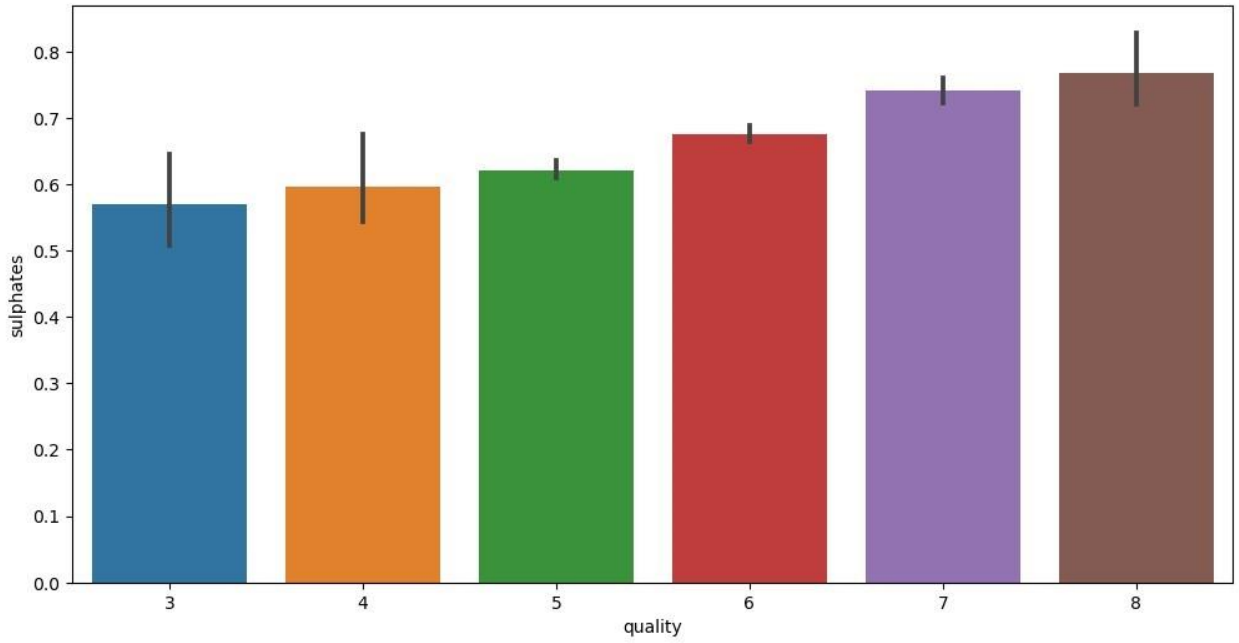

```
plt.figure(figsize=(12,6))
sns.barplot(x='quality',y='free sulfur dioxide',data=data)
plt.show()
```



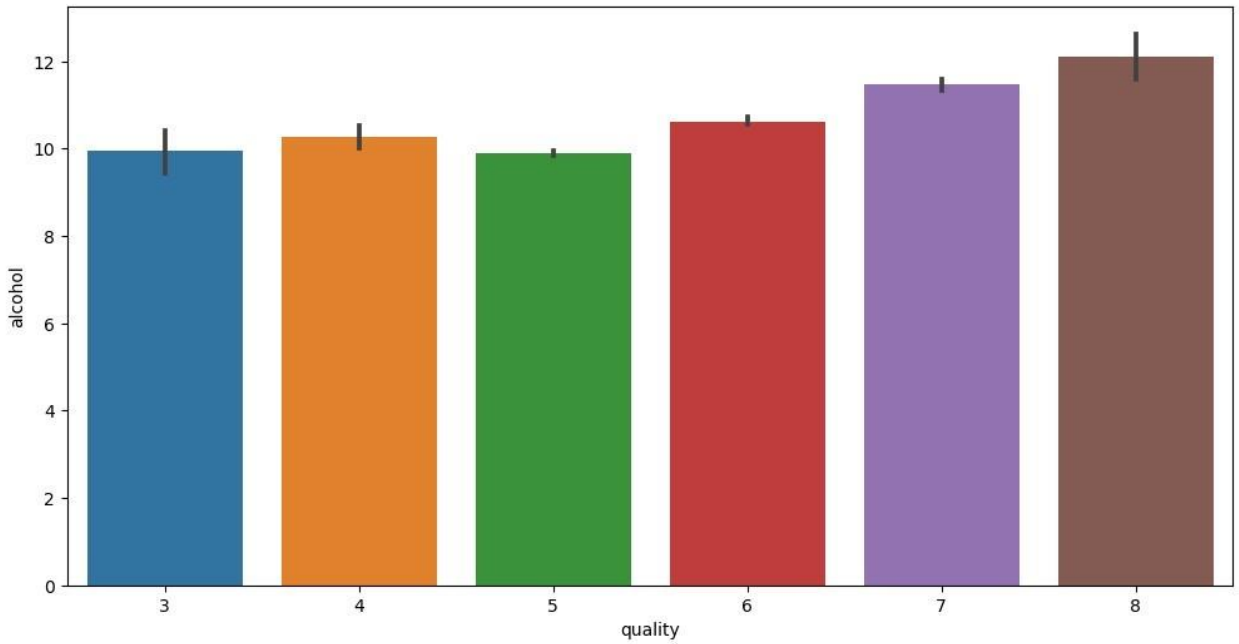

```
plt.figure(figsize=(12,6))
sns.barplot(x='quality',y='total sulfur dioxide',data=data)
plt.show()
```



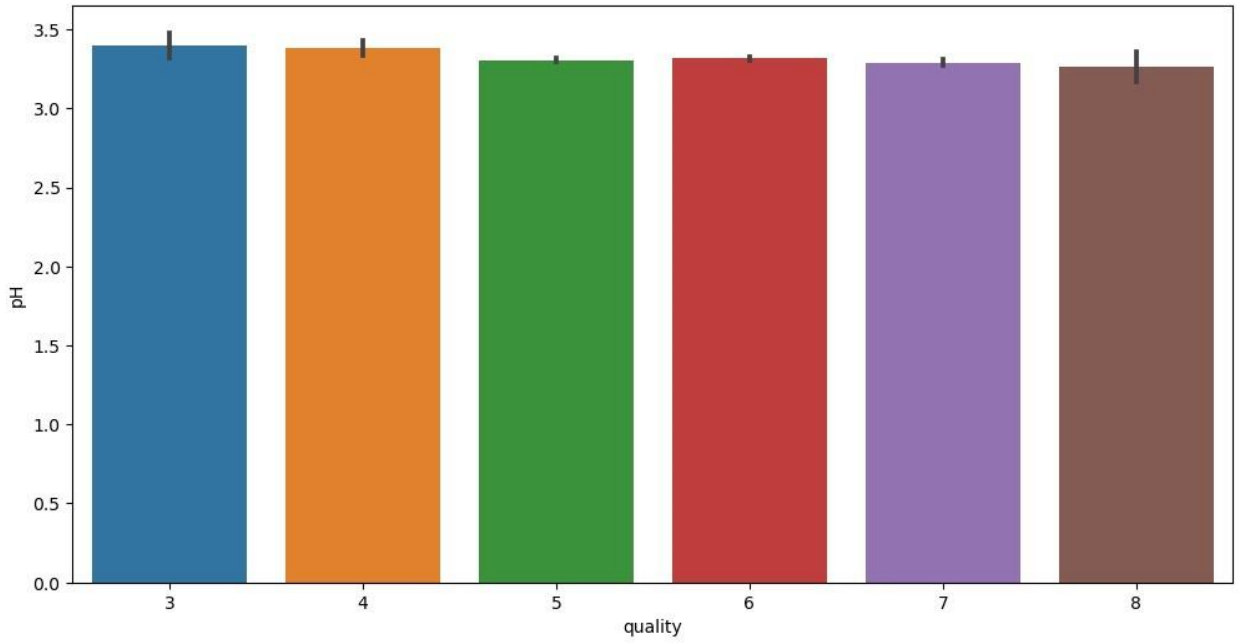

```
plt.figure(figsize=(12,6))
sns.barplot(x='quality',y='sulphates',data=data)
plt.show()
```



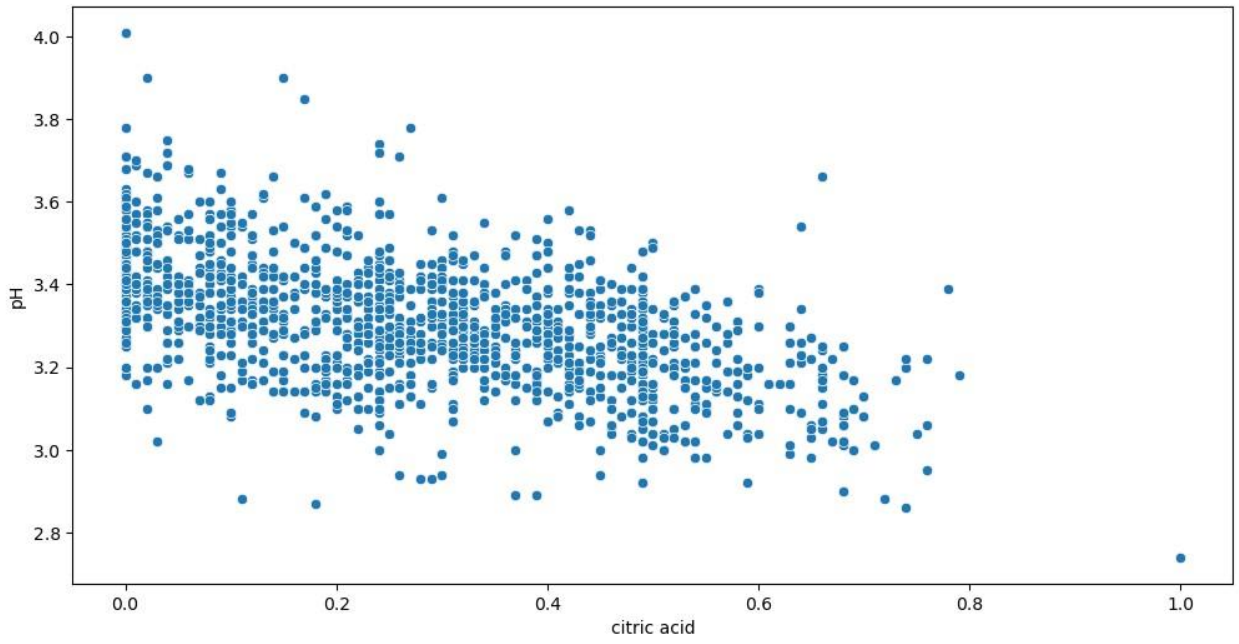

```
plt.figure(figsize=(12,6))
sns.barplot(x='quality',y='alcohol',data=data)
plt.show()
```




```
plt.figure(figsize=(12,6))
sns.barplot(x='quality',y='pH',data=data)
plt.show()
```

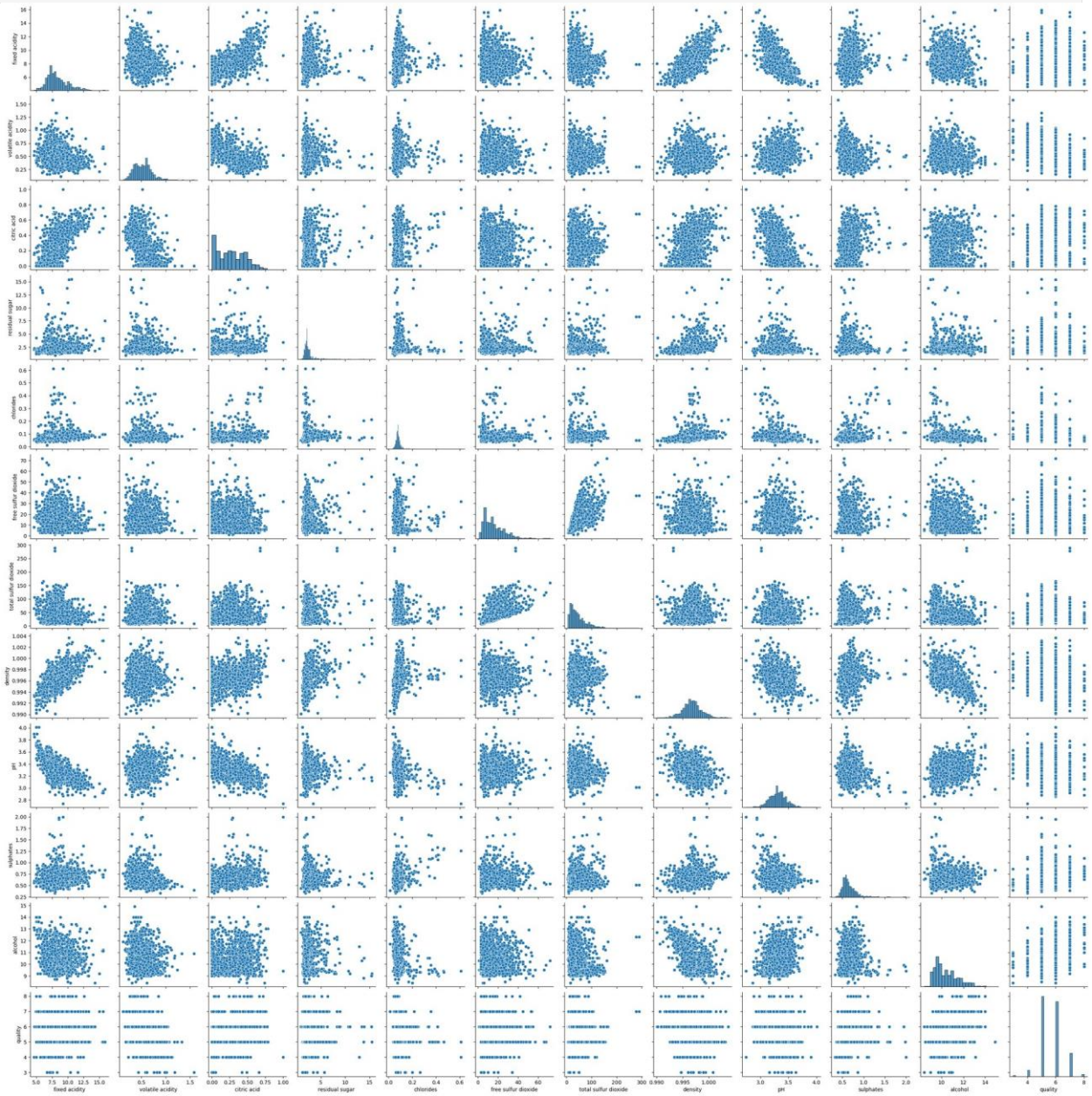



```
plt.figure(figsize=(12,6))
sns.scatterplot(x='citric acid',y='pH',data=data)
plt.show()
```

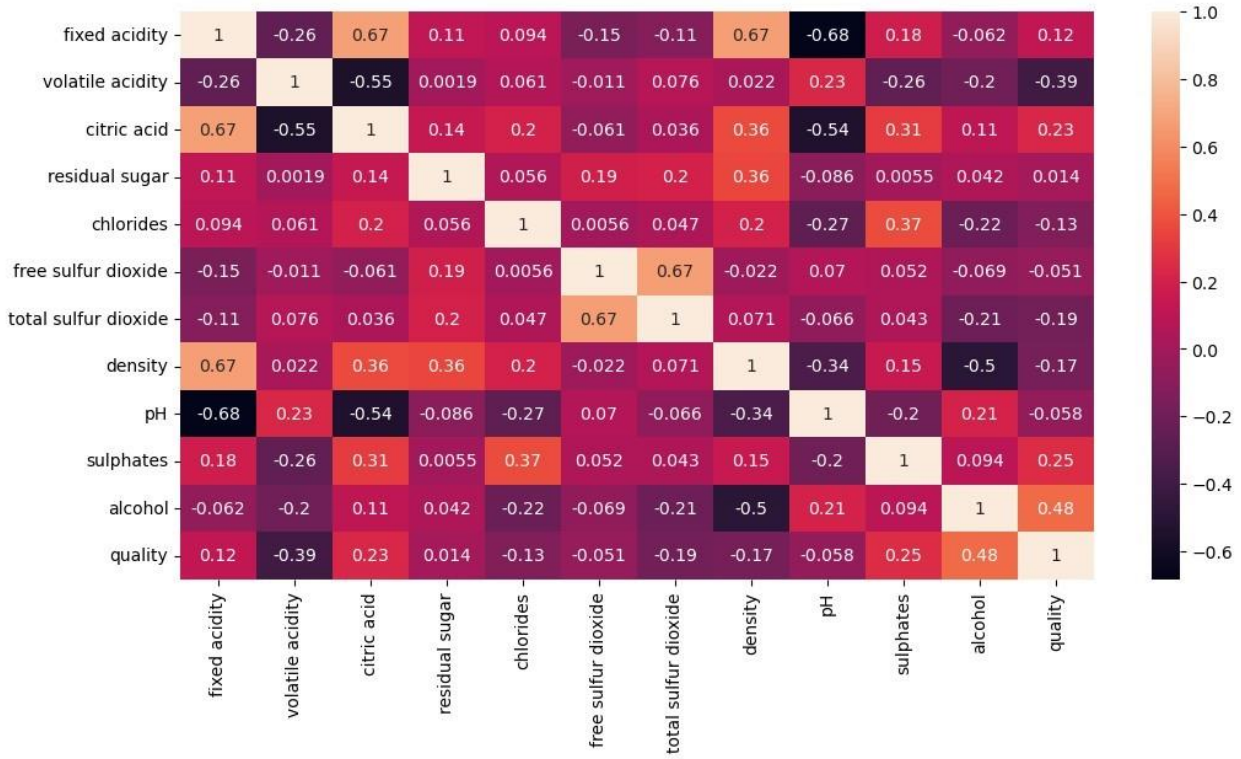



```
plt.figure(figsize=(12,6))
sns.pairplot(data)
plt.show()
```

```
D:\Users\mathi\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)

<Figure size 1200x600 with 0 Axes>
```

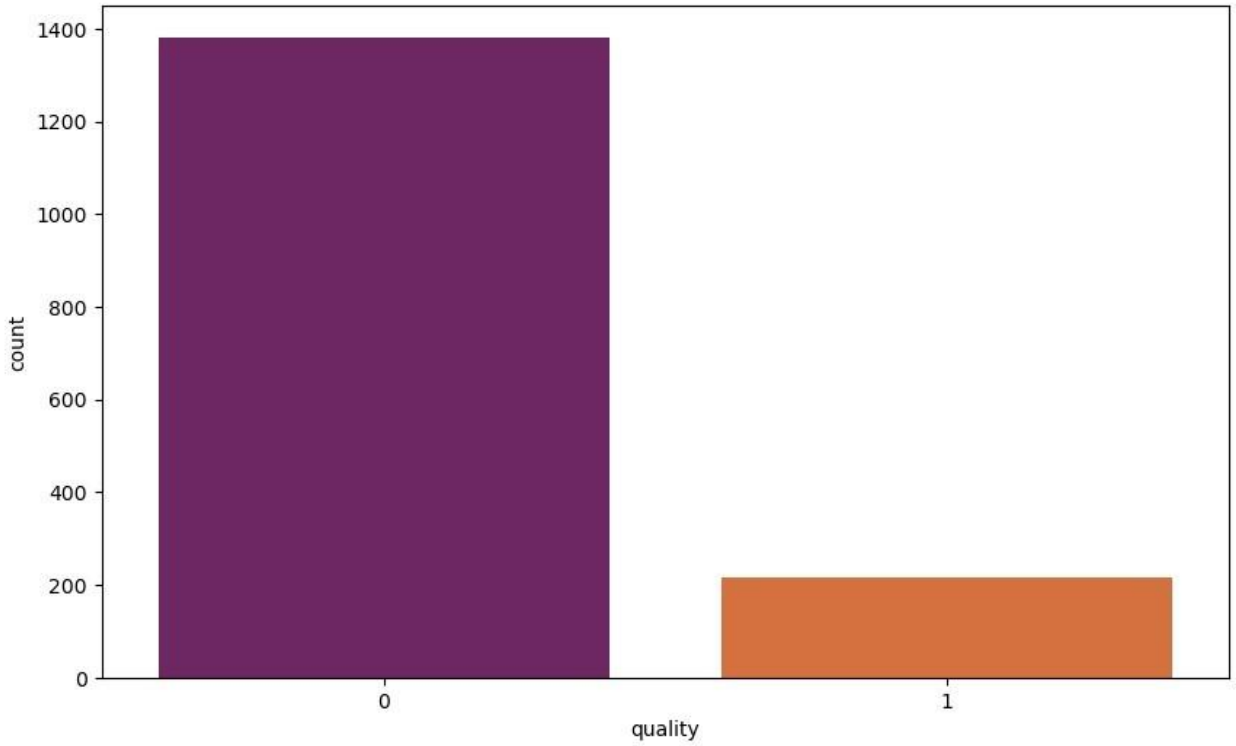



```
plt.figure(figsize=(12,6))
sns.heatmap(data.corr(),annot=True)
plt.show()
```


fixed acidity 1 -0.26 0.67 0.11 0.094 -0.15 -0.11 0.67 -0.68 0.18 -0.062 0.12
volatile acidity -0.26 1 -0.55 0.0019 0.061 -0.011 0.076 0.022 0.23 -0.26 -0.2 -0.39
citric acid 0.67 -0.55 1 0.14 0.2 -0.061 0.036 0.36 -0.54 0.31 0.11 0.23
residual sugar 0.11 0.0019 0.14 1 0.056 0.19 0.2 0.36 -0.086 0.0055 0.042 0.014
chlorides 0.094 0.061 0.2 0.056 1 0.0056 0.047 0.2 -0.27 0.37 -0.22 -0.13
free sulfur dioxide -0.15 -0.011 -0.061 0.19 0.0056 1 0.67 -0.022 0.07 0.052 -0.069 -0.051
total sulfur dioxide -0.11 0.076 0.036 0.2 0.047 0.67 1 0.071 -0.066 0.043 -0.21 -0.19
density 0.67 0.022 0.36 0.36 0.2 -0.022 0.071 1 -0.34 0.15 -0.5 -0.17
pH -0.68 0.23 -0.54 -0.086 -0.27 0.07 -0.066 -0.34 1 -0.2 0.21 -0.058
sulphates 0.18 -0.26 0.31 0.0055 0.37 0.052 0.043 0.15 -0.2 1 0.094 0.25
alcohol -0.062 -0.2 0.11 0.042 -0.22 -0.069 -0.21 -0.5 0.21 0.094 1 0.48
quality 0.12 -0.39 0.23 0.014 -0.13 -0.051 -0.19 -0.17 -0.058 0.25 0.48 1
fixed acidity
volatile acidity
citric acid
residual sugar
chlorides
free sulfur dioxide
total sulfur dioxide
density
pH
sulphates
alcohol
quality
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6

```
#preprocessing the data

data['quality'].value_counts()

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

#classifying the wine quality as good or bad based on its quality
#bad or 0 if quality lies in (3,6)
#good or 1 if quality lies in (7,8)

data['quality']=data['quality'].apply(lambda x:1 if x>6.5 else 0)
data.head()
   fixed acidity  volatile acidity  citric acid  residual sugar
chlorides  \

0            7.4              0.70         0.00             1.9
0.076
1            7.8              0.88         0.00             2.6
0.098
2            7.8              0.76         0.04             2.3
```

```
0.092
3            11.2               0.28         0.56              1.9
0.075
4             7.4               0.70         0.00              1.9
0.076
   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates


                  11.0                  34.0   0.9978  3.51       0.56

\
0

1     25.0                  67.0   0.9968  3.20       0.68

2     15.0                  54.0   0.9970  3.26       0.65 3
17.0                  60.0   0.9980  3.16       0.58 4
11.0                  34.0   0.9978  3.51       0.56
   alcohol  quality
0      9.4        0
1      9.8        0
2      9.8        0
3      9.8        0
4      9.4        0
print(data['quality'].value_counts())
fig=plt.figure(figsize=(10,6))
sns.countplot(x='quality',data=data,palette='inferno')
quality

0     1382
1     217
Name: count, dtype: int64
<Axes: xlabel='quality', ylabel='count'>
```




```
#separating to dependent and independent variables

x=data.drop(['quality'],axis=1)
y=data['quality']

x
```

```
      fixed acidity  volatile acidity  citric acid  residual sugar
chlorides  \
0               7.4             0.700         0.00             1.9
0.076
1               7.8             0.880         0.00             2.6
0.098
2               7.8             0.760         0.04             2.3
0.092
3              11.2             0.280         0.56             1.9
0.075
4               7.4             0.700         0.00             1.9
0.076
...             ...               ...          ...             ...
...
1594            6.2             0.600         0.08             2.0
0.090
1595            5.9             0.550         0.10             2.2
0.062
1596            6.3             0.510         0.13             2.3
0.076
```

```
1597            5.9             0.645         0.12             2.0
0.075
1598            6.0             0.310         0.47             3.6
0.067

      free sulfur dioxide  total sulfur dioxide  density   pH  sulphates
\
0                    11.0                  34.0  0.99780  3.51
0.56
1                    25.0                  67.0  0.99680  3.20
0.68
2                    15.0                  54.0  0.99700  3.26
0.65
3                    17.0                  60.0  0.99800  3.16
0.58
4                    11.0                  34.0  0.99780  3.51
0.56
...                   ...                   ...      ...   ...
...
1594                 32.0                  44.0  0.99490  3.45
0.58
1595                 39.0                  51.0  0.99512  3.52
0.76
1596                 29.0                  40.0  0.99574  3.42
0.75
1597                 32.0                  44.0  0.99547  3.57
0.71
1598                 18.0                  42.0  0.99549  3.39
0.66

      alcohol
0         9.4
1         9.8
2         9.8
3         9.8
4         9.4  ...
...
1594     10.5
1595     11.2
1596     11.0
1597     10.2
1598     11.0

[1599 rows x 11 columns]

y

0       0
1       0
```

2 0

```
3     0
4     0
..
1594    0
1595    0
1596    0
1597    0
1598    0
Name: quality, Length: 1599, dtype: int64
#splitting into train and test sets x_train,x_test,y_train,y_test
=
train_test_split(x,y,test_size=0.2,random_state=42)

print("x-train shape:",x_train.shape) print("x-
test shape:",x_test.shape) print("y-train
shape:",y_train.shape) print("y-test
shape:",y_test.shape)

x-train shape: (1279, 11) x-
test shape: (320, 11) y-
train shape: (1279,) y-test
shape: (320,)

#applying standard scaling to the dataset to scale all the field
values to same scale(approx.) sc=StandardScaler()
x_train=sc.fit_transform(x_train)
x_test=sc.fit_transform(x_test)

#logisticregression

lr=LogisticRegression()
lr.fit(x_train,y_train)
predictions = lr.predict(x_test)
accuracy_score(y_test,predictions)
0.875
#decisiontreeclassifier

dt=DecisionTreeClassifier()
dt.fit(x_train,y_train)
accuracy_score(y_test,dt.predict(x_test))
0.853125
#randomforestclassifier

rf=RandomForestClassifier(random_state=42)
rf.fit(x_train,y_train)
accuracy_score(y_test,rf.predict(x_test))
```

```
0.875
```