Major Project - Corizo Wine Quality Analysis

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```
In [1]: #import all library which required
          import pandas as pd
          import numpy as np
          import seaborn as sns
          import matplotlib.pyplot as plt
          from sklearn.model_selection import train_test_split
          from sklearn.ensemble import RandomForestClassifier
          from sklearn.metrics import accuracy_score
          import warnings
          warnings.filterwarnings('ignore')
 In [4]: #Upload the dataset
          df = pd.read csv('C:/Users/cws/OneDrive/Desktop/Corico Data/1788410-1767134-1729261-1613779-Red wine.csv')
          df.head()
 Out[4]:
                 fixed
                            volatile
                                      citric
                                               residual
                                                                     free sulfur
                                                                                   total sulfur
                                                       chlorides
                                                                                              density
                                                                                                      pH sulphates alcohol quality
                acidity
                            acidity
                                      acid
                                                 sugar
                                                                        dioxide
                                                                                      dioxide
                                       0.00
                                                           0.076
                                                                                              0.9978 3.51
                   7.4
                                                    1.9
                                                                          11.0
                                                                                         34.0
                                                                                                                               5.0
                                      0.00
                   7.8
                              0.88
                                                   26
                                                           0.098
                                                                          25.0
                                                                                         67.0
                                                                                                               0.68
                                                                                                                        98
                                                                                                                               5.0
          1
                                                                                              0.9968 3.20
          2
                   7.8
                              0.76
                                       0.04
                                                   2.3
                                                           0.092
                                                                          15.0
                                                                                         54.0
                                                                                              0.9970 3.26
                                                                                                               0.65
                                                                                                                        9.8
                                                                                                                               5.0
                  11.2
                              0.28
                                       0.56
                                                    1.9
                                                           0.075
                                                                          17.0
                                                                                              0.9980 3.16
                                                                                                               0.58
                                                                                                                        9.8
                                                                                                                               6.0
                                                                                         60.0
                   7 4
                              0.70
                                       0.00
                                                    19
                                                           0.076
                                                                          11 0
                                                                                         34.0 0.9978 3.51
                                                                                                               0.56
                                                                                                                               5.0
                                                                                                                        94
 In [5]: #df.shape
          (1599, 12)
 Out[5]:
 In [9]: #Check the missing value in the data set
          df.isnull().sum()
          fixed acidity
                                    0
 Out[9]:
          volatile acidity
                                    0
          citric acid
                                    0
          residual sugar
                                     0
          chlorides
                                    0
          free sulfur dioxide
                                    0
          total sulfur dioxide
                                    1
          density
                                    0
          рΗ
                                    1
          sulphates
                                    0
                                    0
          alcohol
          quality
                                    1
          dtype: int64
In [17]:
          #drop all the null values
          Df=df.dropna()
In [20]:
          #To check again missing value
          Df.isnull().sum()
          fixed acidity
                                    0
Out[20]:
          volatile acidity
                                    0
          citric acid
                                     0
                                    0
          residual sugar
          chlorides
                                    0
          free sulfur dioxide
                                    0
          total sulfur dioxide
                                    0
          density
                                    0
          рΗ
                                    0
          sulphates
                                    0
          alcohol
                                    0
                                    0
          quality
          dtype: int64
```

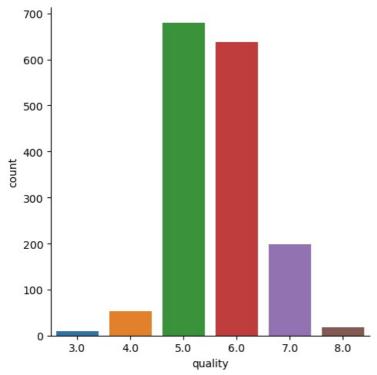
Data Analysis

Out[22]:		fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	
	count	1596.000000	1596.000000	1596.000000	1596.000000	1596.000000	1596.000000	1596.000000	1596.000000	1596.000000	1596.000000	1
	mean	8.321366	0.527666	0.271128	2.536936	0.087487	15.882206	46.431078	0.996745	3.498716	0.658189	
	std	1.742121	0.179154	0.194847	1.408341	0.047107	10.467380	32.893072	0.001889	0.080297	0.169587	
	min	4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.000000	0.990070	2.740000	0.330000	
	25%	7.100000	0.390000	0.090000	1.900000	0.070000	7.000000	22.000000	0.995600	3.520000	0.550000	
	50%	7.900000	0.520000	0.260000	2.200000	0.079000	14.000000	38.000000	0.996745	3.520000	0.620000	
	75%	9.200000	0.640000	0.420000	2.600000	0.090000	21.000000	62.000000	0.997842	3.520000	0.730000	
	max	15.900000	1.580000	1.000000	15.500000	0.611000	72.000000	289.000000	1.003690	3.900000	2.000000	

```
In [70]: #To check number of values
plt.figure(figsize=(12,6))
sns.catplot(x='quality', data=Df, kind='count')
plt.show()
```

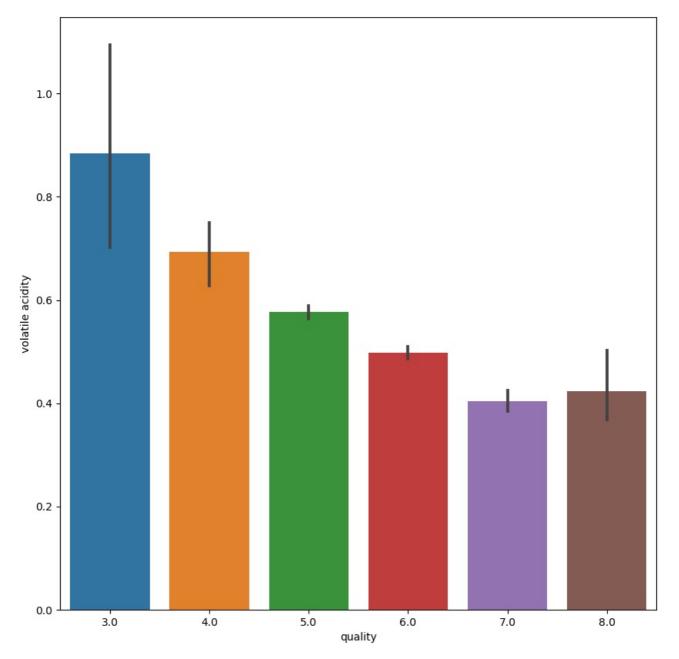
<Figure size 1200x600 with 0 Axes>

4



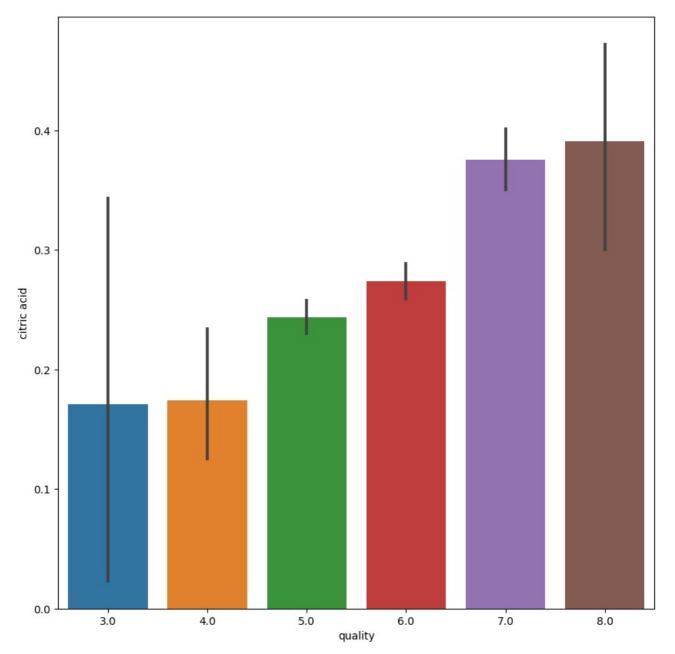
```
In [66]: #volatil acidity vs quality
plot = plt.figure(figsize=(10,10))
sns.barplot(x='quality', y='volatile acidity', data = Df)
```

Out[66]: <Axes: xlabel='quality', ylabel='volatile acidity'>



```
In [76]: #volatil acidity vs quality
plt.figure(figsize=(10,10))
sns.barplot(x='quality', y='citric acid', data = df)
```

Out[76]: <Axes: xlabel='quality', ylabel='citric acid'>

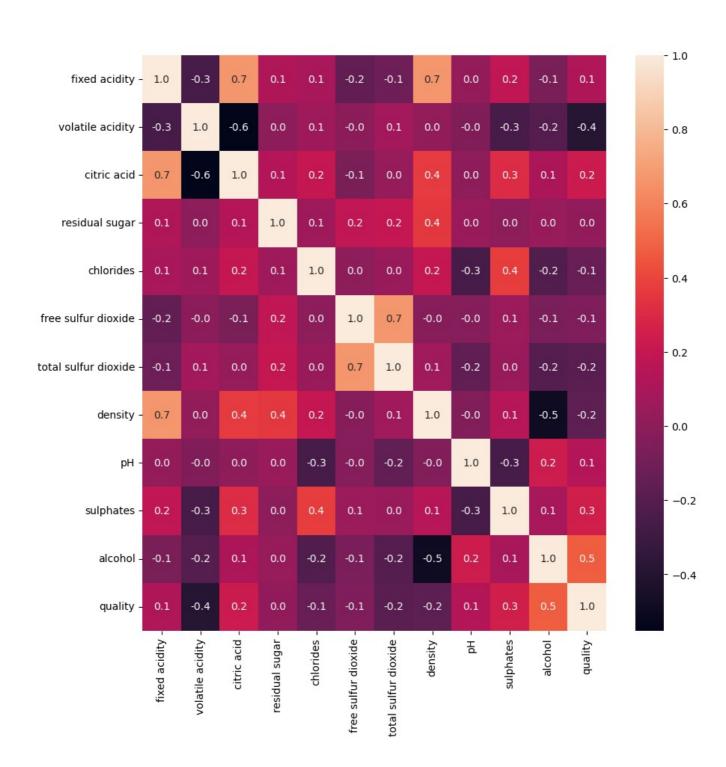


```
In [72]: #correlation between variables
    correlation = df.corr()

In [73]: #constructing heatmap to see the correlation
    plt.figure(figsize=(10,10))
    sns.heatmap(correlation, annot = True, fmt = '0.1f')

Out[73]: 

Axes: >
```



Data Processing

```
print(x)
               fixed acidity volatile acidity citric acid residual sugar chlorides \
                        7.4
                                        0.700
                                                       0.00
                                                                       1.9
                        7.8
         1
                                        0.880
                                                       0.00
                                                                        2.6
                                                                                 0.098
         2
                        7.8
                                        0.760
                                                       0.04
                                                                       2.3
                                                                                 0.092
         3
                                         0.280
                                                                                 0.075
                        7.4
                                        0.700
                                                      0.00
                                                                       1.9
                                                                                 0.076
         1594
                        6.2
                                        0.600
                                                      0.08
                                                                       2.0
                                                                                 0.090
                                        0.550
                                                       0.10
                                                                       2.2
                                                                                 0.062
         1596
                                        0.510
                                                                                 0.076
                         6.3
                                                       0.13
                                                                       2.3
         1597
                                        0.645
                                                       0.12
                                                                        2.0
                                                                                 0.075
         1598
                                        0.310
                                                       0.47
                                                                                 0.067
               free sulfur dioxide total sulfur dioxide density
                                                                    pH sulphates \
                                                    34.0 0.99780 3.51
         0
                              11.0
                                                                              0.56
                                                    67.0 0.99680
                                                                   3.20
         2
                              15.0
                                                    54.0 0.99700
                                                                  3.26
                                                                              0.65
         3
                              17.0
                                                    60.0 0.99800
                                                                  3.16
                                                                              0.58
                              11.0
         4
                                                    34.0 0.99780
                                                                              0.56
                              32.0
                                                    44.0 0.99490
                                                                  3.52
                                                                              0.58
         1594
         1595
                              39.0
                                                    51.0 0.99512
                                                                   3.52
                                                                              0.76
                                                                              0.75
         1596
                              29.0
                                                   40.0 0.99574
                                                                  3.52
                                                   44.0 0.99547
         1597
                              32.0
                                                                   3.52
                                                                              0.71
                                                   42.0 0.99549 3.52
         1598
                             18.0
                                                                              0.66
              alcohol
         0
                  9.4
         1
                   9.8
                  9.8
         3
                   9.8
         4
                  9.4
         1594
                  10.5
         1595
                  11.2
         1596
                  11.0
         1597
                  10.2
         1598
                  11.0
         [1596 rows x 11 columns]
In [79]: #Label encoding
         y = df['quality'].apply(lambda y_value: 1 if y_value>=7 else 0)
         print(y)
         0
                 0
                 0
         1
         2
                 0
         3
                 0
         4
         1594
                0
         1595
                0
         1596
                 0
         1597
                 0
         1598
         Name: quality, Length: 1596, dtype: int64
```

Train & Test Split

```
In [80]: x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state = 3)
         print(y.shape, y_train.shape, y_test.shape)
         (1596,) (1276,) (320,)
```

Model Training: Random Forest# Model Training: Random Forest

```
In [81]: model = RandomForestClassifier()
In [82]: from colorsys import yiq_to_rgb
         model.fit(x train, y train)
Out[82]: RandomForestClassifier
         RandomForestClassifier()
```

Model evaluation

```
In [83]: #Accuracy Score
            x_test_prediction = model.predict(x_test)
test_data_accuracy = accuracy_score(x_test_prediction, y_test)
            print('Accuracy: ', test_data_accuracy)
```

Accuracy: 0.909375

Building a Prediction System

```
In [85]: input_data = (7.8,0.58,0.02,2,0.073,9,18,0.9968,3.36,0.57,9.5)
         #changing input data into numpy array
         input_data_as_numpy_array = np.asarray(input_data)
         #reshaping the data as we are predicting the label for only one instance
         input_data_reshaped = input_data_as_numpy_array.reshape(1,-1)
         prediction = model.predict(input_data_reshaped)
         print(prediction)
         if (prediction[0]==1):
          print("Good Quality Wine")
          print("Bad Quality Wine")
         [1]
         Good Quality Wine
         Thanks
```

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