```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

```
df =pd.read_csv("/content/drive/MyDrive/SEM-5/ML/Evals/Eval2/winequality-red.csv")
```

```
df.head()
```

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulp
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	

```
df.columns
```

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

```
df.shape
```

```
(1599, 12)
```

```
df.size
```

```
19188
```

```
df.ndim
```

```
2
```

```
df.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
```

```
df.dtypes
```

```
fixed acidity           float64
volatile acidity        float64
citric acid             float64
residual sugar          float64
chlorides               float64
free sulfur dioxide     float64
total sulfur dioxide    float64
density                 float64
pH                      float64
sulphates               float64
alcohol                 float64
quality                   int64
dtype: object
```

```
df.value_counts()
```

```
fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  free sulfur dio
7.5            0.510             0.02         1.7             0.084      13.0
7.2            0.695             0.13         2.0             0.076      12.0
6.7            0.460             0.24         1.7             0.077      18.0
7.2            0.360             0.46         2.1             0.074      24.0
9.3            0.360             0.39         1.5             0.080      41.0

8.6            0.420             0.39         1.8             0.068      6.0
               0.450             0.31         2.6             0.086      21.0
               0.470             0.30         3.0             0.076      30.0
                                 0.47         2.4             0.074      7.0
4.6            0.520             0.15         2.1             0.054      8.0
Length: 1359, dtype: int64
```

```
df.describe()
```

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	d
count	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.
mean	8.319637	0.527821	0.270976	2.538806	0.087467	15.874922	46.
std	1.741096	0.179060	0.194801	1.409928	0.047065	10.460157	32.
min	4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.
25%	7.100000	0.390000	0.090000	1.900000	0.070000	7.000000	22.
50%	7.900000	0.520000	0.260000	2.200000	0.079000	14.000000	38.

```
df.isnull().sum()
```

```
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
```

Inference: From this we can say that there are no null values in the dataset

```
df.nunique()
```

```
fixed acidity           96
volatile acidity       143
citric acid             80
residual sugar          91
chlorides              153
free sulfur dioxide     60
total sulfur dioxide   144
density                436
pH                      89
sulphates               96
alcohol                 65
quality                  6
dtype: int64
```

```
print("Dulpicated values:",df.duplicated().sum())
```

```
Dulpicated values: 240
```

```
df.drop_duplicates(keep = 'first', inplace = True)
df.duplicated().sum()
```

```
0
```

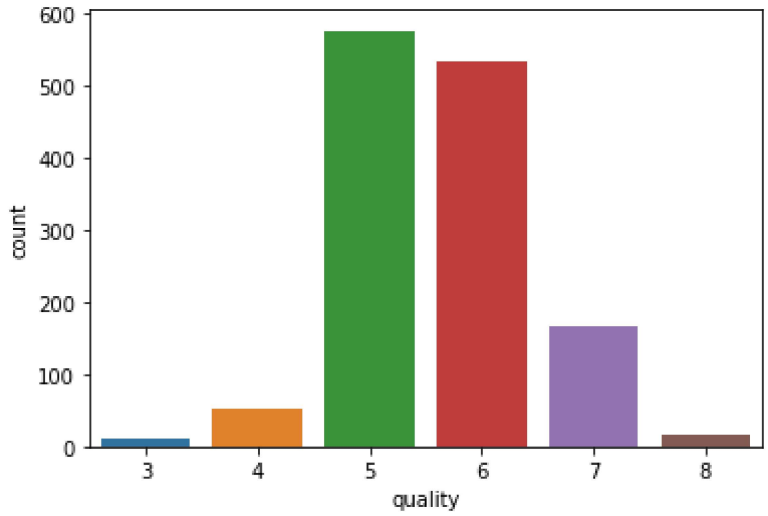
Inference: Removed duplicated values successfully

Data visualisation

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

```
5    577
6    535
7    167
4     53
8     17
3     10
Name: quality, dtype: int64
```

```
sns.countplot(x = 'quality',data = df)
plt.show()
```




```
bins = (2, 6.5, 8)
group_names = ['bad', 'good']
df['quality'] = pd.cut(df['quality'], bins = bins, labels = group_names)
```

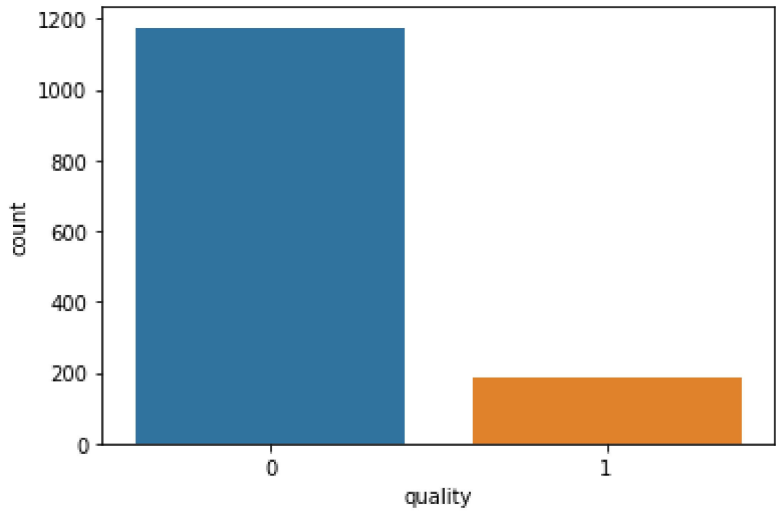
```
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
label_quality = LabelEncoder()
```

```
df['quality'] = label_quality.fit_transform(df['quality'])
```

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

```
0    1175
1     184
Name: quality, dtype: int64
```

```
sns.countplot(df['quality'])
plt.show()
```




```
X = df.drop('quality',axis=1)
y = df['quality']
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=12)
```

```
y_train.value_counts()
```

```
0    941
1    146
Name: quality, dtype: int64
```

```
y_test.value_counts()
```

```
0    234
1     38
Name: quality, dtype: int64
```

Feature Scaling

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.fit_transform(X_test)


model = []                                                                  # Model names
accuracy = []


from sklearn.linear_model import LogisticRegression                         # train a log
from sklearn import metrics
from sklearn import svm
from sklearn.metrics import classification_report

LogReg = LogisticRegression(random_state=2)                                 # instantiate
LogReg.fit(X_train,y_train)                                                 # fit model
predicted_values = LogReg.predict(X_test)                                   # make class
x = metrics.accuracy_score(y_test, predicted_values)
model.append('Logistic Regression')
accuracy.append(x*100)
print(classification_report(y_test, predicted_values))
print("Logistic Regression's Accuracy is: ", x*100)
```

```
                  precision    recall  f1-score   support

               0       0.90      0.97      0.93       234
               1       0.64      0.37      0.47        38

        accuracy                           0.88       272
       macro avg       0.77      0.67      0.70       272
    weighted avg       0.87      0.88      0.87       272

    Logistic Regression's Accuracy is:  88.23529411764706
```

```
from sklearn.tree import DecisionTreeClassifier

DecisionTree = DecisionTreeClassifier(criterion="entropy", random_state=2, max_depth=5)
DecisionTree.fit(X_train, y_train)
predicted_values = DecisionTree.predict(X_test)
x = metrics.accuracy_score(y_test, predicted_values)
model.append('Decision Tree')
accuracy.append(x*100)
print(classification_report(y_test, predicted_values))
print("Decision Trees Accuracy is: ", x*100)
```

```
                  precision    recall  f1-score   support

               0       0.88      0.97      0.92       234
               1       0.53      0.21      0.30        38
```

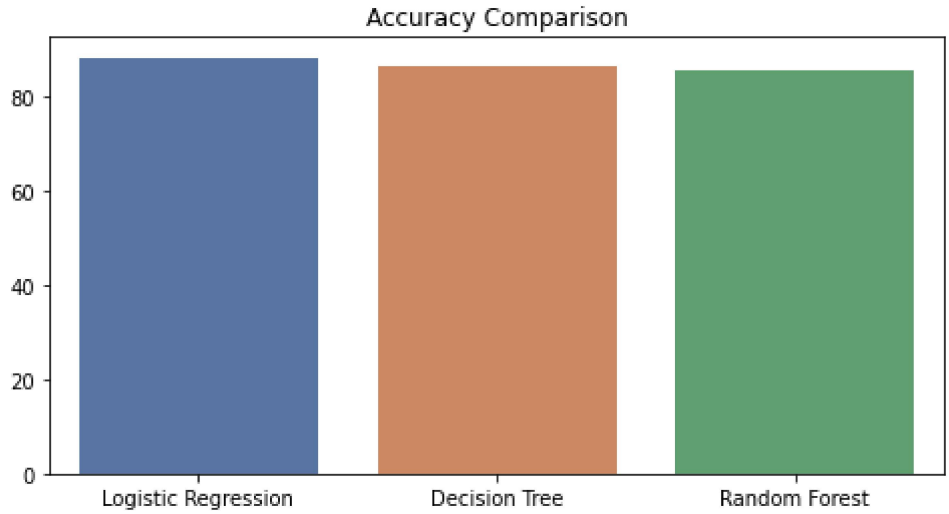
```
          accuracy                           0.86       272
         macro avg       0.71      0.59      0.61       272
      weighted avg       0.83      0.86      0.84       272

      Decision Trees Accuracy is:  86.39705882352942
```

```
from sklearn.ensemble import RandomForestClassifier

RF = RandomForestClassifier(n_estimators=20, random_state=0)
RF.fit(X_train,y_train)
predicted_values = RF.predict(X_test)
x = metrics.accuracy_score(y_test, predicted_values)
accuracy.append(x*100)
model.append('Random Forest')
print(classification_report(y_test,predicted_values))
print("RF's Accuracy is: ", x*100)
```

```
                  precision    recall  f1-score   support

               0       0.89      0.95      0.92       234
               1       0.48      0.26      0.34        38

          accuracy                           0.86       272
         macro avg       0.68      0.61      0.63       272
      weighted avg       0.83      0.86      0.84       272

      RF's Accuracy is:  85.66176470588235
```

```
plt.figure(figsize=(8,4))
plt.title('Accuracy Comparison')
sns.barplot(x=model, y=accuracy, palette='deep')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6236cfd510>
```




```
y_predicted = RF.predict(X_test)
```

```
print('True:', y_test[0:25])                                                    # print the f
print('Pred:', y_predicted[0:25])
```

```
True: 397    0
1071    0
440     1
219     0
613     0
896     1
935     0
30      0
804     0
263     0
1107    1
1503    0
412     0
344     0
687     0
1034    0
1248    0
621     0
1190    0
602     0
192     0
12      0
1400    0
858     1
414     0
Name: quality, dtype: int64
Pred: [0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
```

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test,y_predicted)
cm
```

```
array([[223,  11],
       [ 28,  10]])
```

```
plt.figure(figsize = (7,6))
sns.heatmap(cm, annot=True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

```
Text(42.0, 0.5, 'Truth')
```

Observation:

- In above matrix, X axis contains `predicted values`, and Y axis contains `actual values`.
- Each value of matrix show the number of times predicted value matched with actual value.

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