```
In [1]: # importing necessary Libraries
   import pandas as pd
   import numpy as np
   import seaborn as sns
   import matplotlib.pyplot as plt
   import warnings
   warnings.filterwarnings('ignore')
```

```
In [2]: # reading the wine dataset
df = pd.read_csv('https://raw.githubusercontent.com/shrikant-temburwar/Wine-Quali
```

```
In [3]: # first five rows
df.head()
```

Out[3]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4
4											•

In [4]: # statistical analysis of data
df.describe().T

Out[4]:

	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
рН	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 [5]: #finding the columns of data
df.columns
```

```
In [6]: # checking the length of the columns of data
len(df.columns)
```

Out[6]: 12

```
In [7]: #checking the null values
df.isnull().sum()
```

```
Out[7]: fixed acidity
                                 0
        volatile acidity
                                 0
        citric acid
        residual sugar
        chlorides
        free sulfur dioxide
                                 0
        total sulfur dioxide
                                 0
        density
                                 0
        рΗ
                                 0
        sulphates
        alcohol
                                 0
        quality
                                 0
        dtype: int64
```

```
In [8]: #checking the dulicated values in our dataset
          df.duplicated().sum()
 Out[8]: 240
 In [9]: #droping of duplicated values
          df = df.drop duplicates()
In [10]: #after dropping the duplicated values checking the dataset
          df.head()
Out[10]:
                                                        free
                                                                total
               fixed
                     volatile citric
                                   residual
                                            chlorides
                                                       sulfur
                                                               sulfur
                                                                     density
                                                                              pH sulphates alcohol
              acidity
                      acidity
                              acid
                                     sugar
                                                     dioxide
                                                             dioxide
                                               0.076
           0
                 7.4
                        0.70
                              0.00
                                       1.9
                                                        11.0
                                                                34.0
                                                                      0.9978 3.51
                                                                                        0.56
                                                                                                 9.4
                                               0.098
           1
                 7.8
                        0.88
                              0.00
                                       2.6
                                                        25.0
                                                                67.0
                                                                      0.9968 3.20
                                                                                        0.68
                                                                                                9.8
           2
                 7.8
                        0.76
                              0.04
                                       2.3
                                               0.092
                                                        15.0
                                                                54.0
                                                                      0.9970 3.26
                                                                                        0.65
                                                                                                9.8
           3
                11.2
                        0.28
                              0.56
                                       1.9
                                               0.075
                                                        17.0
                                                                60.0
                                                                      0.9980 3.16
                                                                                        0.58
                                                                                                 9.8
           5
                 7.4
                        0.66
                              0.00
                                       1.8
                                               0.075
                                                        13.0
                                                                40.0
                                                                      0.9978 3.51
                                                                                        0.56
                                                                                                 9.4
In [11]: df.duplicated().sum()
Out[11]: 0
          Observations: Here we do not having duplicated values
In [13]: #checking the unique of quality - dependent variable
          df['quality'].unique()
Out[13]: array([5, 6, 7, 4, 8, 3], dtype=int64)
In [14]: #checking the value counts
          df['quality'].value_counts()
Out[14]: 5
                577
                535
          6
          7
                167
          4
                 53
                 17
                 10
          Name: quality, dtype: int64
In [15]: #demo on dataframe creation n checking duplicated
          df1 = pd.DataFrame([1,2,3,4,54,3,3,4,5,5,5,3,3,3,3,2,2,2])
In [16]: |df1.duplicated().sum()
Out[16]: 12
```

```
#Independent and dependent variable
In [17]: | x = df.iloc[:,:-1] #df.dfrop['quality']
         y = df.iloc[:,-1] #df['y']
In [18]: x.shape , y.shape
Out[18]: ((1359, 11), (1359,))
         ''' from sklearn.preprocessing import StandardScaler
 In [ ]:
         scaler = StandartScaler()
         scaler
         scaler.fit_transform(x_train, y_train)''' # scaling is not required in Decision
In [19]: # splitting the data
         #importing the train, test split from sklearn
         from sklearn.model selection import train_test_split, GridSearchCV
In [20]: x_train, x_test, y_train, y_test = train_test_split(
                x, y, test size=0.33, random state=42)
In [21]: # importing the decision tree classifier from sklearn
         from sklearn.tree import DecisionTreeClassifier
In [22]: DT = DecisionTreeClassifier()
In [23]: DT
Out[23]: DecisionTreeClassifier()
In [24]: #fittign our data in decisionTree model
         DT.fit(x_train,y_train)
Out[24]: DecisionTreeClassifier()
In [25]: #training dataset accuracy
         DT.score(x_train,y_train)
Out[25]: 1.0
In [26]: #prediction of x test
         y pred = DT.predict(x test)
In [27]: #checking accuracy
         from sklearn.metrics import accuracy score
```

```
In [28]: | accuracy_score(y_test, y_pred) #model accuracy (test accuracy)
Out[28]: 0.46325167037861914
         Observations: From DecisionTree model, the accuracy is 47%
         Observations: Training accuracy (Bias) is high and test accuracy(variance) is
         low. Hense this scenario is called Overfitting
In [29]: #model 2: Logistic Regression
         from sklearn.linear model import LogisticRegression
In [30]: lr = LogisticRegression()
In [31]: lr
Out[31]: LogisticRegression()
In [32]: #fitting the data in logistic regression
         lr.fit(x_train, y_train)
Out[32]: LogisticRegression()
In [33]: #predicting value using logistic regression
         y predlr = lr.predict(x test)
In [34]: #checking accuracy score of logistic regression
         accuracy_score(y_test, y_predlr)
Out[34]: 0.5902004454342984
         Observation: From Logtistic Regression we got 59% accuracy
In [35]: #model 3: importing SVC
         from sklearn.svm import SVC
In [36]: svc = SVC()
In [37]: #fitting our data into svc model
         svc.fit(x_train,y_train)
Out[37]: SVC()
In [38]: # predicting the value of x_test in svc model
         y_predsvc = svc.predict(x_test)
```

```
In [39]: | accuracy score(y test, y predsvc)
Out[39]: 0.512249443207127
         Observations: From SVC model we got 51% of accuracy
In [40]: #creating parameters for grid_search CV
         grid_params = {'criterion' : ['gini', 'entropy'],
                         'max_depth' : range(2, 32,1),
                         'min_samples_leaf' : range(1,10,1),
                         'min samples split' : range(2,10,1),
                         'splitter':['best', 'random']}
In [41]: grid_search = GridSearchCV(estimator=DT,
                      param grid=grid params, cv = 5)
In [42]: #fitting our data into gridsearch
         grid_search.fit(x_train, y_train)
Out[42]: GridSearchCV(cv=5, estimator=DecisionTreeClassifier(),
                       param_grid={'criterion': ['gini', 'entropy'],
                                   'max_depth': range(2, 32),
                                   'min_samples_leaf': range(1, 10),
                                   'min_samples_split': range(2, 10),
                                   'splitter': ['best', 'random']})
In [43]: #finding the best params
         grid search.best params
Out[43]: {'criterion': 'gini',
           'max depth': 5,
           'min samples leaf': 7,
           'min samples split': 7,
           'splitter': 'random'}
         Observations: in Gridsearch CV we found that best parameters are criterion =
          'entropy',
             max depth =4,min samples leaf = 4, min samples split= 3, splitter= 'random'
 In [ ]: #criterion = 'entropy', max depth =4,min samples leaf = 4, min samples split= 3,
In [44]: #best params with our model(Decision tree)
         model with best params = DecisionTreeClassifier(criterion = 'entropy', max depth
         )
```