KNN

preprocess

checking values of model for diff k values 1 - 15

test acc and train acc with graph

changing diff parameters, diff algos

classification report, consusion mat decision boundarries

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:
```
df = pd.read_csv("D:\MIT ADT\Third Year - Sem 2\ML LAB\Assign 7 - KNN\wineq
ualityN.csv")
```

In [3]:
```
df.head()
```

Out[3]:

	type	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates
0	white	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.0010	3.00	0.45
1	white	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.9940	3.30	0.49
2	white	8.1	0.28	0.40	6.9	0.050	30.0	97.0	0.9951	3.26	0.44
3	white	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0.40
4	white	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0.40

In [4]:
```
df.isna().sum()
```

Out[4]:
```
type                     0
fixed acidity           10
volatile acidity         8
citric acid              3
residual sugar           2
chlorides                2
free sulfur dioxide      0
total sulfur dioxide     0
density                  0
pH                       9
sulphates                4
alcohol                  0
quality                  0
dtype: int64
```

In [5]:
```
df.duplicated().sum()
```

Out[5]:
```
1168
```

In [6]:
```
df = df.drop_duplicates()
```

In [7]:
```
df.duplicated().sum()
```

Out[7]: 0

In [8]:
```
df.head()
```

Out[8]:

	type	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates
0	white	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.0010	3.00	0.45
1	white	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.9940	3.30	0.49
2	white	8.1	0.28	0.40	6.9	0.050	30.0	97.0	0.9951	3.26	0.44
3	white	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0.40
6	white	6.2	0.32	0.16	7.0	0.045	30.0	136.0	0.9949	3.18	0.47

In [9]:
```
df.columns
```

Out[9]:
```
Index(['type', 'fixed acidity', 'volatile acidity', 'citric acid',
       'residual sugar', 'chlorides', 'free sulfur dioxide',
       'total sulfur dioxide', 'density', 'pH', 'sulphates', 'alcohol',
       'quality'],
      dtype='object')
```

In [10]:
```
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy='most_frequent', missing_values=np.nan)

col_impute = ["fixed acidity", "volatile acidity", "citric acid", 'residual sugar', 'chlorides', 'pH', 'sulphates']

for i in col_impute:
    df[i] = imputer.fit_transform(df[[i]]).ravel()
```

In [11]:
```
from sklearn.preprocessing import LabelEncoder
lbl_enc = LabelEncoder()
df['type'] = lbl_enc.fit_transform(df['type'])
```

In [12]:
```
df.head()
```

Out[12]:

	type	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates
0	1	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.0010	3.00	0.45
1	1	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.9940	3.30	0.49
2	1	8.1	0.28	0.40	6.9	0.050	30.0	97.0	0.9951	3.26	0.44
3	1	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0.40
6	1	6.2	0.32	0.16	7.0	0.045	30.0	136.0	0.9949	3.18	0.47

In [13]:
```
df.corr()
```

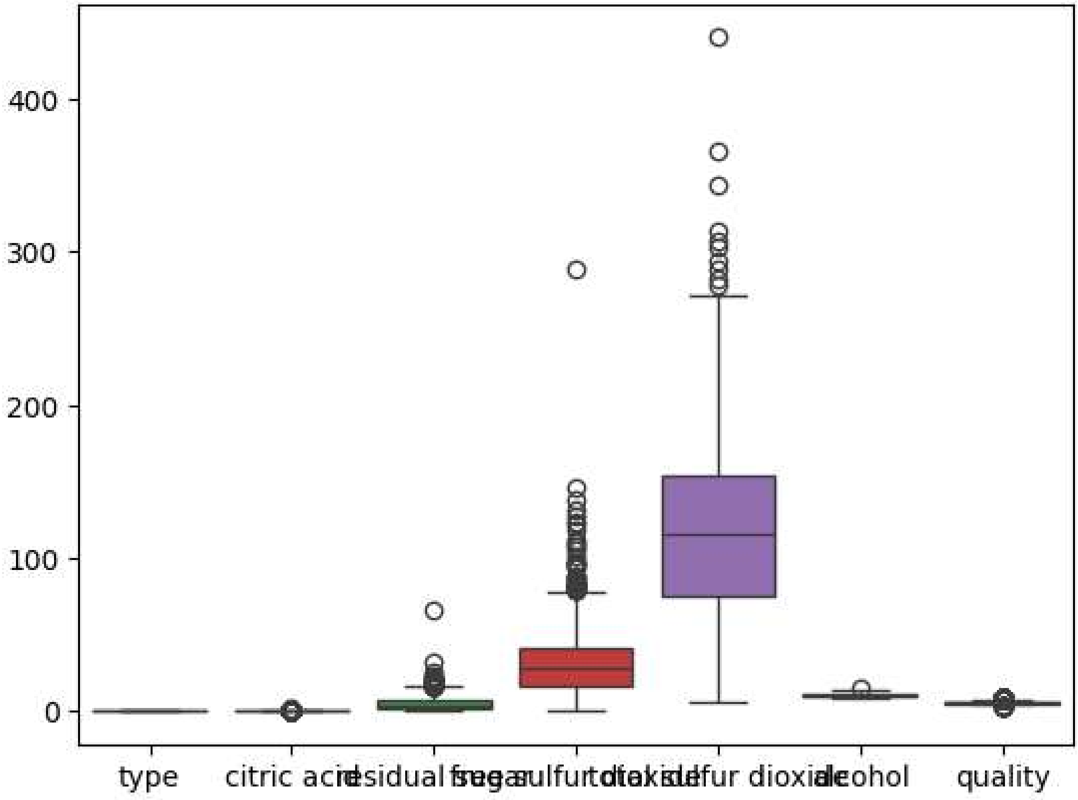
Out[13]:

	type	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	tota sulfu dioxid
type	1.000000	-0.486310	-0.644478	0.183703	0.328597	-0.499735	0.465295	0.69418
fixed acidity	-0.486310	1.000000	0.215063	0.329085	-0.104652	0.288898	-0.281588	-0.32732
volatile acidity	-0.644478	0.215063	1.000000	-0.383113	-0.163926	0.367330	-0.349337	-0.40149
citric acid	0.183703	0.329085	-0.383113	1.000000	0.146526	0.054922	0.132147	0.19508
residual sugar	0.328597	-0.104652	-0.163926	0.146526	1.000000	-0.123314	0.398811	0.48733
chlorides	-0.499735	0.288898	0.367330	0.054922	-0.123314	1.000000	-0.186824	-0.27003
free sulfur dioxide	0.465295	-0.281588	-0.349337	0.132147	0.398811	-0.186824	1.000000	0.72066
total sulfur dioxide	0.694181	-0.327327	-0.401499	0.195084	0.487338	-0.270034	0.720666	1.00000
density	-0.428757	0.477807	0.307121	0.094852	0.521661	0.371442	0.006687	0.00735
pH	-0.310342	-0.270147	0.245854	-0.343196	-0.233905	0.026535	-0.141315	-0.22240
sulphates	-0.489255	0.305710	0.225871	0.060445	-0.174800	0.404614	-0.198378	-0.27461
alcohol	0.057334	-0.102778	-0.064840	-0.005557	-0.306092	-0.269132	-0.170396	-0.24959
quality	0.114889	-0.080482	-0.264307	0.098774	-0.057503	-0.202115	0.054456	-0.05038

In [14]:
```
df = df.drop(["fixed acidity", "volatile acidity", "chlorides", "density",
"pH", "sulphates"], axis=1)
```

In [15]:
```
sns.boxplot(df)
```

Out[15]: `<Axes: >`



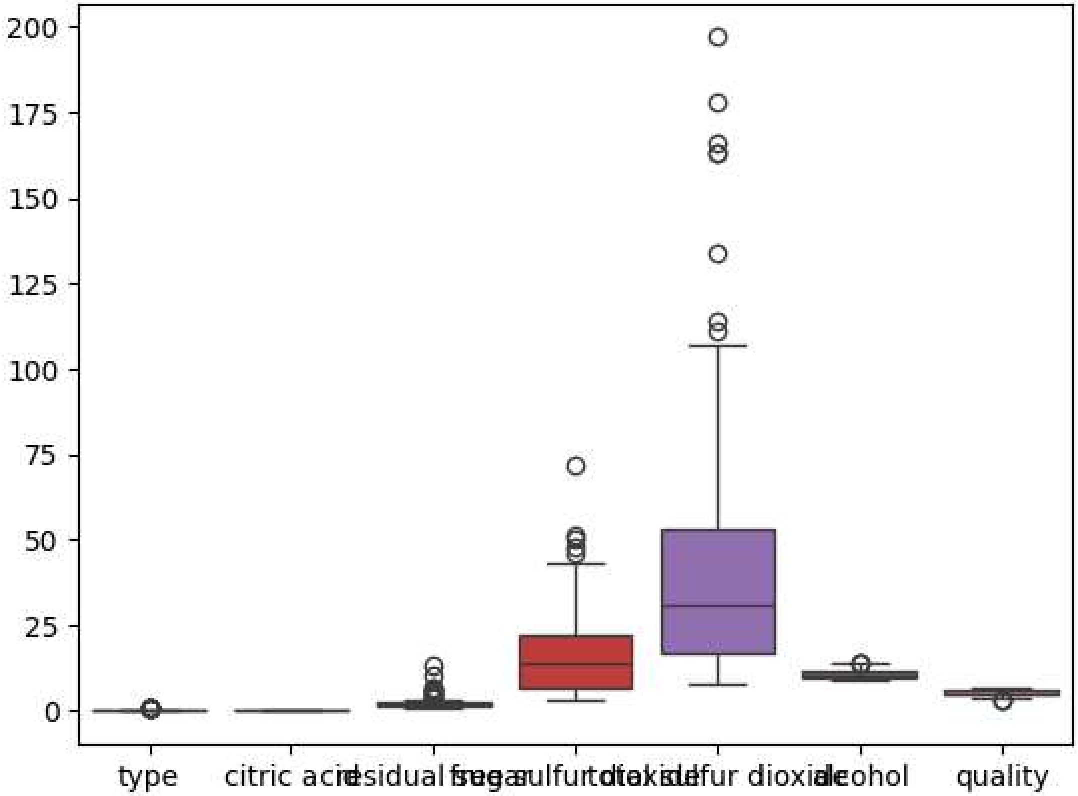
In [16]:
```
df.columns
```

Out[16]:
```
Index(['type', 'citric acid', 'residual sugar', 'free sulfur dioxide',
       'total sulfur dioxide', 'alcohol', 'quality'],
      dtype='object')
```

In [17]:
```
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)

IQR = Q3 - Q1

outliers = ((df<(Q1-1.5*IQR))| df>(Q3+1.5*IQR)).any(axis=1)

df_no_outliers = df[~outliers]
```

In [18]:
```
sns.boxplot(df_no_outliers)
```

Out[18]: <Axes: >



In [19]:
```
X = df.drop("type", axis=1)
y = df["type"]
```

In [20]:
```
from sklearn.model_selection import train_test_split

Xtrain, Xtest, ytrain, ytest = train_test_split(X, y , test_size=0.2,random
_state=0)

print(Xtrain.shape, Xtest.shape)
print(ytrain.shape, ytest.shape)
```

```
(4263, 6) (1066, 6)
(4263,) (1066,)
```

In [21]:
```
#Scale the Data

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

Xtrain_std = scaler.fit_transform(Xtrain)
Xtest_std = scaler.transform(Xtest)
```

class sklearn.neighbors.KNeighborsClassifier(n_neighbors=5, *, weights='uniform', algorithm='auto', leaf_size=30, p=2, metric='minkowski', metric_params=None, n_jobs=None)

In [22]:
```
X.isna().sum()
```

Out[22]:
```
citric acid             0
residual sugar          0
free sulfur dioxide     0
total sulfur dioxide    0
alcohol                 0
quality                 0
dtype: int64
```

In [23]:

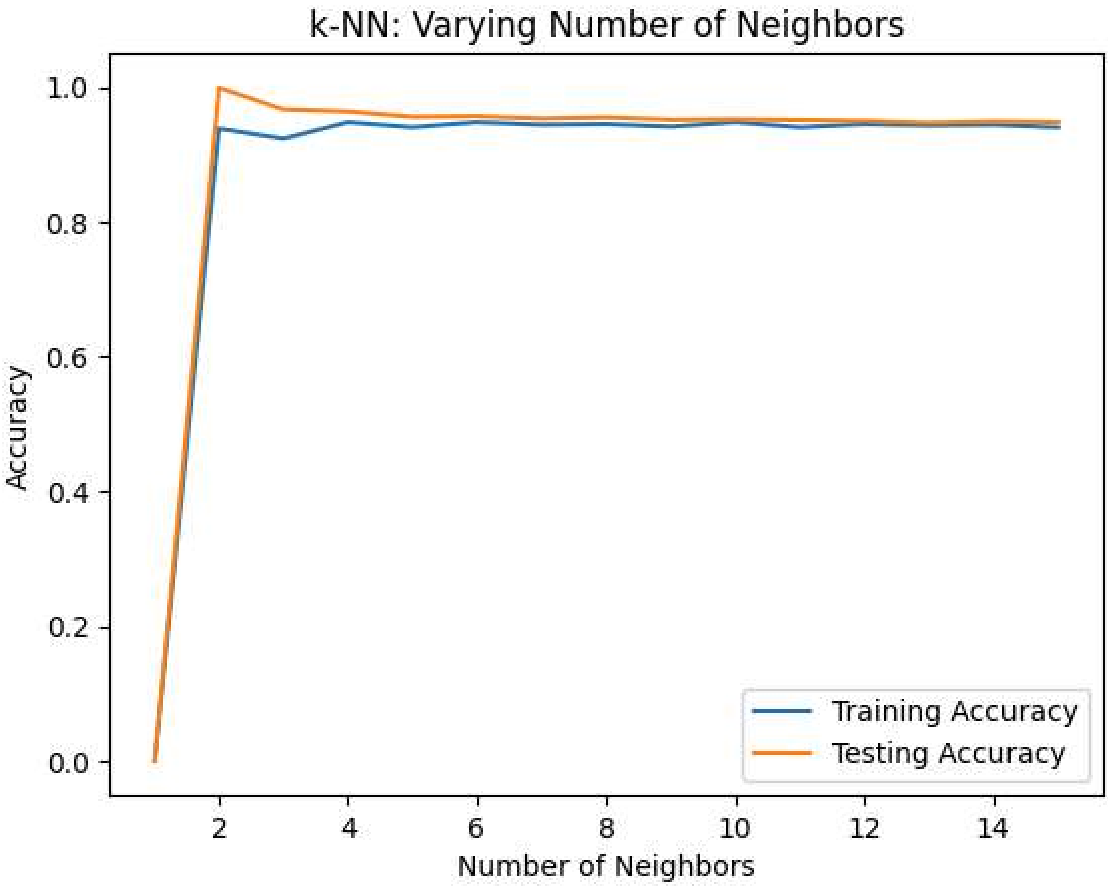
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
#neigh = KNeighborsClassifier(n_neighbors=3)

train_acc = np.zeros(15)
test_acc = np.zeros(15)

for i in range(1,15):
    print("Neighbours: ", i)
    neigh = KNeighborsClassifier(n_neighbors=i)
    neigh.fit(Xtrain_std, ytrain)
    train_acc[i] = neigh.score(Xtrain_std, ytrain)
    test_acc[i] = neigh.score(Xtest_std, ytest)
    print("Training accuracy: ", neigh.score(Xtrain_std, ytrain))
    print("Testing Accuracy: ", neigh.score(Xtest_std, ytest))
    ypred = neigh.predict(Xtest_std)
    print("Accuracy Score: ", accuracy_score(ytest, ypred))
```

```
Neighbours:  1
Training accuracy:  0.9995308468214872
Testing Accuracy:  0.9390243902439024
Accuracy Score:  0.9390243902439024
Neighbours:  2
Training accuracy:  0.9673938540933614
Testing Accuracy:  0.924015009380863
Accuracy Score:  0.924015009380863
Neighbours:  3
Training accuracy:  0.9643443584330283
Testing Accuracy:  0.948405253283302
Accuracy Score:  0.948405253283302
Neighbours:  4
Training accuracy:  0.956368754398311
Testing Accuracy:  0.9409005628517824
Accuracy Score:  0.9409005628517824
Neighbours:  5
Training accuracy:  0.9573070607553367
Testing Accuracy:  0.948405253283302
Accuracy Score:  0.948405253283302
Neighbours:  6
Training accuracy:  0.9537884119164908
Testing Accuracy:  0.9446529080675422
Accuracy Score:  0.9446529080675422
Neighbours:  7
Training accuracy:  0.9556650246305419
Testing Accuracy:  0.9455909943714822
Accuracy Score:  0.9455909943714822
Neighbours:  8
Training accuracy:  0.952146375791696
Testing Accuracy:  0.9418386491557224
Accuracy Score:  0.9418386491557224
Neighbours:  9
Training accuracy:  0.9528501055594651
Testing Accuracy:  0.948405253283302
Accuracy Score:  0.948405253283302
Neighbours:  10
Training accuracy:  0.9516772226131832
Testing Accuracy:  0.9409005628517824
Accuracy Score:  0.9409005628517824
Neighbours:  11
Training accuracy:  0.9505043396669013
Testing Accuracy:  0.9455909943714822
Accuracy Score:  0.9455909943714822
Neighbours:  12
Training accuracy:  0.9474548440065681
Testing Accuracy:  0.9437148217636022
Accuracy Score:  0.9437148217636022
Neighbours:  13
Training accuracy:  0.9498006098991321
Testing Accuracy:  0.9446529080675422
Accuracy Score:  0.9446529080675422
Neighbours:  14
Training accuracy:  0.9486277269528501
Testing Accuracy:  0.9409005628517824
Accuracy Score:  0.9409005628517824
```

In [24]:
```
print(test_acc)
print(train_acc)
```

```
[0.         0.93902439 0.92401501 0.94840525 0.94090056 0.94840525
 0.94465291 0.94559099 0.94183865 0.94840525 0.94090056 0.94559099
 0.94371482 0.94465291 0.94090056]
[0.         0.99953085 0.96739385 0.96434436 0.95636875 0.95730706
 0.95378841 0.95566502 0.95214638 0.95285011 0.95167722 0.95050434
 0.94745484 0.94980061 0.94862773]
```

In [25]:
```
plt.title('k-NN: Varying Number of Neighbors')
plt.plot(range(1,16), test_acc, label='Training Accuracy')
plt.plot(range(1,16), train_acc, label = "Testing Accuracy")
plt.legend()
plt.xlabel('Number of Neighbors')
plt.ylabel('Accuracy')
plt.show()
```



BEST K NEIGHBOURS = 4

class sklearn.neighbors.KNeighborsClassifier(n_neighbors=5, *, weights='uniform', algorithm='auto', leaf_size=30, p=2, metric='minkowski', metric_params=None, n_jobs=None)

Parameters: n_neighborsint, default=5 Number of neighbors to use by default for kneighbors queries.

weights{‘uniform’, ‘distance’}, callable or None, default=’uniform’ Weight function used in prediction. Possible values:

‘uniform’ : uniform weights. All points in each neighborhood are weighted equally.

‘distance’ : weight points by the inverse of their distance. in this case, closer neighbors of a query point will have a greater influence than neighbors which are further away.

[callable] : a user-defined function which accepts an array of distances, and returns an array of the same shape containing the weights.

Refer to the example entitled Nearest Neighbors Classification showing the impact of the weights parameter on the decision boundary.

algorithm{‘auto’, ‘ball_tree’, ‘kd_tree’, ‘brute’}, default=’auto’ Algorithm used to compute the nearest neighbors:

‘ball_tree’ will use BallTree

‘kd_tree’ will use KDTree

‘brute’ will use a brute-force search.

‘auto’ will attempt to decide the most appropriate algorithm based on the values passed to fit method.

In [26]:
```python
algo = ['auto', 'ball_tree', 'kd_tree', 'brute']
weights = ['uniform', 'distance']

for i in weights:
    print("WEIGHT: ", i)

    for j in algo:
        print("Algorith used: ", j)
        knn = KNeighborsClassifier(n_neighbors=4, algorithm=j, weights=i)
        knn.fit(Xtrain_std, ytrain)
        print("Training accuracy: ", knn.score(Xtrain_std, ytrain))
        print("Testing Accuracy: ", knn.score(Xtest_std, ytest))
        print()
```

```
WEIGHT:  uniform
Algorith used:  auto
Training accuracy:  0.956368754398311
Testing Accuracy:  0.9409005628517824

Algorith used:  ball_tree
Training accuracy:  0.956368754398311
Testing Accuracy:  0.9409005628517824

Algorith used:  kd_tree
Training accuracy:  0.956368754398311
Testing Accuracy:  0.9409005628517824

Algorith used:  brute
Training accuracy:  0.956368754398311
Testing Accuracy:  0.9409005628517824

WEIGHT:  distance
Algorith used:  auto
Training accuracy:  0.9995308468214872
Testing Accuracy:  0.9521575984990619

Algorith used:  ball_tree
Training accuracy:  0.9995308468214872
Testing Accuracy:  0.9521575984990619

Algorith used:  kd_tree
Training accuracy:  0.9995308468214872
Testing Accuracy:  0.9521575984990619

Algorith used:  brute
Training accuracy:  0.9995308468214872
Testing Accuracy:  0.9521575984990619
```

In [27]:
```python
from sklearn.metrics import classification_report, confusion_matrix
knn = KNeighborsClassifier(n_neighbors=4, algorithm="auto", weights="unifor
m")
knn.fit(Xtrain_std, ytrain)
y_pred = knn.predict(Xtest_std)
cm = confusion_matrix(ytest, y_pred)
print(cm)
```

```
[[249  24]
 [ 39 754]]
```

In [28]:
```
cr = classification_report(ytest, y_pred)
print(cr)
```

```
              precision    recall  f1-score   support

           0       0.86      0.91      0.89       273
           1       0.97      0.95      0.96       793

    accuracy                           0.94      1066
   macro avg       0.92      0.93      0.92      1066
weighted avg       0.94      0.94      0.94      1066
```

In [29]:
```
from sklearn.metrics import ConfusionMatrixDisplay

disp = ConfusionMatrixDisplay(cm)
disp.plot()
```

Out[29]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1e53be9
0e80>
```