Deep Learning Project

Wine Quality Prediction (Multi-class classification)

In [1]:

```
#importing the libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score,classification_report,r2_score,mean_squared_e
```

In [2]:

```
# call csv file and convert it to dataframe using Pandas function

df3=pd.read_csv('winequalitynew.csv')

# .head() will give the first 5 rows of the dataset by default

df3.head()
```

Out[2]:

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

In [3]:

```
# .info() will give basic info about the dataset
df3.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1596 entries, 0 to 1595
Data columns (total 12 columns):

#	Column	Non-Null Count	Dtype
0	fixed acidity	1596 non-null	float64
1	volatile acidity	1596 non-null	float64
2	citric acid	1596 non-null	float64
3	residual sugar	1596 non-null	float64
4	chlorides	1596 non-null	float64
5	free sulfur dioxide	1596 non-null	float64
6	total sulfur dioxide	1596 non-null	float64
7	density	1596 non-null	float64
8	рН	1596 non-null	float64
9	sulphates	1596 non-null	float64
10	alcohol	1596 non-null	float64
11	quality	1596 non-null	int64
	63	1.1	

dtypes: float64(11), int64(1)

memory usage: 149.8 KB

In [4]:

df3.describe()

Out[4]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total d
count	1596.000000	1596.000000	1596.000000	1596.000000	1596.000000	1596.000000	1596.0
mean	8.314160	0.527954	0.270276	2.535558	0.087120	15.858396	46.3
std	1.732203	0.179176	0.193894	1.405515	0.045251	10.460554	32.8
min	4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.0
25%	7.100000	0.390000	0.090000	1.900000	0.070000	7.000000	22.0
50%	7.900000	0.520000	0.260000	2.200000	0.079000	14.000000	38.0
75%	9.200000	0.640000	0.420000	2.600000	0.090000	21.000000	62.0
max	15.600000	1.580000	0.790000	15.500000	0.611000	72.000000	289.0
4							

In [5]:

.shape will give number of rows and columns respectively

df3.shape

Out[5]:

(1596, 12)

Exploratory Data Analysis

In [6]:

```
# isnull().sum() gives the count of null values present in each column
df3.isnull().sum()
```

Out[6]:

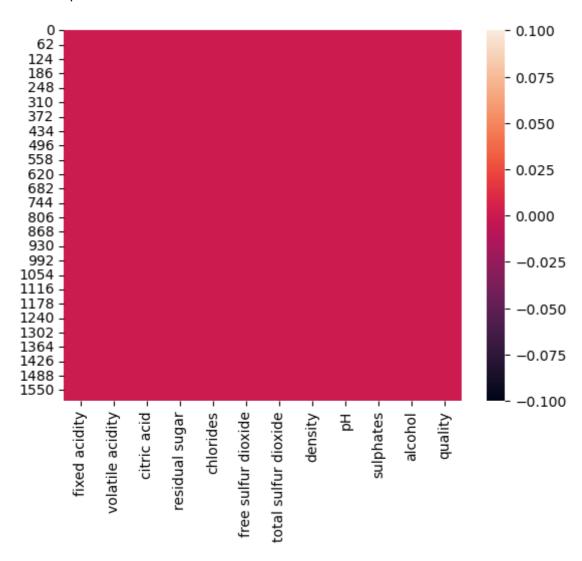
fixed acidity	0
volatile acidity	0
citric acid	0
residual sugar	0
chlorides	0
free sulfur dioxide	0
total sulfur dioxide	0
density	0
рН	0
sulphates	0
alcohol	0
quality	0
dtype: int64	

In [7]:

```
# plot heatmap to find null values present in the dataframe
sns.heatmap(df3.isnull())
```

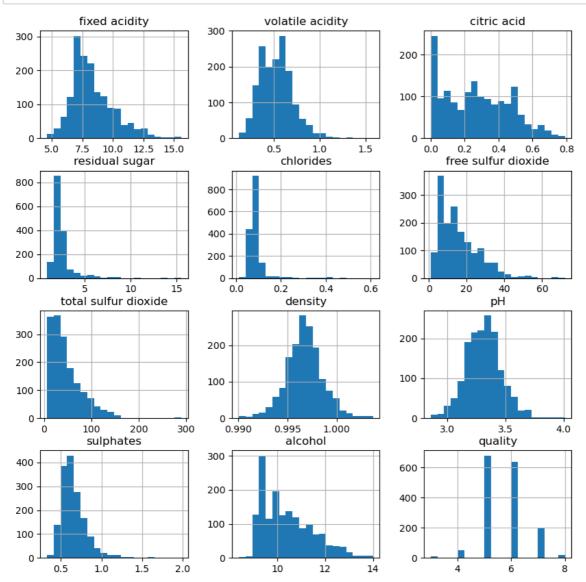
Out[7]:

<AxesSubplot:>



In [8]:

```
# draw the histogram to visualise the distribution of the data with continuous values in
df3.hist(bins=20, figsize=(10, 10))
plt.show()
```



In [9]:

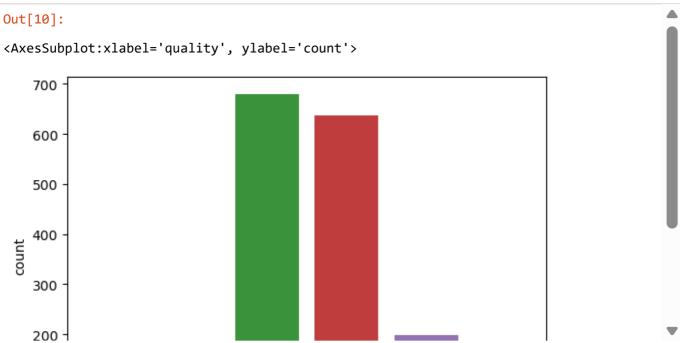
df3["quality"].unique()

Out[9]:

array([5, 6, 7, 4, 8, 3], dtype=int64)

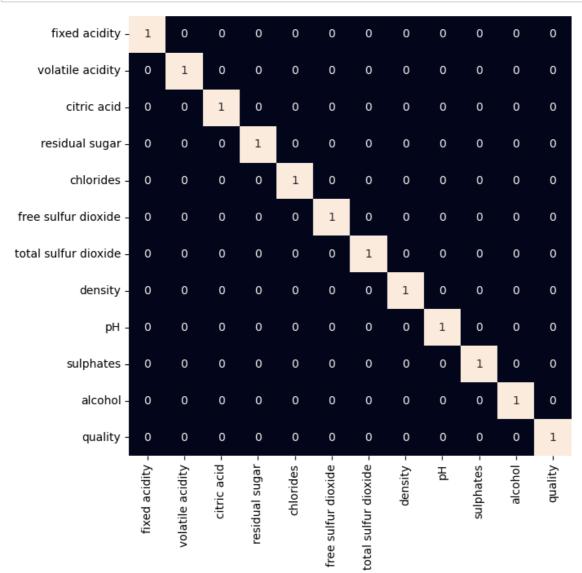
In [10]:

```
# draw the count plot to visualise the number data for each quality of wine.
sns.countplot(data=df3,x="quality")
```



In [11]:

```
plt.figure(figsize=(7, 7))
sns.heatmap(df3.corr() > 0.7, annot=True, cbar=False)
plt.show()
```



In [12]:

```
# split our features and target in x and y respectively
x=df3.iloc[:,:-1]
y=df3.iloc[:,-1]
```

```
In [13]:
```

```
Х
```

Out[13]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates
0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56
1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99680	3.20	0.68
2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99700	3.26	0.65
3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99800	3.16	0.58
4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56
1591	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58
1592	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76
1593	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75
1594	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71
1595	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66

1596 rows × 11 columns

In [14]:

```
у
```

```
Out[14]:
```

```
5
0
1
         5
2
         5
3
         5
        5
1591
1592
        6
1593
         6
1594
         5
```

Name: quality, Length: 1596, dtype: int64

In [15]:

1595

```
from sklearn.preprocessing import LabelEncoder
en=LabelEncoder()
y=en.fit_transform(y)
```

```
In [16]:
```

У

Out[16]:

array([2, 2, 2, ..., 3, 2, 3], dtype=int64)

In [17]:

x.shape

Out[17]:

(1596, 11)

In [18]:

```
sc=StandardScaler()
x=pd.DataFrame(sc.fit_transform(x),columns=x.columns)
x.head()
```

Out[18]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	
0	-0.527910	0.960506	-1.394369	-0.452330	-0.245811	-0.464595	-0.377175	0.559577	1.29
1	-0.296918	1.965419	-1.394369	0.045864	0.240520	0.874186	0.628039	0.029638	-0.73
2	-0.296918	1.295477	-1.188007	-0.167648	0.107884	-0.082086	0.232046	0.135626	-0.33
3	1.666516	-1.384292	1.494706	-0.452330	-0.267917	0.109168	0.414812	0.665565	-0.99
4	-0.527910	0.960506	-1.394369	-0.452330	-0.245811	-0.464595	-0.377175	0.559577	1.29

In [19]:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Dropout
```

In [20]:

```
# split the data for training and testing
xtrain,xtest,ytrain,ytest = train_test_split(x,y,test_size=0.3,random_state=1)
```

In [21]:

```
model=Sequential()
model.add(Dense(1024,activation="relu",input_dim=11))
model.add(Dense(512,activation="relu"))
model.add(Dense(256,activation="relu"))
model.add(Dense(128,activation="relu"))
model.add(Dense(64,activation="relu"))
model.add(Dropout(0.3))
model.add(Dense(6,activation="softmax"))
```

In [22]:

model.compile(optimizer="adam",loss="sparse_categorical_crossentropy",metrics="accuracy"

In [23]:

```
his=model.fit(xtrain,ytrain,epochs=50,batch_size=200)
```

```
Epoch 1/50
6/6 [============ ] - 1s 16ms/step - loss: 1.5986 - ac
curacy: 0.3536
Epoch 2/50
6/6 [=========== ] - 0s 10ms/step - loss: 1.2192 - ac
curacy: 0.5372
Epoch 3/50
6/6 [============== ] - 0s 13ms/step - loss: 1.0990 - ac
curacy: 0.5613
Epoch 4/50
6/6 [========== ] - 0s 13ms/step - loss: 1.0275 - ac
curacy: 0.5640
Epoch 5/50
6/6 [============= ] - 0s 9ms/step - loss: 1.0196 - acc
uracy: 0.5667
Epoch 6/50
6/6 [=========== ] - 0s 11ms/step - loss: 0.9779 - ac
curacy: 0.5909
Epoch 7/50
```

In [24]:

```
his.history["loss"]
Out[24]:
[1.5985742807388306,
 1.2192264795303345,
 1.0990239381790161,
 1.0275427103042603,
 1.0195618867874146,
 0.9778688549995422,
 0.9558177590370178,
 0.9323015809059143,
 0.9322930574417114,
 0.9153008460998535,
 0.8868661522865295,
 0.8807466626167297,
 0.8489855527877808,
 0.8481696844100952,
 0.8285951018333435,
0.8210949301719666,
 0.7880850434303284,
0.7946338653564453.
In [25]:
plt.plot(his.history['loss'])
Out[25]:
[<matplotlib.lines.Line2D at 0x2b0b8d10430>]
 1.6
 1.4
 1.2
 1.0
 0.8
```

0.6

In [26]:

```
ypred=model.predict(xtest)
ypred
15/15 [======== ] - Os 3ms/step
Out[26]:
array([[6.5743268e-05, 2.8209650e-05, 9.9204081e-01, 5.4747961e-03,
        2.3897958e-03, 5.8657469e-07],
       [1.7870902e-05, 4.8415091e-06, 9.4076052e-02, 9.0581959e-01,
        8.1409897e-05, 2.4046389e-07],
       [1.4557431e-03, 1.1085472e-04, 1.8698057e-02, 1.9169832e-03,
       9.7365159e-01, 4.1668084e-03],
       [5.7543931e-03, 2.6994050e-03, 8.9250095e-02, 3.0946878e-01,
        1.8659765e-01, 4.0622967e-01],
       [1.2575396e-02, 5.0412379e-02, 9.3272698e-01, 4.0136403e-03,
       2.6332680e-04, 8.1772714e-06],
       [2.8577106e-04, 3.1008727e-05, 9.7925341e-01, 1.1553658e-03,
        1.9254485e-02, 1.9934165e-05]], dtype=float32)
```

In [27]:

```
ypred=np.argmax(ypred,axis=1)
ypred
```

Out[27]:

```
array([2, 3, 4, 3, 3, 4, 4, 4, 2, 3, 2, 2, 4, 4, 3, 2, 3, 3, 2, 2, 2, 0,
      2, 3, 2, 2, 4, 4, 2, 4, 3, 3, 4, 3, 4, 3, 2, 3, 2, 3, 3, 2, 3, 2,
      4, 3, 3, 3, 2, 2, 2, 4, 3, 2, 2, 3, 3, 2, 2, 2, 4, 4, 2, 2, 2, 2,
      4, 3, 2, 1, 3, 2, 3, 3, 2, 2, 3, 4, 3, 3, 2, 2, 3, 2, 2, 2,
                                                                   2,
       2, 3, 3, 2, 3, 3, 3, 2, 4, 4, 3, 2, 3, 2, 2, 2, 2, 3, 2, 2, 2, 3,
      2, 2, 3, 3, 4, 2, 4, 3, 2, 3, 3, 4, 2, 2, 2, 2, 2, 3, 3, 3, 2, 2,
       3, 2, 2, 2, 3, 2, 2, 3, 3, 4, 3, 2, 3, 3, 2, 2, 3, 2, 2, 3, 2, 3,
      4, 3, 3, 2, 2, 3, 4,
                            2, 2, 2, 2, 3, 3, 2, 2, 3, 2, 3, 2, 2, 2,
      4, 2, 4, 2, 2, 4, 4, 2, 3, 4, 2, 2, 2, 2, 2, 2, 4, 3, 3, 3, 3, 3,
       3, 2, 2, 3, 2, 3, 3, 2, 2, 3, 2, 3, 2, 3, 2, 3, 3, 3, 3, 2, 3, 2,
      4, 2, 3, 3, 2, 2, 2, 2, 4, 4, 3, 2, 3, 2, 4, 4, 4, 2, 3, 3, 2, 4,
       3, 2, 2, 2, 2, 2, 2, 4, 2, 2, 3, 3, 3, 2, 2, 2, 3, 3, 3, 3, 3,
       3, 2, 2, 2, 2, 2, 3, 2, 2, 3, 3, 3, 2, 3, 2, 3, 2, 2, 2, 2, 2, 2, 2,
      2, 2, 3, 3, 3, 2, 2, 3, 2, 2, 3, 3, 2, 2, 2, 2, 2, 3, 3, 3, 1, 4,
      4, 4, 2, 2, 2, 3, 2, 2, 4, 2, 3, 2, 2, 3, 2, 3, 2, 2, 4, 4, 3,
       2, 4, 3, 4, 3, 2, 3, 4, 4, 2, 2, 2, 2, 4, 2, 2, 4, 2, 4, 2, 2, 3,
      1, 3, 4, 2, 2, 3, 3, 2, 2, 4, 2, 2, 4, 2, 2, 2, 2, 2, 2, 2, 2, 3,
       2, 3, 3, 3, 3, 3, 3, 2, 2, 4, 4, 3, 3, 3, 3, 3, 2, 3, 2, 2, 2, 4,
      2, 3, 3, 3, 2, 2, 4, 0, 3, 2, 3, 3, 2, 4, 4, 2, 2, 1, 2, 2, 3,
      3, 3, 2, 3, 2, 2, 4, 4, 4, 4, 2, 3, 2, 2, 3, 3, 2, 3, 2, 2, 2, 3,
      2, 2, 4, 3, 2, 3, 3, 3, 4, 2, 3, 4, 2, 3, 2, 4, 3, 2, 2, 2, 3, 2,
      3, 3, 3, 3, 3, 3, 3, 4, 2, 4, 3, 3, 4, 5, 2, 2], dtype=int64)
```

In [28]:

print(classification_report(ytest,ypred))

	precision	recall	f1-score	support
0	0.00	0.00	0.00	2
1	0.00	0.00	0.00	18
2	0.72	0.78	0.75	212
3	0.66	0.60	0.63	189
4	0.49	0.65	0.56	54
5	0.00	0.00	0.00	4
accuracy			0.65	479
macro avg	0.31	0.34	0.32	479
weighted avg	0.63	0.65	0.64	479

In [29]:

print(accuracy_score(ytest,ypred))

0.6534446764091858