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

In [2]:
```
df=pd.read_csv(r"C:\Users\user\Downloads\11_winequality-red.csv")
df.fillna(0,inplace=True)
df
```

Out[2]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4	5
1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99680	3.20	0.68	9.8	5
2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99700	3.26	0.65	9.8	5
3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99800	3.16	0.58	9.8	6
4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9.4	5
...	...	...	...	...	...	...	...	...	...	...	...	...
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10.5	5
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	11.2	6
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	11.0	6
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10.2	5
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	11.0	6

1599 rows × 12 columns

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

Out[3]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

In [4]:
```
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
```

In [5]:
```
import seaborn as sns
```

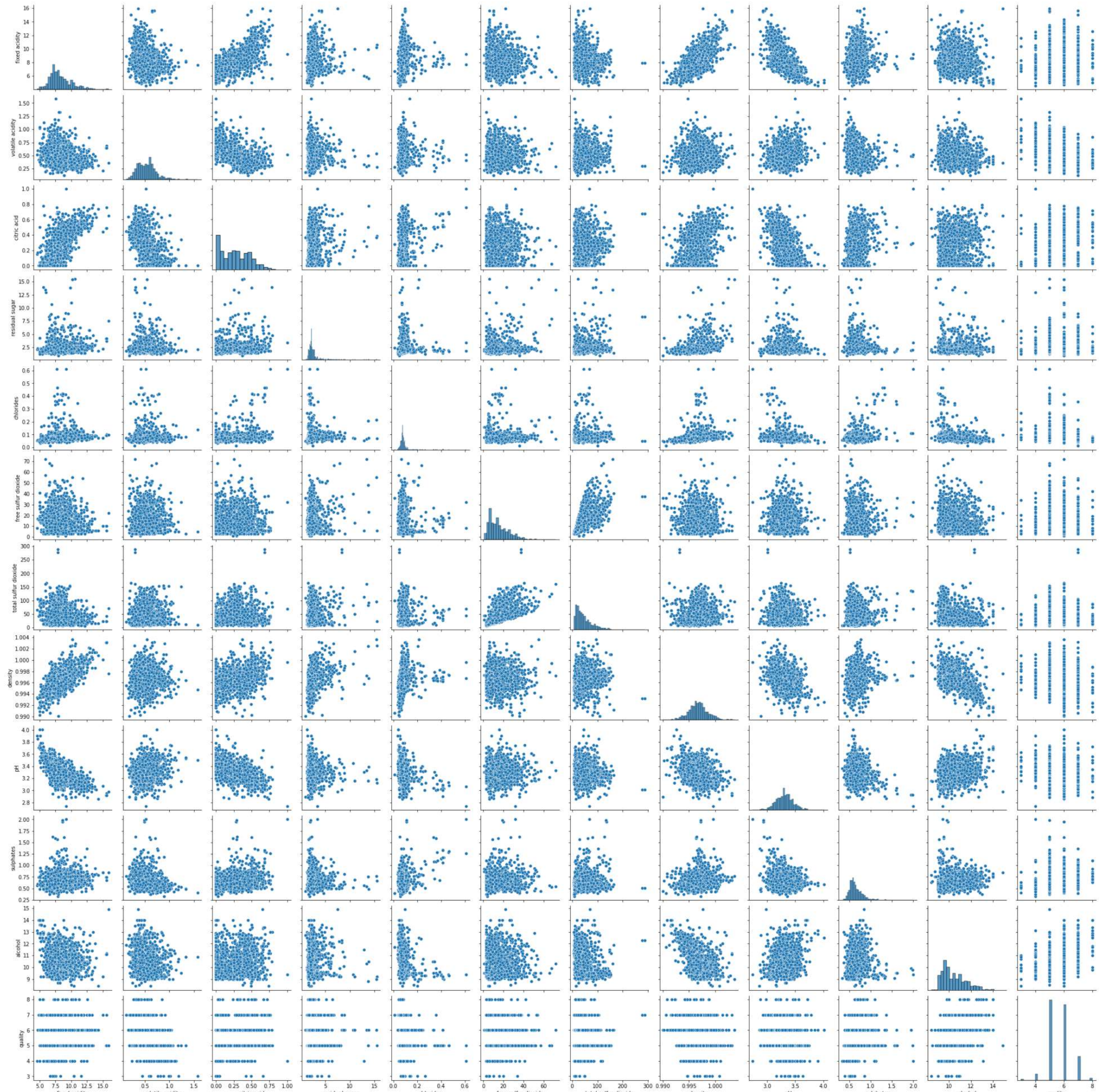
In [6]:
```
df.describe()
```

Out[6]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	der
count	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.00
mean	8.319637	0.527821	0.270976	2.538806	0.087467	15.874922	46.467792	0.996
std	1.741096	0.179060	0.194801	1.409928	0.047065	10.460157	32.895324	0.00
min	4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.000000	0.99
25%	7.100000	0.390000	0.090000	1.900000	0.070000	7.000000	22.000000	0.995
50%	7.900000	0.520000	0.260000	2.200000	0.079000	14.000000	38.000000	0.996
75%	9.200000	0.640000	0.420000	2.600000	0.090000	21.000000	62.000000	0.997
max	15.900000	1.580000	1.000000	15.500000	0.611000	72.000000	289.000000	1.003

In [7]:
```
sns.pairplot(df)
```

Out[7]: <seaborn.axisgrid.PairGrid at 0x235e6ae38e0>

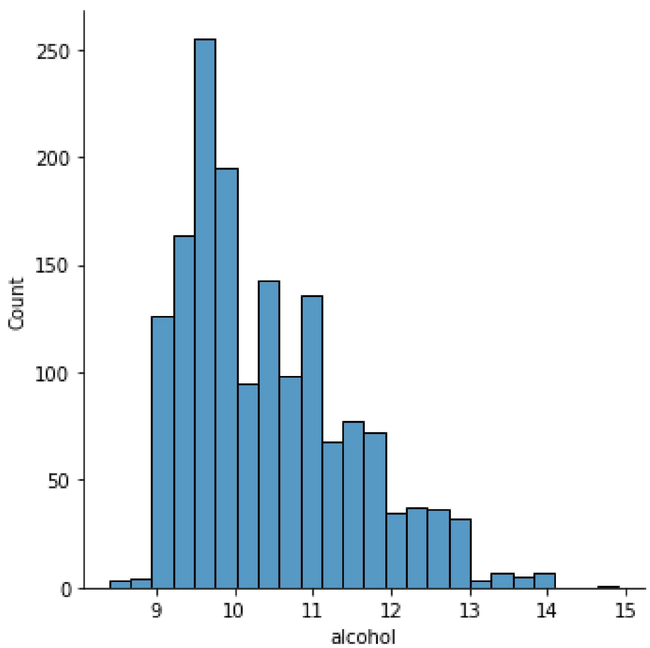


In [8]:
```
df1=df.drop(['citric acid'],axis=1)
df1
df1=df1.drop(df1.index[1537:])
df1.isna().sum()
```

Out[8]:
```
fixed acidity           0
volatile acidity        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
```

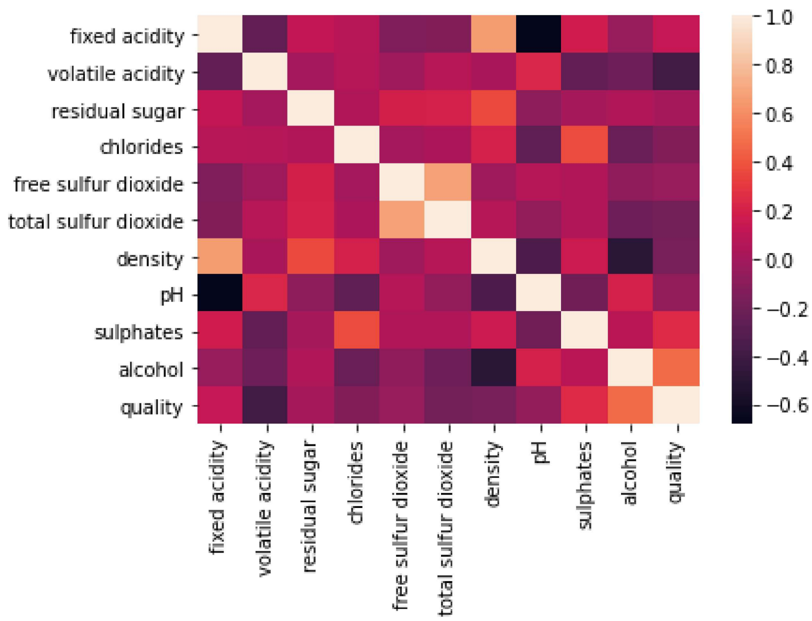
In [9]:
```
sns.displot(df['alcohol'])
```

Out[9]: <seaborn.axisgrid.FacetGrid at 0x235ee5d0b80>



In [10]:
```
sns.heatmap(df1.corr())
```

Out[10]: <AxesSubplot:>



In [11]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

In [12]:
```
df1.isna().sum()
```

Out[12]:
```
fixed acidity           0
volatile acidity        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
```

In [13]:
```
y=df1['fixed acidity']
x=df1.drop(['chlorides','residual sugar'],axis=1)
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
print(x_train)
```

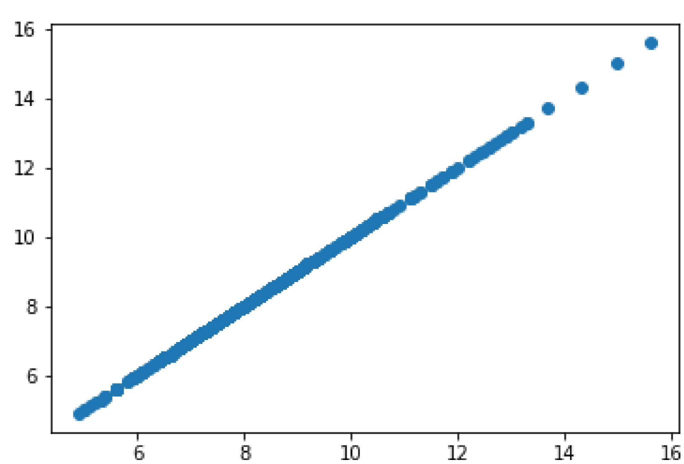
```
      fixed acidity  volatile acidity  free sulfur dioxide  \
1355            6.1             0.320                  5.0
1217            8.2             0.340                 43.0
824             7.1             0.480                  6.0
461             8.3             0.615                  6.0
1149           10.0             0.350                  6.0
...             ...               ...                  ...
1390            6.0             0.490                 15.0
952             8.2             0.310                  6.0
386             7.8             0.540                 23.0
59              7.3             0.390                  9.0
585             7.6             0.510                  8.0

      total sulfur dioxide  density    pH  sulphates  alcohol  quality
1355                  32.0  0.99464  3.36       0.44     10.1        5
1217                  74.0  0.99408  3.23       0.81     12.0        6
824                   16.0  0.99682  3.24       0.53     10.3        5
461                   19.0  0.99820  3.26       0.61      9.3        5
1149                  11.0  0.99585  3.23       0.52     12.0        6
...                    ...      ...   ...        ...      ...      ...
1390                  33.0  0.99292  3.58       0.59     12.5        6
952                   10.0  0.99536  3.31       0.68     11.2        7
386                   48.0  0.99810  3.41       0.74      9.2        6
59                    46.0  0.99620  3.41       0.54      9.4        6
585                   38.0  0.99800  3.47       0.66      9.6        6

[1075 rows x 9 columns]
```

In [14]:
```
model=LinearRegression()
model.fit(x_train,y_train)
model.intercept_
```

Out[14]: 5.329070518200751e-15

In [15]:
```
prediction=model.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[15]: <matplotlib.collections.PathCollection at 0x235f03336a0>



In [16]:
```
model.score(x_test,y_test)
```
Out[16]:
```
1.0
```

In [17]:
```
from sklearn.linear_model import Ridge,Lasso
```

In [18]:
```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
```
Out[18]:
```
Ridge(alpha=10)
```

In [19]:
```
rr.score(x_test,y_test)
```
Out[19]:
```
0.9999860069949209
```

In [20]:
```
la =Lasso(alpha=10)
la.fit(x_train,y_train)
```
Out[20]:
```
Lasso(alpha=10)
```

In [21]:
```
la.score(x_test,y_test)
```
Out[21]:
```
-0.00021750194178205007
```

In [22]:
```
from sklearn.linear_model import ElasticNet
en = ElasticNet()
en.fit(x_train,y_train)
```
Out[22]:
```
ElasticNet()
```

In [23]:
```
print(en.coef_)
```
```
[ 0.70820719 -0.         -0.          -0.0015529   0.          -0.
  0.         -0.          0.        ]
```

In [24]:
```
print(en.intercept_)
```
```
2.5191973790547832
```

In [25]:
```
print(en.predict(x_test))
```

```
[ 7.38719227  7.60774687  9.79354383  8.50945351  7.9407224   8.92195466
  8.4902063   8.56785107 12.15486142  9.99824151  8.87475534  8.87847359
  8.6576345   6.92965715  7.73757761  8.70516179 10.63035683  7.23933925
  9.15460446  6.8252852   6.72806526  7.43782535  8.02241338  8.44889059
  7.05421674  8.37557655  9.50870805  8.71570408  8.65297581  8.87753316
  7.78571736 11.05993984  7.58972459  8.31967232 11.87157855  8.71570408
  8.8545677   7.64812215  9.96407781  7.79908096  9.24749368  9.23257719
  8.43491454  8.05812997  9.14528709  7.42789551  8.72657435  8.72906768
  7.60120732 10.76950494  8.74087838  9.72272311  8.60606098  9.08378374
  7.8829373   9.79354383  8.28612108  6.88212986  7.5288337   7.80063385
  8.7880777  10.91580507  7.265126    8.56196746  8.4249847   7.10390939
  8.80671244 10.04732169  8.00006039  8.72346856  6.33142103  9.00209275
  8.3125203   8.2814624  12.62326681  7.83324465  8.31096741  7.43316666
  7.35924015  7.03308867 10.36881449  8.11746796  7.73757761  7.85686605
  7.74844788  8.01558934  7.87456036  7.38098069  8.30447134  7.44714272
  8.22555817  6.13448782  8.03671741  7.84722071  7.21138713  7.28841943
  5.92419102  6.80975625  8.59114449  6.76938097  9.63171475  9.88238683
 10.91114638  9.01856214  7.90561827  7.91338274  7.2977368   9.46461453
  7.09148623  9.08844242  7.44558982  7.42229639  7.72421401  8.4799485
  8.29576643  9.65190239 11.65290481  7.09459202  6.74204132  7.70092059
  8.69895021  7.59033705 11.60071883 10.71266028  9.40838232  7.43876578
  7.65993285  7.76242393  9.42019303  7.34526409  7.67235601  7.03308867
  7.76242393  7.48069395 10.02092247  7.27599627  9.48635506  9.05117294
  7.02532419  8.77876033 11.52989811  9.50404937  8.56474527  8.61476589
  7.95935714 13.10503578  7.44093114 10.59059402  7.3437112   8.42931542
  9.44565181  8.16871351  7.70713217  6.89300013  7.77639999  7.87983151
  8.61537836  7.91182985  9.99824151  7.9733332   7.47448237  7.52450299
  9.76653215 11.61780068  8.5806022   8.37247075  7.73819007  7.90095958
  7.58412547 10.4309303   9.22358779  8.78963059  9.44969803  9.85970586
  7.16541274  9.20773087  7.92425301  8.52625087  8.91729598  8.33830706
  7.65649909  8.2472987   7.9391695   9.57115184  7.8074579   6.93836206
  7.77639999  9.56865851  8.07925804 10.18896313  8.30414336 10.78192811
  7.8192686  10.09174319  7.88853642  9.25215237  7.9391695   5.97421164
  6.95233812  8.37868234  8.72191567  8.93593072  9.57797588  7.29618391
  7.93046459  9.5953857   8.35538891 10.97730842  8.86045131  8.01060268
  7.04955806  6.44915658  8.65730653  8.70638671  7.24493837  6.25810698
  7.43161377  9.08006549  7.31792444  7.43782535  7.89507597  9.47920304
  7.5732552   9.16796805  7.28686654  6.60971725  8.11996129  7.48474018
  7.17473011  7.37881533  7.41702525  6.46497002  8.10410437 10.91425217
  6.27208304 10.0442159   7.46827079  6.9451861   9.5953857   9.20773087
  7.30488882  9.12975813  6.36403183  9.85038849  8.89555544  6.92033978
  7.38098069 10.50951549  7.2014573   7.23562099  7.46111878  9.02011503
  7.07301547  7.37881533  7.39123849  7.48535264  9.71651153  8.87287448
 11.65290481 10.34613352  7.60431311  9.90506779  7.83479755  9.99513572
  7.36949796  8.37557655  9.70037011 13.50045509  7.71023796  8.60450809
  7.4667179   9.91344473  7.6533933   8.30786162  7.85809098  8.92040177
  9.85038849 11.32675333  9.19747306  7.17317721  8.05502418  6.97563155
  9.55002376  9.85194138  7.89507597  8.30009714  7.64812215  7.96806205
  6.19909696  9.065149    8.58338002  9.47920304  7.78261157  7.24027968
  7.80839833  9.93207947  8.40324417  7.78821069  8.25195739  5.98258858
  7.25270284  7.55927915 11.20219374  7.35025075  8.60450809  7.55927915
 10.63252219  6.48797896  7.53753861  9.73453381  6.48082694  8.72224364
  8.8309463   8.01370847  7.87051414  6.46807581  8.58897914  7.8844902
  8.2370409   8.10876305  9.15460446  8.76167848  7.55772625  8.67067012
  7.31947734  8.7094925   7.87921905  7.66524748  8.33209548  7.66581646
  8.08857542  8.09384656  7.46827079  7.83884377  7.74129586  7.54996178
  9.01606881  7.68788496 11.4115501   7.44403693  8.23332265  7.265126
  8.74925532  6.68458419  7.09614491  7.47914106 11.48392372  8.75330154
  7.35768726  9.52362454  7.90345291  7.55306757  7.78261157  9.56399982
  7.46422457  9.14528709  8.33520127  7.67856759  7.53071457  6.59296337
  7.81211658  9.07912505  7.75931814  6.33607972  9.23723588 11.12671433
```

```
  7.31171286  9.69942968  7.23002188 10.35700379  8.8902843   7.44187157
  6.66035033  9.02011503  7.5748081   7.2887474   7.94288775  7.68477917
  7.7658577   7.59593617  7.51951633  7.83479755  7.63475855  8.73156101
  6.76782807  7.65588662 10.32749878  6.96941996  9.98892414  9.17512007
 11.14722994  7.70247348  7.81677527 10.57817086  8.63961222  8.41223357
  9.86902323  7.97022741  7.55306757  7.15454247  9.46677988  7.41608481
  7.54624352  8.46907823  6.65413875  8.33054258  8.59114449  7.74411716
  8.45260885  6.96165549  8.93748361  7.13995395  8.50324193  9.36800705
  9.20679043  7.87921905  9.64569081  6.176416   10.07216802  8.61537836
  8.8561206   8.62935441  7.4191906  11.85604959  7.04955806  9.43727487
 10.49864523  8.29948468  7.25270284  7.80063385  7.8177157   9.27450536
  7.56238494  8.94835388  8.78497191  7.52572791 11.39757405  7.59965442
  6.79578019  6.39353684  6.66035033  7.89413554  8.05657708  9.84667024
  8.26903924  9.65190239  5.98880016  6.12423002  8.12927866  7.03464156
  8.2370409  11.81318099  8.36160049  7.6770147   7.3437112   9.85504717
  7.95314556 10.30731114  7.05421674  7.41608481  8.39858548  8.23393511]
```

In [26]:
```
print(en.score(x_test,y_test))
```

```
0.9157209899533858
```

EVALUATION METRICS

In [27]:
```
from sklearn import metrics
```

In [28]:
```
print("Mean Absolute Error:",metrics.mean_absolute_error(y_test,prediction))
```

```
Mean Absolute Error: 1.3918640170192439e-15
```

In [29]:
```
print("Mean squarred Error:",metrics.mean_squared_error(y_test,prediction))
```

```
Mean squarred Error: 3.811120217431382e-30
```

In [30]:
```
print("Root Mean squarred Error:",np.sqrt(metrics.mean_squared_error(y_test,prediction))
```

```
Root Mean squarred Error: 1.952209060892655e-15
```

In [ ]:
```

```