diamond-price-prediction

July 30, 2024

1 DIAMOND PRICE PREDICTION

Submitted by : Karunya K

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15. Load the model

PROBLEM STATEMENT The diamond industry is highly competitive, and accurate pricing is crucial for maintaining profitability and customer satisfaction. Diamonds are priced based on multiple attributes, each contributing differently to the overall value. Traditional pricing methods can be subjective and inconsistent, leading to potential discrepancies and loss of revenue. By leveraging data analytics and machine learning, we aim to create a robust model that standardizes and predicts diamond prices with high accuracy.

OBJECTIVE To develop a predictive model that accurately estimates the price of diamonds based on various features such as carat, cut, color, clarity, and other relevant attributes.

DATA COLLECTION

[19]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

dm=pd.read_csv('diamonds.csv')
dm.head()
```

[19]:
```
   Unnamed: 0  carat      cut color clarity  depth  table  price     x     y  \
0           1   0.23    Ideal     E     SI2   61.5   55.0    326  3.95  3.98
1           2   0.21  Premium     E     SI1   59.8   61.0    326  3.89  3.84
2           3   0.23     Good     E     VS1   56.9   65.0    327  4.05  4.07
3           4   0.29  Premium     I     VS2   62.4   58.0    334  4.20  4.23
4           5   0.31     Good     J     SI2   63.3   58.0    335  4.34  4.35

      z
0  2.43
1  2.31
2  2.31
3  2.63
4  2.75
```

1.0.2 DATA DESCRIPTION

This classic dataset contains the prices and other attributes of almost 54,000 diamonds. It's a great dataset for learning to work with data analysis and visualization.

Dataset: https://www.kaggle.com/datasets/shivam2503/diamonds - ***carat*** (0.2-5.01): The carat is the diamond's physical weight measured in metric carats. One carat equals 0.20 gram . - ***cut*** (Fair, Good, Very Good, Premium, Ideal): The quality of the cut. The more precise the diamond is cut, the more captivating the diamond is to the eye thus of high grade. - ***color*** (from J (worst) to D (best)): The colour of gem-quality diamonds occurs in many hues. In the range from colourless to light yellow or light brown. Colourless diamonds are the rarest. Other natural colours (blue, red, pink for example) are known as "fancy," and their colour grading is different than from white colorless diamonds. - ***clarity*** (I1 (worst), SI2, SI1, VS2, VS1, VVS2, VVS1, IF (best)): Diamonds can have internal characteristics known as inclusions or external characteristics known as blemishes. Diamonds without inclusions or blemishes are rare; however, most characteristics can only be seen with magnification. - ***depth*** (43-79): It is the total depth percentage which equals to z / mean(x, y) = 2 * z / (x + y). The depth of the diamond is its height (in millimetres) measured from the culet (bottom tip) to the table (flat, top surface) as referred in the labelled diagram above. - ***table*** (43-95): It is the width of the top of the diamond relative to widest point. It gives diamond stunning fire and brilliance by reflecting lights to all directions which when seen by an observer, seems lustrous. - ***price*** ($$326 - $18826): It is the price of the diamond in US dollars. It is our very target column in the dataset. - ***x*** (0 - 10.74): Length of the diamond (in mm) - ***y*** (0 - 58.9): Width of the diamond (in mm) - ***z*** (0 - 31.8): Depth of the diamond (in mm)widest point (43–95)t (43–95)

1.0.3 EXPLORATORY DATA ANALYSIS

[20]:
```
dm.columns
```

[20]:
```
Index(['Unnamed: 0', 'carat', 'cut', 'color', 'clarity', 'depth', 'table',
       'price', 'x', 'y', 'z'],
      dtype='object')
```

[21]:
```
dm.shape
```

[21]:
```
(53940, 11)
```

[22]:
```
dm.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53940 entries, 0 to 53939
Data columns (total 11 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  53940 non-null  int64
 1   carat       53940 non-null  float64
 2   cut         53940 non-null  object
 3   color       53940 non-null  object
 4   clarity     53940 non-null  object
 5   depth       53940 non-null  float64
 6   table       53940 non-null  float64
 7   price       53940 non-null  int64
 8   x           53940 non-null  float64
 9   y           53940 non-null  float64
 10  z           53940 non-null  float64
dtypes: float64(6), int64(2), object(3)
memory usage: 4.5+ MB
```

[23]:
```
dm.describe()
```

[23]:
```
         Unnamed: 0         carat         depth         table         price  \
count  53940.000000  53940.000000  53940.000000  53940.000000  53940.000000
mean   26970.500000      0.797940     61.749405     57.457184   3932.799722
std    15571.281097      0.474011      1.432621      2.234491   3989.439738
min        1.000000      0.200000     43.000000     43.000000    326.000000
25%    13485.750000      0.400000     61.000000     56.000000    950.000000
50%    26970.500000      0.700000     61.800000     57.000000   2401.000000
75%    40455.250000      1.040000     62.500000     59.000000   5324.250000
max    53940.000000      5.010000     79.000000     95.000000  18823.000000

                  x             y             z
count  53940.000000  53940.000000  53940.000000
mean       5.731157      5.734526      3.538734
std        1.121761      1.142135      0.705699
min        0.000000      0.000000      0.000000
25%        4.710000      4.720000      2.910000
50%        5.700000      5.710000      3.530000
75%        6.540000      6.540000      4.040000
max       10.740000     58.900000     31.800000
```

[24]:
```
dm.dtypes
```

[24]:
```
Unnamed: 0      int64
carat         float64
cut            object
color          object
clarity        object
depth         float64
table         float64
price           int64
x             float64
y             float64
z             float64
dtype: object
```

[25]:
```
dm.isnull().sum()
```

[25]:
```
Unnamed: 0    0
carat         0
cut           0
color         0
clarity       0
depth         0
table         0
price         0
x             0
y             0
```

```
z              0
dtype: int64
```

[26]:
```
dm.nunique()
```

[26]:
```
Unnamed: 0    53940
carat           273
cut               5
color             7
clarity           8
depth           184
table           127
price         11602
x               554
y               552
z               375
dtype: int64
```

[27]:
```
dm["cut"].value_counts()
```

[27]:
```
cut
Ideal        21551
Premium      13791
Very Good    12082
Good          4906
Fair          1610
Name: count, dtype: int64
```

[28]:
```
dm["clarity"].value_counts()
```

[28]:
```
clarity
SI1     13065
VS2     12258
SI2      9194
VS1      8171
VVS2     5066
VVS1     3655
IF       1790
I1        741
Name: count, dtype: int64
```

[29]:
```
dm["color"].value_counts()
```

[29]:
```
color
G    11292
E     9797
F     9542
```

```
H      8304
D      6775
I      5422
J      2808
Name: count, dtype: int64
```

[30]:
```python
dm.duplicated().sum()
```

[30]:
```
0
```

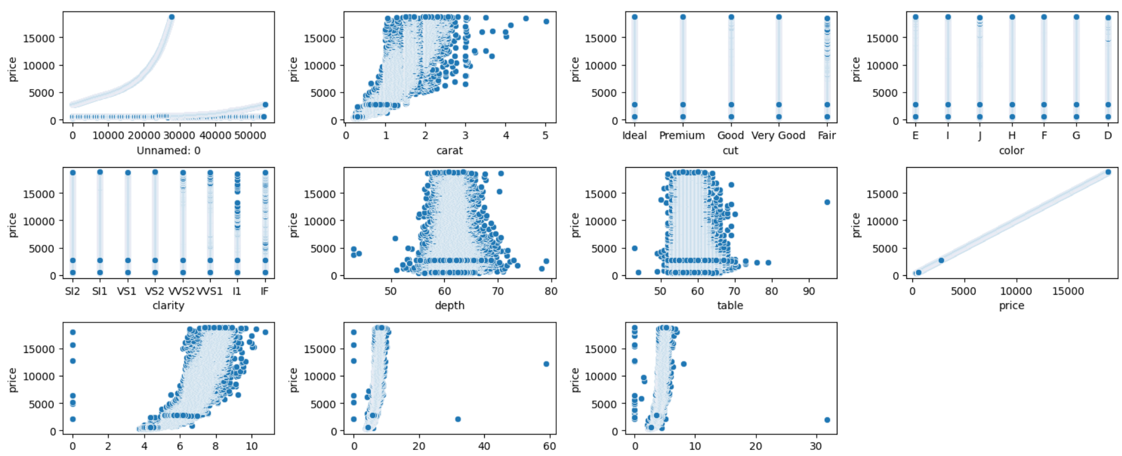
[31]:
```python
num_cols=dm.select_dtypes(include='number').columns
num_cols
```

[31]:
```
Index(['Unnamed: 0', 'carat', 'depth', 'table', 'price', 'x', 'y', 'z'],
dtype='object')
```

[32]:
```python
cat_cols=dm.select_dtypes(include='object').columns
cat_cols
```

[32]:
```
Index(['cut', 'color', 'clarity'], dtype='object')
```

[33]:
```python
# scatter plot to identify the relationship between price and remaining features
plt.figure(figsize=(15, 10))
for i, col in enumerate(dm.columns):
    plt.subplot(5, 4, i+1)
    sns.scatterplot(data=dm,x=col,y='price')
    plt.xlabel(col)
plt.tight_layout()
plt.show()
```



Correlation Matrix

[35]:

```
dmcorr=dm.drop(["cut","color","clarity"],axis=1)
corr1=dmcorr.corr()
corr1
```

[35]:

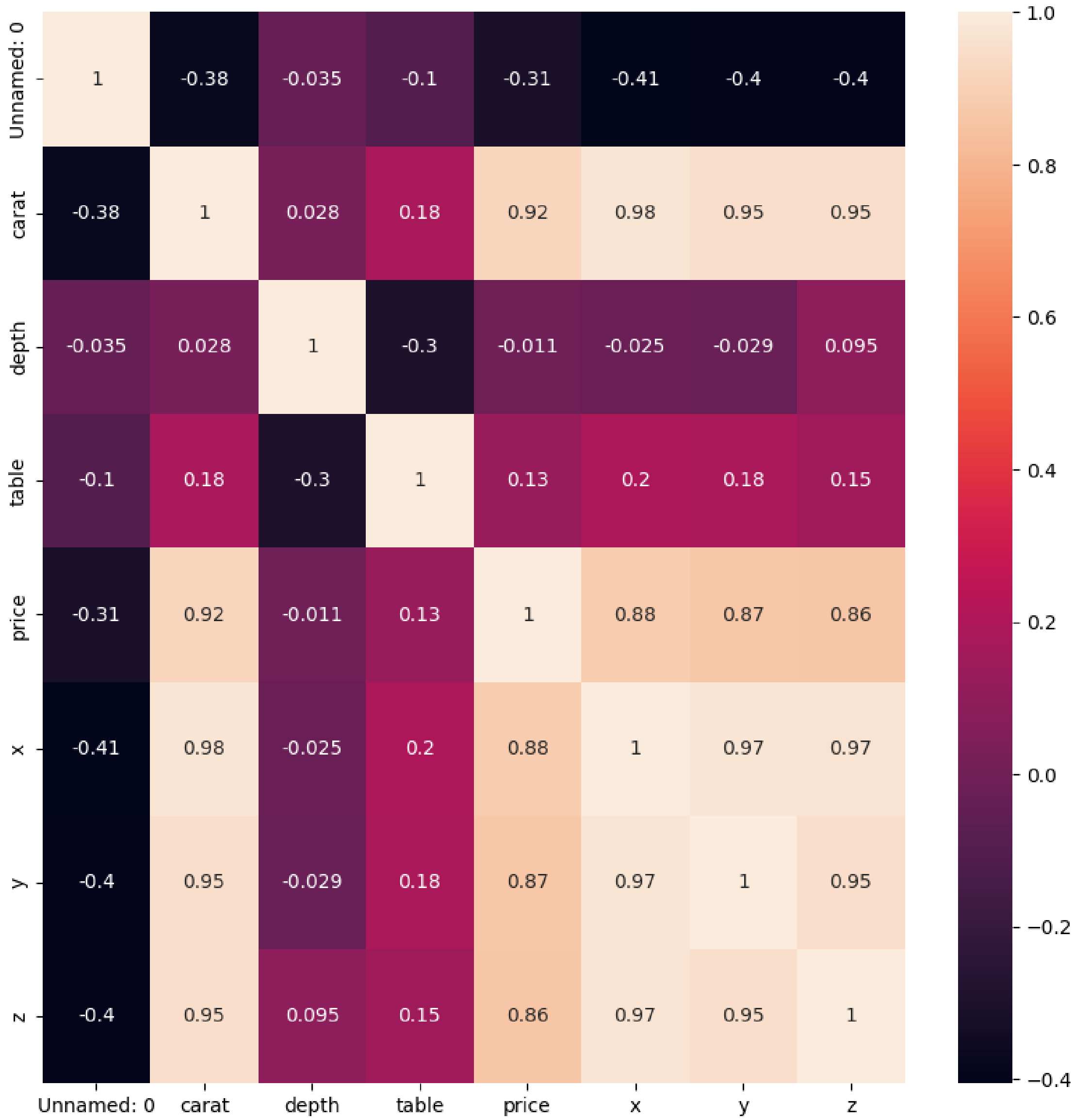
```
            Unnamed: 0     carat     depth     table     price         x  \
Unnamed: 0    1.000000 -0.377983 -0.034800 -0.100830 -0.306873 -0.405440
carat        -0.377983  1.000000  0.028224  0.181618  0.921591  0.975094
depth        -0.034800  0.028224  1.000000 -0.295779 -0.010647 -0.025289
table        -0.100830  0.181618 -0.295779  1.000000  0.127134  0.195344
price        -0.306873  0.921591 -0.010647  0.127134  1.000000  0.884435
x            -0.405440  0.975094 -0.025289  0.195344  0.884435  1.000000
y            -0.395843  0.951722 -0.029341  0.183760  0.865421  0.974701
z            -0.399208  0.953387  0.094924  0.150929  0.861249  0.970772

                   y         z
Unnamed: 0 -0.395843 -0.399208
carat       0.951722  0.953387
depth      -0.029341  0.094924
table       0.183760  0.150929
price       0.865421  0.861249
x           0.974701  0.970772
y           1.000000  0.952006
z           0.952006  1.000000
```

Heat map

[36]:

```
plt.figure(figsize=(10, 10))
sns.heatmap(corr1,annot=True)
plt.show()
```



The feature depth is least correlated (<0.1) with the target variable.

Features with multicollinearity:

carat and x

carat and y

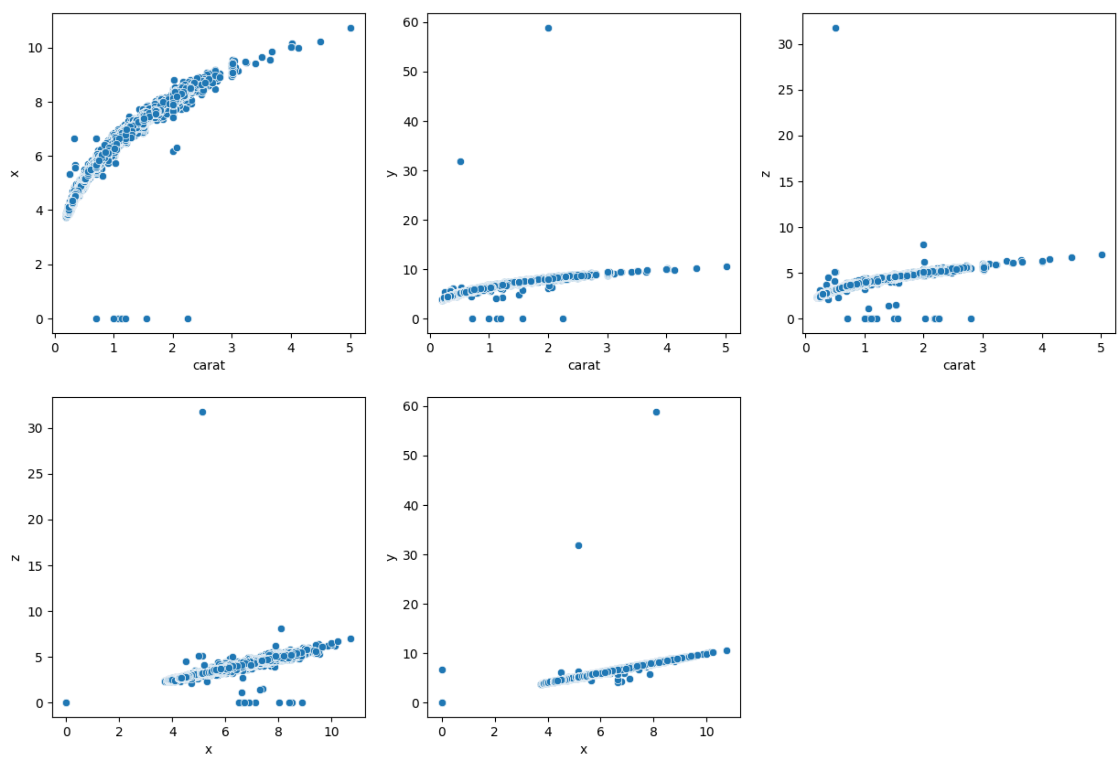
carat and z

x and y

x and z

[39]:
```
fig, axes = plt.subplots(2, 3, figsize=(15, 10))
sns.scatterplot(x='carat', y='x', data=dm, ax=axes[0, 0])
sns.scatterplot(x='carat', y='y', data=dm, ax=axes[0, 1])
sns.scatterplot(x='carat', y='z', data=dm, ax=axes[0, 2])
sns.scatterplot(x='x', y='z', data=dm, ax=axes[1, 0])
sns.scatterplot(x='x', y='y', data=dm, ax=axes[1, 1])
axes[1, 2].axis('off')
```

[39]: (0.0, 1.0, 0.0, 1.0)



[40]:
```
from scipy.stats import skew, kurtosis
# Calculate skewness and kurtosis
skewness = dm[num_cols].apply(skew)
kurt = dm[num_cols].apply(lambda x: kurtosis(x, fisher=False))
print(skewness)
print(kurt)
# Identify positive and negative skewness (absolute value > 1)
positive_skewness = skewness[skewness > 1]
negative_skewness = skewness[skewness < -1]
print('Variables with positive skewness (skew > 1):\n', positive_skewness)
print('Variables with negative skewness (skew < -1):\n', negative_skewness)
```

```python
# Identify platykurtic (kurtosis < 3) and leptokurtic (kurtosis > 3)␣
↪distributions
platykurtic = kurt[kurt < 3]
leptokurtic = kurt[kurt > 3]
print('Variables with platykurtic distribution (kurtosis < 3):\n', platykurtic)
print('Variables with leptokurtic distribution (kurtosis > 3):\n', leptokurtic)
```

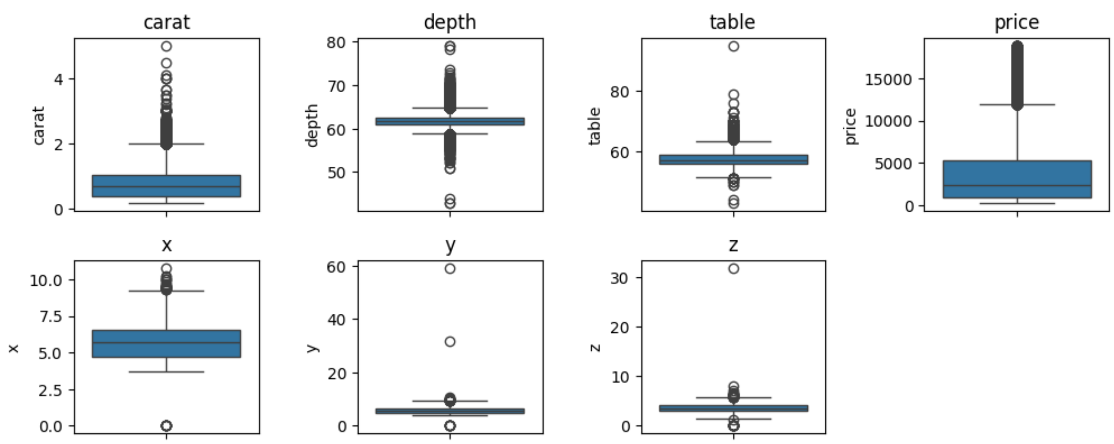
```
Unnamed: 0    0.000000
carat         1.116615
depth        -0.082292
table         0.796874
price         1.618350
x             0.378666
y             2.434099
z             1.522380
dtype: float64
Unnamed: 0     1.800000
carat          4.256408
depth          8.738771
table          5.801486
price          5.177383
x              2.381785
y             94.205991
z             50.082143
dtype: float64
Variables with positive skewness (skew > 1):
 carat    1.116615
price    1.618350
y        2.434099
z        1.522380
dtype: float64
Variables with negative skewness (skew < -1):
 Series([], dtype: float64)
Variables with platykurtic distribution (kurtosis < 3):
 Unnamed: 0    1.800000
x             2.381785
dtype: float64
Variables with leptokurtic distribution (kurtosis > 3):
 carat     4.256408
depth     8.738771
table     5.801486
price     5.177383
y        94.205991
z        50.082143
dtype: float64
```

DATA PREPROCESSING

[41]:
```
dm.drop(["Unnamed: 0"],axis=1,inplace=True)  # drop unwanted column
```

[42]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 10))
num_cols = dm.select_dtypes(include = ["int64","float64"])
for i, col in enumerate(num_cols):
    plt.subplot(5, 4, i+1)
    sns.boxplot(dm[col])
    plt.title(col)
plt.tight_layout()
plt.show()
```



Removing outliers (carat)

[43]:
```
q1c=dm.carat.quantile(0.25)
q3c=dm.carat.quantile(0.75)
iqrc=q3c-q1c
```

[44]:
```
lwc=q1c-1.5*iqrc
uwc=q3c+1.5*iqrc
```

[45]:
```
dmp1=dm[(dm.carat>lwc)&(dm.carat<uwc)]
dmp1
```

[45]:

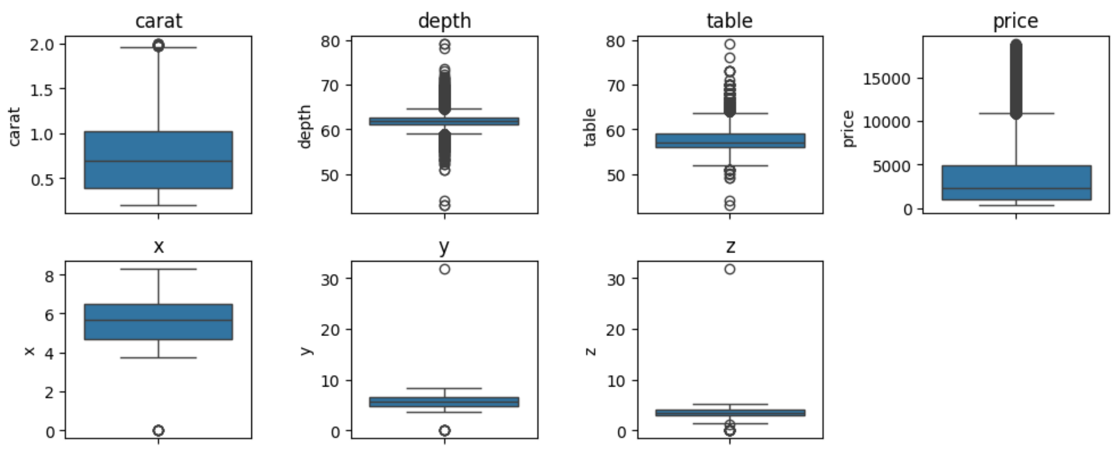
	carat	cut	color	clarity	depth	table	price	x	y	z
0	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
2	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31
3	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63
4	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75
…	…	…	…	…	…	…	…	…	…	…

```
53935   0.72      Ideal   D    SI1   60.8   57.0   2757  5.75  5.76  3.50
53936   0.72       Good   D    SI1   63.1   55.0   2757  5.69  5.75  3.61
53937   0.70  Very Good   D    SI1   62.8   60.0   2757  5.66  5.68  3.56
53938   0.86    Premium   H    SI2   61.0   58.0   2757  6.15  6.12  3.74
53939   0.75      Ideal   D    SI2   62.2   55.0   2757  5.83  5.87  3.64

[51786 rows x 10 columns]
```

[46]:
```python
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 10))
num_cols = dmp1.select_dtypes(include = ["int64","float64"])
for i, col in enumerate(num_cols):
    plt.subplot(5, 4, i+1)
    sns.boxplot(dmp1[col])
    plt.title(col)
plt.tight_layout()
plt.show()
```



Removing outliers(depth)

[47]:
```python
q1d=dmp1.depth.quantile(0.25)
q3d=dmp1.depth.quantile(0.75)
iqrd=q3d-q1d
```

[48]:
```python
lwd=q1d-1.5*iqrd
uwd=q3d+1.5*iqrd
```

[49]:
```python
dmp2=dmp1[(dmp1.depth>lwd)&(dmp1.depth<uwd)]
dmp2
```

[49]:

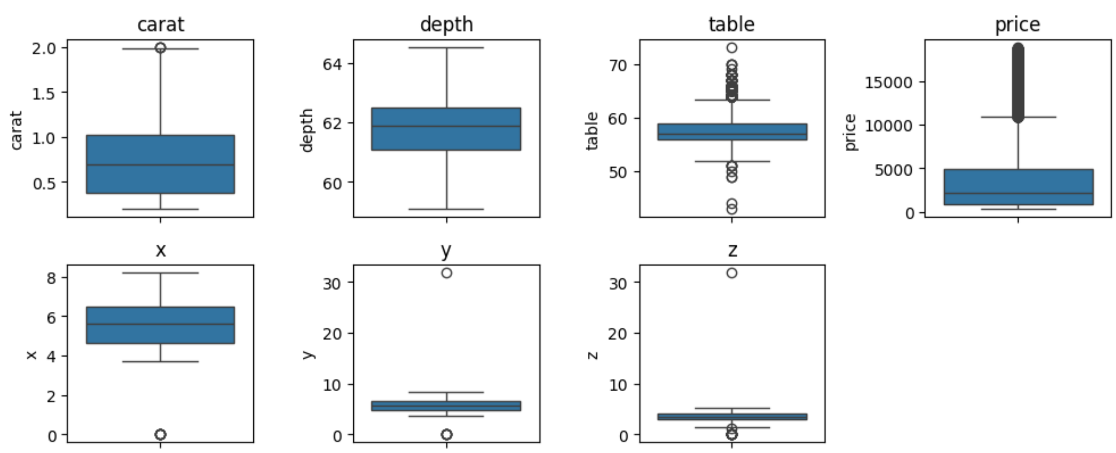
```
        carat        cut color clarity  depth  table  price     x     y     z
0        0.23      Ideal     E     SI2   61.5   55.0    326  3.95  3.98  2.43
1        0.21    Premium     E     SI1   59.8   61.0    326  3.89  3.84  2.31
3        0.29    Premium     I     VS2   62.4   58.0    334  4.20  4.23  2.63
4        0.31       Good     J     SI2   63.3   58.0    335  4.34  4.35  2.75
5        0.24  Very Good     J    VVS2   62.8   57.0    336  3.94  3.96  2.48
…         …         …   …     …    …      …     …    …   …    …
53935    0.72      Ideal     D     SI1   60.8   57.0   2757  5.75  5.76  3.50
53936    0.72       Good     D     SI1   63.1   55.0   2757  5.69  5.75  3.61
53937    0.70  Very Good     D     SI1   62.8   60.0   2757  5.66  5.68  3.56
53938    0.86    Premium     H     SI2   61.0   58.0   2757  6.15  6.12  3.74
53939    0.75      Ideal     D     SI2   62.2   55.0   2757  5.83  5.87  3.64

[48784 rows x 10 columns]
```

[50]:

```python
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 10))
num_cols = dmp2.select_dtypes(include = ["int64","float64"])
for i, col in enumerate(num_cols):
    plt.subplot(5, 4, i+1)
    sns.boxplot(dmp2[col])
    plt.title(col)
plt.tight_layout()
plt.show()
```



Removing outliers (table)

[51]:

```python
q1t=dmp2.table.quantile(0.25)
q3t=dmp2.table.quantile(0.75)
iqrt=q3t-q1t
```

[52]:
```
lwt=q1t-1.5*iqrt
uwt=q3t+1.5*iqrt
```

[53]:
```
dmp3=dmp2[(dmp2.table>lwt)&(dmp2.table<uwt)]
dmp3
```

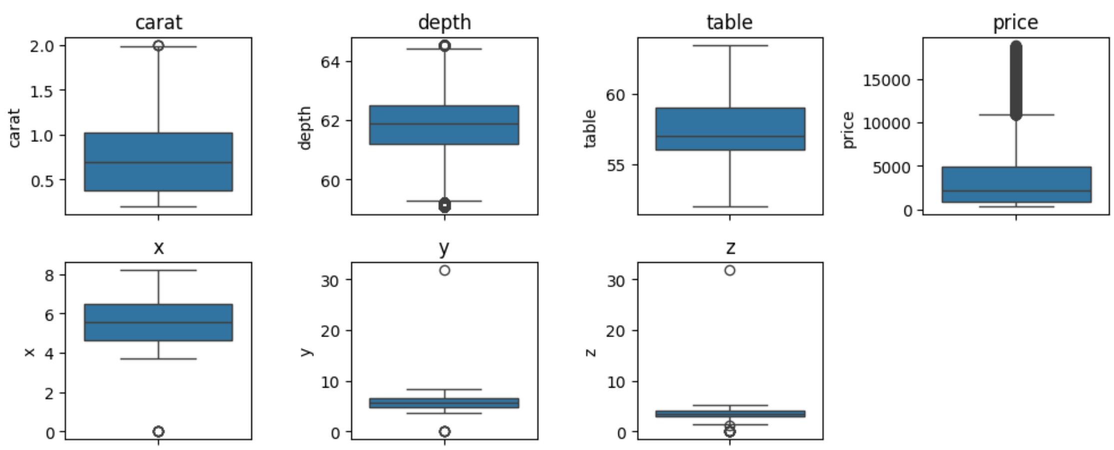
[53]:

	carat	cut	color	clarity	depth	table	price	x	y	z
0	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
3	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63
4	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75
5	0.24	Very Good	J	VVS2	62.8	57.0	336	3.94	3.96	2.48
…	…	…	…	…	…	…	…	…	…	…
53935	0.72	Ideal	D	SI1	60.8	57.0	2757	5.75	5.76	3.50
53936	0.72	Good	D	SI1	63.1	55.0	2757	5.69	5.75	3.61
53937	0.70	Very Good	D	SI1	62.8	60.0	2757	5.66	5.68	3.56
53938	0.86	Premium	H	SI2	61.0	58.0	2757	6.15	6.12	3.74
53939	0.75	Ideal	D	SI2	62.2	55.0	2757	5.83	5.87	3.64

[48451 rows x 10 columns]

[54]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 10))
num_cols = dmp3.select_dtypes(include = ["int64","float64"])
for i, col in enumerate(num_cols):
    plt.subplot(5, 4, i+1)
    sns.boxplot(dmp3[col])
    plt.title(col)
plt.tight_layout()
plt.show()
```



Removing outliers (price)

[55]:
```
q1p=dmp3.price.quantile(0.25)
q3p=dmp3.price.quantile(0.75)
iqrp=q3p-q1p
```

[56]:
```
lwp=q1p-1.5*iqrp
uwp=q3p+1.5*iqrp
```

[57]:
```
dmp4=dmp3[(dmp3.price>lwp)&(dmp3.price<uwp)]
dmp4
```

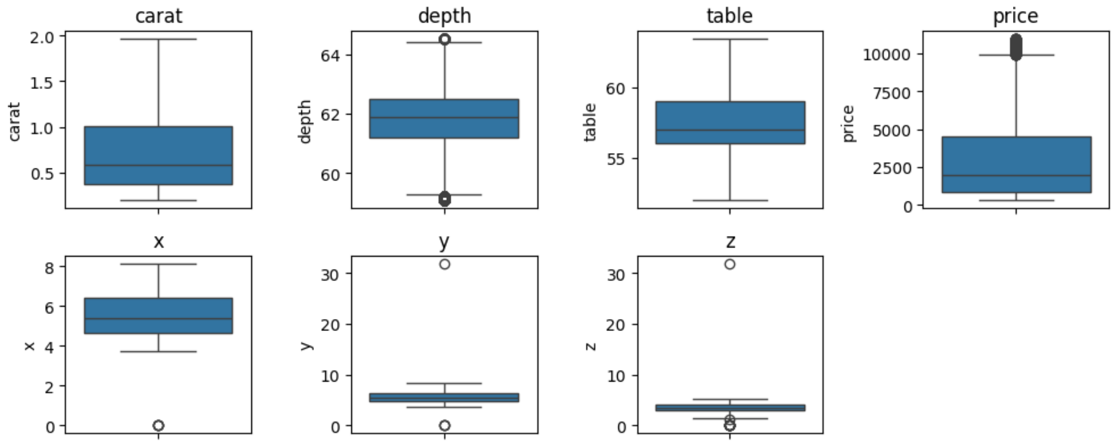
[57]:

	carat	cut	color	clarity	depth	table	price	x	y	z
0	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
3	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63
4	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75
5	0.24	Very Good	J	VVS2	62.8	57.0	336	3.94	3.96	2.48
…	…	…	…	…	…	…	…	…	…	…
53935	0.72	Ideal	D	SI1	60.8	57.0	2757	5.75	5.76	3.50
53936	0.72	Good	D	SI1	63.1	55.0	2757	5.69	5.75	3.61
53937	0.70	Very Good	D	SI1	62.8	60.0	2757	5.66	5.68	3.56
53938	0.86	Premium	H	SI2	61.0	58.0	2757	6.15	6.12	3.74
53939	0.75	Ideal	D	SI2	62.2	55.0	2757	5.83	5.87	3.64

[46184 rows x 10 columns]

[58]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 10))
num_cols = dmp4.select_dtypes(include = ["int64","float64"])
for i, col in enumerate(num_cols):
    plt.subplot(5, 4, i+1)
    sns.boxplot(dmp4[col])
    plt.title(col)
plt.tight_layout()
plt.show()
```




```
[63]: dm1= dmp4.copy() #keeping a copy of pre processed data
```

```
[66]: from scipy.stats import skew, kurtosis
# Calculate skewness and kurtosis
num_cols=dm1.select_dtypes(include='number').columns
skewness = dm1[num_cols].apply(skew)
kurt = dm1[num_cols].apply(lambda x: kurtosis(x, fisher=False))
print(skewness)
print(kurt)
# Identify positive and negative skewness (absolute value > 1)
positive_skewness = skewness[skewness > 1]
negative_skewness = skewness[skewness < -1]
print('Variables with positive skewness (skew > 1):\n', positive_skewness)
print('Variables with negative skewness (skew < -1):\n', negative_skewness)
# Identify platykurtic (kurtosis < 3) and leptokurtic (kurtosis > 3)
↪distributions
platykurtic = kurt[kurt < 3]
leptokurtic = kurt[kurt > 3]
print('Variables with platykurtic distribution (kurtosis < 3):\n', platykurtic)
print('Variables with leptokurtic distribution (kurtosis > 3):\n', leptokurtic)
```

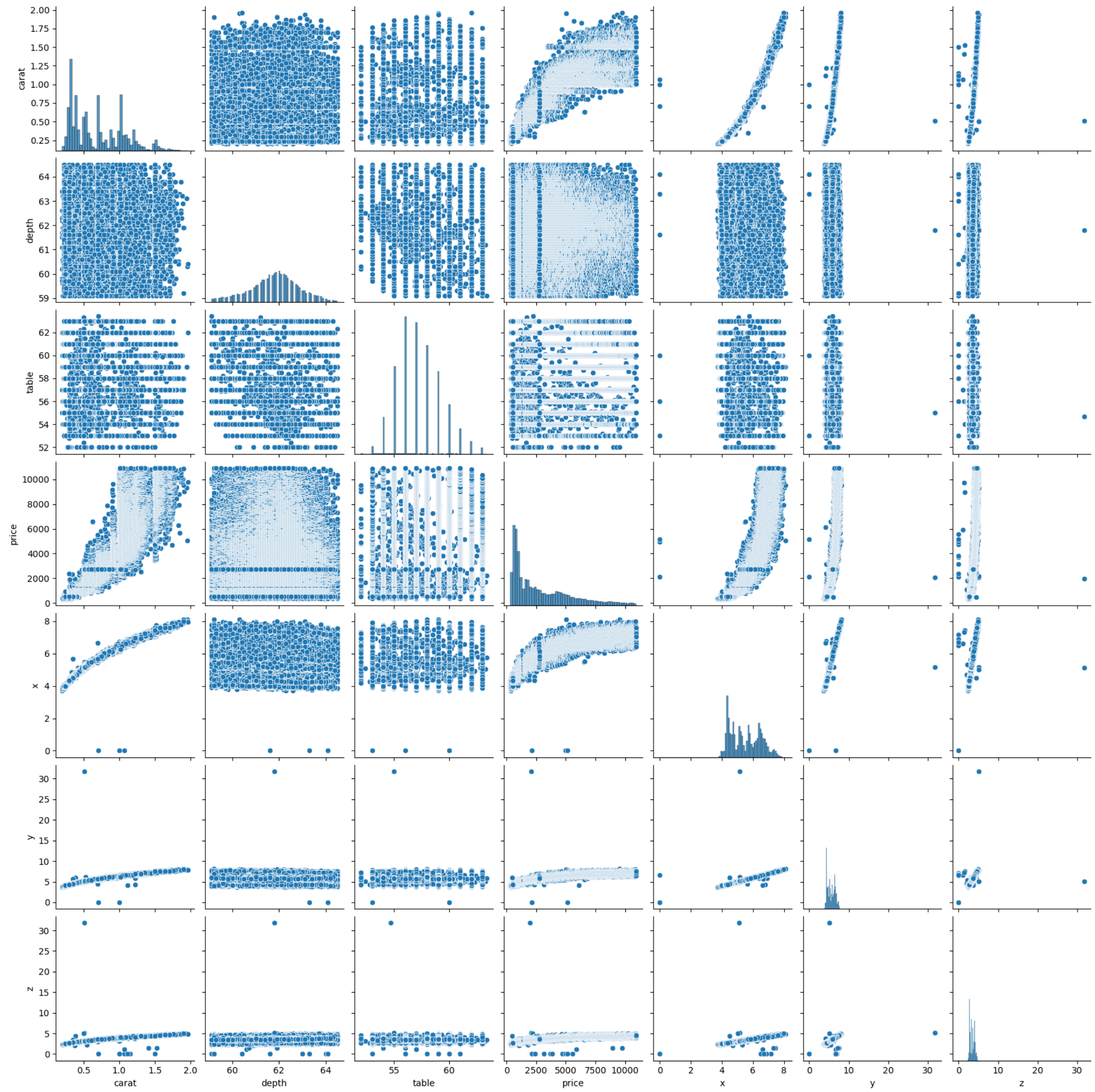
```
carat    0.675461
depth   -0.195611
table    0.400590
price    1.135528
x        0.238078
y        0.666671
z        2.358287
dtype: float64
carat        2.503286
depth        2.874853
table        2.851785
```

```
price      3.420423
x          1.950914
y         13.821676
z        102.445340
dtype: float64
Variables with positive skewness (skew > 1):
 price    1.135528
z        2.358287
dtype: float64
Variables with negative skewness (skew < -1):
 Series([], dtype: float64)
Variables with platykurtic distribution (kurtosis < 3):
 carat    2.503286
depth    2.874853
table    2.851785
x        1.950914
dtype: float64
Variables with leptokurtic distribution (kurtosis > 3):
 price      3.420423
y         13.821676
z        102.445340
dtype: float64
```

1.0.4 VISUALIZATION

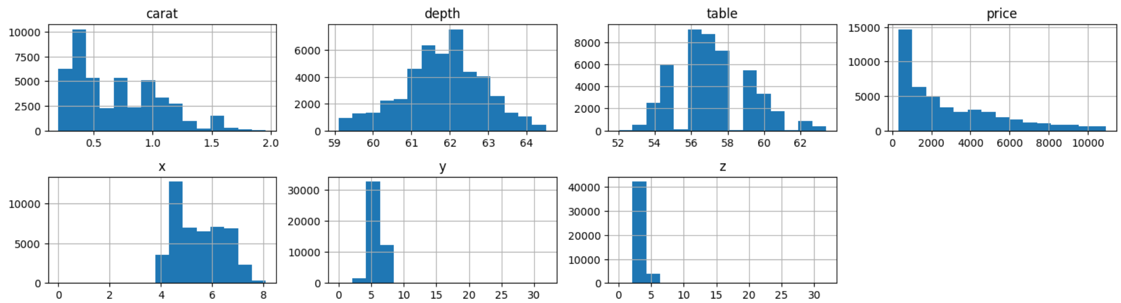
[67]:
```python
#Pair plot - To visualize relationships between multiple pairs of variables.
sns.pairplot(dm1)
```

[67]:
```
<seaborn.axisgrid.PairGrid at 0x262c033b590>
```



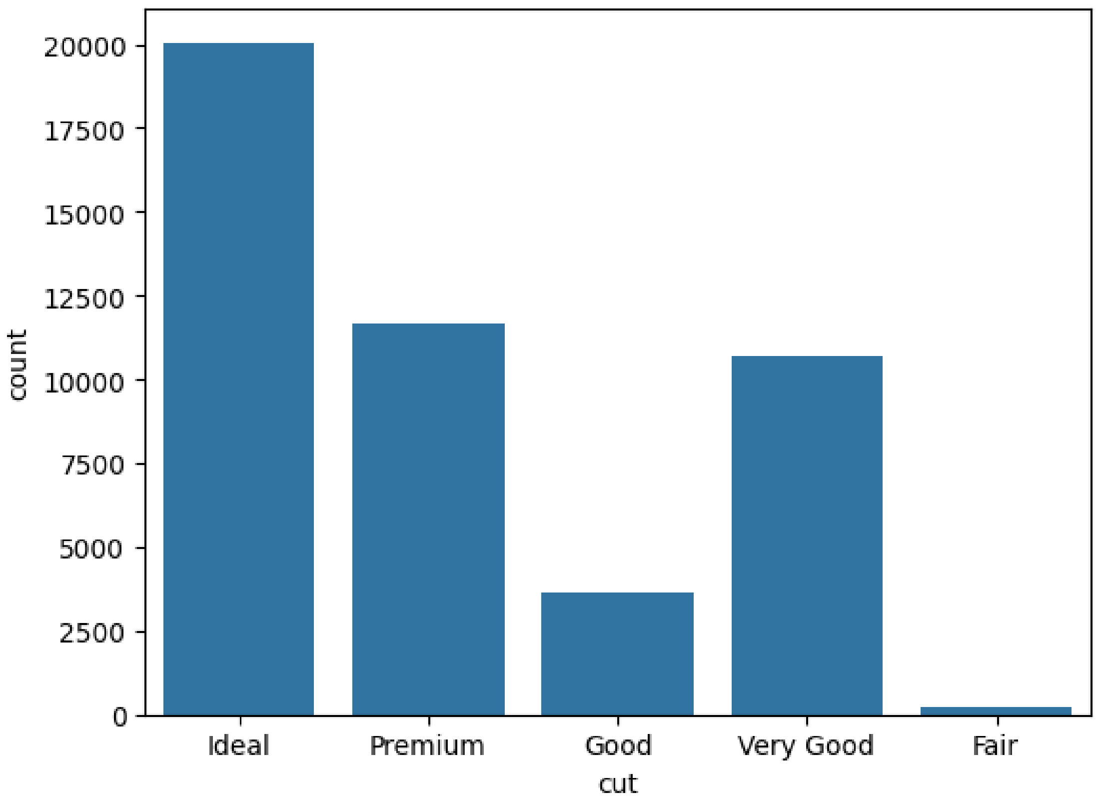
[68]:
```
# Histograms for numerical columns after outlier treatment
num_cols = dm1.select_dtypes(include=['number']).columns

dm1[num_cols].hist(bins=15, figsize=(15, 10), layout=(5, 4))
plt.tight_layout()
plt.show()
```



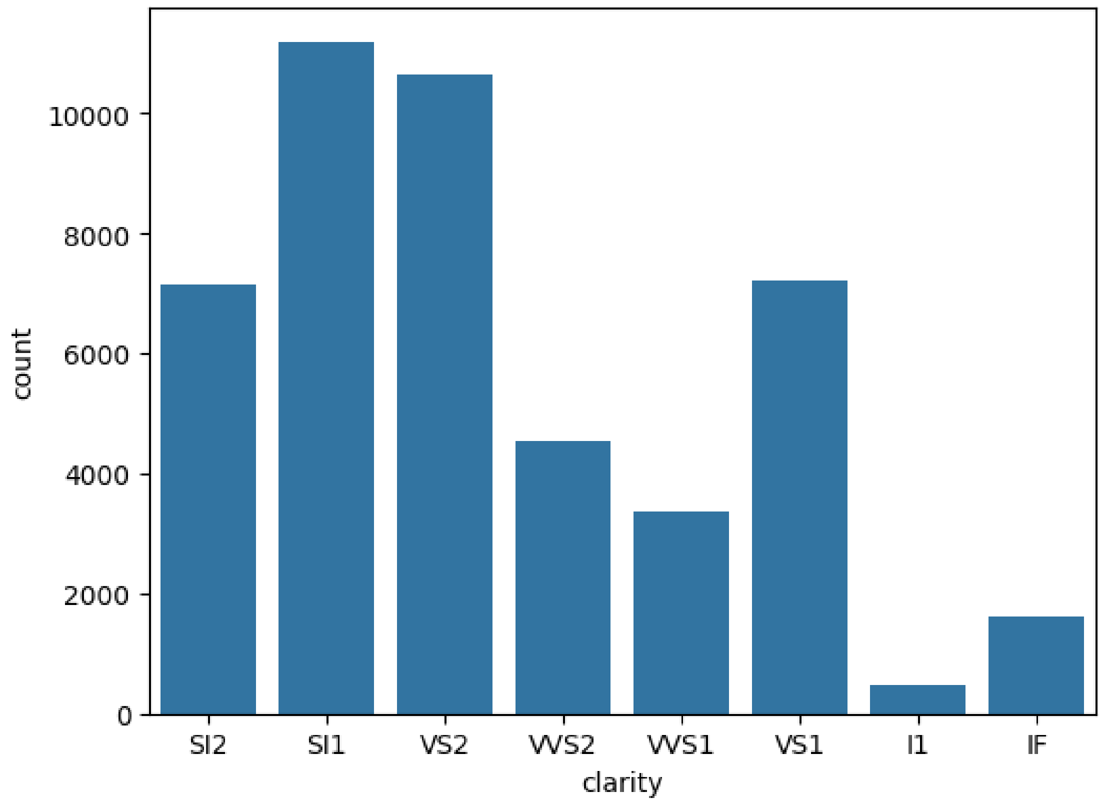
[69]:
```
sns.countplot(x='cut', data=dm1)
```

[69]: <Axes: xlabel='cut', ylabel='count'>



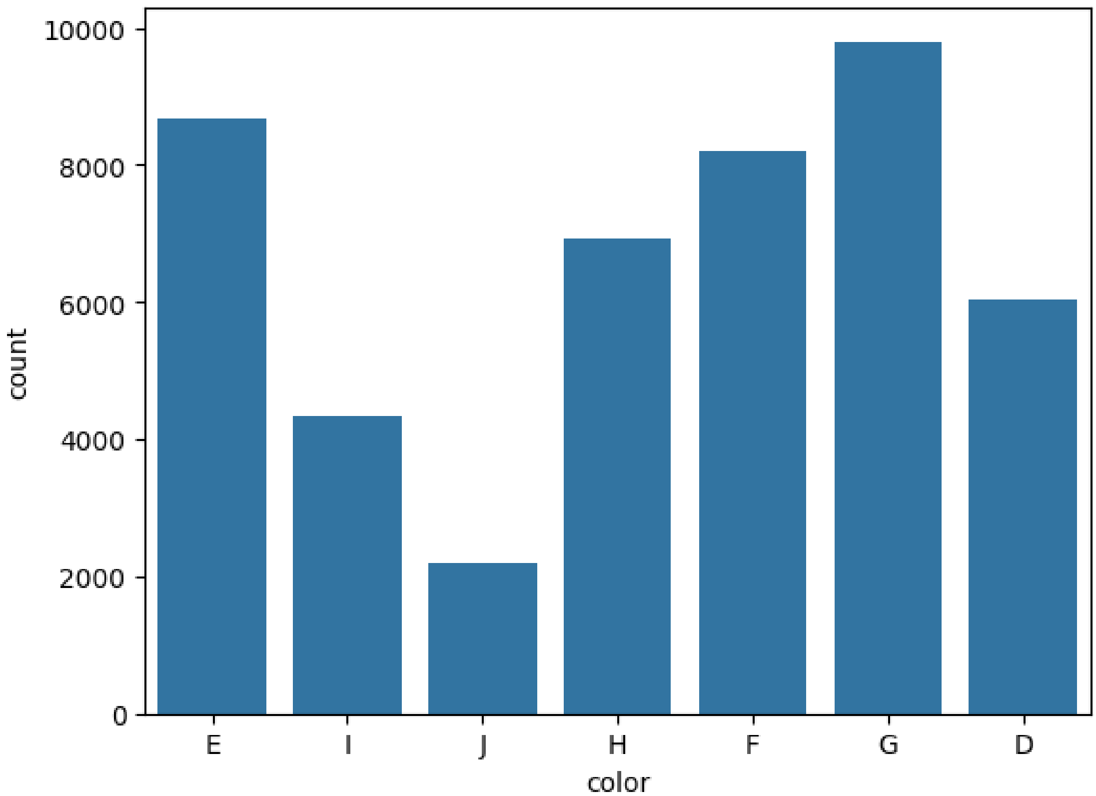
[70]:
```
sns.countplot(x='clarity', data=dm1)
```

[70]: <Axes: xlabel='clarity', ylabel='count'>



[71]:
```
sns.countplot(x='color', data=dm1)
```

[71]: <Axes: xlabel='color', ylabel='count'>



1.0.5 FEATURE ENGINEERING

One hot encoding

[72]:
```
dm1oh = pd.get_dummies(dm1[['cut',"color","clarity"]])
dm1oh = dm1oh.applymap(int)
dm1 = pd.concat([dm1, dm1oh], axis=1)
dm1=dm1.drop(['cut',"color","clarity"],axis=1)
dm1
```

```
C:\Users\karun\AppData\Local\Temp\ipykernel_13428\331167067.py:2: FutureWarning:
DataFrame.applymap has been deprecated. Use DataFrame.map instead.
  dm1oh = dm1oh.applymap(int)
```

[72]:

	carat	depth	table	price	x	y	z	cut_Fair	cut_Good	\
0	0.23	61.5	55.0	326	3.95	3.98	2.43	0	0	
1	0.21	59.8	61.0	326	3.89	3.84	2.31	0	0	
3	0.29	62.4	58.0	334	4.20	4.23	2.63	0	0	
4	0.31	63.3	58.0	335	4.34	4.35	2.75	0	1	
5	0.24	62.8	57.0	336	3.94	3.96	2.48	0	0	
…	…	…	…	…	…	…	…	…	…	
53935	0.72	60.8	57.0	2757	5.75	5.76	3.50	0	0	

```
53936   0.72   63.1   55.0   2757  5.69  5.75  3.61          0         1
53937   0.70   62.8   60.0   2757  5.66  5.68  3.56          0         0
53938   0.86   61.0   58.0   2757  6.15  6.12  3.74          0         0
53939   0.75   62.2   55.0   2757  5.83  5.87  3.64          0         0

       cut_Ideal  …  color_I  color_J  clarity_I1  clarity_IF  clarity_SI1  \
0              1  …        0        0           0           0            0
1              0  …        0        0           0           0            1
3              0  …        1        0           0           0            0
4              0  …        0        1           0           0            0
5              0  …        0        1           0           0            0
…            …  …      …      …         …         …          …
53935          1  …        0        0           0           0            1
53936          0  …        0        0           0           0            1
53937          0  …        0        0           0           0            1
53938          0  …        0        0           0           0            0
53939          1  …        0        0           0           0            0

       clarity_SI2  clarity_VS1  clarity_VS2  clarity_VVS1  clarity_VVS2
0                1            0            0             0             0
1                0            0            0             0             0
3                0            0            1             0             0
4                1            0            0             0             0
5                0            0            0             0             1
…              …          …          …           …           …
53935            0            0            0             0             0
53936            0            0            0             0             0
53937            0            0            0             0             0
53938            1            0            0             0             0
53939            1            0            0             0             0

[46184 rows x 27 columns]
```

[73]:
```python
dm1.shape
```

[73]:
```
(46184, 27)
```

Scaling

[74]:
```python
# Scaling using StandardScaler
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
dm1_scaled = scaler.fit_transform(dm1)
# Convert the result back to a DataFrame
dm1_scaled = pd.DataFrame(dm1_scaled, columns=dm1.columns)
dm1_scaled
```

[74]:
```
          carat     depth     table     price         x         y         z  \
0     -1.294260 -0.290178 -1.109047 -1.030738 -1.626375 -1.598382 -1.602744
1     -1.349875 -1.893071  1.877100 -1.030738 -1.688731 -1.743618 -1.798968
2     -1.127413  0.558412  0.384026 -1.027630 -1.366557 -1.339032 -1.275704
3     -1.071798  1.407002  0.384026 -1.027241 -1.221060 -1.214544 -1.079480
4     -1.266452  0.935563 -0.113665 -1.026853 -1.636767 -1.619130 -1.520984
…           …         …         …         …         …         …         …
46179  0.068321 -0.950193 -0.113665 -0.086082  0.244310  0.248189  0.146919
46180  0.068321  1.218427 -1.109047 -0.086082  0.181954  0.237815  0.326791
46181  0.012705  0.935563  1.379409 -0.086082  0.150775  0.165197  0.245031
46182  0.457629 -0.761617  0.384026 -0.086082  0.660017  0.621652  0.539367
46183  0.151744  0.369836 -1.109047 -0.086082  0.327451  0.362302  0.375847

       cut_Fair  cut_Good  cut_Ideal  …   color_I   color_J  clarity_I1  \
0     -0.064273 -0.292155   1.141835  … -0.322054 -0.222632   -0.099749
1     -0.064273 -0.292155  -0.875784  … -0.322054 -0.222632   -0.099749
2     -0.064273 -0.292155  -0.875784  …  3.105072 -0.222632   -0.099749
3     -0.064273  3.422844  -0.875784  … -0.322054  4.491727   -0.099749
4     -0.064273 -0.292155  -0.875784  … -0.322054  4.491727   -0.099749
…           …         …         …  …  …         …         …
46179 -0.064273 -0.292155   1.141835  … -0.322054 -0.222632   -0.099749
46180 -0.064273  3.422844  -0.875784  … -0.322054 -0.222632   -0.099749
46181 -0.064273 -0.292155  -0.875784  … -0.322054 -0.222632   -0.099749
46182 -0.064273 -0.292155  -0.875784  … -0.322054 -0.222632   -0.099749
46183 -0.064273 -0.292155   1.141835  … -0.322054 -0.222632   -0.099749

       clarity_IF  clarity_SI1  clarity_SI2  clarity_VS1  clarity_VS2  \
0       -0.189562    -0.565581     2.334390    -0.429828    -0.547460
1       -0.189562     1.768092    -0.428377    -0.429828    -0.547460
2       -0.189562    -0.565581    -0.428377    -0.429828     1.826616
3       -0.189562    -0.565581     2.334390    -0.429828    -0.547460
4       -0.189562    -0.565581    -0.428377    -0.429828    -0.547460
…             …            …            …            …            …
46179   -0.189562     1.768092    -0.428377    -0.429828    -0.547460
46180   -0.189562     1.768092    -0.428377    -0.429828    -0.547460
46181   -0.189562     1.768092    -0.428377    -0.429828    -0.547460
46182   -0.189562    -0.565581     2.334390    -0.429828    -0.547460
46183   -0.189562    -0.565581     2.334390    -0.429828    -0.547460

       clarity_VVS1  clarity_VVS2
0         -0.280558     -0.330624
1         -0.280558     -0.330624
2         -0.280558     -0.330624
3         -0.280558     -0.330624
4         -0.280558      3.024583
…               …             …
46179     -0.280558     -0.330624
```

```
46180     -0.280558     -0.330624
46181     -0.280558     -0.330624
46182     -0.280558     -0.330624
46183     -0.280558     -0.330624

[46184 rows x 27 columns]
```

1.0.6 DATA SPLITTING

[75]:
```python
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import pandas as pd

X= dm1_scaled.drop(["price"],axis =1)
Y= dm1_scaled["price"]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2,␣
 ↪random_state=42)
```

1.0.7 MODEL SELECTION

Models Selected - Linear Regressor Model - Decision Tree Regressor Model - Random Forest Regressor Model - Gradient Boosting Regressor Model - Support Vector Regressor

1.0.8 MODEL TRAINING AND EVALUATION (Without Feature Selection & Hyperparameter Tuning)

[76]:
```python
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor,GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
model_name= []
RMSE = []
MSE = []
MAE = []
R2_score = []
models = [
    LinearRegression(),
    DecisionTreeRegressor(),
    RandomForestRegressor(),
    GradientBoostingRegressor(),
    SVR()
]
for model in models :
    model.fit(X_train , y_train)
```

```python
    prediction = model.predict(X_test)

    model_name.append(model.__class__.__name__)

    RMSE.append(mean_squared_error(y_test, prediction, squared=False))
    MSE.append(mean_squared_error(y_test, prediction))
    MAE.append(mean_absolute_error(y_test, prediction))
    R2_score.append(r2_score(y_test, prediction) * 100)

models_df = pd.DataFrame({"Model-Name":model_name, "RMSE": RMSE, "MSE":MSE,␣
 ↪"MAE":MAE, "R2_Score":R2_score})
models_df = models_df.set_index('Model-Name')
models_df.sort_values("R2_Score", ascending = False)
```

```
C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
```

[76]:

Model-Name	RMSE	MSE	MAE	R2_Score
RandomForestRegressor	0.134144	0.017995	0.072999	98.236898
SVR	0.151171	0.022853	0.093801	97.760908
GradientBoostingRegressor	0.177192	0.031397	0.105443	96.923745
DecisionTreeRegressor	0.178332	0.031802	0.096704	96.884038

```
LinearRegression            0.273379  0.074736  0.187907  92.677394
```

1.0.9 FEATURE SELECTION

1.0.10 1. SelectKBest

[77]:
```python
from sklearn.feature_selection import SelectKBest, f_regression
# SelectKBest with f_regression
selector_kbest = SelectKBest(score_func=f_regression, k=25)
X_kbest = selector_kbest.fit_transform(X_train, y_train)
# Get the selected feature indices
selected_indices_kbest = selector_kbest.get_support(indices=True)
# Get the names of the selected features
selected_features_kbest = X_train.columns[selected_indices_kbest]
print("Selected features using SelectKBest:", selected_features_kbest)
```

```
Selected features using SelectKBest: Index(['carat', 'depth', 'table', 'x', 'y',
'z', 'cut_Fair', 'cut_Good',
       'cut_Ideal', 'cut_Premium', 'cut_Very Good', 'color_D', 'color_E',
       'color_F', 'color_G', 'color_H', 'color_I', 'color_J', 'clarity_I1',
       'clarity_IF', 'clarity_SI1', 'clarity_SI2', 'clarity_VS1',
       'clarity_VVS1', 'clarity_VVS2'],
      dtype='object')
```

1.0.11 Training using features selected using SelectKBest

[78]:
```python
X1 = X[['carat', 'depth', 'table', 'x', 'y', 'z', 'cut_Fair', 'cut_Good',
       'cut_Ideal', 'cut_Premium', 'cut_Very Good', 'color_D', 'color_E',
       'color_F', 'color_G', 'color_H', 'color_I', 'color_J', 'clarity_I1',
       'clarity_IF', 'clarity_SI1', 'clarity_SI2', 'clarity_VS1',
       'clarity_VVS1', 'clarity_VVS2']]
X1_train, X1_test, y1_train, y1_test = train_test_split(X1,Y,test_size = 0.
 ↪2,random_state = 42)
model_name= []
RMSE = []
MSE = []
MAE = []
R2_score = []
models = [
    LinearRegression(),
    DecisionTreeRegressor(),
    RandomForestRegressor(),
    GradientBoostingRegressor(),
    SVR(),

]
for model in models :
```

```
    model.fit(X1_train , y1_train)

    prediction = model.predict(X1_test)

    model_name.append(model.__class__.__name__)

    RMSE.append(mean_squared_error(y1_test, prediction, squared=False))
    MSE.append(mean_squared_error(y1_test, prediction))
    MAE.append(mean_absolute_error(y1_test, prediction))
    R2_score.append(r2_score(y1_test, prediction) * 100)

models_df = pd.DataFrame({"Model-Name":model_name, "RMSE": RMSE, "MSE":MSE,␣
↪"MAE":MAE, "R2_Score":R2_score})
models_df = models_df.set_index('Model-Name')
models_df.sort_values("R2_Score", ascending = False)
```

```
C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
```

[78]:

Model-Name	RMSE	MSE	MAE	R2_Score
RandomForestRegressor	0.135173	0.018272	0.073489	98.209745
SVR	0.151229	0.022870	0.093686	97.759180
GradientBoostingRegressor	0.177320	0.031442	0.105570	96.919295

```
DecisionTreeRegressor      0.179365  0.032172  0.096959  96.847823
LinearRegression           0.273393  0.074744  0.187900  92.676620
```

1.0.12 2. SelectFromModel with Lasso (L1 Regularization)

[79]:
```
from sklearn.linear_model import Lasso
 from sklearn.feature_selection import SelectFromModel
 # Lasso model
 lasso_model = Lasso(alpha=0.01)  # Adjust alpha as needed
 # SelectFromModel with Lasso
 selector_lasso = SelectFromModel(lasso_model, max_features=25)
 X_lasso = selector_lasso.fit_transform(X_train, y_train)
 # Get the selected feature indices
 selected_indices_lasso = selector_lasso.get_support(indices=True)
 # Print selected feature names
 selected_features_lasso = X_train.columns[selected_indices_lasso]
 print("Selected features using SelectFromModel with Lasso:",␣
 ↪selected_features_lasso)
```

```
Selected features using SelectFromModel with Lasso: Index(['carat', 'table',
'cut_Fair', 'cut_Good', 'cut_Ideal', 'color_D',
       'color_E', 'color_H', 'color_I', 'color_J', 'clarity_I1', 'clarity_IF',
       'clarity_SI1', 'clarity_SI2', 'clarity_VS1', 'clarity_VVS1',
       'clarity_VVS2'],
      dtype='object')
```

1.0.13 Training using features selected using Lasso

[80]:
```
X2 = X[['carat', 'table', 'cut_Fair', 'cut_Good', 'cut_Ideal', 'color_D',
       'color_E', 'color_H', 'color_I', 'color_J', 'clarity_I1', 'clarity_IF',
       'clarity_SI1', 'clarity_SI2', 'clarity_VS1', 'clarity_VVS1',
       'clarity_VVS2']]
X2_train, X2_test, y2_train, y2_test = train_test_split(X2,Y,test_size = 0.
 ↪2,random_state = 42)
model_name= []
RMSE = []
MSE = []
MAE = []
R2_score = []
models = [
    LinearRegression(),
    DecisionTreeRegressor(),
    RandomForestRegressor(),
    GradientBoostingRegressor(),
    SVR(),

]
```

```python
for model in models :
    model.fit(X2_train , y2_train)

    prediction = model.predict(X2_test)

    model_name.append(model.__class__.__name__)

    RMSE.append(mean_squared_error(y2_test, prediction, squared=False))
    MSE.append(mean_squared_error(y2_test, prediction))
    MAE.append(mean_absolute_error(y2_test, prediction))
    R2_score.append(r2_score(y2_test, prediction) * 100)

models_df = pd.DataFrame({"Model-Name":model_name, "RMSE": RMSE, "MSE":MSE,␣
↪"MAE":MAE, "R2_Score":R2_score})
models_df = models_df.set_index('Model-Name')
models_df.sort_values("R2_Score", ascending = False)
```

```
C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
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deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
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C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
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C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
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C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
```

[80]:

```
                             RMSE       MSE       MAE   R2_Score
Model-Name
RandomForestRegressor    0.152044  0.023117  0.088852  97.734966
SVR                      0.163121  0.026608  0.098388  97.392909
```

```
DecisionTreeRegressor      0.172009  0.029587  0.097455  97.101060
GradientBoostingRegressor  0.182655  0.033363  0.108786  96.731119
LinearRegression           0.279492  0.078116  0.200435  92.346250
```

1.0.14 HYPERPARAMETER TUNING

[81]:
```python
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.model_selection import GridSearchCV,RandomizedSearchCV
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
import pandas as pd
import time
import pickle

# Define parameter grids
param_grids = {
    'LinearRegression': {
        'fit_intercept': [True, False],
    },
    'DecisionTreeRegressor': {
        'max_depth': [10, 20],
        'min_samples_split': [2, 10],
        'min_samples_leaf': [1, 5],
    },
    'RandomForestRegressor': {
        'n_estimators': [200, 300],
        'max_depth': [10, 20],
        'min_samples_split': [2, 10],
    },
    'GradientBoostingRegressor': {
        'learning_rate': [0.01, 0.1],
        'n_estimators': [200, 300],
        'max_depth': [5, 7],
    },
    'SVR': {
        'kernel': ['linear','rbf'],
        'C': [ 1, 10],
        'gamma': ['scale'],
    }
}

# Lists to store the results
model_name = []
RMSE = []
MSE = []
```

```
MAE = []
R2_score = []
best_params = []

# Define the models
models = [
    LinearRegression(),
    DecisionTreeRegressor(),
    RandomForestRegressor(),
    GradientBoostingRegressor(),
    SVR(),
]

# Loop through each model and perform GridSearchCV except for svr use random␣
↪search cv
for model in models:
    model_class_name = model.__class__.__name__
    print(f"Starting tuning for {model_class_name}...")
    if model_class_name == 'SVR':
        search = RandomizedSearchCV(estimator=model,␣
↪param_distributions=param_grids[model_class_name],
                                    scoring='neg_mean_squared_error', cv=3,␣
↪n_iter=5, n_jobs=-1, random_state=42)
    else:
        search = GridSearchCV(estimator=model,␣
↪param_grid=param_grids[model_class_name], scoring='neg_mean_squared_error',␣
↪cv=5, n_jobs=-1)

    start_time = time.time()  # Start timing
    search.fit(X_train, y_train)
    end_time = time.time()  # End timing
    print(f"{model_class_name} tuning runtime: {(end_time - start_time)/60:.2f}␣
↪minutes")

    best_model = search.best_estimator_
    prediction = best_model.predict(X_test)

    model_name.append(model_class_name)
    RMSE.append(mean_squared_error(y_test, prediction,squared=False))
    MSE.append(mean_squared_error(y_test, prediction))
    MAE.append(mean_absolute_error(y_test, prediction))
    R2_score.append(r2_score(y_test, prediction) * 100)
    best_params.append(search.best_params_)  # Store the best parameters
    print(f"{model_class_name} Best Params: {search.best_params_}")

    # Save the best model using pickle
    with open(f'{model_class_name}_best_model.pkl', 'wb') as file:
```

```python
        pickle.dump(best_model, file)
    print(f"Saved {model_class_name} best model to␣
↪{model_class_name}_best_model.pkl")

# Create a DataFrame with the results
models_df = pd.DataFrame({
    "Model-Name": model_name,
    "RMSE": RMSE,
    "MSE": MSE,
    "MAE": MAE,
    "R2_Score": R2_score,
    "Best Params": best_params
})
models_df = models_df.set_index('Model-Name')
models_df = models_df.sort_values("R2_Score", ascending=False)
models_df
```

```
Starting tuning for LinearRegression…
LinearRegression tuning runtime: 0.21 minutes
LinearRegression Best Params: {'fit_intercept': True}
Saved LinearRegression best model to LinearRegression_best_model.pkl
Starting tuning for DecisionTreeRegressor…
```

```
C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
```

```
DecisionTreeRegressor tuning runtime: 0.11 minutes
DecisionTreeRegressor Best Params: {'max_depth': 20, 'min_samples_leaf': 5,
'min_samples_split': 10}
Saved DecisionTreeRegressor best model to DecisionTreeRegressor_best_model.pkl
Starting tuning for RandomForestRegressor…
```

```
C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
```

```
RandomForestRegressor tuning runtime: 11.27 minutes
```

```
C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
```

```
RandomForestRegressor Best Params: {'max_depth': 20, 'min_samples_split': 2,
```

```
'n_estimators': 200}
Saved RandomForestRegressor best model to RandomForestRegressor_best_model.pkl
Starting tuning for GradientBoostingRegressor…
GradientBoostingRegressor tuning runtime: 2.48 minutes
GradientBoostingRegressor Best Params: {'learning_rate': 0.1, 'max_depth': 7,
'n_estimators': 300}
Saved GradientBoostingRegressor best model to
GradientBoostingRegressor_best_model.pkl
Starting tuning for SVR…

C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\model_selection\_search.py:320: UserWarning: The total space of
parameters 4 is smaller than n_iter=5. Running 4 iterations. For exhaustive
searches, use GridSearchCV.
  warnings.warn(

SVR tuning runtime: 23.92 minutes
SVR Best Params: {'kernel': 'rbf', 'gamma': 'scale', 'C': 10}
Saved SVR best model to SVR_best_model.pkl

C:\Users\karun\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\metrics\_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
```

[81]:

```
                               RMSE       MSE       MAE   R2_Score  \
Model-Name
GradientBoostingRegressor  0.132056  0.017439  0.072635  98.291346
RandomForestRegressor      0.133922  0.017935  0.073078  98.242736
SVR                        0.148641  0.022094  0.092367  97.835235
DecisionTreeRegressor      0.157599  0.024837  0.087252  97.566437
LinearRegression           0.273379  0.074736  0.187907  92.677394

                                                                 Best Params
Model-Name
GradientBoostingRegressor  {'learning_rate': 0.1, 'max_depth': 7, 'n_esti…
RandomForestRegressor      {'max_depth': 20, 'min_samples_split': 2, 'n_e…
SVR                             {'kernel': 'rbf', 'gamma': 'scale', 'C': 10}
DecisionTreeRegressor      {'max_depth': 20, 'min_samples_leaf': 5, 'min_…
LinearRegression                                     {'fit_intercept': True}
```

1.0.15 CONCLUSION

GradientBoostingRegressor has the best performance with lowest values of rmse, mse, mae and high value of r2 score

1.0.16 SAVE THE MODEL

Saved the each model with the best parameters using pickle. Saved the model with ".pkl" extension

1.0.17 LOAD THE MODEL

[82]:
```
with open('GradientBoostingRegressor_best_model.pkl','rb') as file: # loading
 ↪the gradient boosting regressor model
    mp=pickle.load(file)
```

[ ]:
```

```