Diamond Price Prediction

The aim of this analysis is to predict the price of diamonds based on their characteristics. The dataset used for this analysis is the Diamonds dataset from Kaggle. The dataset contains 53940 observations and 10 variables. The variables are as follows:

Column Name	Definition
carat	Weight of the diamond
cut	Quality of the cut (Fair, Good, Very Good, Premium, Ideal)
color	Diamond colour, from J (worst) to D (best)
Clarity	How clear the diamond is (I1 (worst), SI2, SI1, VS2, VS1, VVS2, VVS1, IF (best))
x	Length in mm
y	Width in mm
z	Depth in mm
depth	Total depth percentage = z / mean(x, y) = 2 * z / (x + y) (43--79)
table	Width of top of diamond relative to widest point (43--95)
price	Price in US dollars (326--18,823)

```
#importing the libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

#loading the dataset
df = pd.read_csv('diamonds.csv')
df.head()
```

	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

Data Preprocessing

```
df.shape
```

```
(50000, 10)
```

```python
#checking for null values
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 10 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   carat    50000 non-null  float64
 1   cut      50000 non-null  object 
 2   color    50000 non-null  object 
 3   clarity  50000 non-null  object 
 4   depth    50000 non-null  float64
 5   table    50000 non-null  float64
 6   price    50000 non-null  int64  
 7   x        50000 non-null  float64
 8   y        50000 non-null  float64
 9   z        50000 non-null  float64
dtypes: float64(6), int64(1), object(3)
memory usage: 3.8+ MB
```

```python
#checking descriptive statistics
df.describe()
```

```
              carat         depth         table         price
x  \
count  50000.000000  50000.000000  50000.000000  50000.000000
50000.000000
mean       0.799444     61.753006     57.457830   3944.805440
5.734403
std        0.475173      1.431088      2.232092   3997.938105
1.123077
min        0.200000     43.000000     43.000000    326.000000
0.000000
25%        0.400000     61.000000     56.000000    951.000000
4.710000
50%        0.700000     61.800000     57.000000   2410.000000
5.700000
75%        1.040000     62.500000     59.000000   5351.000000
6.540000
max        5.010000     79.000000     95.000000  18823.000000
10.740000

                  y             z
count  50000.000000  50000.000000
mean       5.737956      3.541056
std        1.145579      0.707065
min        0.000000      0.000000
25%        4.720000      2.910000
50%        5.710000      3.530000
```

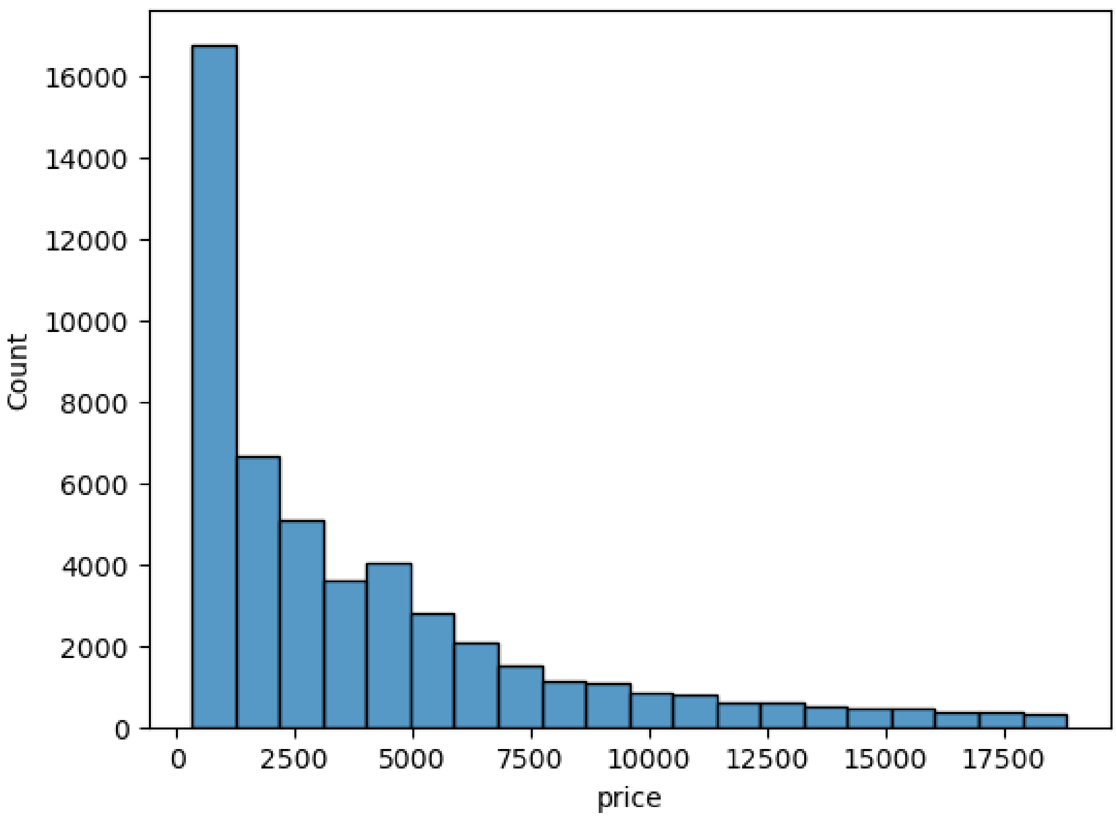
```
75%        6.540000     4.040000
max       58.900000    31.800000


#values count of categorical variables
print(df.cut.value_counts(),'\n',df.color.value_counts(),'\
n',df.clarity.value_counts())

Ideal        19938
Premium      12806
Very Good    11204
Good          4557
Fair          1495
Name: cut, dtype: int64
 G    10452
E     9085
F     8864
H     7711
D     6224
I     5058
J     2606
Name: color, dtype: int64
 SI1     12115
VS2     11404
SI2      8519
VS1      7579
VVS2     4694
VVS1     3369
IF       1632
I1        688
Name: clarity, dtype: int64

df.head(10)

   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
5   0.24  Very Good     J    VVS2   62.8   57.0    336  3.94  3.96
2.48
6   0.24  Very Good     I    VVS1   62.3   57.0    336  3.95  3.98
2.47
```

```
7   0.26  Very Good     H     SI1   61.9   55.0    337  4.07  4.11
2.53
8   0.22       Fair     E     VS2   65.1   61.0    337  3.87  3.78
2.49
9   0.23  Very Good     H     VS1   59.4   61.0    338  4.00  4.05
2.39
```

Exploratory Data Analysis

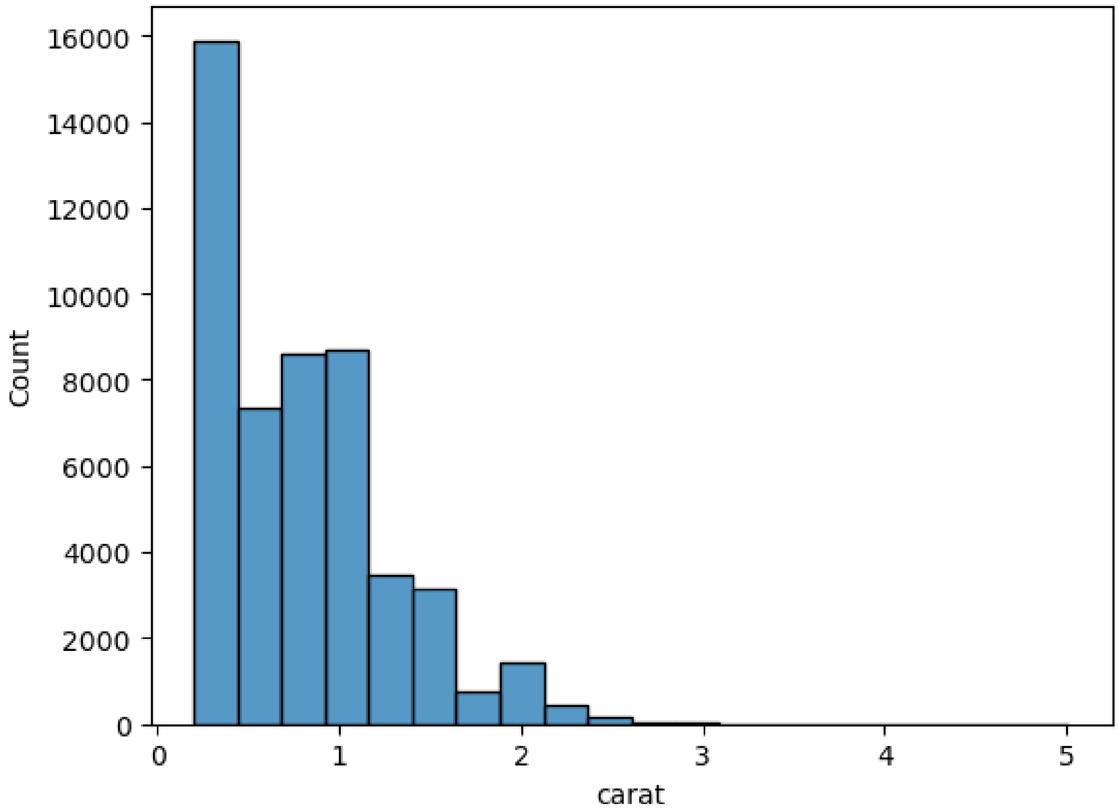
```
sns.histplot(df['price'],bins = 20)
```

```
<Axes: xlabel='price', ylabel='Count'>
```



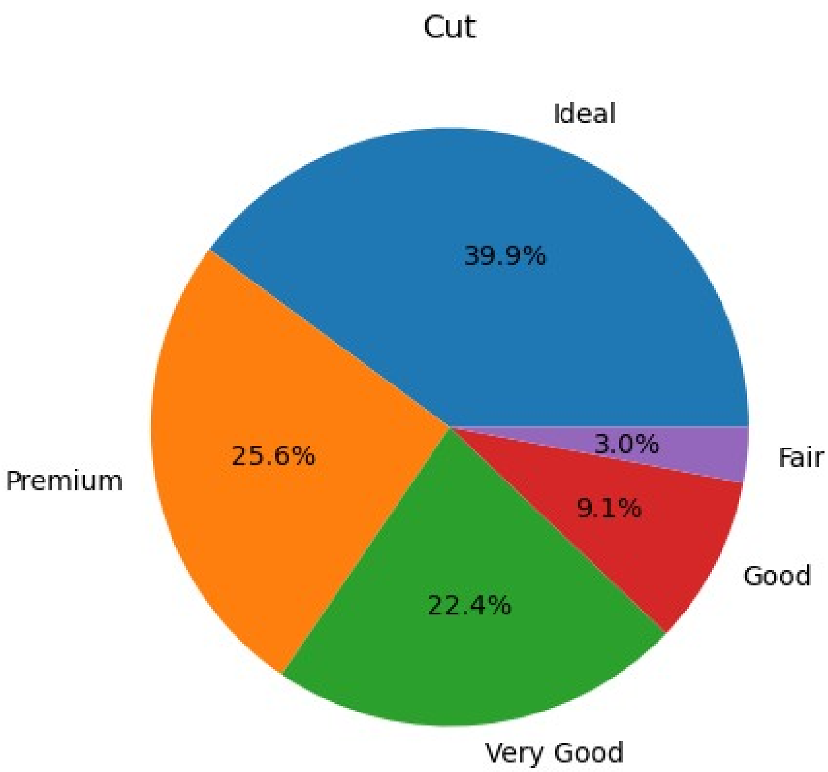

```
sns.histplot(df['carat'],bins=20)
```

```
<Axes: xlabel='carat', ylabel='Count'>
```

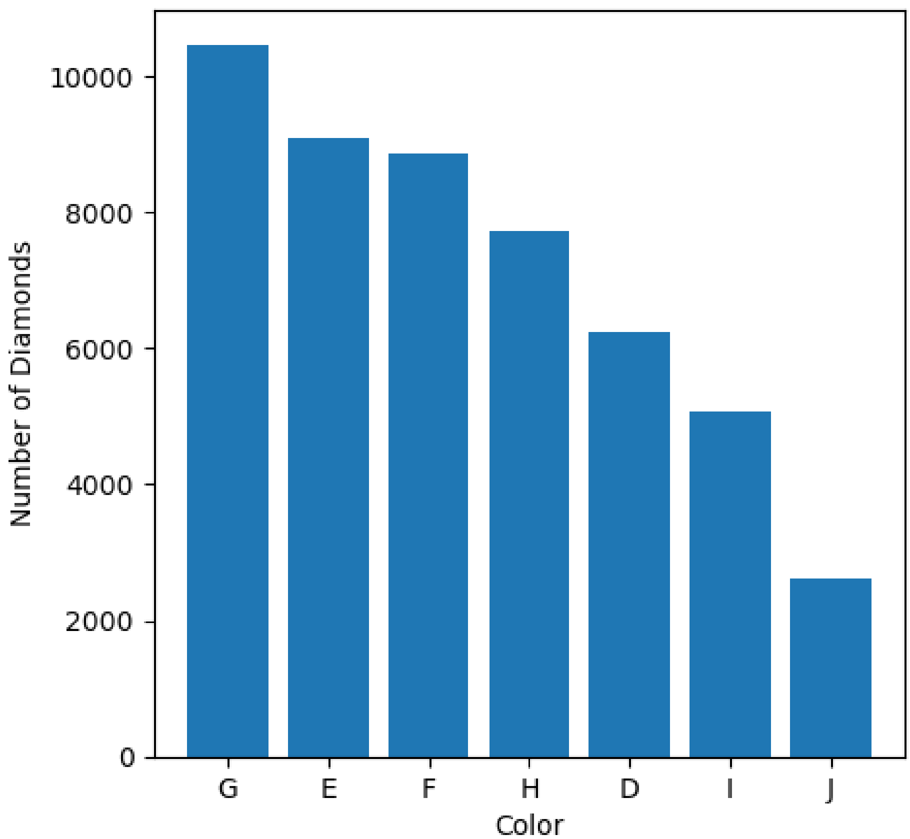


Most of the diamonds are less then 1 carat in weight.

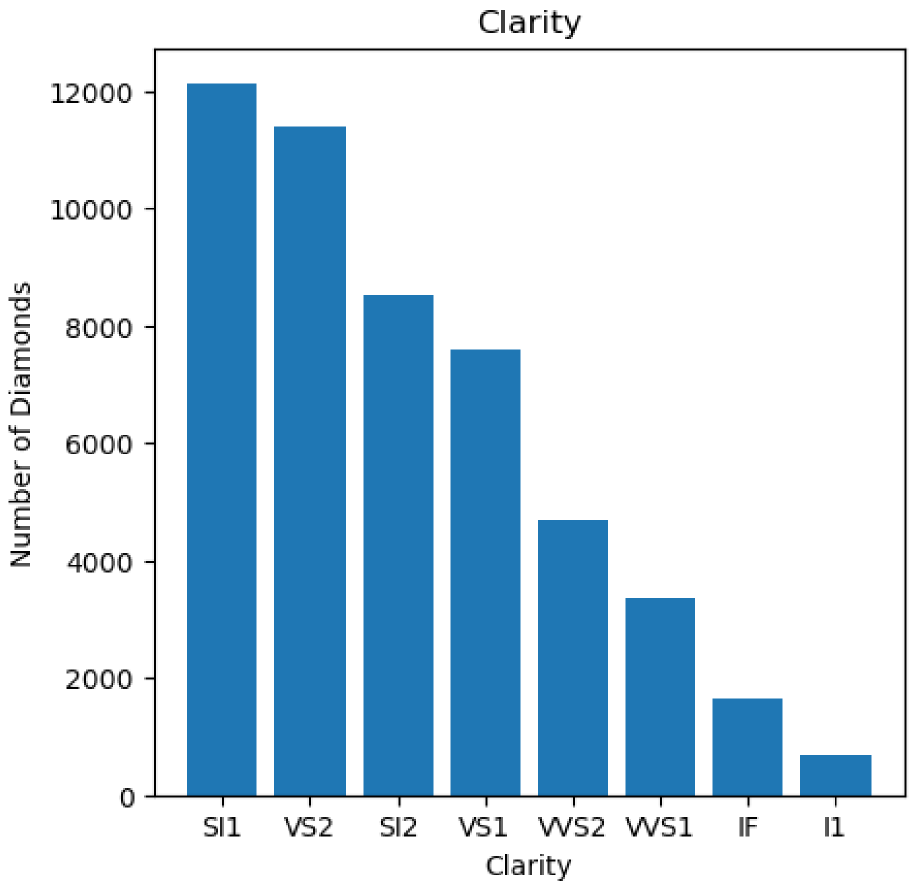
```
plt.figure(figsize=(5,5))
plt.pie(df['cut'].value_counts(),labels=['Ideal','Premium','Very
Good','Good','Fair'],autopct='%1.1f%%')
plt.title('Cut')
plt.show()
```



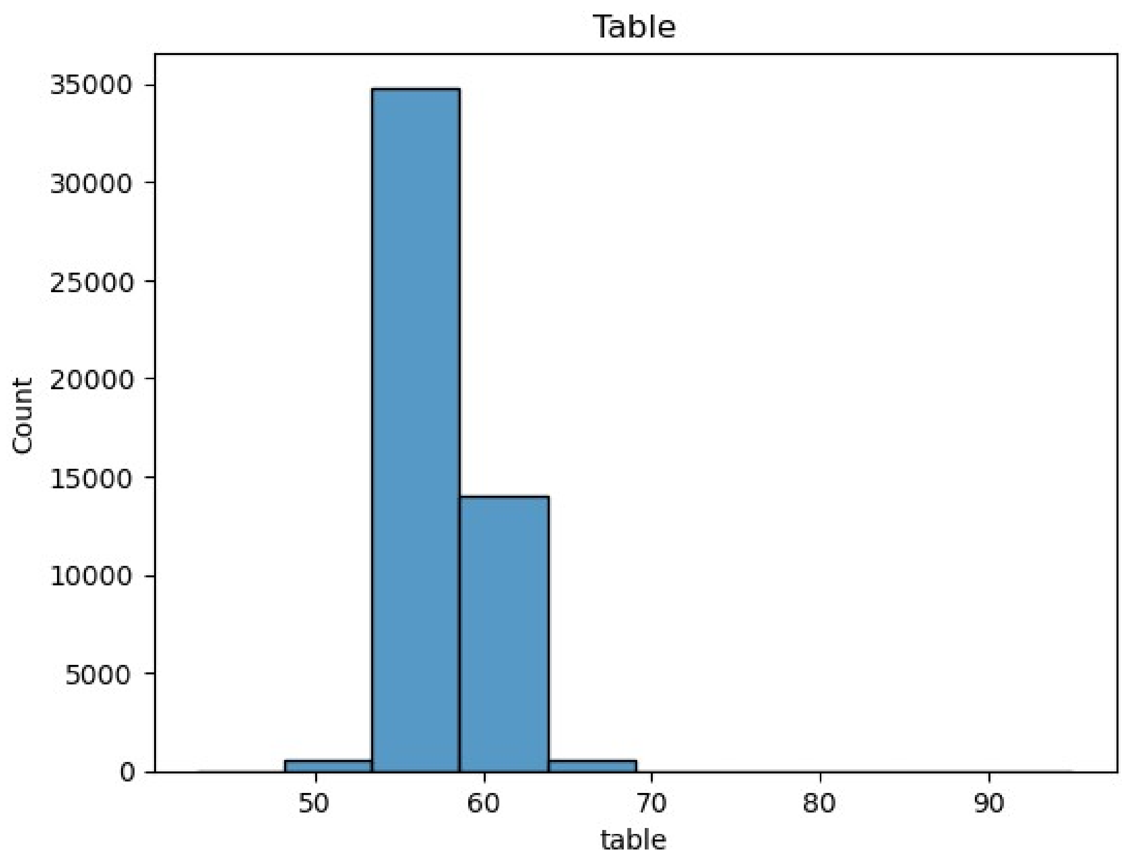

```
plt.figure(figsize=(5,5))
plt.bar(df['color'].value_counts().index,df['color'].value_counts())
plt.ylabel("Number of Diamonds")
plt.xlabel("Color")
plt.show()
```




```
plt.figure(figsize=(5,5))
plt.bar(df['clarity'].value_counts().index,df['clarity'].value_counts(
))
plt.title('Clarity')
plt.ylabel("Number of Diamonds")
plt.xlabel("Clarity")
plt.show()
```



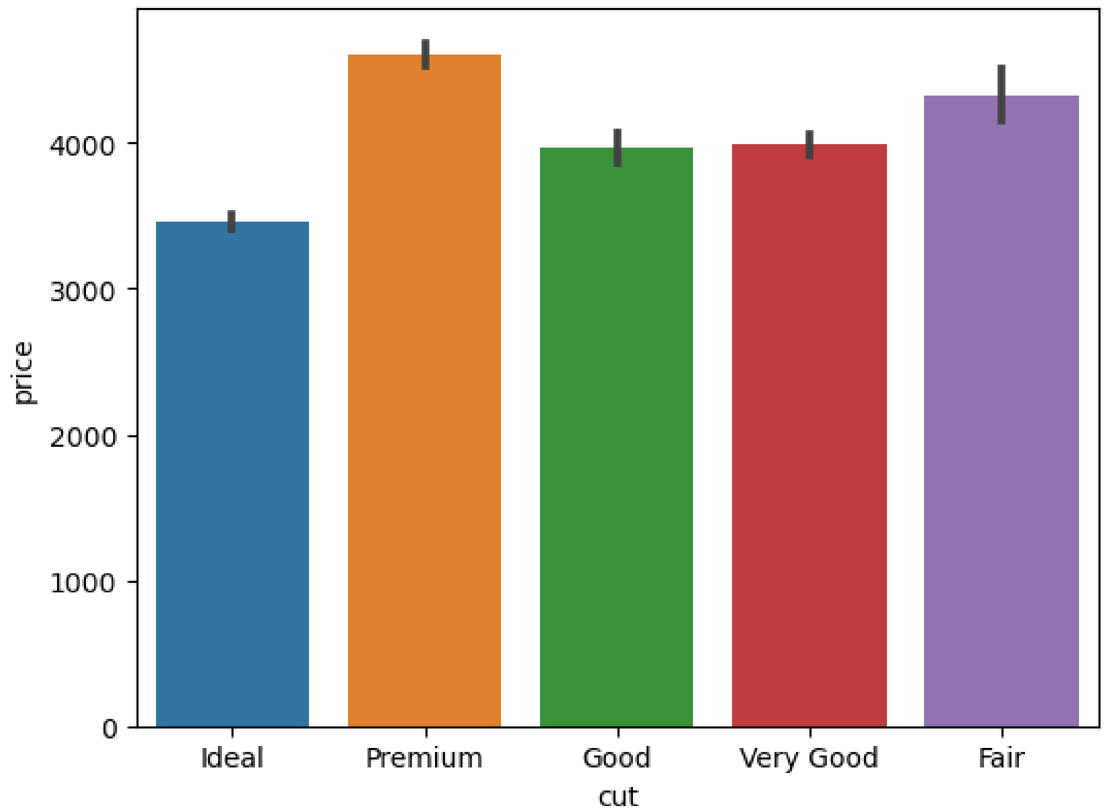

```
sns.histplot(df['table'],bins=10)
plt.title('Table')
plt.show()
```



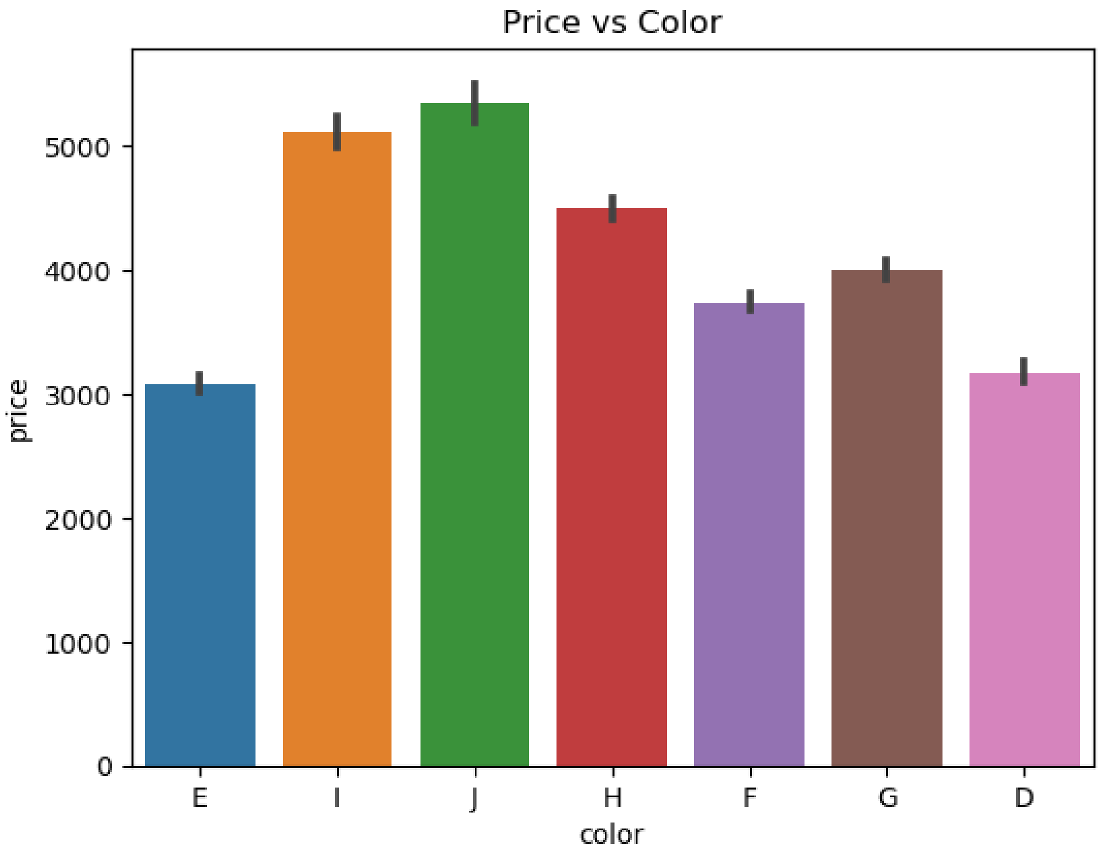
Comparing Diamond's features with Price

```
sns.barplot(x='cut',y='price',data=df)
```

```
<Axes: xlabel='cut', ylabel='price'>
```

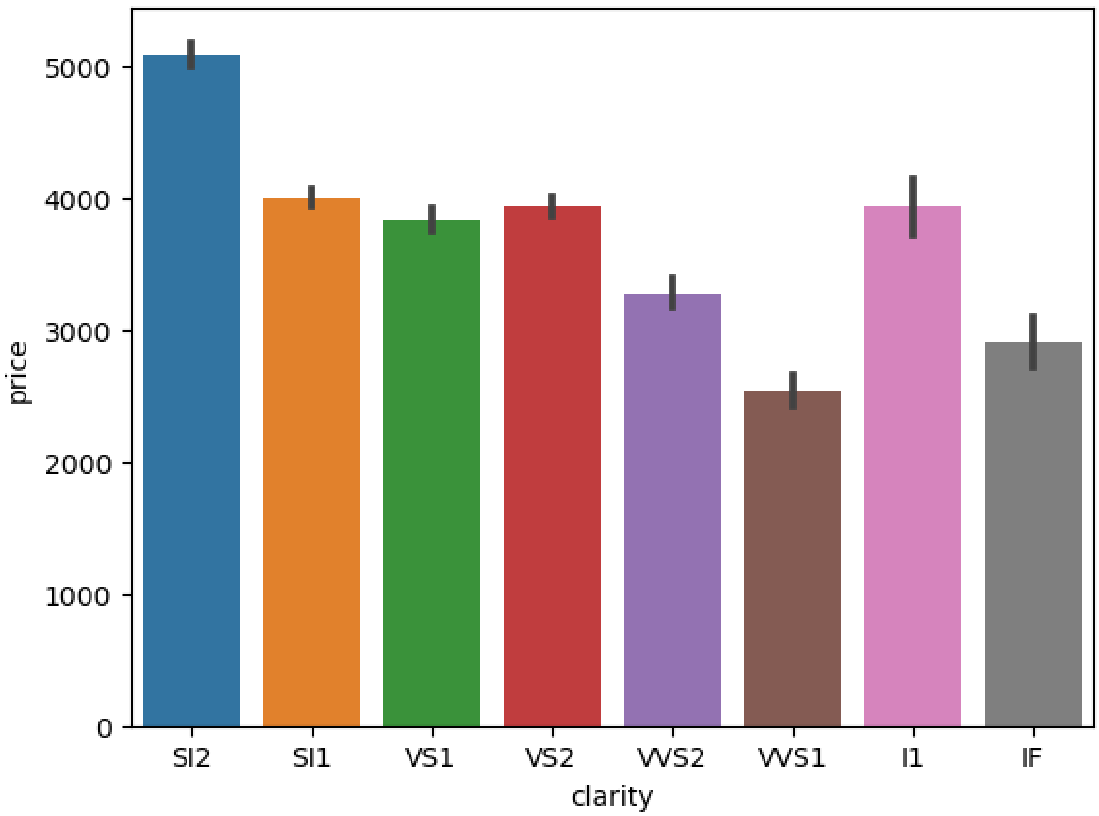



```
sns.barplot(x='color',y='price',data=df)
plt.title('Price vs Color')
plt.show()
```




```
sns.barplot(x = 'clarity', y = 'price', data = df)
```

```
<Axes: xlabel='clarity', ylabel='price'>
```



J color and I1 clarity are worst featiures for a diamond, however when the data is plotted on bar graph, it is seen that the price of diamonds with J color and I1 clarity is higher than the price of diamonds with D color and IF clarity, which is opposite to what I expected.

Lable Encoding the categorical values

```
from sklearn.preprocessing import LabelEncoder

Le = LabelEncoder()

df['cut'] = Le.fit_transform(df['cut'])
df['color'] = Le.fit_transform(df['color'])
df['clarity'] = Le.fit_transform(df['clarity'])

df.head(10)
```

	carat	cut	color	clarity	depth	table	price	x	y	z
0	0.23	2	1	3	61.5	55.0	326	3.95	3.98	2.43
1	0.21	3	1	2	59.8	61.0	326	3.89	3.84	2.31
2	0.23	1	1	4	56.9	65.0	327	4.05	4.07	2.31
3	0.29	3	5	5	62.4	58.0	334	4.20	4.23	2.63
4	0.31	1	6	3	63.3	58.0	335	4.34	4.35	2.75
5	0.24	4	6	7	62.8	57.0	336	3.94	3.96	2.48
6	0.24	4	5	6	62.3	57.0	336	3.95	3.98	2.47
7	0.26	4	4	2	61.9	55.0	337	4.07	4.11	2.53

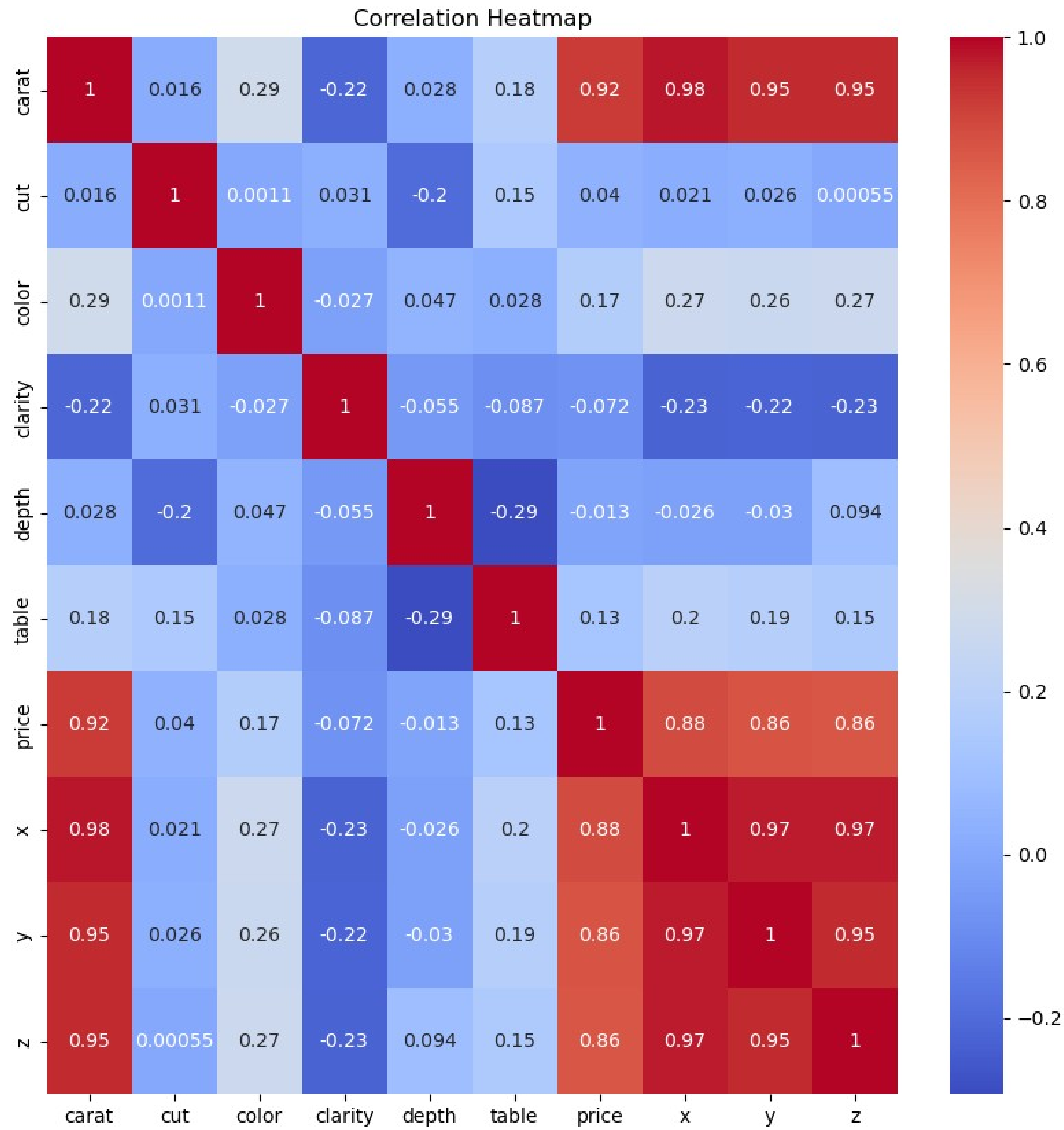
```
8   0.22    0      1        5   65.1    61.0     337  3.87  3.78  2.39
9   0.23    4      4        4   59.4    61.0     338  4.00  4.05  2.39
```

Coorelation

```
#coorelation matrix
df.corr()
```

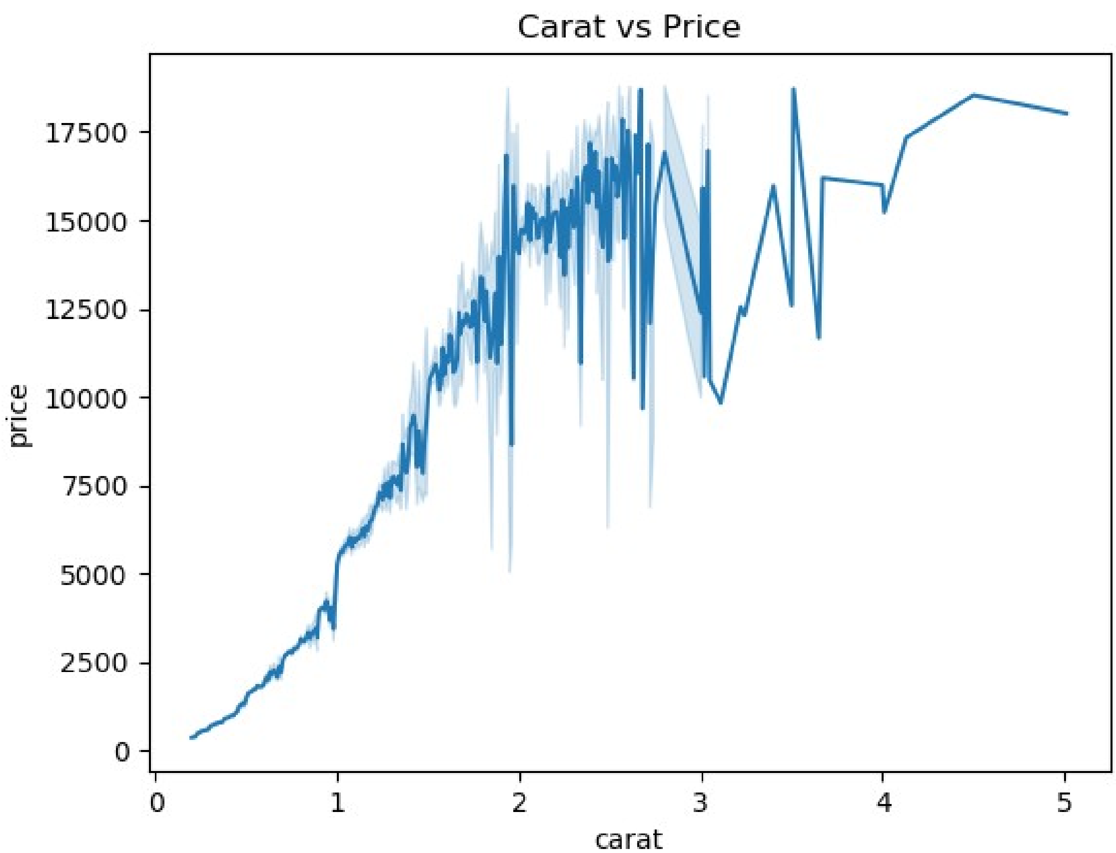
```
            carat       cut     color   clarity     depth     table
price  \
carat    1.000000  0.015933  0.291530 -0.215337  0.027734  0.183639
0.921804
cut      0.015933  1.000000  0.001093  0.030531 -0.199106  0.150916
0.039873
color    0.291530  0.001093  1.000000 -0.027277  0.047426  0.027513
0.172629
clarity -0.215337  0.030531 -0.027277  1.000000 -0.055250 -0.086640 -
0.072434
depth    0.027734 -0.199106  0.047426 -0.055250  1.000000 -0.293012 -
0.012731
table    0.183639  0.150916  0.027513 -0.086640 -0.293012  1.000000
0.129848
price    0.921804  0.039873  0.172629 -0.072434 -0.012731  0.129848
1.000000
x        0.975037  0.021001  0.270529 -0.226871 -0.025563  0.197198
0.884919
y        0.950035  0.026202  0.263395 -0.218385 -0.029809  0.185248
0.864393
z        0.952700  0.000546  0.268388 -0.225797  0.094337  0.153161
0.860963

                x         y         z
carat    0.975037  0.950035  0.952700
cut      0.021001  0.026202  0.000546
color    0.270529  0.263395  0.268388
clarity -0.226871 -0.218385 -0.225797
depth   -0.025563 -0.029809  0.094337
table    0.197198  0.185248  0.153161
price    0.884919  0.864393  0.860963
x        1.000000  0.972977  0.970122
y        0.972977  1.000000  0.950030
z        0.970122  0.950030  1.000000
```

```
#plotting the correlation heatmap
plt.figure(figsize=(10,10))
sns.heatmap(df.corr(),annot=True,cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



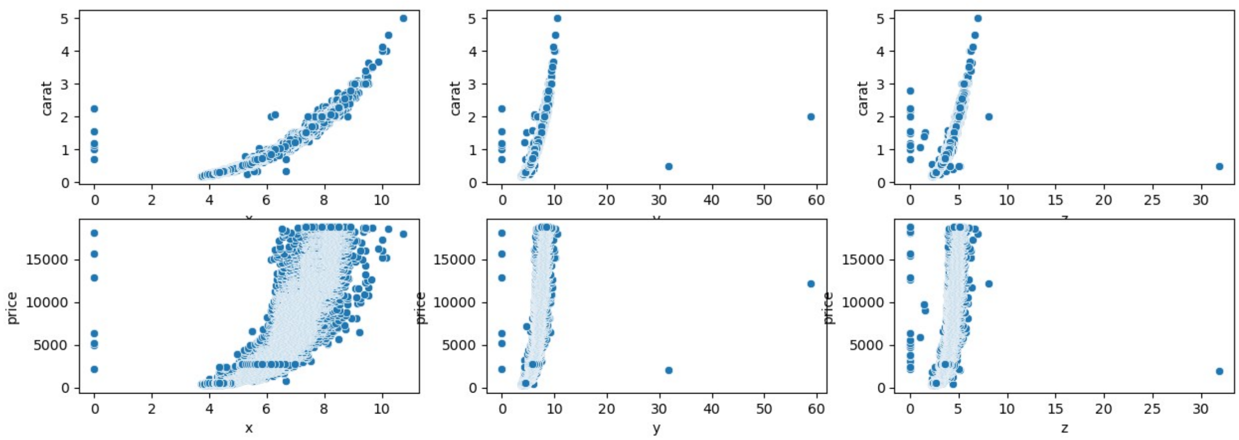
Ploting the relationship between Price and Carat

```
sns.lineplot(x='carat',y='price',data=df)
plt.title('Carat vs Price')
plt.show()
```



From the lineplot it is quite clear that the price of the diamond increases with the increase in the carat of the diamond. However, diamonds with less carat also have high price. This is because of the other factors that affect the price of the diamond.

```
fig, ax = plt.subplots(2,3,figsize=(15,5))
sns.scatterplot(x='x',y='carat',data=df, ax=ax[0,0])
sns.scatterplot(x='y',y='carat',data=df, ax=ax[0,1])
sns.scatterplot(x='z',y='carat',data=df, ax=ax[0,2])
sns.scatterplot(x='x',y='price',data=df, ax=ax[1,0])
sns.scatterplot(x='y',y='price',data=df, ax=ax[1,1])
sns.scatterplot(x='z',y='price',data=df, ax=ax[1,2])
plt.show()
```



Majority of the diamonds have x values between 4 and 8, y values between 4 and 10 and z values between 2 and 6. Diamonds with other dimensions are very rare.

Train Test Split

```
from sklearn.model_selection import train_test_split
x_test,x_train,y_test,y_train =
train_test_split(df.drop('price',axis=1),df['price'],test_size=0.2,ran
dom_state=42)
```

Model Building

Decision Tree Regressor

```
from sklearn.tree import DecisionTreeRegressor
dt = DecisionTreeRegressor()
dt
```

```
DecisionTreeRegressor()
```

```
#training the model
dt.fit(x_train,y_train)
#train accuracy
dt.score(x_train,y_train)
```

```
0.9999995617234543
```

```
#predicting the test set
dt_pred = dt.predict(x_test)
```

Random Forest Regressor

```
from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor()
rf
```

```
RandomForestRegressor()
```

```
#training the model
rf.fit(x_train,y_train)
#train accuracy
rf.score(x_train,y_train)
```

```
0.9967113221441675
```

```
#predicting the test set
rf_pred = rf.predict(x_test)
```

Model Evaluation

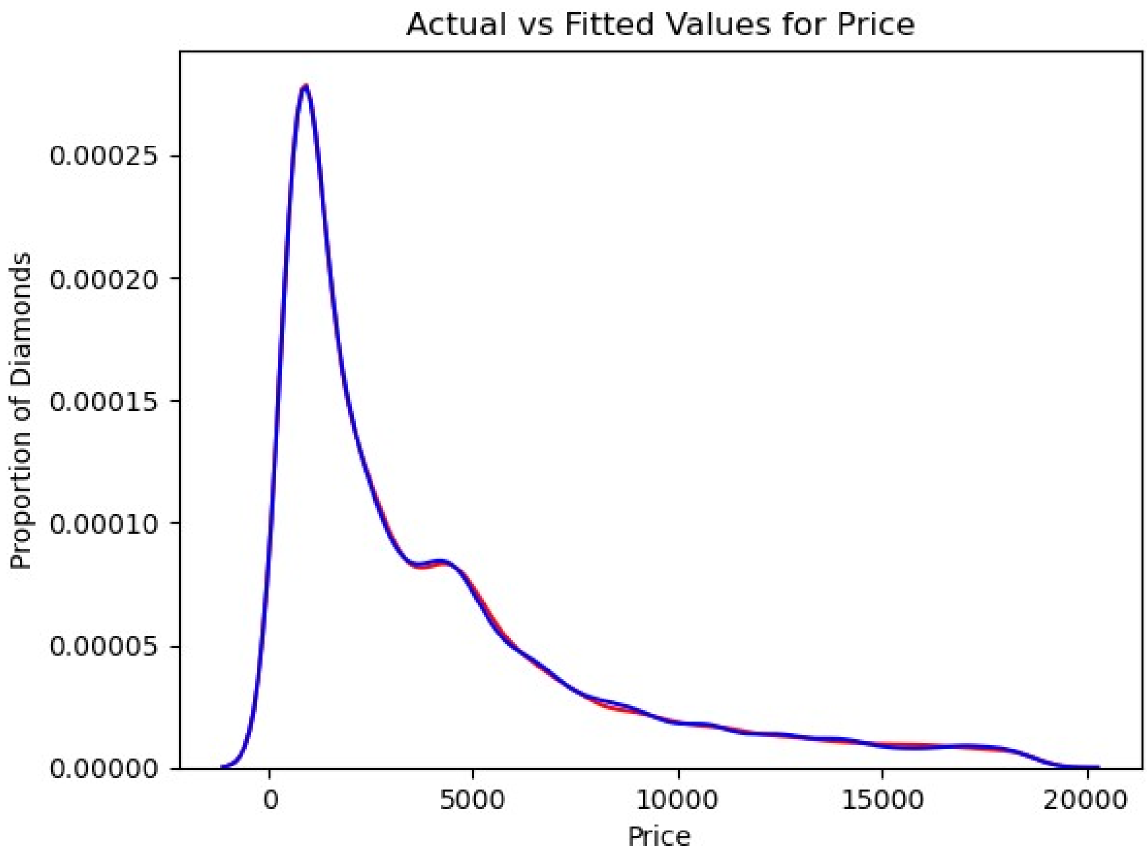
```
from sklearn.metrics import mean_squared_error,mean_absolute_error
```

Decision Tree Regressor

```
#distribution plot for actual and predicted values
ax = sns.distplot(y_test,hist=False,color='r',label='Actual Value')
sns.distplot(dt_pred,hist=False,color='b',label='Fitted Values',ax=ax)
plt.title('Actual vs Fitted Values for Price')
plt.xlabel('Price')
plt.ylabel('Proportion of Diamonds')
plt.show()
```

```
C:\Users\admin\AppData\Local\Temp\ipykernel_5496\3672894792.py:2:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `kdeplot` (an axes-level function for kernel
density plots).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  ax = sns.distplot(y_test,hist=False,color='r',label='Actual Value')
C:\Users\admin\AppData\Local\Temp\ipykernel_5496\3672894792.py:3:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `kdeplot` (an axes-level function for kernel
density plots).
```

```
For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(dt_pred,hist=False,color='b',label='Fitted
Values',ax=ax)
```



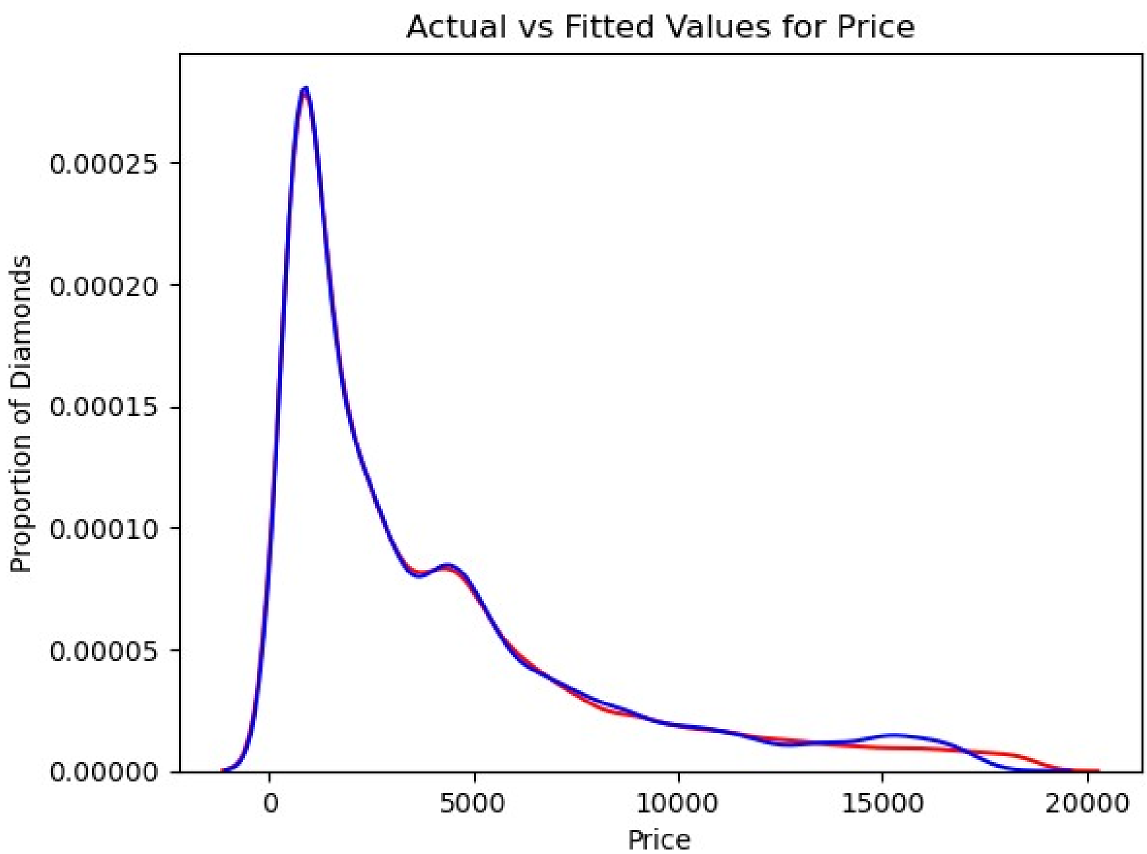

```
print('Decision Tree Regressor
RMSE:',np.sqrt(mean_squared_error(y_test,dt_pred)))
print('Decision Tree Regressor Accuracy:',dt.score(x_test,y_test))
print('Decision Tree Regressor
MAE:',mean_absolute_error(y_test,dt_pred))

Decision Tree Regressor RMSE: 865.5562109129597
Decision Tree Regressor Accuracy: 0.9535066820765383
Decision Tree Regressor MAE: 427.169425
```

Random Forest Regressor

```
#distribution plot for actual and predicted values
ax = sns.distplot(y_test,hist=False,color='r',label='Actual Value')
sns.distplot(rf_pred,hist=False,color='b',label='Fitted Values',ax=ax)
plt.title('Actual vs Fitted Values for Price')
plt.xlabel('Price')
```

```
plt.ylabel('Proportion of Diamonds')
plt.show()
```

```
C:\Users\admin\AppData\Local\Temp\ipykernel_5496\4187378959.py:2:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `kdeplot` (an axes-level function for kernel
density plots).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  ax = sns.distplot(y_test,hist=False,color='r',label='Actual Value')
C:\Users\admin\AppData\Local\Temp\ipykernel_5496\4187378959.py:3:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `kdeplot` (an axes-level function for kernel
density plots).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(rf_pred,hist=False,color='b',label='Fitted
Values',ax=ax)
```




```
print('Random Forest Regressor
RMSE:',np.sqrt(mean_squared_error(y_test,rf_pred)))
print('Random Forest Regressor Accuracy:',rf.score(x_test,y_test))
print('Random Forest Regressor
MAE:',mean_absolute_error(y_test,rf_pred))
```

```
Random Forest Regressor RMSE: 649.985578748383
Random Forest Regressor Accuracy: 0.9737815249579145
Random Forest Regressor MAE: 318.729350847619
```

Conclusion

Both the models have almost same accuracy. However, the Random Forest Regressor model is slightly better than the Decision Tree Regressor model.

There is something interesting about the data. The price of the diamonds with J color and I1 clarity is higher than the price of the diamonds with D color and IF clarity which couldn't be explained by the models. This could be because of the other factors that affect the price of the diamond.