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	Description
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)

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

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

Out[ ]:

	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

In [ ]:
```
df.shape
```

Out[ ]: (50000, 10)

In [ ]:
```
#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
```

In [ ]:
```
#checking descriptive statistics
df.describe()
```

Out[ ]:

	carat	depth	table	price	x	
count	50000.000000	50000.000000	50000.000000	50000.000000	50000.000000	50000.00C
mean	0.799444	61.753006	57.457830	3944.805440	5.734403	5.737
std	0.475173	1.431088	2.232092	3997.938105	1.123077	1.145
min	0.200000	43.000000	43.000000	326.000000	0.000000	0.00C
25%	0.400000	61.000000	56.000000	951.000000	4.710000	4.72C
50%	0.700000	61.800000	57.000000	2410.000000	5.700000	5.71C
75%	1.040000	62.500000	59.000000	5351.000000	6.540000	6.54C
max	5.010000	79.000000	95.000000	18823.000000	10.740000	58.90C

In [ ]:
```
#values count of categorical variables
print(df.cut.value_counts(),'\n',df.color.value_counts(),'\n',df.clarity.value_c
```

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

In [ ]:
```
df.head(10)
```

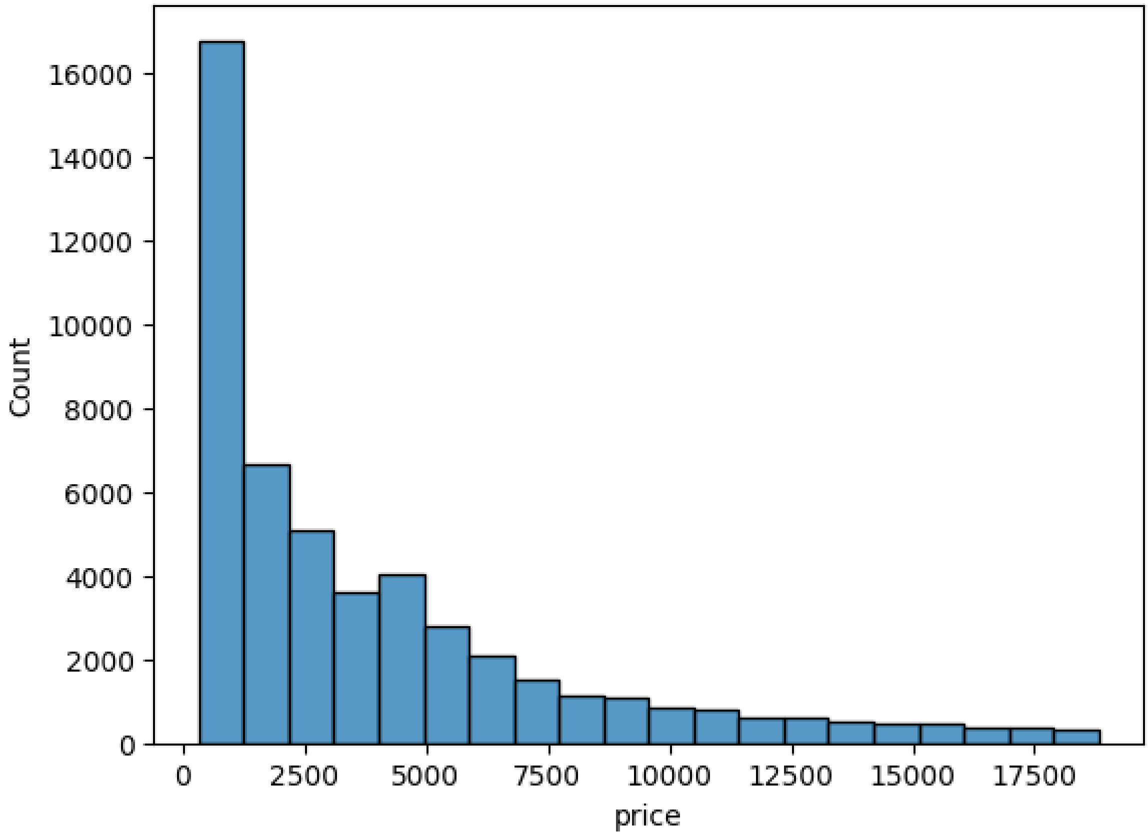
Out[ ]:

	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

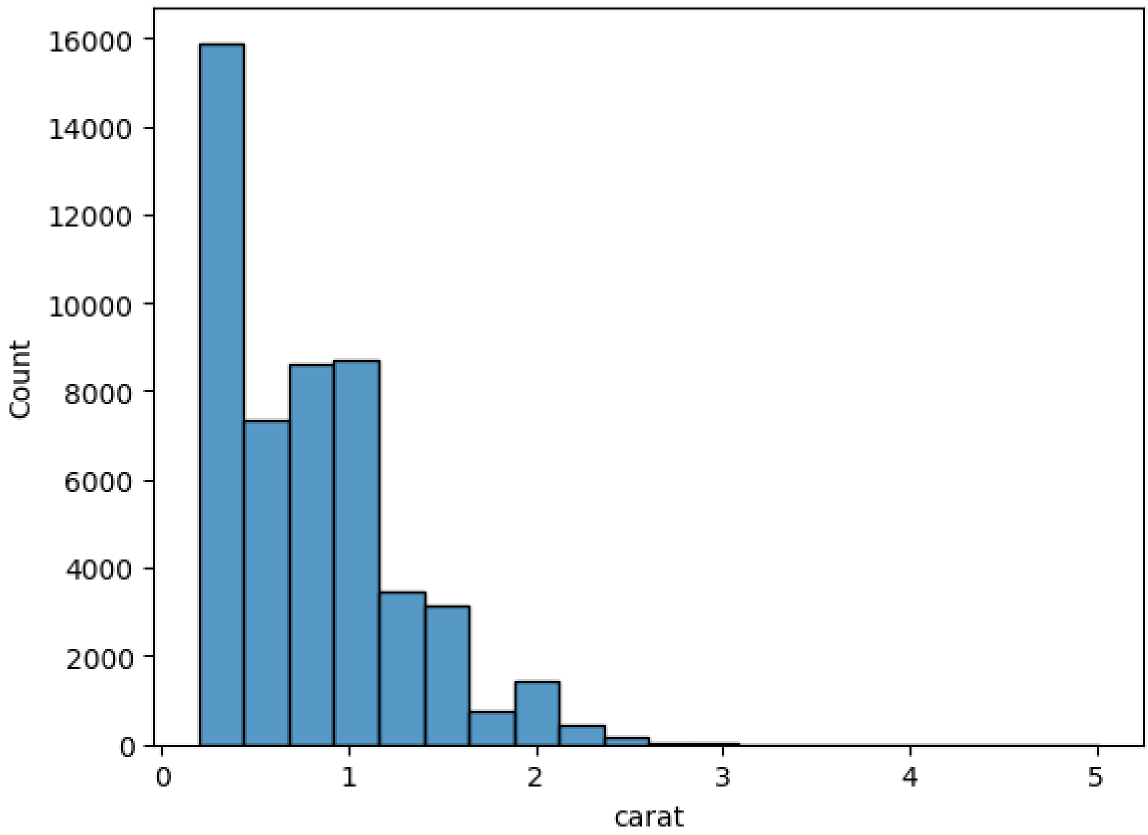
In [ ]:
```
sns.histplot(df['price'],bins = 20)
```

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



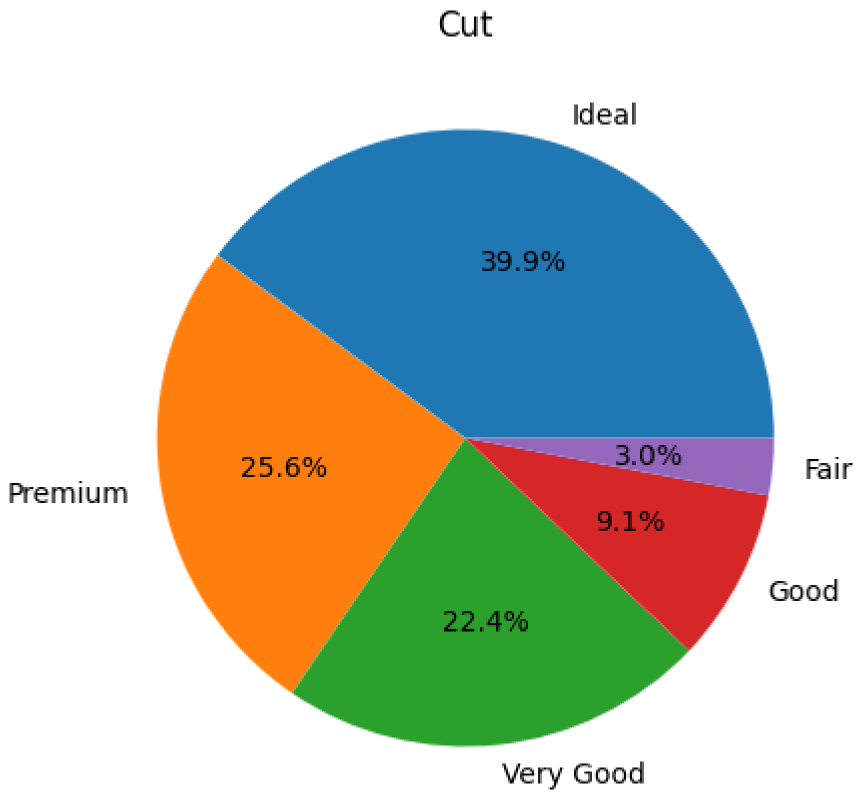
In [ ]:
```
sns.histplot(df['carat'],bins=20)
```

Out[ ]: <Axes: xlabel='carat', ylabel='Count'>

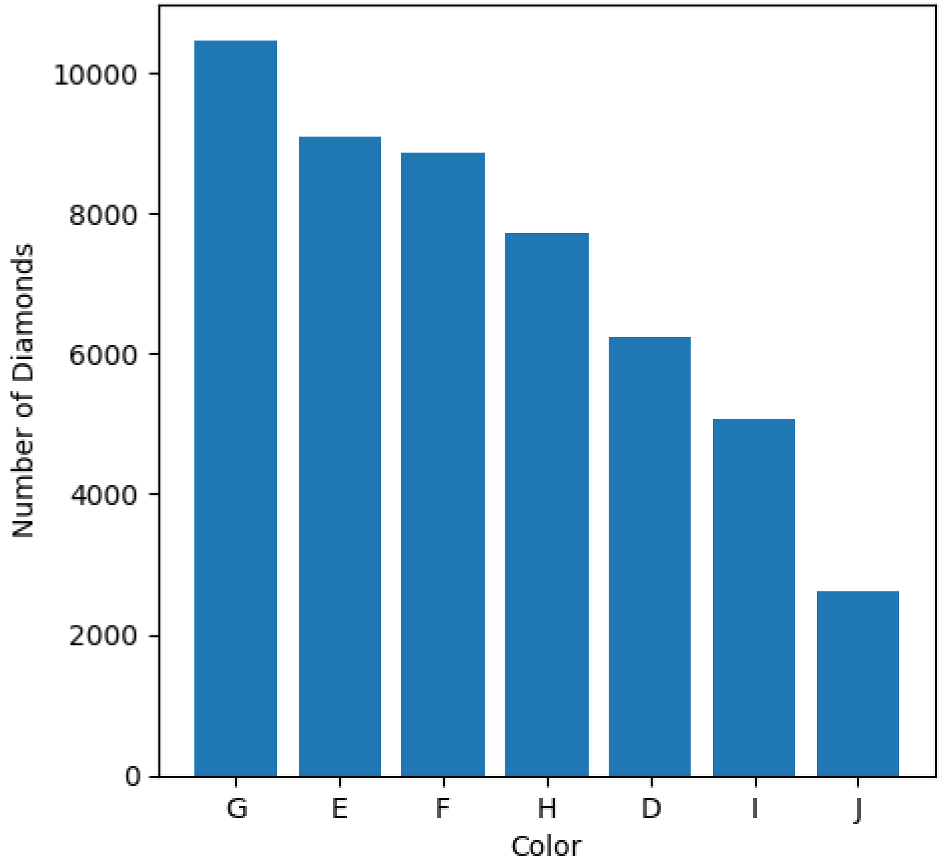


Most of the diamonds are less then 1 carat in weight.

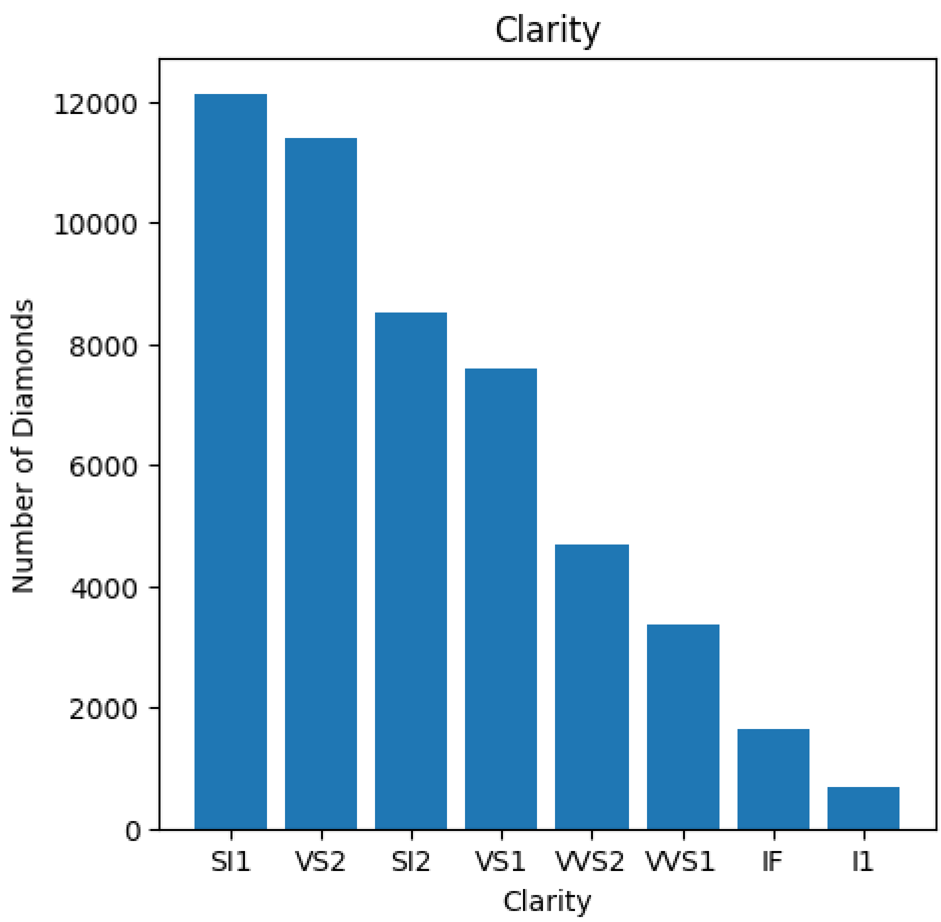
In [ ]:
```
plt.figure(figsize=(5,5))
plt.pie(df['cut'].value_counts(),labels=['Ideal','Premium','Very Good','Good','F
plt.title('Cut')
plt.show()
```



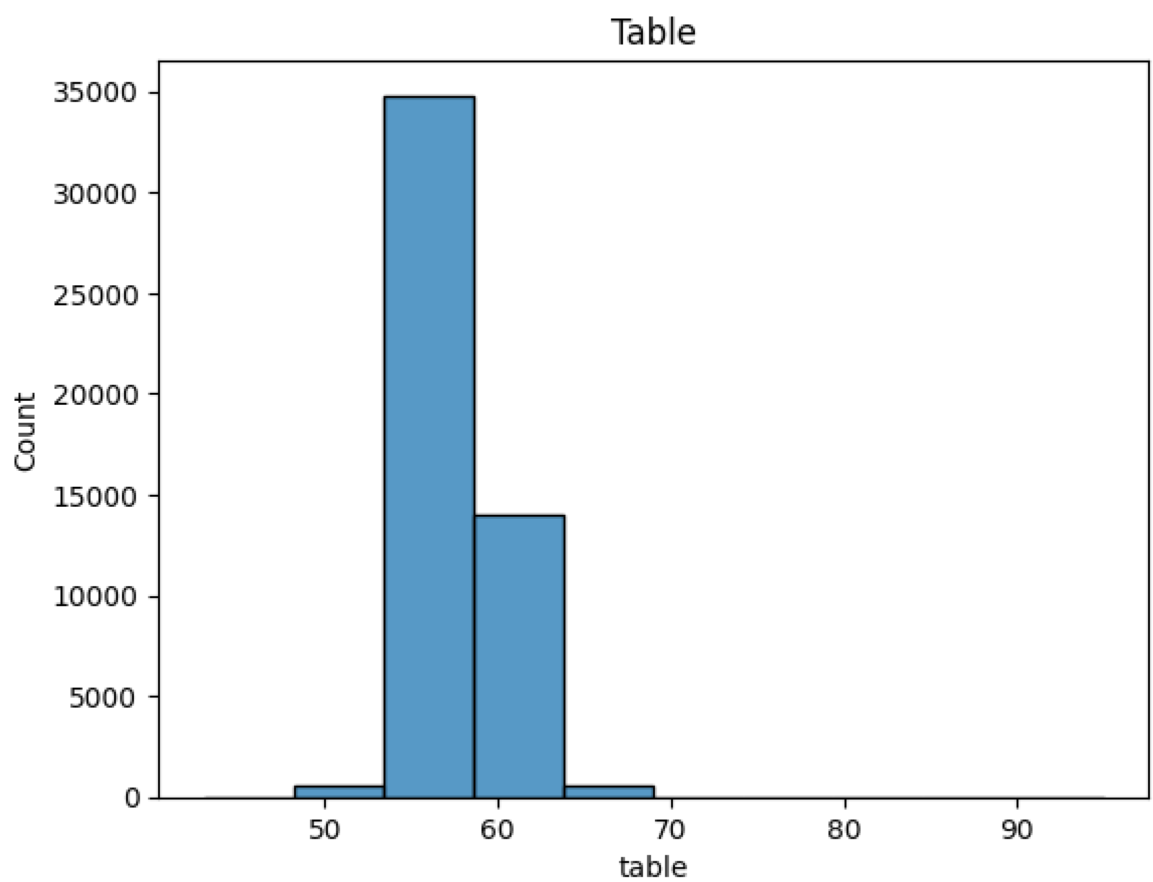
In [ ]:
```
plt.figure(figsize=(5,5))
plt.bar(df['color'].value_counts().index,df['color'].value_counts())
plt.ylabel("Number of Diamonds")
plt.xlabel("Color")
plt.show()
```



In [ ]:
```
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()
```



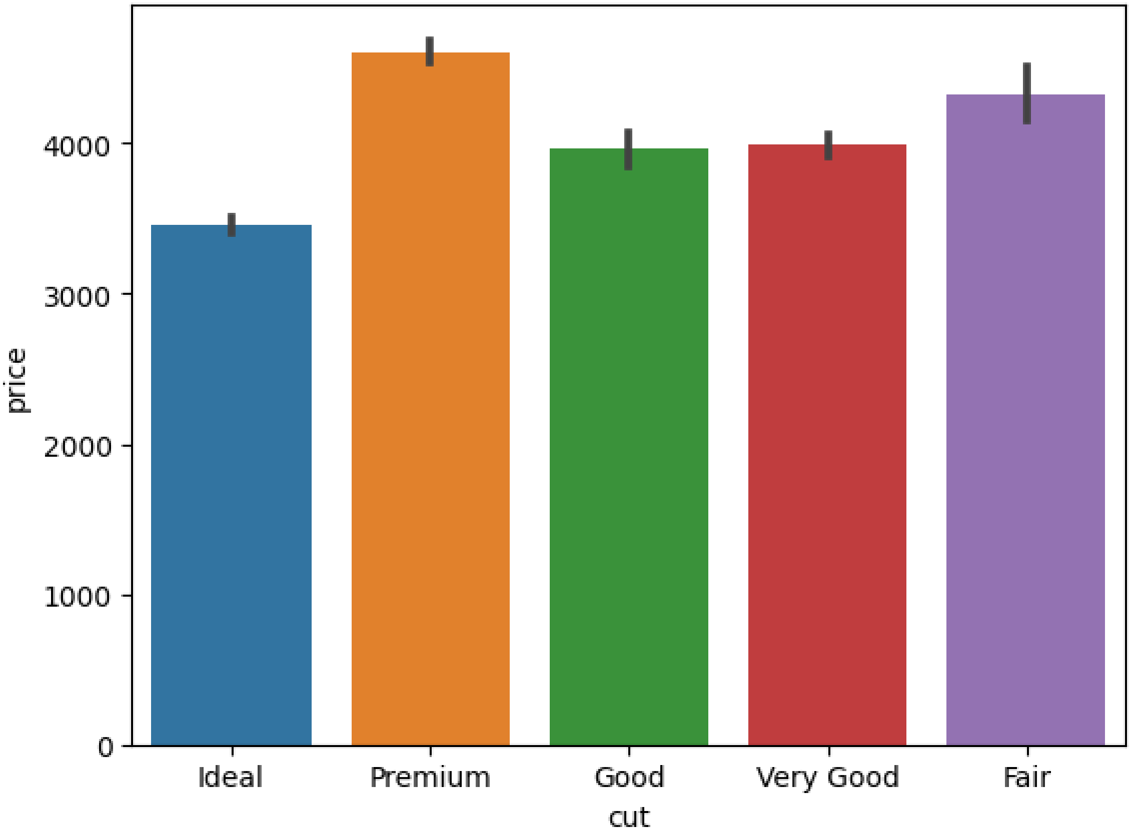
In [ ]:
```
sns.histplot(df['table'],bins=10)
plt.title('Table')
plt.show()
```



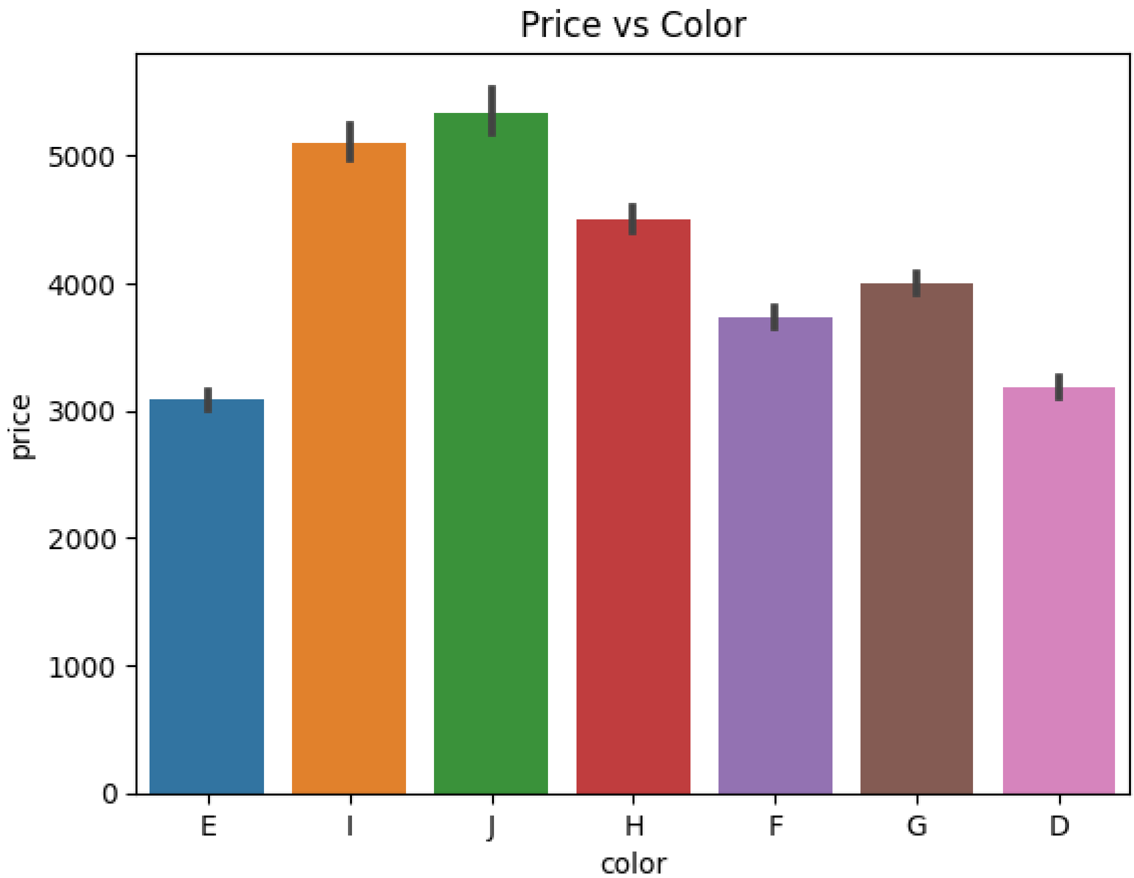
Comparing Diamond's features with Price

In [ ]:
```
sns.barplot(x='cut',y='price',data=df)
```

Out[ ]: <Axes: xlabel='cut', ylabel='price'>

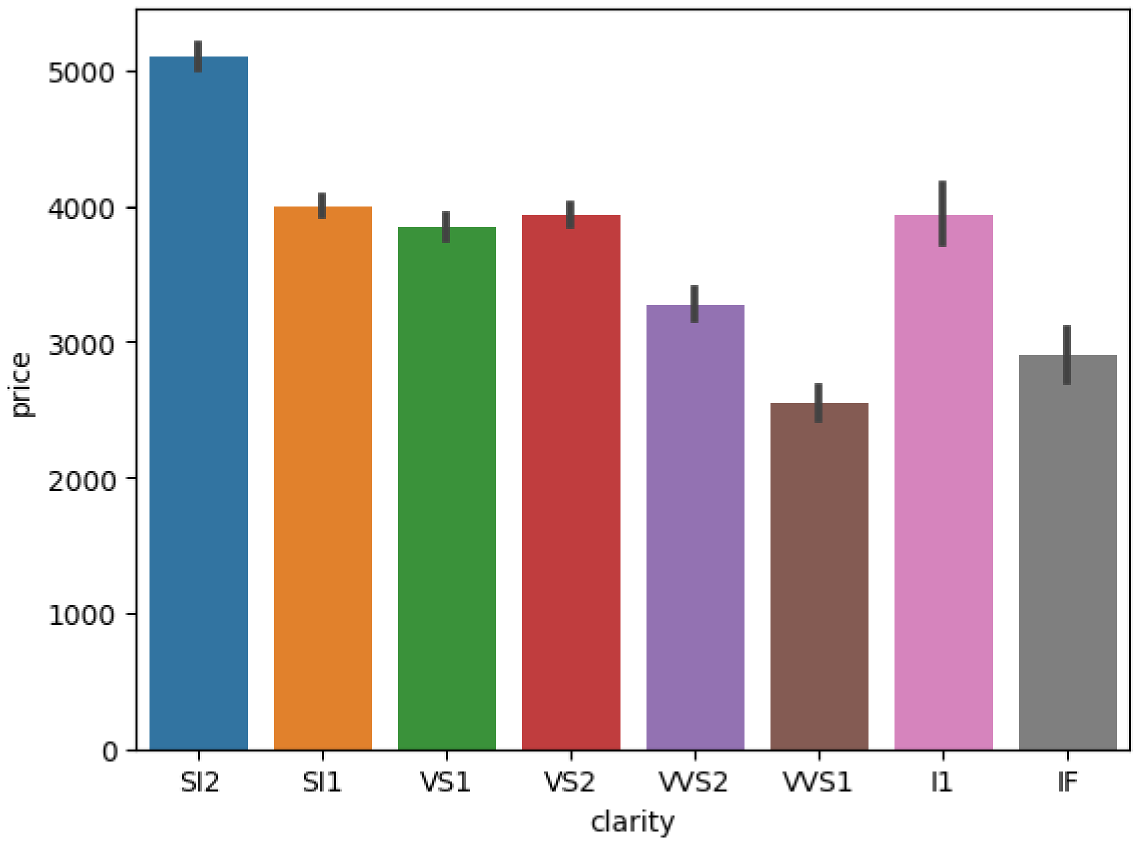


In [ ]:
```
sns.barplot(x='color',y='price',data=df)
plt.title('Price vs Color')
plt.show()
```



In [ ]:
```
sns.barplot(x = 'clarity', y = 'price', data = df)
```

Out[ ]: <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.

Data Preprocessing 2

In [ ]:
```
#changing categorical variables to numerical variables
df['cut'] = df['cut'].map({'Ideal':5,'Premium':4,'Very Good':3,'Good':2,'Fair':1
df['color'] = df['color'].map({'D':7,'E':6,'F':5,'G':4,'H':3,'I':2,'J':1})
df['clarity'] = df['clarity'].map({'IF':8,'VVS1':7,'VVS2':6,'VS1':5,'VS2':4,'SI1
```

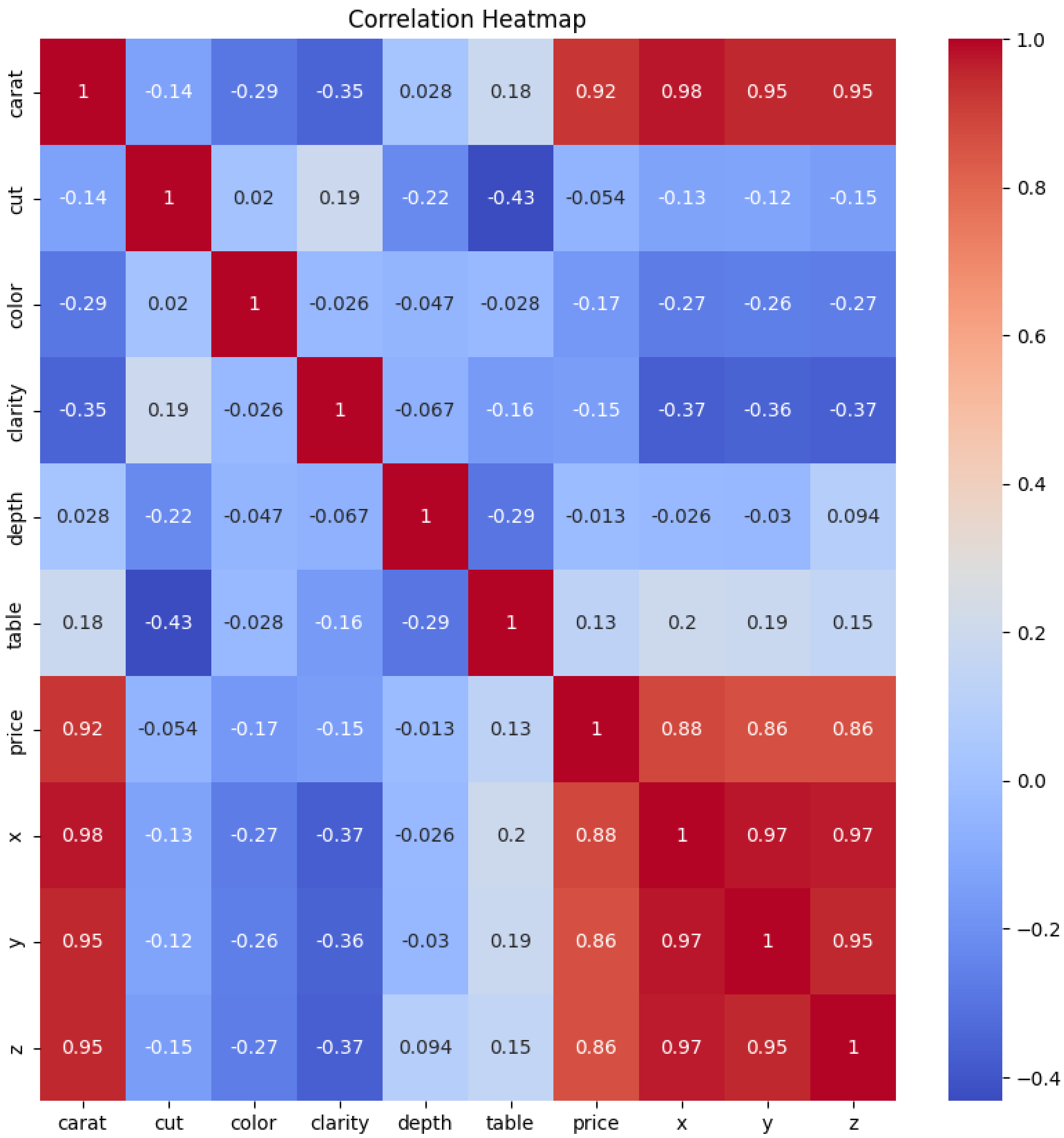
Coorelation

In [ ]:
```
#coorelation matrix
df.corr()
```

Out[ ]:

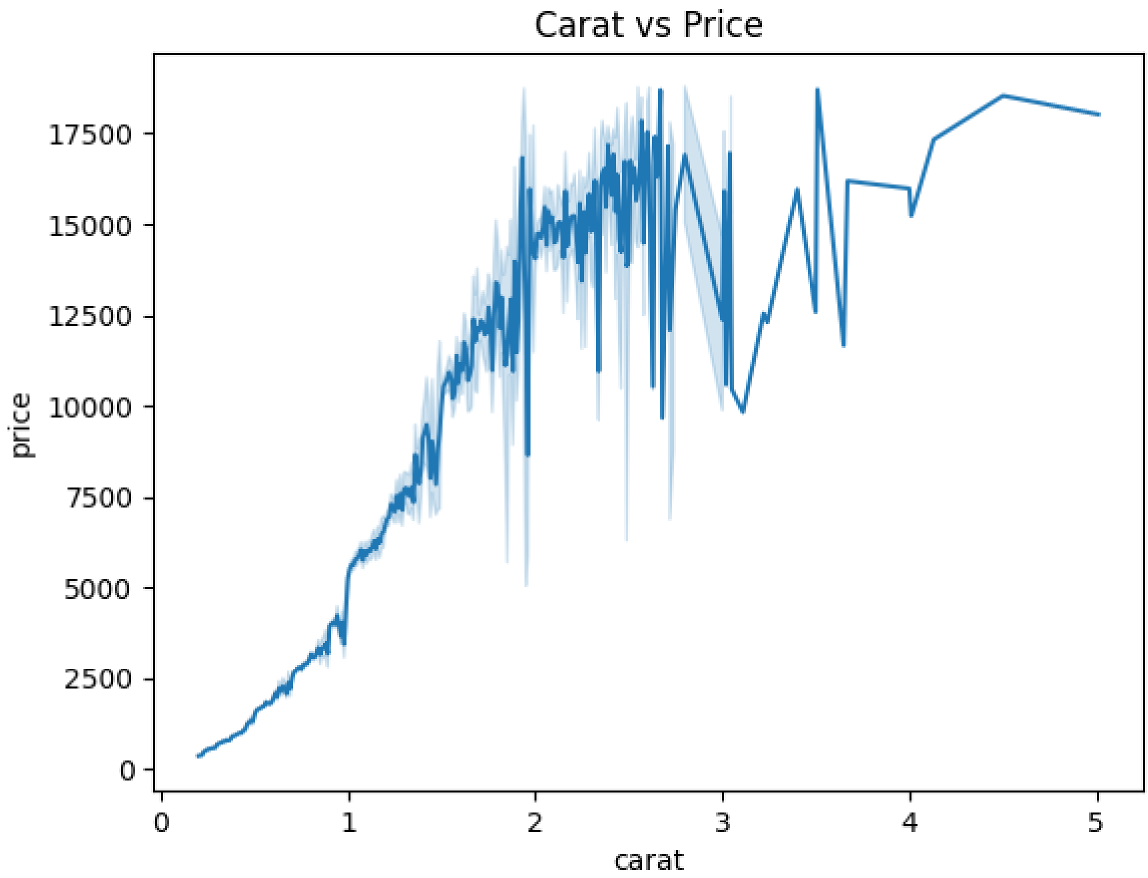
	carat	cut	color	clarity	depth	table	price	
carat	1.000000	-0.135135	-0.291530	-0.352435	0.027734	0.183639	0.921804	0.97
cut	-0.135135	1.000000	0.019548	0.189024	-0.223898	-0.432154	-0.053537	-0.12
color	-0.291530	0.019548	1.000000	-0.026056	-0.047426	-0.027513	-0.172629	-0.27
clarity	-0.352435	0.189024	-0.026056	1.000000	-0.067329	-0.159967	-0.146941	-0.37
depth	0.027734	-0.223898	-0.047426	-0.067329	1.000000	-0.293012	-0.012731	-0.02
table	0.183639	-0.432154	-0.027513	-0.159967	-0.293012	1.000000	0.129848	0.19
price	0.921804	-0.053537	-0.172629	-0.146941	-0.012731	0.129848	1.000000	0.88
x	0.975037	-0.125738	-0.270529	-0.371355	-0.025563	0.197198	0.884919	1.00
y	0.950035	-0.121335	-0.263395	-0.357226	-0.029809	0.185248	0.864393	0.97
z	0.952700	-0.149830	-0.268388	-0.366218	0.094337	0.153161	0.860963	0.97

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



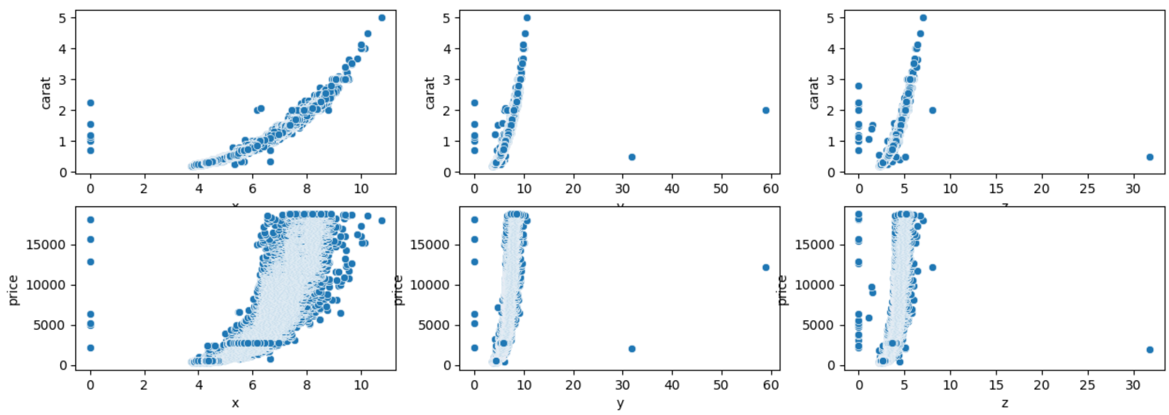
Ploting the relationship between Price and Carat

In [ ]:
```
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.

In [ ]:
```
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

In [ ]:
```
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['pri
```

Model Building

Decision Tree Regressor

In [ ]:
```
from sklearn.tree import DecisionTreeRegressor
dt = DecisionTreeRegressor()
dt
```

Out[ ]:
```
▾ DecisionTreeRegressor
DecisionTreeRegressor()
```

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

Out[ ]: `0.9999995617234543`

In [ ]:
```
#predicting the test set
dt_pred = dt.predict(x_test)
```

Random Forest Regressor

In [ ]:
```
from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor()
rf
```

Out[ ]:
```
▾ RandomForestRegressor
RandomForestRegressor()
```

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

Out[ ]: `0.99711333722628`

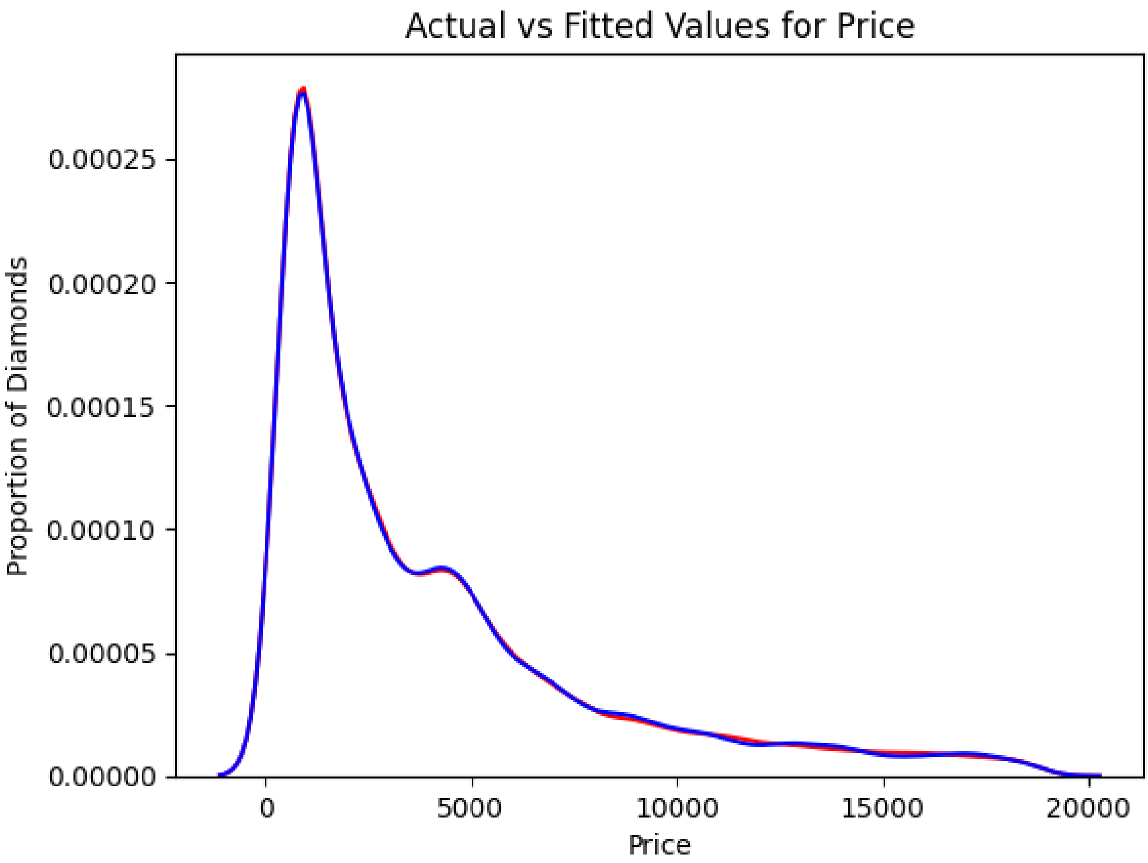
In [ ]:
```
#predicting the test set
rf_pred = rf.predict(x_test)
```

Model Evaluation

In [ ]:
```
from sklearn.metrics import mean_squared_error,mean_absolute_error
```

Decision Tree Regressor

In [ ]:
```
#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()
```

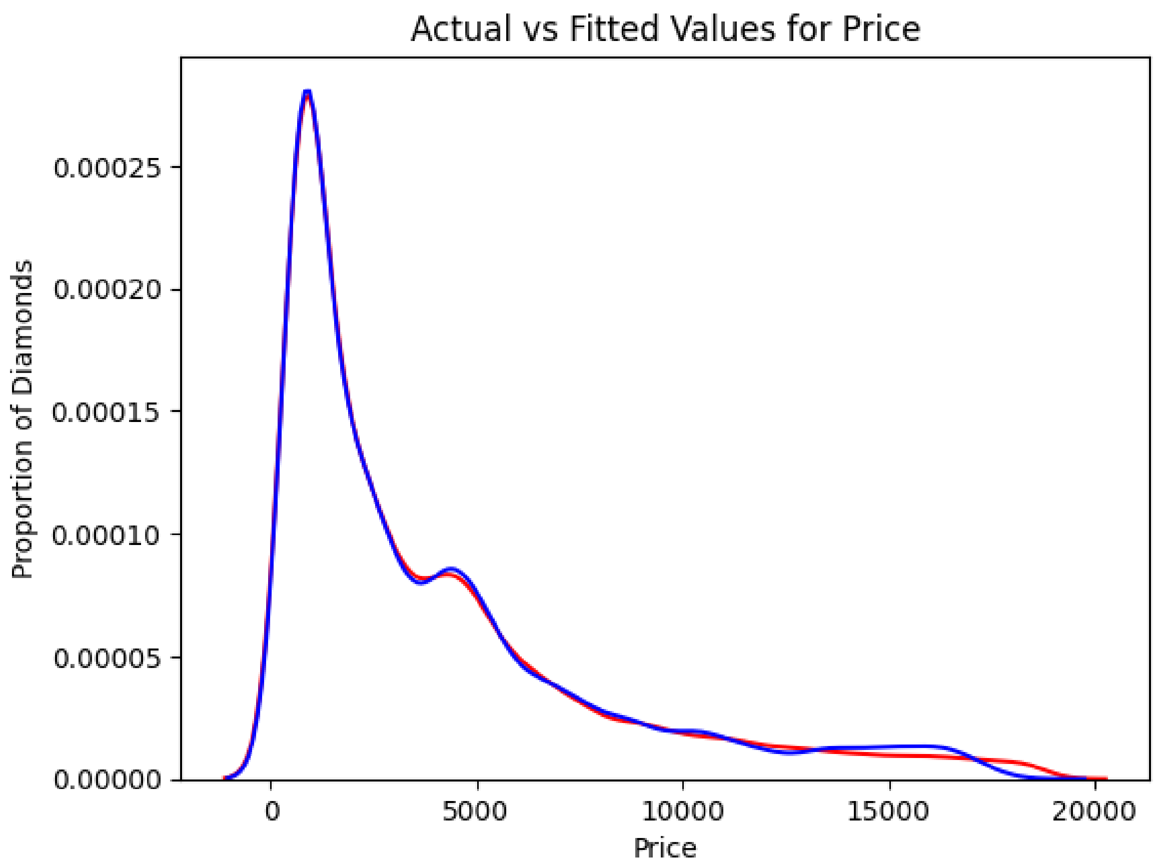


In [ ]:
```
print('Decision Tree Regressor RMSE:',np.sqrt(mean_squared_error(y_test,dt_pred)
print('Decision Tree Regressor Accuracy:',dt.score(x_test,y_test))
print('Decision Tree Regressor MAE:',mean_absolute_error(y_test,dt_pred))
```

```
Decision Tree Regressor RMSE: 803.7869467013631
Decision Tree Regressor Accuracy: 0.9599057693807272
Decision Tree Regressor MAE: 408.96015
```

Random Forest Regressor

In [ ]:
```
#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()
```



In [ ]:
```
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: 620.3188867364595
Random Forest Regressor Accuracy: 0.9761202379789445
Random Forest Regressor MAE: 306.1187898892857
```

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.