Diamonds In Depth Analysis.

The case study interprets the various factors, features and components that affect the price of the diamond. The case study will comprise of data exploration i.e. understanding the relation between each features with the respective prices.

A] Exploring the Dataset.

A1] Importing libraries required.

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

import warnings
warnings.filterwarnings('ignore')

# Regression
from sklearn.linear_model import LinearRegression,Ridge,Lasso,RidgeCV, ElasticNet
from sklearn.ensemble import RandomForestRegressor,BaggingRegressor,GradientBoostingRe
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.neural_network import MLPRegressor

# Regression
from sklearn.metrics import mean_squared_log_error,mean_squared_error, r2_score,mean_a
```

A2] Extracting the dataset.

In [2]:
```
df = pd.read_csv("diamonds.csv")
df
```

Out[2]:

	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

53940 rows × 10 columns

A3] Gathering basic info on the dataset.

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53940 entries, 0 to 53939
Data columns (total 10 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   carat    53940 non-null  float64
 1   cut      53940 non-null  object 
 2   color    53940 non-null  object 
 3   clarity  53940 non-null  object 
 4   depth    53940 non-null  float64
 5   table    53940 non-null  float64
 6   price    53940 non-null  int64  
 7   x        53940 non-null  float64
 8   y        53940 non-null  float64
 9   z        53940 non-null  float64
dtypes: float64(6), int64(1), object(3)
memory usage: 4.1+ MB
```

In [4]:
```
df.shape
```

Out[4]:
```
(53940, 10)
```

In [5]:
```
df.dtypes
```

Out[5]:
```
carat       float64
cut          object
color        object
clarity      object
depth       float64
table       float64
price         int64
x           float64
y           float64
z           float64
dtype: object
```

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

Out[6]:

	carat	depth	table	price	x	y	
count	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000	53940.00(
mean	0.797940	61.749405	57.457184	3932.799722	5.731157	5.734526	3.538
std	0.474011	1.432621	2.234491	3989.439738	1.121761	1.142135	0.705
min	0.200000	43.000000	43.000000	326.000000	0.000000	0.000000	0.00(
25%	0.400000	61.000000	56.000000	950.000000	4.710000	4.720000	2.91(
50%	0.700000	61.800000	57.000000	2401.000000	5.700000	5.710000	3.53(
75%	1.040000	62.500000	59.000000	5324.250000	6.540000	6.540000	4.04(
max	5.010000	79.000000	95.000000	18823.000000	10.740000	58.900000	31.80(

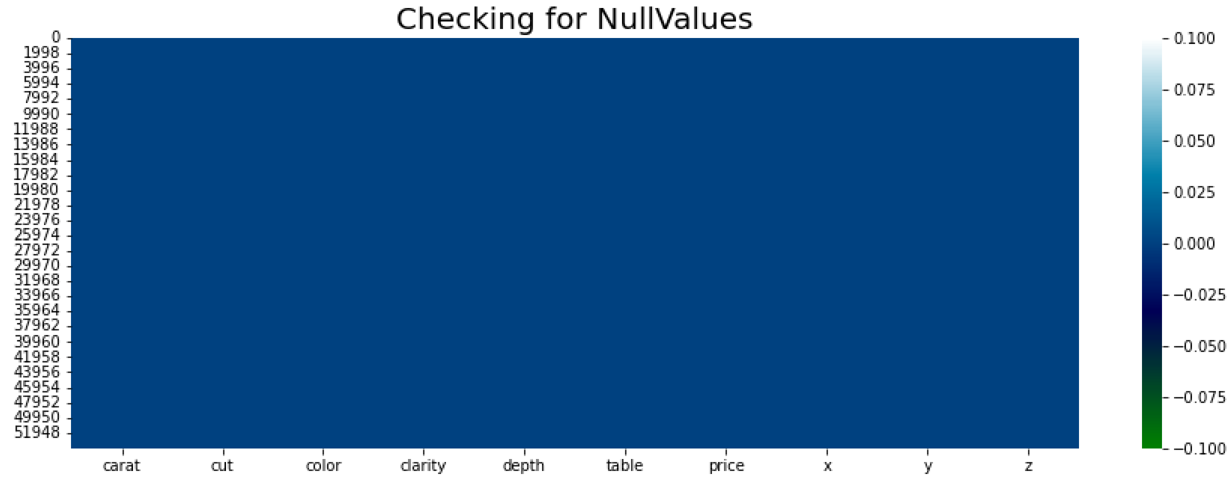
From the information gathered above, we can easily determine that the feature 'price' would be our target variable. We have to build our algorithm around the target variable.

A4] Checking for Null Values in dataset using Heatmap.

In [7]:
```
df.isna().sum()
```

Out[7]:
```
carat      0
cut        0
color      0
clarity    0
depth      0
table      0
price      0
x          0
y          0
z          0
dtype: int64
```

In [8]:
```
plt.figure(figsize = (15,5))
plt.title("Checking for NullValues", fontsize = 20)
sns.heatmap(df.isna(), cmap = 'ocean')
plt.show()
```



It's good that there are no Null Values. But as we can see in 'df.describe' the minimum value for 'x', 'y', 'z' is 0. It is physically impossible for the dimensions of diamond to be 0. These values should be considered as Null.

In [9]:
```
a = df[ (df['x'] == 0) | (df['y'] == 0) | (df['z'] == 0)]
a
```

Out[9]:

	carat	cut	color	clarity	depth	table	price	x	y	z
2207	1.00	Premium	G	SI2	59.1	59.0	3142	6.55	6.48	0.0
2314	1.01	Premium	H	I1	58.1	59.0	3167	6.66	6.60	0.0
4791	1.10	Premium	G	SI2	63.0	59.0	3696	6.50	6.47	0.0
5471	1.01	Premium	F	SI2	59.2	58.0	3837	6.50	6.47	0.0
10167	1.50	Good	G	I1	64.0	61.0	4731	7.15	7.04	0.0
11182	1.07	Ideal	F	SI2	61.6	56.0	4954	0.00	6.62	0.0
11963	1.00	Very Good	H	VS2	63.3	53.0	5139	0.00	0.00	0.0
13601	1.15	Ideal	G	VS2	59.2	56.0	5564	6.88	6.83	0.0
15951	1.14	Fair	G	VS1	57.5	67.0	6381	0.00	0.00	0.0
24394	2.18	Premium	H	SI2	59.4	61.0	12631	8.49	8.45	0.0
24520	1.56	Ideal	G	VS2	62.2	54.0	12800	0.00	0.00	0.0
26123	2.25	Premium	I	SI1	61.3	58.0	15397	8.52	8.42	0.0
26243	1.20	Premium	D	VVS1	62.1	59.0	15686	0.00	0.00	0.0
27112	2.20	Premium	H	SI1	61.2	59.0	17265	8.42	8.37	0.0
27429	2.25	Premium	H	SI2	62.8	59.0	18034	0.00	0.00	0.0
27503	2.02	Premium	H	VS2	62.7	53.0	18207	8.02	7.95	0.0
27739	2.80	Good	G	SI2	63.8	58.0	18788	8.90	8.85	0.0
49556	0.71	Good	F	SI2	64.1	60.0	2130	0.00	0.00	0.0
49557	0.71	Good	F	SI2	64.1	60.0	2130	0.00	0.00	0.0
51506	1.12	Premium	G	I1	60.4	59.0	2383	6.71	6.67	0.0

In [10]:

```
len(a)
```

Out[10]:

```
20
```

As the number of invalid entries in dataset are very minimal, dropping those instead of replacing them with their respective mean or median would be a better idea.

A5] Dropping the invalid entries.

In [11]:

```
df = df[(df[['x','y','z']] != 0).all(axis=1)]
```

A6] Cross checking if all the invalid entries have been dropped.

In [12]:

```
df.loc[(df['x']==0) | (df['y']==0) | (df['z']==0)]
```

Out[12]:

carat	cut	color	clarity	depth	table	price	x	y	z

B] Feature Co-relation.

B1] Finding Co-relation between features.

In [13]:
```
corr = df.corr()
corr
```

Out[13]:

	carat	depth	table	price	x	y	z
carat	1.000000	0.028259	0.181646	0.921592	0.977779	0.953991	0.961048
depth	0.028259	1.000000	-0.295733	-0.010729	-0.025017	-0.029069	0.095023
table	0.181646	-0.295733	1.000000	0.127245	0.196097	0.184493	0.152483
price	0.921592	-0.010729	0.127245	1.000000	0.887231	0.867864	0.868206
x	0.977779	-0.025017	0.196097	0.887231	1.000000	0.974918	0.975435
y	0.953991	-0.029069	0.184493	0.867864	0.974918	1.000000	0.956744
z	0.961048	0.095023	0.152483	0.868206	0.975435	0.956744	1.000000

In [14]:
```
plt.figure(figsize=(15,10))
sns.heatmap(data=corr, square=True , annot=True, cbar=True)
plt.yticks(rotation=0);
```

From the above heatmap we can conclude that :-

1] The feature 'price' is highly co-related with the feature 'carat'.

2] The feature 'depth' is inversly related with the feature 'price', as more the depth of the diamond, it looses its ability to reflect light. Resulting in the reduction of prices of the diamond.

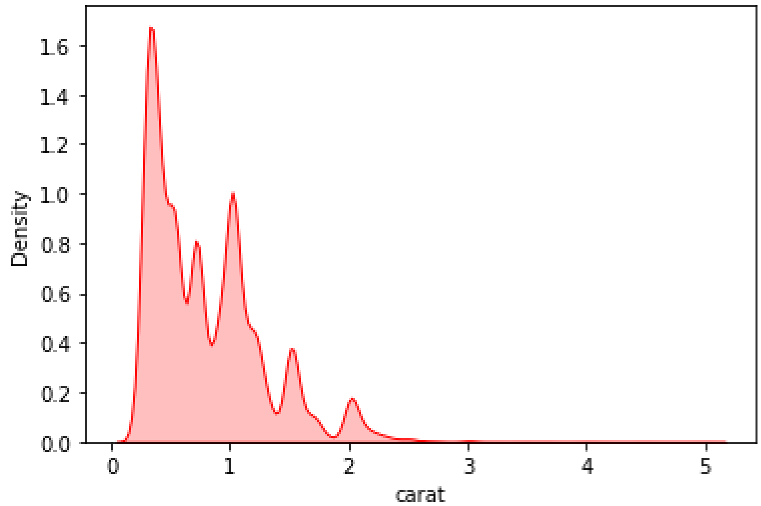
3] The feature 'price' is also highy co-related with the dimensions i.e. 'x', 'y', 'z' features. This is expected as bigger the volume of the diamond, it will cost more.

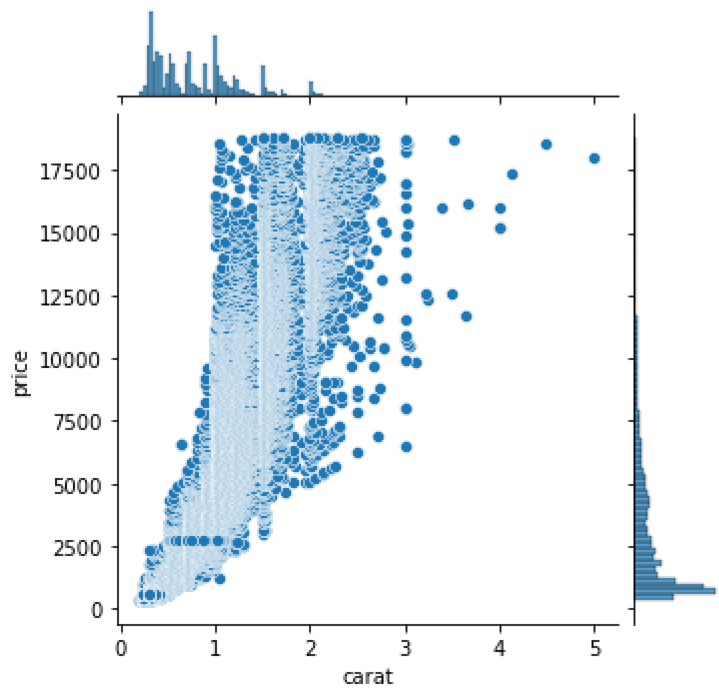
C] Visualizing each feature with the target variable.

C.i] Carat Vs Price.

In [15]:
```
sns.kdeplot(df['carat'], shade=True , color='r')
sns.jointplot(x='carat' , y='price' , data=df , size=5)
```

Out[15]: <seaborn.axisgrid.JointGrid at 0x228c721be50>





The price of the diamond is linearly depended on the carat. More the carat, more is the price.

C.ii] Cut Vs Price.

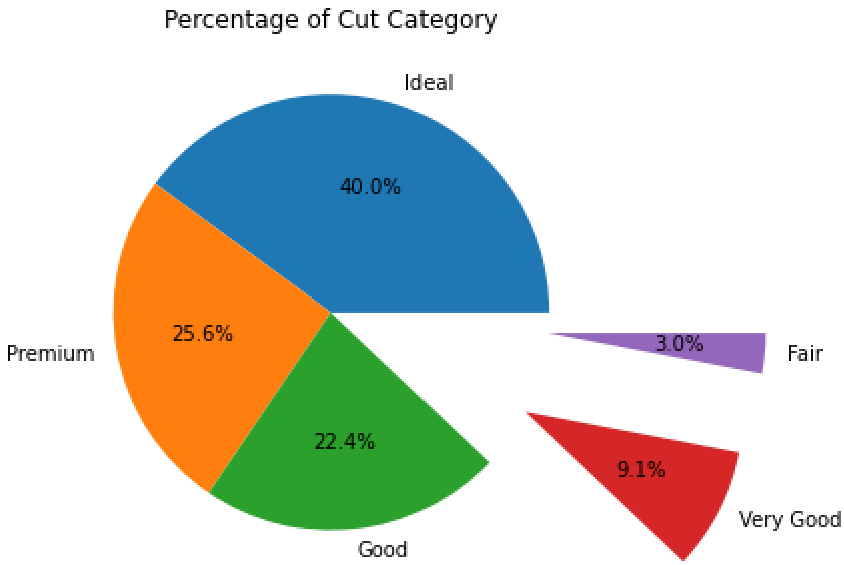
In [16]:
```
b = np.array(df['cut'].unique())
b
```

Out[16]:
```
array(['Ideal', 'Premium', 'Good', 'Very Good', 'Fair'], dtype=object)
```

In [17]:
```
df['cut'].value_counts()
```

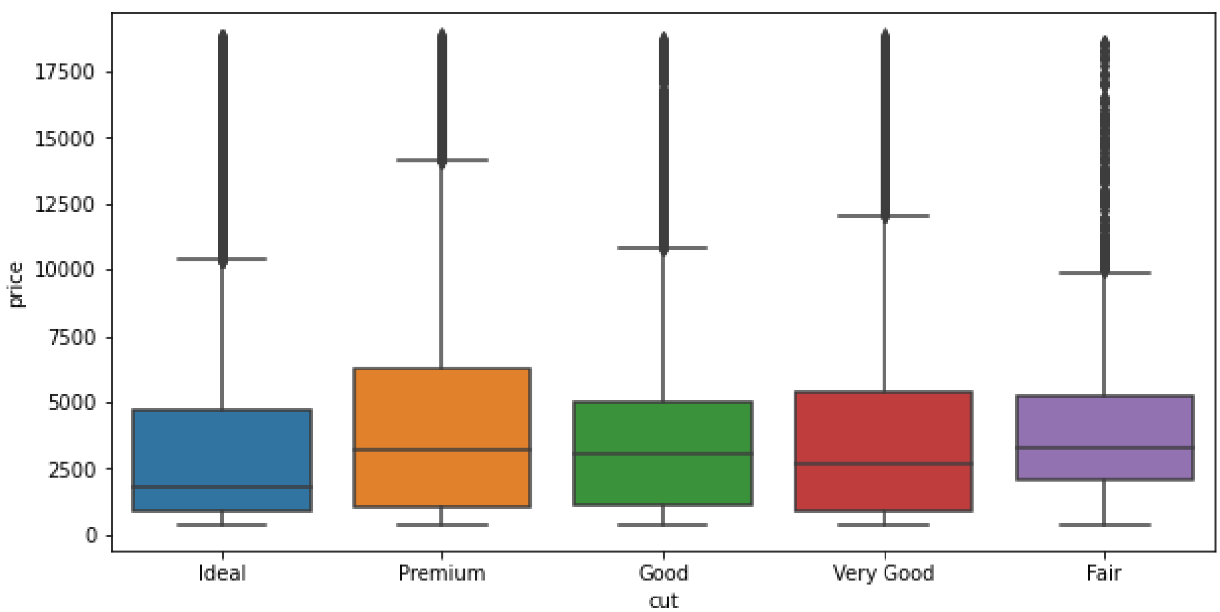
Out[17]:
```
Ideal        21548
Premium      13780
Very Good    12081
Good          4902
Fair          1609
Name: cut, dtype: int64
```

In [18]:
```
plt.figure(figsize = (15,5))
plt.title("Percentage of Cut Category")
plt.pie(df['cut'].value_counts(), labels = b , explode = (0,0,0,1,1), autopct = "%1.1f
plt.show()
```



In [19]:
```
plt.figure(figsize = (10,5))
sns.boxplot(data = df, x = 'cut', y = 'price')
```

Out[19]:
```
<AxesSubplot:xlabel='cut', ylabel='price'>
```



Premium cut diamonds are the most expensive type of diamonds.

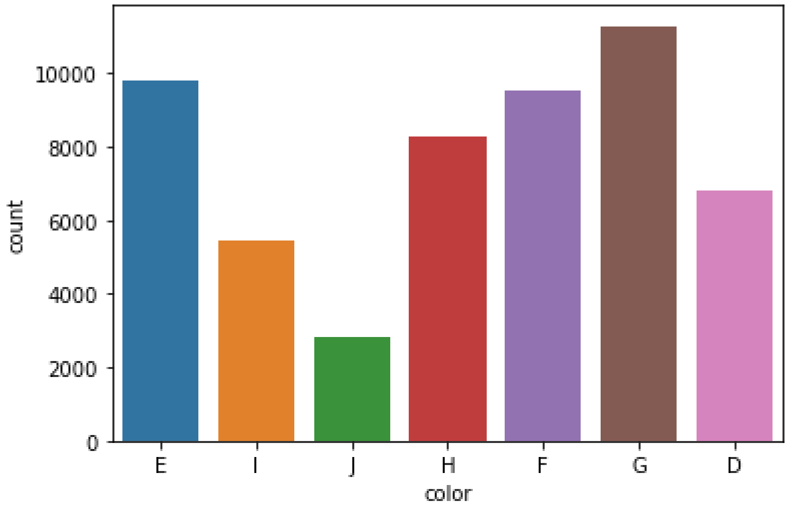
C.iii] Color Vs Price.

In [20]:
```
c = np.array(df['color'].unique())
c
```

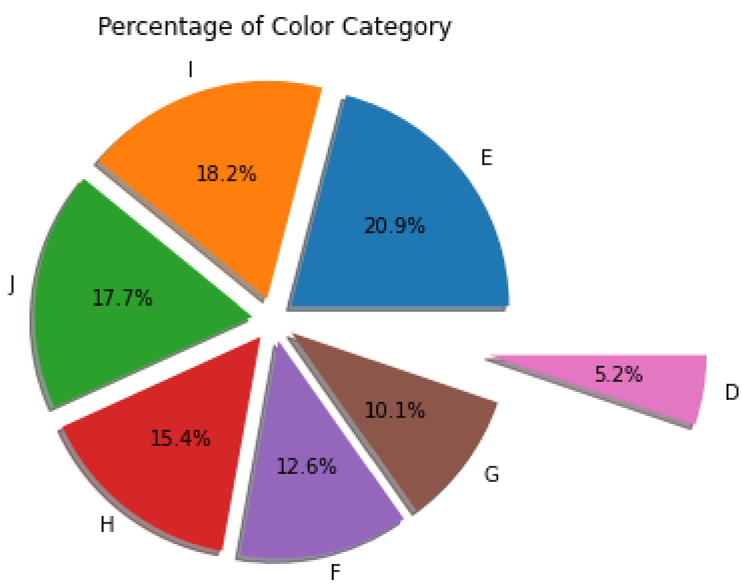
Out[20]:
```
array(['E', 'I', 'J', 'H', 'F', 'G', 'D'], dtype=object)
```

In [21]:
```
sns.countplot(data = df, x = 'color')
```

Out[21]: <AxesSubplot:xlabel='color', ylabel='count'>

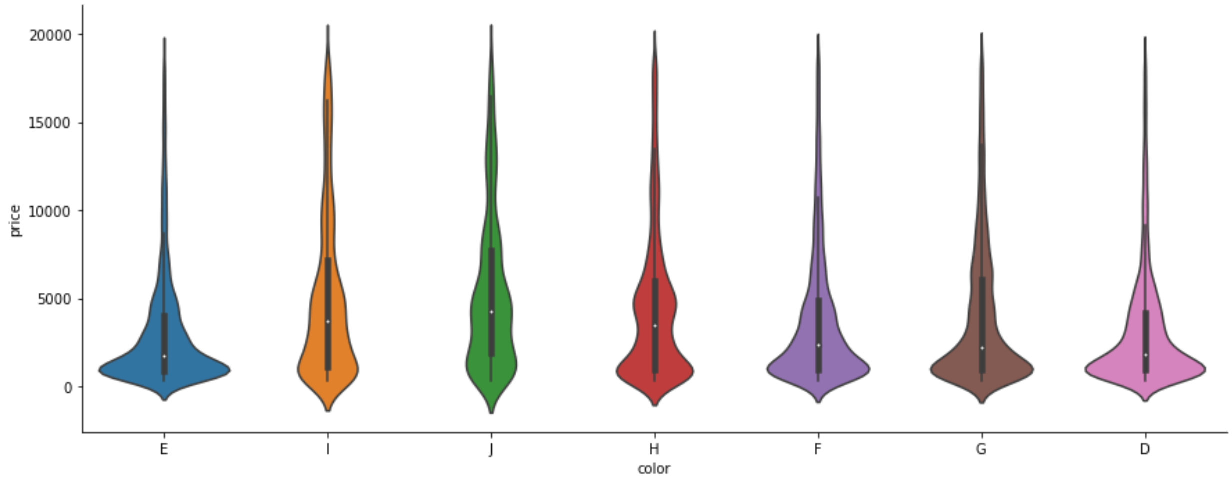


In [22]:
```
plt.figure(figsize = (15,5))
plt.title("Percentage of Color Category")
plt.pie(df['color'].value_counts(), labels = c , explode = (0.1,0.1,0.1,0.1,0.1,0.1,1)
plt.show()
```



In [23]:
```
sns.factorplot(x='color', y='price' , data=df , kind='violin', aspect=2.5)
```

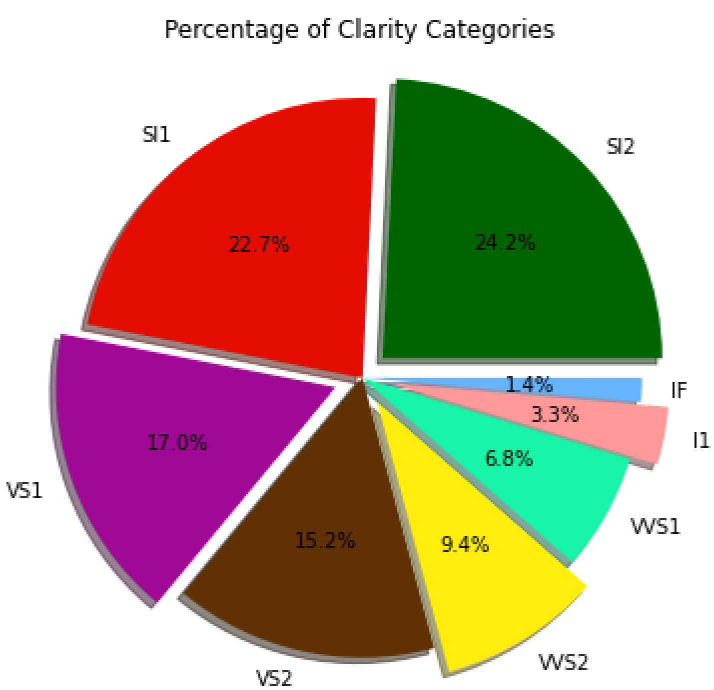
Out[23]: <seaborn.axisgrid.FacetGrid at 0x228c74a6100>



The colorless diamonds are more expensive as compared to the diamonds with color.

C.iv] Clarity Vs Price

In [24]:
```
labels = df.clarity.unique().tolist()
sizes = df.clarity.value_counts().tolist()
colors = ['#006400', '#E40E00', '#A00994', '#613205', '#FFED0D', '#16F5A7','#ff9999','
explode = (0.1, 0.0, 0.1, 0, 0.1, 0, 0.1,0)
plt.pie(sizes, explode=explode, labels=labels, colors=colors,autopct='%1.1f%%', shadow
plt.axis('equal')
plt.title("Percentage of Clarity Categories")
plt.plot()
fig=plt.gcf()
fig.set_size_inches(6,6)
plt.show()
```

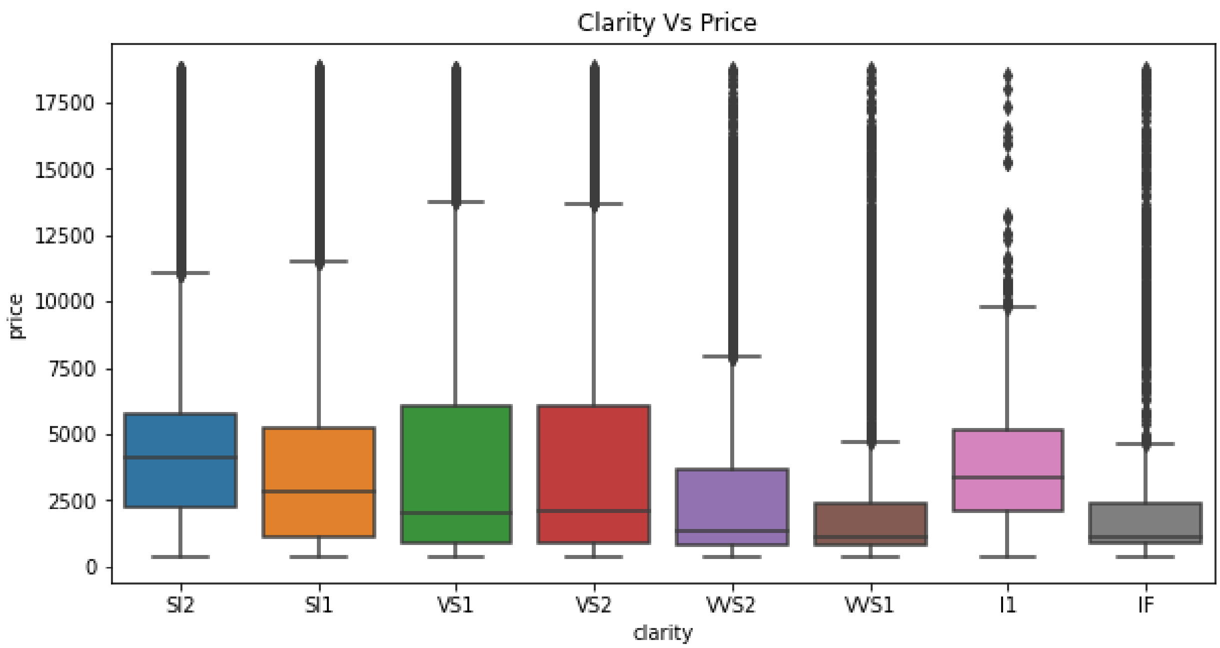


In [25]:
```
plt.figure(figsize = (10,5))
plt.title(" Clarity Vs Price")
```

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

Out[25]:

```
<AxesSubplot:title={'center':' Clarity Vs Price'}, xlabel='clarity', ylabel='price'>
```



From the boxplot, we can conclude that the cut type 'VS1' and 'VS2' are more expensive from the rest.

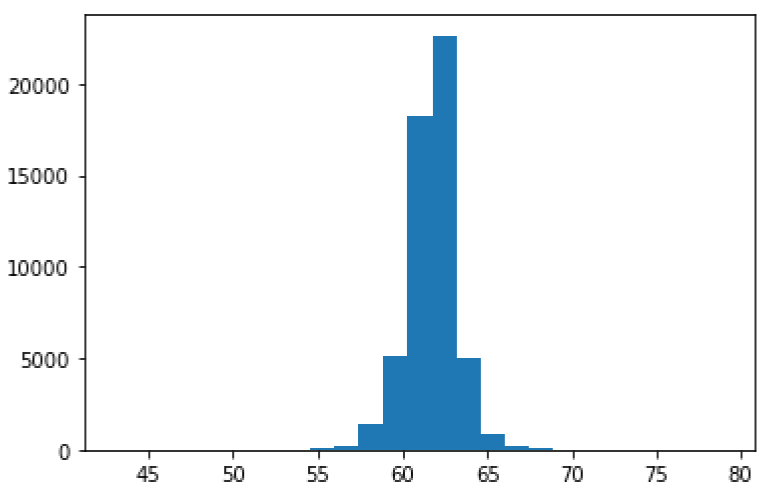
C.v] Depth Vs Price

In [26]:

```
plt.hist('depth' , data=df , bins=25)
```

Out[26]:

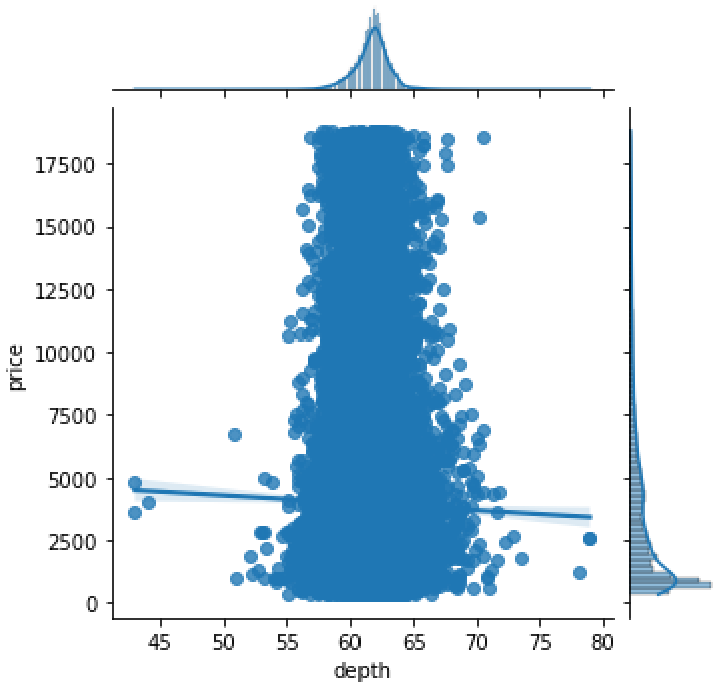
```
(array([3.0000e+00, 0.0000e+00, 0.0000e+00, 0.0000e+00, 0.0000e+00,
        2.0000e+00, 4.0000e+00, 1.1000e+01, 4.3000e+01, 2.1900e+02,
        1.4240e+03, 5.0730e+03, 1.8242e+04, 2.2649e+04, 5.0330e+03,
        8.5100e+02, 2.3400e+02, 8.7000e+01, 2.7000e+01, 1.1000e+01,
        3.0000e+00, 1.0000e+00, 0.0000e+00, 0.0000e+00, 3.0000e+00]),
 array([43.  , 44.44, 45.88, 47.32, 48.76, 50.2 , 51.64, 53.08, 54.52,
        55.96, 57.4 , 58.84, 60.28, 61.72, 63.16, 64.6 , 66.04, 67.48,
        68.92, 70.36, 71.8 , 73.24, 74.68, 76.12, 77.56, 79.  ]),
 <BarContainer object of 25 artists>)
```



In [27]:

```
sns.jointplot(x='depth', y='price' , data=df , kind='reg', size=5)
```

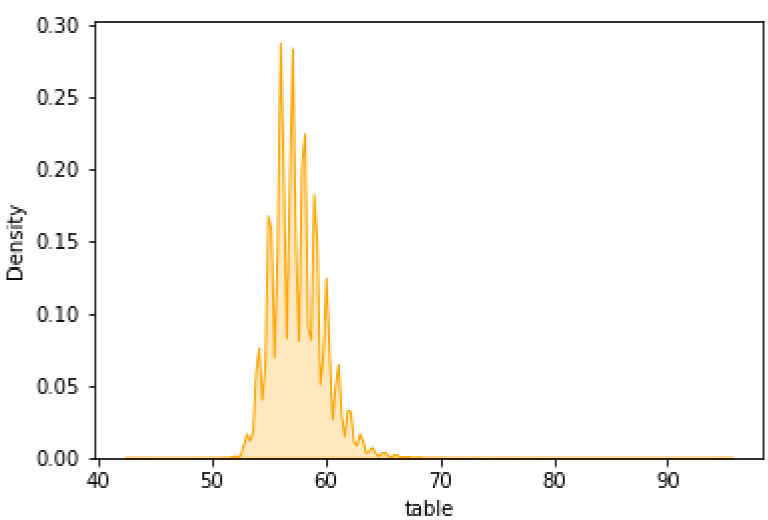
Out[27]: <seaborn.axisgrid.JointGrid at 0x228c72574c0>



C.vi] Table Vs Price.

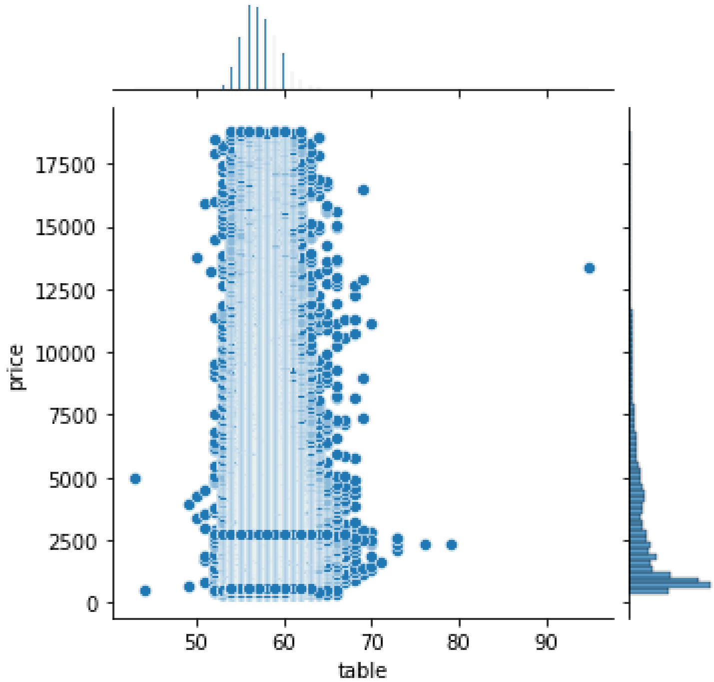
In [28]:
```
sns.kdeplot(df['table'] ,shade=True , color='orange')
```

Out[28]: <AxesSubplot:xlabel='table', ylabel='Density'>



In [29]:
```
sns.jointplot(x='table', y='price', data=df , size=5)
```

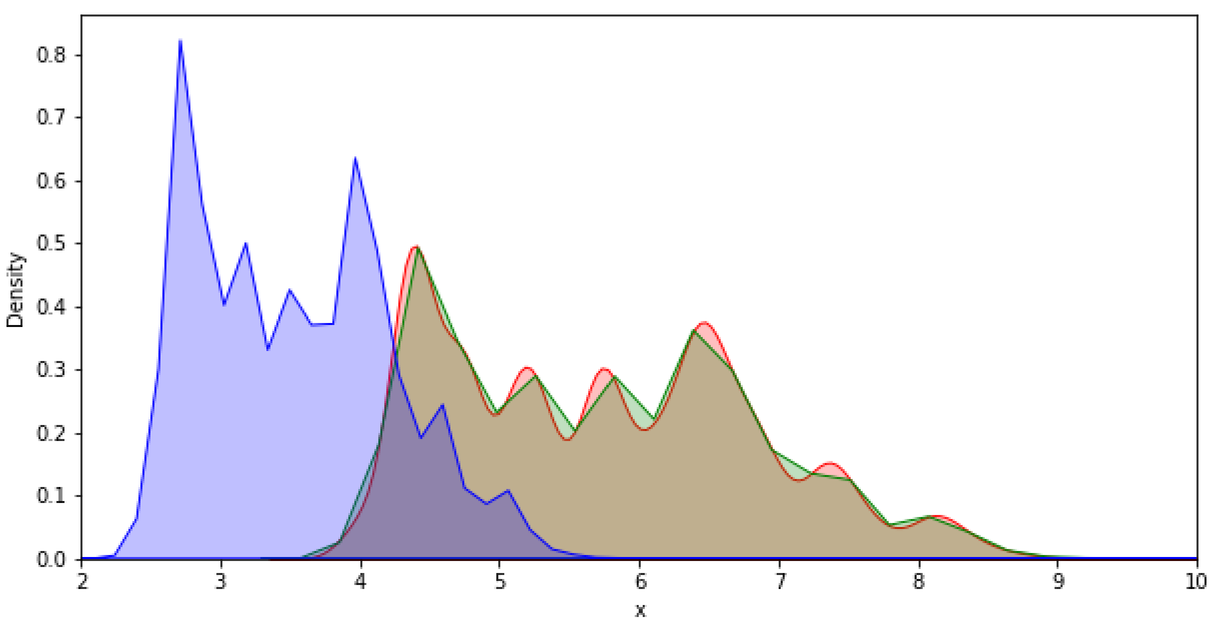
Out[29]: <seaborn.axisgrid.JointGrid at 0x228c8a051c0>



C.vii] Dimensions Vs Price.

In [30]:
```
plt.figure(figsize = (10,5))
sns.kdeplot(df['x'] ,shade=True , color='r' )
sns.kdeplot(df['y'] , shade=True , color='g' )
sns.kdeplot(df['z'] , shade= True , color='b')
plt.xlim(2,10)
```

Out[30]:
```
(2.0, 10.0)
```



It was obvious that increase in dimension or volume of diamond would increase the price.

D] Feature Engineering.

As we can see that the features 'x', 'y' &'z' are the dimensions of the diamonds. We can converge these into a anew feature volume for better analysis.

D1] Creating a new Feature 'volume'.

In [31]:
```
df['volume'] = df['x']*df['y']*df['z']
df.head()
```

Out[31]:

	carat	cut	color	clarity	depth	table	price	x	y	z	volume
0	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43	38.202030
1	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31	34.505856
2	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31	38.076885
3	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63	46.724580
4	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75	51.917250

D2] Dropping the features 'x', 'y' & 'z'.

In [32]:
```
df.drop(['x','y','z'], axis=1, inplace= True)
df.head()
```

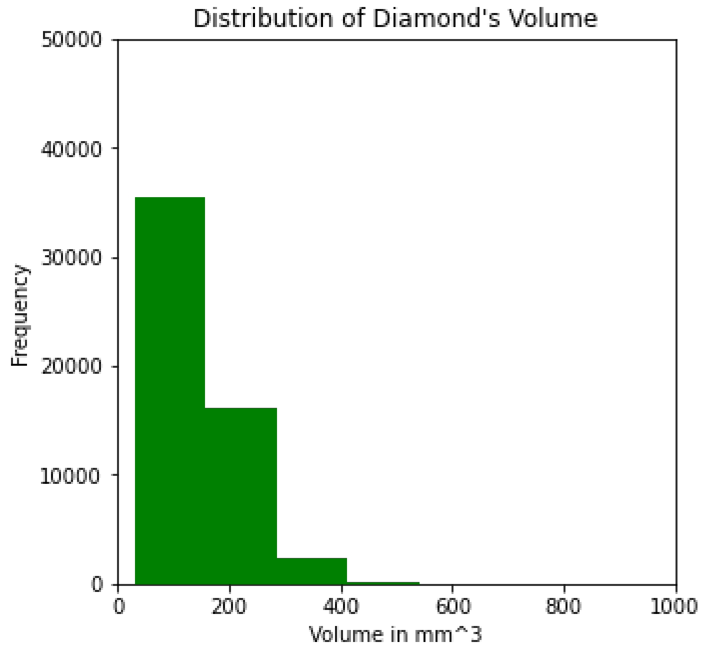
Out[32]:

	carat	cut	color	clarity	depth	table	price	volume
0	0.23	Ideal	E	SI2	61.5	55.0	326	38.202030
1	0.21	Premium	E	SI1	59.8	61.0	326	34.505856
2	0.23	Good	E	VS1	56.9	65.0	327	38.076885
3	0.29	Premium	I	VS2	62.4	58.0	334	46.724580
4	0.31	Good	J	SI2	63.3	58.0	335	51.917250

D3] Assessing the new feature w.r.t. 'price'.

In [33]:
```
plt.figure(figsize=(5,5))
plt.hist( x=df['volume'] , bins=30 ,color='g')
plt.xlabel('Volume in mm^3')
plt.ylabel('Frequency')
plt.title('Distribution of Diamond\'s Volume')
plt.xlim(0,1000)
plt.ylim(0,50000)
```

Out[33]:
```
(0.0, 50000.0)
```



E] Label Encoding.

As we can see that out dataset contains categorical data, we need to label encode them.

E1] Splitting the dataset into categorical and numerical.

In [34]:
```
df_cat = df.select_dtypes('object')
df_num = df.select_dtypes(['int64', 'float64'])
```

In [35]:
```
df_cat
```

Out[35]:

	cut	color	clarity
0	Ideal	E	SI2
1	Premium	E	SI1
2	Good	E	VS1
3	Premium	I	VS2
4	Good	J	SI2
...	...	...	...
53935	Ideal	D	SI1
53936	Good	D	SI1
53937	Very Good	D	SI1
53938	Premium	H	SI2
53939	Ideal	D	SI2

53920 rows × 3 columns

E2] Label encoding the categorical data.

In [36]:

```
categorical_col = []
for i in df.dtypes.index:
    if df.dtypes[i] == 'object' :
        categorical_col.append(i)
print("Categorical columns present in the datasets are: \n", categorical_col)
```

```
Categorical columns present in the datasets are: 
 ['cut', 'color', 'clarity']
```

In [37]:

```
from sklearn.preprocessing import LabelEncoder

LE = LabelEncoder()
df[categorical_col]= df[categorical_col].apply(LE.fit_transform)
```

In [38]:

```
df.head()
```

Out[38]:

	carat	cut	color	clarity	depth	table	price	volume
0	0.23	2	1	3	61.5	55.0	326	38.202030
1	0.21	3	1	2	59.8	61.0	326	34.505856
2	0.23	1	1	4	56.9	65.0	327	38.076885
3	0.29	3	5	5	62.4	58.0	334	46.724580
4	0.31	1	6	3	63.3	58.0	335	51.917250

F] Feature Scaling.

We need to scale down the values in our dataset to ease out our calculations.

F1] Splitting dataset into Train & Test.

In [39]:
```
from sklearn.model_selection import train_test_split
```

In [40]:
```
x = df.drop(['price'], axis=1)
y = df['price']

x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.25, random_state=1
```

F2] Building a model for algorithm testing.

In [41]:
```
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.model_selection import GridSearchCV, cross_val_score
from sklearn.metrics import mean_squared_log_error,mean_squared_error, r2_score,mean_a
```

In [42]:
```
R2_Scores = []
models = ['Linear Regression' , 'Lasso Regression' , 'AdaBoost Regression' , 'Ridge Re
          'RandomForest Regression' ,
         'KNeighbours Regression']
```

In [51]:
```
def mymodel(model):
    model.fit(x_train, y_train)
    accuracies = cross_val_score(estimator = model, X = x_train, y = y_train, cv = 5,v
    y_pred = model.predict(x_test)


    train = model.score(x_train, y_train)
    test = model.score(x_test, y_test)

    print(f"Training Accuracy : {train}\nTesting Accuracy : {test}\n\n")

    print('')
    print("*****", model , "*****")
    print('Score : %.4f' % model.score(x_test, y_test))
    print(accuracies)

    mse = mean_squared_error(y_test, y_pred)
    mae = mean_absolute_error(y_test, y_pred)
    rmse = mean_squared_error(y_test, y_pred)**0.5
    r2 = r2_score(y_test, y_pred)

    print('')
    print('MSE    : %0.2f ' % mse)
    print('MAE    : %0.2f ' % mae)
    print('RMSE   : %0.2f ' % rmse)
    print('R2     : %0.2f ' % r2)

    R2_Scores.append(r2)

    return model
```

In [52]:
```
lr = mymodel(LinearRegression())
ar = mymodel(AdaBoostRegressor())
```

```
rr = mymodel(Ridge())
gbr = mymodel(GradientBoostingRegressor())
rf = mymodel(RandomForestRegressor())
kn = mymodel(KNeighborsRegressor())
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:    0.0s finished
Training Accuracy : 0.8804080171332576
Testing Accuracy : 0.8800909499700584



***** LinearRegression() *****
Score : 0.8801
[0.87848956 0.87629556 0.87867783 0.88025387 0.7093961 ]

MSE    : 1821460.45
MAE    : 919.67
RMSE   : 1349.61
R2     : 0.88
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:   15.4s finished
Training Accuracy : 0.890644596608649
Testing Accuracy : 0.8812761920980259



***** AdaBoostRegressor() *****
Score : 0.8813
[0.88611227 0.89245285 0.8909148  0.87861447 0.90610449]

MSE    : 1803456.21
MAE    : 1034.73
RMSE   : 1342.93
R2     : 0.88
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:    0.0s finished
Training Accuracy : 0.880407792509302
Testing Accuracy : 0.8800926270307836



***** Ridge() *****
Score : 0.8801
[0.87849191 0.87630519 0.87868344 0.88026172 0.70476027]

MSE    : 1821434.97
MAE    : 919.61
RMSE   : 1349.61
R2     : 0.88
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:   33.5s finished
```

```
Training Accuracy : 0.9724667530365758
Testing Accuracy : 0.9688813785691008



***** GradientBoostingRegressor() *****
Score : 0.9689
[0.96984316 0.97037084 0.97119175 0.97088402 0.97297908]

MSE    : 472702.75
MAE    : 362.60
RMSE   : 687.53
R2     : 0.97
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:  2.1min finished
Training Accuracy : 0.997288819349
Testing Accuracy : 0.9791811711920834



***** RandomForestRegressor() *****
Score : 0.9792
[0.98045926 0.97980839 0.97960191 0.97954892 0.97964676]

MSE    : 316245.30
MAE    : 275.29
RMSE   : 562.36
R2     : 0.98
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:    2.7s finished
Training Accuracy : 0.9611090790990229
Testing Accuracy : 0.9369285011406803



***** KNeighborsRegressor() *****
Score : 0.9369
[0.93550213 0.93568615 0.93705141 0.93913071 0.94071929]

MSE    : 958078.15
MAE    : 485.76
RMSE   : 978.81
R2     : 0.94
```

As we can see that, the algorithm of "Random Forest Regressor" has the best R2 Score and both the training and testing accuracy are appropiate for the model.

F3] Hyper-paramter Tuning.

In [60]:
```
from sklearn.model_selection import GridSearchCV
parameters = {
    'n_estimators':[100],
    'n_jobs':[-1],
    'max_features':["auto",'sqrt','log2']}
```

In [63]:
```
grid = GridSearchCV(RandomForestRegressor(),  #model
```

```
                    parameters,             #hyperparameters
                    verbose=3,              #way of computation
                    cv=5,                   #cross validation
                    scoring="r2")     #metrics
```

In [64]:
```
grid.fit(x_train, y_train)
```

```
Fitting 5 folds for each of 3 candidates, totalling 15 fits
[CV 1/5] END max_features=auto, n_estimators=100, n_jobs=-1;, score=0.980 total time=
7.9s
[CV 2/5] END max_features=auto, n_estimators=100, n_jobs=-1;, score=0.980 total time=
5.1s
[CV 3/5] END max_features=auto, n_estimators=100, n_jobs=-1;, score=0.980 total time=
5.0s
[CV 4/5] END max_features=auto, n_estimators=100, n_jobs=-1;, score=0.980 total time=
5.1s
[CV 5/5] END max_features=auto, n_estimators=100, n_jobs=-1;, score=0.980 total time=
5.1s
[CV 1/5] END max_features=sqrt, n_estimators=100, n_jobs=-1;, score=0.977 total time=
2.7s
[CV 2/5] END max_features=sqrt, n_estimators=100, n_jobs=-1;, score=0.976 total time=
2.7s
[CV 3/5] END max_features=sqrt, n_estimators=100, n_jobs=-1;, score=0.975 total time=
2.6s
[CV 4/5] END max_features=sqrt, n_estimators=100, n_jobs=-1;, score=0.976 total time=
2.5s
[CV 5/5] END max_features=sqrt, n_estimators=100, n_jobs=-1;, score=0.977 total time=
2.7s
[CV 1/5] END max_features=log2, n_estimators=100, n_jobs=-1;, score=0.977 total time=
2.6s
[CV 2/5] END max_features=log2, n_estimators=100, n_jobs=-1;, score=0.976 total time=
2.5s
[CV 3/5] END max_features=log2, n_estimators=100, n_jobs=-1;, score=0.975 total time=
2.5s
[CV 4/5] END max_features=log2, n_estimators=100, n_jobs=-1;, score=0.976 total time=
2.6s
[CV 5/5] END max_features=log2, n_estimators=100, n_jobs=-1;, score=0.978 total time=
2.7s
```

Out[64]:
```
GridSearchCV(cv=5, estimator=RandomForestRegressor(),
             param_grid={'max_features': ['auto', 'sqrt', 'log2'],
                         'n_estimators': [100], 'n_jobs': [-1]},
             scoring='r2', verbose=3)
```

In [65]:
```
grid.best_params_
```

Out[65]:
```
{'max_features': 'auto', 'n_estimators': 100, 'n_jobs': -1}
```

In [66]:
```
grid.best_score_
```

Out[66]:
```
0.9798103317476053
```

In [67]:
```
grid.best_estimator_
```

Out[67]:
```
RandomForestRegressor(n_jobs=-1)
```

In [68]:
```
dt = mymodel(grid.best_estimator_)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:   19.6s finished
Training Accuracy : 0.9972922365589991
Testing Accuracy : 0.9792476433165977



***** RandomForestRegressor(n_jobs=-1) *****
Score : 0.9792
[0.98048648 0.97976915 0.97968511 0.97954329 0.97975857]

MSE    : 315235.56
MAE    : 275.63
RMSE   : 561.46
R2     : 0.98
```

With the R2 Score of 0.98 and accuracy score of 0.9792, we can conclude that the algorithm 'Random Forest Regressor' is the best for our model.