Importing Required Modules

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

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

Out[2]:

	Unnamed: 0	carat	cut	color	clarity	depth	table	price	x	y	z
0	1	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	2	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
2	3	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31
3	4	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63
4	5	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75

Columns in DataFrame :

price price in US dollars ($326 - -$18,823)

carat weight of the diamond (0.2--5.01)

cut quality of the cut (Fair, Good, Very Good, Premium, Ideal)

color diamond colour, from J (worst) to D (best)

clarity a measurement of how clear the diamond is (I1 (worst), SI2, SI1, VS2, VS1, VVS2, VVS1, IF (best))

x length in mm (0--10.74)

y width in mm (0--58.9)

z depth in mm (0--31.8)

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)

Data Cleaning

In [3]:
```
df.drop(['Unnamed: 0'],inplace=True,axis=1)
```

In [4]:
```
df.head()
```

Out[4]:

	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

We drop our column which is not in use for our work

In [5]:
```
df.isnull().sum()
```

Out[5]:
```
carat       0
cut         0
color       0
clarity     0
depth       0
table       0
price       0
x           0
y           0
z           0
dtype: int64
```

No null values in Dataset

In [6]:
```
df.duplicated().sum()
```

Out[6]:
```
146
```

We have 146 duplicate records we have to drop that duplicate values

In [7]:
```
df.drop_duplicates(inplace=True)
df.duplicated().sum()
```

Out[7]:
```
0
```

After dropping duplicate values we can check again for it. Now we do not have duplicate values in our dataset.

In [8]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 53794 entries, 0 to 53939
Data columns (total 10 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   carat    53794 non-null  float64
 1   cut      53794 non-null  object 
 2   color    53794 non-null  object 
 3   clarity  53794 non-null  object 
 4   depth    53794 non-null  float64
 5   table    53794 non-null  float64
 6   price    53794 non-null  int64  
 7   x        53794 non-null  float64
 8   y        53794 non-null  float64
 9   z        53794 non-null  float64
dtypes: float64(6), int64(1), object(3)
memory usage: 4.5+ MB
```

Total no. of records are 53940, 9 features and price is our target column

In [9]:
```
df.describe()
```

Out[9]:

	carat	depth	table	price	x	y	
count	53794.00000	53794.000000	53794.000000	53794.000000	53794.000000	53794.000000	5379
mean	0.79778	61.748080	57.458109	3933.065082	5.731214	5.734653	
std	0.47339	1.429909	2.233679	3988.114460	1.120695	1.141209	
min	0.20000	43.000000	43.000000	326.000000	0.000000	0.000000	
25%	0.40000	61.000000	56.000000	951.000000	4.710000	4.720000	
50%	0.70000	61.800000	57.000000	2401.000000	5.700000	5.710000	
75%	1.04000	62.500000	59.000000	5326.750000	6.540000	6.540000	
max	5.01000	79.000000	95.000000	18823.000000	10.740000	58.900000	3

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

Out[10]:

	carat	depth	table	price	x	y	z
carat	1.000000	0.027861	0.181091	0.921548	0.975380	0.951908	0.953542
depth	0.027861	1.000000	-0.297669	-0.011048	-0.025348	-0.029389	0.094757
table	0.181091	-0.297669	1.000000	0.126566	0.194855	0.183231	0.150270
price	0.921548	-0.011048	0.126566	1.000000	0.884504	0.865395	0.861208
x	0.975380	-0.025348	0.194855	0.884504	1.000000	0.974592	0.970686
y	0.951908	-0.029389	0.183231	0.865395	0.974592	1.000000	0.951844
z	0.953542	0.094757	0.150270	0.861208	0.970686	0.951844	1.000000

Data Visualization

Top 10 price of diamonds from the dataset

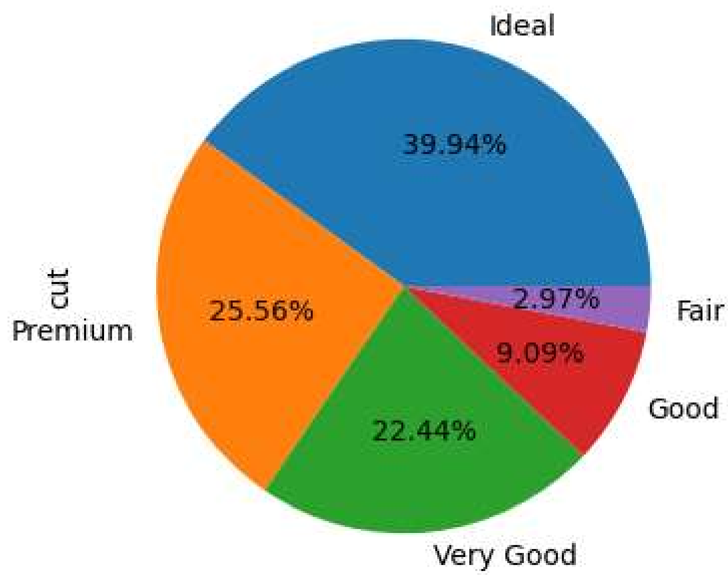
In [11]:
```
df.sort_values(by=['price'],ascending=False).head(10)
```

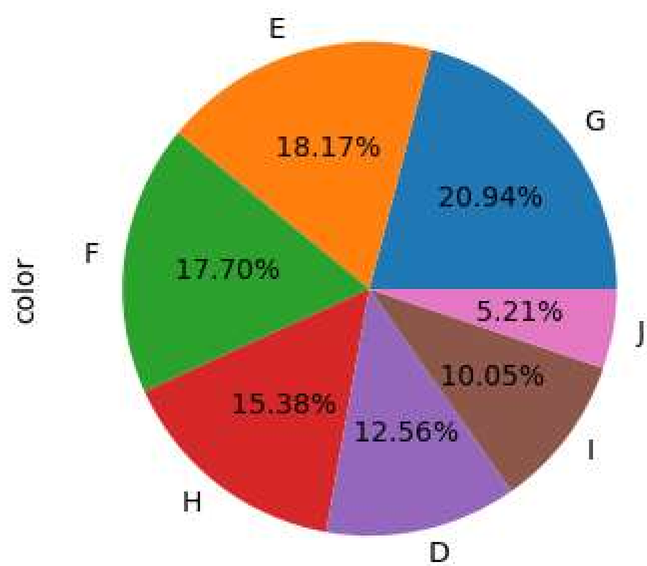
Out[11]:

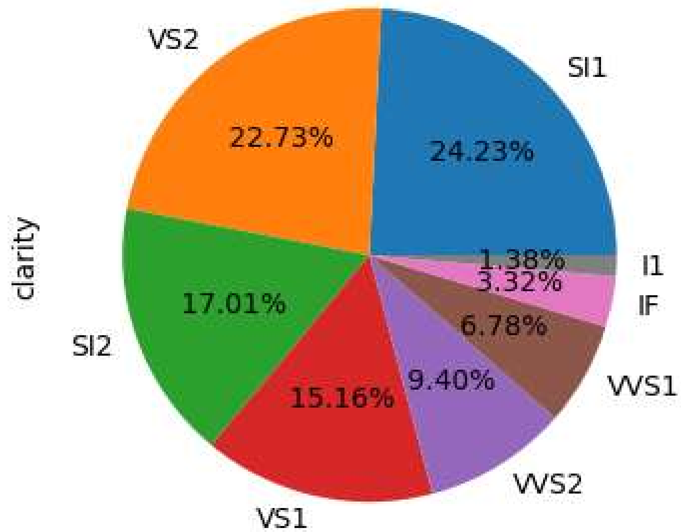
	carat	cut	color	clarity	depth	table	price	x	y	z
27749	2.29	Premium	I	VS2	60.8	60.0	18823	8.50	8.47	5.16
27748	2.00	Very Good	G	SI1	63.5	56.0	18818	7.90	7.97	5.04
27747	1.51	Ideal	G	IF	61.7	55.0	18806	7.37	7.41	4.56
27746	2.07	Ideal	G	SI2	62.5	55.0	18804	8.20	8.13	5.11
27745	2.00	Very Good	H	SI1	62.8	57.0	18803	7.95	8.00	5.01
27744	2.29	Premium	I	SI1	61.8	59.0	18797	8.52	8.45	5.24
27742	2.04	Premium	H	SI1	58.1	60.0	18795	8.37	8.28	4.84
27743	2.00	Premium	I	VS1	60.8	59.0	18795	8.13	8.02	4.91
27740	1.71	Premium	F	VS2	62.3	59.0	18791	7.57	7.53	4.70
27741	2.15	Ideal	G	SI2	62.6	54.0	18791	8.29	8.35	5.21

Visualization according categorical features

In [12]:
```
cat_col = df.select_dtypes('object').columns
for i in cat_col:
    plt.figure(figsize=(4,4))
    df[i].value_counts().plot.pie(autopct='% 1.2f%%')
    plt.show()
```







Split into x & y

In [13]:
```
x=df.drop(['price'],axis=1)
y=df['price']
```

We splits our dataset into features(x) & target(y)

In [14]:
```
x.head()
```

Out[14]:

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

In [15]:
```
y.head()
```

Out[15]:
```
0     326
1     326
2     327
3     334
4     335
Name: price, dtype: int64
```

Feature Scaling

In [16]:
```
num_col = x.select_dtypes(['int64','float64']).columns
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x[num_col] = sc.fit_transform(x[num_col])
x.head()
```

Out[16]:

	carat	cut	color	clarity	depth	table	x	y	z
0	-1.199402	Ideal	E	SI2	-0.173495	-1.100486	-1.589399	-1.537553	-1.572574
1	-1.241651	Premium	E	SI1	-1.362393	1.585691	-1.642938	-1.660231	-1.742780
2	-1.199402	Good	E	VS1	-3.390512	3.376475	-1.500168	-1.458689	-1.742780
3	-1.072656	Premium	I	VS2	0.455922	0.242603	-1.366321	-1.318485	-1.288899
4	-1.030407	Good	J	SI2	1.085338	0.242603	-1.241397	-1.213332	-1.118694

We performed feature scaling on numerical features for standardization our data.

Encoding Categorical features

In [17]:
```
from sklearn.preprocessing import OrdinalEncoder
oe=OrdinalEncoder()
x[cat_col]=oe.fit_transform(x[cat_col])
```

We also performed Encoding our categorical features to fed data to our model.

In [18]:
```
x.head()
```

Out[18]:

	carat	cut	color	clarity	depth	table	x	y	z
0	-1.199402	2.0	1.0	3.0	-0.173495	-1.100486	-1.589399	-1.537553	-1.572574
1	-1.241651	3.0	1.0	2.0	-1.362393	1.585691	-1.642938	-1.660231	-1.742780
2	-1.199402	1.0	1.0	4.0	-3.390512	3.376475	-1.500168	-1.458689	-1.742780
3	-1.072656	3.0	5.0	5.0	0.455922	0.242603	-1.366321	-1.318485	-1.288899
4	-1.030407	1.0	6.0	3.0	1.085338	0.242603	-1.241397	-1.213332	-1.118694

Splits into training and testing data

In [19]:
```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.2,random_state=1)
```

After Splitting x & y into training & testing data to build the model

In [20]:
```
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import r2_score
```

We will try different types of algorithm to build the model and check accuracy. Select one model which gives highest accuracy and try for hypertunning to increase the model accuracy.

In [21]:
```
lr = LinearRegression()
knn = KNeighborsRegressor()
dt = DecisionTreeRegressor()
```

In [22]:
```
def mymodel(model):
    model.fit(xtrain,ytrain) # build model
    ypred = model.predict(xtest) #predicted value of y
    train = model.score(xtrain,ytrain)
    test = model.score(xtest,ytest)
    print(f'training accuracy : {train}')
    print(f'testing accuracy : {test}')
    print(f'Model Name : {model}')
    print(f'Accuracy of model : {round(r2_score(ytest,ypred)*100,2)} %')
```

In [23]:
```
mymodel(lr)
```

```
training accuracy : 0.8855345674157292
testing accuracy : 0.8830196054670751
Model Name : LinearRegression()
Accuracy of model : 88.3 %
```

In [24]:
```
mymodel(knn)
```

```
training accuracy : 0.9773739292617025
testing accuracy : 0.9660433358208882
Model Name : KNeighborsRegressor()
Accuracy of model : 96.6 %
```

In [25]:
```
mymodel(dt)
```

```
training accuracy : 0.9999952511667353
testing accuracy : 0.9662980433792141
Model Name : DecisionTreeRegressor()
Accuracy of model : 96.63 %
```

My KNN model gives me accuracy almost equal to Decision Tree model. but we consider Decision Tree model because KNN take time to work on large dataset, so we build our model on Decision Tree. so we perform hypertunning on Decision Tree to increase our accuracy as well as to reduce overfitting. we will use Random Forest as hypertune parameter for Decision Tree

In [26]:
```
from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor()
rf.fit(xtrain,ytrain) # build model
ypred = rf.predict(xtest) #predicted value of y
train = rf.score(xtrain,ytrain)
test = rf.score(xtest,ytest)
print(f'training accuracy : {train}')
print(f'testing accuracy : {test}')
print(f'Accuracy of model : {round(r2_score(ytest,ypred)*100,2)} %')
```

```
training accuracy : 0.9973022459704362
testing accuracy : 0.982125067802318
Accuracy of model : 98.21 %
```

Perform pickling on scaling feature object, encoding object and prediction model

In [27]:
```
import pickle
pickle.dump(sc , open("stdscl.pkl" , "wb"))
```

In [28]:
```
import pickle
pickle.dump(oe , open("ordencode.pkl" , "wb"))
```

In [29]:
```
import pickle
pickle.dump(rf , open("predict.pkl" , "wb"))
```

Reporting

The aim of this study was to create regression model for the diamond dataset and to predict the price of Diamond by creating model and to obtain maximum accuracy score in the established models. The work done is as follows:

Diamond Data Set read.

With Exploratory Data Analysis; The data set's structural data were checked. The types of variables in the dataset were examined. Size information of the dataset was accessed. Descriptive statistics of the data set were examined. It was concluded that there were no missing observations and outliers in the data set. Duplicate values removed from the datasets.

During Model Building; Logistic Regression, KNN, DT like using machine learning models Accuracy Score were calculated. Later Random Forest hyperparameter optimizations optimized to increase Accuracy score.

Result; The model created as a result of Random Forest became the model with the maximum Accuracy Score. (0.9821)

In [ ]:
```
```