SMARTPHONE PRICE PREDICTION

Objective

- The objective of this project is to develop a Machine Learning model that can accurately predict smartphone prices based on key specifications. By analyzing a dataset containing various smartphone features, the model helps users estimate the price of a phone before making a purchase decision.

Key Goals:

- Identify the most influential factors affecting phone prices (e.g., RAM, Storage, Camera Quality).
- Compare multiple Machine Learning models to determine the best-performing one.
- Build an interactive Streamlit app that allows users to input specifications and get an instant price prediction.
- Provide data-driven insights for consumers and manufacturers.

Feature Descriptions

1. Brand – The manufacturer of the phone.
2. Model – The specific model name of the phone.
3. RAM (GB) – The amount of Random Access Memory (RAM), which affects performance.
4. Storage (GB) – The internal storage capacity of the phone.
5. Camera_Quality (MP) – The primary camera resolution in megapixels.
6. Processor_Type – The chipset used in the phone.
7. Screen_Size (inches) – The display size of the phone in inches.
8. Battery_Life (mAh) – The battery capacity, which influences usage time.
9. OS_Version – The operating system version.
10. Release_Year – The year the phone was released.
11. Network – The supported network type.
12. Price (INR) – The phone's price.

In [1]:
```python
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:
```
df = pd.read_csv('/content/drive/MyDrive/Data Science/Project/Machine Learning/Dataset/Phone_Price_Prediction_Dataset.csv')
```

1. Data Inspection and Cleaning

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

Out[3]:

	Brand	Model	RAM	Storage	Camera_Quality	Processor_Type	Screen_Size	Battery_Life	OS_Version	Release_Year	Network	Price (INR)
0	Vivo	V23	4	256	48	A15 Bionic	6.4	4000	iOS 15	2023	5G	60257
1	Google	Pixel 7	6	512	64	Exynos 2100	5.8	6000	iOS 14	2022	5G	73211
2	Google	Pixel 5	12	128	12	A15 Bionic	6.1	5000	iOS 15	2020	5G	65920

In [4]:
```
df.tail(3)
```

Out[4]:

	Brand	Model	RAM	Storage	Camera_Quality	Processor_Type	Screen_Size	Battery_Life	OS_Version	Release_Year	Network	Price (INR)
9997	Realme	Realme 9	12	128	108	A14 Bionic	6.1	4000	Android 12	2020	5G	69095
9998	Xiaomi	Mi 11	12	64	12	Snapdragon 888	6.4	5000	Android 12	2021	4G	44034
9999	Samsung	Galaxy S21	6	128	108	MediaTek Dimensity 1200	6.1	4000	iOS 14	2021	5G	53670

In [5]:
```
df.describe()
```

Out[5]:

	RAM	Storage	Camera_Quality	Screen_Size	Battery_Life	Release_Year	Price (INR)
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	7.485600	238.272000	58.384800	6.381270	4597.400000	2021.518500	61999.912100
std	2.942968	170.974472	34.607706	0.392899	865.498786	1.127557	18043.516001
min	4.000000	64.000000	12.000000	5.800000	3500.000000	2020.000000	23367.000000
25%	4.000000	128.000000	48.000000	6.100000	4000.000000	2020.000000	48609.000000
50%	8.000000	128.000000	64.000000	6.400000	4500.000000	2022.000000	59908.000000
75%	8.000000	256.000000	108.000000	6.700000	5000.000000	2023.000000	72963.500000
max	12.000000	512.000000	108.000000	6.900000	6000.000000	2023.000000	136982.000000

In [6]:

```
for i in df.columns:
  print(df[i].value_counts(),i)
  print('*'*100)
```

```
Brand
Google     1283
OnePlus    1282
Samsung    1263
Xiaomi     1260
Apple      1256
Realme     1240
Vivo       1235
Oppo       1181
Name: count, dtype: int64 Brand
****************************************************************************************************
Model
Redmi Note 10    342
Pixel 7          341
OnePlus 8T       338
iPhone SE        334
X70              329
OnePlus 9        326
Realme X7        325
Pixel 5          323
OnePlus 10T      323
Galaxy A52       319
Galaxy M32       319
Galaxy S22       317
Realme 8         316
iPhone 14        316
Pixel 6a         314
Realme 9         314
X60              314
Mi 11            313
iPhone 13        310
Redmi Note 11    309
V21              308
Galaxy S21       308
Pixel 6          305
Reno 6           301
Find X3          301
Poco X3          296
iPhone 12        296
Reno 5           295
OnePlus Nord     295
Realme GT        285
```

```
Reno 7           284
V23              284
Name: count, dtype: int64 Model
****************************************************************************************************
RAM
8     2598
4     2520
12    2450
6     2432
Name: count, dtype: int64 RAM
****************************************************************************************************
Storage
128    2587
64     2484
256    2465
512    2464
Name: count, dtype: int64 Storage
****************************************************************************************************
Camera_Quality
108    2554
64     2502
12     2484
48     2460
Name: count, dtype: int64 Camera_Quality
****************************************************************************************************
Processor_Type
A15 Bionic                 2051
A14 Bionic                 1997
MediaTek Dimensity 1200    1993
Exynos 2100                1982
Snapdragon 888             1977
Name: count, dtype: int64 Processor_Type
****************************************************************************************************
Screen_Size
6.1    2070
6.7    2066
6.4    2010
6.9    1933
5.8    1921
Name: count, dtype: int64 Screen_Size
****************************************************************************************************
Battery_Life
```

```
3500    2047
6000    2018
4000    2001
5000    1989
4500    1945
Name: count, dtype: int64 Battery_Life
****************************************************************************************************
OS_Version
Android 12    2070
iOS 15        2056
iOS 14        1980
iOS 16        1966
Android 11    1928
Name: count, dtype: int64 OS_Version
****************************************************************************************************
Release_Year
2023    2582
2022    2547
2020    2526
2021    2345
Name: count, dtype: int64 Release_Year
****************************************************************************************************
Network
4G    5052
5G    4948
Name: count, dtype: int64 Network
****************************************************************************************************
Price (INR)
60126    4
57491    4
67081    3
76074    3
75218    3
        ..
47892    1
92243    1
64521    1
82842    1
53670    1
Name: count, Length: 9268, dtype: int64 Price (INR)
****************************************************************************************************
```

In [7]:
```
for i in df.columns:
  print(df[i].unique(),i)
  print('*'*100)
```

```
['Vivo' 'Google' 'Samsung' 'Oppo' 'Xiaomi' 'OnePlus' 'Realme' 'Apple'] Brand
****************************************************************************************************
['V23' 'Pixel 7' 'Pixel 5' 'Galaxy A52' 'Reno 7' 'Mi 11' 'Galaxy S21'
 'OnePlus 9' 'Redmi Note 11' 'X70' 'Realme GT' 'Galaxy S22' 'V21' 'Reno 6'
 'iPhone 13' 'X60' 'Realme 9' 'Poco X3' 'Redmi Note 10' 'Reno 5'
 'iPhone SE' 'iPhone 12' 'OnePlus Nord' 'iPhone 14' 'Realme X7' 'Pixel 6'
 'Realme 8' 'Galaxy M32' 'OnePlus 10T' 'Find X3' 'Pixel 6a' 'OnePlus 8T'] Model
****************************************************************************************************
[ 4  6 12  8] RAM
****************************************************************************************************
[256 512 128  64] Storage
****************************************************************************************************
[ 48  64  12 108] Camera_Quality
****************************************************************************************************
['A15 Bionic' 'Exynos 2100' 'A14 Bionic' 'MediaTek Dimensity 1200'
 'Snapdragon 888'] Processor_Type
****************************************************************************************************
[6.4 5.8 6.1 6.7 6.9] Screen_Size
****************************************************************************************************
[4000 6000 5000 3500 4500] Battery_Life
****************************************************************************************************
['iOS 15' 'iOS 14' 'Android 11' 'iOS 16' 'Android 12'] OS_Version
****************************************************************************************************
[2023 2022 2020 2021] Release_Year
****************************************************************************************************
['5G' '4G'] Network
****************************************************************************************************
[60257 73211 65920 ... 69095 44034 53670] Price (INR)
****************************************************************************************************
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 12 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Brand           10000 non-null  object 
 1   Model           10000 non-null  object 
 2   RAM             10000 non-null  int64  
 3   Storage         10000 non-null  int64  
 4   Camera_Quality  10000 non-null  int64  
 5   Processor_Type  10000 non-null  object 
 6   Screen_Size     10000 non-null  float64
 7   Battery_Life    10000 non-null  int64  
 8   OS_Version      10000 non-null  object 
 9   Release_Year    10000 non-null  int64  
 10  Network         10000 non-null  object 
 11  Price (INR)     10000 non-null  int64  
dtypes: float64(1), int64(6), object(5)
memory usage: 937.6+ KB
```

In [9]:
```
df.shape
```

Out[9]:
```
(10000, 12)
```

In [10]:
```
df.size
```

Out[10]:
```
120000
```

In [11]:
```
df.columns
```

Out[11]:
```
Index(['Brand', 'Model', 'RAM', 'Storage', 'Camera_Quality', 'Processor_Type',
       'Screen_Size', 'Battery_Life', 'OS_Version', 'Release_Year', 'Network',
       'Price (INR)'],
      dtype='object')
```

In [12]:
```
df.index
```

Out[12]:
```
RangeIndex(start=0, stop=10000, step=1)
```

In [13]:
```
df.dtypes
```

Out[13]:

	0
Brand	object
Model	object
RAM	int64
Storage	int64
Camera_Quality	int64
Processor_Type	object
Screen_Size	float64
Battery_Life	int64
OS_Version	object
Release_Year	int64
Network	object
Price (INR)	int64

dtype: object

In [14]:

```
df.isnull().sum()
```

Out[14]:

	0
Brand	0
Model	0
RAM	0
Storage	0
Camera_Quality	0
Processor_Type	0
Screen_Size	0
Battery_Life	0
OS_Version	0
Release_Year	0
Network	0
Price (INR)	0

dtype: int64

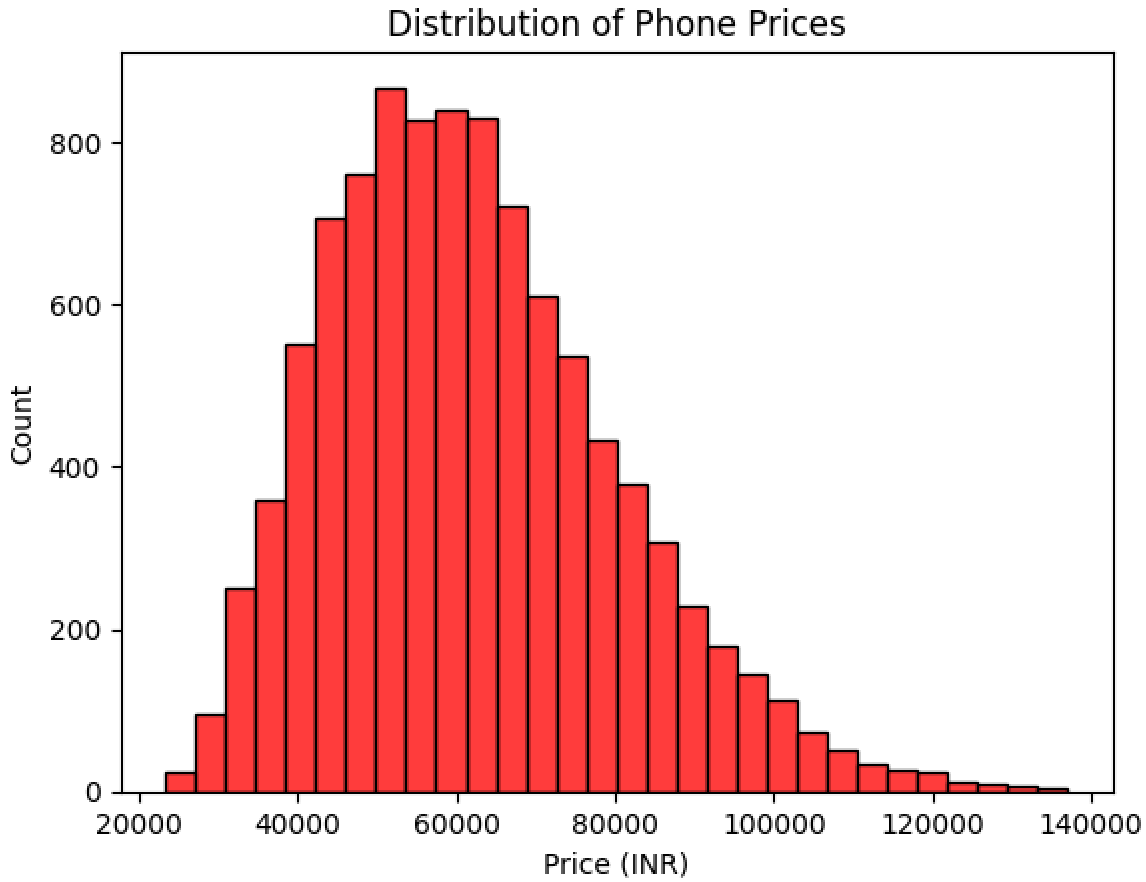
In [15]:
```
df.duplicated().sum()
```

Out[15]: 0

2. Data Visualization

1. Phone Price Distribution

In [16]:
```
sns.histplot(df['Price (INR)'], bins=30,color='r')
plt.title('Distribution of Phone Prices')
plt.show()
```



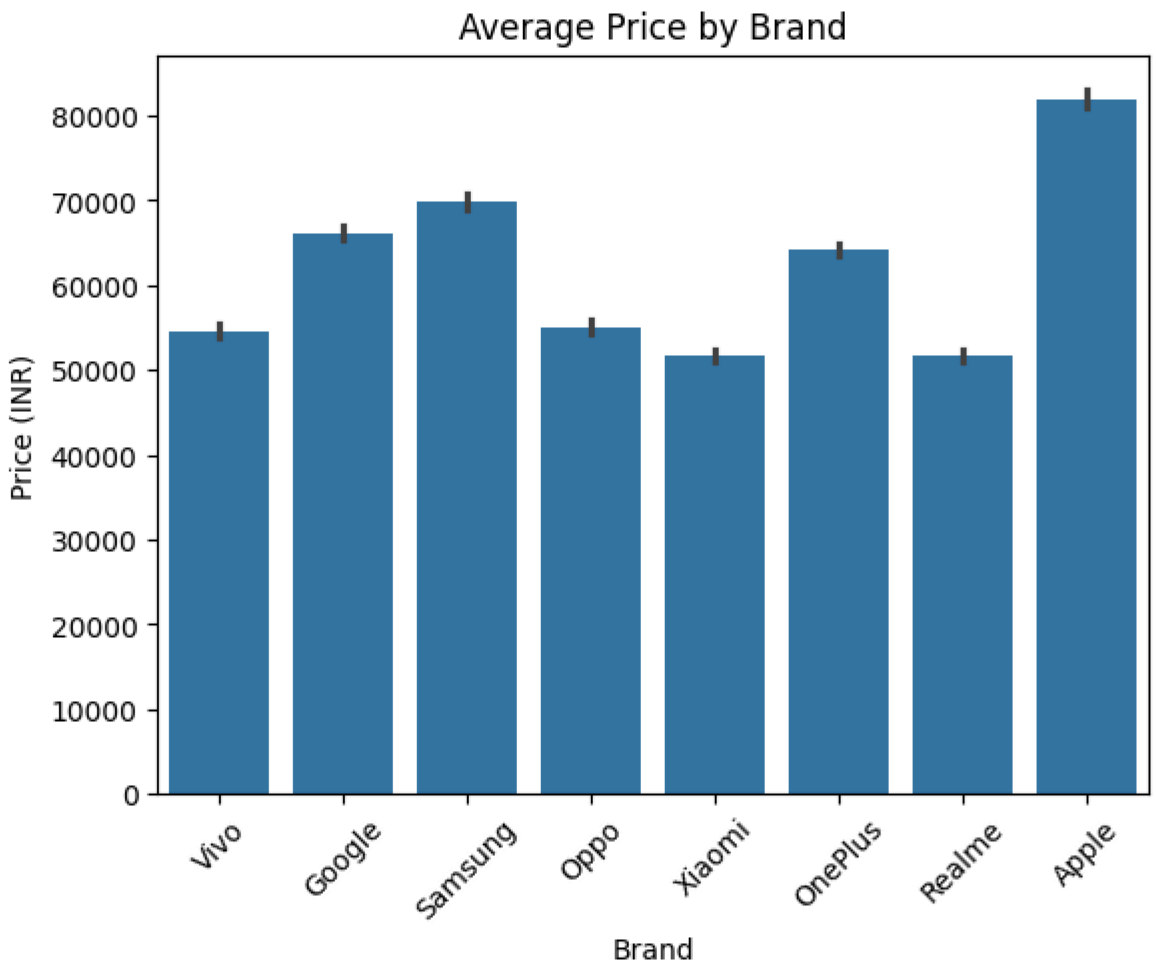
This histogram shows how phone prices are distributed in the dataset.

- Most phones are priced between **₹40,000 - ₹70,000**, with a peak around ₹60,000.
- A few premium models are priced **above ₹1,00,000**.
- This indicates that flagship models are limited compared to mid-range smartphones.
- This suggests that mid-range smartphones are more common than high-end models in the dataset.

2. Average Price by Brand

In [17]:
```
sns.barplot(x='Brand', y='Price (INR)', data=df)
plt.xticks(rotation=45)
```

```
plt.title('Average Price by Brand')
plt.show()
```

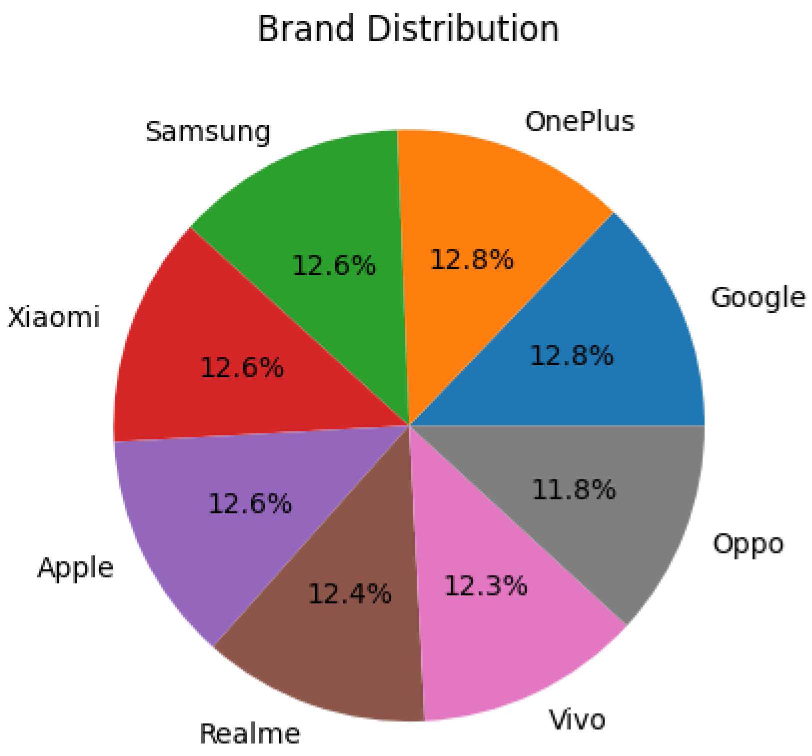


This bar chart displays the **average smartphone price for each brand**.

- **Apple** has the **highest average price**, followed by **Samsung and Google**.
- **Realme, Xiaomi, and Oppo** focus more on **budget-friendly and mid-range models**.

3. Brand Distribution

In [18]:
```
brand_counts = df['Brand'].value_counts()
plt.pie(brand_counts, labels=brand_counts.index, autopct='%1.1f%%')
plt.title('Brand Distribution')
plt.show()
```

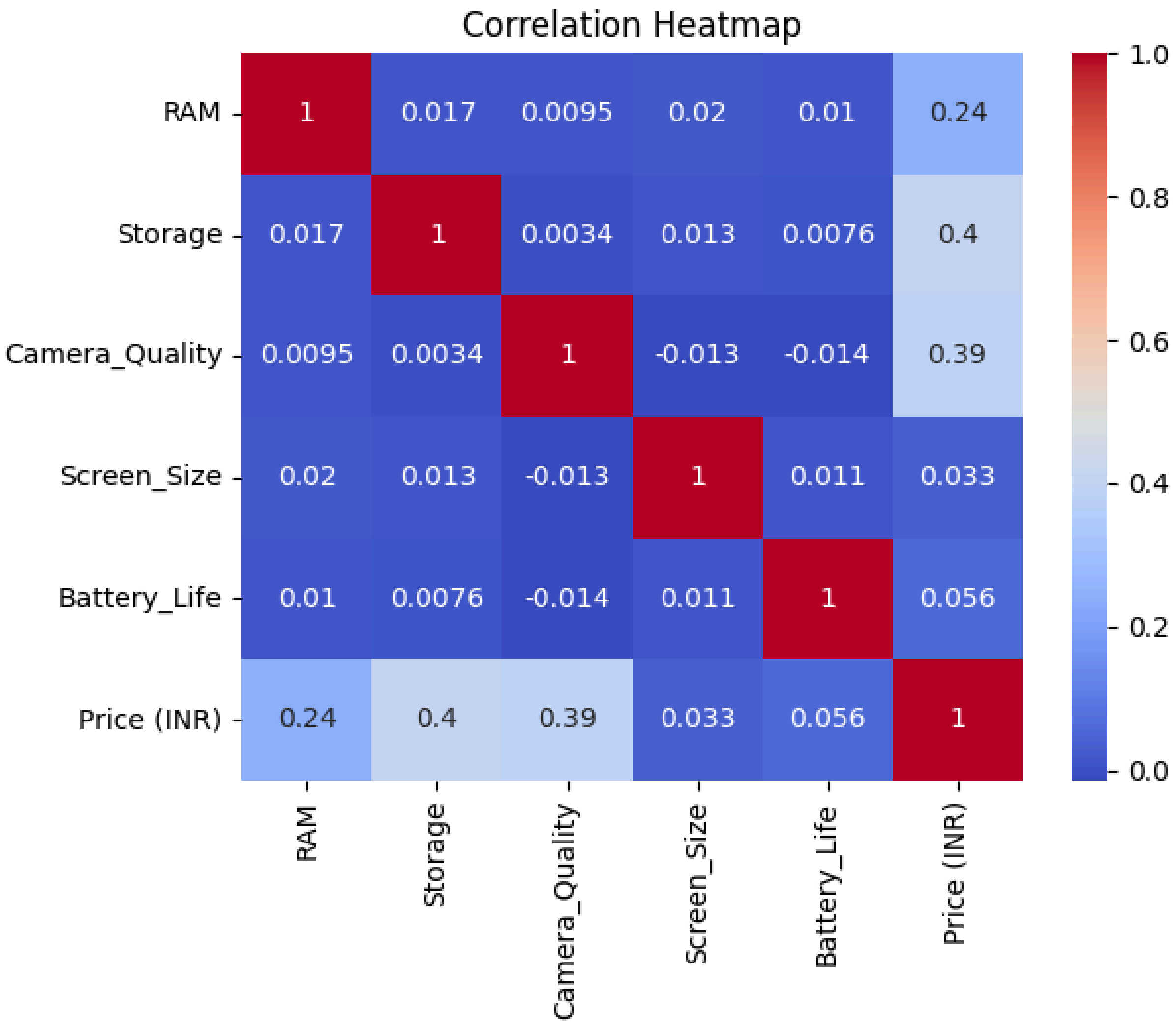


This pie chart represents the distribution of smartphone brands in the dataset.

- **OnePlus and Google** have the **highest representation** at **12.8% each**.
- **Samsung, Xiaomi, and Apple** follow closely, each making up **12.6%** of the dataset.
- **Realme and Vivo** have slightly lower shares at **12.4% and 12.3%**, respectively.
- **Oppo has the lowest representation** at **11.8%**.

4. Correlation Heatmap

In [19]:
```
corr = df[['RAM', 'Storage', 'Camera_Quality', 'Screen_Size', 'Battery_Life', 'Price (INR)']].corr()
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



This heatmap shows the correlation between different smartphone features and price.

- **Storage (0.40), Camera Quality (0.39), and RAM (0.24)** have a **moderate correlation** with price, meaning they influence phone pricing significantly.
- **Screen Size (0.033) and Battery Life (0.056)** have a **very weak correlation** with price, indicating they have little impact.

3.DataType Conversion

In [20]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 12 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Brand            10000 non-null  object 
 1   Model            10000 non-null  object 
 2   RAM              10000 non-null  int64  
 3   Storage          10000 non-null  int64  
 4   Camera_Quality   10000 non-null  int64  
 5   Processor_Type   10000 non-null  object 
 6   Screen_Size      10000 non-null  float64
 7   Battery_Life     10000 non-null  int64  
 8   OS_Version       10000 non-null  object 
 9   Release_Year     10000 non-null  int64  
 10  Network          10000 non-null  object 
 11  Price (INR)      10000 non-null  int64  
dtypes: float64(1), int64(6), object(5)
memory usage: 937.6+ KB
```

Brand

In [21]:
```
df['Brand'].unique()
```

Out[21]:
```
array(['Vivo', 'Google', 'Samsung', 'Oppo', 'Xiaomi', 'OnePlus', 'Realme',
       'Apple'], dtype=object)
```

In [22]:
```
from sklearn.preprocessing import OneHotEncoder
one=OneHotEncoder(sparse_output=False)
one.fit(df[['Brand']])
out=one.transform(df[['Brand']])
```

In [23]:
```
one.get_feature_names_out()
```

Out[23]:
```
array(['Brand_Apple', 'Brand_Google', 'Brand_OnePlus', 'Brand_Oppo',
       'Brand_Realme', 'Brand_Samsung', 'Brand_Vivo', 'Brand_Xiaomi'],
      dtype=object)
```

In [24]:
```
brand_df=pd.DataFrame(out,columns=one.get_feature_names_out())
```

In [25]:
```
df=df.reset_index(drop=True)
brand_df=brand_df.reset_index(drop=True)
```

In [26]:
```
df=pd.concat([df,brand_df],axis=1)
```

In [27]:
```
df.drop('Brand',axis=1,inplace=True)
```

In [28]:
```
df.head(1)
```

Out[28]:

	Model	RAM	Storage	Camera_Quality	Processor_Type	Screen_Size	Battery_Life	OS_Version	Release_Year	Network	Price (INR)	Brand_Apple	Brand_Google	Brand_OnePlu
0	V23	4	256	48	A15 Bionic	6.4	4000	iOS 15	2023	5G	60257	0.0	0.0	0.

Model

In [29]:
```
df['Model'].unique()
```

Out[29]:
```
array(['V23', 'Pixel 7', 'Pixel 5', 'Galaxy A52', 'Reno 7', 'Mi 11',
       'Galaxy S21', 'OnePlus 9', 'Redmi Note 11', 'X70', 'Realme GT',
       'Galaxy S22', 'V21', 'Reno 6', 'iPhone 13', 'X60', 'Realme 9',
       'Poco X3', 'Redmi Note 10', 'Reno 5', 'iPhone SE', 'iPhone 12',
       'OnePlus Nord', 'iPhone 14', 'Realme X7', 'Pixel 6', 'Realme 8',
       'Galaxy M32', 'OnePlus 10T', 'Find X3', 'Pixel 6a', 'OnePlus 8T'],
      dtype=object)
```

In [30]:
```
from sklearn.preprocessing import OneHotEncoder
one1=OneHotEncoder(sparse_output=False)
one1.fit(df[['Model']])
out1=one1.transform(df[['Model']])
```

In [31]:
```
one1.get_feature_names_out()
```

Out[31]:
```
array(['Model_Find X3', 'Model_Galaxy A52', 'Model_Galaxy M32',
       'Model_Galaxy S21', 'Model_Galaxy S22', 'Model_Mi 11',
       'Model_OnePlus 10T', 'Model_OnePlus 8T', 'Model_OnePlus 9',
       'Model_OnePlus Nord', 'Model_Pixel 5', 'Model_Pixel 6',
       'Model_Pixel 6a', 'Model_Pixel 7', 'Model_Poco X3',
       'Model_Realme 8', 'Model_Realme 9', 'Model_Realme GT',
       'Model_Realme X7', 'Model_Redmi Note 10', 'Model_Redmi Note 11',
       'Model_Reno 5', 'Model_Reno 6', 'Model_Reno 7', 'Model_V21',
       'Model_V23', 'Model_X60', 'Model_X70', 'Model_iPhone 12',
       'Model_iPhone 13', 'Model_iPhone 14', 'Model_iPhone SE'],
      dtype=object)
```

In [32]:
```
model_df=pd.DataFrame(out1,columns=one1.get_feature_names_out())
```

In [33]:
```
df=df.reset_index(drop=True)
model_df=model_df.reset_index(drop=True)
```

In [34]:
```
df=pd.concat([df,model_df],axis=1)
```

In [35]:
```
df.drop('Model',axis=1,inplace=True)
```

In [36]:
```
df.head(1)
```

Out[36]:

	RAM	Storage	Camera_Quality	Processor_Type	Screen_Size	Battery_Life	OS_Version	Release_Year	Network	Price (INR)	...	Model_Reno 6	Model_Reno 7	Model_V21	Model_
0	4	256	48	A15 Bionic	6.4	4000	iOS 15	2023	5G	60257	...	0.0	0.0	0.0	

1 rows × 50 columns

Processor_Type

In [37]:
```
df['Processor_Type'].unique()
```

Out[37]:
```
array(['A15 Bionic', 'Exynos 2100', 'A14 Bionic',
       'MediaTek Dimensity 1200', 'Snapdragon 888'], dtype=object)
```

In [38]:
```
from sklearn.preprocessing import OneHotEncoder
one2=OneHotEncoder(sparse_output=False)
one2.fit(df[['Processor_Type']])
out2=one2.transform(df[['Processor_Type']])
```

In [39]:
```
one2.get_feature_names_out()
```

Out[39]:
```
array(['Processor_Type_A14 Bionic', 'Processor_Type_A15 Bionic',
       'Processor_Type_Exynos 2100',
       'Processor_Type_MediaTek Dimensity 1200',
       'Processor_Type_Snapdragon 888'], dtype=object)
```

In [40]:
```
pro_df=pd.DataFrame(out2,columns=one2.get_feature_names_out())
```

In [41]:
```
df=df.reset_index(drop=True)
pro_df=pro_df.reset_index(drop=True)
```

In [42]:
```
df=pd.concat([df,pro_df],axis=1)
```

In [43]:
```
df.drop('Processor_Type',axis=1,inplace=True)
```

In [44]:
```
df.head(1)
```

Out[44]:

	RAM	Storage	Camera_Quality	Screen_Size	Battery_Life	OS_Version	Release_Year	Network	Price (INR)	Brand_Apple	...	Model_X70	Model_iPhone 12	Model_iPhone 13	Model
0	4	256	48	6.4	4000	iOS 15	2023	5G	60257	0.0	...	0.0	0.0	0.0	

1 rows × 54 columns

Os_Version

In [45]:
```
df['OS_Version'].unique()
```

Out[45]:
```
array(['iOS 15', 'iOS 14', 'Android 11', 'iOS 16', 'Android 12'],
      dtype=object)
```

In [46]:
```
from sklearn.preprocessing import LabelEncoder
le1=LabelEncoder()
le1.fit(df['OS_Version'])
df['OS_Version']=le1.transform(df['OS_Version'])
```

Network

In [47]:
```
df['Network'].unique()
```

Out[47]:
```
array(['5G', '4G'], dtype=object)
```

In [48]:
```
from sklearn.preprocessing import OneHotEncoder
one3=OneHotEncoder(sparse_output=False)
one3.fit(df[['Network']])
out3=one3.transform(df[['Network']])
```

In [49]:
```
one3.get_feature_names_out()
```

Out[49]:
```
array(['Network_4G', 'Network_5G'], dtype=object)
```

In [50]:
```
network_df=pd.DataFrame(out3,columns=one3.get_feature_names_out())
```

In [51]:
```
df=df.reset_index(drop=True)
network_df=network_df.reset_index(drop=True)
```

In [52]:
```
df=pd.concat([df,network_df],axis=1)
```

In [53]:
```
df.drop('Network',axis=1,inplace=True)
```

In [54]:
```
df.head(1)
```

Out[54]:

	RAM	Storage	Camera_Quality	Screen_Size	Battery_Life	OS_Version	Release_Year	Price (INR)	Brand_Apple	Brand_Google	...	Model_iPhone 13	Model_iPhone 14	Model_iPhone SE
0	4	256	48	6.4	4000	3	2023	60257	0.0	0.0	...	0.0	0.0	0.0

1 rows × 55 columns

In [55]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 55 columns):
 #   Column                                 Non-Null Count  Dtype  
---  ------                                 --------------  -----  
 0   RAM                                    10000 non-null  int64  
 1   Storage                                10000 non-null  int64  
 2   Camera_Quality                         10000 non-null  int64  
 3   Screen_Size                            10000 non-null  float64
 4   Battery_Life                           10000 non-null  int64  
 5   OS_Version                             10000 non-null  int64  
 6   Release_Year                           10000 non-null  int64  
 7   Price (INR)                            10000 non-null  int64  
 8   Brand_Apple                            10000 non-null  float64
 9   Brand_Google                           10000 non-null  float64
 10  Brand_OnePlus                          10000 non-null  float64
 11  Brand_Oppo                             10000 non-null  float64
 12  Brand_Realme                           10000 non-null  float64
 13  Brand_Samsung                          10000 non-null  float64
 14  Brand_Vivo                             10000 non-null  float64
 15  Brand_Xiaomi                           10000 non-null  float64
 16  Model_Find X3                          10000 non-null  float64
 17  Model_Galaxy A52                       10000 non-null  float64
 18  Model_Galaxy M32                       10000 non-null  float64
 19  Model_Galaxy S21                       10000 non-null  float64
 20  Model_Galaxy S22                       10000 non-null  float64
 21  Model_Mi 11                            10000 non-null  float64
 22  Model_OnePlus 10T                      10000 non-null  float64
 23  Model_OnePlus 8T                       10000 non-null  float64
 24  Model_OnePlus 9                        10000 non-null  float64
 25  Model_OnePlus Nord                     10000 non-null  float64
 26  Model_Pixel 5                          10000 non-null  float64
 27  Model_Pixel 6                          10000 non-null  float64
 28  Model_Pixel 6a                         10000 non-null  float64
 29  Model_Pixel 7                          10000 non-null  float64
 30  Model_Poco X3                          10000 non-null  float64
 31  Model_Realme 8                         10000 non-null  float64
 32  Model_Realme 9                         10000 non-null  float64
 33  Model_Realme GT                        10000 non-null  float64
 34  Model_Realme X7                        10000 non-null  float64
 35  Model_Redmi Note 10                    10000 non-null  float64
 36  Model_Redmi Note 11                    10000 non-null  float64
```

```
 37  Model_Reno 5                          10000 non-null  float64
 38  Model_Reno 6                          10000 non-null  float64
 39  Model_Reno 7                          10000 non-null  float64
 40  Model_V21                             10000 non-null  float64
 41  Model_V23                             10000 non-null  float64
 42  Model_X60                             10000 non-null  float64
 43  Model_X70                             10000 non-null  float64
 44  Model_iPhone 12                       10000 non-null  float64
 45  Model_iPhone 13                       10000 non-null  float64
 46  Model_iPhone 14                       10000 non-null  float64
 47  Model_iPhone SE                       10000 non-null  float64
 48  Processor_Type_A14 Bionic             10000 non-null  float64
 49  Processor_Type_A15 Bionic             10000 non-null  float64
 50  Processor_Type_Exynos 2100            10000 non-null  float64
 51  Processor_Type_MediaTek Dimensity 1200  10000 non-null  float64
 52  Processor_Type_Snapdragon 888         10000 non-null  float64
 53  Network_4G                            10000 non-null  float64
 54  Network_5G                            10000 non-null  float64
dtypes: float64(48), int64(7)
memory usage: 4.2 MB
```

In [56]:
```
df.rename(columns={'Price (INR)':'Price_in_Rupees'},inplace=True)
```

In [57]:
```
corr_matrix=df.corr()['Price_in_Rupees']
corr_matrix
```

Out[57]:

	Price_in_Rupees
RAM	0.244725
Storage	0.400036
Camera_Quality	0.389840
Screen_Size	0.033115
Battery_Life	0.055749
OS_Version	0.032715
Release_Year	0.093300
Price_in_Rupees	1.000000
Brand_Apple	0.419304
Brand_Google	0.089275
Brand_OnePlus	0.047185
Brand_Oppo	-0.141031
Brand_Realme	-0.216479
Brand_Samsung	0.166310
Brand_Vivo	-0.153525
Brand_Xiaomi	-0.218351
Model_Find X3	-0.048022
Model_Galaxy A52	0.083959
Model_Galaxy M32	0.089224
Model_Galaxy S21	0.065545
Model_Galaxy S22	0.076982
Model_Mi 11	-0.110950

	Price_in_Rupees
Model_OnePlus 10T	0.026634
Model_OnePlus 8T	0.014587
Model_OnePlus 9	0.028832
Model_OnePlus Nord	0.019559
Model_Pixel 5	0.031169
Model_Pixel 6	0.049738
Model_Pixel 6a	0.050377
Model_Pixel 7	0.038608
Model_Poco X3	-0.104284
Model_Realme 8	-0.095674
Model_Realme 9	-0.108005
Model_Realme GT	-0.100237
Model_Realme X7	-0.107692
Model_Redmi Note 10	-0.099959
Model_Redmi Note 11	-0.099970
Model_Reno 5	-0.072175
Model_Reno 6	-0.081070
Model_Reno 7	-0.067696
Model_V21	-0.066361
Model_V23	-0.078403
Model_X60	-0.072680
Model_X70	-0.074825

	Price_in_Rupees
Model_iPhone 12	0.203744
Model_iPhone 13	0.212493
Model_iPhone 14	0.196153
Model_iPhone SE	0.185239
Processor_Type_A14 Bionic	0.250787
Processor_Type_A15 Bionic	0.269874
Processor_Type_Exynos 2100	-0.178939
Processor_Type_MediaTek Dimensity 1200	-0.454944
Processor_Type_Snapdragon 888	0.110089
Network_4G	-0.072401
Network_5G	0.072401

dtype: float64

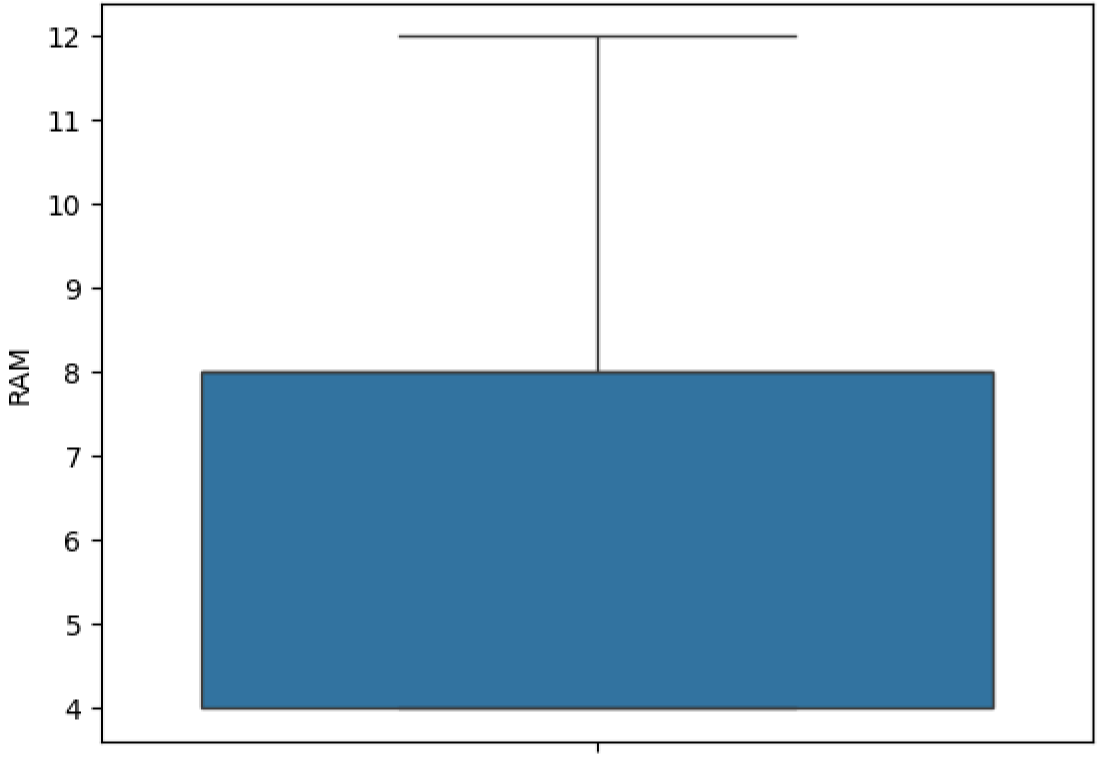
Correlation of Price with-respect-to Other Features

Feature	Correlation with Price
RAM	0.244725
Storage	0.400036
Camera Quality	0.389840
Screen Size	0.033115
Battery Life	0.055749
OS Version	0.032715
Release Year	0.093300
Processor Type - A14 Bionic	0.250787
Processor Type - A15 Bionic	0.269874
Processor Type - Exynos 2100	-0.178939
Processor Type - MediaTek Dimensity 1200	-0.454944
Processor Type - Snapdragon 888	0.110089
Network - 4G	-0.072401
Network - 5G	0.072401

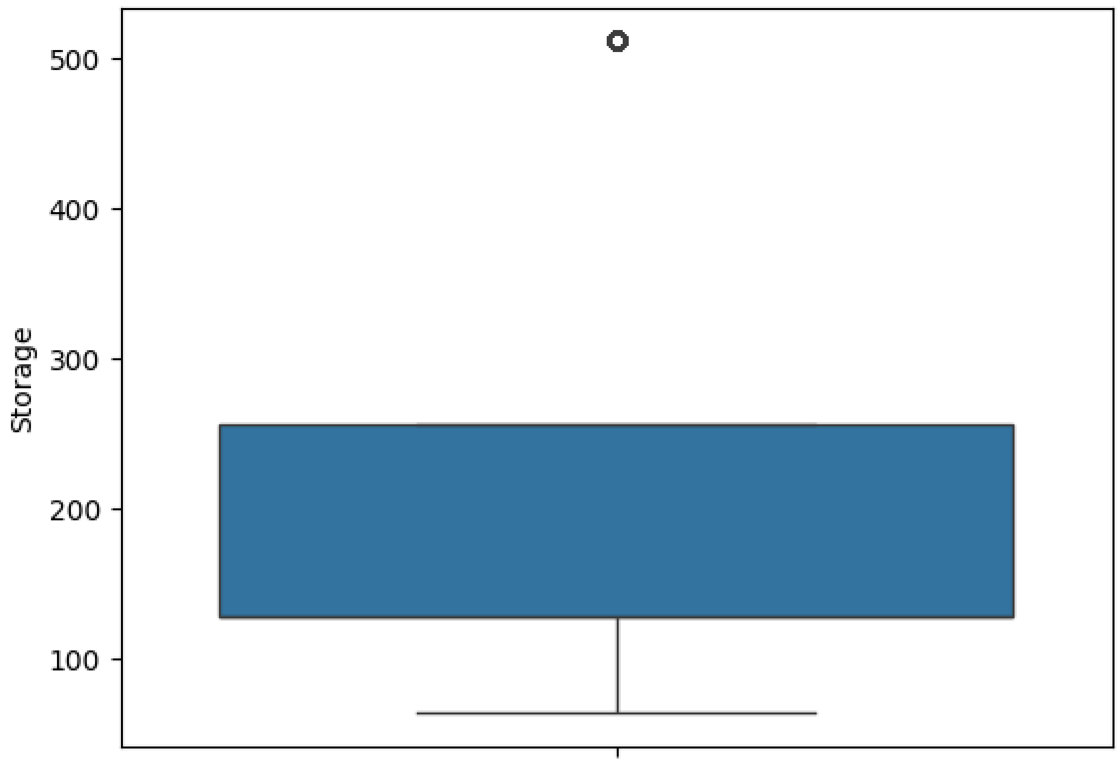
4.Finding Outliers

In [58]:
```
import seaborn as sns
import matplotlib.pyplot as plt
```

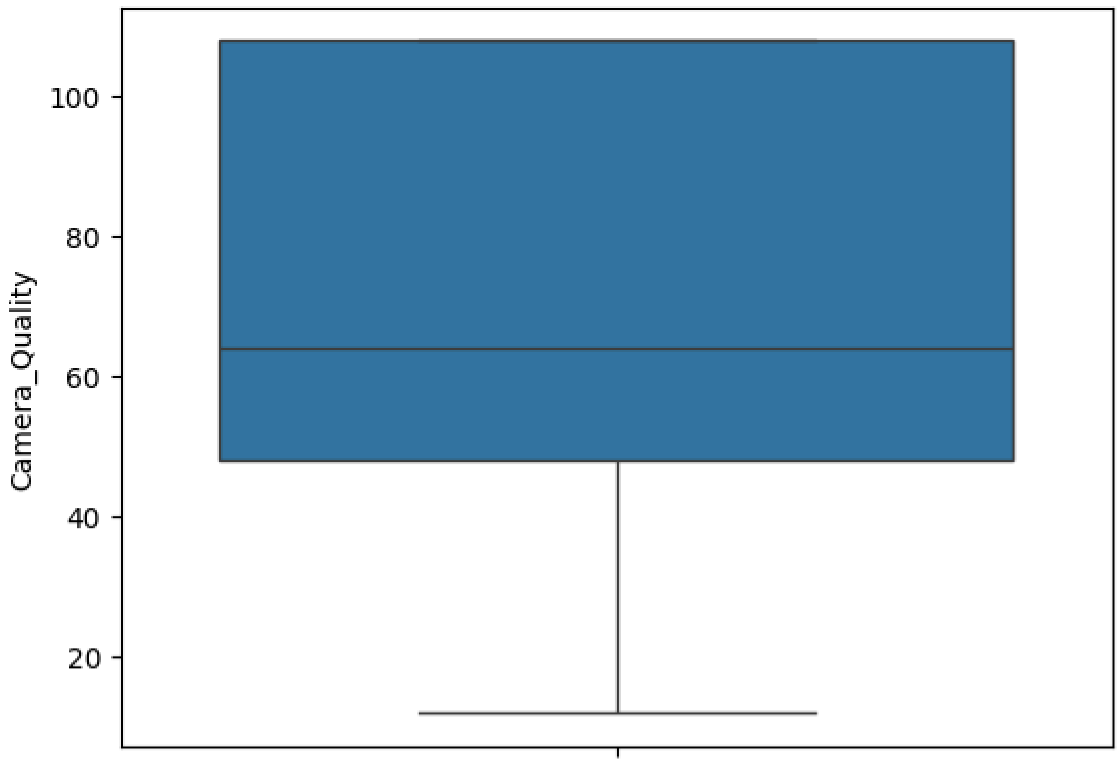
In [59]:
```
sns.boxplot(df['RAM'])
plt.show()
```



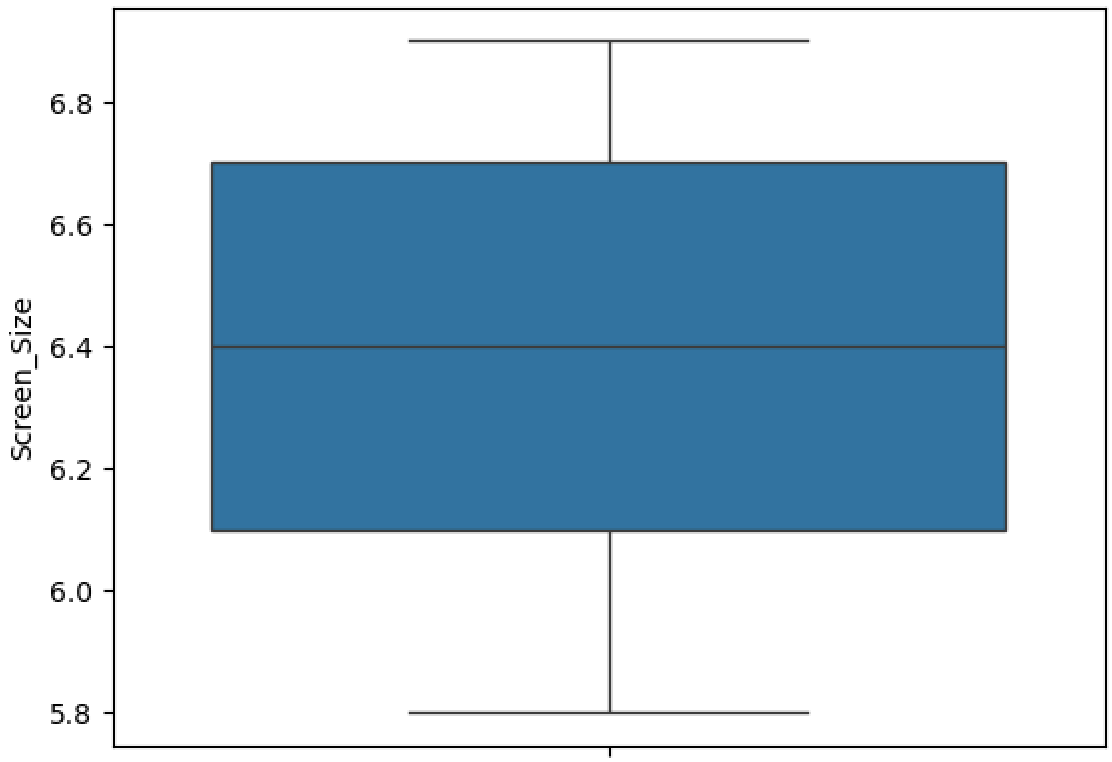
In [60]:
```
sns.boxplot(df['Storage'])
plt.show()
```



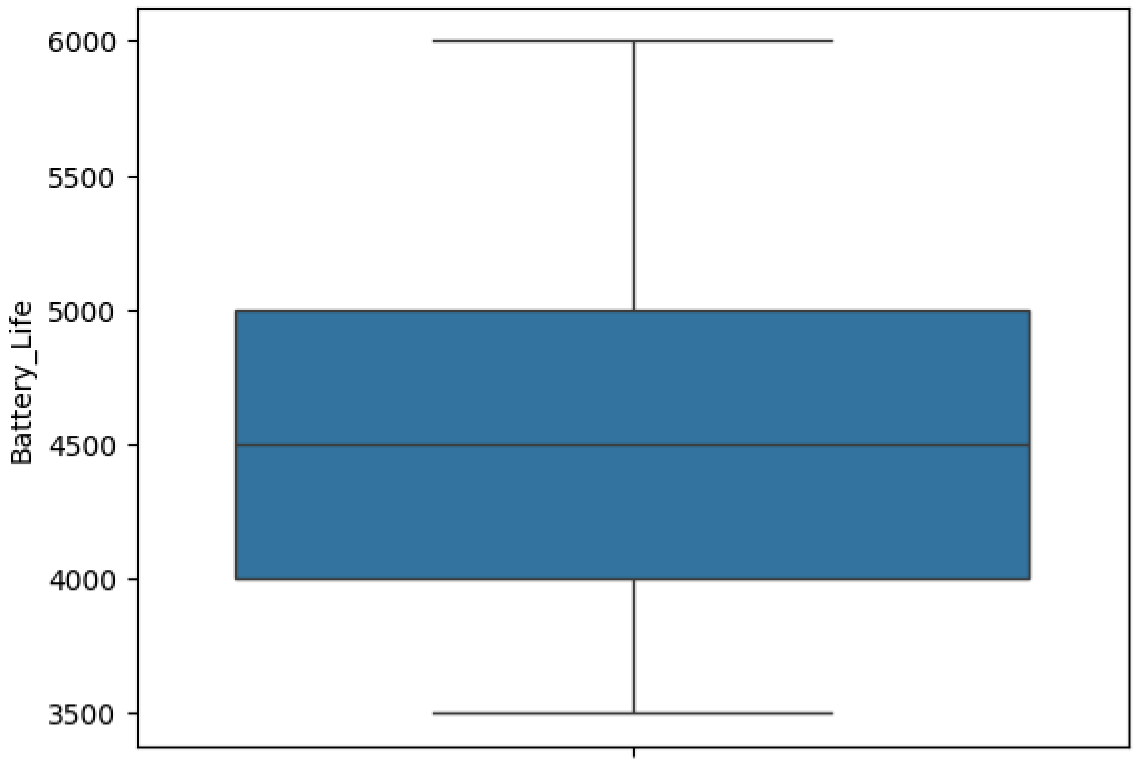
In [61]:
```
sns.boxplot(df['Camera_Quality'])
plt.show()
```



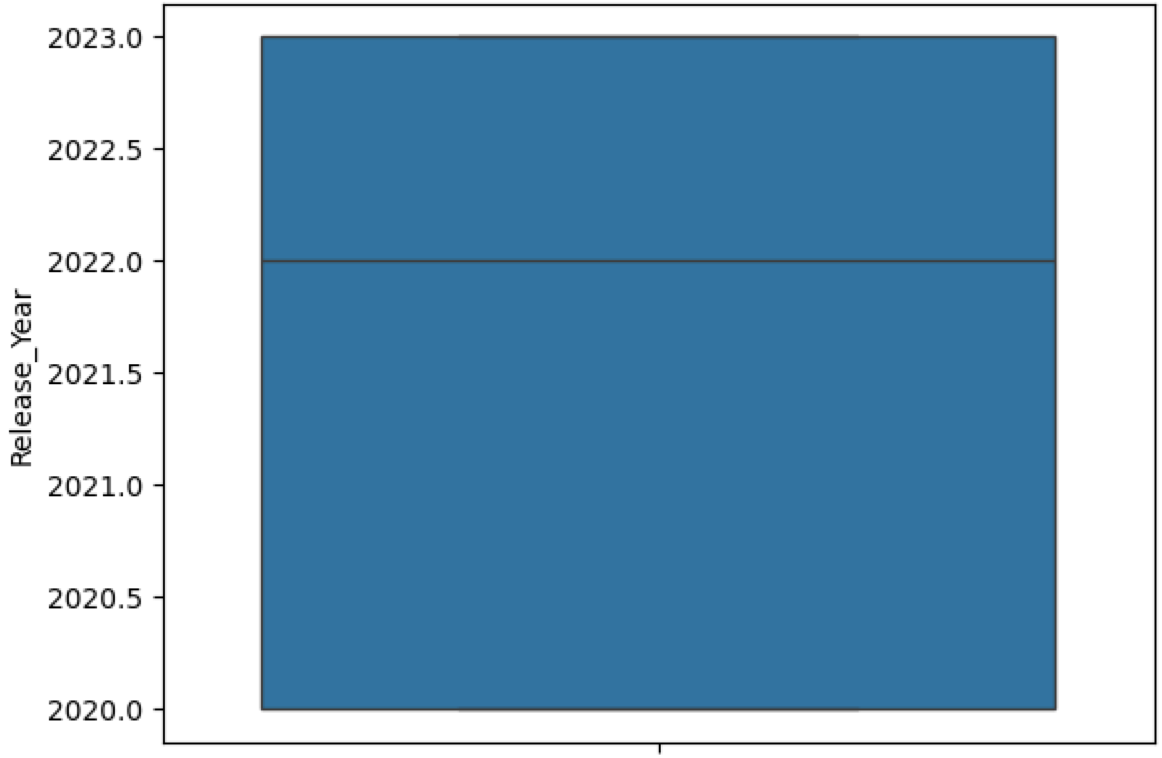
In [62]:
```
sns.boxplot(df['Screen_Size'])
plt.show()
```



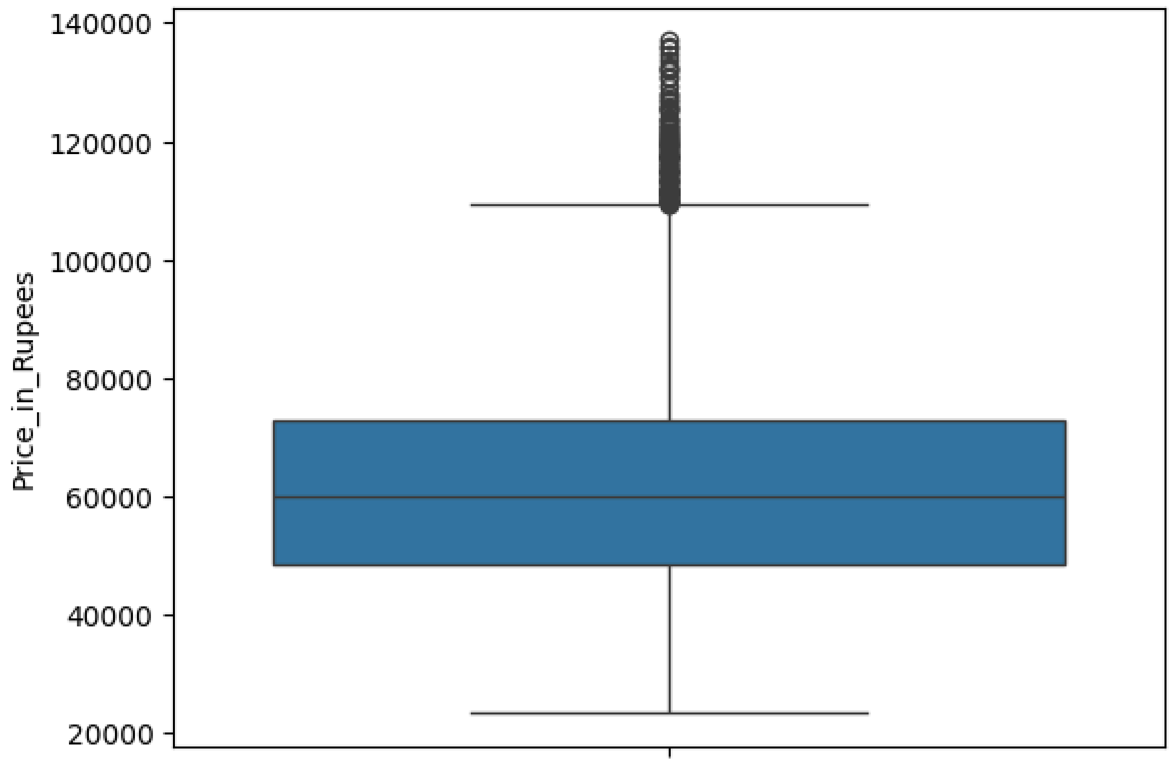
In [63]:
```
sns.boxplot(df['Battery_Life'])
plt.show()
```



In [64]:
```
sns.boxplot(df['Release_Year'])
plt.show()
```



In [65]:
```
sns.boxplot(df['Price_in_Rupees'])
plt.show()
```



5.Model Training

Spliiting the data into Input and Output

In [66]:
```
x=df.drop('Price_in_Rupees',axis=1)
y=df['Price_in_Rupees']
```

Preprocessing the data

In [67]:
```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
sc.fit(x)
x=sc.transform(x)
```

Splitting the data into Training and Testing Sets

In [68]:
```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.2,random_state=1)
```

Model Building

KNN Model

In [ ]:
```
from sklearn.neighbors import KNeighborsRegressor
knn=KNeighborsRegressor()
```

In [ ]:
```
para={'n_neighbors':[3,5,7,9,11,13],'weights':['uniform','distance'],'algorithm':['auto', 'ball_tree', 'kd_tree', 'brute'],'leaf_size':[15,20,25,30,35,40],'p
```

In [ ]:
```
from sklearn.model_selection import RandomizedSearchCV
rs=RandomizedSearchCV(knn,para,cv=5,scoring='r2')
rs.fit(xtrain,ytrain)
```

Out[ ]:

▸ RandomizedSearchCV

▸ best_estimator_: KNeighborsRegressor

▸ KNeighborsRegressor

In [ ]:
```
rs.best_params_
```

Out[ ]:
```
{'weights': 'distance',
 'p': 1,
 'n_neighbors': 5,
 'metric': 'manhattan',
 'leaf_size': 20,
 'algorithm': 'auto'}
```

In [ ]:
```
knn1=KNeighborsRegressor(n_neighbors=5,weights='distance',metric='manhattan',p=1,leaf_size=20,algorithm='auto')
knn1.fit(xtrain,ytrain)
```

Out[ ]:
```
KNeighborsRegressor
KNeighborsRegressor(leaf_size=20, metric='manhattan', p=1, weights='distance')
```

Model Prediction

In [ ]:
```
pred=knn1.predict(xtest)
```

In [ ]:
```
pred
```

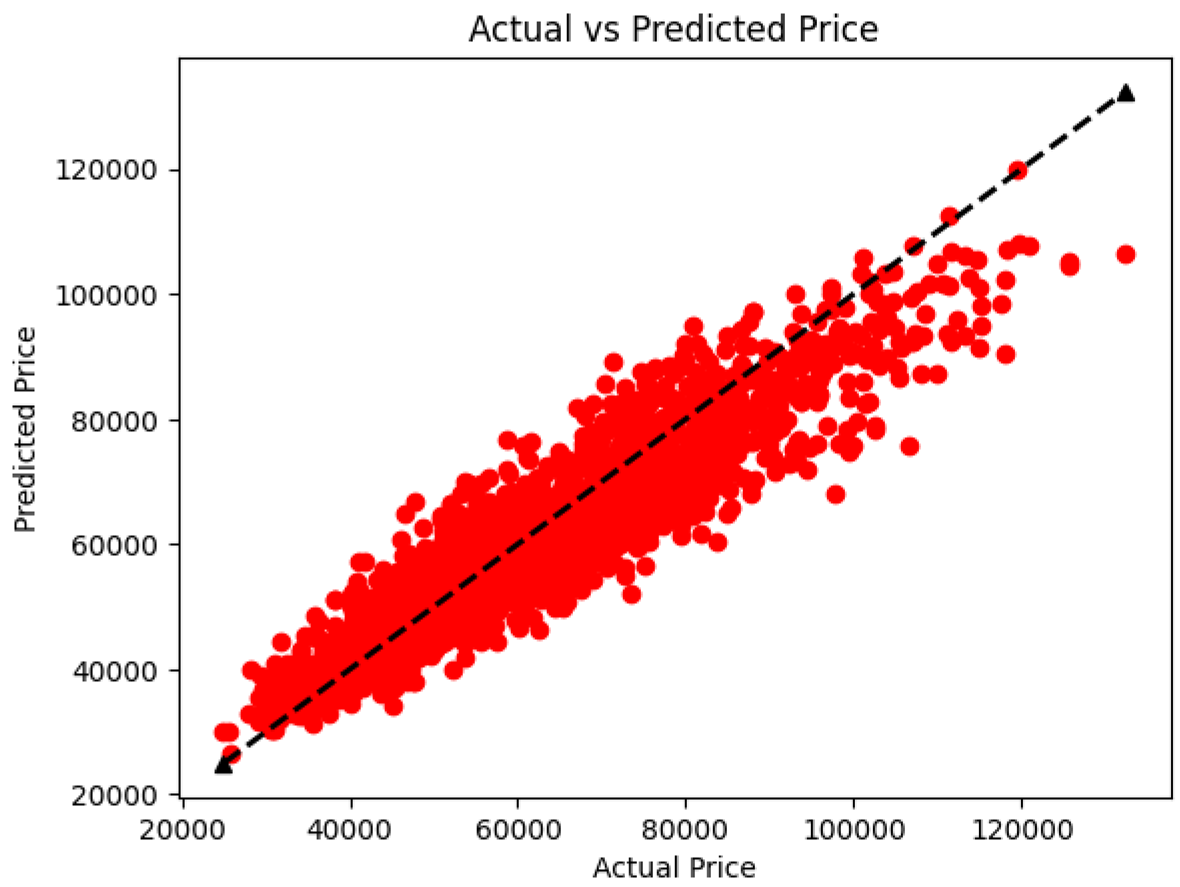
Out[ ]:
```
array([54973.21782562, 48334.47182823, 53590.94199672, ...,
       64733.84655756, 54429.50707711, 99598.89249276])
```

Model Evaluation

In [ ]:
```
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score
print('MAE=',mean_absolute_error(ytest,pred))
print('MSE=',mean_squared_error(ytest,pred))
print('R2_Score=',r2_score(ytest,pred))
```

```
MAE= 5449.620084738901
MSE= 50070480.771481976
R2_Score= 0.8475676497234111
```

In [ ]:
```
import matplotlib.pyplot as plt
plt.scatter(ytest,pred,color='r')
plt.plot([ytest.min(),ytest.max()],[ytest.min(),ytest.max()],'k--',lw=2,marker='^')
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
plt.title('Actual vs Predicted Price')
plt.show()
```



DecisionTree Regressor Model

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

In [ ]:
```
from scipy.stats import randint
para1={'criterion':["squared_error", "friedman_mse", "absolute_error","poisson"],'splitter':["best", "random"],'max_depth':randint(3,11),'min_samples_split':
```

In [ ]:
```
from sklearn.model_selection import RandomizedSearchCV
rs1=RandomizedSearchCV(dtr,para1,cv=5,scoring='r2')
rs1.fit(xtrain,ytrain)
```

Out[ ]:
```
RandomizedSearchCV

best_estimator_:
DecisionTreeRegressor

DecisionTreeRegressor
```

In [ ]:
```python
rs1.best_params_
```

Out[ ]:
```
{'criterion': 'friedman_mse',
 'max_depth': 7,
 'max_features': 6,
 'min_samples_leaf': 7,
 'min_samples_split': 5,
 'splitter': 'random'}
```

Model Building

In [ ]:
```python
dtr1=DecisionTreeRegressor(criterion='friedman_mse',max_depth=7,max_features=6,min_samples_leaf=7,min_samples_split=5,splitter='random')
dtr1.fit(xtrain,ytrain)
```

Out[ ]:
```
DecisionTreeRegressor

DecisionTreeRegressor(criterion='friedman_mse', max_depth=7, max_features=6,
                      min_samples_leaf=7, min_samples_split=5,
                      splitter='random')
```

Model Prediction

In [ ]:
```python
pred1=dtr1.predict(xtest)
pred1
```

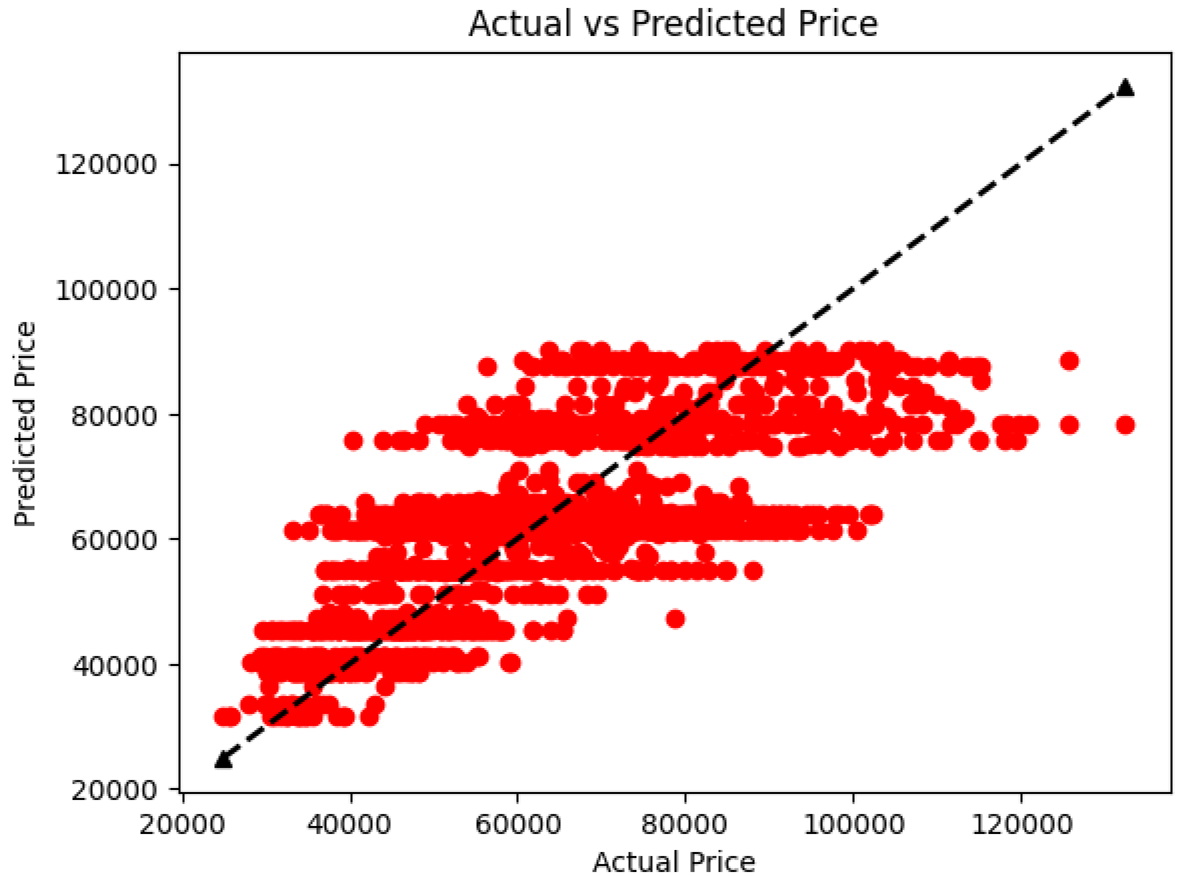
Out[ ]:
```
array([64018.61791045, 61441.23253012, 61441.23253012, ...,
       78335.97623762, 55123.08189655, 87720.34006734])
```

Model Evaluation

In [ ]:
```
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score
print('MAE=',mean_absolute_error(ytest,pred1))
print('MSE=',mean_squared_error(ytest,pred1))
print('R2_Score=',r2_score(ytest,pred1))
```

```
MAE= 9513.473566639708
MSE= 152338543.66762468
R2_Score= 0.5362272961797747
```

In [ ]:
```
import matplotlib.pyplot as plt
plt.scatter(ytest,pred1,color='r')
plt.plot([ytest.min(),ytest.max()],[ytest.min(),ytest.max()],'k--',lw=2,marker='^')
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
plt.title('Actual vs Predicted Price')
plt.show()
```



LinearRegression Model

In [69]:
```
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
```

In [70]:
```
from scipy.stats import randint
para2 = {'fit_intercept':[True,False],'positive':[True,False],'copy_X':[True,False],'n_jobs':randint(1,11)}
```

In [71]:
```
from sklearn.model_selection import RandomizedSearchCV
rs2 = RandomizedSearchCV(lr,para2,cv=5,scoring='r2')
rs2.fit(xtrain,ytrain)
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/model_selection/_validation.py:528: FitFailedWarning:
25 fits failed out of a total of 50.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
25 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.11/dist-packages/sklearn/model_selection/_validation.py", line 866, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.11/dist-packages/sklearn/base.py", line 1389, in wrapper
    return fit_method(estimator, *args, **kwargs)
           ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_base.py", line 640, in fit
    self.coef_ = optimize.nnls(X, y)[0]
                 ^^^^^^^^^^^^^^^^^^^
  File "/usr/local/lib/python3.11/dist-packages/scipy/optimize/_nnls.py", line 93, in nnls
    raise RuntimeError("Maximum number of iterations reached.")
RuntimeError: Maximum number of iterations reached.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/usr/local/lib/python3.11/dist-packages/sklearn/model_selection/_search.py:1108: UserWarning: One or more of the test scores are non-finite: [-11.06362217
nan   0.97142235          nan   0.97142235
   0.97142235          nan          nan          nan -11.06362217]
  warnings.warn(
```

Out[71]:

```
▸ RandomizedSearchCV
▸ best_estimator_: LinearRegression
  ▸ LinearRegression
```

In [72]:

```python
rs2.best_params_
```

Out[72]:

```
{'copy_X': False, 'fit_intercept': True, 'n_jobs': 4, 'positive': False}
```

Model Building

In [73]:
```
lr1=LinearRegression(copy_X=False,fit_intercept=True,n_jobs=4,positive=False)
lr1.fit(xtrain,ytrain)
```

Out[73]:
```
LinearRegression
LinearRegression(copy_X=False, n_jobs=4)
```

Model Prediction

In [74]:
```
pred2=lr1.predict(xtest)
pred2
```

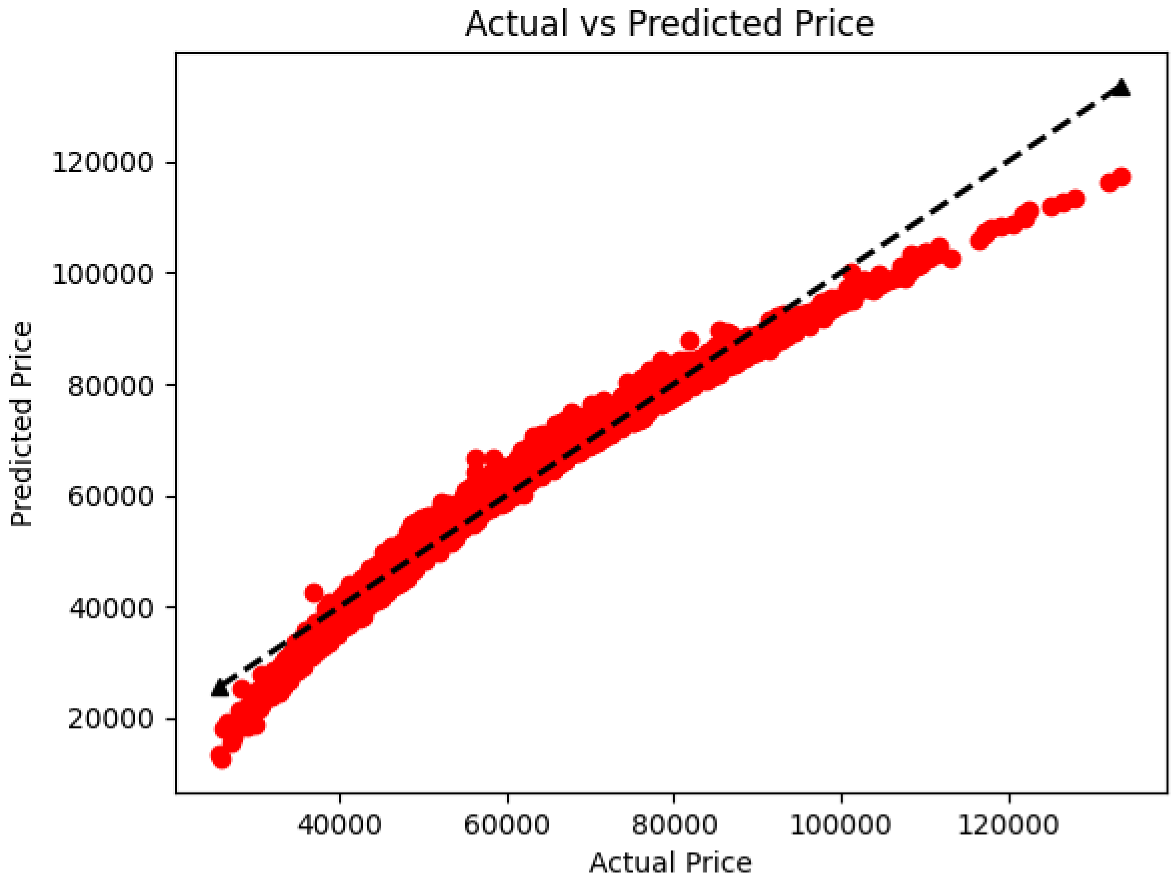
Out[74]:
```
array([ 57725.91703892,  52993.26783193, 100280.5718617 , ...,
        54896.18428252,  68341.31946535,  71987.45763334])
```

Model Evaluation

In [75]:
```
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score
print('MAE=',mean_absolute_error(ytest,pred2))
print('MSE=',mean_squared_error(ytest,pred2))
print('R2_Score=',r2_score(ytest,pred2))
```

```
MAE= 2192.4469423734413
MSE= 8956175.968024211
R2_Score= 0.9726146794401552
```

In [76]:
```
import matplotlib.pyplot as plt
plt.scatter(ytest,pred2,color='r')
plt.plot([ytest.min(),ytest.max()],[ytest.min(),ytest.max()],'k--',lw=2,marker='^')
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
plt.title('Actual vs Predicted Price')
plt.show()
```



SVM Model

In [ ]:
```
from sklearn.svm import SVR
svr=SVR()
```

In [ ]:
```
from scipy.stats import randint
para3= {
    'kernel': ['linear', 'rbf'],
    'gamma': ['scale', 'auto'],
    'C': randint(1, 6),
    'shrinking': [True, False]}
```

In [ ]:
```
rs3=RandomizedSearchCV(svr,para3,cv=5,scoring='r2')
rs3.fit(xtrain,ytrain)
```

Out[ ]:
```
▸ RandomizedSearchCV
▸ best_estimator_:
  SVR
  ▸ SVR
```

In [ ]:
```
rs3.best_params_
```

Out[ ]:
```
{'C': 5, 'gamma': 'scale', 'kernel': 'linear', 'shrinking': True}
```

Model Building

In [ ]:
```
svr1=SVR(C=5,gamma='scale',kernel='linear',shrinking=True)
svr1.fit(xtrain,ytrain)
```

Out[ ]:
```
▾ SVR
SVR(C=5, kernel='linear')
```

Model Prediction

In [ ]:
```
pred3=svr1.predict(xtest)
pred3
```

Out[ ]:
```
array([51987.15183396, 47665.11219102, 46338.69902059, ...,
       79163.04538726, 52376.96240849, 94354.16141716])
```

Model Evaluation

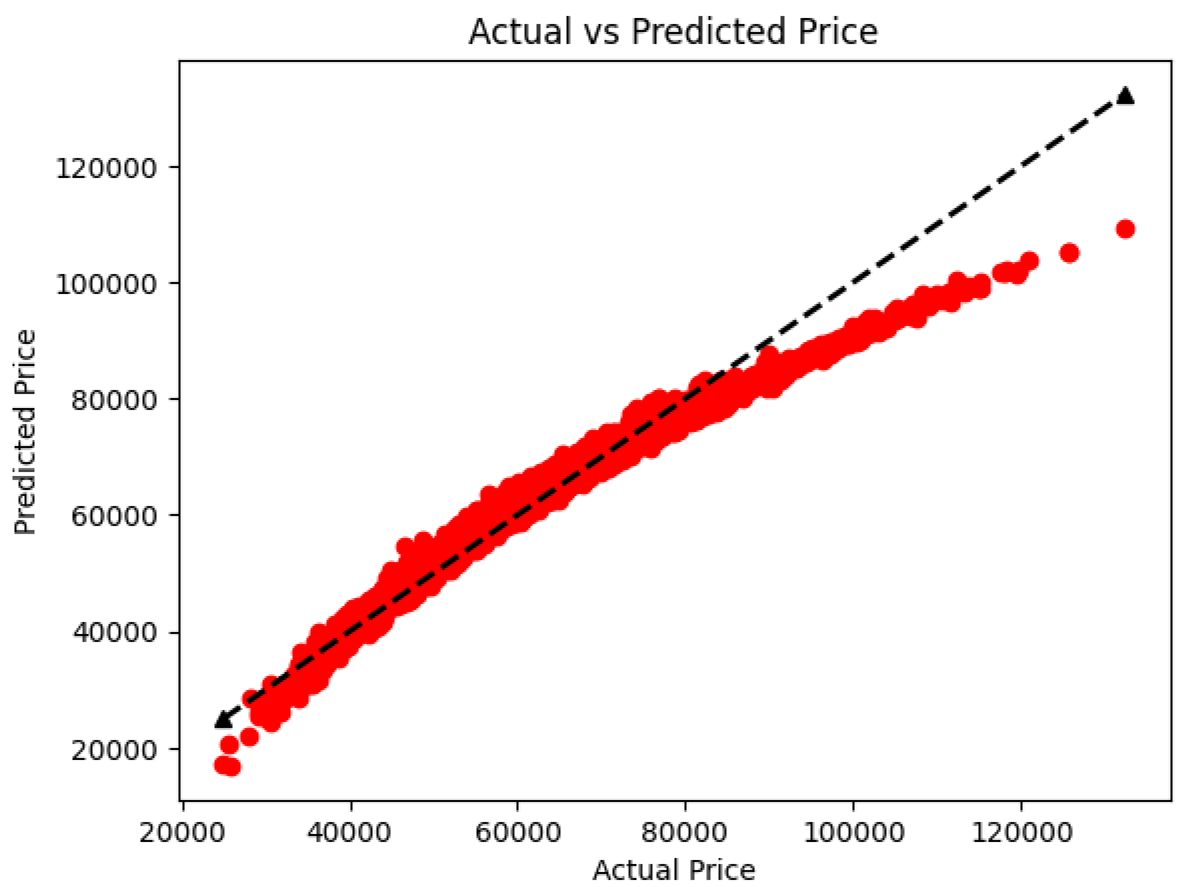
In [ ]:
```
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score
print('MAE=',mean_absolute_error(ytest,pred3))
```

```
print('MSE=',mean_squared_error(ytest,pred3))
print('R2_Score=',r2_score(ytest,pred3))
```

```
MAE= 2429.823624115302
MSE= 13354439.76406546
R2_Score= 0.959344336053928
```

In [ ]:

```
import matplotlib.pyplot as plt
plt.scatter(ytest,pred3,color='r')
plt.plot([ytest.min(),ytest.max()],[ytest.min(),ytest.max()],'k--',lw=2,marker='^')
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
plt.title('Actual vs Predicted Price')
plt.show()
```



AdaBoosting

In [ ]:
```
from sklearn.ensemble import AdaBoostRegressor
ada=AdaBoostRegressor()
```

In [ ]:
```
from scipy.stats import randint,uniform

para4={'n_estimators':randint(10,51),
       'learning_rate':uniform(0.01,0.98),
       'loss':['linear', 'square', 'exponential'],
       'random_state':randint(1,43)}
```

In [ ]:
```
from sklearn.model_selection import RandomizedSearchCV
rs4=RandomizedSearchCV(ada,para4,cv=5,scoring='r2')
rs4.fit(xtrain,ytrain)
```

Out[ ]:
```
▸ RandomizedSearchCV
▸ best_estimator_: AdaBoostRegressor
  ▸ AdaBoostRegressor
```

In [ ]:
```
rs4.best_params_
```

Out[ ]:
```
{'learning_rate': 0.7604708830388562,
 'loss': 'square',
 'n_estimators': 27,
 'random_state': 30}
```

Buidling Model

In [ ]:
```
from sklearn.tree import DecisionTreeRegressor
ada1=AdaBoostRegressor(estimator=DecisionTreeRegressor(max_depth=6),learning_rate=0.7604708830388562,loss='square',n_estimators=27,random_state=30)
ada1.fit(xtrain,ytrain)
```

Out[ ]:
```
▸ AdaBoostRegressor
▸ estimator: DecisionTreeRegressor
  ▸ DecisionTreeRegressor
```

Model Predicition

In [ ]:
```
pred4=ada1.predict(xtest)
pred4
```

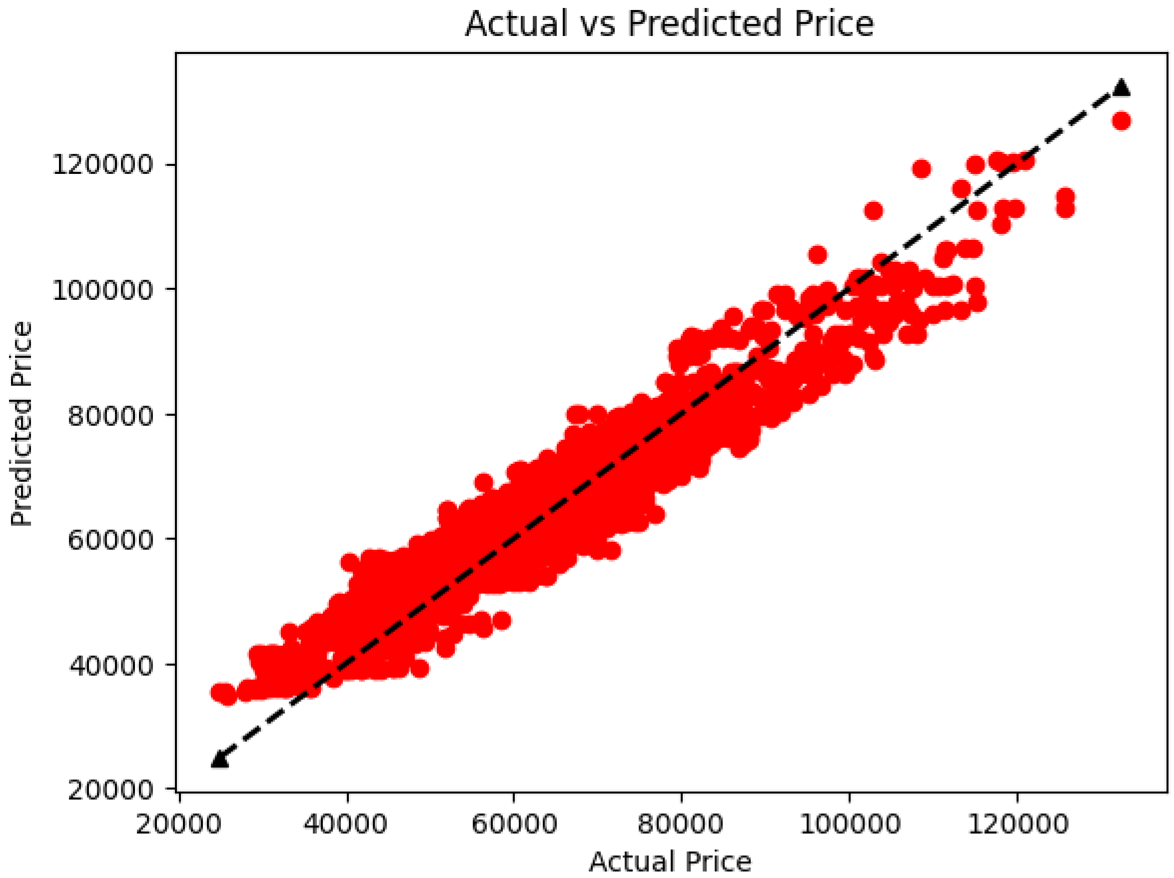
Out[ ]:
```
array([ 56421.58565737,  51020.51677852,  53884.97967914, ...,
        91619.85472973,  56435.67167543, 101332.        ])
```

Model Evaluation

In [ ]:
```
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score
print('MAE=',mean_absolute_error(ytest,pred4))
print('MSE=',mean_squared_error(ytest,pred4))
print('R2_Score=',r2_score(ytest,pred4))
```

```
MAE= 4581.580466189107
MSE= 30335454.239667263
R2_Score= 0.9076480889495655
```

In [ ]:
```
import matplotlib.pyplot as plt
plt.scatter(ytest,pred4,color='r')
plt.plot([ytest.min(),ytest.max()],[ytest.min(),ytest.max()],'k--',lw=2,marker='^')
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
plt.title('Actual vs Predicted Price')
plt.show()
```


Actual vs Predicted Price
Predicted Price
120000
100000
80000
60000
40000
20000
20000
40000
60000
80000
100000
120000
Actual Price

For GUI

In [77]:
```
import pickle

pickle.dump(lr1,open('model.sav','wb'))
pickle.dump(sc,open('scaler.sav','wb'))

pickle.dump(one,open('one.sav','wb'))
pickle.dump(one1,open('one1.sav','wb'))
pickle.dump(one2,open('one2.sav','wb'))
pickle.dump(one3,open('one3.sav','wb'))
pickle.dump(le1,open('le1.sav','wb'))
```