BACKGROUND AND CONTEXT

Introduction: The smartphone industry has experienced remarkable growth over the past decade, with billions of smartphones being sold worldwide each year. As the market continues to expand, both consumers and manufacturers are faced with the challenge of accurately predicting smartphone prices. Price prediction plays a crucial role in various aspects of the industry, including product positioning, marketing strategies, and customer purchasing decisions. In response to this demand, a smartphone price prediction project aims to leverage advanced data analysis and machine learning techniques to forecast smartphone prices with greater accuracy and efficiency.

Objective

The objective of the smartphone price prediction project is to develop a predictive model that accurately forecasts smartphone prices based on various factors, benefiting manufacturers, retailers, and consumers by optimizing pricing strategies, enabling informed purchasing decisions, and enhancing market transparency.

Loading the libraries

In [54]:

```
import pandas as pd
import numpy as np
import re

import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px

# Removes the Limit from the number of displayed columns and rows.
# This is so I can see the entire dataframe when I print it
pd.set_option("display.max_columns", None)

# pd.set_option('display.max_rows", None)
pd.set_option("display.max_rows", 200)

# To build Linear model for statistical analysis and prediction
import statsmodels.stats.api as sms
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import (
    RandomForestRegressor,
    AdaBoostRegressor,
    GradientBoostingRegressor,
    StackingRegressor,
)

from sklearn.neural_network import MLPRegressor
from xgboost import XGBRegressor

import warnings

warnings.filterwarnings("ignore")

from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

Loading and Exploring The Data

In [55]:
```
data = pd.read_csv('smartphones - smartphones.csv')
print(f'There are {data.shape[0]} rows and {data.shape[1]} columns. ')

data.head(n=10)
```

```
There are 1020 rows and 11 columns.
```

Out[55]:

	model	price	rating	sim	processor	ram	battery	display	camera	card	os
0	OnePlus 11 5G	₹54,999	89.0	Dual Sim, 3G, 4G, 5G, VoLTE, Wi-Fi, NFC	Snapdragon 8 Gen2, Octa Core, 3.2 GHz Processor	12 GB RAM, 256 GB inbuilt	5000 mAh Battery with 100W Fast Charging	6.7 inches, 1440 x 3216 px, 120 Hz Display wit...	50 MP + 48 MP + 32 MP Triple Rear & 16 MP Fron...	Memory Card Not Supported	Android v13
1	OnePlus Nord CE 2 Lite 5G	₹19,989	81.0	Dual Sim, 3G, 4G, 5G, VoLTE, Wi-Fi	Snapdragon 695, Octa Core, 2.2 GHz Processor	6 GB RAM, 128 GB inbuilt	5000 mAh Battery with 33W Fast Charging	6.59 inches, 1080 x 2412 px, 120 Hz Display wi...	64 MP + 2 MP + 2 MP Triple Rear & 16 MP Front ...	Memory Card (Hybrid), upto 1 TB	Android v12
2	Samsung Galaxy A14 5G	₹16,499	75.0	Dual Sim, 3G, 4G, 5G, VoLTE, Wi-Fi	Exynos 1330, Octa Core, 2.4 GHz Processor	4 GB RAM, 64 GB inbuilt	5000 mAh Battery with 15W Fast Charging	6.6 inches, 1080 x 2408 px, 90 Hz Display with...	50 MP + 2 MP + 2 MP Triple Rear & 13 MP Front ...	Memory Card Supported, upto 1 TB	Android v13
3	Motorola Moto G62 5G	₹14,999	81.0	Dual Sim, 3G, 4G, 5G, VoLTE, Wi-Fi	Snapdragon 695, Octa Core, 2.2 GHz Processor	6 GB RAM, 128 GB inbuilt	5000 mAh Battery with Fast Charging	6.55 inches, 1080 x 2400 px, 120 Hz Display wi...	50 MP + 8 MP + 2 MP Triple Rear & 16 MP Front ...	Memory Card (Hybrid), upto 1 TB	Android v12
4	Realme 10 Pro Plus	₹24,999	82.0	Dual Sim, 3G, 4G, 5G, VoLTE, Wi-Fi	Dimensity 1080, Octa Core, 2.6 GHz Processor	6 GB RAM, 128 GB inbuilt	5000 mAh Battery with 67W Fast Charging	6.7 inches, 1080 x 2412 px, 120 Hz Display wit...	108 MP + 8 MP + 2 MP Triple Rear & 16 MP Front...	Memory Card Not Supported	Android v13
5	Samsung Galaxy F23 5G (6GB RAM + 128GB)	₹16,999	80.0	Dual Sim, 3G, 4G, 5G, VoLTE, Wi-Fi, NFC	Snapdragon 750G, Octa Core, 2.2 GHz Processor	6 GB RAM, 128 GB inbuilt	5000 mAh Battery with 25W Fast Charging	6.6 inches, 1080 x 2408 px, 120 Hz Display wit...	50 MP + 8 MP + 2 MP Triple Rear & 8 MP Front C...	Memory Card Supported, upto 1 TB	Android v12
6	Apple iPhone 14	₹65,999	81.0	Dual Sim, 3G, 4G, 5G, VoLTE, Wi-Fi, NFC	Bionic A15, Hexa Core, 3.22 GHz Processor	6 GB RAM, 128 GB inbuilt	3279 mAh Battery with Fast Charging	6.1 inches, 1170 x 2532 px Display with Small ...	12 MP + 12 MP Dual Rear & 12 MP Front Camera	Memory Card Not Supported	iOS v16
7	Xiaomi Redmi Note 12 Pro Plus	₹29,999	86.0	Dual Sim, 3G, 4G, 5G, VoLTE, Wi-Fi, IR Blaster	Dimensity 1080, Octa Core, 2.6 GHz Processor	8 GB RAM, 256 GB inbuilt	4980 mAh Battery with 120W Fast Charging	6.67 inches, 1080 x 2400 px, 120 Hz Display wi...	200 MP + 8 MP + 2 MP Triple Rear & 16 MP Front...	Memory Card Not Supported	Android v12
8	Nothing Phone 1	₹26,749	85.0	Dual Sim, 3G, 4G, 5G, VoLTE, Wi-Fi, NFC	Snapdragon 778G Plus, Octa Core, 2.5 GHz Proce...	8 GB RAM, 128 GB inbuilt	4500 mAh Battery with 33W Fast Charging	6.55 inches, 1080 x 2400 px, 120 Hz Display wi...	50 MP + 50 MP Dual Rear & 16 MP Front Camera	Android v12	No FM Radio
9	OnePlus Nord 2T 5G	₹28,999	84.0	Dual Sim, 3G, 4G, 5G, VoLTE, Wi-Fi, NFC	Dimensity 1300, Octa Core, 3 GHz Processor	8 GB RAM, 128 GB inbuilt	4500 mAh Battery with 80W Fast Charging	6.43 inches, 1080 x 2400 px, 90 Hz Display wit...	50 MP + 8 MP + 2 MP Triple Rear & 32 MP Front ...	Android v12	No FM Radio

In [56]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1020 entries, 0 to 1019
Data columns (total 11 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   model      1020 non-null   object
 1   price      1020 non-null   object
 2   rating     879 non-null    float64
 3   sim        1020 non-null   object
 4   processor  1020 non-null   object
 5   ram        1020 non-null   object
 6   battery    1020 non-null   object
 7   display    1020 non-null   object
 8   camera     1019 non-null   object
 9   card       1013 non-null   object
 10  os         1003 non-null   object
dtypes: float64(1), object(10)
memory usage: 87.8+ KB
```

Only one column is of the type float. For better results we will covert the rest of the columns to suitable data types.

In [57]:
```
print(f'LOADING HELPER FUNCTIONS...')

# Extract ROM
def rom(s):
    pattern = r"\d+\D+(\d+)"
    match = re.search(pattern, s)  # find a sequence of digits followed by a non-digit and capture the second sequence of digits
    if match:
        number = match.group(1)   # extract the captured second sequence of digits as a string
        return int(number)

# Extract RAM
def ram(s):
    pattern = r"\d+"
    match = re.search(pattern, s)  # find a sequence of digits followed by a non-digit and capture the second sequence of digits
    if match:
        number = match.group()   # extract the captured second sequence of digits as a string
        return int(number)

# Extract battery power
def battery(s):
    pattern = r"\d+\D+(\d+)"
    match = re.search(pattern, s)  # find a sequence of digits followed by a non-digit and capture the second sequence of digits
    if match:
        number = match.group(1)   # extract the captured second sequence of digits as a string
        return int(number)

# Extract screen size
def screen_size(s):
    pattern = r"(\d+\.\d+) inches"
    match = re.search(pattern, s)
    if match:
        screen_size = float(match.group(1))
        return int(screen_size)

# Extract screen resolution width
def width(s):
    pattern = r"(\d+) x (\d+) px"
    match = re.search(pattern, s)
    if match:
        width = int(match.group(1))
        return width

# Extract screen resolution height
def height(s):
    pattern = r"(\d+) x (\d+) px"
    match = re.search(pattern, s)
    if match:
        height = int(match.group(2))
        return height

# Extract Frequency
def frequency(s):
    pattern = r"\b\d+\b(?=\s*Hz)"
    match = re.search(pattern, s)  # find a sequence of digits before the string " Hz"
    if match:
        number = match.group()  # extract the matched sequence of digits as a string
        return int(number)

# Exercise
def android_version(s):
    pass
# complete this function and add android version column

print(f'HELPER FUNCTION LOADED!')
```

```
LOADING HELPER FUNCTIONS...
HELPER FUNCTION LOADED!
```

Creating a new data frame

In [58]:
```
print(f'Creating a New Dataframe')
df = pd.DataFrame()
df['company'] = data['model'].apply(lambda x:x.split()[0])
df['price'] = data['price'].apply(lambda x: int(''.join(x[1:].split(','))))
df['rating'] = data['rating']
df['processor'] = data['processor'].apply(lambda x:x.split()[0])
df['ram'] = data['ram'].apply(ram)
df['battery'] = data['battery'].apply(battery)
df['screen_size'] = data['display'].apply(screen_size)
df['width'] = data['display'].apply(width)
df['height'] = data['display'].apply(height)
df['refresh rate'] = data['display'].apply(frequency)
df['rom'] = data['ram'].apply(rom)

# df['android_version']                    ----------------------------exercise----------------------------------------

print(f'Data Preprocessed and new dataframe is created!')
print(f'Displaying Newly Created Dataframe!')

df.head()
```

```
Creating a New Dataframe
Data Preprocessed and new dataframe is created!
Displaying Newly Created Dataframe!
```

Out[58]:

	company	price	rating	processor	ram	battery	screen_size	width	height	refresh rate	rom
0	OnePlus	54999	89.0	Snapdragon	12.0	100.0	6.0	1440.0	3216.0	120.0	256.0
1	OnePlus	19989	81.0	Snapdragon	6.0	33.0	6.0	1080.0	2412.0	120.0	128.0
2	Samsung	16499	75.0	Exynos	4.0	15.0	6.0	1080.0	2408.0	90.0	64.0
3	Motorola	14999	81.0	Snapdragon	6.0	NaN	6.0	1080.0	2400.0	120.0	128.0
4	Realme	24999	82.0	Dimensity	6.0	67.0	6.0	1080.0	2412.0	120.0	128.0

In [59]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1020 entries, 0 to 1019
Data columns (total 11 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   company       1020 non-null   object
 1   price         1020 non-null   int64
 2   rating        879 non-null    float64
 3   processor     1020 non-null   object
 4   ram           1019 non-null   float64
 5   battery       801 non-null    float64
 6   screen_size   967 non-null    float64
 7   width         987 non-null    float64
 8   height        987 non-null    float64
 9   refresh rate  611 non-null    float64
 10  rom           997 non-null    float64
dtypes: float64(8), int64(1), object(2)
memory usage: 87.8+ KB
```

Now we have just 2 categorical columns and the rest are numerical columns.

In [60]:
```
df.describe()
```

Out[60]:

	price	rating	ram	battery	screen_size	width	height	refresh rate	rom
count	1020.000000	879.000000	1019.000000	801.000000	967.000000	987.000000	987.000000	611.000000	997.000000
mean	31371.767647	78.258248	22.645731	46.329588	5.921406	1060.914894	2179.227964	111.638298	134.635908
std	39168.942590	7.402854	132.347036	42.285177	0.632150	309.291602	572.898548	18.530837	88.907531
min	99.000000	60.000000	1.000000	1.000000	1.000000	120.000000	160.000000	90.000000	1.000000
25%	12464.250000	74.000000	4.000000	18.000000	6.000000	1080.000000	1612.000000	90.000000	64.000000
50%	19815.000000	80.000000	6.000000	33.000000	6.000000	1080.000000	2400.000000	120.000000	128.000000
75%	34999.000000	84.000000	8.000000	66.000000	6.000000	1080.000000	2408.000000	120.000000	128.000000
max	650000.000000	89.000000	1800.000000	720.000000	8.000000	2460.000000	3840.000000	240.000000	640.000000

In [61]:
```
null_values = df.isnull()

# Count the number of null values in each column
null_count = null_values.sum()

# Display the columns with null values
columns_with_null = null_count[null_count > 0]
print("Columns with null values:")
print(columns_with_null)

# Display the rows with null values
rows_with_null = df[df.isnull().any(axis=1)]
print("Rows with null values:")
print(rows_with_null)
```

```
Columns with null values:
rating          141
ram               1
battery         219
screen_size      53
width            33
height           33
refresh rate    409
rom              23
dtype: int64
Rows with null values:
       company   price  rating   processor   ram  battery  screen_size  \
3     Motorola   14999    81.0  Snapdragon   6.0      NaN          6.0
6        Apple   65999    81.0      Bionic   6.0      NaN          6.0
14     Samsung  114990     NaN  Snapdragon   8.0     45.0          6.0
15       Apple   62999    79.0      Bionic   4.0      NaN          6.0
16        Vivo    9999    65.0       Helio   3.0     10.0          6.0
...        ...     ...     ...         ...   ...      ...          ...
1012      itel    4787     NaN  Spreadtrum   2.0      NaN          NaN
1014      Vivo  119990     NaN  Snapdragon  12.0     66.0          8.0
1016     Honor   14990    75.0  Snapdragon   6.0     22.0          6.0
1018  Motorola   19990    80.0  Snapdragon   6.0      NaN          6.0
1019   Samsung   24990    74.0        Octa   8.0      NaN          6.0

       width  height  refresh rate    rom
3     1080.0  2400.0         120.0  128.0
6     1170.0  2532.0           NaN  128.0
14    1440.0  3088.0         120.0  256.0
15    1170.0  2532.0           NaN  128.0
16     720.0  1600.0           NaN   32.0
...      ...     ...           ...    ...
1012   854.0   480.0           NaN   32.0
1014  1916.0  2160.0         120.0  256.0
1016   720.0  1600.0           NaN  128.0
1018  1080.0  2400.0           NaN  128.0
1019  1080.0  2400.0           NaN  128.0

[503 rows x 11 columns]
```

In [62]:
```
#Imputing the missing values by taking the median

for i in df.columns:
    if df[i].dtype != "object":
        median = df[i].median()
        df[i] = df[i].fillna(median)
```

In [63]:
```
null_values = df.isnull()

# Count the number of null values in each column
null_count = null_values.sum()

# Display the columns with null values
columns_with_null = null_count[null_count > 0]
print("Columns with null values:")
print(columns_with_null)

# Display the rows with null values
rows_with_null = df[df.isnull().any(axis=1)]
print("Rows with null values:")
print(rows_with_null)
```

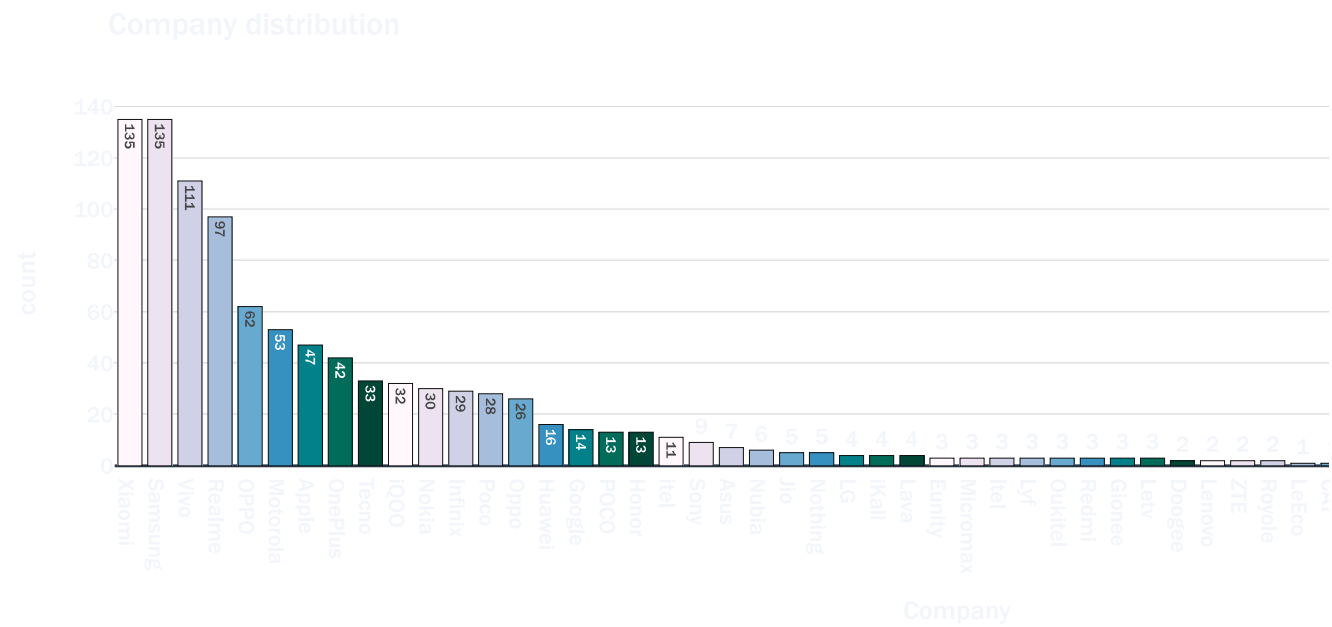
```
Columns with null values:
Series([], dtype: int64)
Rows with null values:
Empty DataFrame
Columns: [company, price, rating, processor, ram, battery, screen_size, width, height, refresh rate, rom]
Index: []
```

In [64]:
```
df.head()
```

Out[64]:

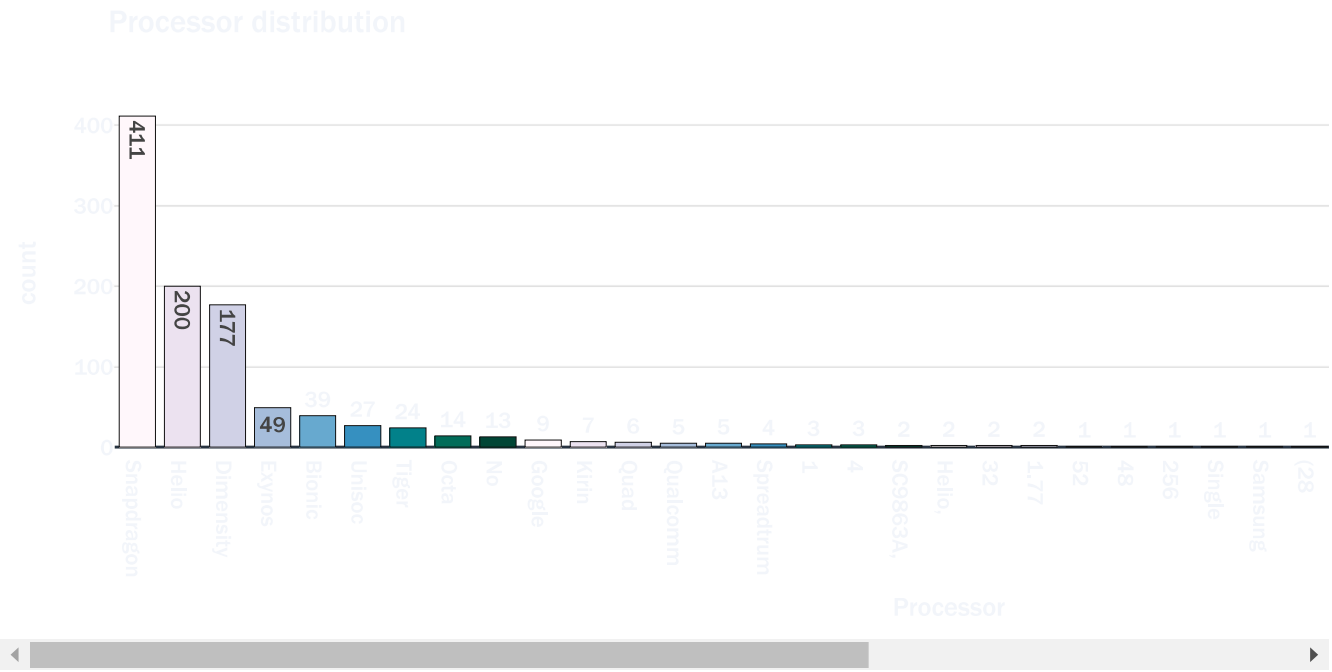
	company	price	rating	processor	ram	battery	screen_size	width	height	refresh rate	rom
0	OnePlus	54999	89.0	Snapdragon	12.0	100.0	6.0	1440.0	3216.0	120.0	256.0
1	OnePlus	19989	81.0	Snapdragon	6.0	33.0	6.0	1080.0	2412.0	120.0	128.0
2	Samsung	16499	75.0	Exynos	4.0	15.0	6.0	1080.0	2408.0	90.0	64.0
3	Motorola	14999	81.0	Snapdragon	6.0	33.0	6.0	1080.0	2400.0	120.0	128.0
4	Realme	24999	82.0	Dimensity	6.0	67.0	6.0	1080.0	2412.0	120.0	128.0

In [65]:
```
Company = df['company'].value_counts()
fig = px.bar(y=Company.values,
             x=Company.index,
             color = Company.index,
             color_discrete_sequence=px.colors.sequential.PuBuGn,
             text=Company.values,
             title= 'Company distribution',
             template= 'plotly_dark',
             width=1500, height=500)
fig.update_layout(
    xaxis_title="Company",
    yaxis_title="count",
    font = dict(size=17,family="Franklin Gothic"))

fig.show()
```



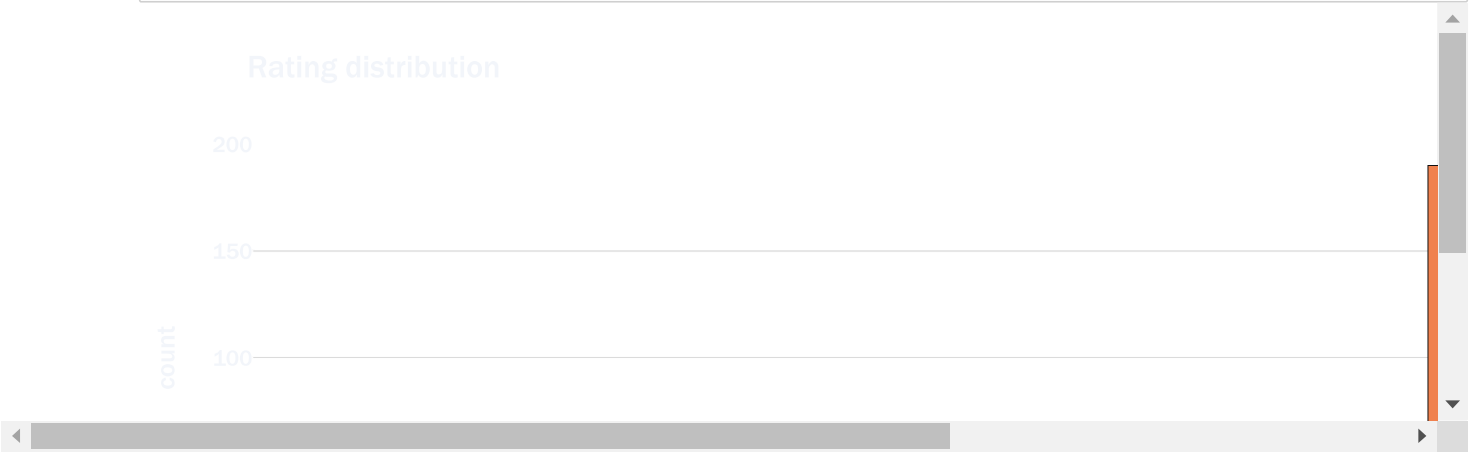
Market leaders are Xiaomi and Samsung, followed by Vivo and Realme

In [66]:
```
Processor = df['processor'].value_counts()
fig = px.bar(y=Processor.values,
             x=Processor.index,
             color = Processor.index,
             color_discrete_sequence=px.colors.sequential.PuBuGn,
             text=Processor.values,
             title= 'Processor distribution',
             template= 'plotly_dark',
             width=1500, height=500)
fig.update_layout(
    xaxis_title="Processor",
    yaxis_title="count",
    font = dict(size=17,family="Franklin Gothic"))

fig.show()
```



Most popular processor is Snapdragon

In [67]:
```
Rating = df['rating'].value_counts()
fig = px.bar(y=Rating.values,
             x=Rating.index,
             color = Rating.index,
             color_discrete_sequence=px.colors.sequential.PuBuGn,
             text=Rating.values,
             title= 'Rating distribution',
             template= 'plotly_dark',
             width=1500, height=500)
fig.update_layout(
    xaxis_title="Rating",
    yaxis_title="count",
    font = dict(size=17,family="Franklin Gothic"))
fig.show()
```



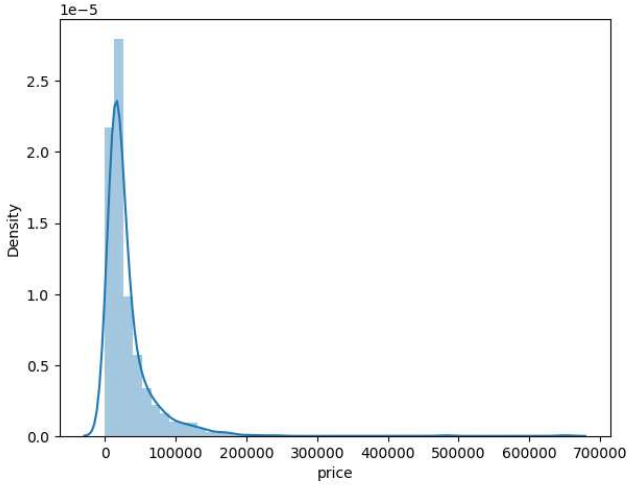
Ratings are skewed to the left

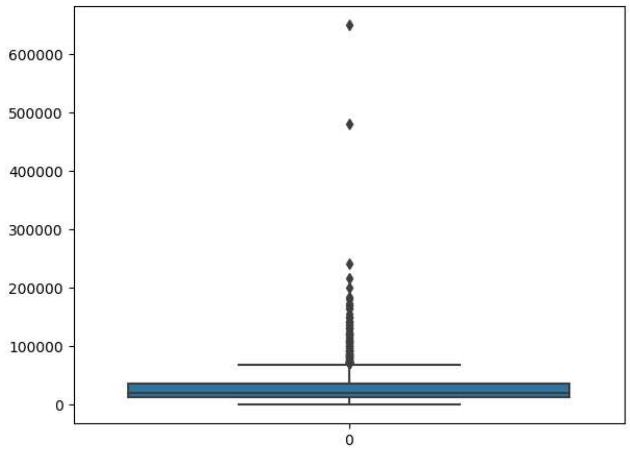
In [68]:
```
plt.figure(figsize=(20,10))
dnew = df.select_dtypes(exclude=['object'])

sns.heatmap(dnew.corr(),annot = True, fmt = '.2')
plt.show()
```

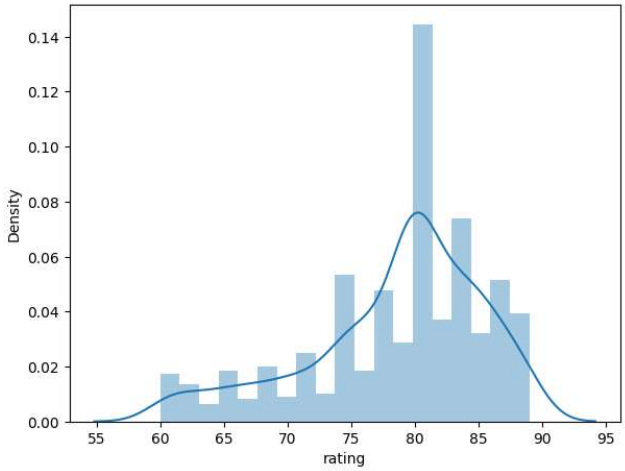
Higher correlation between the dependent variable Price and ROM

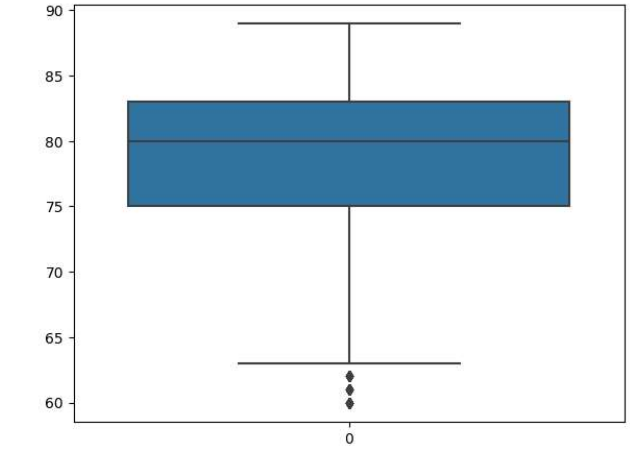
Removing Outliers

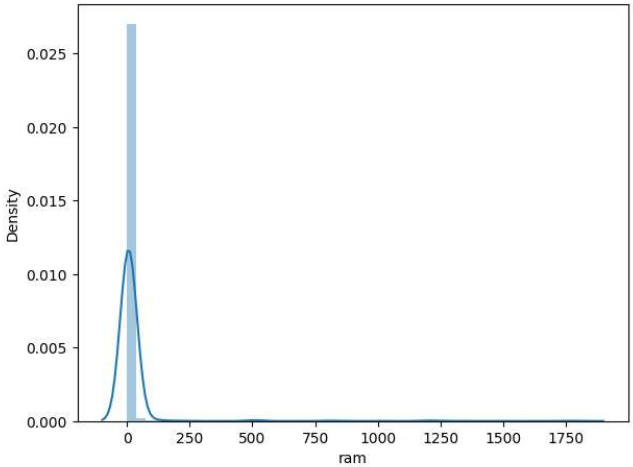
In [69]:
```
a=1
plt.figure(figsize=(15, 80))
for i in df[
    [
    'price',
    'rating',
    'ram',
    'battery',
    'screen_size',
    'width',
    'height',
    'refresh rate',
    'rom',
    ]
]:

    if df[i].dtype != "object":
        plt.subplot(13, 2, a)
        sns.distplot(df[i])
        # plt. title( Histogram for:" + i)
        plt.subplot(13, 2, a + 1)
        sns.boxplot(df[i])
        # plt.title("Boxplot for:" + i)
        a += 2
```

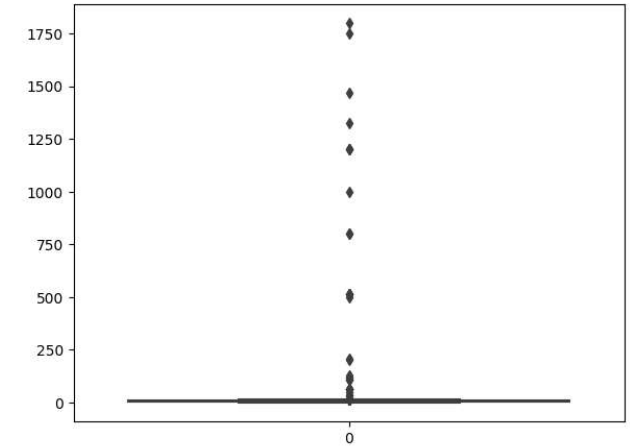

1e−5
Density
price

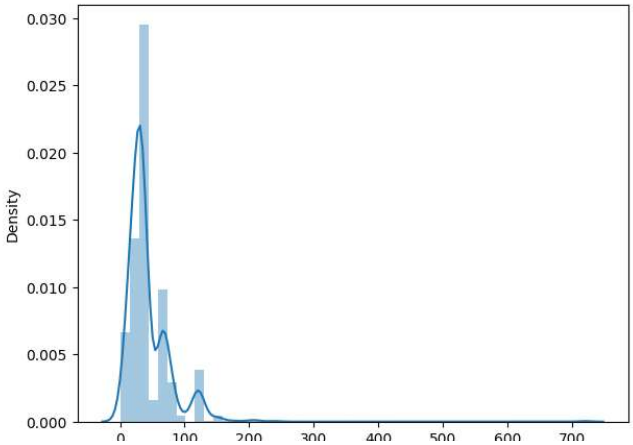


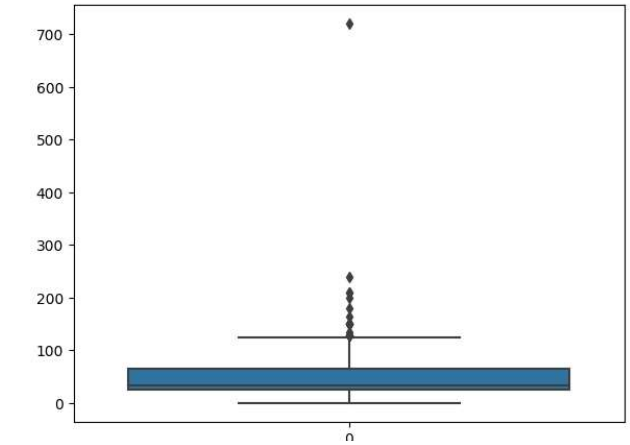

Density
rating

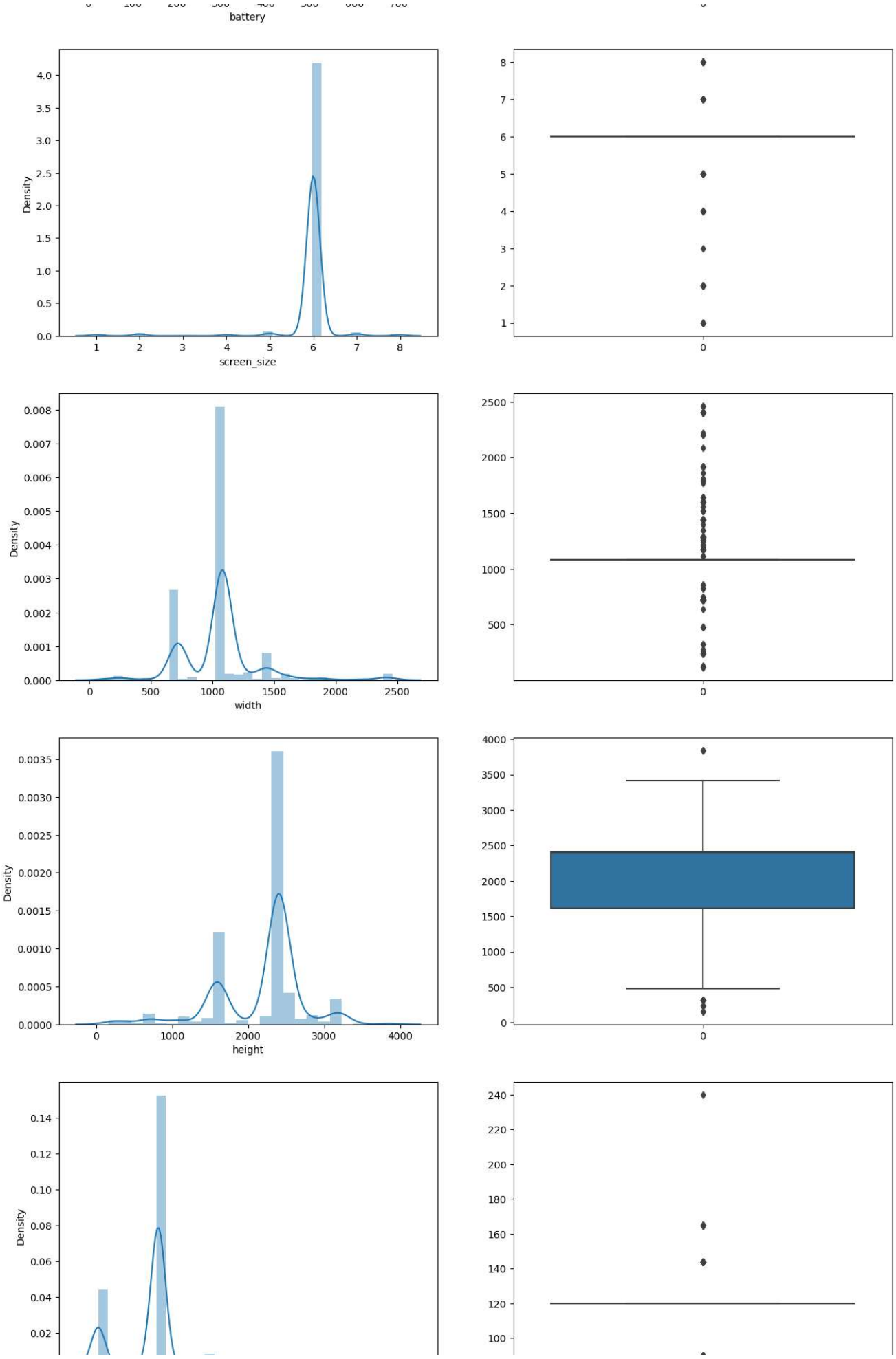


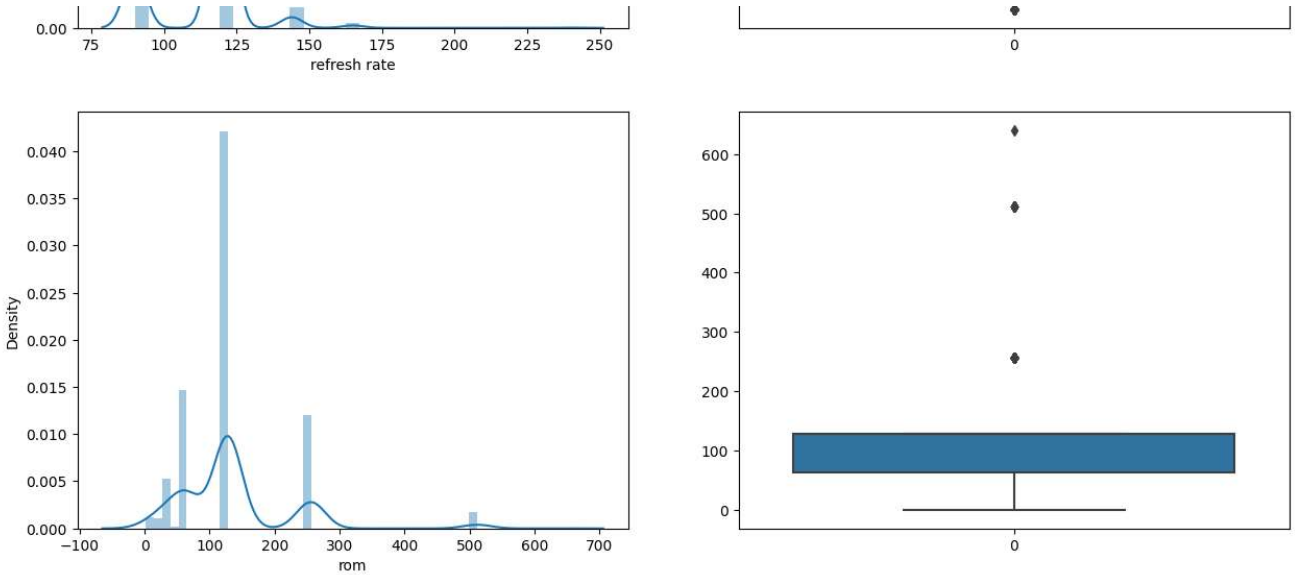

Density
ram




Density




battery
Density
screen_size
width
height

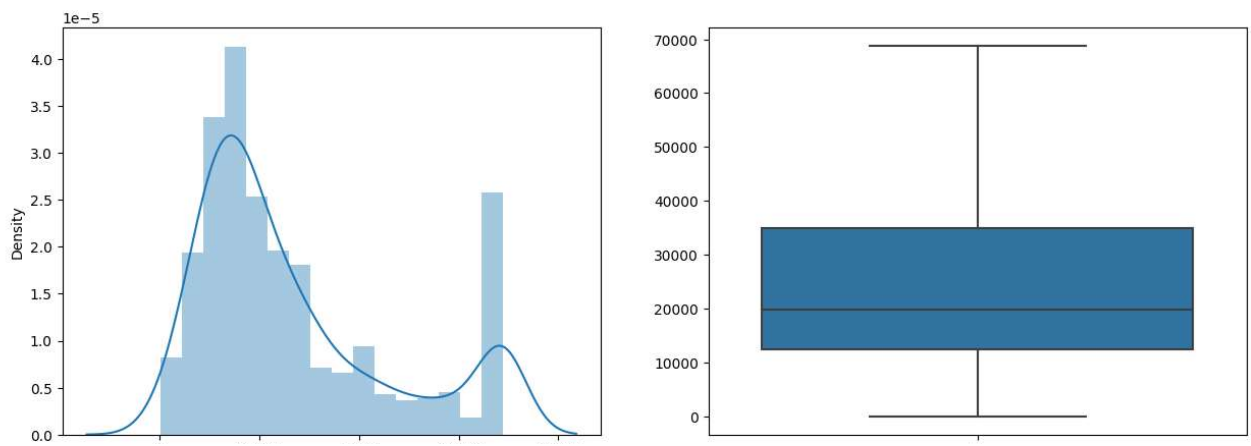


Price and Battery outliers need to be removed

In [70]:
```
def remove_outlier(col):
    sorted(col)
    q1,q3 = np.quantile(col,[0.25,0.75])
    iqr = q3 - q1
    ll = q1 - 1.5 * iqr
    ul = q3 + 1.5 * iqr
    return ll,ul
```

In [71]:
```
for i in df[
    [
    'price',
    'battery',
    'rating',
    ]
]:
    if df[i].dtype!= "object":
        ll,ul = remove_outlier(df[i])
        df[i] = np.where(df[i]>ul,ul,df[i])
        df[i] = np.where(df[i]<ll,ll,df[i])
```

In [72]:
```
a=1
plt.figure(figsize=(15, 80))
for i in df[
    [
    'price',
    'rating',
    'ram',
    'battery',
    'screen_size',
    'width',
    'height',
    'refresh rate',
    'rom',
    ]
]:

    if df[i].dtype != "object":
        plt.subplot(13, 2, a)
        sns.distplot(df[i])
        # plt. title( Histogram for:" + i)
        plt.subplot(13, 2, a + 1)
        sns.boxplot(df[i])
        # plt.title("Boxplot for:" + i)
        a += 2
```



Data Preparation

In [73]:
```
X = df.drop("price",axis = 1)
y = df[['price']]

X.head()
```

Out[73]:

	company	rating	processor	ram	battery	screen_size	width	height	refresh rate	rom
0	OnePlus	89.0	Snapdragon	12.0	100.0	6.0	1440.0	3216.0	120.0	256.0
1	OnePlus	81.0	Snapdragon	6.0	33.0	6.0	1080.0	2412.0	120.0	128.0
2	Samsung	75.0	Exynos	4.0	15.0	6.0	1080.0	2408.0	90.0	64.0
3	Motorola	81.0	Snapdragon	6.0	33.0	6.0	1080.0	2400.0	120.0	128.0
4	Realme	82.0	Dimensity	6.0	67.0	6.0	1080.0	2412.0	120.0	128.0

In [74]:
```
X = pd.get_dummies(X,columns=['company','processor'],drop_first = True)
X.head()
```

Out[74]:

	rating	ram	battery	screen_size	width	height	refresh rate	rom	company_Asus	company_BLU	company_BlackZone	company_Blackview	company_CAT	c
0	89.0	12.0	100.0	6.0	1440.0	3216.0	120.0	256.0	False	False	False	False	False	
1	81.0	6.0	33.0	6.0	1080.0	2412.0	120.0	128.0	False	False	False	False	False	
2	75.0	4.0	15.0	6.0	1080.0	2408.0	90.0	64.0	False	False	False	False	False	
3	81.0	6.0	33.0	6.0	1080.0	2400.0	120.0	128.0	False	False	False	False	False	
4	82.0	6.0	67.0	6.0	1080.0	2412.0	120.0	128.0	False	False	False	False	False	

In [75]:
```
#splitting the data

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    X,y,test_size = 0.3, random_state = 42
)
```

Choose Model, Train and Evaluate

Linear Regression

In [76]:
```
linearregression = LinearRegression()
linearregression.fit(X_train, y_train)
```

Out[76]:
```
▾ LinearRegression
LinearRegression()
```

In [77]:
```
#coefficients for each of the indpendent attributes

for idx, col_name in enumerate(X_train.columns):
    print(
        'The coefficient for {} is {}'.format(col_name,linearregression.coef_[0][idx])
    )
```

```
The coefficient for rating is 328.1514144112877
The coefficient for ram is -1.7088093416904648
The coefficient for battery is 137.40020432459696
The coefficient for screen_size is 1038.9782768748923
The coefficient for width is 9.25058857364878
The coefficient for height is 5.983783004672894
The coefficient for refresh rate is 113.36136235309073
The coefficient for rom is 56.44104123224872
The coefficient for company_Asus is 12368.091223742955
The coefficient for company_BLU is -17782.863166221738
The coefficient for company_BlackZone is 3915.500837663747
The coefficient for company_Blackview is -4.6516106522176415e-09
The coefficient for company_CAT is -1.1568772606551647e-09
The coefficient for company_Cola is -6253.435508630371
The coefficient for company_DIZO is 5826.345463935702
The coefficient for company_Doogee is -5423.466839062316
The coefficient for company_Duoqin is -828.3435359368412
The coefficient for company_Eunity is 6102.856021519359
The coefficient for company_Gionee is -16706.575838604647
The coefficient for company_Google is -462.3867288424335
The coefficient for company_Honor is -8036.248374500832
The coefficient for company_Huawei is -1828.226236166758
The coefficient for company_Infinix is -13222.134486873794
The coefficient for company_Itel is -8417.132325339728
The coefficient for company_Jio is -5827.125131823694
The coefficient for company_Karbonn is 9.549694368615746e-11
The coefficient for company_LG is 24054.35615404498
The coefficient for company_Lava is -9242.598049551649
The coefficient for company_LeEco is -9630.250239228719
The coefficient for company_Leitz is 6.912159733474255e-11
The coefficient for company_Lenovo is -8871.17693550395
The coefficient for company_Letv is -13843.828591892176
The coefficient for company_Lyf is -18489.425355631818
The coefficient for company_Micromax is -10348.470612653073
The coefficient for company_Motorola is -8320.512510101687
The coefficient for company_Namotel is -4169.245106478771
The coefficient for company_Nokia is -2304.5771116342494
The coefficient for company_Nothing is -8327.139761229513
The coefficient for company_Nubia is 1685.5655393114962
The coefficient for company_OPPO is -6594.862546073669
The coefficient for company_OnePlus is -5373.439686240733
The coefficient for company_Oppo is 775.8585474469619
The coefficient for company_Oukitel is -14210.16954082254
The coefficient for company_POCO is -10114.180489405708
The coefficient for company_Poco is -13161.57408854725
The coefficient for company_Realme is -10955.889544061214
The coefficient for company_Redmi is -15524.133360871425
The coefficient for company_Royole is 30986.877507580335
The coefficient for company_Samsung is 1254.3688666033904
The coefficient for company_Sharp is 8201.200139855573
The coefficient for company_Sony is 6327.334794066007
The coefficient for company_TCL is 1.0913936421275139e-11
The coefficient for company_Tecno is -7924.454478532831
The coefficient for company_Tesla is 1.8189894035458565e-12
The coefficient for company_Vertu is 48911.63195340945
The coefficient for company_Vivo is -5971.61880330007
The coefficient for company_XTouch is -16208.073401378002
The coefficient for company_Xiaomi is -11109.677850428765
The coefficient for company_ZTE is 872.5642195868056
The coefficient for company_Zanco is 1.8189894035458565e-11
The coefficient for company_iKall is -4418.373372474116
The coefficient for company_iQOO is -12932.756754689975
The coefficient for company_itel is -15248.771902874028
The coefficient for processor_1 is -26050.408402078618
The coefficient for processor_1.77 is 6102.856021518261
The coefficient for processor_1450 is -1409.2907973533074
The coefficient for processor_2000 is -3223.3171155813707
The coefficient for processor_256 is -2.7284841053187847e-12
The coefficient for processor_32 is -25536.178423591373
The coefficient for processor_4 is -12437.032307993471
The coefficient for processor_48 is -6364.170975502933
The coefficient for processor_52 is 0.0
The coefficient for processor_8 is -8203.252841356536
The coefficient for processor_800 is -12402.419074130485
The coefficient for processor_A13 is 47512.99939798347
The coefficient for processor_Apple is 64026.04222018909
The coefficient for processor_Bionic is 40816.901038328564
The coefficient for processor_Dimensity is 10844.74250018343
The coefficient for processor_Dual is 20869.04925269696
The coefficient for processor_Exynos is 13638.782049233003
The coefficient for processor_Fusion is 49980.82276391752
The coefficient for processor_Google is 26018.816245363734
The coefficient for processor_Helio is 10299.239653487666
The coefficient for processor_Helio, is 11228.666686232393
The coefficient for processor_Kirin is 23789.94662286736
The coefficient for processor_No is -1587.2806266804891
```

```
The coefficient for processor_Octa is 9663.685560013386
The coefficient for processor_Quad is 10743.297155230213
The coefficient for processor_Qualcomm is 10247.641713688034
The coefficient for processor_SC6531E, is 5826.345463938586
The coefficient for processor_SC9863A, is 16630.452367848615
The coefficient for processor_Samsung is 7893.560414717258
The coefficient for processor_Sanpdragon is -2335.4272639054107
The coefficient for processor_Single is 3915.500837665427
The coefficient for processor_Snapdragon is 14091.876656691968
The coefficient for processor_Spreadtrum is 13796.521884544167
The coefficient for processor_Tiger is 16900.627831412792
The coefficient for processor_Unisoc is 12498.112696683105
The coefficient for processor_Unisoc, is 14682.586309557562
```

This model suggests the brand and processor affect the phone price the most.

In [78]:
```
print('The intercept for our model is {}'.format(linearregression.intercept_[0]))
```

```
The intercept for our model is -62257.7140992833
```

In [79]:
```
pred_train = linearregression.predict(X_train)
pred_test = linearregression.predict(X_test)
```

In [80]:
```
#R Squared Value:
lrscore_train = linearregression.score(X_train,y_train)
lrscore_test = linearregression.score(X_test,y_test)
print(lrscore_train)
print(lrscore_test)
```

```
0.7937937954104113
0.7425005729517467
```

Values near 75% indicate this is a decent model, with the difference between the test and train set value lesser than 10%.

In [81]:
```
#RMSE
rmse_lr_train = mean_squared_error(y_train,pred_train,squared = False)
rmse_lr_test = mean_squared_error(y_test,pred_test,squared = False)
print(rmse_lr_train)
print(rmse_lr_test)
```

```
8856.610988829176
10143.288876357623
```

RMSE value is very high, indicating inaccuracy.

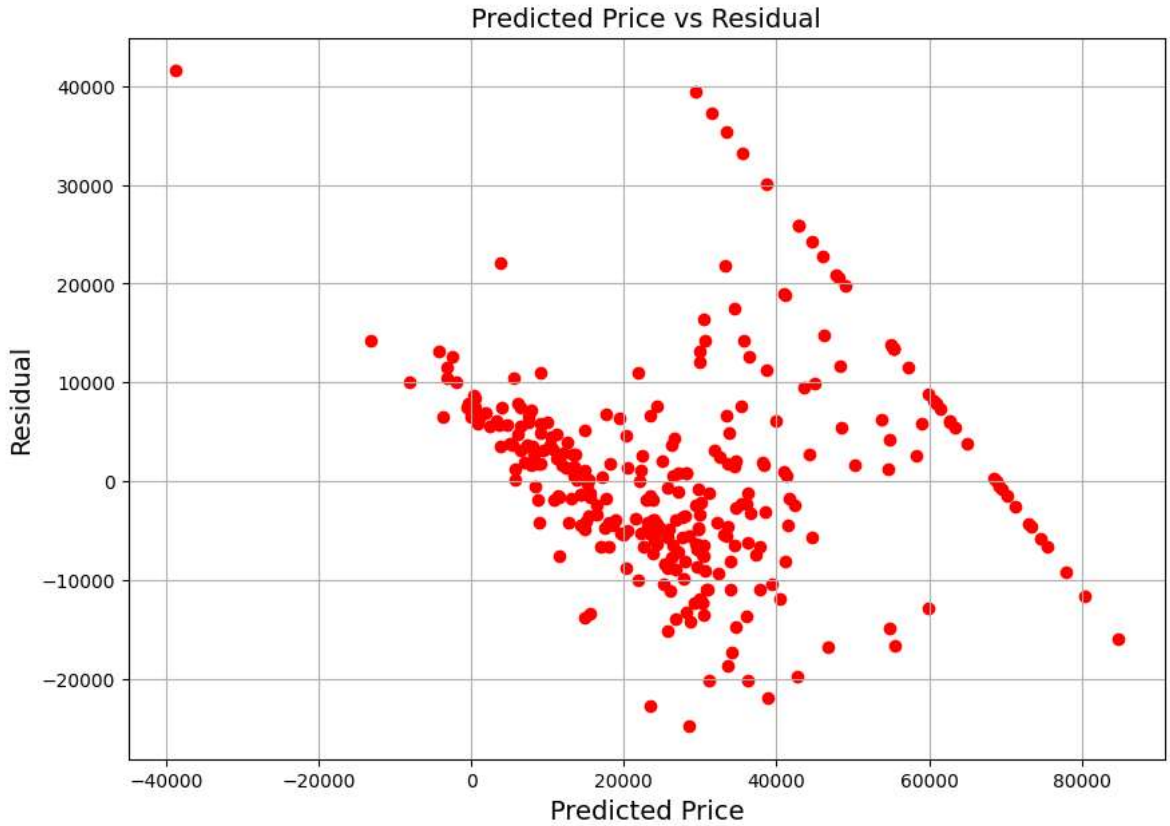
Now performing some diagnostic analysis

In [82]:
```
data = y_test.copy()
data['pred'] = pred_test
data['residual'] = data['price'] - data['pred']
data.head()
```

Out[82]:

	price	pred	residual
523	24494.0	28006.910323	-3512.910323
602	24999.0	22385.073683	2613.926317
526	49959.0	38627.471813	11331.528187
31	20999.0	25861.815162	-4862.815162
616	19990.0	28074.428335	-8084.428335

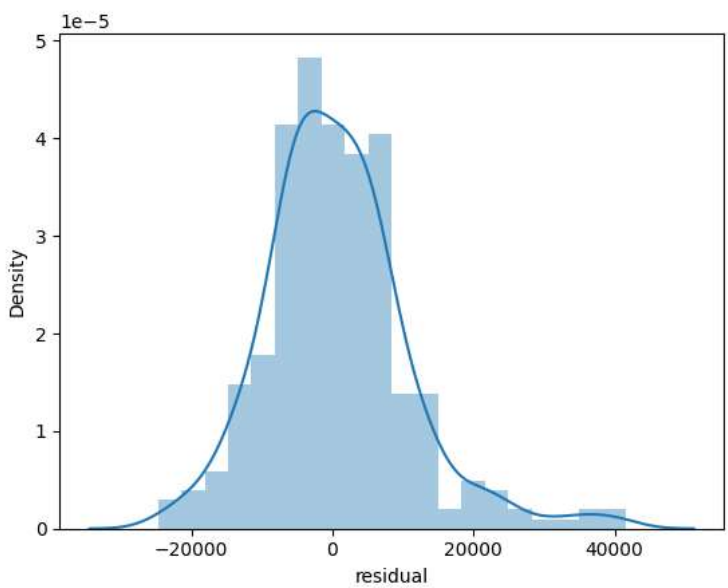
In [83]:
```
plt.figure(figsize=(10,7))
plt.scatter(data['pred'],data['residual'],color='red')
plt.title('Predicted Price vs Residual', fontsize = 14)
plt.xlabel('Predicted Price', fontsize = 14)
plt.ylabel('Residual', fontsize = 14)
plt.grid(True)
plt.show()
```



This model is clearly not a good fit, with negative values being predicted. This could be due to the dependent variable being skewed.

In [84]:
```
sns.distplot(data.residual)
```

Out[84]: <Axes: xlabel='residual', ylabel='Density'>



A little similar to normal distiribution

Being the oldest model, linear regression is not the best model due to the complexities in today's data.

Random Forest Regressor

In [85]:
```
rfregressor = RandomForestRegressor(max_depth = 20, min_samples_split = 30, criterion = 'friedman_mse')
rfregressor.fit(X_train, y_train)
```

Out[85]:
```
RandomForestRegressor
RandomForestRegressor(criterion='friedman_mse', max_depth=20,
                      min_samples_split=30)
```

In [86]:
```
pred_train = rfregressor.predict(X_train)
pred_test = rfregressor.predict(X_test)
```

In [87]:
```
#R Squared Value:
rfscore_train = rfregressor.score(X_train,y_train)
rfscore_test = rfregressor.score(X_test,y_test)
print(rfscore_train)
print(rfscore_test)
```

```
0.8887887125208057
0.8515998078877932
```

In [88]:
```
#RMSE
rmse_rf_train = mean_squared_error(y_train,pred_train,squared = False)
rmse_rf_test = mean_squared_error(y_test,pred_test,squared = False)
print(rmse_rf_train)
print(rmse_rf_test)
```

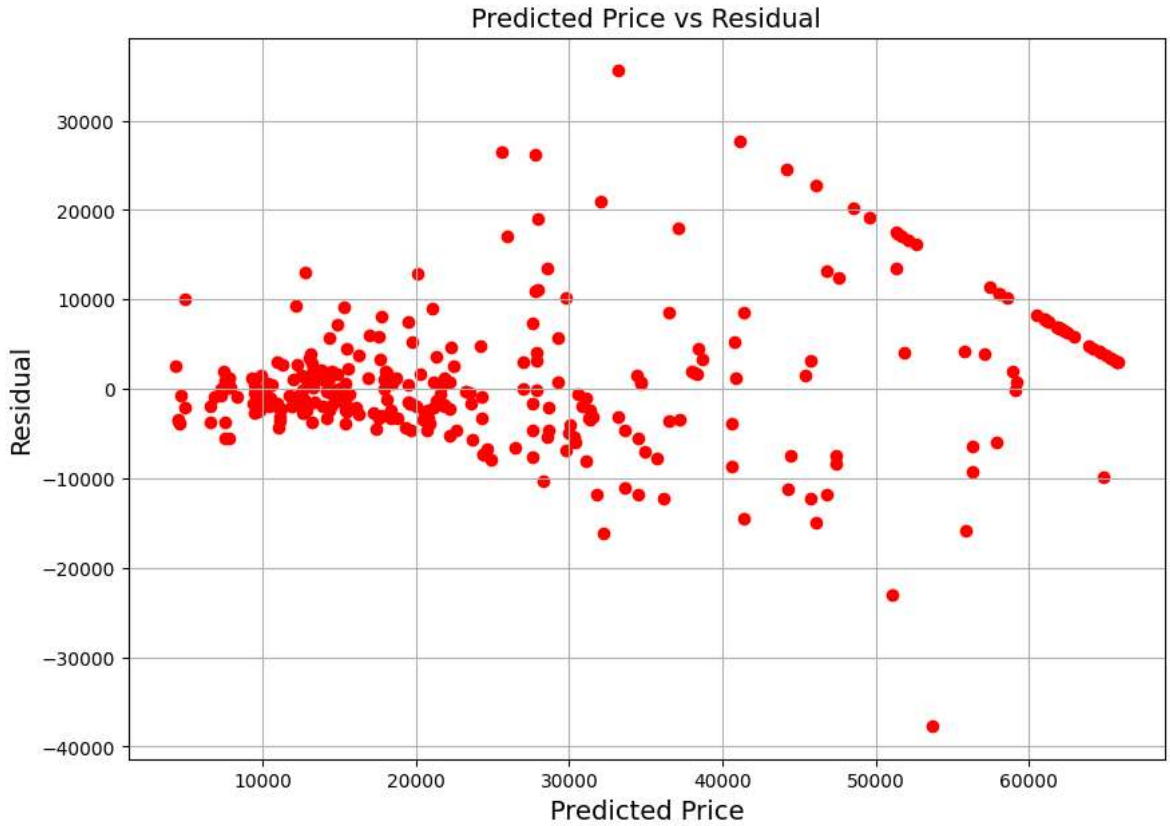
```
6504.158849376948
7700.304376364609
```

In [89]:
```
data = y_test.copy()
data['pred'] = pred_test
data['residual'] = data['price'] - data['pred']
data.head()
```

Out[89]:

	price	pred	residual
523	24494.0	30392.342642	-5898.342642
602	24999.0	21320.836192	3678.163808
526	49959.0	56354.578906	-6395.578906
31	20999.0	21611.358372	-612.358372
616	19990.0	26511.178190	-6521.178190

In [90]:
```
plt.figure(figsize=(10,7))
plt.scatter(data['pred'],data['residual'],color='red')
plt.title('Predicted Price vs Residual', fontsize = 14)
plt.xlabel('Predicted Price', fontsize = 14)
plt.ylabel('Residual', fontsize = 14)
plt.grid(True)
plt.show()
```



Results are much better for lower end smartphones.

In [91]:
```
pd.DataFrame(rfregressor.feature_importances_,index = X_test.columns).sort_values(
    0,ascending = False
)
```

Out[91]:

	0
height	4.451025e-01
rating	1.738249e-01
rom	1.269300e-01
ram	4.867733e-02
width	4.260200e-02
processor_Bionic	3.367894e-02
battery	2.958750e-02
screen_size	2.029455e-02
refresh rate	1.100746e-02
company_LG	8.651063e-03
company_Vertu	7.928867e-03

Indicates the height or size of the phone to be of the most importance.

We can say that the Random Forest Regressor model is a better fit.

Adaboost Regressor

In [92]:
```
adaboost = AdaBoostRegressor(
    base_estimator = DecisionTreeRegressor(
        max_depth = 10, min_samples_split = 25, random_state = 42
    ),
    random_state = 42,
)
adaboost.fit(X_train,y_train)
```

Out[92]:
```
▸ AdaBoostRegressor
▸ base_estimator: DecisionTreeRegressor
  ▸ DecisionTreeRegressor
```

In [93]:
```
pred_train = adaboost.predict(X_train)
pred_test = adaboost.predict(X_test)
```

In [94]:
```
#R Squared Value:
adascore_train = adaboost.score(X_train,y_train)
adascore_test = adaboost.score(X_test,y_test)
print(adascore_train)
print(adascore_test)
```

```
0.9345559382716397
0.8628254963171413
```

In [95]:
```
#RMSE
rmse_ada_train = mean_squared_error(y_train,pred_train,squared = False)
rmse_ada_test = mean_squared_error(y_test,pred_test,squared = False)
print(rmse_ada_train)
print(rmse_ada_test)
```

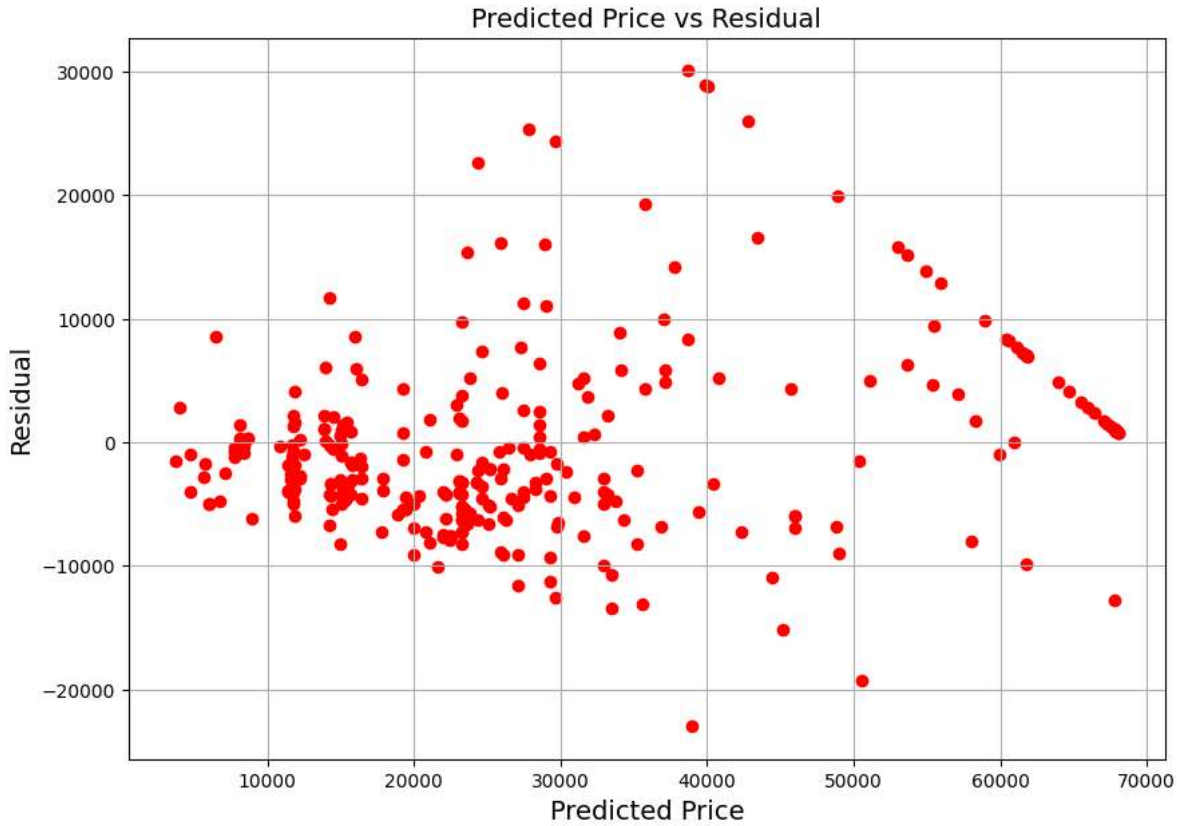
```
4989.440269689693
7403.33428093985
```

In [96]:
```
data = y_test.copy()
data['pred'] = pred_test
data['residual'] = data['price'] - data['pred']
data.head()
```

Out[96]:

	price	pred	residual
523	24494.0	28309.851485	-3815.851485
602	24999.0	23261.291667	1737.708333
526	49959.0	58000.517857	-8041.517857
31	20999.0	24233.423077	-3234.423077
616	19990.0	26118.400000	-6128.400000

In [97]:
```
plt.figure(figsize=(10,7))
plt.scatter(data['pred'],data['residual'],color='red')
plt.title('Predicted Price vs Residual', fontsize = 14)
plt.xlabel('Predicted Price', fontsize = 14)
plt.ylabel('Residual', fontsize = 14)
plt.grid(True)
plt.show()
```



XGB Regressor

In [98]:
```
xgbregressor = XGBRegressor(max_depth = 10, learning_rate = 0.05, reg_alpha = 1, random_state = 42)
xgbregressor.fit(X_train,y_train)
```

Out[98]:
```
XGBRegressor
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.05, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=10, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             n_estimators=100, n_jobs=None, num_parallel_tree=None,
```

In [99]:
```
pred_train = xgbregressor.predict(X_train)
pred_test = xgbregressor.predict(X_test)
```

In [100]:
```
#R Squared Value:
xgbscore_train = xgbregressor.score(X_train,y_train)
xgbscore_test = xgbregressor.score(X_test,y_test)
print(xgbscore_train)
print(xgbscore_test)
```

```
0.982929783805738
0.8490658176306083
```

In [101]:
```
#RMSE
rmse_xgb_train = mean_squared_error(y_train,pred_train,squared = False)
rmse_xgb_test = mean_squared_error(y_test,pred_test,squared = False)
print(rmse_xgb_train)
print(rmse_xgb_test)
```

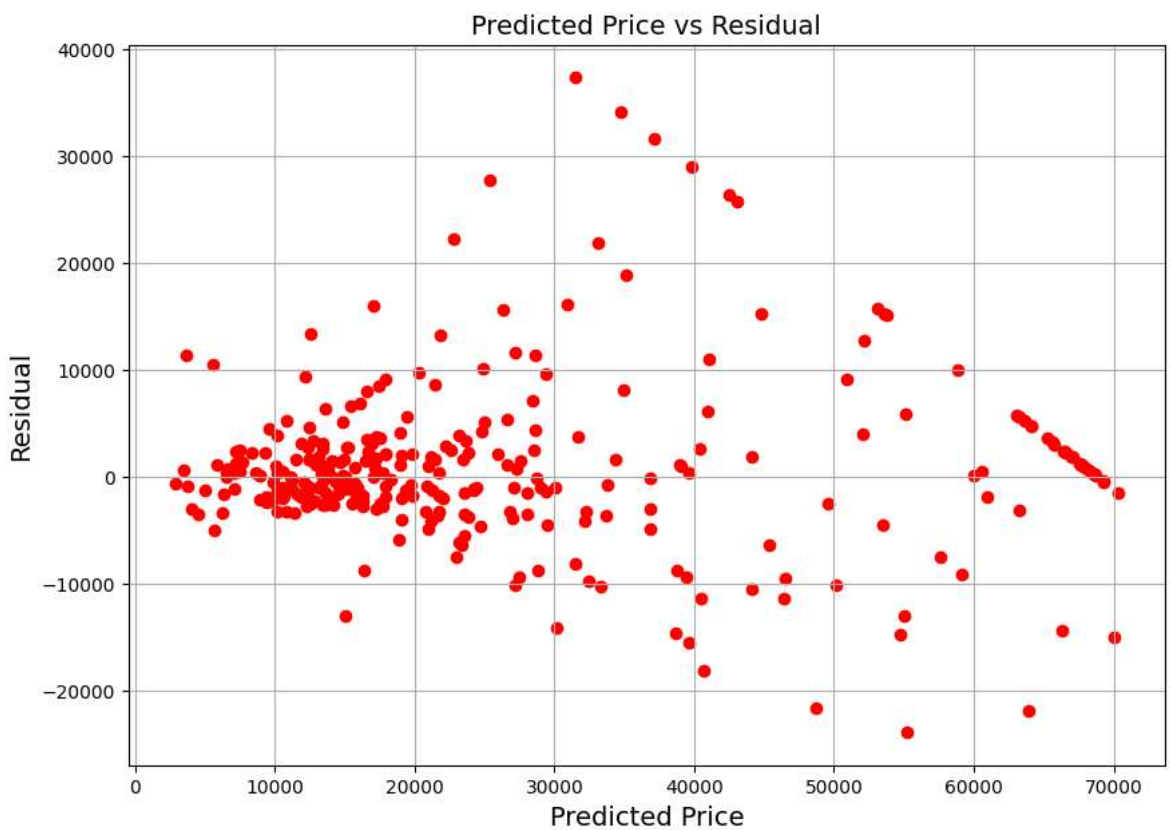
```
2548.21586838926
7765.768928005183
```

In [102]:
```
data = y_test.copy()
data['pred'] = pred_test
data['residual'] = data['price'] - data['pred']
data.head()
```

Out[102]:

	price	pred	residual
523	24494.0	28009.197266	-3515.197266
602	24999.0	22210.285156	2788.714844
526	49959.0	57568.781250	-7609.781250
31	20999.0	17261.498047	3737.501953
616	19990.0	23812.900391	-3822.900391

In [103]:
```
plt.figure(figsize=(10,7))
plt.scatter(data['pred'],data['residual'],color='red')
plt.title('Predicted Price vs Residual', fontsize = 14)
plt.xlabel('Predicted Price', fontsize = 14)
plt.ylabel('Residual', fontsize = 14)
plt.grid(True)
plt.show()
```



Comparision and Conclusion

In [104]:
```
train_score = []
train_score.extend(
    [
        lrscore_train,
        rfscore_train,
        adascore_train,
        xgbscore_train,
    ]
)

test_score = []
test_score.extend(
    [
        lrscore_test,
        rfscore_test,
        adascore_test,
        xgbscore_test,
    ]
)

rmse_train = []
rmse_train.extend(
    [
        rmse_lr_train,
        rmse_rf_train,
        rmse_ada_train,
        rmse_xgb_train,
    ]
)

rmse_test = []
rmse_test.extend(
    [
        rmse_lr_test,
        rmse_rf_test,
        rmse_ada_test,
        rmse_xgb_test,
    ]
)
```

In [106]:
```
comparison_frame = pd.DataFrame(
    {
        'Model': [
            'Linear Regression',
            'Random Forest',
            'Ada Boost',
            'XGBoost',
        ],
        'Train Score': train_score,
        'Test Score': test_score,
        'Train_RMSE': rmse_train,
        'Test_RMSE': rmse_test,
    }
)

comparison_frame['Diff_in_Score'] = np.abs(
    comparison_frame['Train Score'] - comparison_frame['Test Score']
)

#sorting models in decreasing order of test recall
comparison_frame.sort_values(by='Diff_in_Score',ascending = True)
```

Out[106]:

	Model	Train Score	Test Score	Train_RMSE	Test_RMSE	Diff_in_Score
1	Random Forest	0.888789	0.851600	6504.158849	7700.304376	0.037189
0	Linear Regression	0.793794	0.742501	8856.610989	10143.288876	0.051293
2	Ada Boost	0.934556	0.862825	4989.440270	7403.334281	0.071730
3	XGBoost	0.982930	0.849066	2548.215868	7765.768928	0.133864

When considering the choice between Random Forest and XGBoost, an important factor to consider is the R square difference between the train and test sets. In this context, Random Forest exhibits a significant advantage over XGBoost, as it has a lower R square difference of less than 4 percent. On the other hand, XGBoost demonstrates a higher R square difference exceeding 10 percent. Despite XGBoost potentially having lower root mean square error (RMSE) values, the substantial difference in R square values suggests that Random Forest may provide more consistent and reliable generalization performance. The smaller R square difference indicates that Random Forest is better at capturing the underlying patterns and relationships in the data, making it a favorable choice over XGBoost when seeking a model that exhibits greater stability and consistency in predicting outcomes.