Assignment 2 - CBD3334 - Data Mining and Analysis

Topic: Mobile Price prediction using phone Specifications - Regression

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Main Sections

1. Data collection
2. Pandas profiling report
3. EDA
4. Data Pre-processing
5. Model Pre-processing
6. Modelling and testing Pipeline
7. Hyper-parameter tuning
8. Tuned parameters computing models
9. Conclusions

Importing packages

- all the required packages are imported starting from the loading the dataset in the form csv till the validation of model performance and plotting the values using visualization tools

In [1]:
```
from pandas import read_csv
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from tabulate import tabulate
import numpy as np
from sklearn.preprocessing import LabelEncoder
import scipy.stats as stats
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.ensemble import RandomForestRegressor,GradientBoostingRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split
import hvplot.pandas
import plotly.express as px
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.feature_selection import SelectKBest, f_regression

import ydata_profiling as pp
```

```python
import warnings
warnings.filterwarnings('ignore')
```

1. Data Collection

We gathered the data from Kaggle source (https://www.kaggle.com/datasets/pratikgarai/mobile-phone-specifications-and-prices).

Our data consist on Mobile Phone specifications along with the numerical-continuous target **price** of the phones.

Dataset Description:

- **Name** - Name of the mobile phone
- **Brand** - The Brand name of the particular mobile phone
- **Model** - Model name specifces the version of the particular mobile phone (eg: iphone13 has mini,pro,promax as model names)
- **Battery capacity (mAh)** - Defines the battey capacity in milli Amphere (hour)
- **Screen size (inches)** - diagonal measurement of the screen in inches
- **Resolution x & y** - are the pixel values of respective axes
- **Processor** - total number of physical and virtual processor
- **RAM (MB)** - processing memory is specified in MegaBytes
- **Internal Storage (GB)** - storage size of the phone in GigaBytes
- **Rear and Front Camera** - pixel capturing ability of the phonee using camera lens in MegaPixels
- **Operating System** - the operating system of the phone
- **Number of SIMs** - total number of SIM cards that can be accomodated in the phone
- Boolean columns that define if the phone has the following features:
  - **Touchscreen**
  - **Wi-Fi**
  - **Bluetooh**
  - **GPS**
  - **3G**
  - **4G/ LTE**
- **Price** (Target variable) - price of the phone in indian rupees (INR)

In [2]:
```python
#creation of pandas dataframe and defining the read_csv function to load the data
df = read_csv(r'ndtv_data_final.csv')
```

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

Out[3]:

	Unnamed: 0	Name	Brand	Model	Battery capacity (mAh)	Screen size (inches)	Touchscreen	Resolution x	Resolution y	Processor	...	Rear camera	Front camera	Operating system	Wi-Fi	Bluetooth	GPS	Number of SIMs	3G	4G/ LTE	Price
0	0	OnePlus 7T Pro McLaren Edition	OnePlus	7T Pro McLaren Edition	4085	6.67	Yes	1440	3120	8	...	48.0	16.0	Android	Yes	Yes	Yes	2	Yes	Yes	58998
1	1	Realme X2 Pro	Realme	X2 Pro	4000	6.50	Yes	1080	2400	8	...	64.0	16.0	Android	Yes	Yes	Yes	2	Yes	Yes	27999
2	2	iPhone 11 Pro Max	Apple	iPhone 11 Pro Max	3969	6.50	Yes	1242	2688	6	...	12.0	12.0	iOS	Yes	Yes	Yes	2	Yes	Yes	106900
3	3	iPhone 11	Apple	iPhone 11	3110	6.10	Yes	828	1792	6	...	12.0	12.0	iOS	Yes	Yes	Yes	2	Yes	Yes	62900
4	4	LG G8X ThinQ	LG	G8X ThinQ	4000	6.40	Yes	1080	2340	8	...	12.0	32.0	Android	Yes	Yes	Yes	1	No	No	49990

5 rows × 22 columns

In [4]:
```
# function to show the number of columns and rows of a dataset, including column names
def display_shape_and_columns(df, colnames=True):
    print("# of Rows:", df.shape[0])
    print("# of Columns:", df.shape[1])
    if colnames:
        print("Column names:", df.columns.to_list())
display_shape_and_columns(df)
```

```
# of Rows: 1359
# of Columns: 22
Column names: ['Unnamed: 0', 'Name', 'Brand', 'Model', 'Battery capacity (mAh)', 'Screen size (inches)', 'Touchscreen', 'Resolution x', 'Resolution y', 'Processor', 'RAM (MB)', 'Internal storage (GB)', 'Rear came
ra', 'Front camera', 'Operating system', 'Wi-Fi', 'Bluetooth', 'GPS', 'Number of SIMs', '3G', '4G/ LTE', 'Price']
```

In [5]:
```
# get rid of the unnecesary unnamed column
df.drop('Unnamed: 0', axis=1, inplace=True)
display_shape_and_columns(df)
```

```
# of Rows: 1359
# of Columns: 21
Column names: ['Name', 'Brand', 'Model', 'Battery capacity (mAh)', 'Screen size (inches)', 'Touchscreen', 'Resolution x', 'Resolution y', 'Processor', 'RAM (MB)', 'Internal storage (GB)', 'Rear camera', 'Front ca
mera', 'Operating system', 'Wi-Fi', 'Bluetooth', 'GPS', 'Number of SIMs', '3G', '4G/ LTE', 'Price']
```

2. Pandas Profiling Report

Pandas Profiling Report is a powerful tool that allows to perform a complete Exploratory Data Analysis on a very few lines of code.

Let's generate this report and save it, using our phone dataset.

In [6]:
```
pandas_profile_report=pp.ProfileReport(df)
```

In [7]:
```
pandas_profile_report.to_file('analytics.html')
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]
Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]
Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]
Export report to file:   0%|          | 0/1 [00:00<?, ?it/s]
```

3. Exploratory Data Analysis

Let's dive into an exploratory data analysis of our available dataset.

We will define a Class for the EDA

Methods used in the following class are:

- Check for missing values
- Check for duplicated values
- Numeric column summary and statistics
- Clear information on the data_types present in the columns
- colPrice method helps in understanding the distribution of the numeric values and articulate primary idea of the data
- calculateOutliers and outliersBox methods are used to detect the extreme values present in the numeric columns
- frecount and bollvalue plots are used to list out the categorical values and also frequency chart for each unique values present in the partciular categorical columns
- corr method is utlised to check the general correaltion of numeric features present in the data

In [8]:
```
class EDABasic:
    def __init__(self, df, numcols, catcols):
        #constructor is used to initalize the dataframe, numeric columns and categoical columns
        self.df = df
        self.numcols = numcols
        self.catcols = catcols
        self.basicEDA()

    def basicEDA(self):
        '''
            function: basicEDA -> This function is used for the basic EDA of data frame such as shape, statstic summary
            arg: None
            return: None
        '''
        # checking the shape of the data frame
        shape = self.df.shape
        print("SHAPE OF DATAFRAME:")
        print('Columns = {}'.format(shape[0]))
        print('Rows = {}\n\n'.format(shape[1]))

        # cheking the missing values
        nullValues = self.df.isna().sum()
        noNull = 'No Null values' if nullValues.sum == 0 else nullValues
        print('Checking the missing values:\n')
        print('Missing values:\n{}\n\n'.format(noNull))

        # checking the duplicates
        duplicates = self.df.duplicated().sum()
        noduplicates = 'No Duplicat values' if duplicates == 0 else duplicates
        print('Checking the Duplicate values:')
        print('Duplicate values = {}\n\n'.format(noduplicates))

        # statstic summary of data frame
        print('The static summary: ')
        des = self.df.describe().T.reset_index()
        des.rename({'Index': 'Stats'}, inplace=True)
        dasData = des.to_dict(orient='list')
        table = tabulate(dasData, headers='keys', tablefmt='github', numalign='right') # tabulate converts data into table format
        print(table, '\n\n')

        # information of the data set
        print('The information: ')
        print(self.df.info(),'\n\n')

    def colPrice(self):
```

```python
        '''
            function: colPrice -> shows the distribution of price in against other numaric columns in data frame using line graph
            arg: df (pandas.core.frame.DataFrame) -> data frame
            return: None
        '''
        #gathering all numerical column names into a list for easy access
        numlist = self.numcols.columns.tolist()
        plt.figure(figsize=(5, 5))

        #plotting the distribution of data against price values
        for column in range(0, len(numlist)-1, 2):
            #subplots are created to have a comprised view of the distribution
            fig, axes = plt.subplots(1, 2, figsize=(10, 5))
            sns.lineplot(x=self.numcols[numlist[column]], y=self.df['Price'], data=self.numcols, ax=axes[0])
            axes[0].set_title(numlist[column])

            sns.lineplot(x=self.numcols[numlist[column + 1]], y=self.df['Price'], data=self.numcols, ax=axes[1])
            axes[1].set_title(numlist[column + 1])

            plt.show()

    def calculateOutlires(self):
        '''
            function: calculateOutlires -> calculates the outlires in each numarical columns using IQR method
            arg: df (pandas.core.frame.DataFrame) -> data frame
            return: None
        '''
        numlist = self.numcols.columns.tolist()
        #essential 5 number summaries of the numeric values are calculated
        dataList = [['Name', 'q1', 'q3', 'IQR', 'Count']]
        #quantiles are measured to isolate the outliear values present in each columns
        for column in range(len(numlist)-1):
            q1 = self.numcols[numlist[column]].quantile(0.25)
            q3 = self.numcols[numlist[column]].quantile(0.75)

            IQR = q3 - q1

            lB = q1 - 1.5 * IQR
            uB = q3 + 1.5 * IQR
            dataList.append([numlist[column],q1,q3,IQR,((self.numcols[numlist[column]] < lB) | (self.numcols[numlist[column]] > uB)).sum()])
        table = tabulate(dataList, tablefmt='pretty') # tabulate converts data into table format
        print(table)

    def outliresBox(self):
        '''
            function: outliresBox -> shows the distribution of outlires using box plots
            arg: df (pandas.core.frame.DataFrame) -> data frame
            return: None
        '''
        numlist = self.numcols.columns.tolist()
        for column in range(0, len(numlist)-1, 2):
            fig, axes = plt.subplots(1, 2, figsize=(10, 5))
            #plotting boxplots with the same combination of 2-axis
            sns.boxplot(self.numcols[numlist[column]], ax=axes[0])
            axes[0].set_title(numlist[column])

            sns.boxplot(self.numcols[numlist[column + 1]], ax=axes[1])
            axes[1].set_title(numlist[column + 1])

    def bollValuePlot(self, df):
        '''
            function: bollValuePlot -> shows the distribution of boolean features from the data set using pie charts
```

```
        arg: df (pandas.core.frame.DataFrame) -> data frame
        return: None
    '''
    #pie-chart to visualize the binary value columns
    fig, axes = plt.subplots(2, 3, figsize=(10,7))
    #flatten the axes to have side-side view
    axes = axes.flatten()
    #color palettes for the different binary values
    palettes = ['pastel', 'deep', 'bright', 'muted', 'colorblind', 'viridis']
    font_size = 15
    title_font = 20

    for i, (columnNmae, ax) in enumerate(zip(df.columns, axes)):
        size = df[columnNmae].value_counts()
        palette = sns.color_palette(palettes[i])
        ax.pie(size, labels=size.index, colors=palette, autopct='%1.1f%%', startangle=140, textprops={'fontsize': font_size})
        ax.set_title(columnNmae, fontsize=title_font)

    plt.tight_layout()
    plt.show()

def FreCount(self, col, figsize_, dispercent):
    '''
        function: FreCount -> counts the percentage of catagorical columns and show the distribution using bar plots
        arg: col (pandas.core.series.Series) -> column of the data set
             figsize_ (tuple) -> size of the graph
             dispercent (boolean) -> 1: display the percentage of the distribution
                                     0: does not display the percentage of the distribution
        return: None
    '''
    df_brand = col.value_counts()
    #calculating the percentage of the unique values frequency
    percent = round((df_brand * 100) / self.df.shape[0], 2)

    plt.figure(figsize=figsize_)
    ax = sns.barplot(x=percent.index, y=percent.values, palette='dark')
    plt.xlabel(col.name)
    plt.ylabel('Frequency')
    plt.xticks(rotation=90)
    if dispercent:
        for i, value in enumerate(percent):
            plt.text(i, value, str(value), ha='center', va='bottom')
    plt.show()

def corr(self):
    '''
        function: corr -> Represent the correlation of each numaric column using heat map
        arg: None
        return: None
    '''
    #using pearson correlation to plot the numeric value contributions
    coff = self.df.corr(method='pearson', numeric_only=True)
    plt.figure(figsize=(12,10))
    sns.heatmap(data=coff, cmap="coolwarm", annot=True, fmt=".2f", linewidths=1, linecolor='black')
    plt.show()
```

We will separate the dataframe into **numeric and categorical columns** using our pre-defined function

Let's also **drop the Name column**, as it is not giving any significance to the prediction on analysis.

In [9]:
```
numcols = df.select_dtypes(include='number') # numeric column data set
catCols = df.select_dtypes(exclude='number') # catagorical column data set
catCols.drop(columns=['Name'], inplace=True)
```

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

Out[10]:

	Battery capacity (mAh)	Screen size (inches)	Resolution x	Resolution y	Processor	RAM (MB)	Internal storage (GB)	Rear camera	Front camera	Number of SIMs	Price
0	4085	6.67	1440	3120	8	12000	256.0	48.0	16.0	2	58998
1	4000	6.50	1080	2400	8	6000	64.0	64.0	16.0	2	27999
2	3969	6.50	1242	2688	6	4000	64.0	12.0	12.0	2	106900
3	3110	6.10	828	1792	6	4000	64.0	12.0	12.0	2	62900
4	4000	6.40	1080	2340	8	6000	128.0	12.0	32.0	1	49990

In [11]:
```
print('BASIC EDA\n')
eda = EDABasic(df, numcols, catCols) # creating a class instance
```

```
BASIC EDA

SHAPE OF DATAFRAME:
Columns = 1359
Rows = 21


Checking the missing values:

Missing values:
Name                       0
Brand                      0
Model                      0
Battery capacity (mAh)     0
Screen size (inches)       0
Touchscreen                0
Resolution x               0
Resolution y               0
Processor                  0
RAM (MB)                   0
Internal storage (GB)      0
Rear camera                0
Front camera               0
Operating system           0
Wi-Fi                      0
Bluetooth                  0
GPS                        0
Number of SIMs             0
3G                         0
4G/ LTE                    0
Price                      0
dtype: int64


Checking the Duplicate values:
Duplicate values = No Duplicat values


The static summary:
| index                  |   count |    mean |       std |    min |     25% |    50% |    75% |     max |
|------------------------|---------|---------|-----------|--------|---------|--------|--------|---------|
| Battery capacity (mAh) |    1359 | 2938.49 |   873.514 |   1010 |    2300 |   3000 |   3500 |    6000 |
| Screen size (inches)   |    1359 | 5.29131 |  0.671357 |    2.4 |       5 |    5.2 |    5.7 |     7.3 |
| Resolution x           |    1359 | 811.543 |   270.707 |    240 |     720 |    720 |   1080 |    2160 |
| Resolution y           |    1359 | 1490.78 |    557.78 |    320 |    1280 |   1280 |   1920 |    3840 |
| Processor              |    1359 | 5.55114 |   2.19656 |      1 |       4 |      4 |      8 |      10 |
| RAM (MB)               |    1359 | 2488.78 |   1664.44 |     64 |    1000 |   2000 |   3000 |   12000 |
| Internal storage (GB)  |    1359 | 30.6549 |   36.9502 |  0.064 |       8 |     16 |     32 |     512 |
| Rear camera            |    1359 | 12.0702 |   8.94834 |      0 |       8 |   12.2 |     13 |     108 |
| Front camera           |    1359 | 7.03797 |   6.29545 |      0 |       2 |      5 |      8 |      48 |
| Number of SIMs         |    1359 |  1.8337 |  0.374457 |      1 |       2 |      2 |      2 |       3 |
| Price                  |    1359 | 11465.8 |   13857.5 |    494 |  4763.5 |   6999 |  11999 |  174990 |


The information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1359 entries, 0 to 1358
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   Name                    1359 non-null   object
 1   Brand                   1359 non-null   object
```

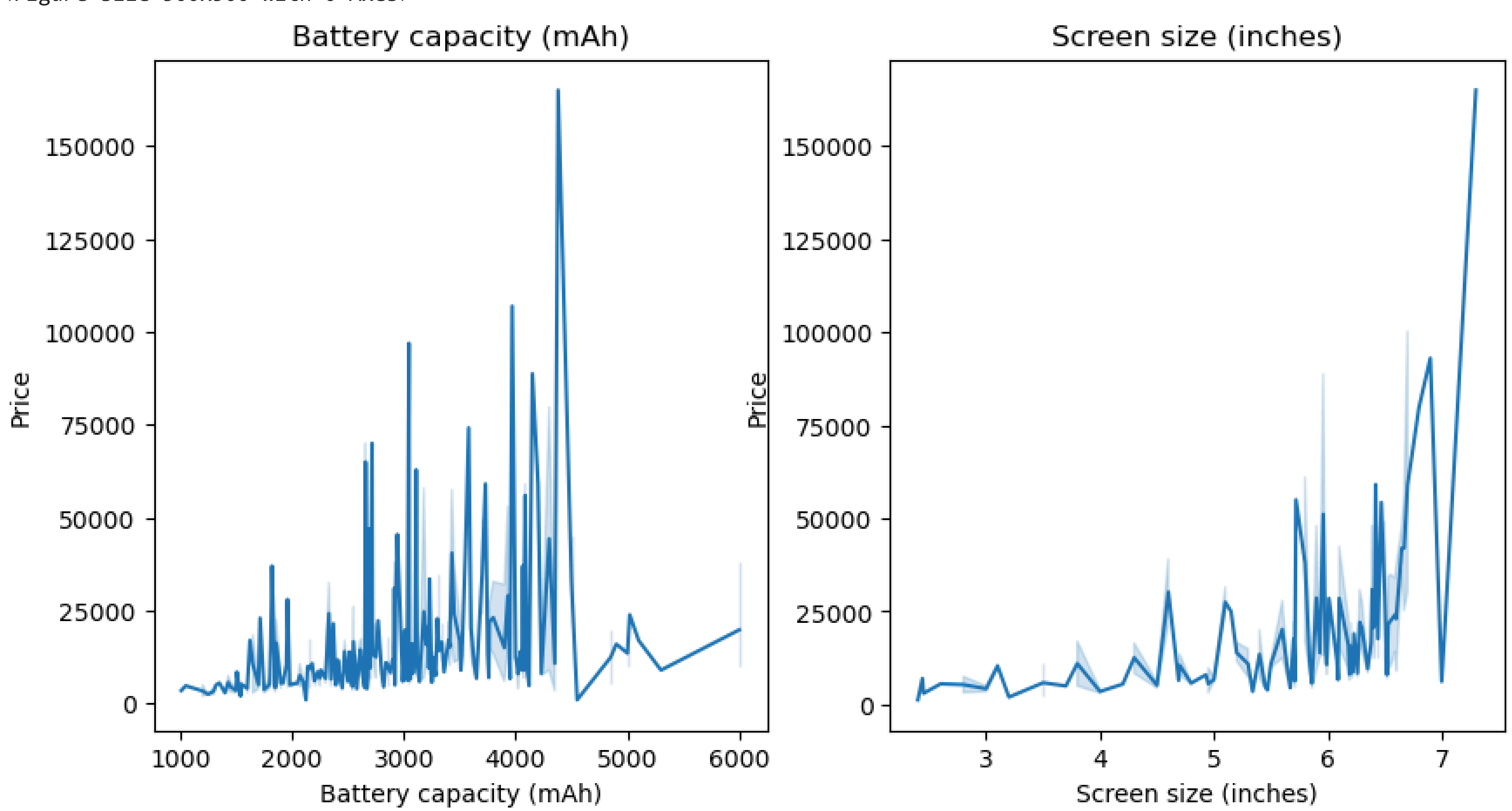
```
 2   Model                   1359 non-null   object 
 3   Battery capacity (mAh)  1359 non-null   int64  
 4   Screen size (inches)    1359 non-null   float64
 5   Touchscreen             1359 non-null   object 
 6   Resolution x            1359 non-null   int64  
 7   Resolution y            1359 non-null   int64  
 8   Processor               1359 non-null   int64  
 9   RAM (MB)                1359 non-null   int64  
 10  Internal storage (GB)   1359 non-null   float64
 11  Rear camera             1359 non-null   float64
 12  Front camera            1359 non-null   float64
 13  Operating system        1359 non-null   object 
 14  Wi-Fi                   1359 non-null   object 
 15  Bluetooth               1359 non-null   object 
 16  GPS                     1359 non-null   object 
 17  Number of SIMs          1359 non-null   int64  
 18  3G                      1359 non-null   object 
 19  4G/ LTE                 1359 non-null   object 
 20  Price                   1359 non-null   int64  
dtypes: float64(4), int64(7), object(10)
memory usage: 223.1+ KB
None
```

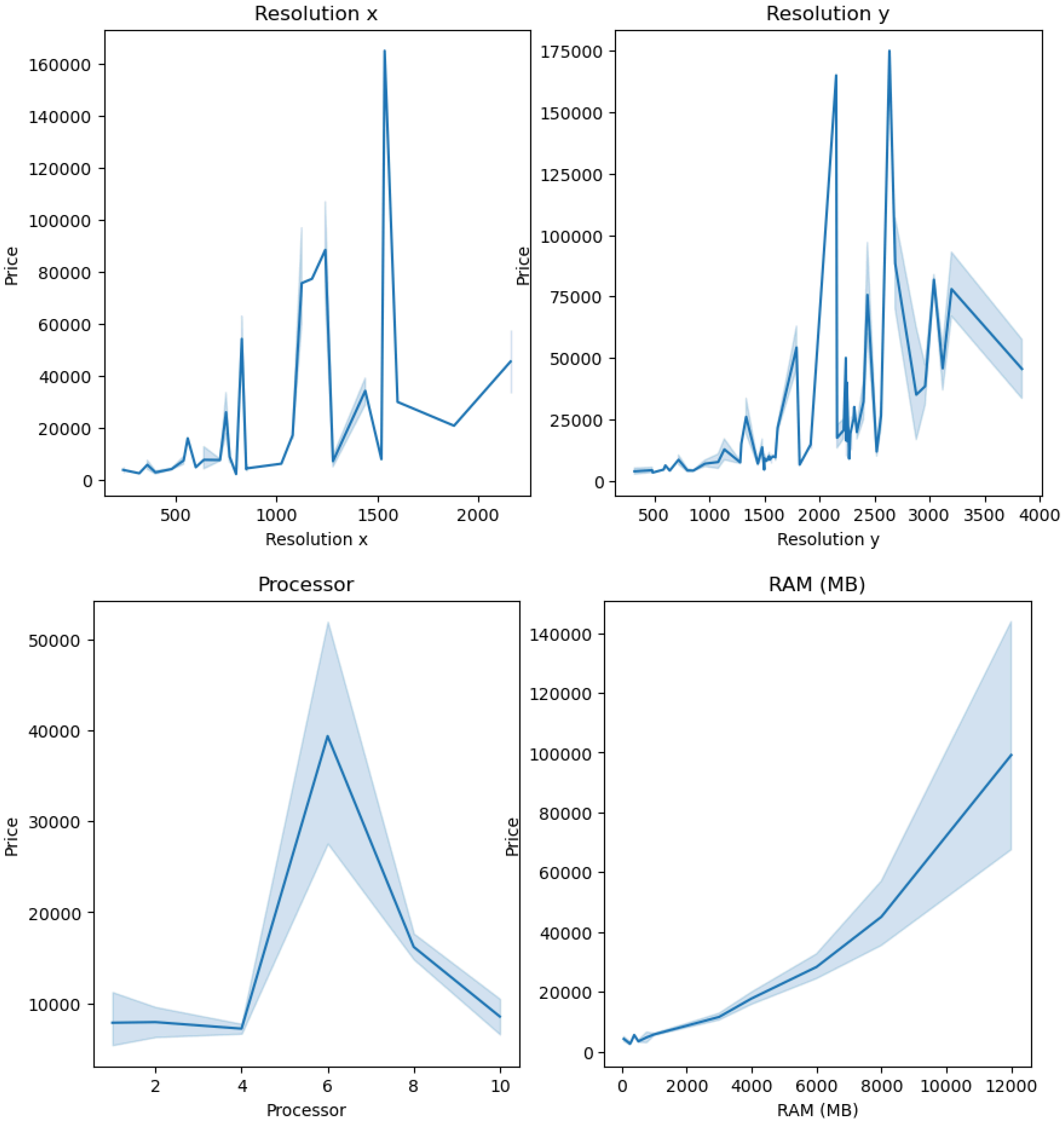
Let's plot the relationship of each numerical column with our target price.

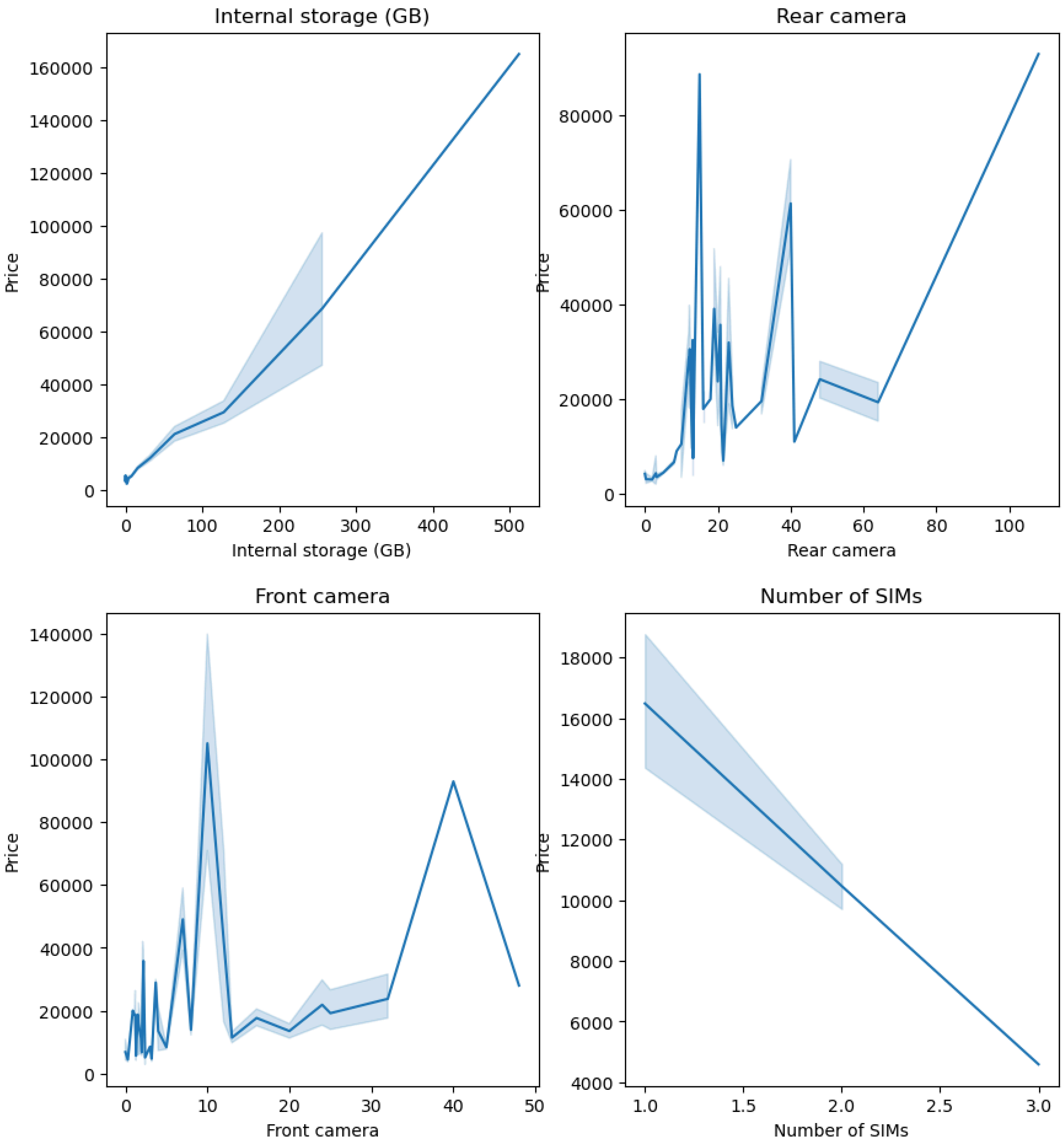
We will **visualize how the price changes depending on the behaviour of each feature.**

In [12]:
```
eda.colPrice()  #creating a method instance to plot the distrubtion of numeric values
```

```
<Figure size 500x500 with 0 Axes>
```




Resolution x
Price
Resolution x
Resolution y
Price
Resolution y
Processor
Price
Processor
RAM (MB)
Price
RAM (MB)



Insights:

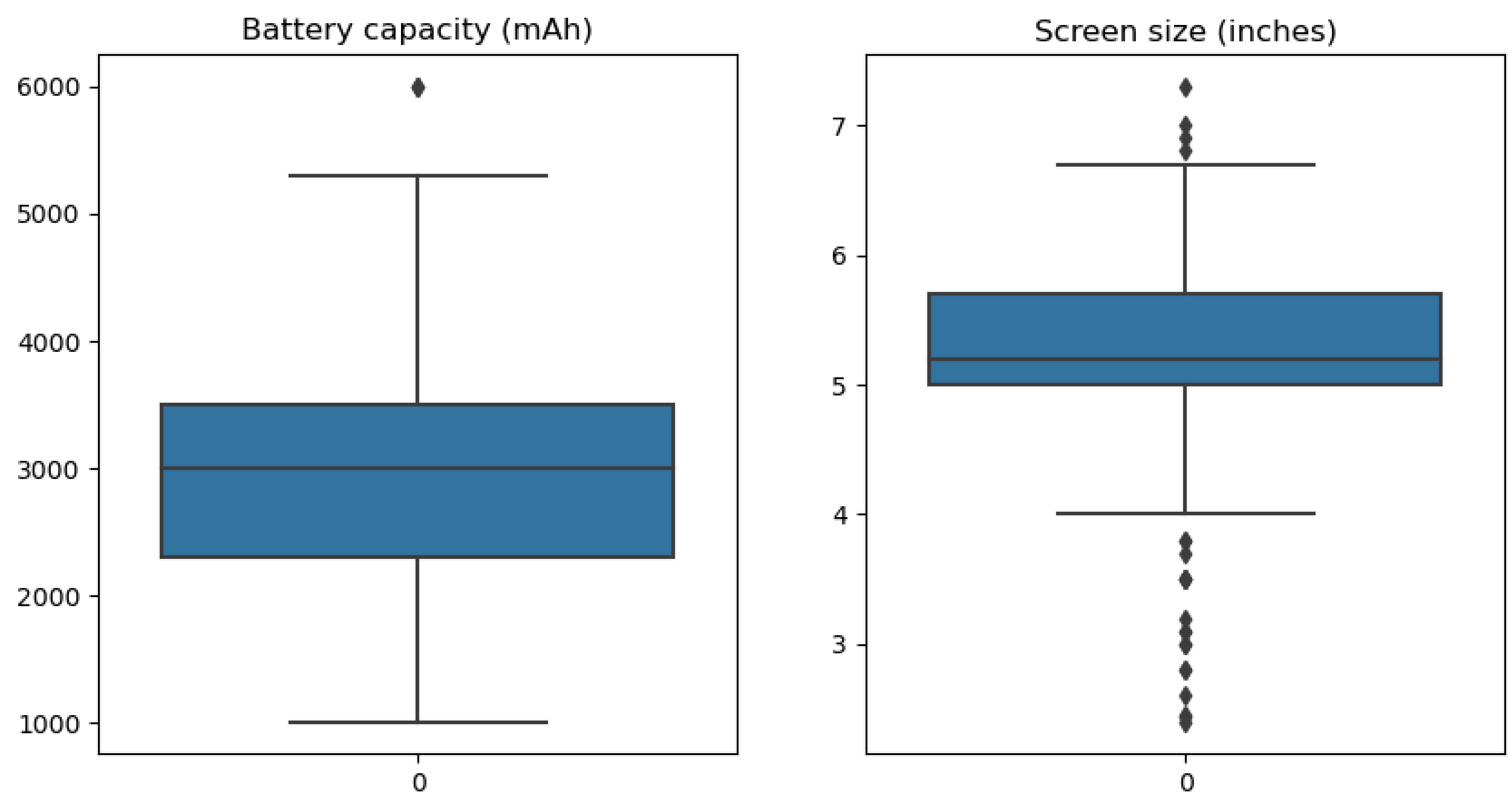
- Nearly all columns show a positive correlation between the feature and the price.
- Internal Storage (GB) and RAM (MB), both features show the strongest positive correlation to the target price.

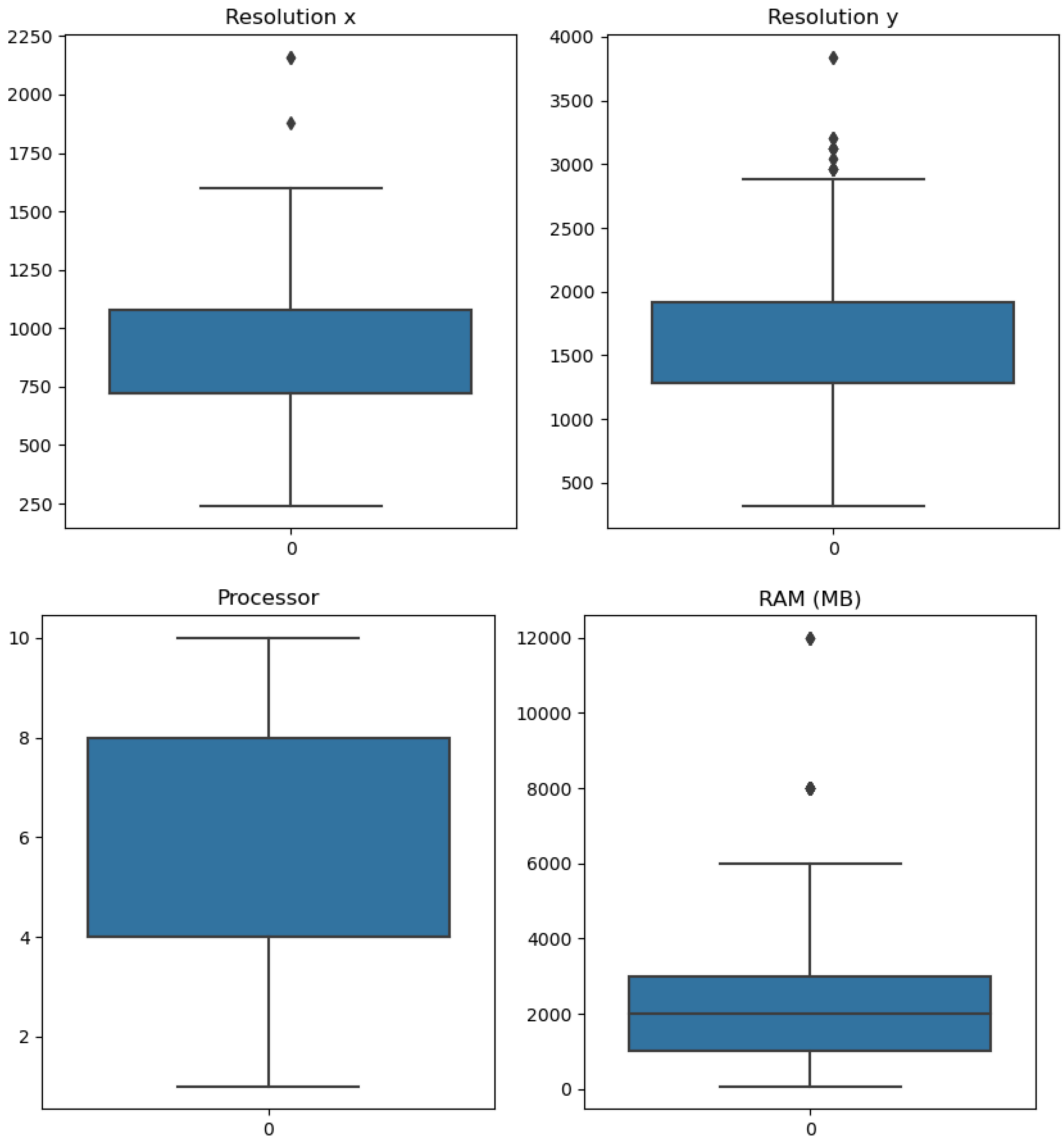
- Number of SIMs of the phone shows a negative correlation to the price, as price goes down when having more SIM cards.
- Some features (rear and front camera, processor) seem to be uncorrelated to the target, as prices have high variance

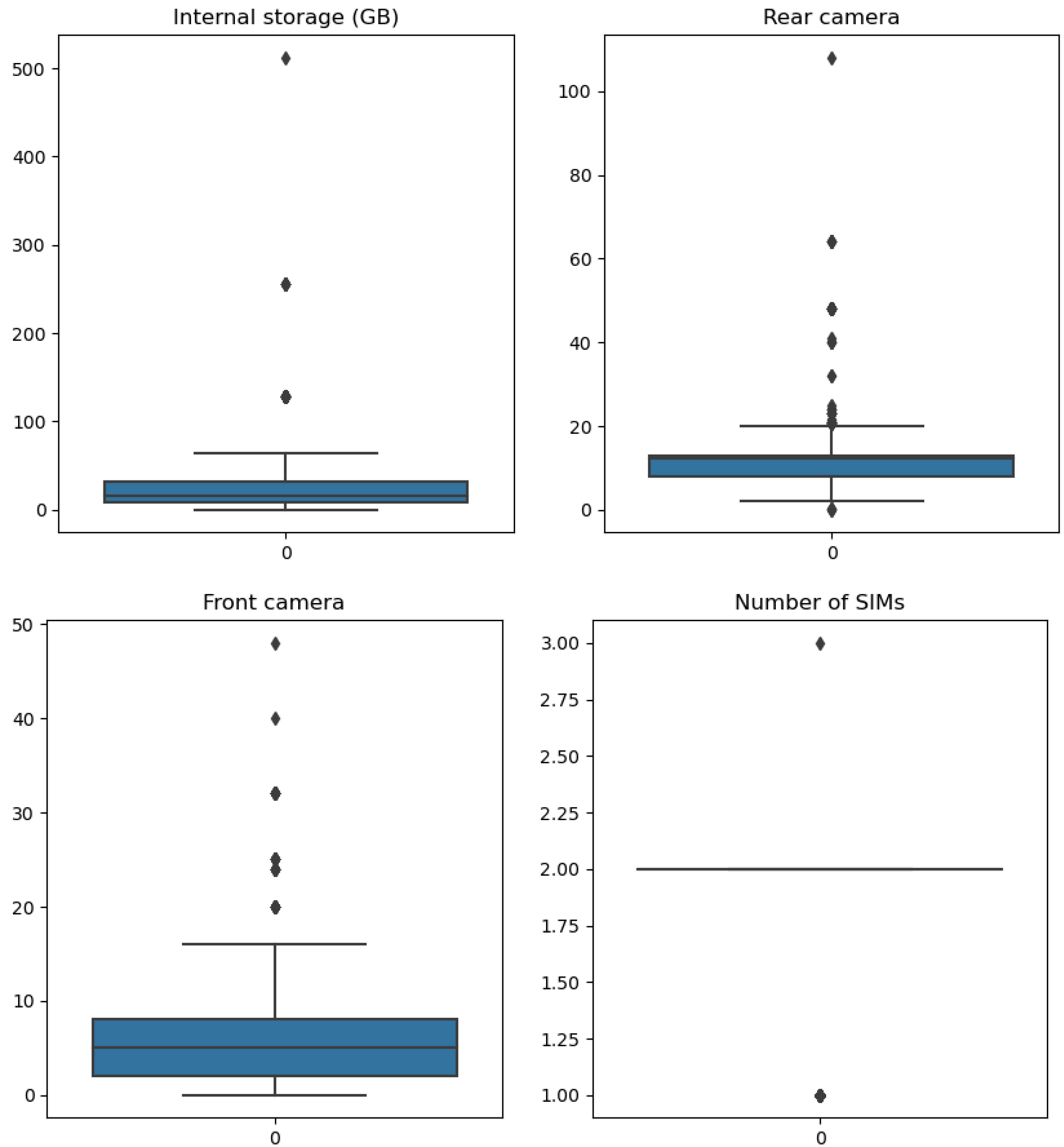
In [13]:
```
eda.calculateOutlires() #creating 5 number statistical summeries and the count values
eda.outliresBox() #plotting the boxplot
```

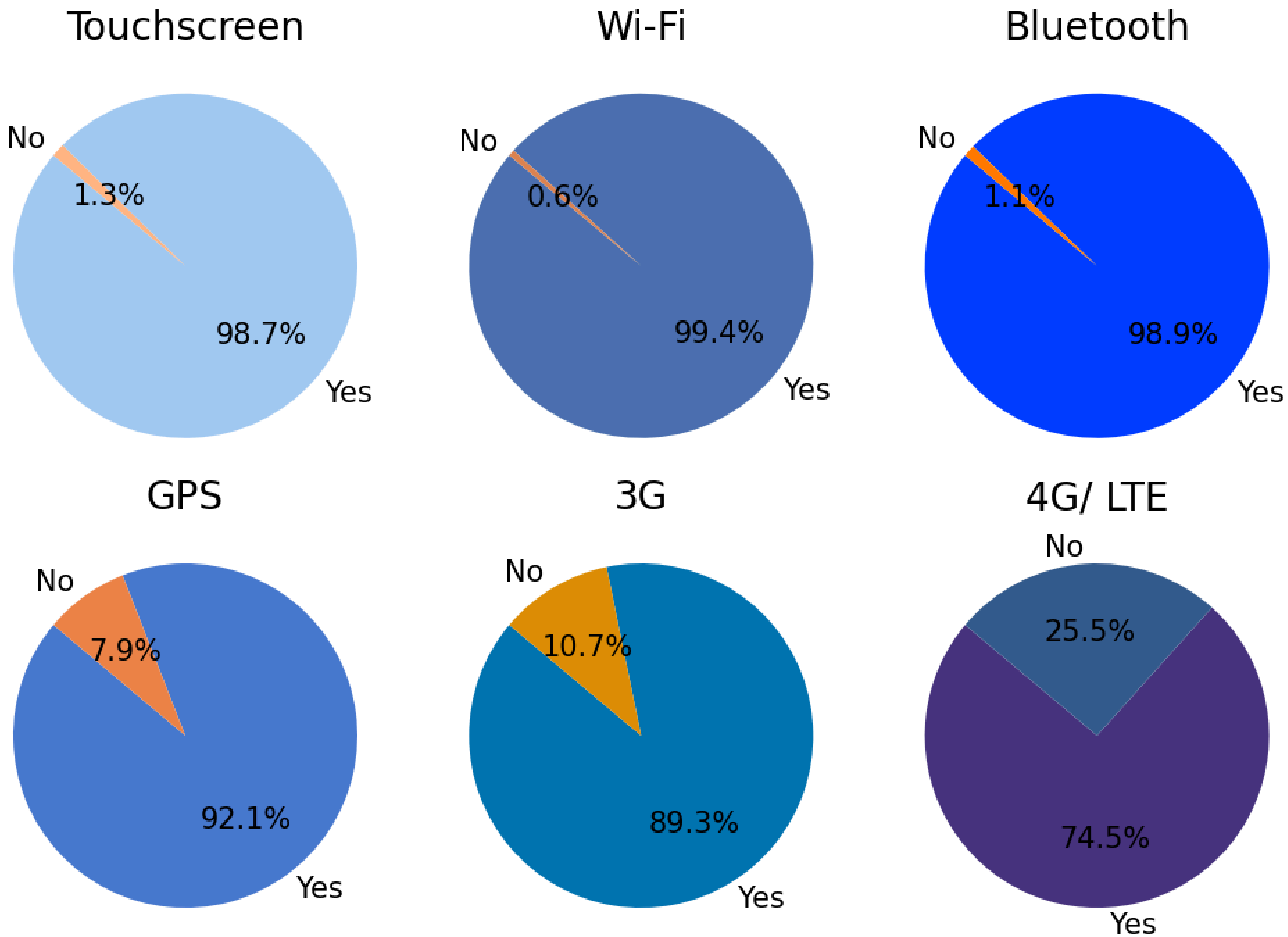
Name	q1	q3	IQR	Count
Battery capacity (mAh)	2300.0	3500.0	1200.0	3
Screen size (inches)	5.0	5.7	0.7000000000000002	22
Resolution x	720.0	1080.0	360.0	3
Resolution y	1280.0	1920.0	640.0	21
Processor	4.0	8.0	4.0	0
RAM (MB)	1000.0	3000.0	2000.0	33
Internal storage (GB)	8.0	32.0	24.0	79
Rear camera	8.0	13.0	5.0	91
Front camera	2.0	8.0	6.0	79
Number of SIMs	2.0	2.0	0.0	228

In [14]:
```
eda.bollValuePlot(catCols.drop(columns=['Brand', 'Model', 'Operating system'])) #ignoring the categorical values
```




Resolution x
2250
2000
1750
1500
1250
1000
750
500
250
0
Resolution y
4000
3500
3000
2500
2000
1500
1000
500
0
Processor
10
8
6
4
2
0
RAM (MB)
12000
10000
8000
6000
4000
2000
0
0

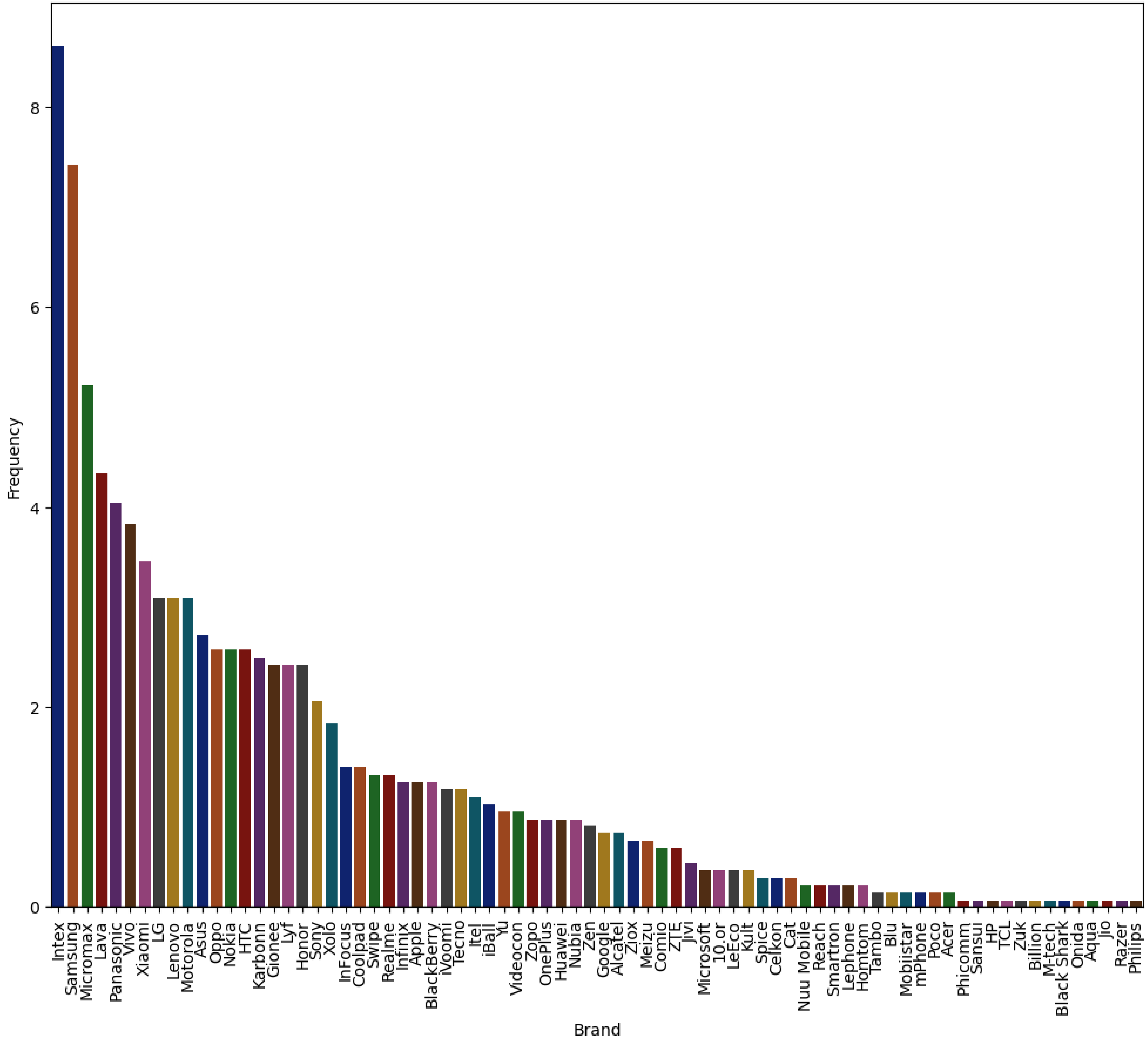

Internal storage (GB)
0
100
200
300
400
500
0
Rear camera
0
20
40
60
80
100
0
Front camera
0
10
20
30
40
50
0
Number of SIMs
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
0



Insights:

- Most features are present in most phones
- These boolean features have imbalanced classes, as most rows are having True values.
- Using boxplots we could visualize some outliers on our numerical columns.

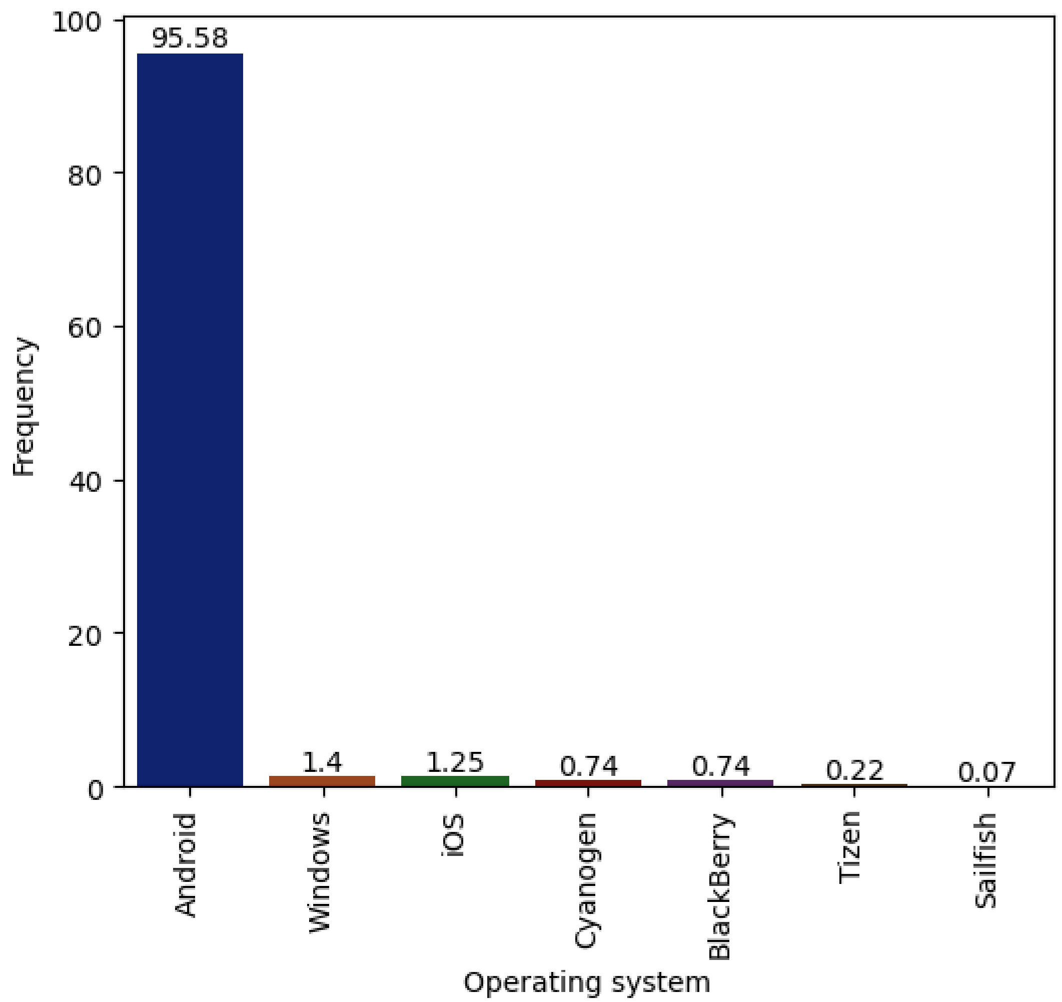
In [15]:
```
eda.FreCount(df['Brand'], (12, 10), 0) #frequency plot on the Brand name of the mobile phones
```



Insights:

- Intex is the most common brand upon the phones
- Most phones belong to 20% of the brands, while the rest are accross 80% of the brands.

In [16]:
```
eda.FreCount(df['Operating system'], (6,5), 1) #frequency plot on the operating systems of the mobile phones
```

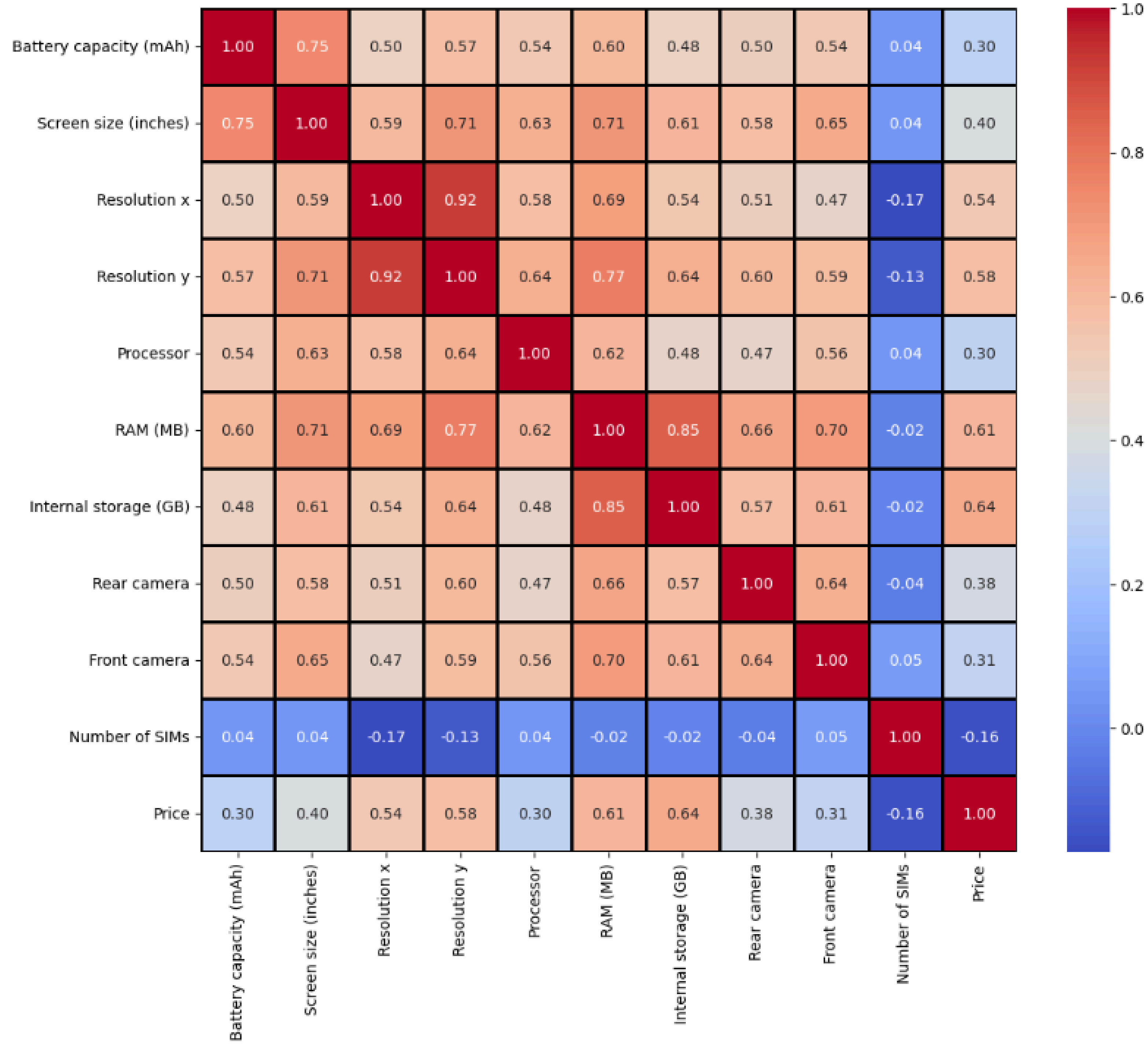


Insights:

- Our Operating System feature is totally imbalanced, showing a 95% values for Android systems
- This suggests that the feature has very low correlation to our target, as most values are equal.
- This feature could be irrelevant, as it mostly has 1 single value.

Let's **plot a heatmap** to find the relation between all our numeric features

In [17]:
```
# eda.corr()
```



Insights:

- As we suspected before, the most correlated features to our target are RAM and Internal Storage
- After those 2 features, the next 2 most correlated are Resolution X & Y of the phone.
- Most of our features are positively correlated to our target (with the exception of Number of SIMs)
- Most of our features have < 50% correlation to our target
- We have some features correlated between themselves:
  - Internal Storage vs RAM
  - RAM vs Resolution Y
  - Resolution X vs Resolution Y
  - Screen Size vs Battery capacity

These **correlation between independent variables are dangerous to future models** as the could affect the model stabilization.

4. Data Pre-processing

Let's start with the pre-processing by defining a new class **col_analyser.**

This class is in charge of the following methods:

- Analyzing categorical features of our dataframe
- Analyzing numerical features of our dataframe
- Identifying features with high correlation between themselves and to the target
- Make various visualizations for the feature analysis using QQplot.

In [18]:
```
class col_analyser:
    def __init__(self,data):
        """
        arg: dataframe to be processed for analysising the numeric and categorical columns

        function: class_constructor

        return: None
        """
        #initialising the dataframe for the following methods in the class
        self.df=data

    def categorical_analyze(self):
        """
        arg: None

        function: detailed analysis (unique value and its count) of categorical columns present in the dataframe

        return: dataframe describing each categorical variable characteristic --> used to transform for pre-processing
        """
        #creating temp_categorical column name list
        self.categorical_columns=self.df.select_dtypes(include=['object']).columns.tolist()

        cat_tab=[]
        for i in self.categorical_columns:
            #loading the number of unique values present
            unique_element_counts=self.df[i].nunique()
            #(distinct)unique values
            unique_elements=self.df[i].unique()
            cat_tab.append({'cat_column_name':i,'unique_value_counts':unique_element_counts,'unique_values':unique_elements})
        return pd.DataFrame(cat_tab)


    def numerical_analyze(self):
        """
        arg: None

        function: Visualizing the distribution and QQ plots to apply standradization on top of the numeric values before training

        return: None

        call: initiate the validation method
        """
        self.numerical_columns=self.df.select_dtypes(include='number').columns.tolist()
         #creating temp_numerical column name list
        for i in self.numerical_columns:
            unique_element_counts=self.df[i].nunique()
            sns.set_style('darkgrid')
```

```
        fig,axs=plt.subplots(1,2,figsize=(14,6))
        sns.histplot(df[i],ax=axs[1])
        stats.probplot(df[i],plot=axs[0],fit=True)
        #using prob_plot to analyse the theoretical distribution values with the actual values
        axs[0].set_title('QQ_plot')
        axs[1].set_title('distribution')
        #comparing the distribution plot
        fig.suptitle("numerical column analysis - {}".format(i))
        plt.tight_layout()
        plt.show()
    self.validation_()


def validation_(self):

    """
    arg: None

    function: overall numeric and categorical columns post analysis

    return: None
    """
    print("Categorical columns are :{}".format(self.categorical_columns))
    print("numerical columns are :{}".format(self.numerical_columns))

def correlation_with_target(self,df,target):

    """
    arg: dataframe on which correlation need to be applied
    arg: target column to calculate the correlation

    function: correlation analysis (numeric values with respect to target variable)

    return: correlation values in descending (importance) order
    """
    #target variable based correlation analysis on the numeric columns present
    return(df.corr()[target].round(3).sort_values(ascending=False))

def possible_high_correlation(self,df):


    """
    arg: dataframe

    function: identifying features of high correlation

    return:  columns which are having possiblity of correlations
    """
    #reanalysing the correaltion done prior to check the multi-collinear data present
    correlation_=df.corr()
    unique_columns_with_high_correlations=set()
    for i in range(len(correlation_.columns)):
        for j in range(i):
            #setting our threshold to 0.6 (60%) of correaltion to be allowed
            if abs(correlation_.iloc[i,j])>0.6:
                suspect_column=correlation_.columns[i]
                unique_columns_with_high_correlations.add(suspect_column)
    return(unique_columns_with_high_correlations)
```

In [19]:
```
feature_analyze=col_analyser(df) #creating the class instance for the col_analyser
```

Let's start by **analyzing unique values of our categorical features**.

In [20]:
```
feature_analyze.categorical_analyze() #analysing of the unique values and its counts (categorical values )
```

Out[20]:

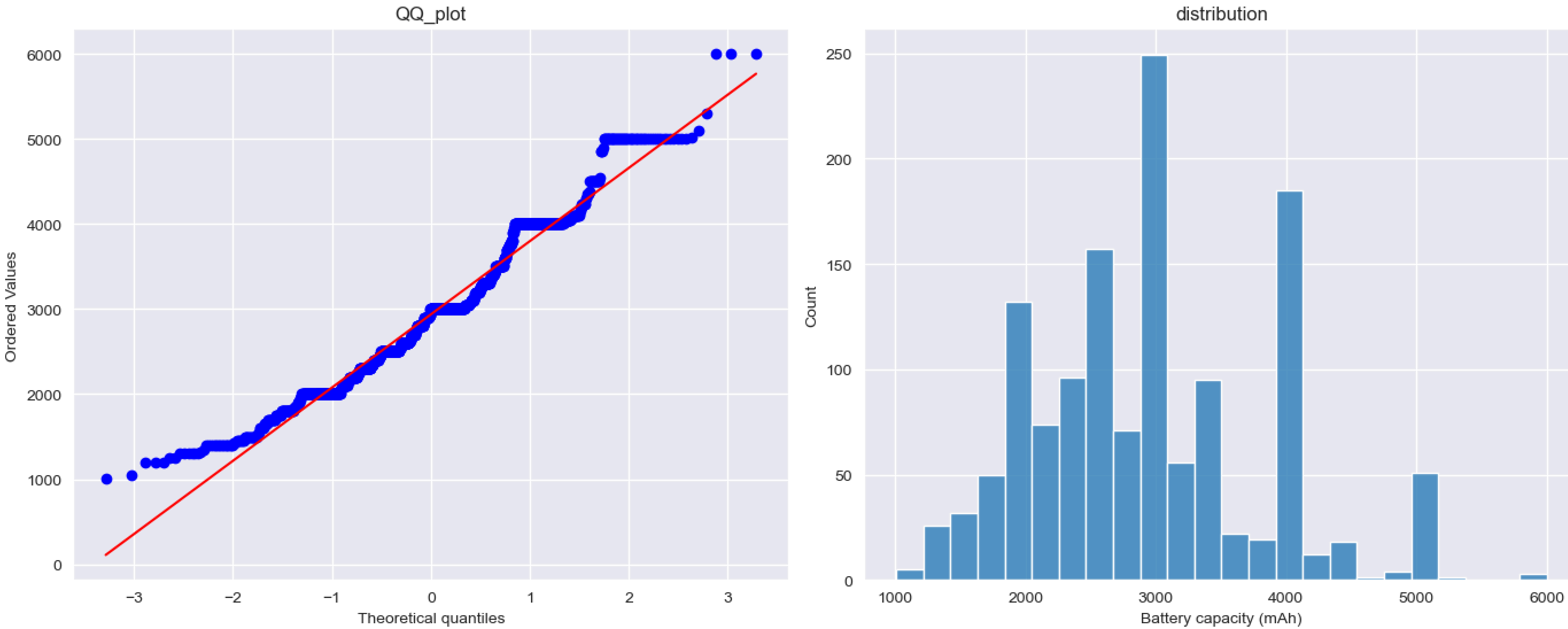
	cat_column_name	unique_value_counts	unique_values
0	Name	1359	[OnePlus 7T Pro McLaren Edition, Realme X2 Pro...
1	Brand	76	[OnePlus, Realme, Apple, LG, Samsung, Asus, Xi...
2	Model	1321	[7T Pro McLaren Edition, X2 Pro, iPhone 11 Pro...
3	Touchscreen	2	[Yes, No]
4	Operating system	7	[Android, iOS, Cyanogen, BlackBerry, Windows, ...
5	Wi-Fi	2	[Yes, No]
6	Bluetooth	2	[Yes, No]
7	GPS	2	[Yes, No]
8	3G	2	[Yes, No]
9	4G/ LTE	2	[Yes, No]

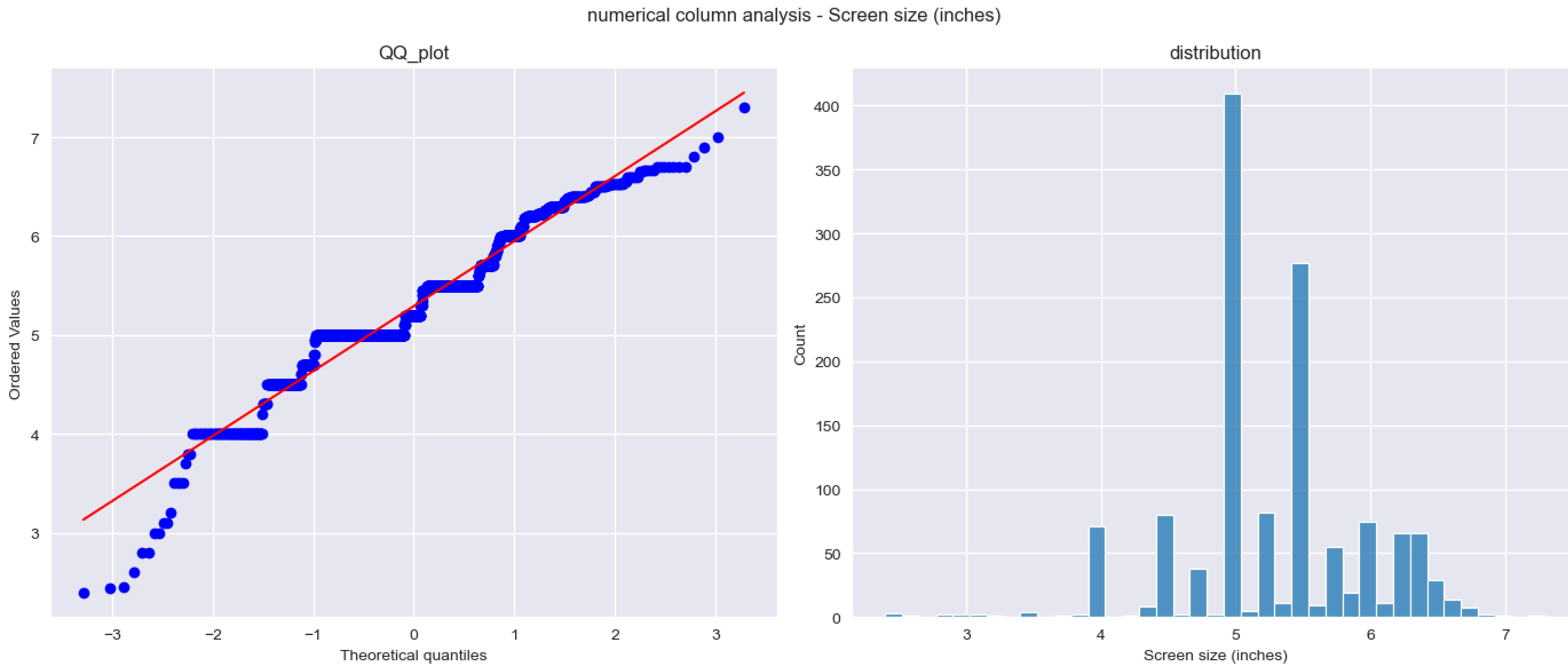
Plot distribution maps using QQ_plot

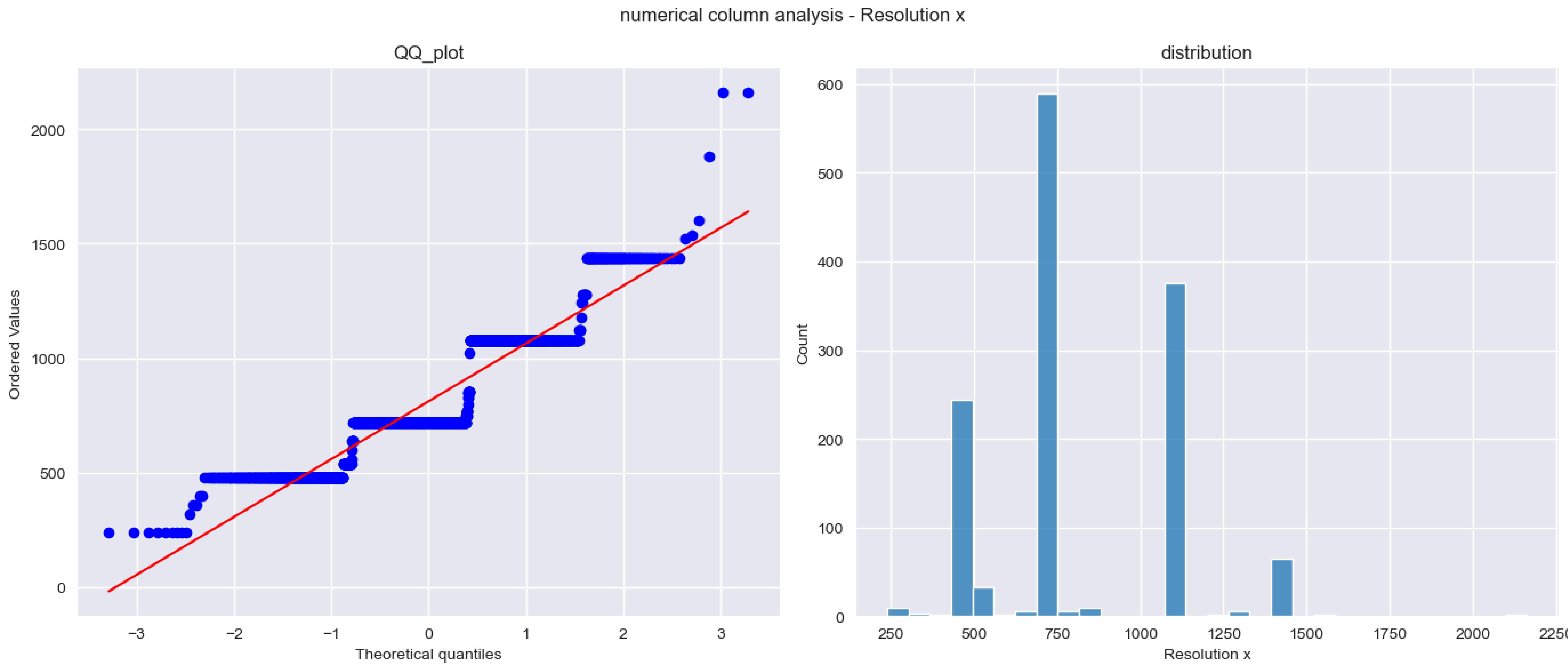
- along with the boxplot analysis that we created before, we are using QQplot now to check the numeric column analysis
- the distribution and the probability plots are displayed to do compartive analysis on the projected theoratical values and the actual values
- the discrete set of values are being ignored as they are trivial

In [21]:
```
feature_analyze.numerical_analyze()
```

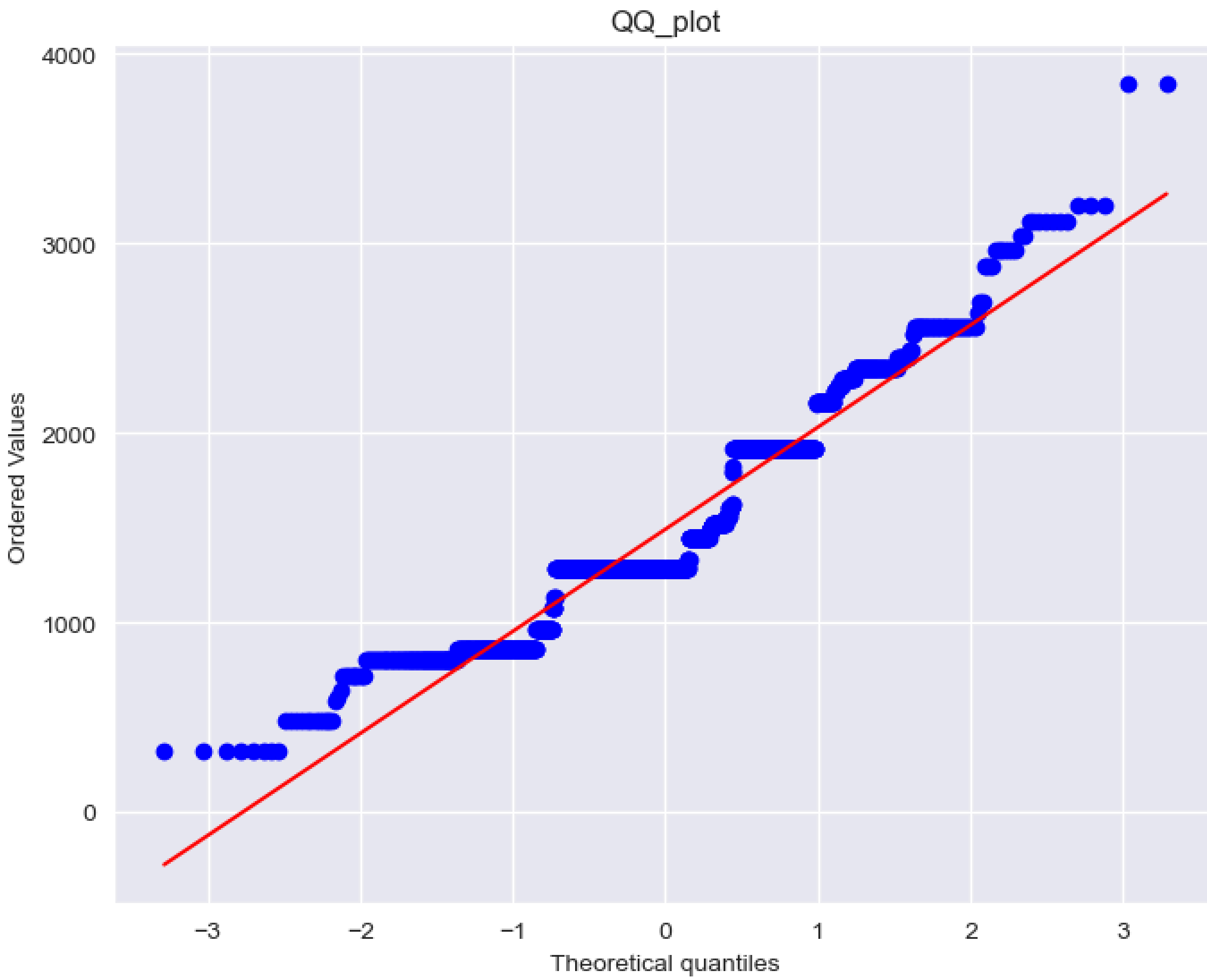
numerical column analysis - Battery capacity (mAh)

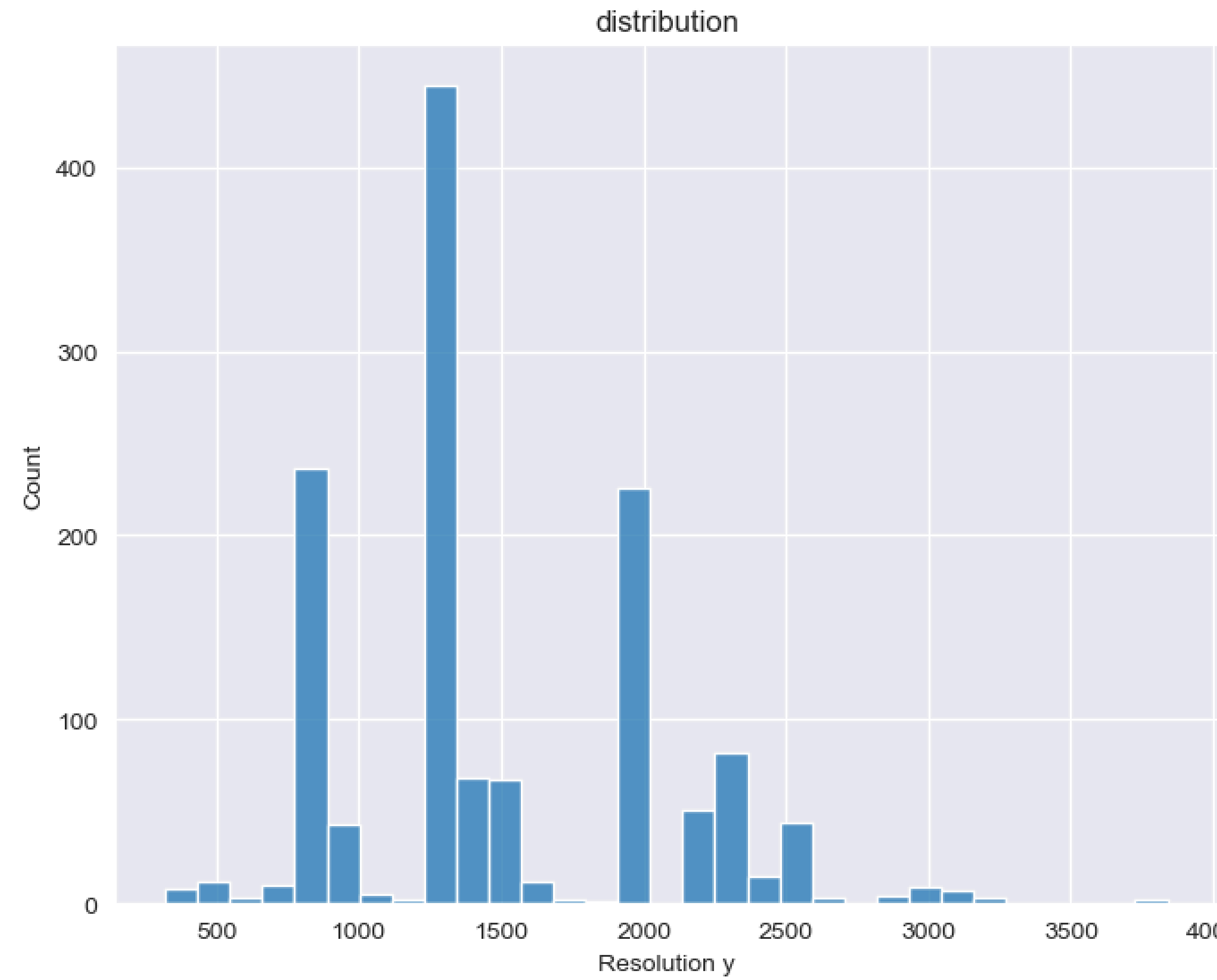


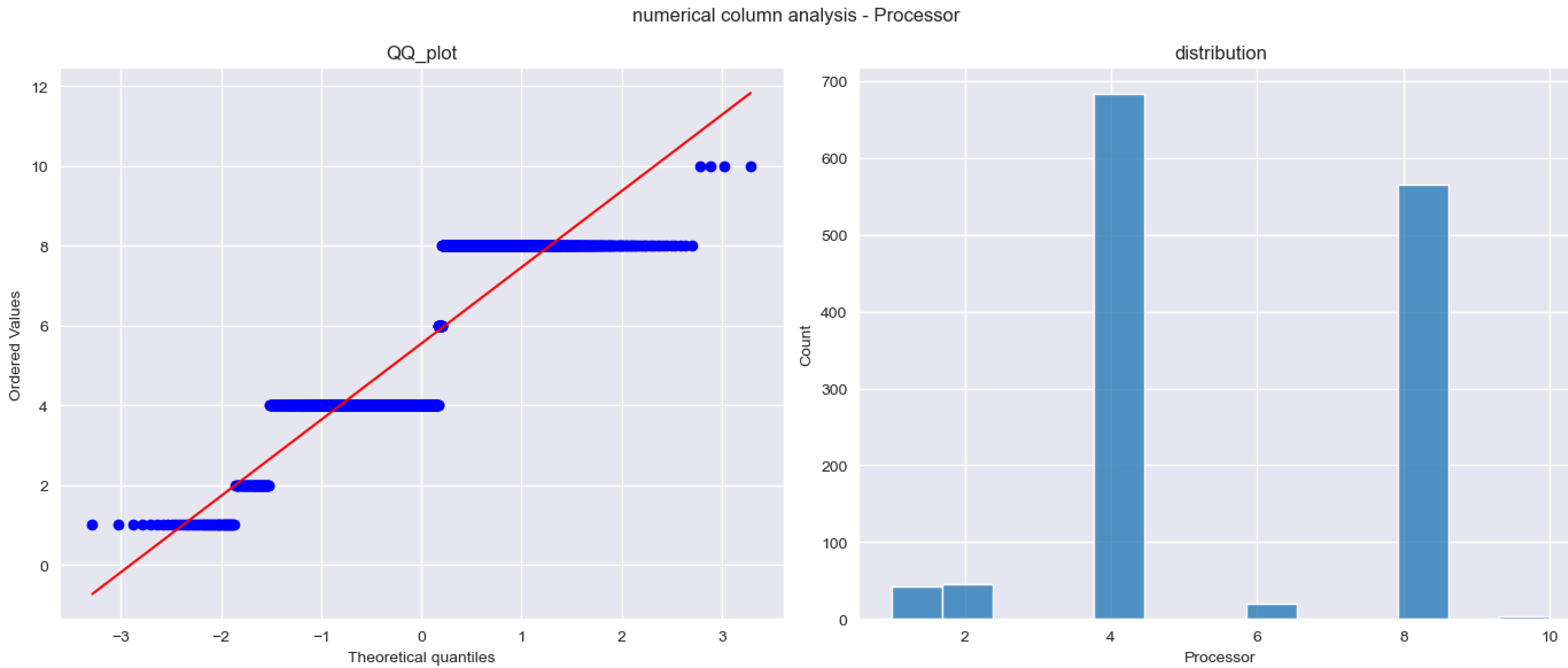

numerical column analysis - Screen size (inches)
QQ_plot
Ordered Values
Theoretical quantiles
distribution
Count
Screen size (inches)

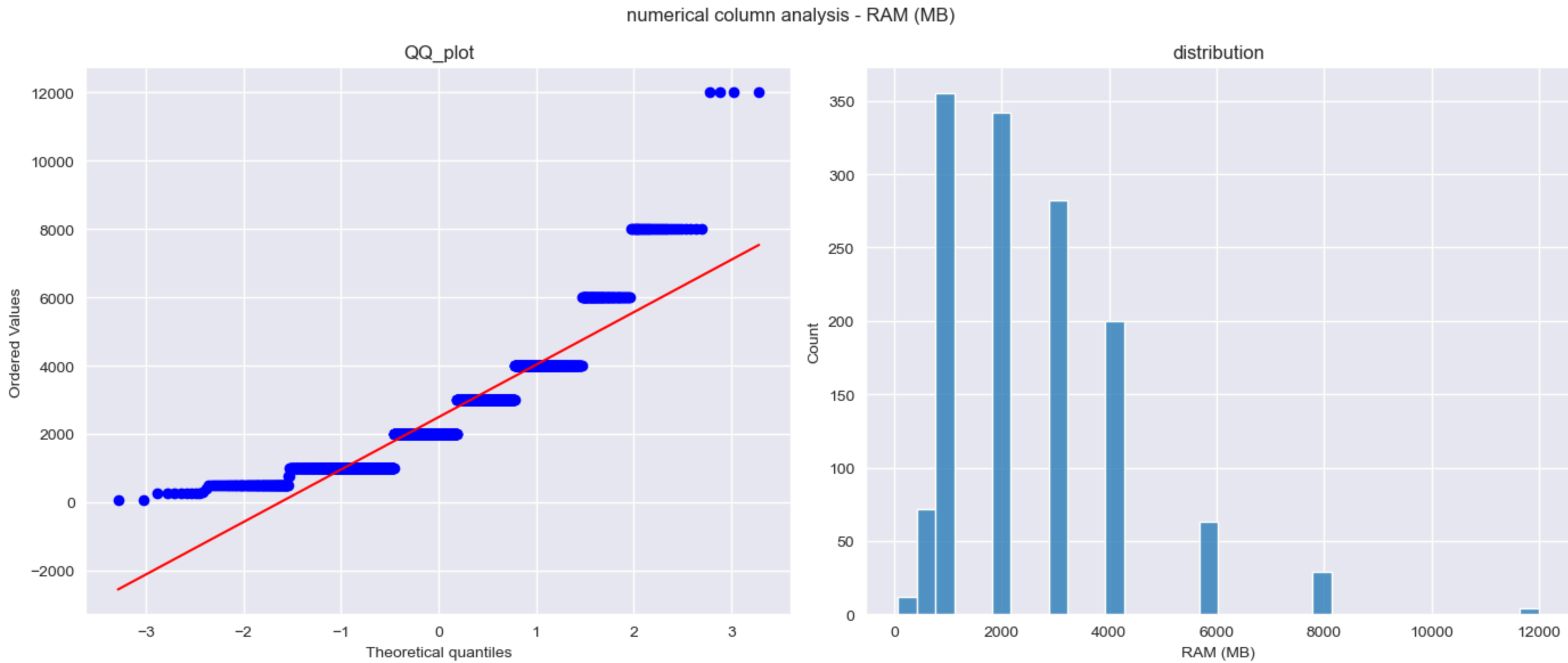

numerical column analysis - Resolution x
QQ_plot
Ordered Values
Theoretical quantiles
distribution
Count
Resolution x

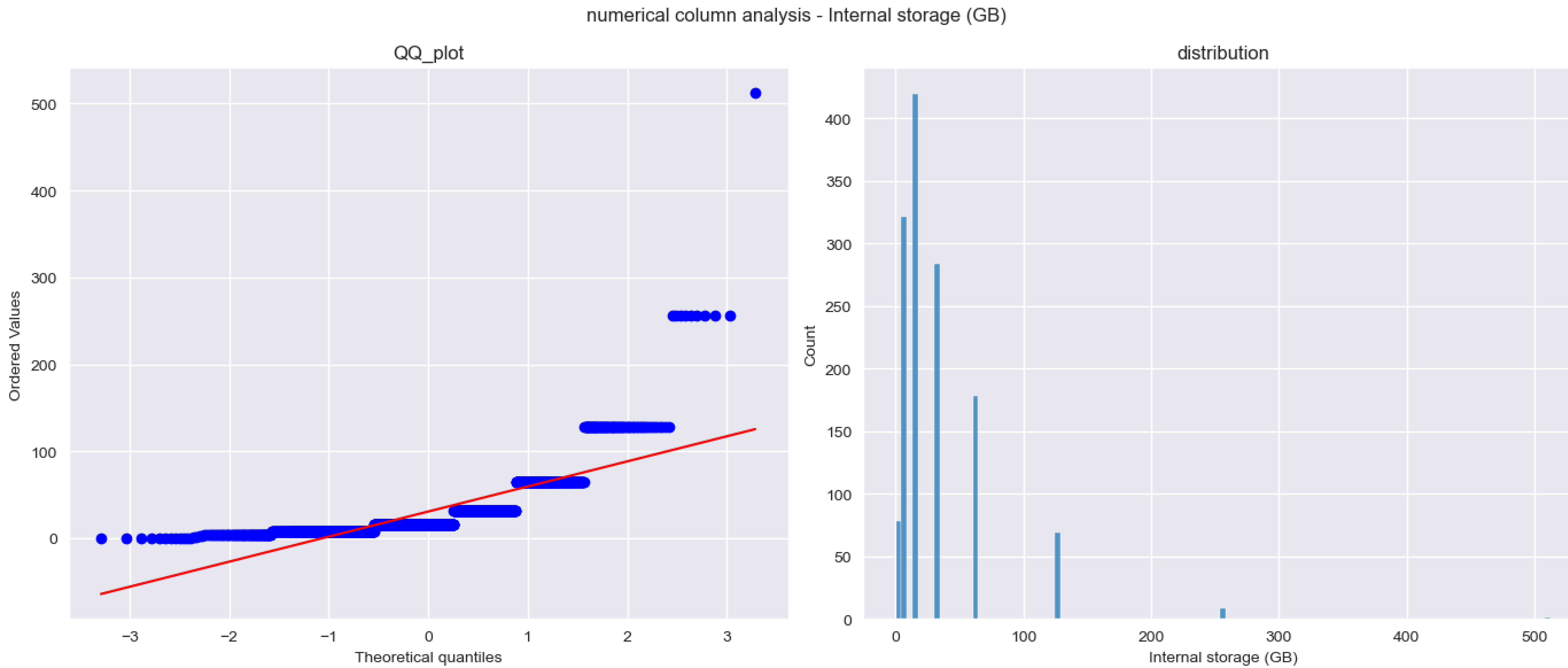
numerical column analysis - Resolution y



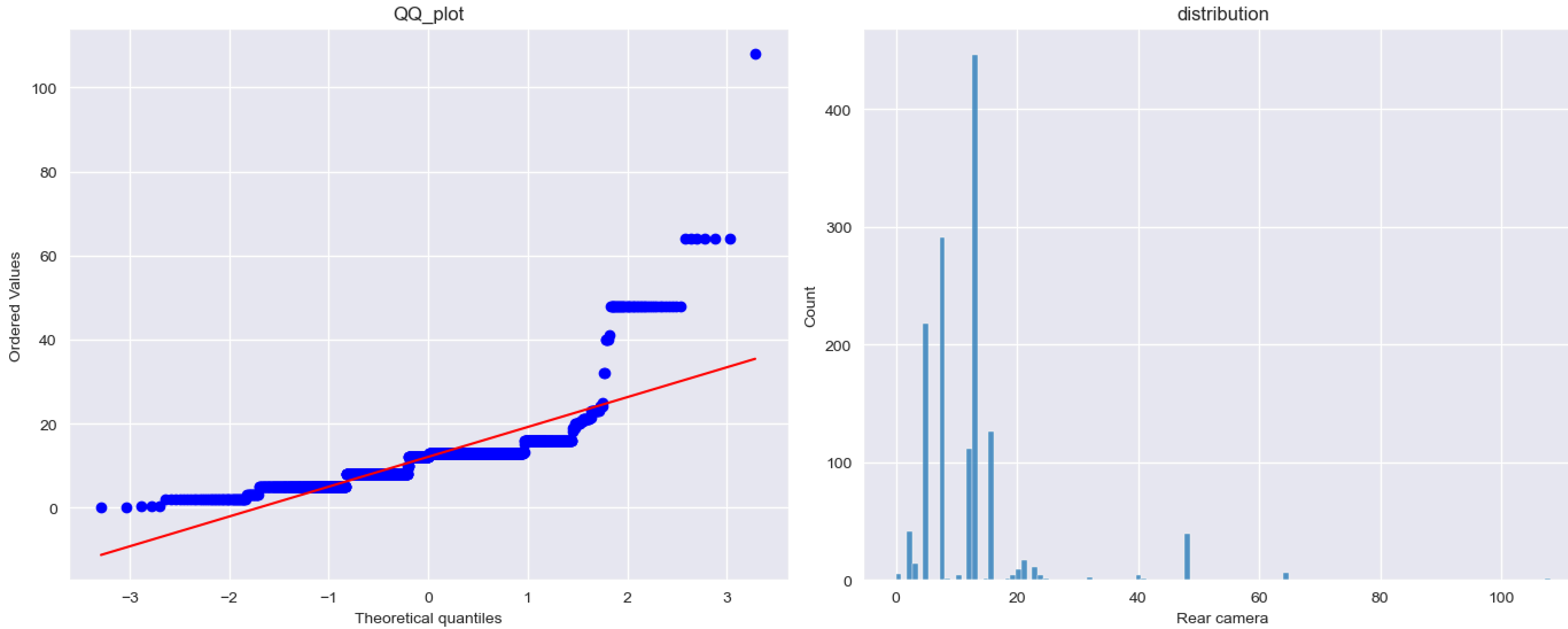


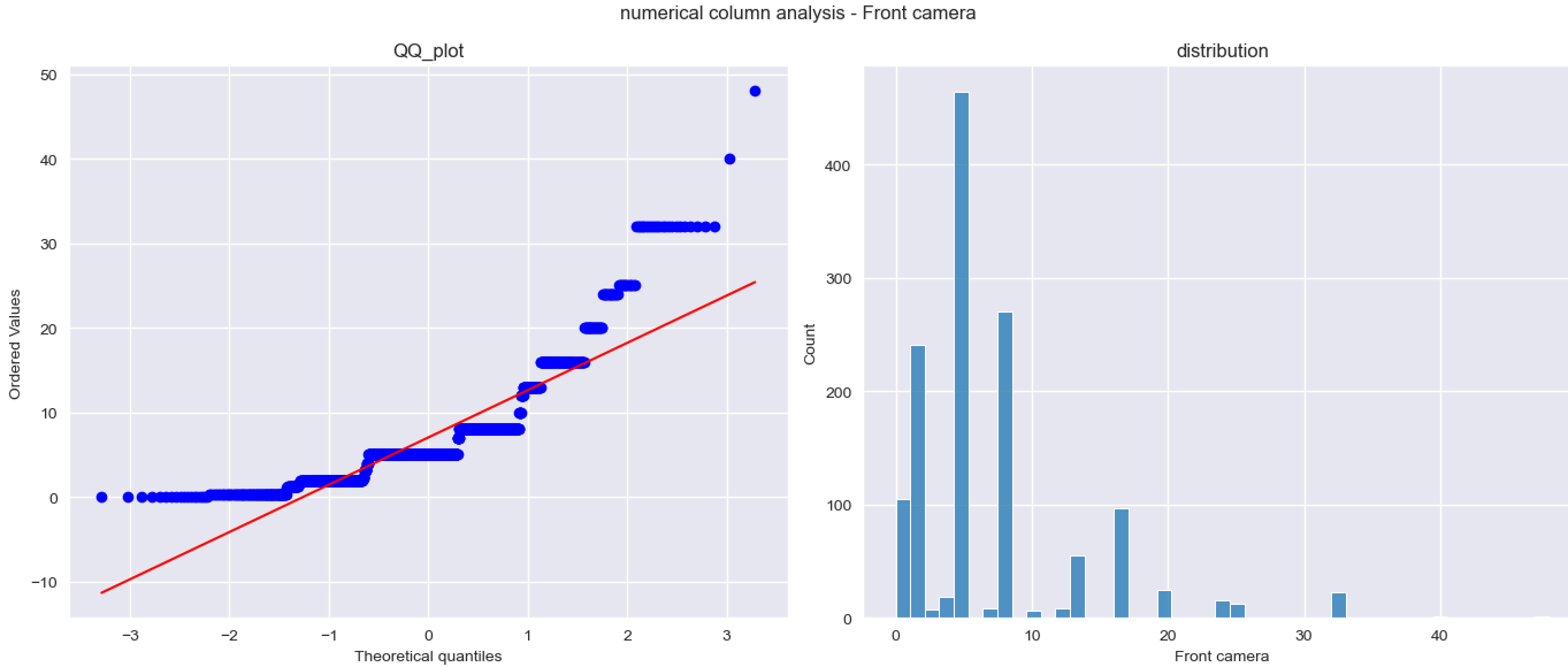

numerical column analysis - Processor
QQ_plot
Ordered Values
Theoretical quantiles
distribution
Count
Processor


numerical column analysis - RAM (MB)
QQ_plot
Ordered Values
Theoretical quantiles
distribution
Count
RAM (MB)

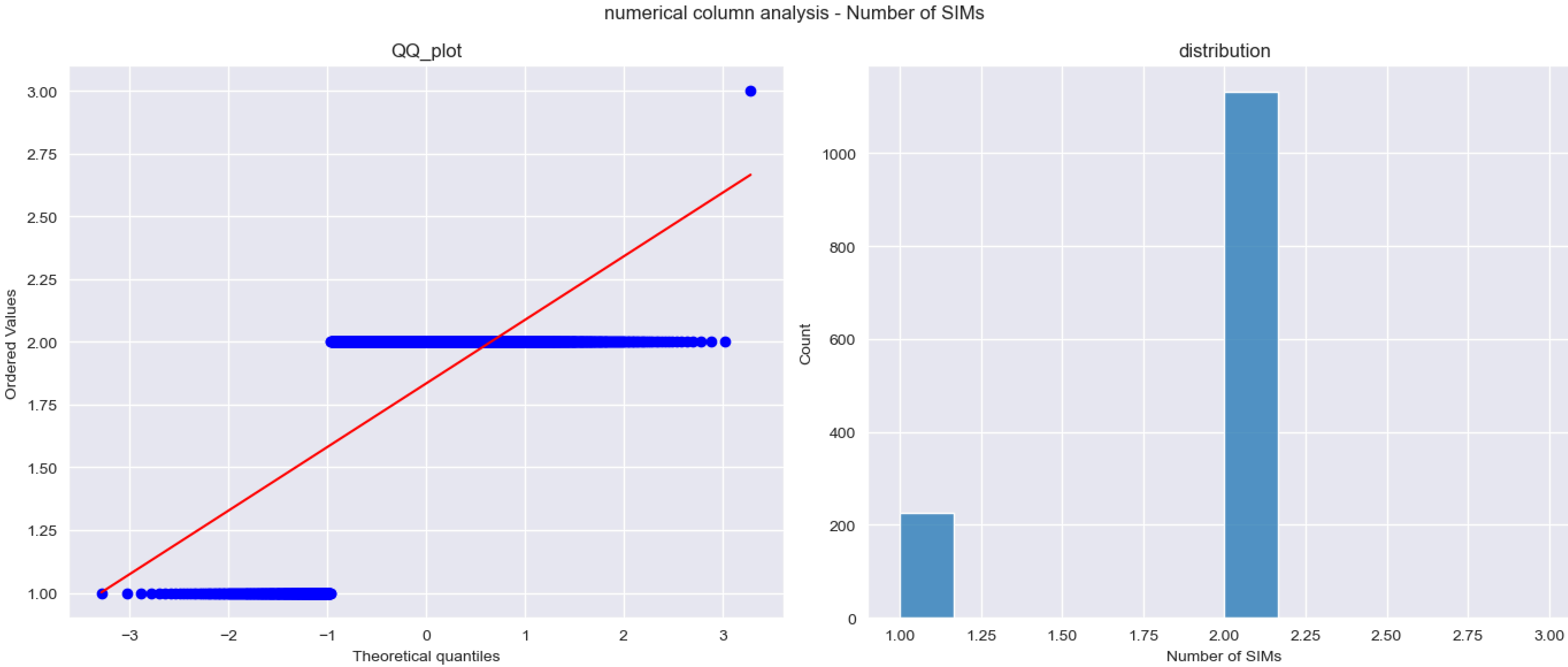

numerical column analysis - Internal storage (GB)
QQ_plot
Ordered Values
Theoretical quantiles
distribution
Count
Internal storage (GB)

numerical column analysis - Rear camera

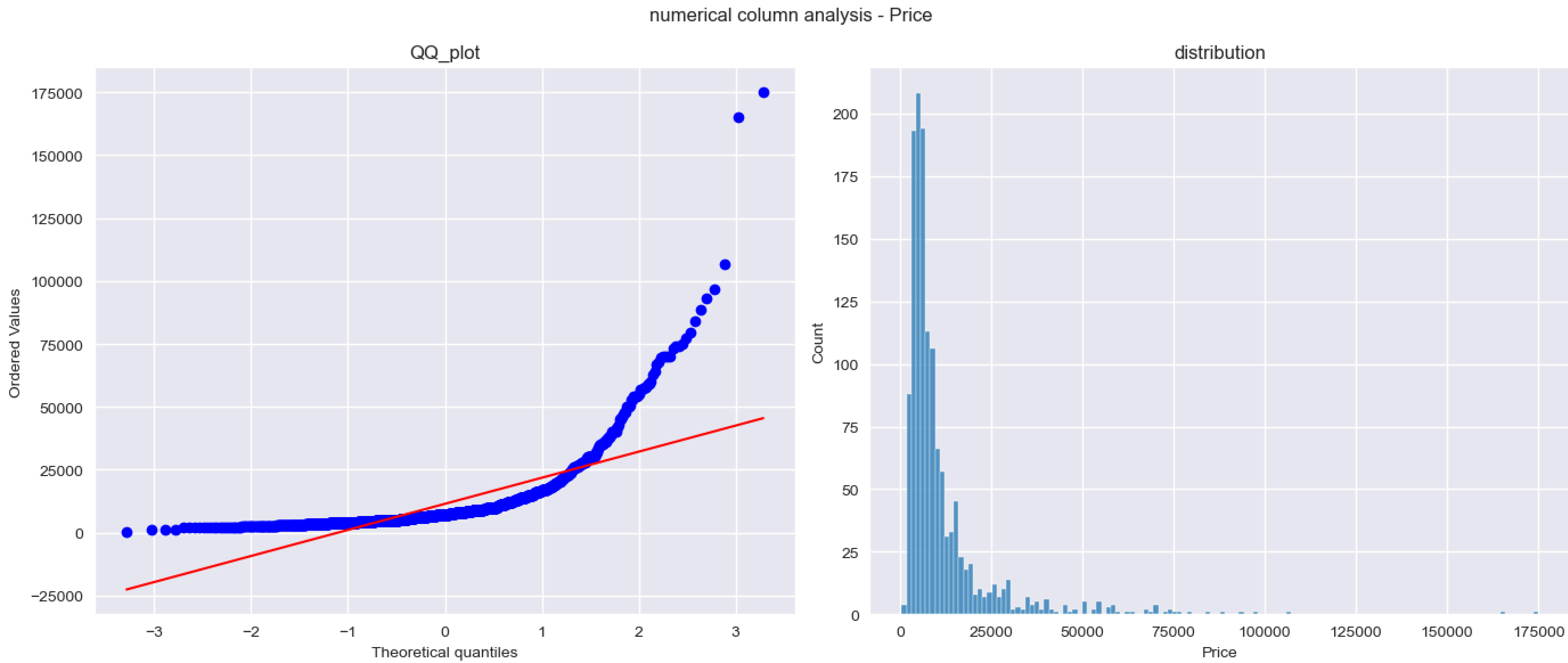




numerical column analysis - Front camera
QQ_plot
Ordered Values
Theoretical quantiles
distribution
Count
Front camera



numerical column analysis - Number of SIMs
QQ_plot
Ordered Values
Theoretical quantiles
distribution
Count
Number of SIMs




```
Categorical columns are :['Name', 'Brand', 'Model', 'Touchscreen', 'Operating system', 'Wi-Fi', 'Bluetooth', 'GPS', '3G', '4G/ LTE']
numerical columns are :['Battery capacity (mAh)', 'Screen size (inches)', 'Resolution x', 'Resolution y', 'Processor', 'RAM (MB)', 'Internal storage (GB)', 'Rear camera', 'Front camera', 'Number of SIMs', 'Pric
e']
```

In [22]:
```
feature_analyze.correlation_with_target(numcols,'Price') #TARGET VARIABLE CORREALTION
```

Out[22]:
```
Price                     1.000
Internal storage (GB)     0.644
RAM (MB)                  0.613
Resolution y              0.576
Resolution x              0.541
Screen size (inches)      0.402
Rear camera               0.379
Front camera              0.311
Processor                 0.302
Battery capacity (mAh)    0.298
Number of SIMs           -0.162
Name: Price, dtype: float64
```

In [23]:
```
feature_analyze.possible_high_correlation(numcols)  #columns possessing high correlation among themselves
```

Out[23]:
```
{'Front camera',
 'Internal storage (GB)',
 'Price',
 'Processor',
 'RAM (MB)',
 'Rear camera',
 'Resolution y',
 'Screen size (inches)'}
```

5. Model Pre-Processing

- The **outliers** are handled using various method using experimentation (trail/error)
- **Log transformation** is used on the target and numeric columns to address the outliers
- **Visual comparision** of the transformed columns are carried to verify the applied log_transformation
- **Label encoding** is used for the converting the categorical features to near numeric representation

In [24]:
```
class preProcessing:
    def __init__(self, df):
        #initialising the dataframe(numeric) to be used in this class methods
        self.df = df

    def outlireHandeling(self, col):
        '''
            function: outlireHandeling -> Performs the log transformation on the columnn
            arg: col (pandas.core.series.Series) -> column of the data set
            return: 'This column does not exsist in data set' (str) -> if the column does not exsist
        '''
        if col not in self.df.columns.tolist():
            return 'This column does not exsist in data set'
        #applying lograthemic transformation on the target variable
        self.df['logTranforedPrice'] = np.log10(df[col] + 1)

    def log_tranformation(self,df):

        """
        arg: dataframe(numeric_columns_only)

        function: applying lograthemic transformation on all the numeric columns

        return: None

        """
        for col in df:
            #using lambda to apply log on each rows of the numeric valies
            self.df[col]=self.df[col].map(lambda i: np.log10(i) if i>0 else 0)

    def comparisionofResults(self, col1, col2):
        '''
            function: comparisionofResults -> shows the visual comaparision of two columns in two bar graph
            arg: col1 (pandas.core.series.Series) -> column of the data set
                 col2 (pandas.core.series.Series) -> column of the data set
            return: None
        '''
        fig, axes = plt.subplots(1, 2, figsize=(14, 4))
        plt.suptitle('Comparision of original price v/s log transformation', fontsize=20)
        sns.histplot(ax=axes[0], x=self.df['Price'], bins=70, kde=True, color=(0.95, 0.1, 0.85))
        axes[0].set_xlabel('Price', fontsize=15)
        axes[0].set_ylabel('Frequency', fontsize=15)
        sns.histplot(ax=axes[1], x=self.df['logTranforedPrice'], bins=50, kde=True, color=(0.2, 0.85, 0.95))
```

```python
        axes[1].set_xlabel('Log Transformed Price', fontsize=15)
        axes[1].set_ylabel('Frequency', fontsize=15)
        plt.show()

    def labelEncoding(self, column):
        '''
            function: labelEncoding -> performs label encoding on the catagorical columns
            arg: column (pandas.core.indexes.base.Index) -> index of the columns
            return: None
        '''
        #initalizing tthe labelencoder method
        labelEncoder = LabelEncoder()
        for col in column:
            self.df[col] = labelEncoder.fit_transform(self.df[col])
```

In [25]:
```python
preprocess = preProcessing(df) #creating instance of the class preprocessing
```

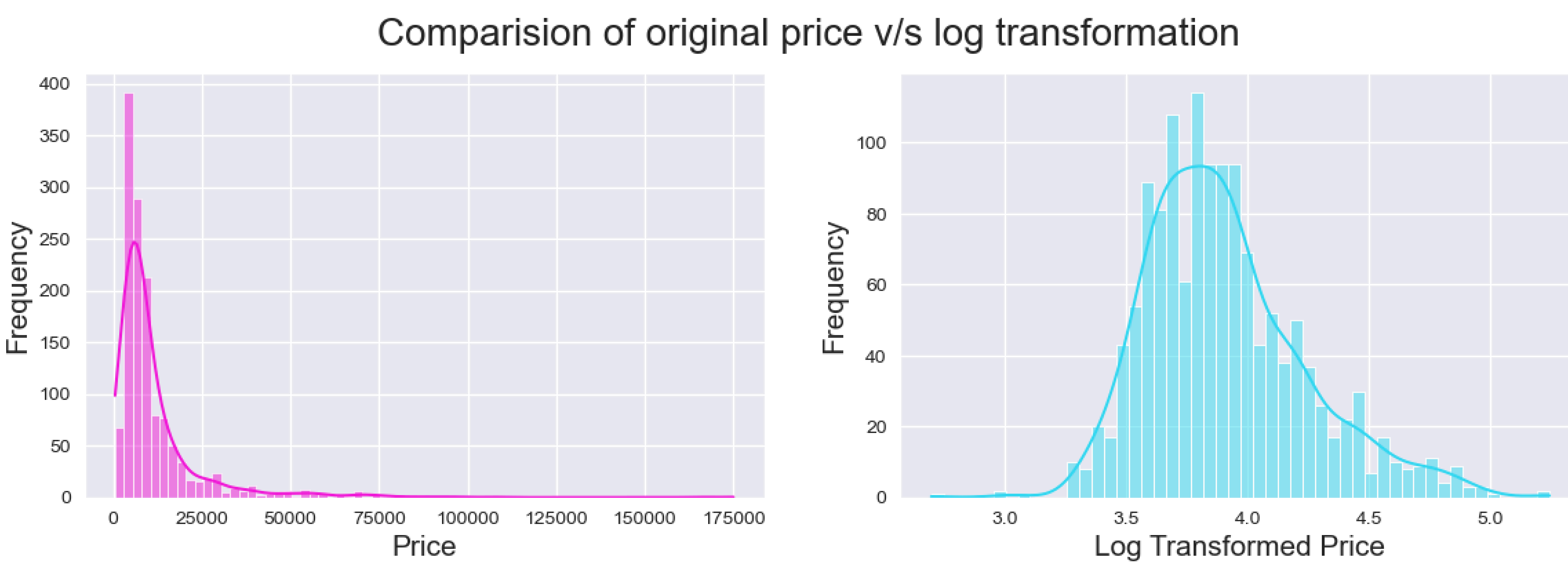
Given that our target is always a positive number,

we can apply **log transformation** on our target variable to reduce the skewness and number of outliers.

In [26]:
```python
preprocess.log_tranformation(numcols.drop(columns='Price')) #calling the class_method to apply log_transform
```

In [27]:
```python
preprocess.outlireHandeling('Price')
```

In [28]:
```python
preprocess.comparisionofResults('Price', 'logTranforedPrice')
```



Insights:

- Applying a Log Transformation technique has converted the distribution into a more normal distribution and symmetrical.
- The distribution is no longer right-skewed (skewness > 0) but it is closer to zero (skewness near 0)
- The number of outliers has been significantly reduced

Let's also apply **Label Encoding technique** to convert our **binary ('Yes' and 'No') features into numerical (0 and 1)** by mapping values:

- 'Yes' --> 1
- 'No' --> 0

In [29]:
```
preprocess.labelEncoding(catCols.drop(columns=['Brand']).columns) #label encoding of all the categorical columns
```

In [30]:
```
df.head()
```

Out[30]:

	Name	Brand	Model	Battery capacity (mAh)	Screen size (inches)	Touchscreen	Resolution x	Resolution y	Processor	RAM (MB)	...	Front camera	Operating system	Wi-Fi	Bluetooth	GPS	Number of SIMs	3G	4G/ LTE	Price	logTranforedPrice
0	OnePlus 7T Pro McLaren Edition	OnePlus	49	3.611192	0.824126	1	3.158362	3.494155	0.903090	4.079181	...	1.204120	0	1	1	1	0.30103	1	1	58998	4.770845
1	Realme X2 Pro	Realme	1142	3.602060	0.812913	1	3.033424	3.380211	0.903090	3.778151	...	1.204120	0	1	1	1	0.30103	1	1	27999	4.447158
2	iPhone 11 Pro Max	Apple	1288	3.598681	0.812913	1	3.094122	3.429429	0.778151	3.602060	...	1.079181	6	1	1	1	0.30103	1	1	106900	5.028982
3	iPhone 11	Apple	1286	3.492760	0.785330	1	2.918030	3.253338	0.778151	3.602060	...	1.079181	6	1	1	1	0.30103	1	1	62900	4.798658
4	LG G8X ThinQ	LG	522	3.602060	0.806180	1	3.033424	3.369216	0.903090	3.778151	...	1.505150	0	1	1	1	0.00000	0	0	49990	4.698892

5 rows × 22 columns

6. Modelling and testing Pipeline

1. **feature selection**: check for the best features present in the data using selectKbest
2. **process_module**: - dropping non-significant columns from the process pipeline

   ```
   - creating new feature named 'latest_tech_stack' from the
   columns req_1=['Touchscreen', 'Wi-Fi', 'Bluetooth', 'GPS', '3G', '4G/ LTE']

   -transform pipelin for the numeric columns are created

   - passthorough flag is used to carry the other columns as it is

   -numeric columns passed through the pipeline are :
   numeric=['Battery capacity (mAh)', 'Screen size (inches)', 'Resolution x','Processor', 'RAM (MB)', 'Internal storage   (GB)','Rear camera', 'Front camera', 'Number of SIMs']

   -standardscaler is applied to transform the numeric values

   - baseline model and other models are defines : 'Linear Regression','Random Forest Regressor','Gradient Boosting Regressor','Ridge Regression'

   - other evaluation metrics are calculated like MSE,MAE, R2 and the RMSE for each model --> stored in the dict
   ```
3. **vis_predction**: plotting the actual and predicted values of each model and compare the performance through interactive graph
4. **tuning_parameter**: defined hyperparameters are processed to check the best model params and the training fit is completed
5. **post_analysis**: this method is used to compare the top5 best features of each model to the selected features to undersntad the importance of each model and mainly the weights given for the respective features
6. **res_comp**: the evaluation metrics are calculated and tabluated against each other for the training and the testing set

In [31]:
```
class training_pipeline:
    def __init__(self,df,target,numeric,categorical,req_1,aplha):
```

```python
        """
        arg: dataframe
        arg: target --> target variable
        arg: numeric --> numeric columns post_pre_processing and feature selection
        arg: req_1 --> required features for feature engineering
        arg: aplha --> alpha value for the regularizarion techniques

        function: class_constructor

        return: None
        """
        self.df=df
        self.target=target
        self.numeric=numeric
        self.categorical=categorical
        self.combining_features_cat=req_1
        self.alpha=aplha
        self.results = []

    def feature_selection(self):
        """
        arg: None

        function: checking the best features present in the dataset using selectKBest

        return: None
        """
        k = 5
        selector = SelectKBest(score_func=f_regression, k=k)
        X_selected = selector.fit_transform(self.X, self.y)
        selected_feature_indices = selector.get_support(indices=True)
        self.selected_features = list(self.X.columns[selected_feature_indices])
        print("="*50)
        print(self.selected_features)
        print("="*50)
    def process_module(self):

        """
        arg: None

        function: creating new feature (dimension reduction), process and traiing pipeline

        return: None
        """
        self.df['latest_tech_stack']=self.df[self.combining_features_cat].all(axis=1).astype(int)
        self.column_to_drop_trainig=['Name','Brand','Model','Touchscreen','Resolution y','Wi-Fi','Bluetooth','GPS','3G','4G/ LTE','Price','logTranforedPrice']
        self.X=self.df.drop(columns=self.column_to_drop_trainig)
        self.y=self.df[self.target]
        self.feature_selection()
        numeric_transformer = Pipeline(steps=[('scaler', StandardScaler())])
        preprocessor = ColumnTransformer(transformers=[('num', numeric_transformer, self.numeric)],remainder='passthrough')
        self.X_train, self.X_test, self.y_train, self.y_test = train_test_split(self.X, self.y, test_size=0.3, random_state=55)
#         print(type(self.X_train))
        models = {'Linear Regression': LinearRegression(),'Random Forest Regressor': RandomForestRegressor(),'Gradient Boosting Regressor': GradientBoostingRegressor(),
                  'Ridge Regression': Ridge(alpha=self.alpha)}
#         print((self.X_train[:4]))
#         print(type(self.X_train))
        pipeline=Pipeline(steps=[('preprocessor',preprocessor)])
        self.X_train=pipeline.fit_transform(self.X_train)
#         print(self.X_train[:4])
        self.X_test=pipeline.transform(self.X_test)
```

```
#         print(self.X_test[:1])
        for model_name,model in models.items():
            self.reg=model
            self.reg.fit(self.X_train,self.y_train)
            self.y_train_pred=self.reg.predict(self.X_train)
            self.y_test_pred=self.reg.predict(self.X_test)

            #evaluation
            train_r2=r2_score(self.y_train,self.y_train_pred).round(3)
            test_r2=r2_score(self.y_test,self.y_test_pred).round(3)
            #eval_mse
            train_mse=mean_squared_error(np.power(10, self.y_train), np.power(10, self.y_train_pred)).round(3)
            test_mse=mean_squared_error(np.power(10, self.y_test), np.power(10, self.y_test_pred)).round(3)
#             train_mse=mean_squared_error(self.y_train,self.y_train_pred).round(3)
#             test_mse=mean_squared_error(self.y_test,self.y_test_pred).round(3)
            #eval_mae

            train_mae=mean_absolute_error(np.power(10, self.y_train), np.power(10, self.y_train_pred)).round(3)
            test_mae=mean_absolute_error(np.power(10, self.y_test), np.power(10, self.y_test_pred)).round(3)

#             train_mae=mean_absolute_error(self.y_train,self.y_train_pred).round(3)
#             test_mae=mean_absolute_error(self.y_test,self.y_test_pred).round(3)
            self.sorted_=self.post_analysis(model_name)
            result={'model':model_name,'mae_train':train_mae,'mae_test':test_mae,'mse_train':train_mse,'mse_test':test_mse,'train_r2':train_r2,'test_r2':test_r2,'feature_seletion':self.selected_features,'feature
            self.results.append(result)
            self.vis_prediction(model_name)


    def vis_prediction(self,model_name):
        """
        arg: name of the model to be plotted

        function: using scatter plot to visulaise the regression model's prediction

        return: None
        """
        vis_df=pd.DataFrame({'Actual_value':self.y_test,'Prediction':self.y_test_pred})
        fig=px.scatter(vis_df,x='Actual_value',y='Prediction',trendline='ols',title="Performance_{}".format(model_name))
        fig.update_traces(marker=dict(color='blue', size=10))
        fig.update_layout(xaxis=dict(scaleanchor="y",scaleratio=1),yaxis=dict(scaleanchor="x",scaleratio=1))
        fig.show()


        diff_val=pd.DataFrame({'Difference|Error':(self.y_test-self.y_test_pred)})
        fig2=px.histogram(diff_val,x='Difference|Error',title="Erroe_distribution_in_{}".format(model_name),nbins=25,histnorm='probability density')
        fig2.show()



    def tuning_parameters(self):

        """
        arg: None

        function: hyper paramters tuning for the selected models and evaluation of the model resutls

        return: None
        """
        models={'hp_random_forest':{'base':RandomForestRegressor(),'params':{'n_estimators':[50,75,100],'min_samples_split': [2, 5, 10],'max_depth':[2,6,8]}},
               'hp_boosring':{'base':GradientBoostingRegressor(),'params':{'n_estimators':[50,100,120],'learning_rate': [0.01, 0.05, 0.1],'max_depth':[2,4]}},
               'hp_lasso':{'base':Lasso(),'params':{'alpha':[0.005,.03,.02,.1,.5,10,15,12,25]}}}
        for model_name,model in models.items():
```

```
            search=RandomizedSearchCV(model['base'],model['params'],cv=5,n_iter=3,random_state=42,scoring='neg_mean_squared_error')
            search.fit(self.X_train,self.y_train)
            best=search.best_estimator_
            self.reg=best
            self.y_train_pred=self.reg.predict(self.X_train)
            self.y_test_pred=self.reg.predict(self.X_test)

            #evaluation
            train_r2=r2_score(self.y_train,self.y_train_pred).round(3)
            test_r2=r2_score(self.y_test,self.y_test_pred).round(3)
            #eval_mse

            train_mse=mean_squared_error(np.power(10, self.y_train), np.power(10, self.y_train_pred)).round(3)
            test_mse=mean_squared_error(np.power(10, self.y_test), np.power(10, self.y_test_pred)).round(3)
#             train_mse=mean_squared_error(self.y_train,self.y_train_pred).round(3)
#             test_mse=mean_squared_error(self.y_test,self.y_test_pred).round(3)
            #eval_mae
            train_mae=mean_absolute_error(np.power(10, self.y_train), np.power(10, self.y_train_pred)).round(3)
            test_mae=mean_absolute_error(np.power(10, self.y_test), np.power(10, self.y_test_pred)).round(3)
#             train_mae=mean_absolute_error(self.y_train,self.y_train_pred).round(3)
#             test_mae=mean_absolute_error(self.y_test,self.y_test_pred).round(3)
            self.sorted_=self.post_analysis(model_name)

            result={'model':model_name,'mae_train':train_mae,'mae_test':test_mae,'mse_train':train_mse,'mse_test':test_mse,'train_r2':train_r2,'test_r2':test_r2,'feature_seletion':self.selected_features,'feature
            self.results.append(result)
            self.vis_prediction(model_name)


    def post_analysis(self,model_name):

        """
        arg: model_name

        function: finding the best feature set used in that particualr model and get the feature importance

        return: list of top 5 important features identified in that particular model
        """
        if model_name in['hp_lasso','Linear Regression','Ridge Regression']:
            imp=self.reg.coef_
            print("="*50)
            print(self.reg.coef_)
            print("="*50)
        else:
            imp=self.reg.feature_importances_
            print("="*50)
            print(self.reg.feature_importances_)
            print("="*50)
        impo=pd.DataFrame({'feature_imp':imp}, index=self.X.columns)
        sorted_=impo.sort_values(by='feature_imp',ascending=False).head(5)
        print("="*50)
        print(sorted_)
        print("="*50)
        return(sorted_.index.tolist())



    def res_comp(self):

        """
        arg: None

        function: initializing and forming dataframe
```

```
        return: Evaluation metrics of the trained models
        """

        return pd.DataFrame(self.results)
```

Let's define constants with the **required columns, numeric columns and the categorical variables**.

In [32]:
```
numeric=['Battery capacity (mAh)', 'Screen size (inches)', 'Resolution x','Processor', 'RAM (MB)', 'Internal storage (GB)','Rear camera', 'Front camera', 'Number of SIMs']
req_1=['Touchscreen', 'Wi-Fi', 'Bluetooth', 'GPS', '3G', '4G/ LTE']
categorical=['Operating system','latest_tech_stack']
```

We will test & train the following models:

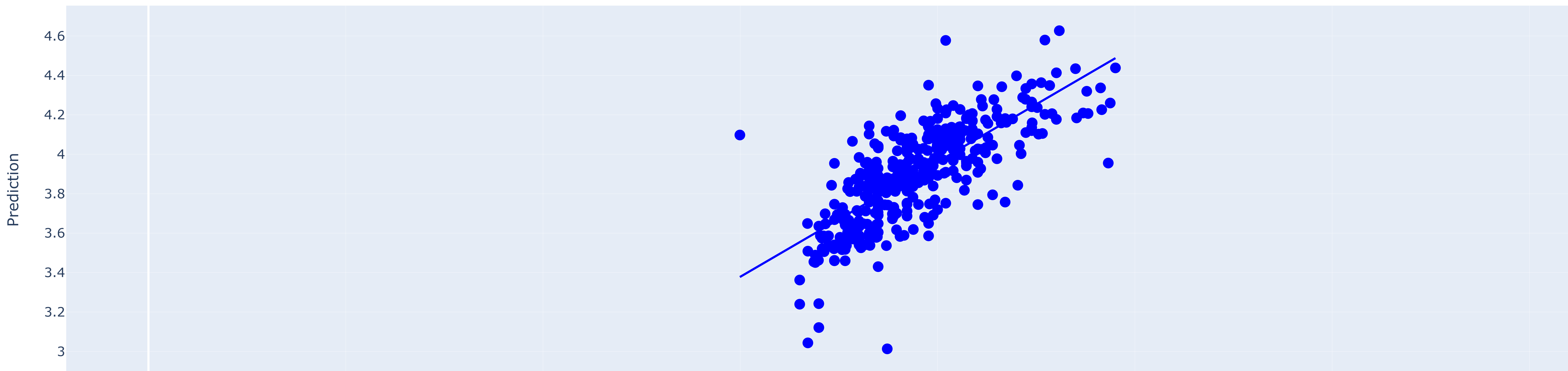
- **Linear Regression**: because it is easy to understand and it uses low time and cpu resources, suitable for hyperparameter tuning
- **Random Forest**: because it is widely used for both classification and regression problems, and also easy to grasp
- **Gradient Boosting**: because it is a powerful algorithm for regression, based on multiple weak models, adding a layer on top of random forest
- **Ridge Regression**: because it is a common and widely use model for regression problems

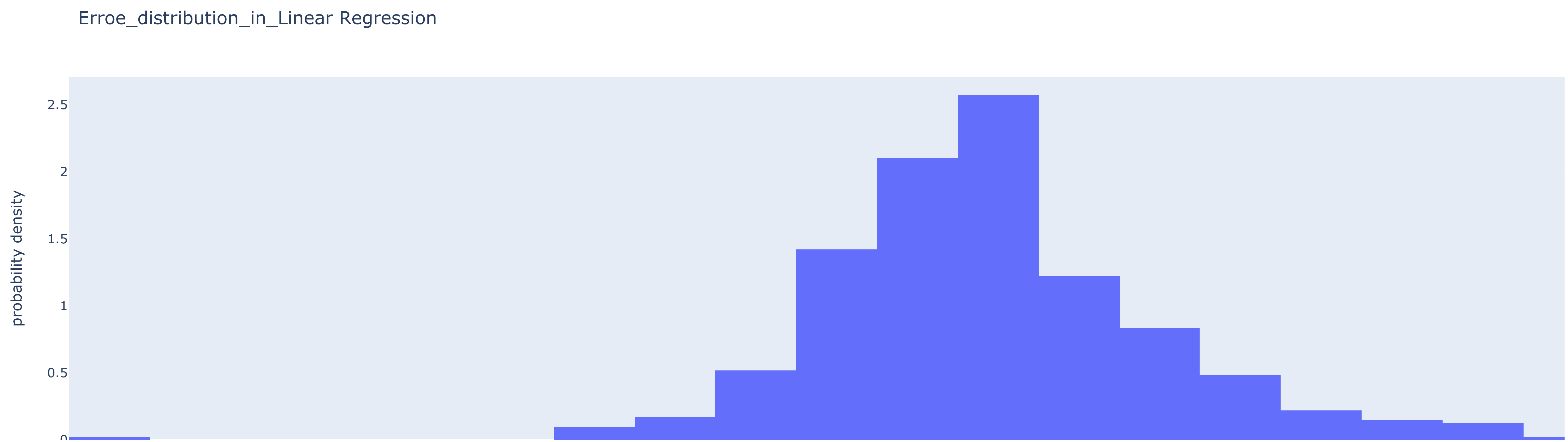
In [35]:
```
model_training=training_pipeline(df,'logTranforedPrice',numeric,categorical,req_1,0.5)
```

In [36]:
```
model_training.process_module()
```

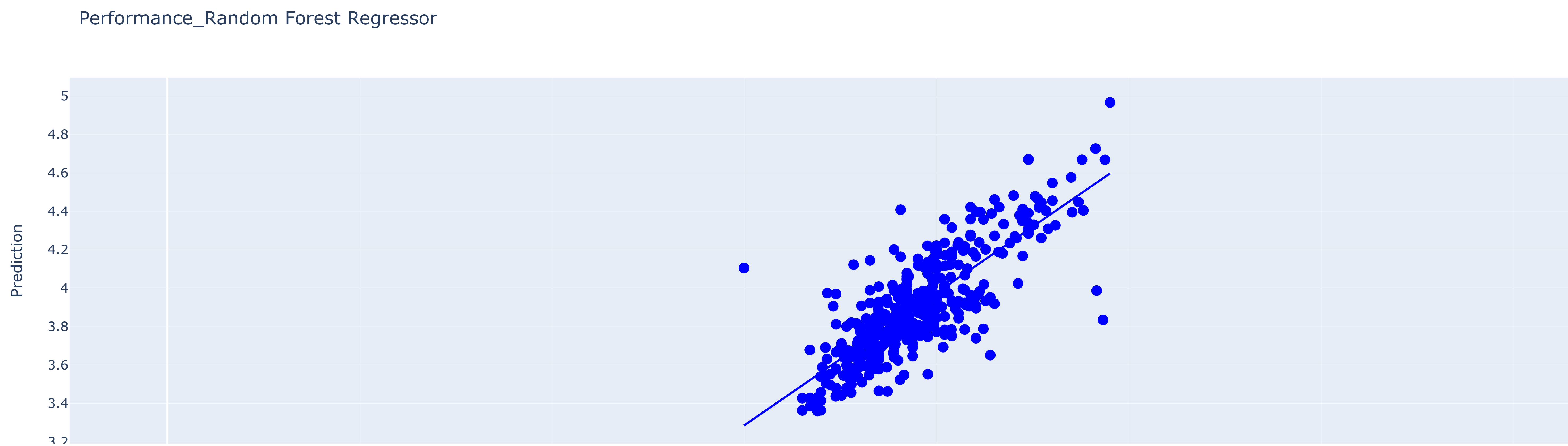
```
==================================================
['Screen size (inches)', 'Resolution x', 'RAM (MB)', 'Internal storage (GB)', 'Rear camera']
==================================================
==================================================
[-0.00754886  0.00379769  0.09820305 -0.01222565  0.06799212  0.08641511
  0.06465935 -0.04585342 -0.02436228  0.06983926 -0.00437083]
==================================================
==================================================
                       feature_imp
Resolution x              0.098203
Internal storage (GB)     0.086415
Number of SIMs            0.069839
RAM (MB)                  0.067992
Rear camera               0.064659
==================================================
```

Performance_Linear Regression



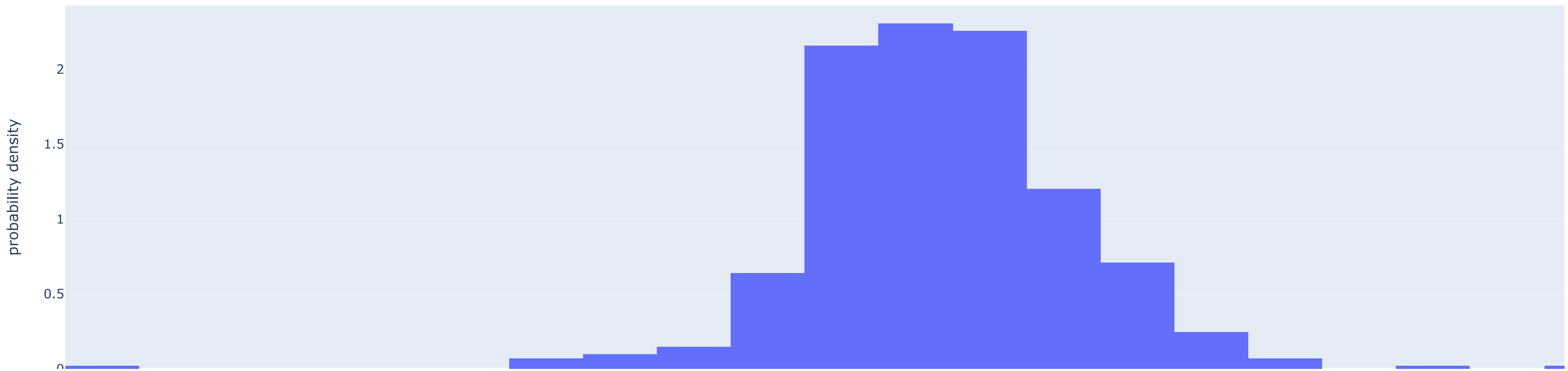



```
================================================
[0.08473493 0.07050539 0.38576167 0.01784956 0.05757034 0.14156369
 0.11719072 0.05086973 0.02764863 0.02773013 0.01857521]
================================================
================================================
                        feature_imp
Resolution x               0.385762
Internal storage (GB)      0.141564
Rear camera                0.117191
Battery capacity (mAh)     0.084735
Screen size (inches)       0.070505
================================================
```

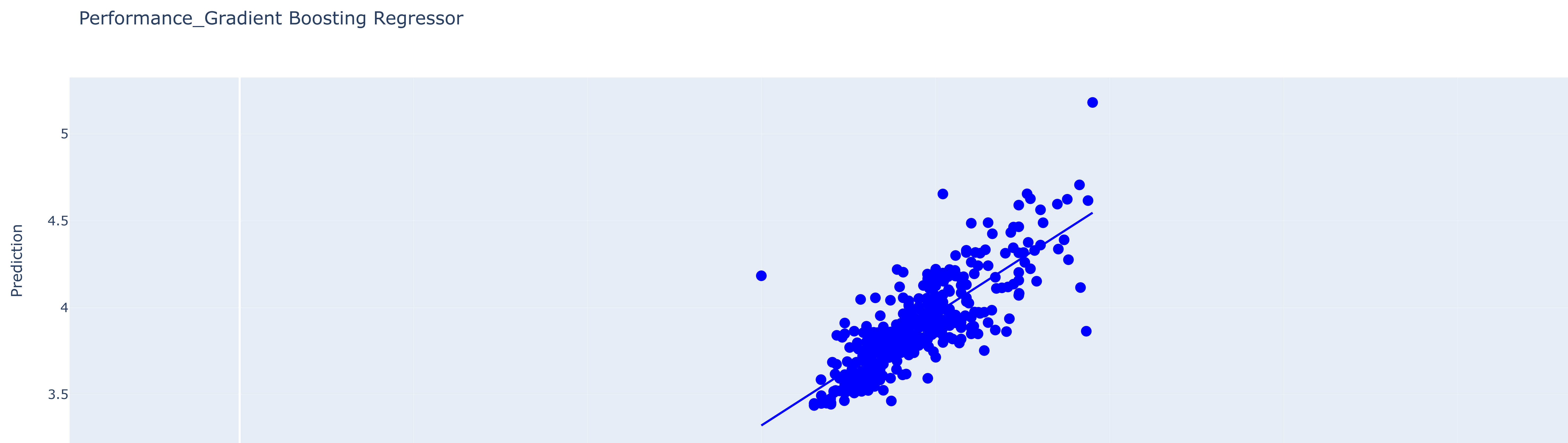


Performance_Random Forest Regressor
Prediction
5
4.8
4.6
4.4
4.2
4
3.8
3.6
3.4
3.2

Erroe_distribution_in_Random Forest Regressor

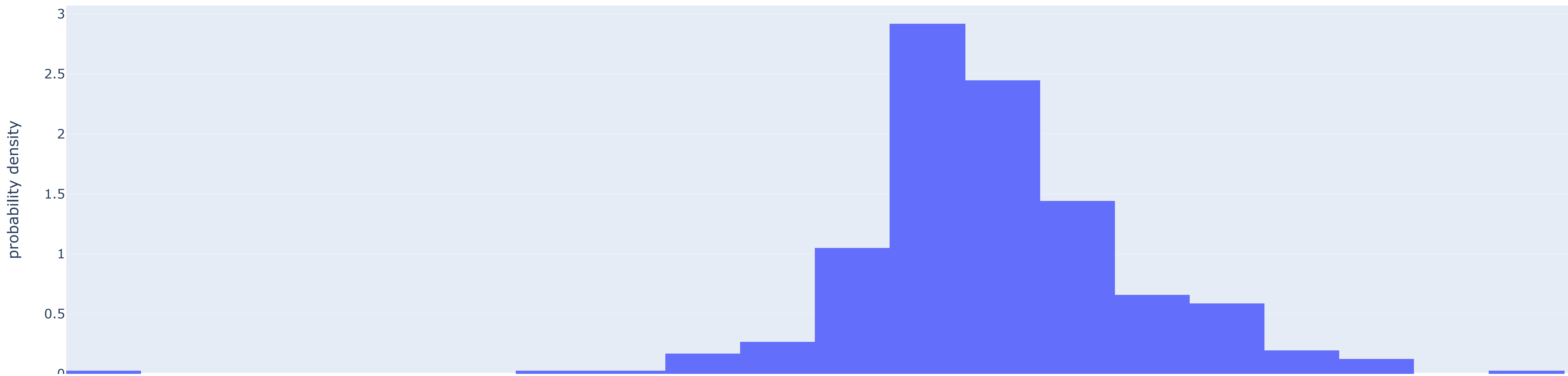



```
================================================
[0.02460044 0.05708354 0.40088338 0.00876346 0.05985265 0.21683976
 0.12772152 0.02855048 0.02602235 0.04107986 0.00860257]
================================================
================================================
                      feature_imp
Resolution x             0.400883
Internal storage (GB)    0.216840
Rear camera              0.127722
RAM (MB)                 0.059853
Screen size (inches)     0.057084
================================================
```



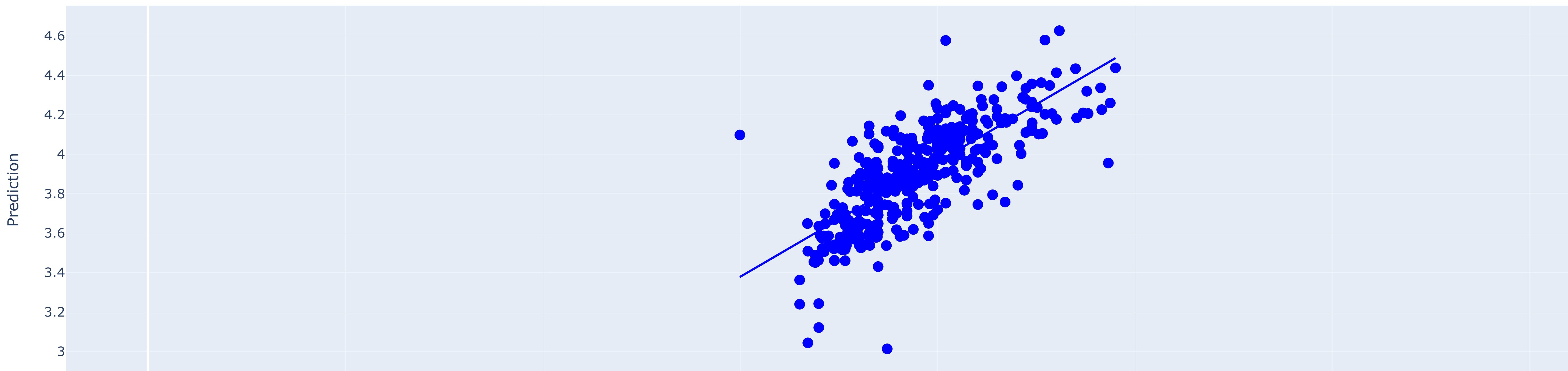
Performance_Gradient Boosting Regressor
Prediction
5
4.5
4
3.5

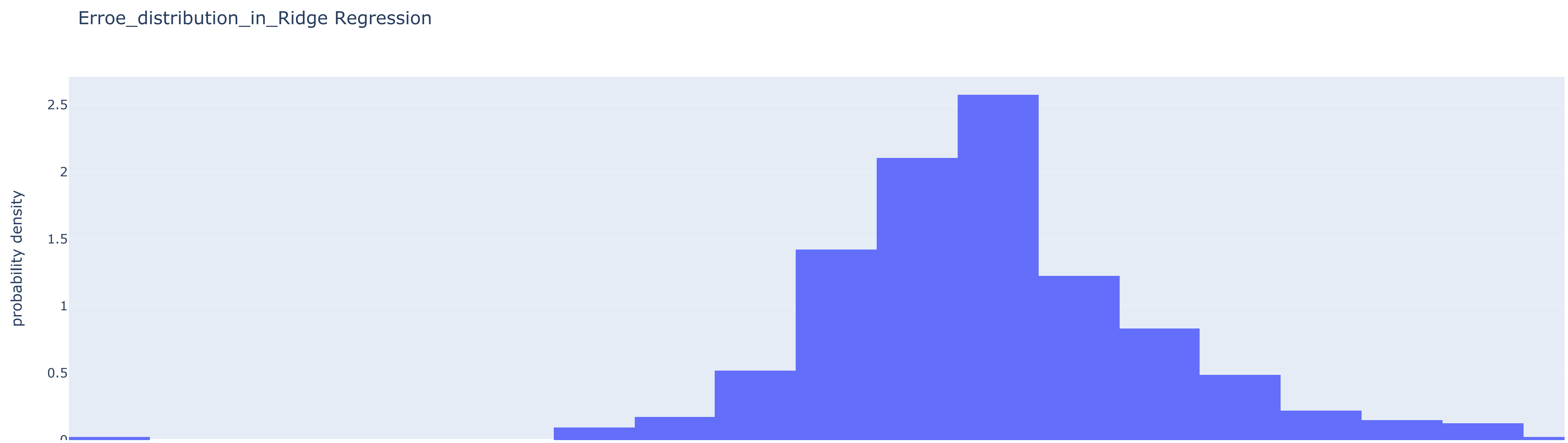
Erroe_distribution_in_Gradient Boosting Regressor




```
==================================================
[-0.00751863  0.0038438   0.09812662 -0.01218841  0.0679705   0.08631409
  0.06459599 -0.04573011 -0.02439011  0.06981474 -0.00431878]
==================================================
==================================================
                       feature_imp
Resolution x              0.098127
Internal storage (GB)     0.086314
Number of SIMs            0.069815
RAM (MB)                  0.067970
Rear camera               0.064596
==================================================
```

Performance_Ridge Regression





Insights: Baseline model and other computing models

- Linear regression shows decent performance in both the training and testing (unknown) dataset
- Random forest is highly overfitting with the training data
- Gradient boosting is slight overfitting
- Ridge regressiin shows good performance in the first experimentation and offers balanced performances

The residuals are plotted using histogram method

In [38]:
```
model_training.res_comp()
```

Out[38]:

	model	mae_train	mae_test	mse_train	mse_test	train_r2	test_r2	feature_seletion	feature_importance
0	Linear Regression	4860.557	4176.584	1.301979e+08	7.766114e+07	0.596	0.566	[Screen size (inches), Resolution x, RAM (MB),...	[Resolution x, Internal storage (GB), Number o...
1	Random Forest Regressor	1848.239	3592.292	2.048822e+07	4.856458e+07	0.940	0.646	[Screen size (inches), Resolution x, RAM (MB),...	[Resolution x, Internal storage (GB), Rear cam...
2	Gradient Boosting Regressor	3249.357	3864.197	3.940010e+07	6.825721e+07	0.787	0.638	[Screen size (inches), Resolution x, RAM (MB),...	[Resolution x, Internal storage (GB), Rear cam...
3	Ridge Regression	4860.885	4176.439	1.302352e+08	7.766983e+07	0.596	0.566	[Screen size (inches), Resolution x, RAM (MB),...	[Resolution x, Internal storage (GB), Number o...

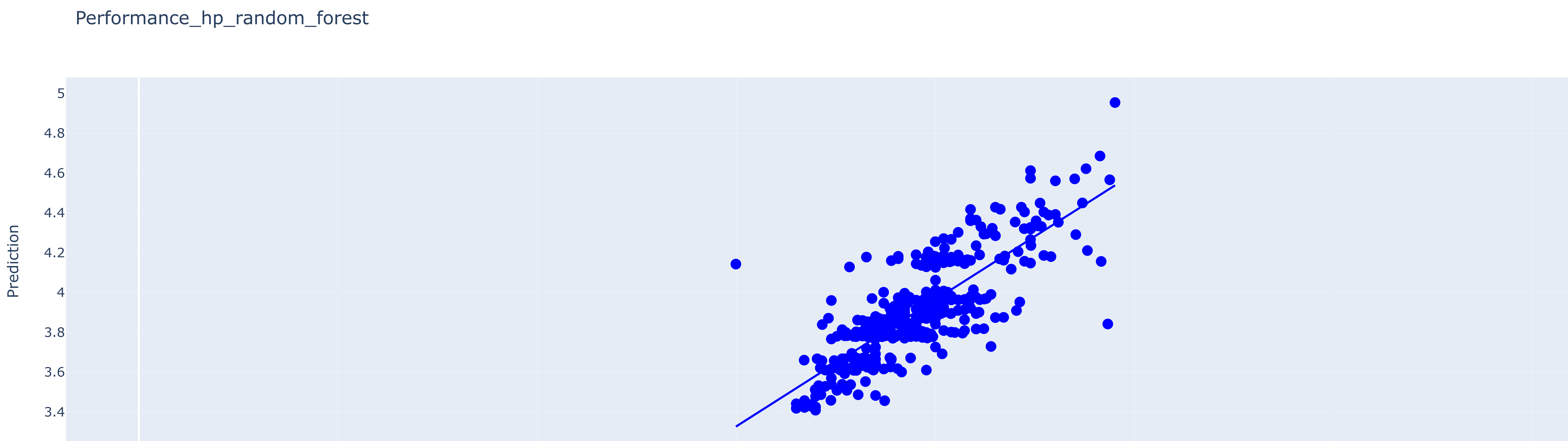
7. Hyper-parameter tuning

Before running into conclusions let's find the best parameters for each model by performing hyper-parameter tuning.

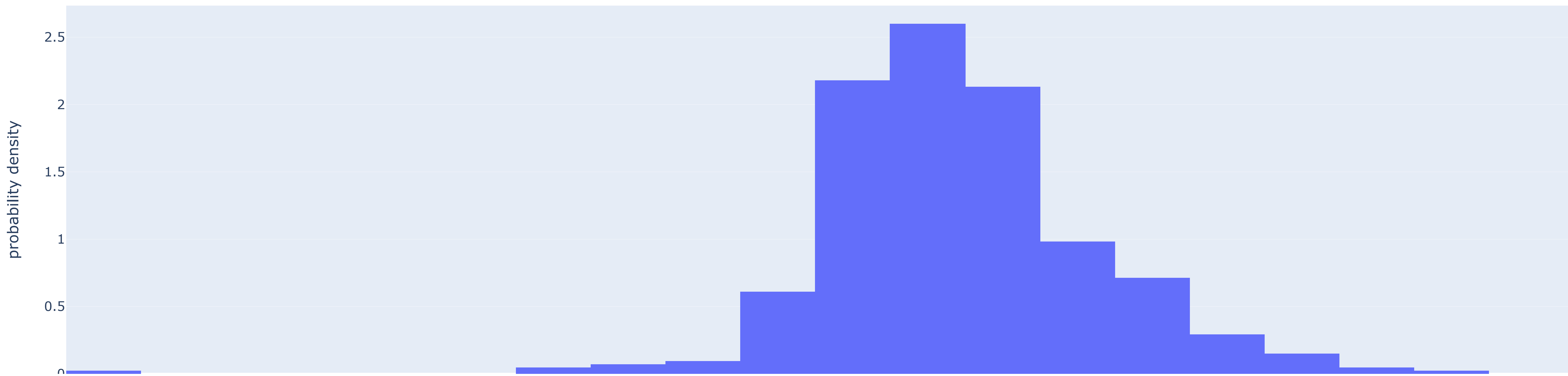
We will use a **Randomized Search CV** (cross validation) with 5 folds. This will allow us to test multiple parameters randomly without exhausting our computing resources, and **executing our pipeline efficiently.**

In [40]:
```
model_training.tuning_parameters()
```

```
================================================
[0.02520789 0.04837883 0.46092997 0.0114821  0.05590662 0.17575995
 0.12453419 0.02636012 0.02622511 0.03559472 0.0096205 ]
================================================
================================================
                      feature_imp
Resolution x             0.460930
Internal storage (GB)    0.175760
Rear camera              0.124534
RAM (MB)                 0.055907
Screen size (inches)     0.048379
================================================
```

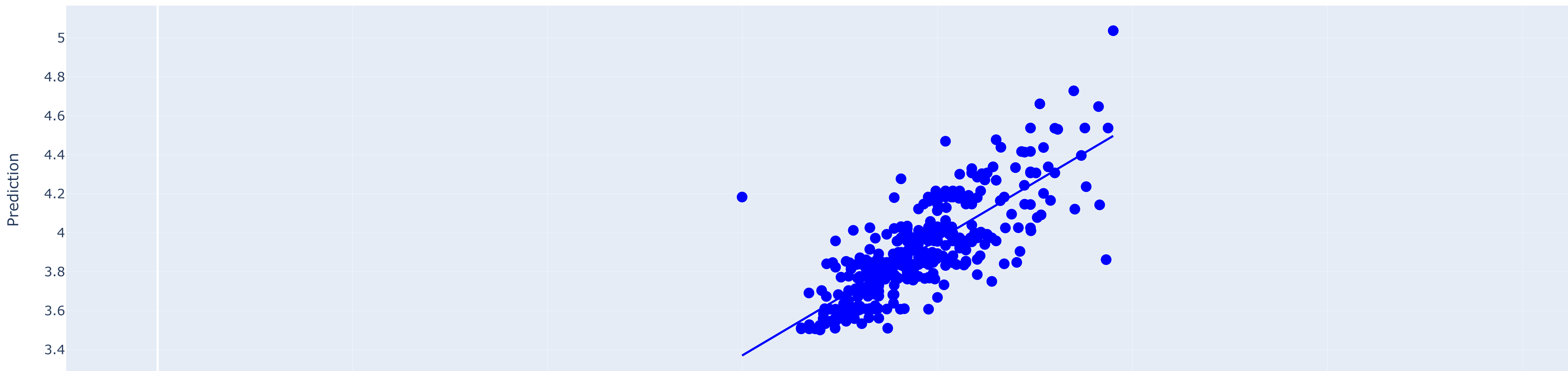


Erroe_distribution_in_hp_random_forest

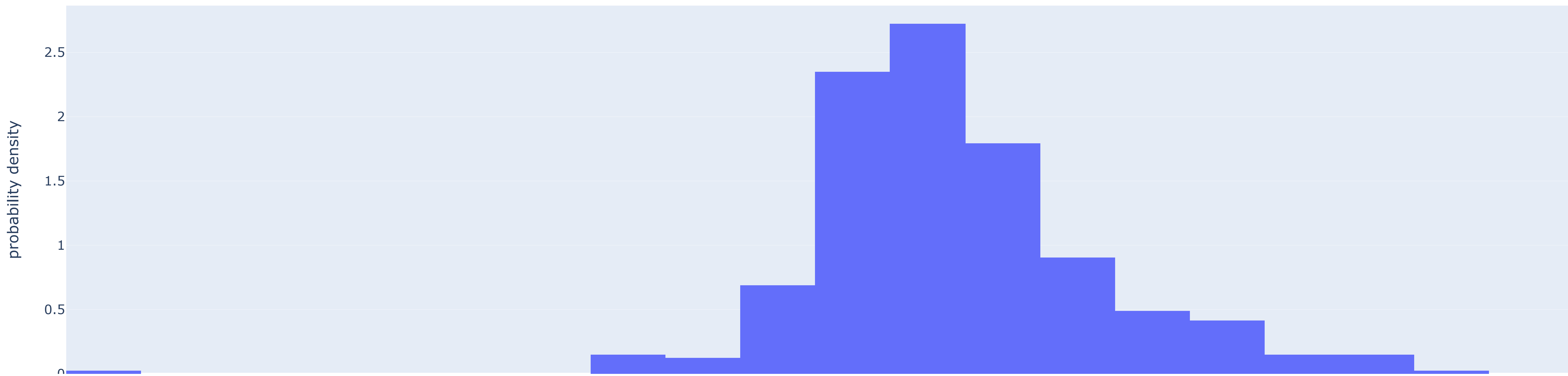



```
=================================================
[0.00490857 0.03685575 0.44007787 0.00057217 0.07732252 0.21207579
 0.14803776 0.01134364 0.01617534 0.05013084 0.00249976]
=================================================
=================================================
                      feature_imp
Resolution x             0.440078
Internal storage (GB)    0.212076
Rear camera              0.148038
RAM (MB)                 0.077323
Number of SIMs           0.050131
=================================================
```

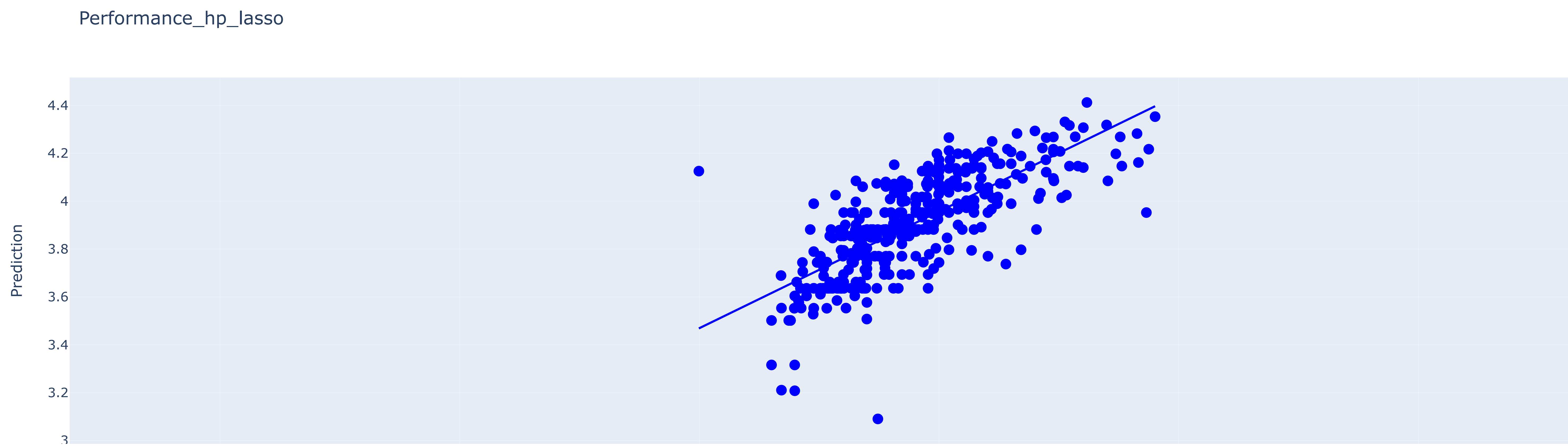
Performance_hp_boosring

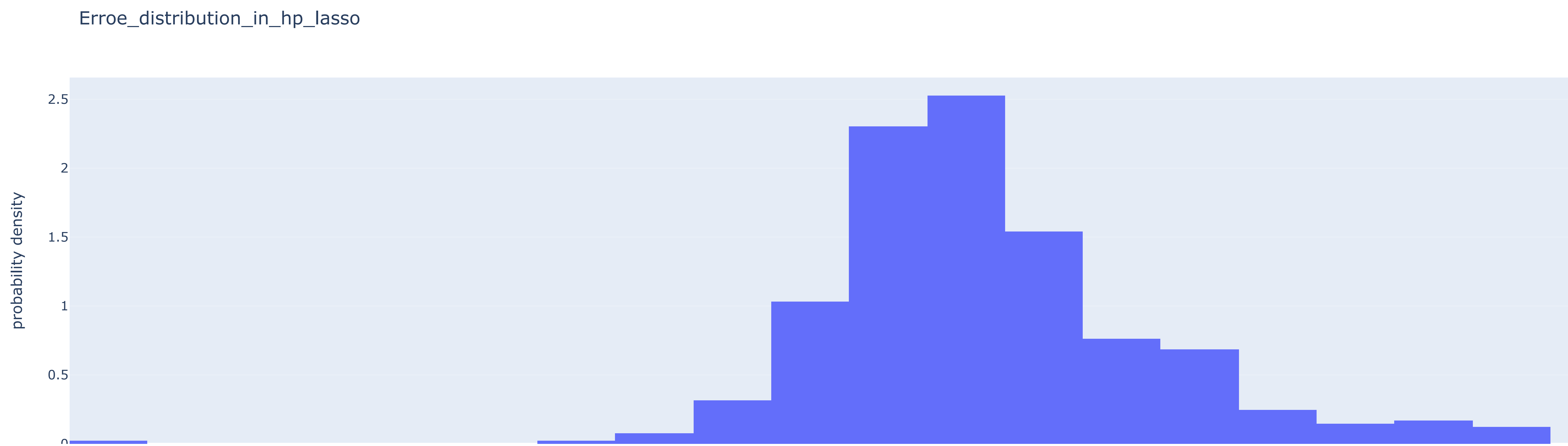


Erroe_distribution_in_hp_boosring




```
================================================
[ 0.          0.          0.09019238  0.          0.03324367  0.072875
  0.03473938  0.         -0.0091246   0.04540981  0.        ]
================================================
================================================
                       feature_imp
Resolution x              0.090192
Internal storage (GB)     0.072875
Number of SIMs            0.045410
Rear camera               0.034739
RAM (MB)                  0.033244
================================================
```


Performance_hp_lasso
Prediction
4.4
4.2
4
3.8
3.6
3.4
3.2
3



Insights:

- Our Hyperparameter tuning has reduced the error on most of our models.
- We have found the best parameter for each of our 4 models.
- The most important features mostly repeat themselves among our models

Let's calculate some metrics for both Test and Train subsets, for a fair comparison between models, and to make a decision:

- **MAE** (Mean Absolute Error)
- **MSE** (Mean Squared Error)
- **R2** (R Squared)

In [42]:
```
results=model_training.res_comp()
```

In [43]:
```
results
```

Out[43]:

	model	mae_train	mae_test	mse_train	mse_test	train_r2	test_r2	feature_seletion	feature_importance
0	Linear Regression	4860.557	4176.584	1.301979e+08	7.766114e+07	0.596	0.566	[Screen size (inches), Resolution x, RAM (MB),...	[Resolution x, Internal storage (GB), Number o...
1	Random Forest Regressor	1848.239	3592.292	2.048822e+07	4.856458e+07	0.940	0.646	[Screen size (inches), Resolution x, RAM (MB),...	[Resolution x, Internal storage (GB), Rear cam...
2	Gradient Boosting Regressor	3249.357	3864.197	3.940010e+07	6.825721e+07	0.787	0.638	[Screen size (inches), Resolution x, RAM (MB),...	[Resolution x, Internal storage (GB), Rear cam...
3	Ridge Regression	4860.885	4176.439	1.302352e+08	7.766983e+07	0.596	0.566	[Screen size (inches), Resolution x, RAM (MB),...	[Resolution x, Internal storage (GB), Number o...
4	hp_random_forest	3436.422	3646.559	5.147385e+07	5.300268e+07	0.778	0.648	[Screen size (inches), Resolution x, RAM (MB),...	[Resolution x, Internal storage (GB), Rear cam...
5	hp_boosring	3975.002	3816.670	7.062987e+07	6.065147e+07	0.705	0.619	[Screen size (inches), Resolution x, RAM (MB),...	[Resolution x, Internal storage (GB), Rear cam...
6	hp_lasso	5143.518	4329.775	1.536169e+08	8.470098e+07	0.565	0.550	[Screen size (inches), Resolution x, RAM (MB),...	[Resolution x, Internal storage (GB), Number o...

Validation and inference:

In [46]:

```
results.iloc[:,:-2]
```

Out[46]:

	model	mae_train	mae_test	mse_train	mse_test	train_r2	test_r2
0	Linear Regression	4860.557	4176.584	1.301979e+08	7.766114e+07	0.596	0.566
1	Random Forest Regressor	1848.239	3592.292	2.048822e+07	4.856458e+07	0.940	0.646
2	Gradient Boosting Regressor	3249.357	3864.197	3.940010e+07	6.825721e+07	0.787	0.638
3	Ridge Regression	4860.885	4176.439	1.302352e+08	7.766983e+07	0.596	0.566
4	hp_random_forest	3436.422	3646.559	5.147385e+07	5.300268e+07	0.778	0.648
5	hp_boosring	3975.002	3816.670	7.062987e+07	6.065147e+07	0.705	0.619
6	hp_lasso	5143.518	4329.775	1.536169e+08	8.470098e+07	0.565	0.550

8. Tuned parameters computing models

We will define a class called Inference to perform the following actions:

- Linear regression model is utilizing the lasso regularisation technique on top with various alpha parameters, the best params gives the best model for this project activity
- Finetuning the hyper_parameters in the Random Forest and gradient boosting models are not giving excepted resutls as thers is slight overfitting
- **Display features and feature importance for each model**
- **Compare test and train metrics for each model using bar plots**

In [47]:

```
class inference:
    def __init__(self,data):
        """
        arg: data --> dataframe to be visulalised and compared

        function: class constructor

        return: None
        """
        self.df=data

    def feature_understanding(self):
        """
        arg: None
```

```
        function: concatinating the feature importance and feature selection columns to check for the match values

        aim :  to verify the feature selection by validating the important features of various model

        return: dataframe consists of model name, feature importance and feature selection before training (reference)
        """
        self.exp1=self.df.iloc[:,0]
        self.exp2=self.df.iloc[:,[-2,-1]]
        return(pd.concat([self.exp1,self.exp2],axis=1))

    def general_plot(self,x):

        """
        arg: scoring metric to be plotted

        function: plotting bar graph to check the scoring and evaluation metrics for various models

        return: None
        """
        df=self.df

        if df.index.name!='model':
            df.set_index('model',inplace=True)
        df[x].plot(kind='barh',figsize=(14,7))
        plt.show()

    def sort_plot(self,x,y):

        """
        arg: x--> train set metrics
        arg: y --> test set metrics


        function: unstacked bar chart to compare the model performance and indentify the overfitting and underfitting cases


        return: None
        """
        comp=self.df[[x,y]].plot(kind='bar',stacked=False,figsize=(12,6))
        plt.title('Comprasion of {} vs {}'.format(x,y))
        plt.xlabel('Model')
        plt.xticks(rotation=45, ha='right')

        plt.show()

    def plotyy(self,x,y):

        """
        arg: x--> train set metrics
        arg: y --> test set metrics


        function: interactive bar graph to closely analyse the results

        return: None
        """
        unstacked = self.df.reset_index().melt(id_vars='model', value_vars=[x, y], var_name='type', value_name='values')
        fig = px.bar(unstacked, x='model', y='values', color='type', barmode='group', )
        fig.show()
```

In [48]:
```
inf_=inference(results)
```

In [49]:
```
pd.set_option('display.max_colwidth', None)
```

Let's check the **feature importance of our models.**

In [50]:
```
inf_.feature_understanding()
```

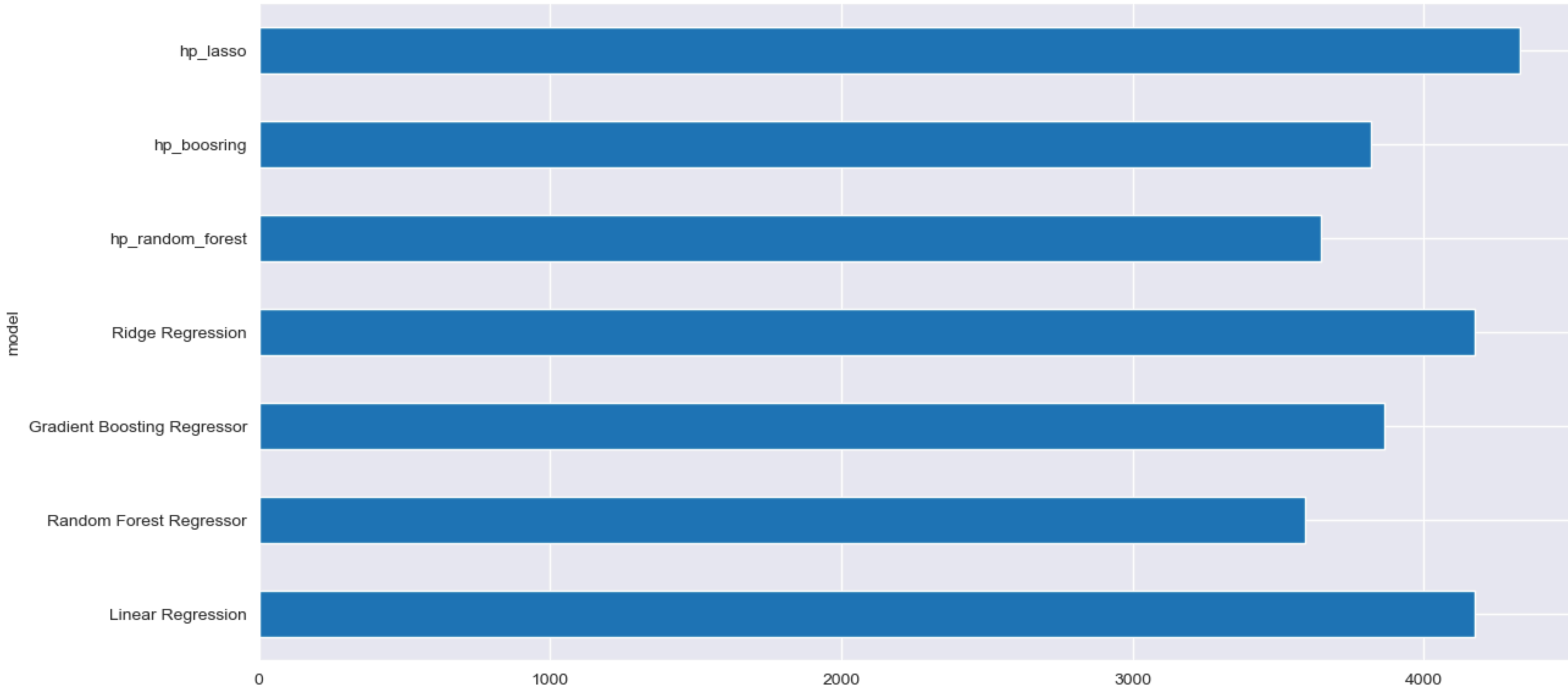
Out[50]:

	model	feature_seletion	feature_importance
0	Linear Regression	[Screen size (inches), Resolution x, RAM (MB), Internal storage (GB), Rear camera]	[Resolution x, Internal storage (GB), Number of SIMs, RAM (MB), Rear camera]
1	Random Forest Regressor	[Screen size (inches), Resolution x, RAM (MB), Internal storage (GB), Rear camera]	[Resolution x, Internal storage (GB), Rear camera, Battery capacity (mAh), Screen size (inches)]
2	Gradient Boosting Regressor	[Screen size (inches), Resolution x, RAM (MB), Internal storage (GB), Rear camera]	[Resolution x, Internal storage (GB), Rear camera, RAM (MB), Screen size (inches)]
3	Ridge Regression	[Screen size (inches), Resolution x, RAM (MB), Internal storage (GB), Rear camera]	[Resolution x, Internal storage (GB), Number of SIMs, RAM (MB), Rear camera]
4	hp_random_forest	[Screen size (inches), Resolution x, RAM (MB), Internal storage (GB), Rear camera]	[Resolution x, Internal storage (GB), Rear camera, RAM (MB), Screen size (inches)]
5	hp_boosring	[Screen size (inches), Resolution x, RAM (MB), Internal storage (GB), Rear camera]	[Resolution x, Internal storage (GB), Rear camera, RAM (MB), Number of SIMs]
6	hp_lasso	[Screen size (inches), Resolution x, RAM (MB), Internal storage (GB), Rear camera]	[Resolution x, Internal storage (GB), Number of SIMs, Rear camera, RAM (MB)]

Let's **plot bars to compare metrics between our models** using:

- MAE
- MSE
- R2

In [52]:
```
inf_.general_plot('mae_test')
```



Insights:

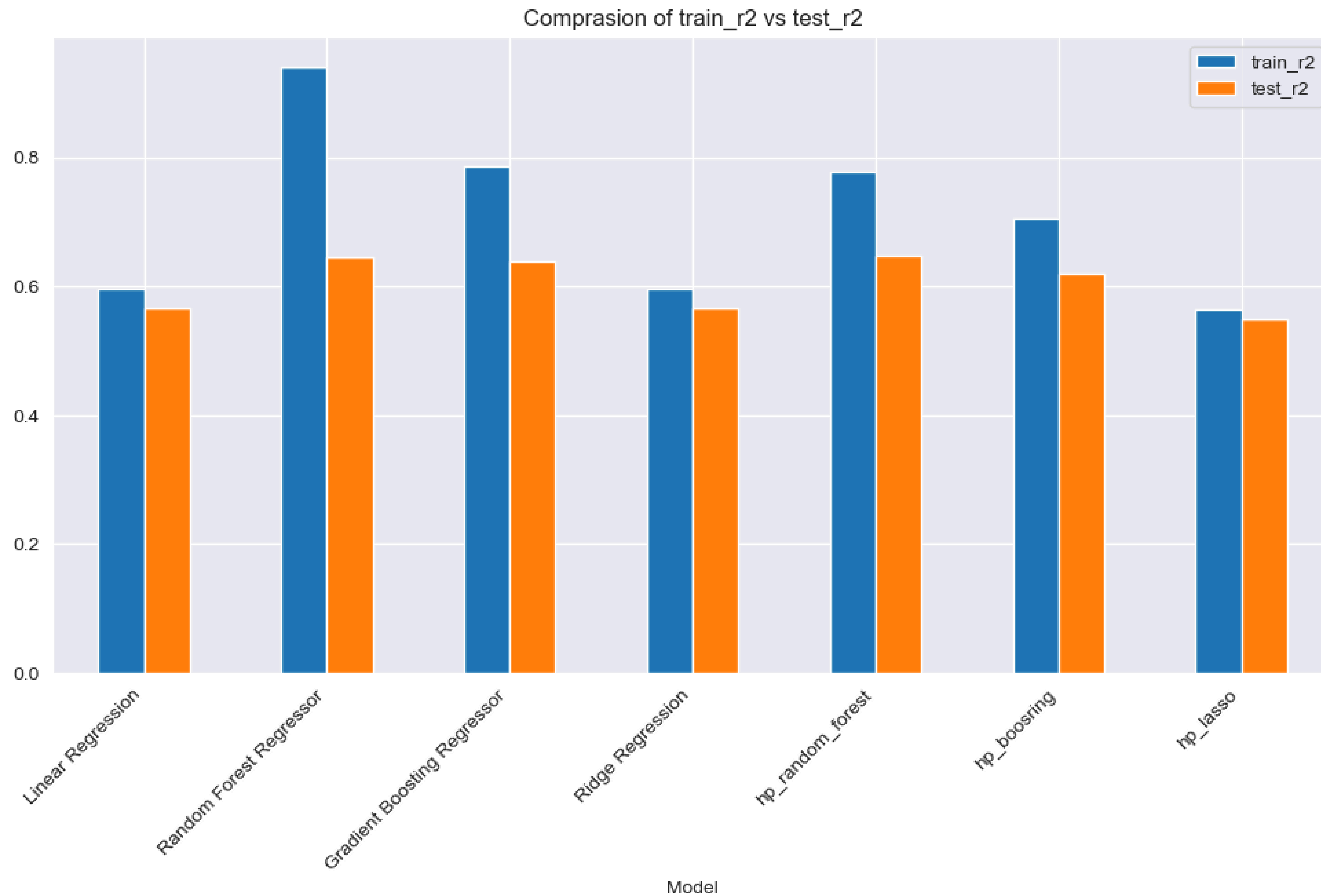
The **models presenting less absolute error** are:

- HP Random Forest
- Gradient Boosting Regressor
- Random Forest Regressor

The **models presenting large absolute errors** are:

- HP Lasso
- Ridge Regression
- Linear Regression

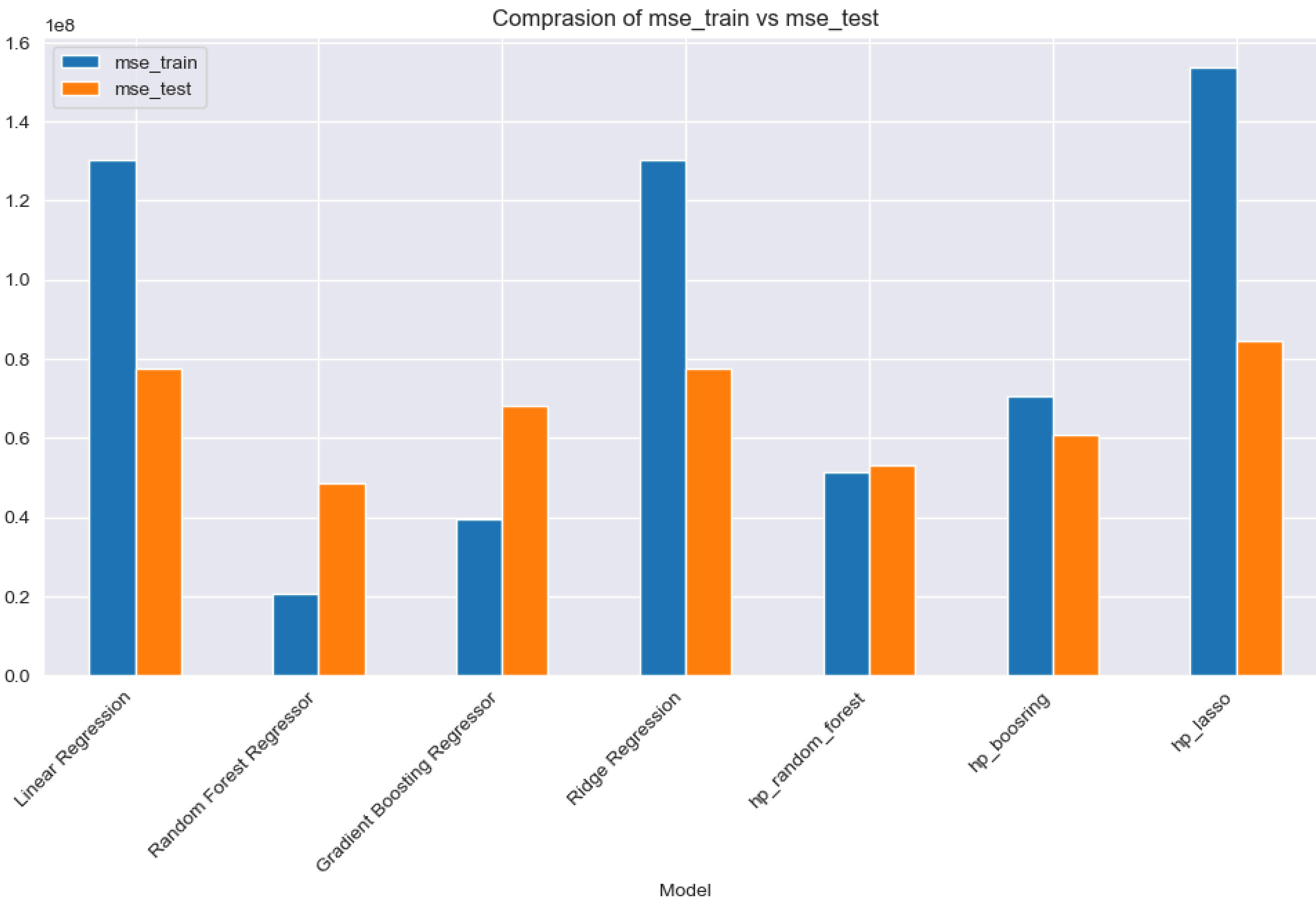
In [53]:
```
inf_.sort_plot('train_r2','test_r2')
```



Insights:

- Linear Regression, Ridge and Lasso are showing more **stability between their test and train R2 Scores**. However their **scores are low (<60%)** indicating **underfitting problems**.
- Random Forest models and Gradient Boosting are showing **overfitting problems** as their **Train scores are way higher than ther test scores**.

In [56]:
```
inf_.sort_plot('mse_train','mse_test')
```

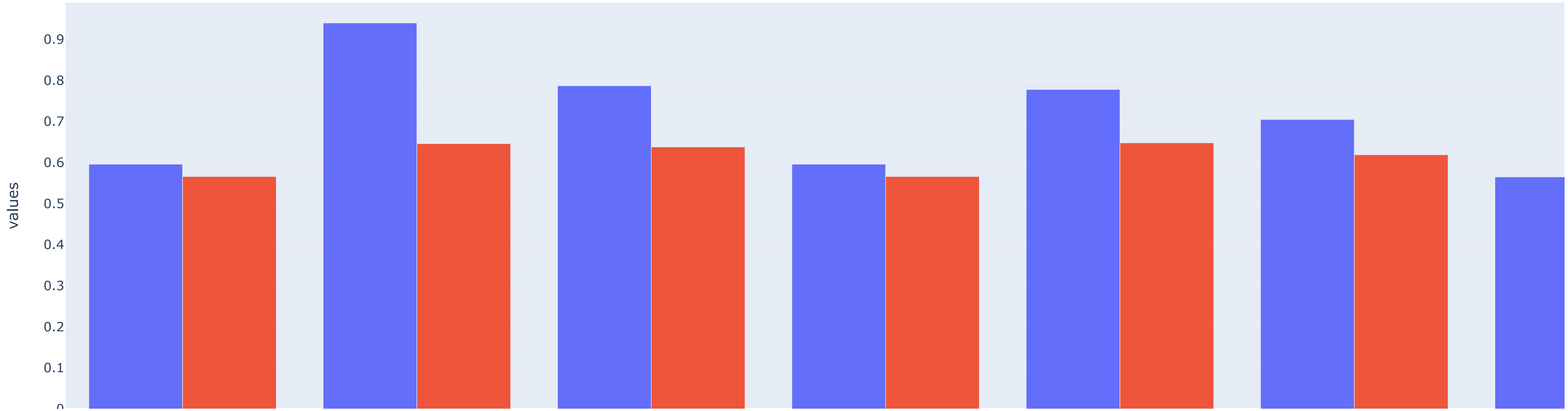


Insights:

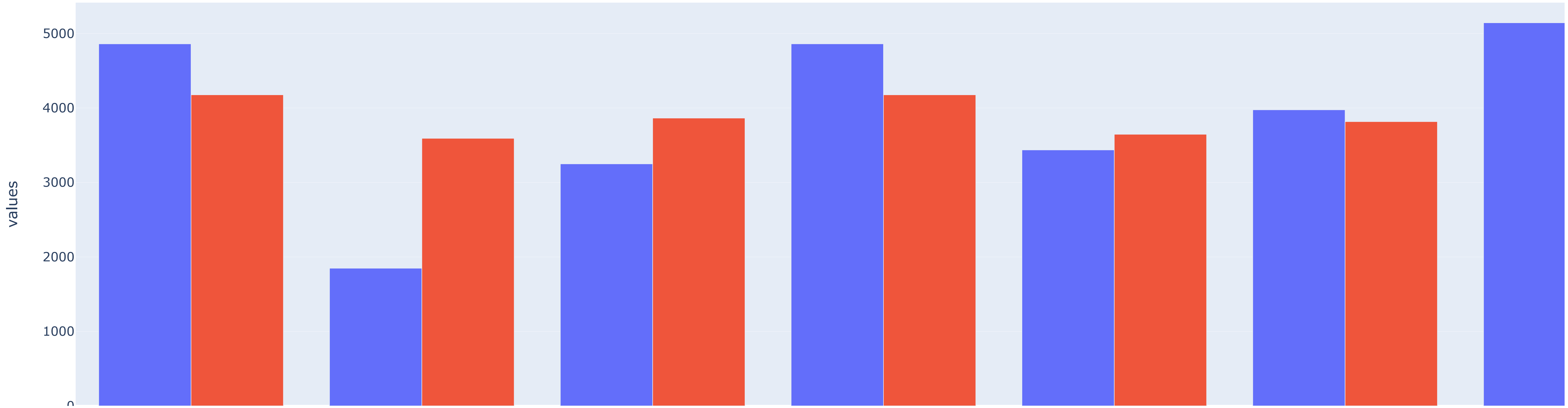
- MSE metric shows similar results than R2 scores
- However, Random Forest is showing overfitting with very little train error and large test error.
- The most stable models according to MSE are Linear Regression, Ridge, and Lasso

Finally let's compare R2 scores and MSE for test and training using grouped bar plots.

In [57]:
```
inf_.plotyy('train_r2','test_r2')
```



In [58]:
```
inf_.plotyy('mae_train','mae_test')
```



9. Conclusions

Inference of features and its impact in the model functionality

- Linear regression model is giving more weights to the following features [Resolution x, Internal storage (GB), Number of SIMs, RAM (MB), Rear camera] which confirms our inital feature selections of top 5 features
- Randomforest model is matching out 3 features with low weightage to the RAM
- Gradient boosting consider all the 5 features as its top 5 important feature but the weighting is not consistent and having large bias
- ridge,lasso and hyper parameter tuned models are reflecting the same 4 features as the greatest importance and their by providing decent prediction