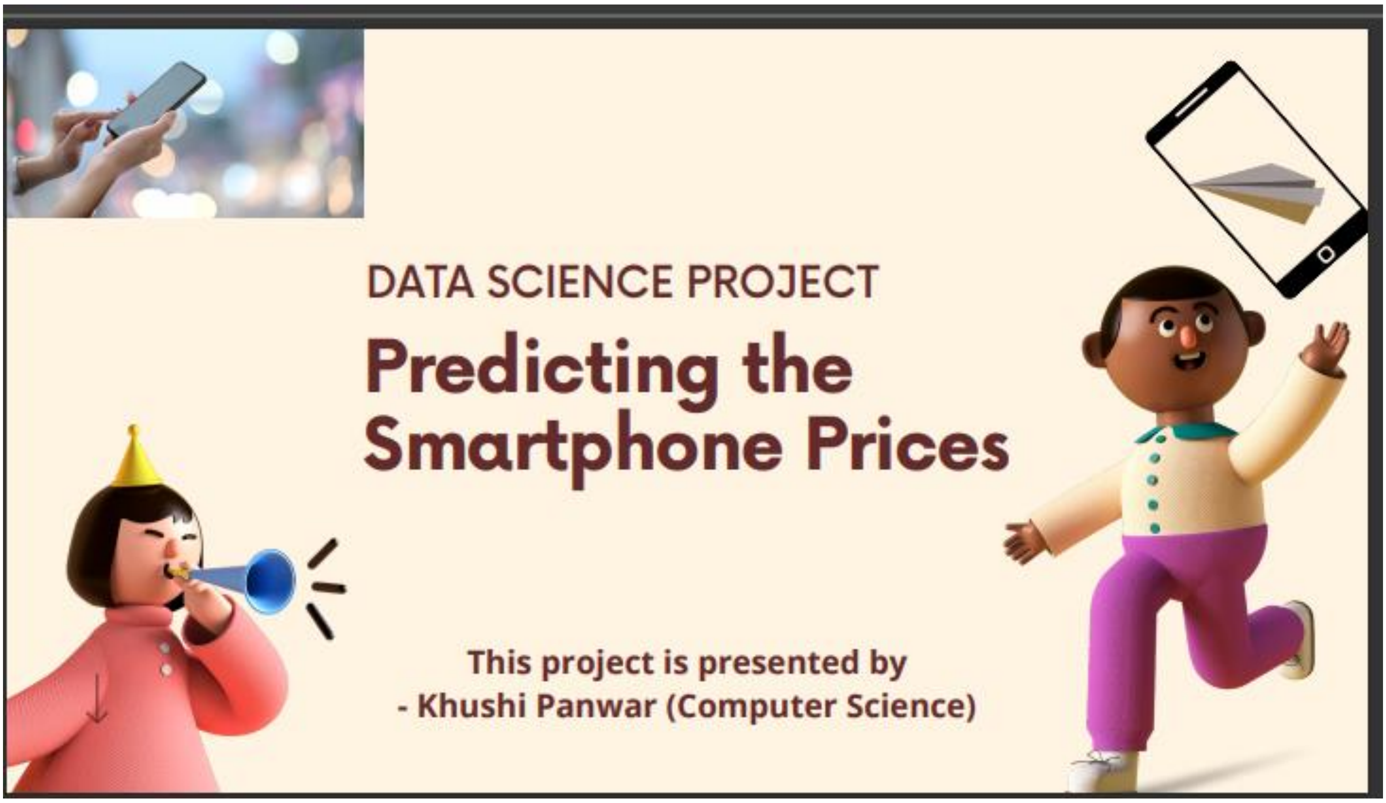
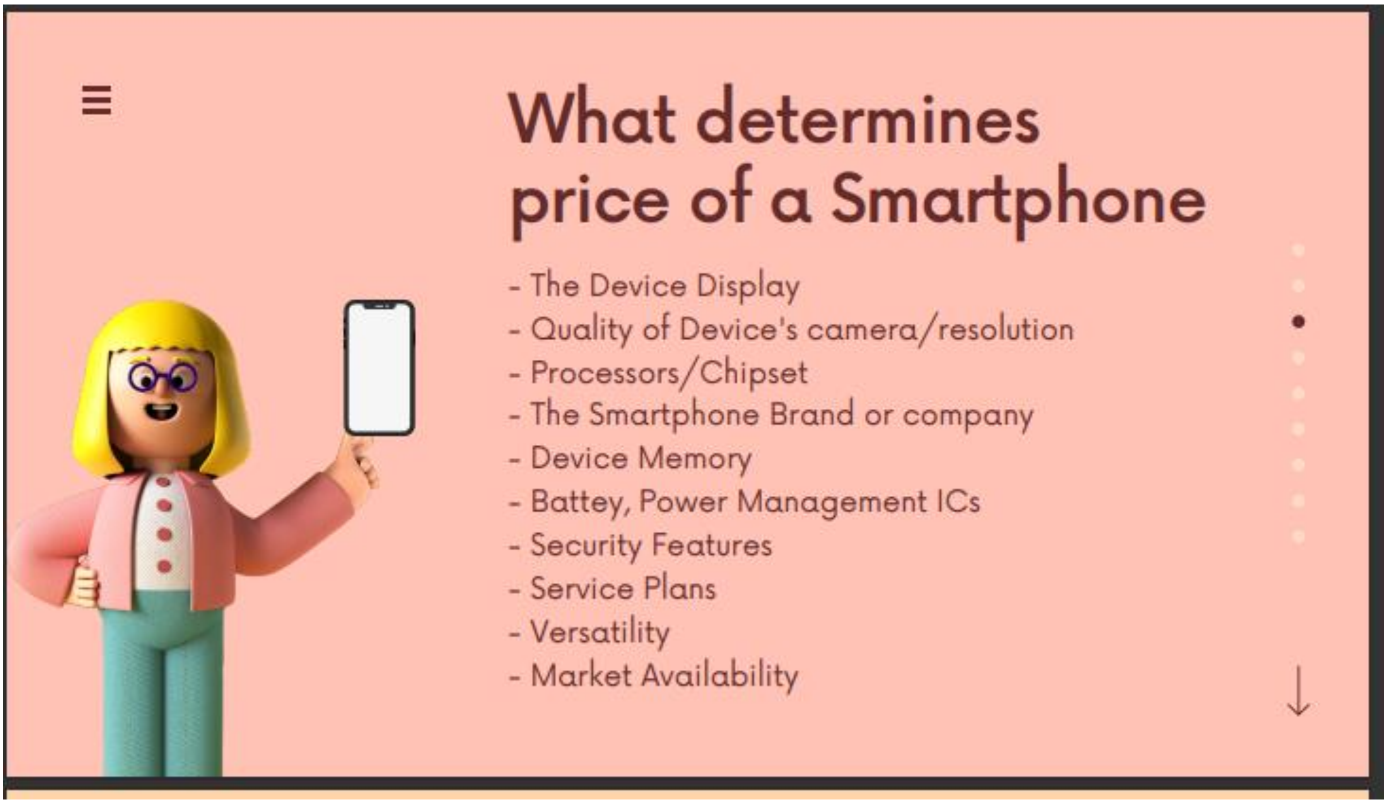

DATA SCIENCE PROJECT
Predicting the Smartphone Prices
This project is presented by
- Khushi Panwar (Computer Science)


What determines price of a Smartphone
- The Device Display
- Quality of Device's camera/resolution
- Processors/Chipset
- The Smartphone Brand or company
- Device Memory
- Battey, Power Management ICs
- Security Features
- Service Plans
- Versatility
- Market Availability

ABOUT DATASET

This data set is collected from Kaggle.com.

The Dataset holds the detailed information regarding the attributes of a smartphone and contains several constraints such as : Battery Backup of device. screen width & height, memory, display, speed, sim & services, resolution and price ranges (as low, moderate and highly expensive).

CONTENT

iNFORMATION ABOUT THE COLUMNS

- id: ID
- battery_power: Total energy a battery can store in one time (mAh)
- clock_speed: Speed at which microprocessor executes instructions
- dual_sim: Support dual sim or not
- fc: Front Camera mega pixels
- four_g: Support 4G or not
- int_memory: Internal Memory (GB)
- m_dep: Mobile Depth (cm)
- mobile_wt: Weight of mobile phone
- n_cores: Number of cores of processor
- pc: Primary Camera mega pixels
- px_height: Pixel Resolution Height
- px_width: Pixel Resolution Width
- ram: Random Access Memory (MB)
- sc_h: Screen Height of mobile (cm)
- sc_w: Screen Width of mobile (cm)
- talk_time: Time that a single battery charge will last
- three_g: Support 3G or not
- touch_screen: Has touch screen or not
- wifi: Support wifi or not

```
data_train.head()
```

	battery_power	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mobile_wt	n_cores	pc	px_height	px_width	ram	sc_h	sc_w	talk_time	three_g	touch_screen	wifi	price_range
0	842	2.2	0	1	0	7	0.6	188	2	2	20	756	2549	9	7	19	0	0	1	1
1	1021	0.5	1	0	1	53	0.7	136	3	6	905	1988	2631	17	3	7	1	1	0	2
2	563	0.5	1	2	1	41	0.9	145	5	6	1263	1716	2603	11	2	9	1	1	0	2
3	615	2.5	0	0	0	10	0.8	131	6	9	1216	1786	2769	16	8	11	1	0	0	2
4	1821	1.2	0	13	1	44	0.6	141	2	14	1208	1212	1411	8	2	15	1	1	0	1

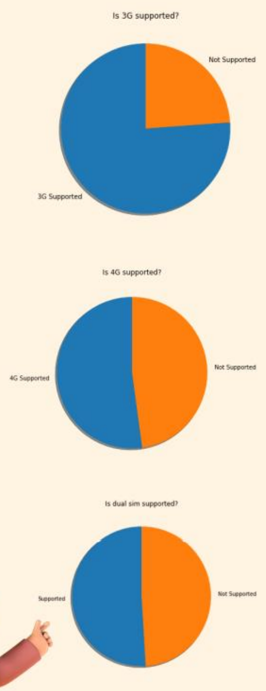
III HEATMAP & CORRELATION

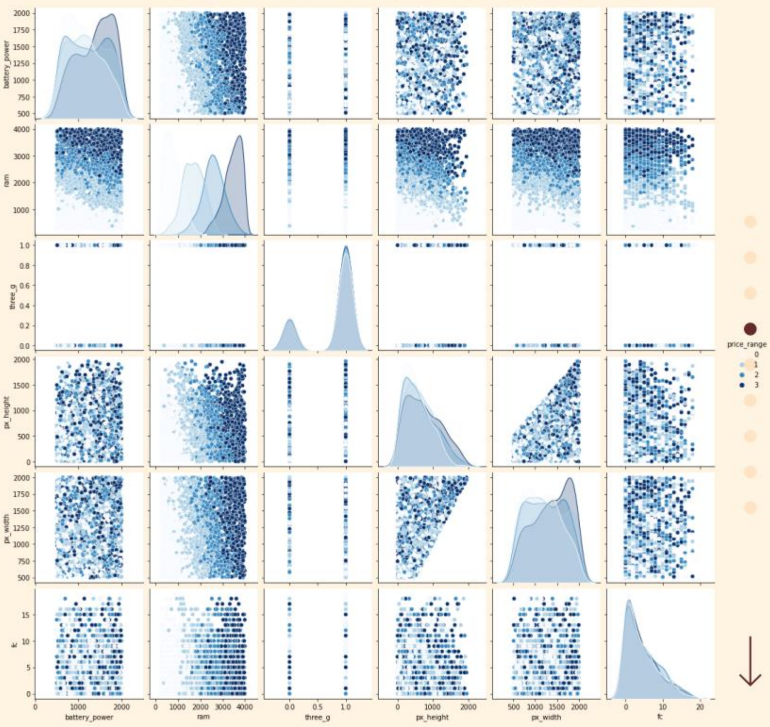
sns.heatmap(correlation_rate, annot = True, cmap = "Greens")

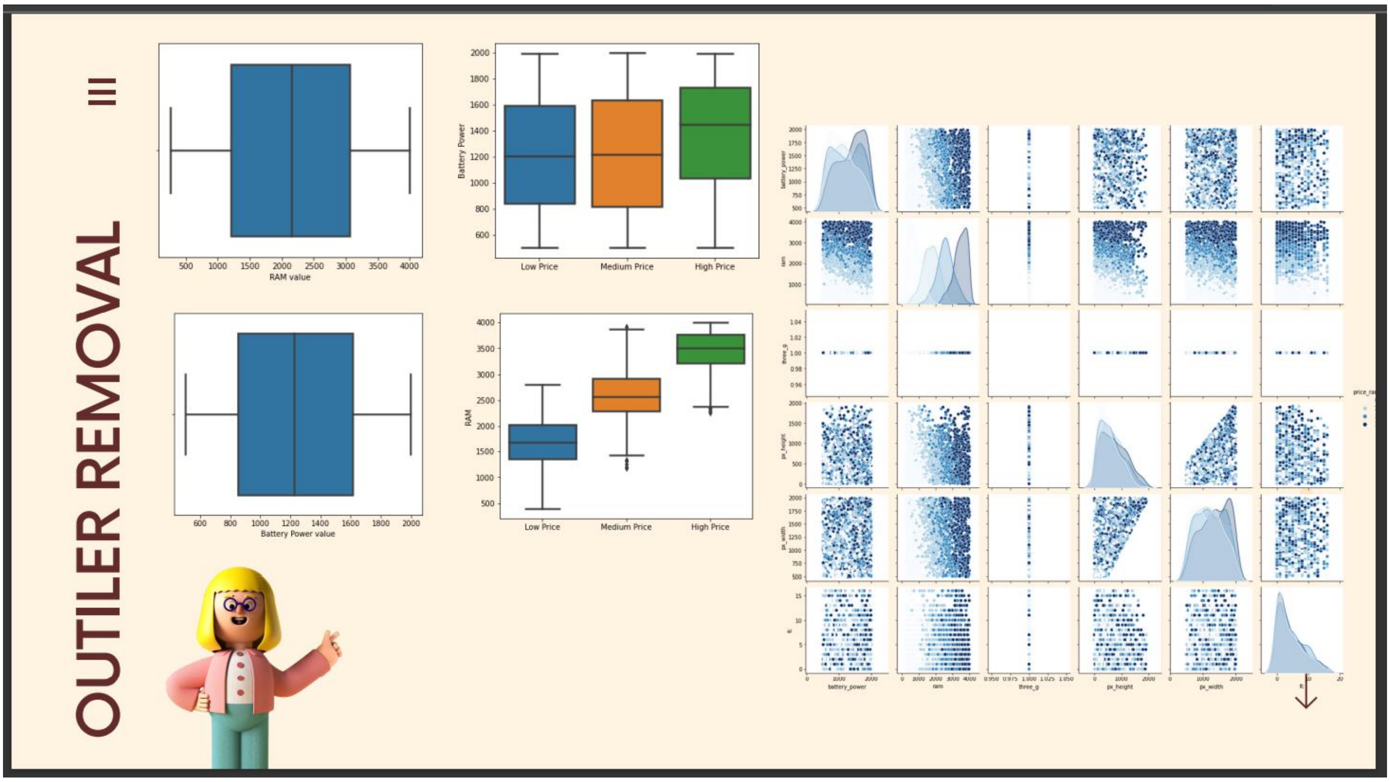
A heat map is a two-dimensional representation of data in which values are represented by colors. We can see that there is strong positive correlation between price range and RAM. Also, price range, battery power and 4G/3G. Hence, these columns were explored and used to modelling

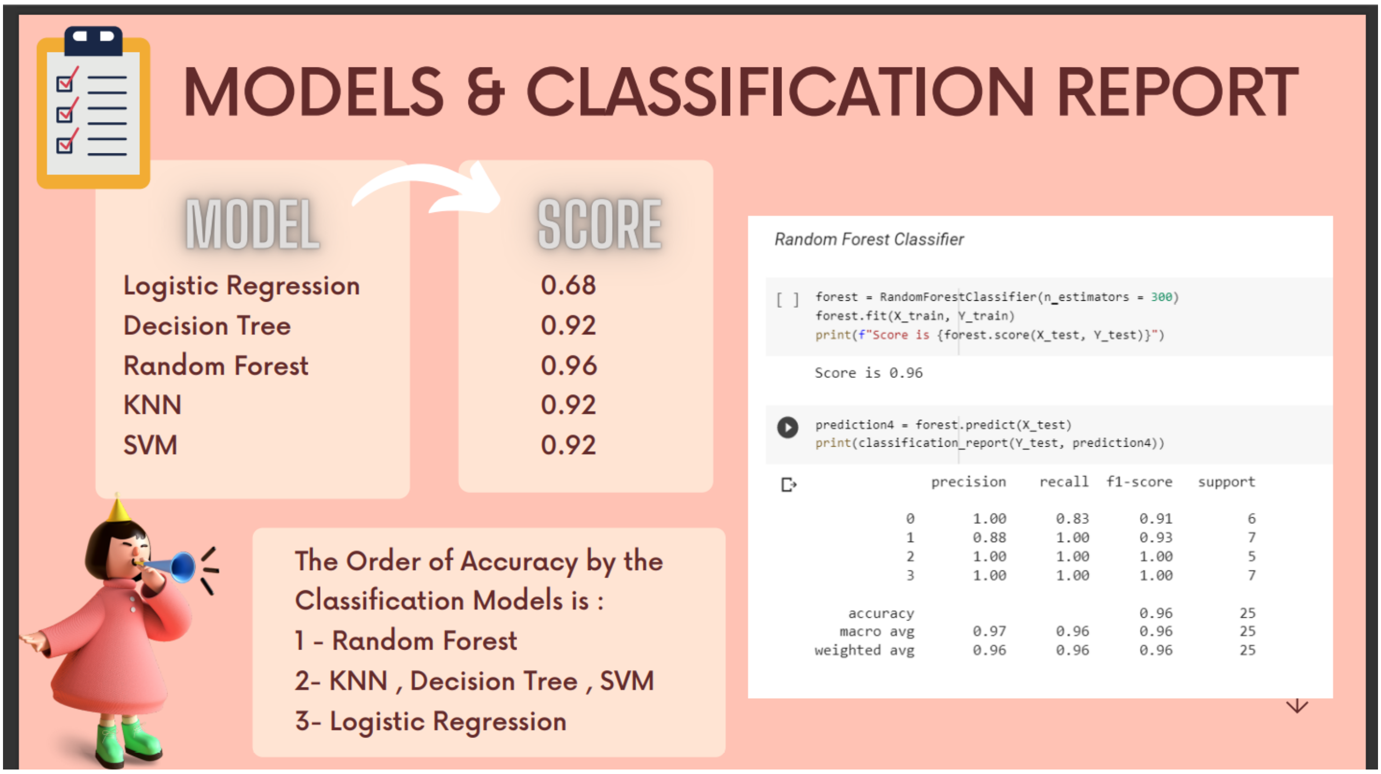
III DATA VISUALIZATION

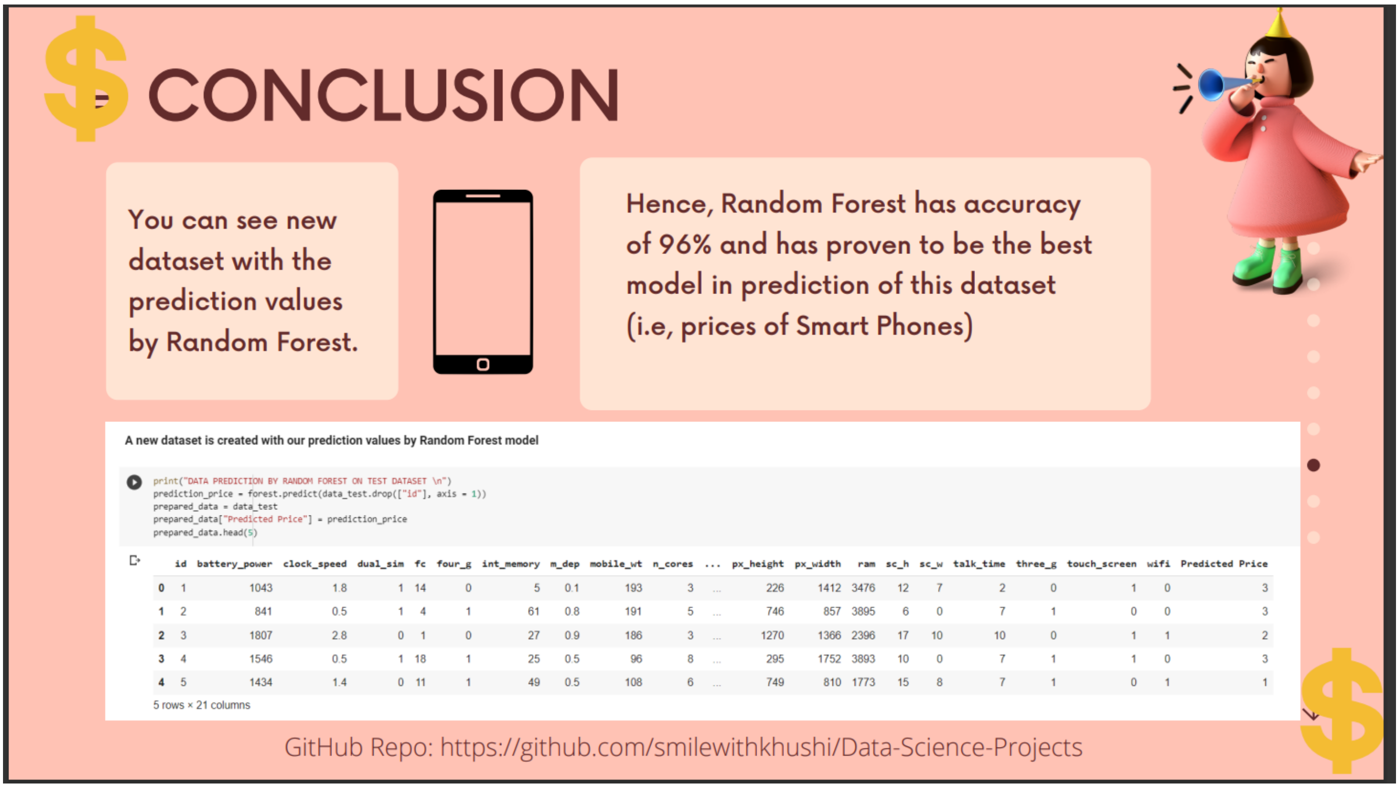
sns.pairplot(data_train[selected],hue='price_range', palette="Blues")






OUTILER REMOVAL
RAM value
Battery Power value
Battery Power
RAM
Low Price
Medium Price
High Price


MODELS & CLASSIFICATION REPORT
MODEL
SCORE
Logistic Regression 0.68
Decision Tree 0.92
Random Forest 0.96
KNN 0.92
SVM 0.92
The Order of Accuracy by the Classification Models is :
1 - Random Forest
2- KNN , Decision Tree , SVM
3- Logistic Regression
Random Forest Classifier
forest = RandomForestClassifier(n_estimators = 300)
forest.fit(X_train, Y_train)
print(f"Score is {forest.score(X_test, Y_test)}")
Score is 0.96
prediction4 = forest.predict(X_test)
print(classification_report(Y_test, prediction4))
precision recall f1-score support
0 1.00 0.83 0.91 6
1 0.88 1.00 0.93 7
2 1.00 1.00 1.00 5
3 1.00 1.00 1.00 7
accuracy 0.96 25
macro avg 0.97 0.96 0.96 25
weighted avg 0.96 0.96 0.96 25



DATA SCIENCE PROJECT : Analyze the dataset about smartphones features and then predict the price accordingly. Submitted By – Khushi Panwar, Computer Science

1) Import data and libraries : import all useful libraries. Then, load the data.

```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

import sklearn
from  sklearn.model_selection  import  train_test_split
from sklearn.metrics import classification_report

from  sklearn.linear_model  import  LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from  sklearn.ensemble  import  RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier


# load data (for exploring and cleaning we load test and train datasets)
data_train = pd.read_csv("train.csv")
data_test = pd.read_csv("test.csv")
```

2) Fast looking on data : Let`s see head of our data frames, list of columns, sizes, descriptions and nan/null values in these datasets.

```
# fast looking (size of dataframe, columns, 5 first rows of data, info and describing)
print(f"The train dataset has {data_train.shape[0]} rows.")
print(f"And {data_train.shape[1]} columns atleast")
print('-' * 50)
```

```
print(f"The test dataset has {data_test.shape[0]} rows.")
print(f"And {data_test.shape[1]} columns.")
print('-' * 50)
print(f"List of train dataset columns: {data_train.columns}")
print('-' * 50)
print(f"List of test dataset columns: {data_test.columns}")

print("-" * 50, data_train.info())
print('-' * 50, data_test.info())
```

```
      dtype='object')
--------------------------------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 20 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   battery_power  2000 non-null   int64
 1   clock_speed    2000 non-null   float64
 2   dual_sim       2000 non-null   int64
 3   fc             2000 non-null   int64
 4   four_g         2000 non-null   int64
 5   int_memory     2000 non-null   int64
 6   m_dep          2000 non-null   float64
```

```
 7   mobile_wt      2000 non-null   int64
 8   n_cores        2000 non-null   int64
 9   pc             2000 non-null   int64
 10  px_height      2000 non-null   int64
 11  px_width       2000 non-null   int64
 12  ram            2000 non-null   int64
 13  sc_h           2000 non-null   int64
 14  sc_w           2000 non-null   int64
 15  talk_time      2000 non-null   int64
 16  three_g        2000 non-null   int64
 17  touch_screen   2000 non-null   int64
 18  wifi           2000 non-null   int64
 19  price_range    2000 non-null   int64
dtypes: float64(2), int64(18)
memory usage: 312.6 KB
--------------------------------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 20 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             1000 non-null   int64
 1   battery_power  1000 non-null   int64
 2   clock_speed    1000 non-null   float64
 3   dual_sim       1000 non-null   int64
 4   fc             1000 non-null   int64
 5   four_g         1000 non-null   int64
 6   int_memory     1000 non-null   int64
 7   m_dep          1000 non-null   float64
 8   mobile_wt      1000 non-null   int64
 9   n_cores        1000 non-null   int64
 10  pc             1000 non-null   int64
 11  px_height      1000 non-null   int64
 12  px_width       1000 non-null   int64
 13  ram            1000 non-null   int64
 14  sc_h           1000 non-null   int64
 15  sc_w           1000 non-null   int64
 16  talk_time      1000 non-null   int64
 17  three_g        1000 non-null   int64
 18  touch_screen   1000 non-null   int64
 19  wifi           1000 non-null   int64
dtypes: float64(2), int64(18)
memory usage: 156.4 KB
```

Information about columns:

- **id: ID**
- **battery_power: Total energy a battery can store in one time (mAh)**
- **clock_speed: Speed at which microprocessor executes instructions**
- **dual_sim: Support dual sim or not**
- **fc: Front Camera mega pixels**
- **four_g: Support 4G or not**
- **int_memory: Internal Memory (GB)**
- **m_dep: Mobile Depth (cm)**

- mobile_wt: Weight of mobile phone
- n_cores: Number of cores of processorpc:
- Primary Camera mega pixels
- px_height: Pixel Resolution Height
- px_width: Pixel Resolution Width ram:
- Random Access Memory (MB)sc_h:
- Screen Height of mobile (cm)sc_w:
- Screen Width of mobile (cm)
- talk_time: Time that a single battery charge will last
- three_g: Support 3G or not
- touch_screen: Has touch screen or not
- wifi: Support wifi or not

```
data_train.head()
```

	battery_power	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mobile_wt	n
0	842	2.2	0	1	0	7	0.6	188	
1	1021	0.5	1	0	1	53	0.7	136	
2	563	0.5	1	2	1	41	0.9	145	
3	615	2.5	0	0	0	10	0.8	131	
4	1821	1.2	0	13	1	44	0.6	141	

```
data_train.describe()
```

	battery_power	clock_speed	dual_sim	fc	four_g	int_memory
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000
mean	1238.518500	1.522250	0.509500	4.309500	0.521500	32.046500
std	439.418206	0.816004	0.500035	4.341444	0.499662	18.145715
min	501.000000	0.500000	0.000000	0.000000	0.000000	2.000000
25%	851.750000	0.700000	0.000000	1.000000	0.000000	16.000000
50%	1226.000000	1.500000	1.000000	3.000000	1.000000	32.000000
75%	1615.250000	2.200000	1.000000	7.000000	1.000000	48.000000
max	1998.000000	3.000000	1.000000	19.000000	1.000000	64.000000

Null and NAN values.

```
procent_of_null = data_train.isnull().sum() / data_train.shape[0]
print(procent_of_null)
print("-" * 20)
procent_of_nan = data_train.isna().sum() / data_train.shape[0]
print(procent_of_nan)
```

```
battery_power     0.0
clock_speed       0.0
dual_sim          0.0
fc                0.0
four_g            0.0
int_memory        0.0
m_dep             0.0
mobile_wt         0.0
n_cores           0.0
pc                0.0
px_height         0.0
px_width          0.0
ram               0.0
sc_h              0.0
sc_w              0.0
talk_time         0.0
three_g           0.0
touch_screen      0.0
wifi              0.0
price_range       0.0
dtype: float64
--------------------
battery_power     0.0
clock_speed       0.0
dual_sim          0.0
fc                0.0
four_g            0.0
int_memory        0.0
m_dep             0.0
mobile_wt         0.0
n_cores           0.0
pc                0.0
px_height         0.0
px_width          0.0
ram               0.0
sc_h              0.0
sc_w              0.0
talk_time         0.0
three_g           0.0
touch_screen      0.0
wifi              0.0
price_range       0.0
dtype: float64
```

```
procent_of_null = data_test.isnull().sum() / data_test.shape[0]
print(procent_of_null)
print("-" * 20)
procent_of_nan = data_test.isna().sum() / data_test.shape[0]
print(procent_of_nan)
```

```
id                0.0
battery_power     0.0
clock_speed       0.0
```

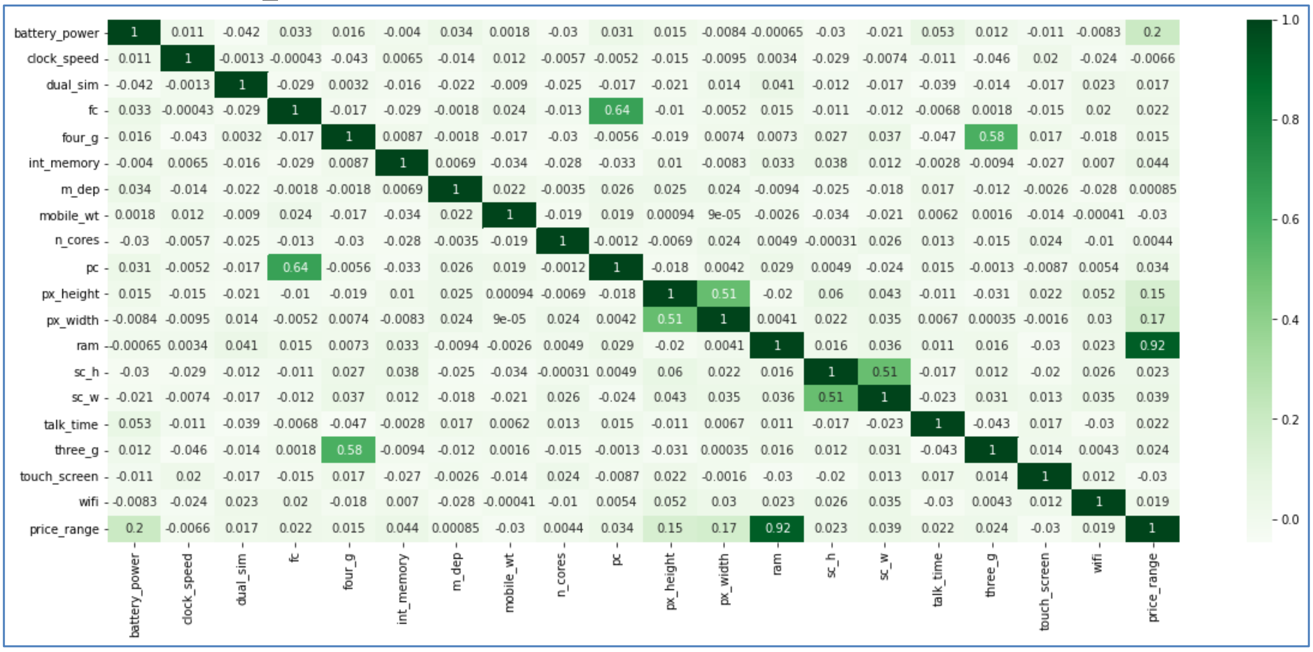
```
dual_sim         0.0
fc               0.0
four_g           0.0
int_memory       0.0
m_dep            0.0
mobile_wt        0.0
n_cores          0.0
pc               0.0
px_height        0.0
px_width         0.0
ram              0.0
sc_h             0.0
sc_w             0.0
talk_time        0.0
three_g          0.0
touch_screen     0.0
wifi             0.0
dtype: float64
--------------------
id               0.0
battery_power    0.0
clock_speed      0.0
dual_sim         0.0
fc               0.0
four_g           0.0
int_memory       0.0
m_dep            0.0
mobile_wt        0.0
n_cores          0.0
pc               0.0
px_height        0.0
px_width         0.0
ram              0.0
sc_h             0.0
sc_w             0.0
talk_time        0.0
three_g          0.0
touch_screen     0.0
wifi             0.0
dtype: float64
```

Now we can see train dataset includes 2000 rows and 20 columns, but test dataset includes 1000 rows and 20. We can look on names of columns and understand what they mean. Also, fortunately, we can see that there are not nan and null values.

3) Cleaning : Firstly, before modelling, we have to delete unnecessary columns to prevent overfitting, but to learn which columns we should drop we must create correlation matrix.

```
plt.figure(figsize=(20, 8))
correlation_rate = data_train.corr()
sns.heatmap(correlation_rate, annot = True, cmap = "Greens")
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f2abac441d0>



Here we can see that there is strong positive correlation between price range and RAM. Also,price range, battery power and 4G/3G. Other features have small positive correlation.

4) Exploring : We will explore columns of TRAIN dataset about RAM, 4G/3G and BatteryPower, because these columns are important for our future modeling.

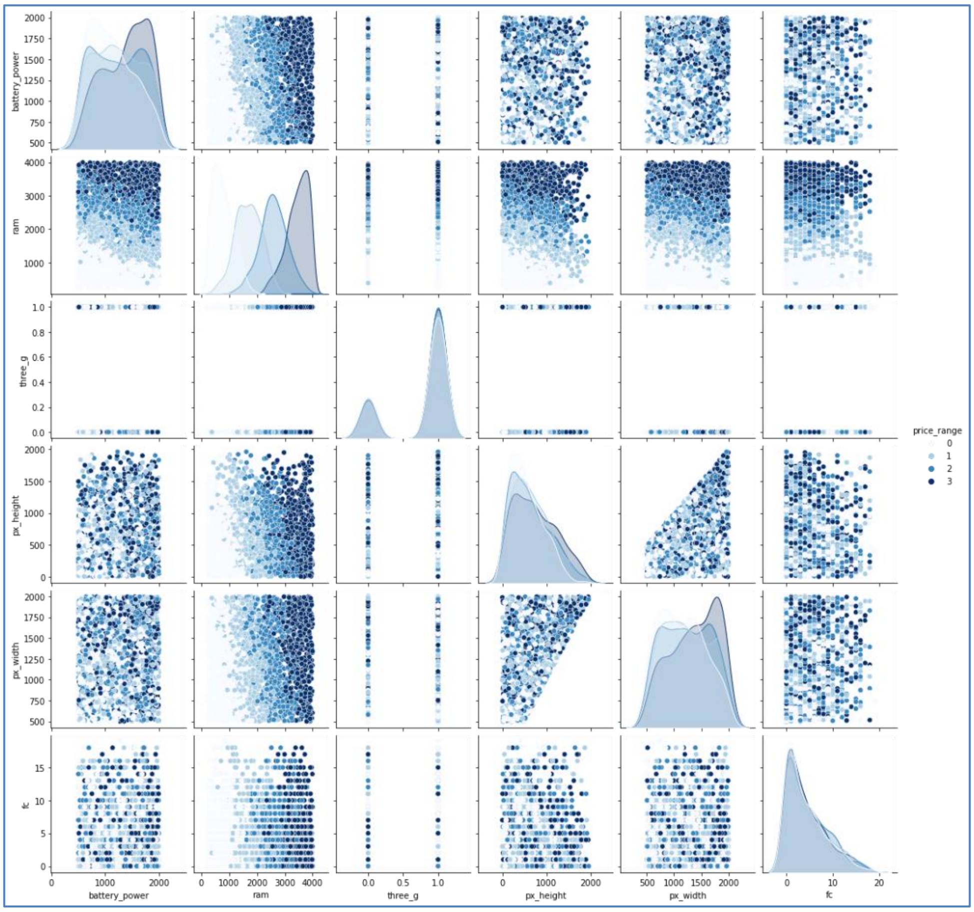
```
data_train.columns
```

```
Index(['battery_power', 'clock_speed', 'dual_sim', 'fc', 'four_g','int_memory', 'm_dep',
'mobile_wt', 'n_cores', 'pc', 'px_height','px_width', 'ram', 'sc_h', 'sc_w', 'talk_time',
'three_g','touch_screen', 'wifi', 'price_range'],dtype='object')
```

```
selected=["battery_power", "ram" , "three_g", "price_range", "px_height" , "px_width", "fc"]
sns.pairplot(data_train[0:],hue='price_range', palette="Blues" )
```

```
<seaborn.axisgrid.PairGrid at 0x7f2ab7f28810>
```

```
sns.pairplot(data_train[selected],hue='price_range', palette="Blues" )
```



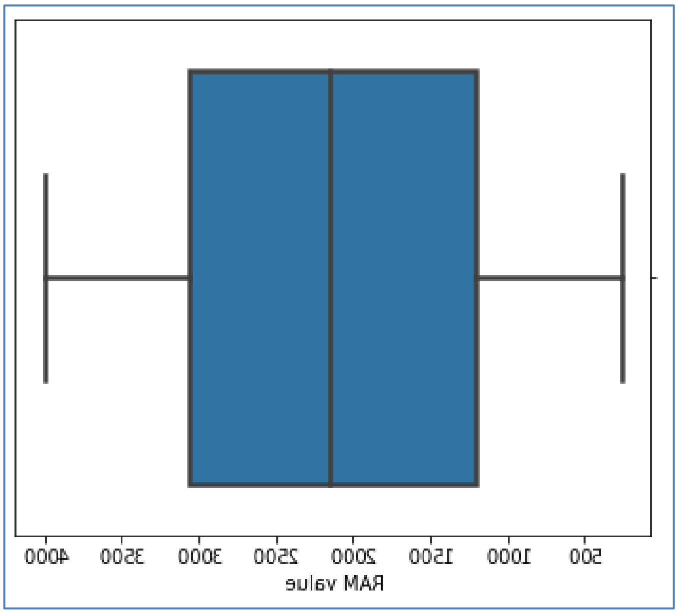

```
<seaborn.axisgrid.PairGrid at 0x7f2aace67450>
```

4.1) RAM

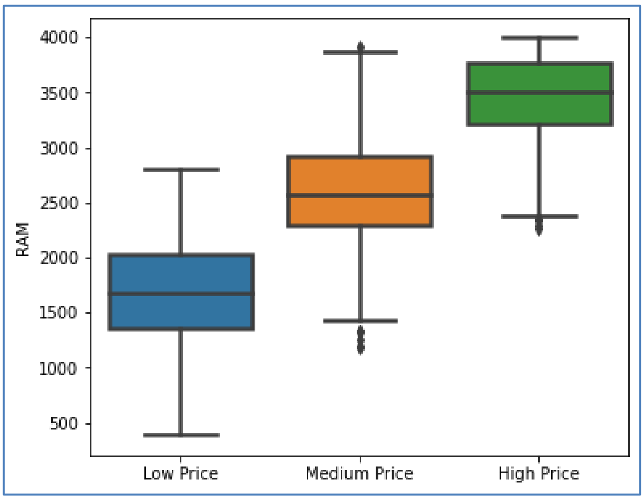
```
print(f"Max RAM value is: {data_train['ram'].max()} MB")
print(f"Min RAM value is: {data_train['ram'].min()} MB")
print(f"Mean of RAM values is: {round(data_train['ram'].mean())} MB")
```

```
Max RAM value is: 3998 MB
Min RAM value is: 256 MB
Mean of RAM values is: 2124 MB
```

```
plt.figure(figsize=[6, 5])
sns.boxplot(data_train['ram'], linewidth=2.5)
plt.xlabel("RAM value")
```



```
cheap = data_train["ram"][data_train["price_range"] == 1]
medium = data_train["ram"][data_train["price_range"] == 2]
expensive = data_train["ram"][data_train["price_range"] == 3]
price_ram_data = pd.DataFrame({"Low Price" : cheap,   "Medium Price" : medium,  "High Price" : expensive}
)

plt.figure(figsize=[6, 5])
sns.boxplot(data = price_ram_data, linewidth=2.5)
plt.ylabel("RAM")
```



In these boxplots we can see: 1) In the first graph we can see maximum, minimum, median andmean of whole RAM column. 2) In the second graph we can see comparison of price ranges and RAM amount in smartphones of these ranges.

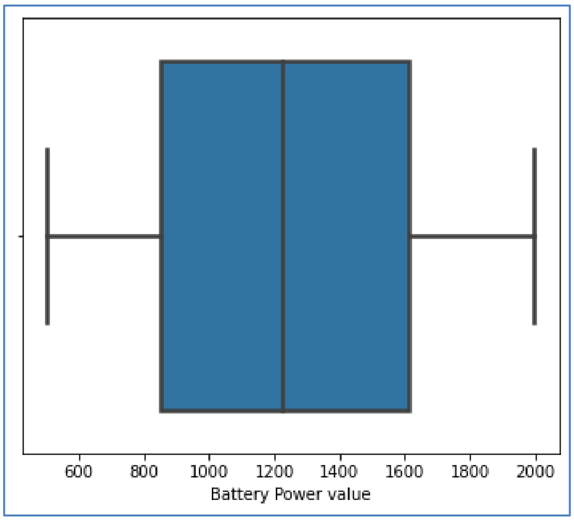
4.2) Battery power

```
print(f"Max Battery Power value is: {data_train['battery_power'].max()} mAh")
print(f"Min Battery Power value is: {data_train['battery_power'].min()} mAh")
print(f"Mean of Battery Power values is: {round(data_train['battery_power'].mean())} mAh")
```

```
Max Battery Power value is: 1998 mAh
Min Battery Power value is: 501 mAh
Mean of Battery Power values is: 1239 mAh
```

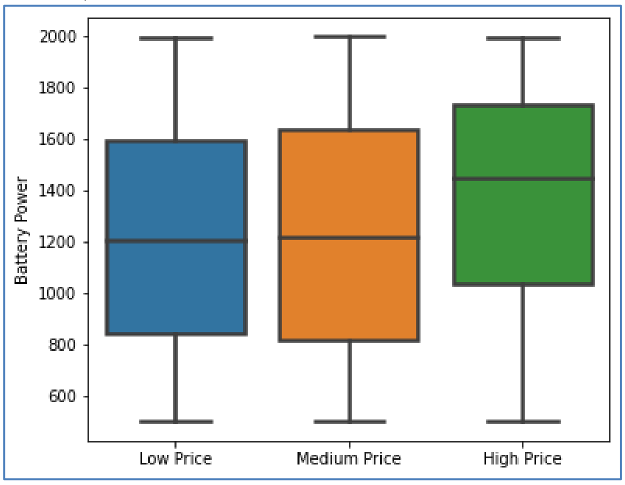
```
plt.figure(figsize=[6, 5])
sns.boxplot(data_train['battery_power'], linewidth=2.5)
plt.xlabel("Battery Power value")
```

```
Text(0.5, 0, 'Battery Power value')
```



```
cheap = data_train["battery_power"][data_train["price_range"] == 1]
medium = data_train["battery_power"][data_train["price_range"] == 2]
expensive = data_train["battery_power"][data_train["price_range"] == 3]
price_bp_data = pd.DataFrame({"Low Price" : cheap, "Medium Price" : medium, "High Price" : expensive})
plt.figure(figsize=[6, 5])
sns.boxplot(data = price_bp_data, linewidth=2.5)
plt.ylabel("Battery Power")
```

```
Text(0, 0.5, 'Battery Power')
```

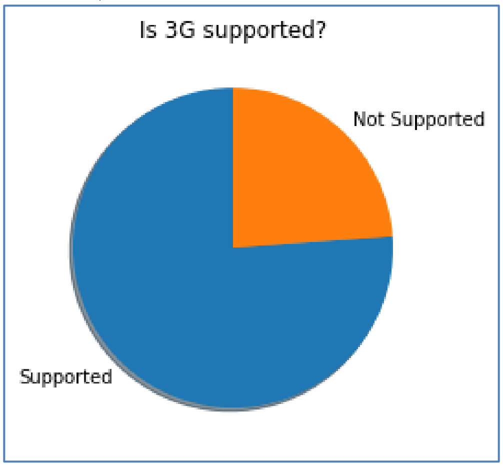


In these boxplots we can see that: 1) In the first graph we can see maximum, minimum, medianand mean of whole Battery Power column. 2) In the second graph we can see comparison of price ranges and Battery Power amount in smartphones of these ranges.

4.3) 3G/4G

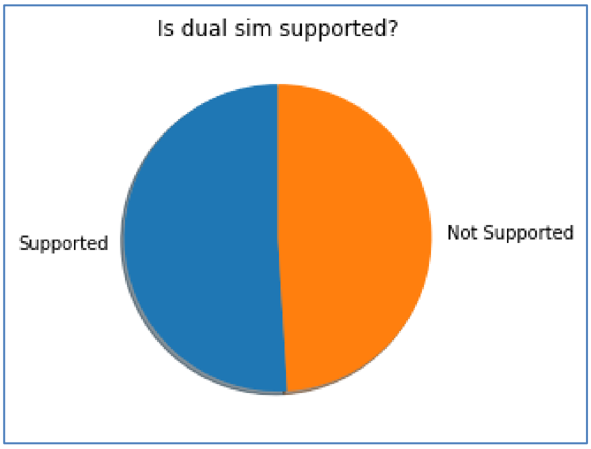
```
three_g  =  data_train["three_g"].value_counts().values
labels = ["Supported", "Not Supported"]

plt.figure(figsize=[6, 4])
plt.pie(three_g, labels = labels, shadow=True, startangle=90)
plt.title("Is 3G supported?")
```

```
Text(0.5, 1.0, 'Is 3G supported?')
```



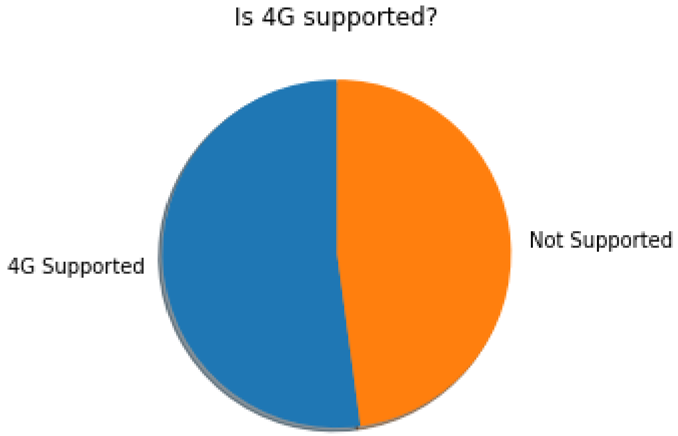

```
dual_sim  =  data_train["dual_sim"].value_counts().values
plt.figure(figsize=[6, 4])
plt.pie(dual_sim, labels = labels, shadow=True, startangle=90)
plt.title("Is dual sim supported?")
```

```
Text(0.5, 1.0, 'Is dual sim supported?')
```




```
four_g  =  data_train["four_g"].value_counts().values
labels = ["4G Supported", "Not Supported"]

plt.figure(figsize=[6, 4])
plt.pie(four_g, labels = labels, shadow=True, startangle=90)
plt.title("Is 4G supported?")
```

```
Text(0.5, 1.0, 'Is 4G supported?')
```



REMOVING OUTLIERS

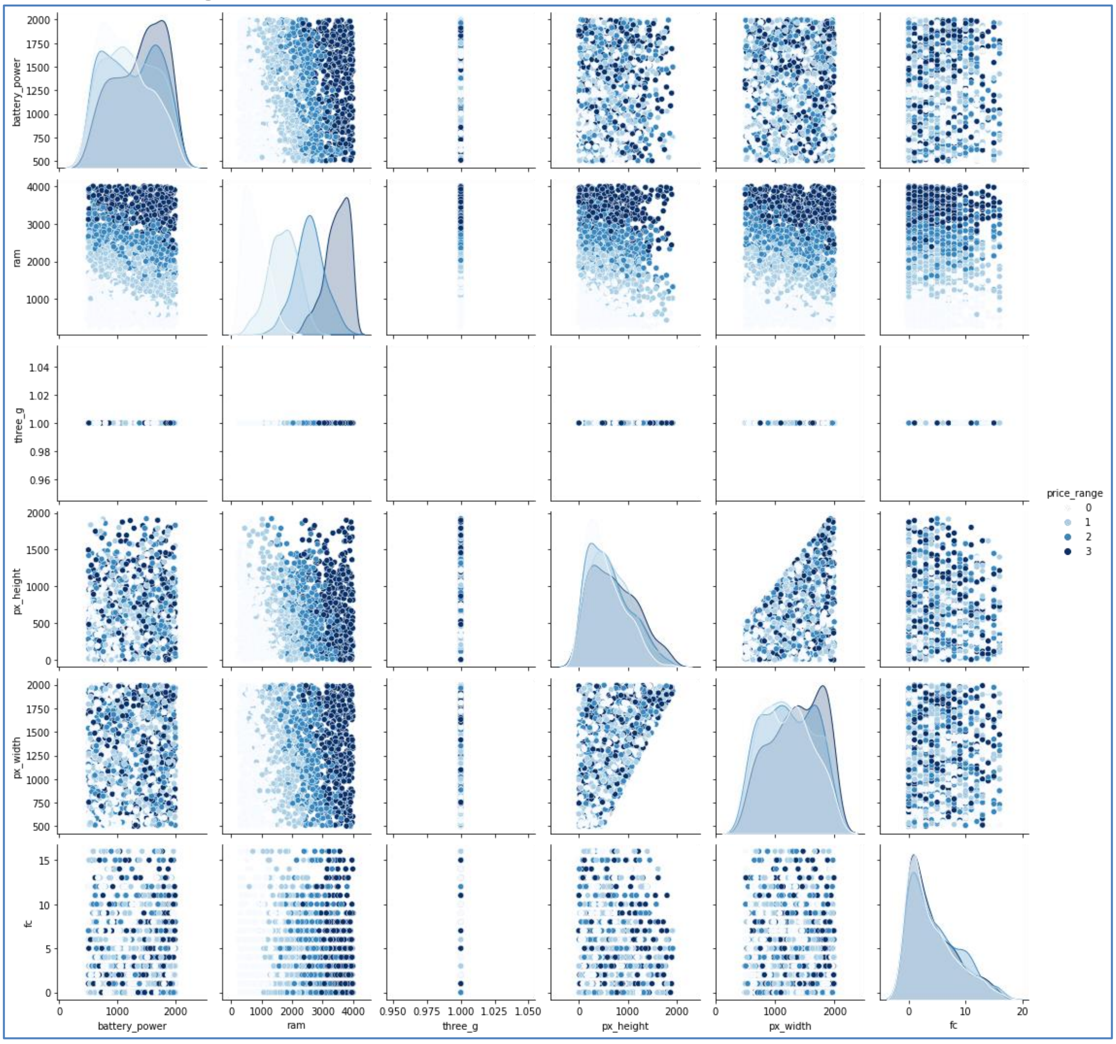
```
''' Box plot use the IQR method to display data and outliers(shape of the data) but in order to be get a list of id
we will need to use the mathematical formula and retrieve the outlier data.'''
# First we will calculate IQR,
Q1 = data_train.quantile(0.25)
Q3 = data_train.quantile(0.75)
IQR = Q3 - Q1
print("IQR details for all columns : ", IQR)

'''  As we now have the IQR scores, it’s time to get hold on outliers. The below code will give an output with some
The data point where we have False that means these values are valid whereas True indicates presence of an outlier.

new_data= data_train[~((data_train < (Q1 - 1.5 * IQR)) |(data_train > (Q3 + 1.5 * IQR))).any(axis=1)]
print("Data after removing outliers : ", new_data)
new_data.shape
```

```
four_g            1.00
int_memory       32.00
m_dep             0.60
mobile_wt        61.00
n_cores           4.00
pc               10.00
```

```
px_height          664.50
px_width           758.25
ram               1857.00
sc_h                 7.00
sc_w                 7.00
talk_time           10.00
three_g              0.00
touch_screen         1.00
wifi                 1.00
price_range          1.50
dtype: float64

Data after removing outliers :
                                        battery_power  clock_speed  dual_sim  fc  f

1               1021          0.5          1    0       1           53    0.7
2                563          0.5          1    2       1           41    0.9
3                615          2.5          0    0       0           10    0.8
4               1821          1.2          0   13       1           44    0.6
5               1859          0.5          1    3       0           22    0.7
...              ...          ...        ...   ..     ...          ...    ...
1995             794          0.5          1    0       1            2    0.8
1996            1965          2.6          1    0       0           39    0.2
1997            1911          0.9          1    1       1           36    0.7
1998            1512          0.9          0    4       1           46    0.1
1999             510          2.0          1    5       1           45    0.9

      mobile_wt  n_cores  pc  px_height  px_width   ram  sc_h  sc_w  \
1           136        3   6        905      1988  2631    17     3
2           145        5   6       1263      1716  2603    11     2
3           131        6   9       1216      1786  2769    16     8
4           141        2  14       1208      1212  1411     8     2
5           164        1   7       1004      1654  1067    17     1
...         ...      ...  ..        ...       ...   ...   ...   ...
1995        106        6  14       1222      1890   668    13     4
1996        187        4   3        915      1965  2032    11    10
1997        108        8   3        868      1632  3057     9     1
1998        145        5   5        336       670   869    18    10
1999        168        6  16        483       754  3919    19     4

      talk_time  three_g  touch_screen  wifi  price_range
1             7        1             1     0            2
2             9        1             1     0            2
3            11        1             0     0            2
4            15        1             1     0            1
5            10        1             0     0            1
...         ...      ...           ...   ...          ...
1995         19        1             1     0            0
1996         16        1             1     1            2
1997          5        1             1     0            3
1998         19        1             1     1            0
1999          2        1             1     1            3

[1506  rows x 20  columns]
```

```
sns.pairplot(new_data[selected],hue='price_range', palette="Blues" )
```

<seaborn.axisgrid.PairGrid at 0x7f2aab6f8e10>



5) Modelling and Preparing Data : Before modelling we have to prepare data. Let's do this:

```
X = data_train.drop(["price_range"], axis = 1)
Y = data_train["price_range"]
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 25)
```

```
Print(new_data.columns)
```

```
Index(['battery_power', 'clock_speed', 'dual_sim', 'fc', 'four_g', 'int_memory', 'm_dep',
'mobile_wt', 'n_cores', 'pc', 'px_height','px_width', 'ram', 'sc_h', 'sc_w', 'talk_time',
'three_g', 'touch_screen', 'wifi', 'price_range'], dtype='object')
```

```
X = new_data.drop(["price_range"], axis = 1)
Y = new_data["price_range"]
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 25)
```

Now various models will be used. As our task is to classify price range (1,2,3) ; thats why creating classification models.

```
Print(X.info)
```

```
<bound method DataFrame.info of        battery_power  clock_speed  dual_sim  fc
four_g  int_memory  m_dep  \
1              1021          0.5         1   0       1          53    0.7
2               563          0.5         1   2       1          41    0.9
3               615          2.5         0   0       0          10    0.8
4              1821          1.2         0  13       1          44    0.6
5              1859          0.5         1   3       0          22    0.7
...             ...          ...       ...  ..     ...         ...    ...
1995            794          0.5         1   0       1           2    0.8
1996           1965          2.6         1   0       0          39    0.2
1997           1911          0.9         1   1       1          36    0.7
1998           1512          0.9         0   4       1          46    0.1
1999            510          2.0         1   5       1          45    0.9

      mobile_wt  n_cores  pc  px_height  px_width   ram  sc_h  sc_w  \
1           136        3   6        905      1988  2631    17     3
2           145        5   6       1263      1716  2603    11     2
3           131        6   9       1216      1786  2769    16     8
4           141        2  14       1208      1212  1411     8     2
5           164        1   7       1004      1654  1067    17     1
...         ...      ...  ..        ...       ...   ...   ...   ...
1995        106        6  14       1222      1890   668    13     4
1996        187        4   3        915      1965  2032    11    10
1997        108        8   3        868      1632  3057     9     1
1998        145        5   5        336       670   869    18    10
1999        168        6  16        483       754  3919    19     4

      talk_time  three_g  touch_screen  wifi
1             7        1             1     0
2             9        1             1     0
3            11        1             0     0
4            15        1             1     0
5            10        1             0     0
...         ...      ...           ...   ...
1995         19        1             1     0
1996         16        1             1     1
1997          5        1             1     0
1998         19        1             1     1
1999          2        1             1     1

[1506 rows x 19 columns]>
```

Logistic Regression

```
log_reg = LogisticRegression()
log_reg.fit(X_train,  Y_train)
print(f"Score is {log_reg.score(X_test, Y_test)}")
```

```
Score is 0.68
      /usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic.py:818: Conver
```

```
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
```

```
prediction1=log_reg.predict(X_test)
print(classification_report(Y_test,  prediction1))
```

```
              precision    recall  f1-score   support

           0       0.86      1.00      0.92         6
           1       0.86      0.86      0.86         7
           2       0.33      0.40      0.36         5
           3       0.60      0.43      0.50         7

    accuracy                           0.68        25
   macro avg       0.66      0.67      0.66        25
weighted avg       0.68      0.68      0.67        25
```

Decision Tree

```
tree = DecisionTreeClassifier(max_depth = 9)
tree.fit(X_train, Y_train)
print(f"Score is {tree.score(X_test, Y_test)}")
```

```
Score is 0.92
```

```
prediction2=tree.predict(X_test)
print(classification_report(Y_test,  prediction2))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         6
           1       1.00      0.86      0.92         7
           2       0.71      1.00      0.83         5
           3       1.00      0.86      0.92         7

    accuracy                           0.92        25
   macro avg       0.93      0.93      0.92        25
weighted avg       0.94      0.92      0.92        25
```

KNN

```
knn = KNeighborsClassifier(n_neighbors = 15)
knn.fit(X_train, Y_train)
print(f"Score is {knn.score(X_test, Y_test)}")
```

```
Score is 0.92
```

```
prediction3 = knn.predict(X_test)
print(classification_report(Y_test,  prediction3))
```

```
              precision    recall  f1-score   support

           0       1.00      0.83      0.91         6
           1       0.86      0.86      0.86         7
           2       0.83      1.00      0.91         5
           3       1.00      1.00      1.00         7

    accuracy                           0.92        25
   macro avg       0.92      0.92      0.92        25
weighted avg       0.93      0.92      0.92        25
```

Random Forest Classifier

```
forest = RandomForestClassifier(n_estimators = 300)
forest.fit(X_train, Y_train)
print(f"Score is {forest.score(X_test, Y_test)}")
```

```
Score is 0.96
```

```
prediction4  =  forest.predict(X_test)
print(classification_report(Y_test,  prediction4))
```

```
              precision    recall  f1-score   support

           0       1.00      0.83      0.91         6
           1       0.88      1.00      0.93         7
           2       1.00      1.00      1.00         5
           3       1.00      1.00      1.00         7

    accuracy                           0.96        25
   macro avg       0.97      0.96      0.96        25
weighted avg       0.96      0.96      0.96        25
```

SVM

```
from sklearn.svm import SVC
supvec=SVC(kernel='rbf')
supvec.fit(X_train,  Y_train)
prediction5=supvec.predict(X_test)
```

```
print(f"Score is {supvec.score(X_test, Y_test)}")
print(classification_report(Y_test, prediction5))
```

```
Score is 0.92
              precision    recall  f1-score   support

           0       1.00      0.83      0.91         6
           1       0.88      1.00      0.93         7
```

```
              2       1.00      0.80      0.89         5
              3       0.88      1.00      0.93         7

       accuracy                           0.92        25
      macro avg       0.94      0.91      0.92        25
   weighted avg       0.93      0.92      0.92        25
```

**** Random Forest has given high accuracy/score..****

6) Conclusion.

```
data_test.columns
```

```
Index(['id', 'battery_power', 'clock_speed', 'dual_sim', 'fc', 'four_g',
       'int_memory', 'm_dep', 'mobile_wt', 'n_cores', 'pc', 'px_height',
       'px_width', 'ram', 'sc_h', 'sc_w', 'talk_time', 'three_g',
       'touch_screen', 'wifi'],
      dtype='object')
```

```
data_train.columns
```

```
Index(['battery_power', 'clock_speed', 'dual_sim', 'fc', 'four_g',
       'int_memory', 'm_dep', 'mobile_wt', 'n_cores', 'pc', 'px_height',
       'px_width', 'ram', 'sc_h', 'sc_w', 'talk_time', 'three_g',
       'touch_screen', 'wifi', 'price_range'],
      dtype='object')
```

A new dataset is created with our prediction values by Random Forest model

```
print("DATA PREDICTION BY RANDOM FOREST ON TEST DATASET \n")
prediction_price = forest.predict(data_test.drop(["id"], axis = 1))
prepared_data = data_test
prepared_data["Predicted Price"] = prediction_price
prepared_data.head(5)
```

	id	battery_power	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mobile_w
0	1	1043	1.8	1	14	0	5	0.1	19
1	2	841	0.5	1	4	1	61	0.8	19
2	3	1807	2.8	0	1	0	27	0.9	18
3	4	1546	0.5	1	18	1	25	0.5	9
4	5	1434	1.4	0	11	1	49	0.5	10