Capstone Project - 3

Mobile Price Range Prediction

By

Pooja Hoolageri

Data Science Trainee

AlmaBetter

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Introduction

We take into account a lot of factors before purchasing a mobile device because we use them for a variety of purposes, like keeping in touch with family, playing games, and shooting pictures to save our memories. Hence, features like RAM, internal memory, Wi-Fi, 3G/4G connectivity, etc., are crucial when choosing a mobile phone. Periodically analyses this crucial component to determine the ideal set of specs and price points that will encourage users to purchase mobile devices. So, using the various ML modules, we will assist the company in estimating the price range of mobile devices based on feature, allowing for the highest possible sales.

Problem Statement :

The problem statement is to predict the price range of mobile phones based on the features available(price range indicating how high the price is). Here is the description of target classes :

- 0 - Low cost Phones
- 1 - Medium cost phones
- 2 - High cost phones
- 3 - Very High cost phones

This will basically help companies to estimate price of mobiles to give tough competition to other mobile manufacturer. Also, it will be useful for consumers to verify that they are paying best price for a mobile.

- **As the competition of smartphones get more and more competitive each day, finding the best pricing range for a smartphone would be a key strategy to have a profitable smartphone company.**
- **However as there are more and more smartphone it's getting harder and harder for a company to justified a price range of a phone.**
- **If a company set a smartphone that's too expensive with low computational power nobody is going to buy it, and if a company set a smartphone price range too low based on it's computational power the smartphone company is going to lose on potential profit.**

DataSummary

- **Independent Variables :**
- **Battery_power** - Total energy a battery can store in one time measured in mAh
- **Blue** - Has bluetooth or not
- **Clock_speed** - speed at which microprocessor executes instructions
- **Dual_sim** - Has dual sim support or not
- **Fc** - Front camera mega pixels
- **Four_g** - Has 4G or not
- **Int_memory** - Internal Memory in Gigabytes
- **M_dep** - mobile depth in cm

Data Summary:

- **Mobile_wt** - Weight of mobile phone
- **N_cores** - Number of course of processor
- **Pc** - primary camera mega pixels
- **Px_height** -Pixel Resolution Height
- **Px_width** - pixel resolution width
- **Ram** - random access memory in megabytes
- **Sc_h** -Screen height of mobile in cm
- **Sc_w** -Screen width of mobile in cm
- **Talk_time** - Longest time data single battery charge will last when you are

Data Summary:

Three_g - Has 3G or not

Touch_screen - Has touch screen or not

Wifi - Has wifi or not

Dependent variables :

Price_range - This is the target variable with value of

0 (low cost) ,

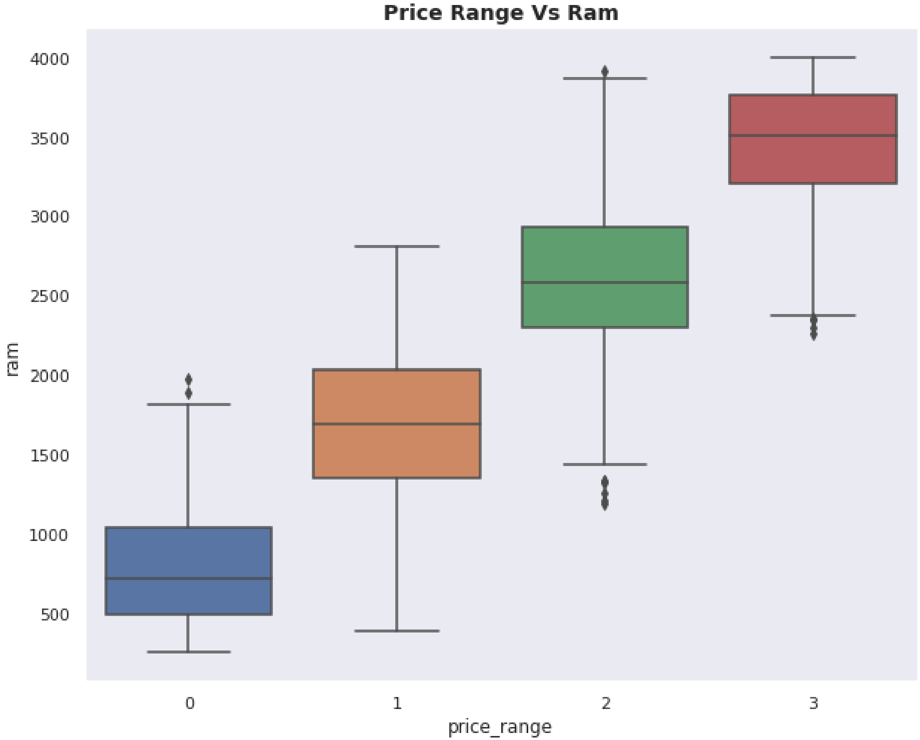
1 (medium cost) ,

2 (high cost) ,

And 3 (very high cost) .

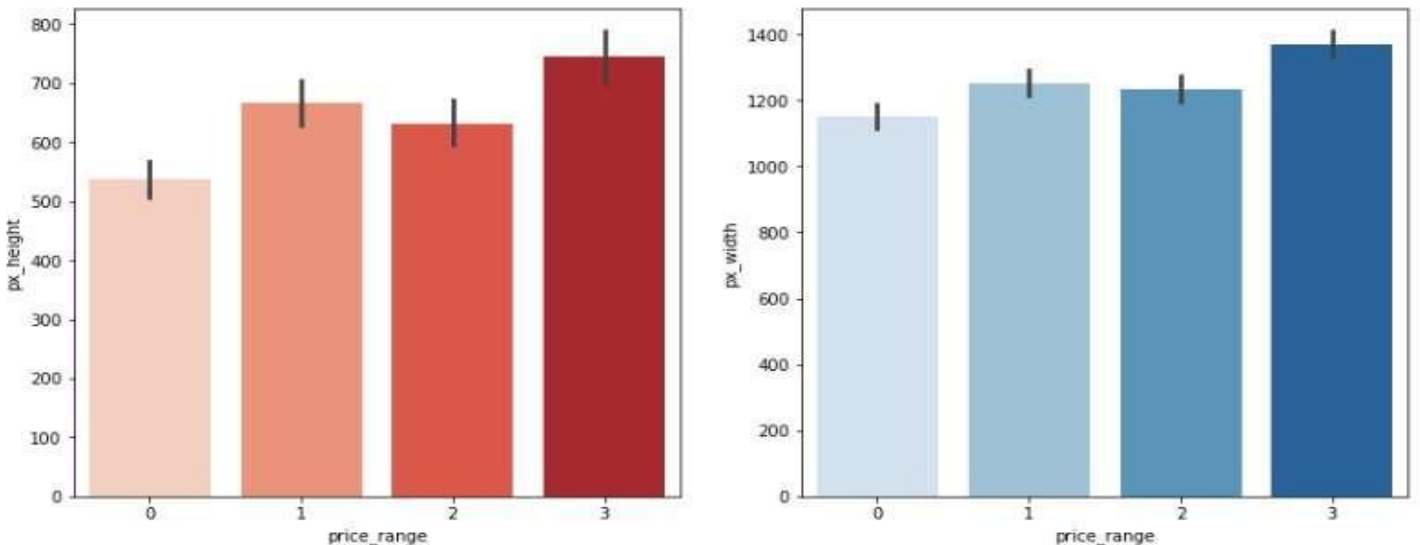
EDA and Feature engineering Relation Between Price Range & Ram :

- This is a positive relationship, with increase in RAM, price too increases. There are 4 types of price range
- Type 1(low cost): RAM ranges between 216 to 1974 megabytes
- Type 2(medium cost): RAM ranges between 387 to 2811 megabytes
- Type 3(high cost): RAM ranges between 1185 to 3916 megabytes
- Type 4(very high cost): RAM ranges between 2255 to 4000 megabytes



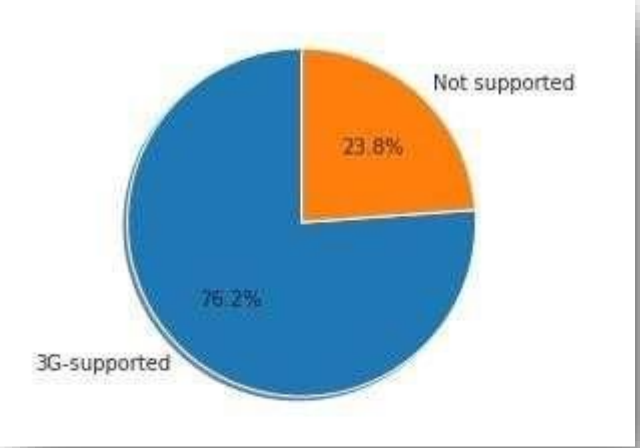
Relationship between the Price Range and Pixel Height/ Width :

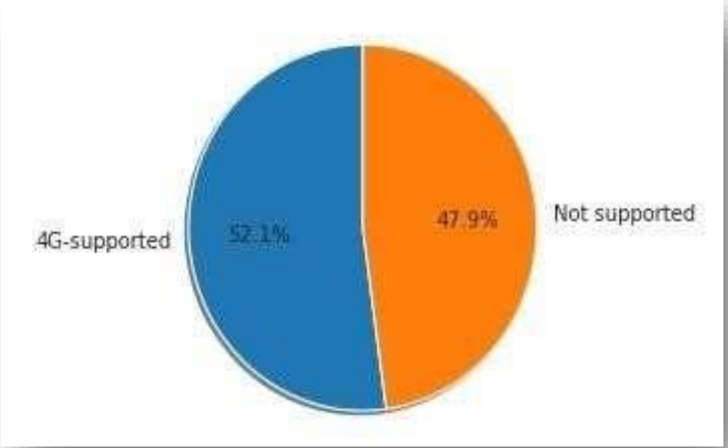
- From the below bar plot, we can see that the average pixel height and width are highest for the price range 3(very high cost).
- Low-cost phones have smaller average pixel width and pixel height.
- We can observe from this Bar plot that pixel height and pixel width are roughly equal in relevance when it comes to model development for prediction.



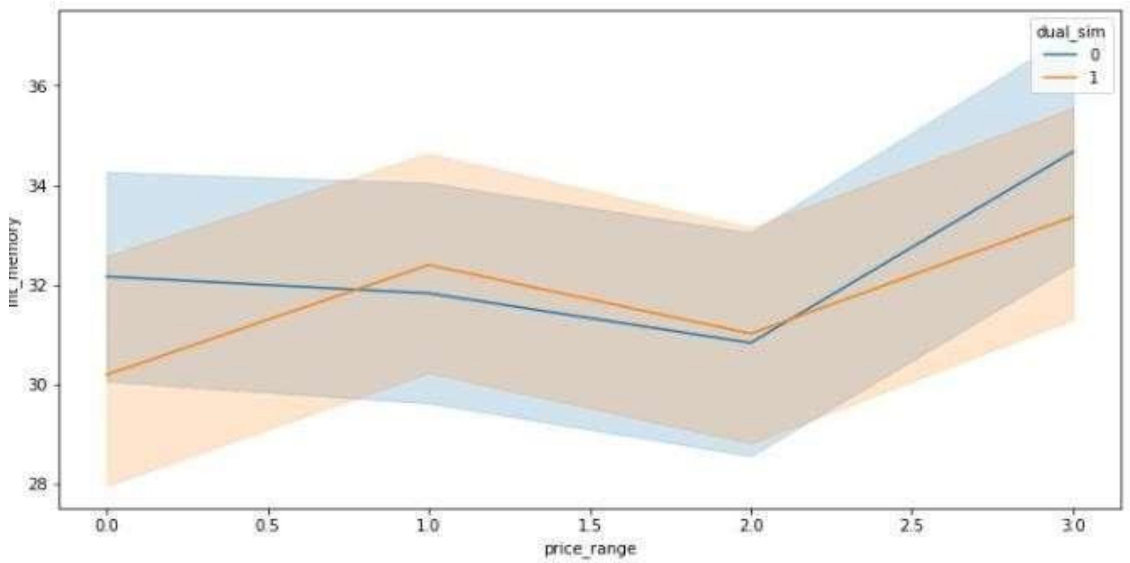
Exploratory Data Analysis :

- **3G-4G Supported and Non-supported**





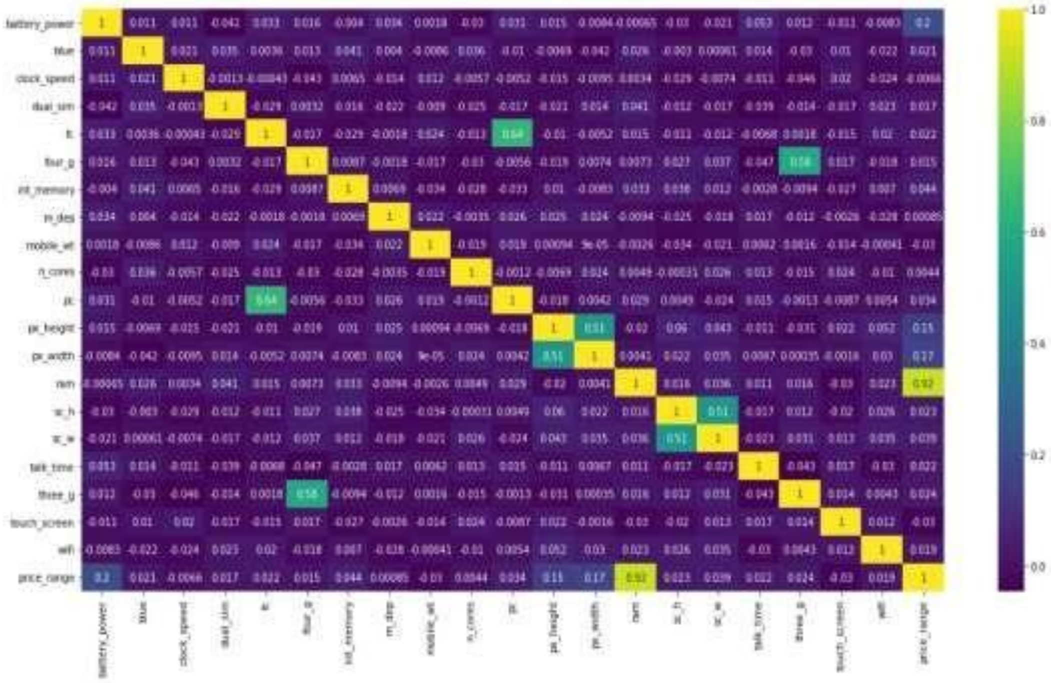
Multivariate analysis – int_memory , mobile_wt :



- There is drastic increase in internal memory for vey high prices.
- Also there is drastic Decrease in mobile weight for very high price.

Multivariate analysis

- Pc is correlated with Fc.
- px_height and px_width are moderately correlated.
- Sc_h and sc_w are moderately correlated.
- Ram is highly correlated wi th price_range.



Preparing dataset for modeling

Task : multiclass classification

Train set : (1340 , 20)

Test set : (660 , 20)

Response : 0-1-2-3

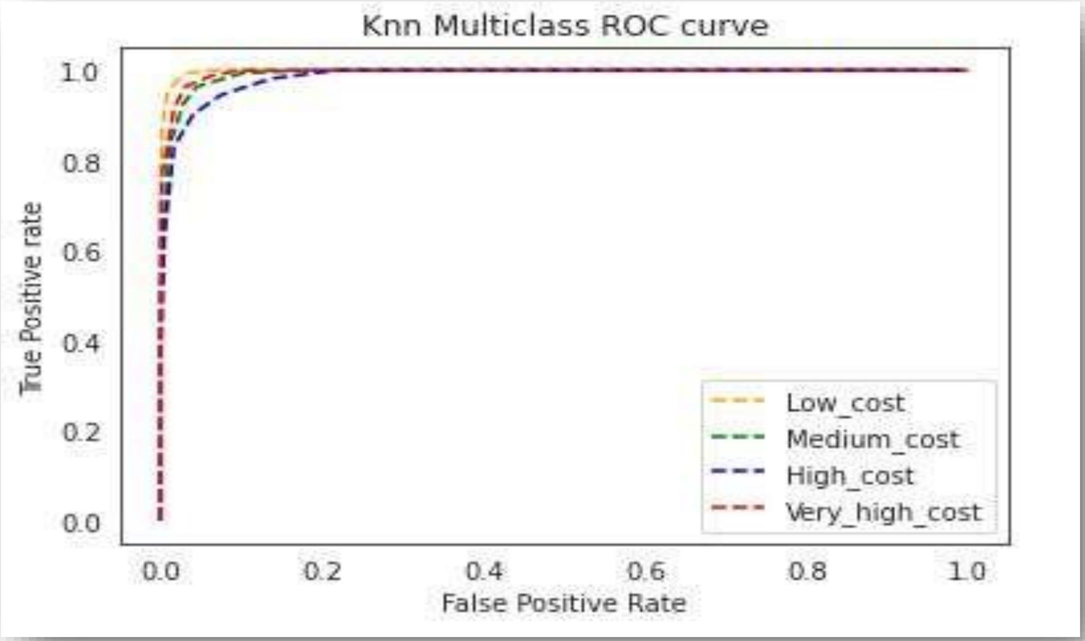
battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mobile_wt	n_cores	pc	px_height
842	0	2.2	0	1	0	7	0.6	188	2	2	20
1021	1	0.5	1	0	1	53	0.7	136	3	6	905
563	1	0.5	1	2	1	41	0.9	145	5	6	1263
615	1	2.5	0	0	0	10	0.8	131	6	9	1216
1821	1	1.2	0	13	1	44	0.6	141	2	14	1208
1859	0	0.5	1	3	0	22	0.7	164	1	7	1004
1821	0	1.7	0	4	1	10	0.8	139	8	10	381
1954	0	0.5	1	0	0	24	0.8	187	4	0	512
1445	1	0.5	0	0	0	53	0.7	174	7	14	386
509	1	0.6	1	2	1	9	0.1	93	5	15	1137
769	1	2.9	1	0	0	9	0.1	182	5	1	248
1520	1	2.2	0	5	1	33	0.5	177	8	18	151
1815	0	2.8	0	2	0	33	0.6	159	4	17	607

Applying Model

Implementing K-Neighbours Classifier

TPR(True Positive rate) = TP/(TP+FN)

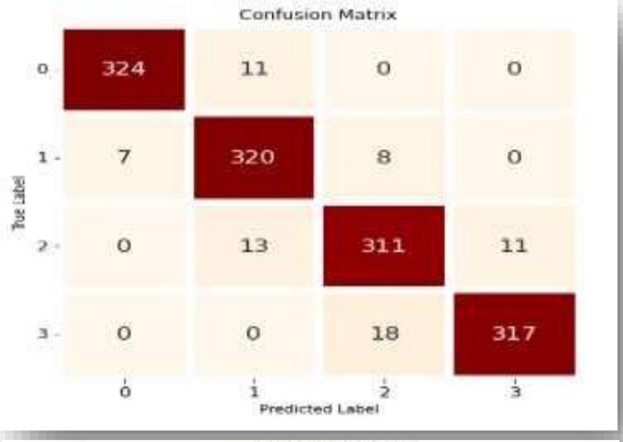
FPR(False Positiverate) = FP/(FP+TN)



Implementing KNeighbours Classifier :

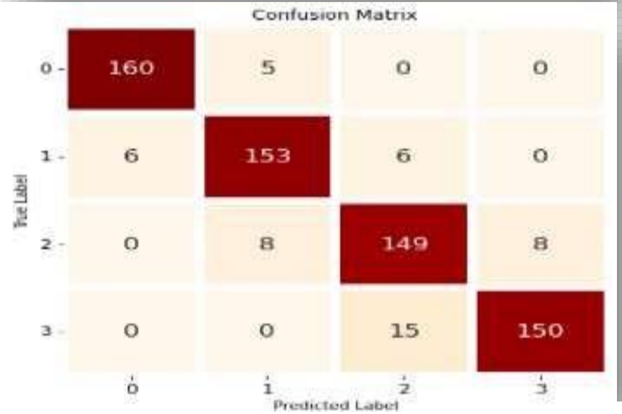
Train metrics

	precision	recall	f1-score	support
0	0.98	0.96	0.97	228
1	0.93	0.96	0.94	212
2	0.93	0.93	0.93	229
3	0.96	0.95	0.96	228
accuracy			0.95	897
macro avg	0.95	0.95	0.95	897
weighted avg	0.95	0.95	0.95	897



Test metrics

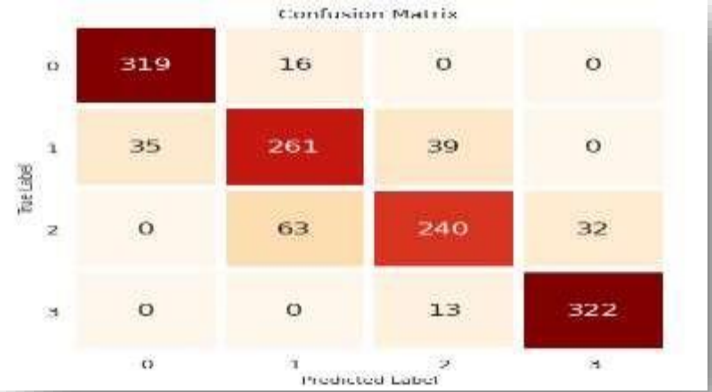
	precision	recall	f1-score	support
0	0.96	0.96	0.96	165
1	0.92	0.93	0.92	165
2	0.88	0.90	0.89	165
3	0.95	0.92	0.93	165
accuracy			0.93	660
macro avg	0.93	0.93	0.93	660
weighted avg	0.93	0.93	0.93	660



Implementing Random Forest Classifier :

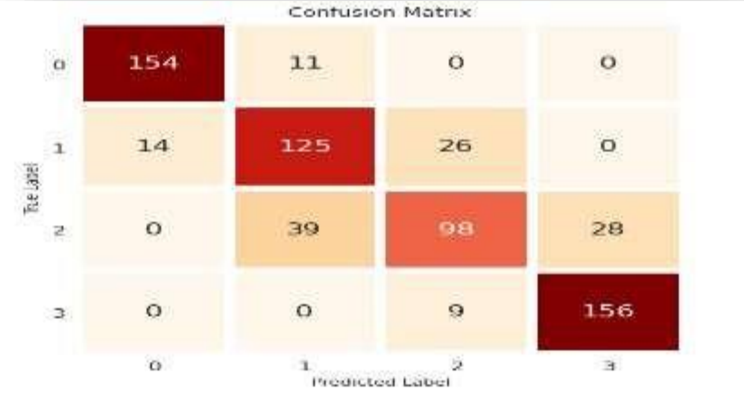
Train metrics

	precision	recall	f1-score	support
0	0.90	0.95	0.93	335
1	0.77	0.78	0.77	335
2	0.82	0.72	0.77	335
3	0.91	0.96	0.93	335
accuracy			0.85	1340
macro avg	0.85	0.85	0.85	1340
weighted avg	0.85	0.85	0.85	1340



Test metrics

	precision	recall	f1-score	support
0	0.92	0.93	0.92	165
1	0.71	0.76	0.74	165
2	0.74	0.59	0.66	165
3	0.85	0.95	0.89	165
accuracy			0.81	660
macro avg	0.80	0.81	0.80	660
weighted avg	0.80	0.81	0.80	660



Implementing Gradient Boosting Classifier :

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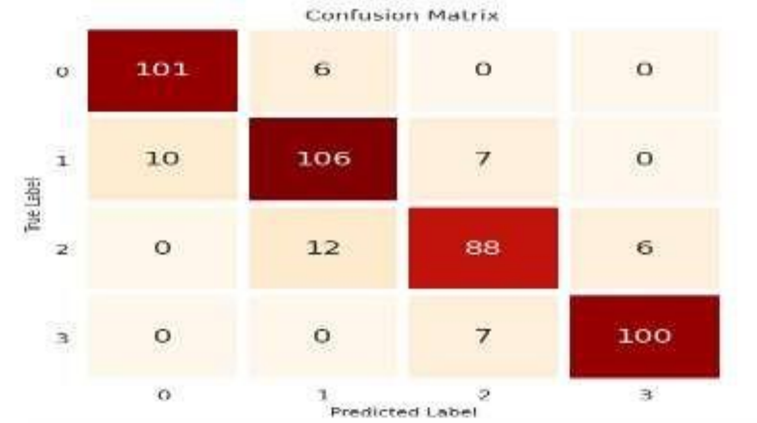
Classification Report

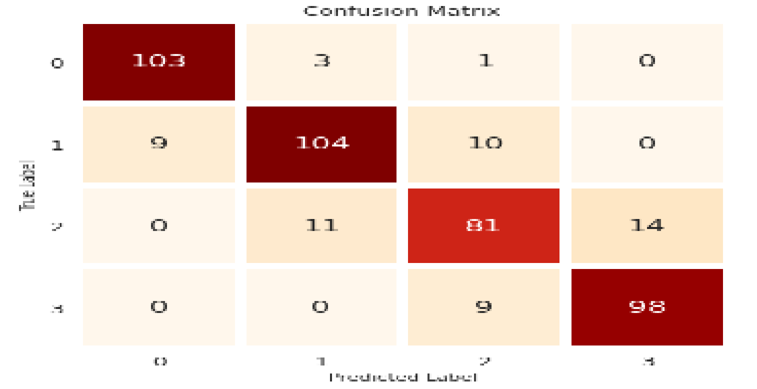
	precision	recall	f1-score	support
0	0.91	0.94	0.93	107
1	0.85	0.86	0.86	123
2	0.86	0.83	0.85	106
3	0.94	0.93	0.94	107
accuracy			0.89	443
macro avg	0.89	0.89	0.89	443
weighted avg	0.89	0.89	0.89	443



Test metrics

Classification Report

	precision	recall	f1-score	support
0	0.92	0.96	0.94	107
1	0.88	0.85	0.86	123
2	0.80	0.76	0.78	106
3	0.88	0.92	0.89	107
accuracy			0.87	443
macro avg	0.87	0.87	0.87	443
weighted avg	0.87	0.87	0.87	443

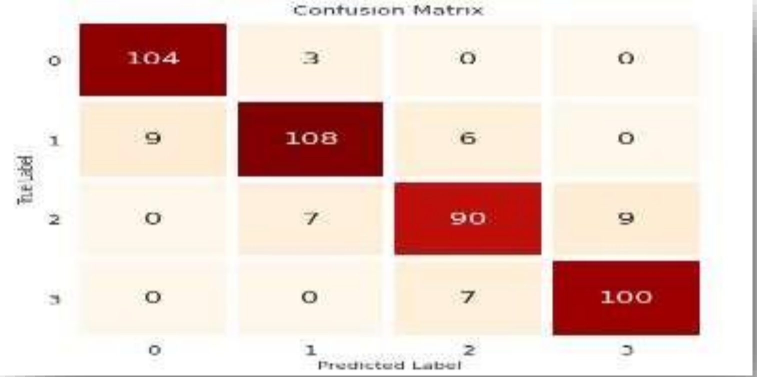


Implementing XGBClassifier :

Train metrics

Classification Report

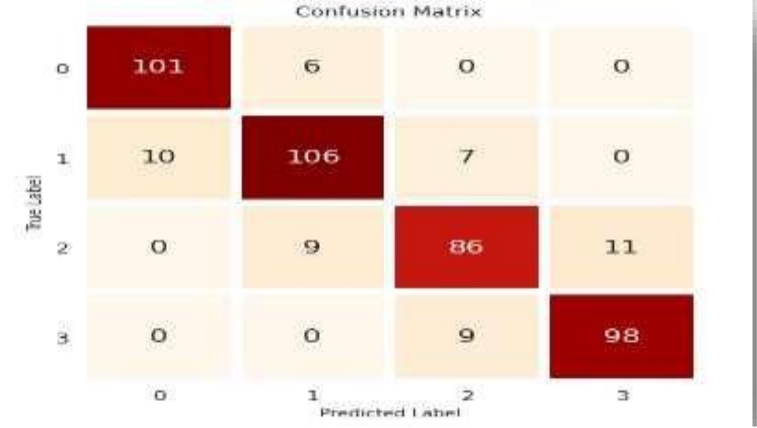
	precision	recall	f1-score	support
0	0.92	0.97	0.95	107
1	0.92	0.88	0.90	123
2	0.87	0.85	0.86	106
3	0.92	0.93	0.93	107
accuracy			0.91	443
macro avg	0.91	0.91	0.91	443
weighted avg	0.91	0.91	0.91	443



Test metrics

Classification Report

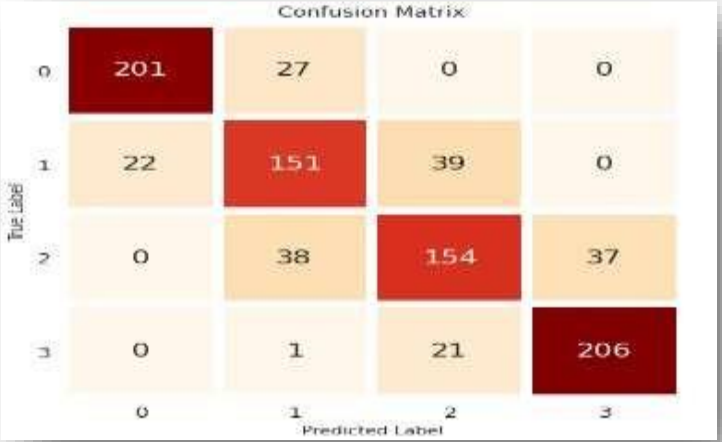
	precision	recall	f1-score	support
0	0.91	0.94	0.93	107
1	0.88	0.86	0.87	123
2	0.84	0.81	0.83	106
3	0.90	0.92	0.91	107
accuracy			0.88	443
macro avg	0.88	0.88	0.88	443
weighted avg	0.88	0.88	0.88	443



Implementing Logistic regression :

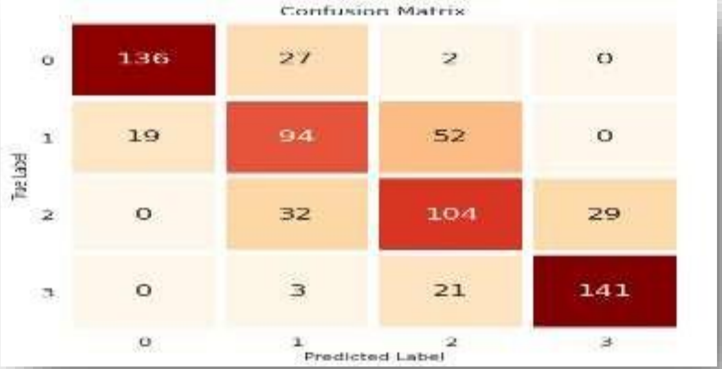
Train metrics

	precision	recall	f1-score	support
0	0.90	0.88	0.89	228
1	0.70	0.71	0.70	212
2	0.72	0.67	0.70	229
3	0.85	0.90	0.87	228
accuracy			0.79	897
macro avg	0.79	0.79	0.79	897
weighted avg	0.79	0.79	0.79	897



Test metrics

	precision	recall	f1-score	support
0	0.88	0.82	0.85	165
1	0.60	0.57	0.59	165
2	0.58	0.63	0.60	165
3	0.83	0.85	0.84	165
accuracy			0.72	660
macro avg	0.72	0.72	0.72	660
weighted avg	0.72	0.72	0.72	660



Model Validation & Selection contd…

Observations:

1. As seen in the above slides Random forest classifier is not giving great results , Gradient Boosting Classifier is bit better than Random forest in recall and precision

2. XGboost classifier is giving the better results than GB but the recall of random forest classifier is somewhat similar.

3. KNeighbors is giving the best results among all of the algorithms

4. Logistic regression is giving low results among all of them

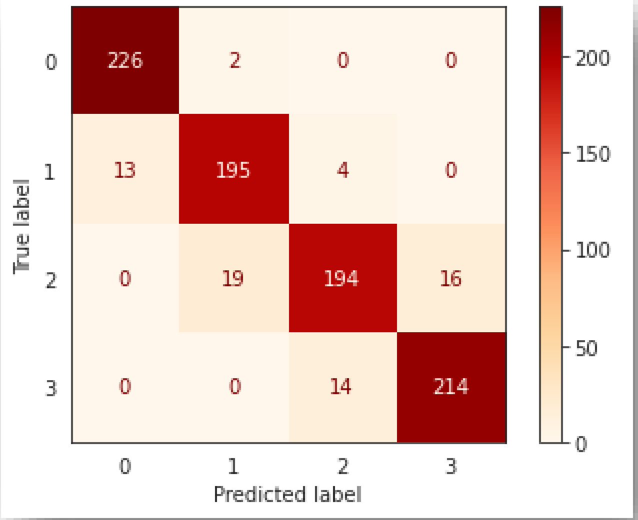
Model Validation & Selection contd…

So we had chosen Kneighbors classifier for the prediction and the best hyperparameters obtained are as below

Best hyperparameters :
Train : (algorithm='auto', leaf_size=30, metric=‘Euclidean', metric_params=None, n_jobs=None, n_neighbors=11, p=2, weights='distance’)

Test : (algorithm='auto', leaf_size=30, metric='euclidean', metric_params=None, n_jobs=None, n_neighbors=17, p=2, weights='distance')

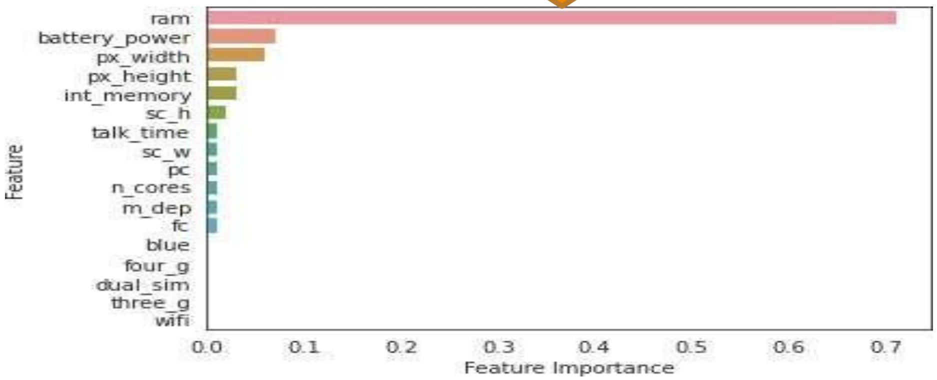
Model Validation & Selection (Hyperparameter tuned) :



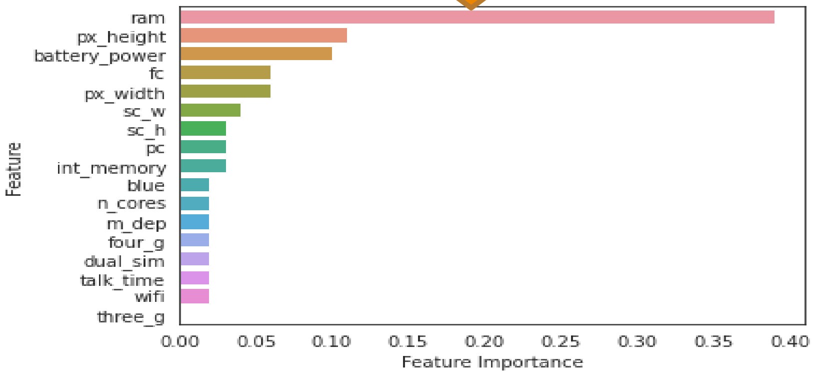
	precision	recall	f1-score	support
0	0.95	0.99	0.97	228
1	0.90	0.92	0.91	212
2	0.92	0.85	0.88	229
3	0.93	0.94	0.93	228
accuracy			0.92	897
macro avg	0.92	0.92	0.92	897
weighted avg	0.92	0.92	0.92	897

Feature Importance

Random Forest Classifier



XGBoost Classifier



- The most important features in determining the predictions are ram, battery power, px_height.
- Higher values of ram are increasing the predicted class.
- Higher values of battery power are increasing the predicted class.
- Higher values of px_height and px_weight are increasing the predicted class.

Conclusion

- Ram , Battery_power features were found to be the most relevant feature for predicting price range of mobiles and dropping negative correlation features which are clock speed , mobile_wt , touch_screen .

- Kneighbors and Xgboost are given best accuracy score 95 % test , 93 % train and 91 % train , 88 % test respectively and roc_auc score for kneighbors is 99 % .

- Tuning the hyperparameters by GridSearch CV on kneighbors but not getting much difference in results but the best parameters n_neighbors for train and test are 11 and 17

Conclusion

- ❖ **So we conclude that kneighbors classifier is giving the best results for these dataset**

- ❖ **So we can say that in the price range prediction as the ram and battery power increases the price range will increase for sure**

- From EDA we can see that here are mobile phones in 4 price ranges. The number of elements is almost similar.
- Half the devices have Bluetooth, and half don’t.
- There is a gradual increase in battery as the price range increases.
- Ram has continuous increase with price range while moving from Low cost to Very high cost.
- Costly phones are lighter.
- RAM, battery power, pixels played more significant role in deciding the price range of mobile phone.
- Form all the above experiments we can conclude that SVM classifier, gradient boosting and, KNN with confusion matrix got good accuracy.

Thank You