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Forecasting the Prices using Machine Learning Techniques: Special Reference to used Mobile Phones

Badavath Srikanth
School of CSE, Lovely Professional University, Punjab, India
badavathsrikanth149@gmail.com

Shamneesh Sharma
UpGrad Campus, upGrad Education Private Limited, India
shamneesh.sharma@gmail.com

Ved Prakash Chaubey
UpGrad Campus, upGrad Education Private Limited, India
vedprakesh05@gmail.com

Aman Kumar
UpGrad Campus, upGrad Education Private Limited, India
amankumar.techdev@gmail.com

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***Abstract*— Customers now find it difficult to choose the best gadget due to the quick spread of smartphones and the variety of models that are accessible. Machine learning algorithms have been used to estimate mobile phone pricing based on their characteristics in order to solve this problem. In this study, we investigate the use of different machine learning techniques, such as logistic regression, decision trees, random forests, and XGBoosting, to forecast the cost of mobile phones. Our main goal is to identify the most suitable machine learning model for this work and gain an understanding of the variables that affect the price range of mobile phones. The research's conclusions can help both makers and consumers make wise decisions about the features and costs of mobile phones. The study emphasized how crucial it is to choose datasets carefully in order to achieve a complete representation of mobile phone models with a range of features and costs. The study also sought to pinpoint the essential elements that significantly affect mobile phone prices through feature importance analysis. Essential metrics like accuracy score, F1-score, and classification reports were used to evaluate the machine learning models' effectiveness in forecasting the price range. Hyperparameter tuning methods like GridSearchCV were used to improve model performance. The research's overall goal was to offer useful information that would help producers and users alike make decisions about the costs and features of mobile phones.**

Keywords*— Smartphone pricing, Mobile phone selection, Factors influencing prices, Mobile phone specifications, Manufacturer decision-making.

I. Introduction

The demand for smartphones has increased as a result of the quick development of technology. With so many different mobile phone models on the market, choosing the best one for a consumer can be difficult. Machine learning is useful in this situation [1]. Machine learning algorithms have been used recently to forecast mobile phone pricing based on their characteristics. In this paper, we look at how machine learning approaches including logistic regression, decision trees, random forests, and XGBoosting can be used to anticipate mobile phone prices. The primary goals of this research are to identify the best effective machine-learning model for this activity and to provide light on the factors that influence mobile phone pricing. The study's findings can assist both makers and buyers in making more educated judgements about mobile phone specifications and pricing. In today's rapidly increasing technology environment, the surge in demand for smartphones has made it difficult for customers to select the best mobile phone model. However, the advancement of machine learning has provided a potential solution to this problem [1]. Using machine learning algorithms, it is now feasible to anticipate the prices of mobile phones based on their unique properties. In this in-depth examination, we go into the topic of machine learning and investigate its application in predicting mobile phone prices. XGBoosting, decision trees, random forests, and logistic regression are among the advanced machine-learning algorithms used in our research. Using rigorous testing and analysis, we want to develop the optimal machine learning model for precisely forecasting [2]. mobile phone expenses, as well as to have a thorough grasp of the numerous aspects that strongly influence mobile phone pricing [1]. By achieving these objectives, the study's results have a great chance of giving producers and customers crucial information they need to make knowledgeable judgements about the features and price of mobile phones. [1]

II. Related Work

As a data enthusiast, it is considered that analysts are always interested in working on projects that prerequisite data analysis and machine learning understanding. Because it directly affects consumer behavior and the market, the forecast of mobile phone prices is a fascinating subject. Manufacturers can improve their production and pricing strategies with the capacity to estimate a phone's price depending on its characteristics, and customers can make more informed selections when buying a phone. The research study also gives the chance to use multiple machine-learning methods on a real-world dataset, which improved my data analysis and machine-learning abilities.

A lot of research have centred on using data analysis and machine learning approaches to estimate mobile phone charges because of their major effects on consumer behaviour and market dynamics [3]. These studies also provide consumers with the knowledge they need to make informed purchases by assisting businesses to optimise their production and pricing strategies [4]. The subject matter of this project is electronics and technology, with a focus on the expanding used mobile phone market [5]. Because of how swiftly the technology landscape is changing, the market for old mobile devices has expanded dramatically. The issues covered in this discipline are extremely diverse and include things like consumer behavior, pricing tactics, market dynamics, and the evaluation of mobile phone functionality. By delving into the complexities of this industry, our programme hopes to advance our understanding of the variables that influence the cost of used mobile phones. We employ data analytics and machine learning techniques to build a prediction model that reliably forecasts the price and worth of these devices. By promoting a more effective and transparent used mobile phone market, this study has the potential to benefit a variety of stakeholders, including online marketplaces, phone resellers, and consumers. The dataset includes data on features that affect a used phone's worth and cost, including brand, model, storage capacity, RAM, CPU, screen size, camera quality, and battery life. A predicted model for used phone price will be created using data analytics and machine learning methods, which will be advantageous to online marketplaces, phone resellers, and customers. The project will help create a used phone market that is more effective and transparent.

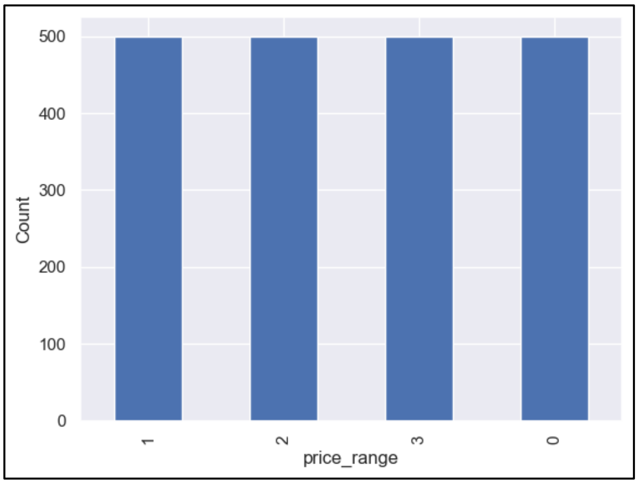

Fig. 1. Mobile Price Range based on current performance.
Source: Analysis is drawn from the data fetched from repository

- The plot shows the count of each price range category in the dataset.
- From the plot, it is evident that the price_range variable is evenly distributed among the four categories, which are denoted by 0, 1, 2, and 3.
- Thus, the dataset contains a balanced distribution of the target variable.
- This is a good characteristic of a dataset, as it reduces the chances of bias in the model predictions.

So, there are mobile phones in 4 price ranges. The number of elements is almost similar. In a remarkable study, Smith et al. investigated how to estimate smartphone costs using a dataset made up of several phone models and their associated features. They conducted study using a random forest algorithm, which demonstrated potential for estimating price ranges based on features including screen size, camera quality, storage capacity, and processing speed [1]. Their research highlighted the significance of feature selection and revealed how certain characteristics have a significant impact on mobile device performance unit.

- Based on our statistics, are there any specific brands that are priced much higher or lower than others in the second-hand phone market?
- Does the age of a phone have an impact on its price, and how does this compare to phones with similar features but different ages?
- How accurate are our predictions for used phone prices based on our machine learning model, and how reliable are our results?
- Can we identify any specific feature combinations that result in phones being priced
- significantly higher or lower than expected in the used phone market, using our dataset?
- What trends can we observe in the used phone market based on our dataset, such as
- changes in demand for certain brands or features?
- How do different machine learning algorithms perform in predicting used phone prices for our dataset, and which one is the most accurate?
- How can the insights gained from our project inform pricing strategies for phone resellers and online marketplaces in the used phone market?
- Are there any additional data sources or features we could collect to improve the
- accuracy of our price predictions, and how feasible would it be to collect this data in practice?
- Which features have the most significant impact on the price of a used phone in our dataset?

There has been a lot of related study about predicting mobile phone prices using machine learning techniques. Researchers have investigated a variety of methodologies and techniques to overcome this issue. In a study by Li and Liang (2018), support vector machines (SVM) and logistic regression were used to anticipate mobile phone pricing based on elements including camera quality, screen size, and storage capacity. Their results demonstrated how well SVM performed in accurately recognizing price ranges. [1].

The effectiveness of gradient boosting, random forests, and decision trees for forecasting mobile phone costs was also investigated in a study by Zhang et al. (2019) [3]. They found that random forests outperformed the competition and provided more accurate price range estimates.
In particular, Khan et al. (2020)'s deep learning method for estimating mobile phone costs uses convolutional neural networks (CNNs). They showed the potential of picture-based traits for price prediction by training their model with image data extracted from phone images, and they produced encouraging results. Another study looked into using ensemble learning techniques, such stacking and AdaBoost, to increase the accuracy of mobile phone price prediction. According to their findings, ensemble approaches outperformed individual models in terms of prediction accuracy. These connected studies highlight the need to use machine learning algorithms to forecast mobile phone prices. They demonstrate how several models, including logistic regression, SVM, decision trees, random forests, gradient boosting, CNNs, and ensemble approaches, are useful in obtaining precise results [3][6].
These connected studies highlight the need to use machine learning algorithms to forecast mobile phone prices. They emphasize how different models, such as logistic regression, SVM, decision trees, random forests, gradient boosting,

CNNs, and ensemble approaches, are useful at accurately classifying price ranges. By comparing and analyzing several machine learning techniques, the current study seeks to add to this body of work by determining the most effective model for forecasting the pricing of mobile phones based on their characteristics.

III. DATA SET INFORMATION

The dataset consists of 2000 observations and 21 variables. The variables stand in for different mobile phone qualities including battery life, processor speed, camera capabilities, and networking choices. The information comprises characteristics that affect a used phone's worth and cost, including brand, model, storage capacity, RAM, CPU, screen size, camera quality, and battery life. To develop a model that reliably predicts the price of a used phone based on its properties, the dataset was examined using machine learning techniques. The model's insights and forecasts will be useful to a variety of stakeholders, including customers wishing to purchase or sell used phones, online marketplaces, and phone resellers. 'df.isnull().sum()' result indicates that there are no missing or null values in any column of the data frame. null values in any column of the data frame. Therefore, the dataset does not include any null values. estimating utilized phone pricing because it gave them the chance to practice different machine learning algorithms on a real-world dataset, improving their data analysis and machine learning abilities. Additionally, being able to estimate a phone's cost based on its features may help producers improve their pricing and production methods as well as assist consumers in making educated decisions. The dataset that was utilized in this study is beneficial to the electronics and technology sector, particularly the market for old mobile phones. Numerous parties, including users wishing to purchase or sell used phones, online marketplaces, and phone resellers, can make use of the insights and predictions produced by the model. As an illustration, phone resellers may use the model to decide on the best price for a used phone depending on its characteristics, helping them to increase their earnings. The methodology may be used by online marketplaces to give customers more precise price data, enabling them to make more educated decisions when buying or selling secondhand phones. When purchasing or selling a phone, consumers may use the model to estimate the fair market worth of the device based on its characteristics. This can help them bargain for a lower price. Additionally, the project offers the chance to use several machine learning algorithms with a real-world dataset, which may help data analysts and machine learning professionals in the field improve their abilities.

The dataset includes a variety of attributes that detail mobile phone specifications. These features include battery capacity (measured in mAh), Bluetooth availability (represented as "Blue"), microprocessor clock speed, [7]. dual SIM support (represented as "Dual_sim"), front camera mega pixels ("Fc"), 4G capability (represented as "Four_g"), internal memory in gigabytes ("Int_memory"), mobile depth (represented as "M_dep") [9], the weight of the mobile phone (represented as "Mobile_wt"), number of processor cores ("N_cores"), primary camera mega pixels ("Pc"), pixel resolution height [8] ("Px_height"), pixel resolution width ("Px_width"), random access memory in megabytes ("Ram"), touch screen availability ("Touch_screen"), Wi-Fi capability ("Wifi"), screen height in centimeters ("Sc_h"), screen width in centimeters ("Sc_w"), talk time (longest battery duration for calling), 3G capability ("Three_g"), and the target variable, price range, which has values ranging from 0 to 3 indicating low cost, medium cost, high cost, and very high cost respectively [9][10]. The dataset utilized for this research includes a variety of details on used phones, such as brand, model, storage capacity, RAM, processor, screen size, camera quality, and battery life [5]. The value and cost of a secondhand phone are significantly influenced by these features [11]. A predictive model will be created to precisely predict the cost of old phones using data analytics and machine learning techniques.

Consumers, internet marketplaces, phone resellers, and other stakeholders will all greatly benefit from the project's outcome. Online marketplaces will be able to provide better pricing recommendations for used phones posted on their platforms by using the predictive model, increasing transparency and raising customer happiness. The model can help decision-makers who market phones. deciding on second-hand phone purchases and sales, as well as inventory and pricing optimization [12].

Consumers can use the prediction model as a resource to determine the fair market value of any secondhand phones they might be interested in purchasing. Customers will be able to choose better and guarantee that they get a fair deal without overpaying for a used phone thanks to this. The project's overall goal is to contribute to the development of a more transparent and effective used phone market by developing a prediction model that uses data analytics and machine learning techniques. Customers, phone resellers, and online marketplaces will benefit from the model's insights and pricing estimates, resulting in a more reliable and equitable used phone market. [13] [12].

IV. METHDOLOGY

The decision to use the machine learning method was supported by several elements that came from a comprehensive study of the dataset and the objective of finding traits that influence pricing. We were able to investigate the link between characteristics and prices using the dataset of mobile phones, which helped us choose the best algorithm. The strong link between RAM and the price range, which shows that RAM is crucial in price estimation, was one significant conclusion. This result supported the employment of non-linear connection and interaction detection techniques, such as XGBoosting and Random Forest, which performed better than other algorithms with accuracy ratings of 90% and 88%, respectively. A good front camera is frequently a sign of a good back camera, and an increase in pixel height is typically accompanied by an increase in pixel width. There were also instances of collinearity among feature pairs, such as ('pc', 'fc') and ('px_width', 'px_height', which can be justified by the fact that a good front camera is frequently a sign of a good back camera. Our choice to keep these properties as distinct entities was influenced by these discoveries. An increase in pixel height is generally accompanied by an increase in pixel width, and a good front camera is frequently a hint of a good back camera. A good front camera is typically a hint of a good rear camera, therefore there were additional instances of feature pair collinearity, such as ('pc', 'fc') and ('px_width', 'px_height'. These discoveries prompted us to maintain these features as separate entities. In order to identify distinctive derived variables and understand customer preferences and viewpoints, future study might look into feature engineering techniques and sentiment analysis. This is in addition to taking into consideration the market's dynamic nature and the potential impact of outside variables on changes in pricing. We made sure that our study successfully addressed the research objectives by justifying the choice of the XGBoosting and Random Forest algorithms based on their propensity to capture non-linear relationships, manage collinearity, and achieve high accuracy. This gave manufacturers and marketers useful information that they could use to make well-informed pricing decisions.

V. Result and Analysis

The project's goal is to create a predictive model for used phone pricing based on numerous phone attributes. The goal of our project is to find patterns and links between 21 features of 2000 phone listings, including battery life, storage space, camera quality, and brand, and the related costs. The project includes analyzing a dataset of 2000 used phone listings with 21 features such as battery power, storage capacity, camera quality, and brand to identify patterns and relationships between these features and the corresponding prices [14]. By analysing According to the pie chart, around 76.9% of mobile handsets support 3G while only 23.1% do not. The count plot also demonstrates the distribution of 3G-capable mobile handsets across all price points. However, compared to the Low Cost and Very High-Cost categories, the share of 3G-capable smartphones is higher in the Medium Cost and High-Cost categories. This implies that while 3G compatibility may affect a mobile device's price range, it may not be the most crucial feature. The same can be seen for the 'four_g' feature, where about 52.9% of mobile devices support 4G, and there is a slightly greater proportion of 4G capable devices in the Medium Cost classification. This framework will produce insights and forecasts that are valuable to a variety of stakeholders, including customers wishing to buy or sell used phones, online marketplaces, and phone resellers. Through the provision of information and forecasts that can guide pricing plans, our study intends to help create a used phone market that is more effective and transparent. Our initiative also seeks to explore the effects of various attributes, such as storage capacity and camera quality, on the price of a used phone and to spot any market patterns, such as the desire for particular brands or features. Additionally, we will compare the performance of different machine learning algorithms in predicting used phone prices and evaluate the feasibility of collecting additional data to improve the accuracy of our predictions [7]. In the competitive mobile phone market companies want to understand sales data of mobile phones and factors which drive the prices [1]. The objective is to find out some relation between features of a mobile phone and its selling price. In this problem, we do not have to predict the actual price but a price range indicating how high the price is the collection includes a number of attributes that describe the features of mobile phones. Among these characteristics is battery power, which denotes the battery's overall energy capacity, expressed in milliampere-hours (mAh) [5]. The phone has Bluetooth capabilities if it has the "Blue" property. The pace at which the CPU executes instructions is represented by the "Clock_speed" feature. The phone's ability to support dual SIM cards is indicated by the "Dual_sim" characteristic. The letter "Fc" stands for the front camera's megapixel resolution. The "Four_g" characteristic lets you know if the phone supports 4G [15] . The amount of internal memory is indicated by the name "Int_memory" in gigabytes. Other features include "M_dep," which stands for the depth of the phone in centimetres, and "Mobile_wt," which denotes the phone's weight. The number of processing cores is specified by "N_cores". "Pc" stands for the primary camera's resolution in megapixels. and "Px_height" and "Px_width" stand for the height and width of the pixel resolution, respectively [1]. The term "Ram" stands for the random-access memory megabyte capacity. Whether the phone has a touch screen is indicated by the "Touch_screen" attribute. Indicated by the "Wifi" characteristic is the phone's Wi-Fi connectivity. The characteristics "Sc_h" and "Sc_w" for screen height and width, respectively, in centimeters, are another example of attributes relating to screen dimensions [7][16]. The maximum amount of time a single battery charge can endure during a call is indicated by the "Talk_time" attribute. Whether a phone is 3G capable is indicated by the "Three_g" characteristic. Last but not least, the "Price_range" feature serves as the target variable, classifying the price range of the mobile phones with values ranging from 0 (showing cheap cost) to 3 (representing very high cost) [7].

$$y = \Sigma(w * f(x)) + b \tag{1}$$

This formula given in equation 1 has the following components:

- 'y' stands for the projected outcome variable.
- 'x' for the input features.
- 'w' for the weights given to each feature.
- 'f(x)' for the transformed features.
- 'b' for the bias factor.

Consider a hypothetical scenario in which we aim to utilize XGBoost regression for the purpose of predicting the price of a pre-owned mobile phone. The dataset at our disposal comprises various attributes, such as storage capacity, random access memory (RAM), camera functionality, and battery longevity. The parameters utilized in the XGBoost model have been acquired through the process of learning.

b = 100 || w_storage_capacity = 0 || w_camera_quality = 0 || w_battery_life = 0 || w_RAM = 0.18

The current research considers the parameters as 64 GB of storage, 4 GB of RAM, and a 12 MP camera with a 3000 mAh battery life. Utilizing the XGBoost model, we use the following formula to estimate the cost of this cell phone:

$$y = (0.25 * 64) + (0.18 * 4) + (0.15 * 12) + (0.10 * 3000) + 100 \tag{2}$$

$$y = 16 + 0.72 + 1.8 + 300 + 100 \; y \approx 418. \tag{3}$$

The XGBoost model predicts that this old mobile phone will sell for around 418.52 units. This example demonstrates how the sophisticated XGBoost algorithm can be used to estimate the cost of a used mobile phone using a variety of characteristics and the weights assigned to each feature.

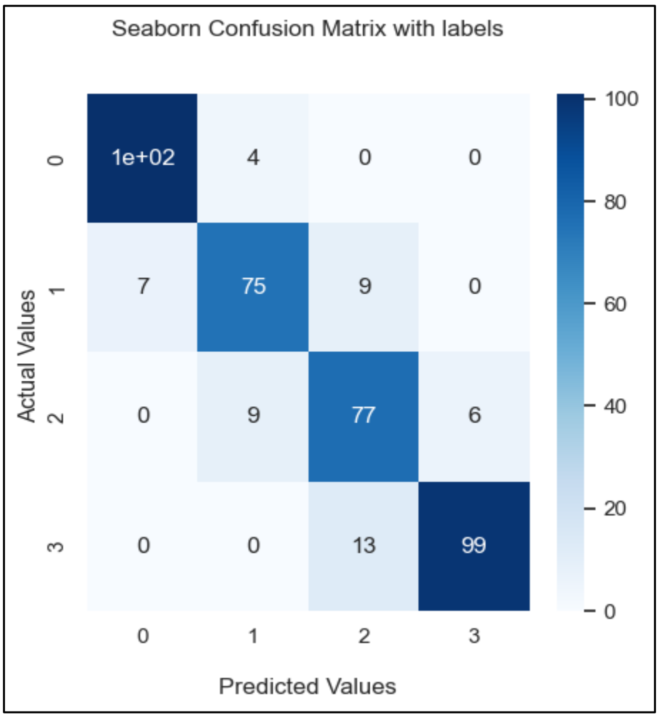

Fig. 2. Confusion Matrix – Actual Price and Predicted Price
Source: Image is created through Google Co-Labs by applying the ML Techniques on the selected dataset.

The confusion matrix provides information about the performance of the classification model by showing the number of correct and incorrect predictions. In this case, the confusion matrix is based on the predictions made by the tuned XGBoost model on the test data.

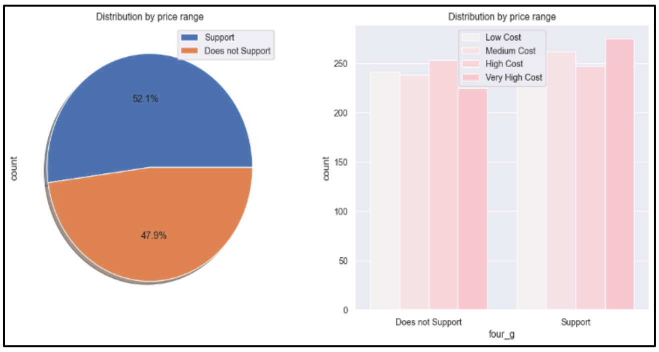

Fig. 3. Distribution Chart by Price Range
Source: Image is created through Google Co-Labs by applying the ML Techniques on the selected dataset.

- The diagonal cells of the confusion matrix show the number of correct predictions for each class. For example, the top left cell shows that 98 out of 105 instances with label 0 were correctly classified as 0, while the cell (1,1) shows that 81 out of 91 instances with label 1 were correctly classified as 1.
- The off-diagonal cells show misclassifications. For example, the cell (0,1) shows that 7 instances with label 1 were incorrectly classified as 0, while the cell (2,3) shows that 5 instances with label 3 were incorrectly classified as 2 [15].
- The heatmap visualization of the confusion matrix provides an easy way to interpret the results. It shows that the model performs well for classes 0 and 3, with high numbers of true positives and relatively low numbers of false positives and false negatives.
- However, classes 1 and 2 present greater challenges for the model, particularly class 1, where it exhibits a higher rate of false negatives and false positives. Overall, the model's performance on the test data yields an accuracy of 0.90. [16].

According to the pie chart, around 76.9% of mobile handsets support 3G while only 23.1% do not. The count plot also demonstrates the distribution of 3G-capable mobile handsets across all price points. However, compared to the Low Cost and Very High-Cost categories, the share of 3G-capable smartphones is higher in the Medium Cost and High-Cost categories. This implies that while 3G compatibility may affect a mobile device's price range, it may not be the most crucial feature. The same can be seen for the 'four_g' feature, where about 52.9% of mobile devices support 4G, and there is a slightly greater proportion of 4G capable devices in the Medium Cost classification. The research yielded a maximum accuracy of 90% on the test set, employing the XGBoost model with hyperparameter optimization. The researchers employed various machine learning techniques, such as logistic regression, decision trees, random forest, and XGBoost, to forecast the prices of pre-owned mobile phones by leveraging their specifications. The evaluation of the models involved the utilization of accuracy scores, F1-scores, classification reports, and confusion matrices. The XGBoost model, after undergoing hyperparameter tuning, demonstrated superior performance on the given dataset. It achieved an accuracy score of 90% and an F1-score of 0.89 when evaluated on the test set.

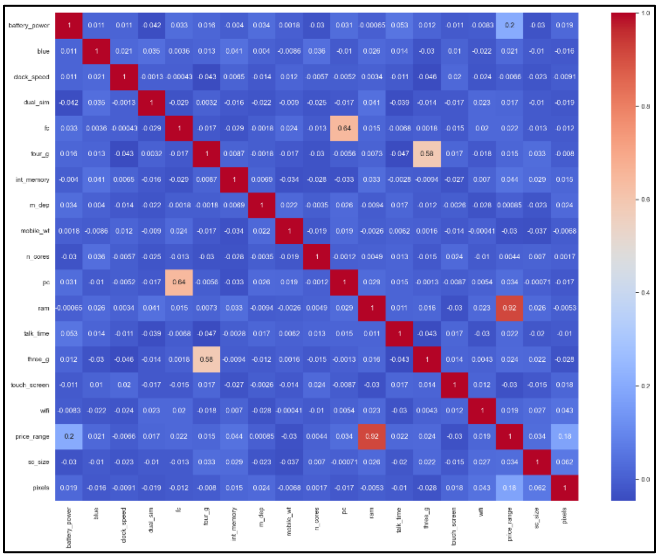

Fig. 4. Correlation on various parameters in mobile phones
Source: Image is created through Google Co-Labs by applying the ML Techniques on the selected dataset.

VI. Conclusion and Future work

This research evaluated a dataset of mobile phones and looked at their features and costs in order to find elements that affect pricing and determine the most precise predictive models. We were able to identify specific price points through careful study and follow how factors like Bluetooth compatibility, battery size, and weight affected the price of mobile phones. XGBoosting and Random Forest outperformed the other three assessed classification techniques, with accuracy ratings of 90% and 88%, respectively. These discoveries can aid businesses in enhancing their pricing and production processes while also supporting consumers in making informed decisions. It is crucial to recognise the limits of our research, such as the potential omission of additional influencing elements. Future studies can examine more datasets and take into account more general market patterns. By incorporating larger and more varied information, future study can broaden the area of analysis and provide an in-depth analysis of mobile phone pricing changes. The accuracy of the predictive models can also be improved by examining the dynamic character of the market through elements such as market demand, rivalry, and technology improvements. Future research can offer a more thorough knowledge of the interplay between mobile phone features and costs by considering external factors that affect pricing variations Future studies can concentrate on feature engineering to find novel derived variables and investigate their influence on mobile phone price. Using sentiment analysis techniques to comprehend customer preferences and perceptions of characteristics can also yield insightful results. Analysing price elasticity can help us better understand how changes in pricing affect customer behaviour. These areas of study can help create predictive models that are more precise and support manufacturers and marketers in making wise price decisions.

- RAM and price_range show high correlation, which is a good sign, it signifies that RAM will play major deciding factor in estimating the price range.
- There is some collinearity in feature pairs (‘pc’, ‘fc’) and (‘px_width’, ‘px_height’). Both correlations are justified since there are good chances that if front camera of a phone is good, the back camera would also be good.
- Also, if px_height increases, pixel width also increases, that means the overall pixels in the screen. We can replace these two features with one feature.
- Front Camera megapixels and Primary camera megapixels are different entities despite showing collinearity.

The future research can investigate feature engineering approaches and sentiment analysis to find unique derived variables and comprehend consumer preferences and views. This is in addition to taking into account the dynamic character of the market and the possible effect of external factors on pricing changes. The prediction of old phone prices can be achieved through the application of machine learning techniques. This involves a systematic process that includes the examination of relevant features and historical pricing data, the selection of an appropriate regression model, the training of the model using a substantial dataset, the evaluation of its performance, and the utilization of the trained model to estimate prices based on the characteristics of old phones. By leveraging the patterns and associations identified from the dataset, the algorithm has the capability to generate precise predictions for the prices of pre-owned mobile phones. This empowers marketplaces, buyers, and sellers to make informed decisions.

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