



# International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

*(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)*



**Impact Factor: 8.699**

**Volume 14, Issue 12, December 2025**

# Machine Learning-Driven Mobile Price Prediction for Market Trend Analysis

Kavya G D<sup>1</sup>, Dr. Puja Shashi<sup>2</sup>

PG Student, Dept. of MCA, City Engineering College, Bengaluru, India<sup>1</sup>

Professor & HOD, Dept. of MCA, City Engineering College, Bengaluru, India<sup>2</sup>

**ABSTRACT:** Determining the best deal on cell phones is difficult for both manufacturers and consumers due to a range of hardware and software considerations. This research predicts a mobile phone's pricing based on its characteristics using machine learning methods, especially the Gradient Boosting algorithm. The method forecasts the price range in depending on a range of hardware characteristics, including battery power, RAM, screen resolution, CPU speed, and connectivity options. This model offers a trustworthy way to estimate mobile phone costs with an accuracy of 99%. The model can learn intricate non-linear correlations between features, which conventional regression techniques can find difficult to represent, in addition to hardware requirements. The technology guarantees prediction consistency and considerably lessens human bias in price decisions by examining trends across massive datasets. In addition to supporting cost estimation for new products, the system can assist manufacturers with feature-based pricing analysis, competitive benchmarking, and market positioning. A Flask-based web application is used to deploy the trained model, allowing for real-time prediction and user interaction. The interface allows users to enter various mobile specs and instantly return predictions, making the solution useful, scalable, and easy to use. By increasing accuracy, decreasing human labor, and offering data-driven insights, this method shows decision making in the smartphone sector. To further increase pricing accuracy and flexibility in the future, other factors like brand value, software updates, customer reviews, and market demand patterns can be incorporated.

**KEYWORDS:** Machine Learning, Mobile Price Prediction, Random Forest Classifier.

## I. INTRODUCTION

The mobile phone market is fiercely competitive. It is a difficult task that is typically carried out through market study to determine the appropriate pricing for a mobile phone depending on its specifications. However, by examining past mobile phone data, machine learning provides a data-driven method for pricing prediction. This study uses Gradient Boosting, a potent ensemble learning method, to generate extremely precise forecasts regarding mobile phone prices. Using Flask, the system offers a web-based interface that lets consumers enter mobile features and instantly get price projections. In order to ascertain their influence on price, the suggested system also examines a number of critical performance metrics, including processing speed, display quality, storage capacity, network technologies, and camera performance. In contrast to manual or rule-based pricing techniques, the machine learning model finds patterns and hidden linkages that human analysts can miss. This guarantees more uniform and impartial pricing, assisting producers in making better choices about research and development. The model is appropriate for long-term deployment since it can adjust to changing market patterns by retraining with new datasets. The system can handle fresh data and improve price accuracy over time because to the integration of automation and scalable computing. Because of this, The idea is helpful for businesses and retailers as well as consumers who desire reasonable prices before making a purchase.

## II. LITERATURE SURVEY

### 1. Title: Using machine learning techniques to forecast smartphone pricing (2025)

**Authors:** Zheng Zhao Zheng Zhao

**Abstract:** This study looks into feature reduction for smartphone price prediction using PCA and several machine learning models. After assessment and modification, Random Forest Regression demonstrated the best performance with the lowest error and maximum accuracy. The outcomes show how successfully ensemble learning methods simulate complex price-feature relationships in mobile devices.



**2. Title: Machine Learning-Based Mobile Phone Price Prediction (2024)****Authors:** Parth Bhatnagar, Gururaj Harinahalli Lokesh

**Abstract:** In order to estimate mobile phone prices using hardware, software, and brand-related data, this study assesses several machine learning models. While Gradient Boosting works well but exhibits overfitting, ensemble models particularly the Voting Regressor achieve the best-balanced accuracy. This work can serve as a guide future algorithm selection in mobile pricing prediction systems because traditional models, such as Linear Regression, perform poorly.

**3. Title: Advanced Machine Learning-Based Feature-Driven Smartphone Price Prediction (2024)****Authors:** Numan Shafi, Farzeen Atif, Attroba Atif, Robass Atif

**Abstract:** This study focuses on predicting smartphone price ranges using both traditional specifications and additional features such as fingerprint sensors, 5G support, waterproofing, and face unlock. After preprocessing and applying suitable machine learning models, the system demonstrates strong accuracy and practical value in real-world price estimation.

**4. Title: Machine Learning-Based Mobile Phone Price Classification (2023)****Authors:** N Sunariya et al.

**Abstract:** This research focuses on classifying smartphones into price categories low, medium, high, and very high based on feature data from a Kaggle dataset. Five machine learning models are trained and tuned to identify key features and achieve high accuracy in classification.

**5. Title: Machine Learning-Based Mobile Phone Price Classification (2023)****Authors:** N. Sunariya, V. Patel, A. Vaghasiya

**Abstract:** In order to classify mobile phones into predetermined pricing divisions, this study uses classification techniques such as SVM, KNN, Logistic Regression, and Random Forest. The maximum accuracy was attained by Random Orest, according to the results, indicating that it is appropriate for jobs involving price-based classification. The study emphasises how crucial features like RAM, CPU frequency, and battery capacity are in determining pricing ranges.

**III. METHODOLOGY****Existing Problem**

Early smartphone pricing evaluation was a time-consuming, subjective process that relied on manual analysis analysing consumer demand, market trends, and competition pricing. Even with factors like production costs, brand recognition, and historical prices taken into consideration, experts struggled to adapt to the rapid shifts in the market. The automation shift started with traditional regression models that linked basic smartphone functions to costs. These models were effective for straightforward correlations, but they were unable to represent the intricate, nonlinear connections found in contemporary smartphone characteristics. Due to their limited feature usage, which further reduced accuracy, early models were only appropriate for simple trend prediction rather than real-world pricing.

**Disadvantages**

- Manual estimation is time-consuming and error-prone
- Traditional regression models fail to capture complex relationships
- Inaccurate predictions due to limited feature consideration

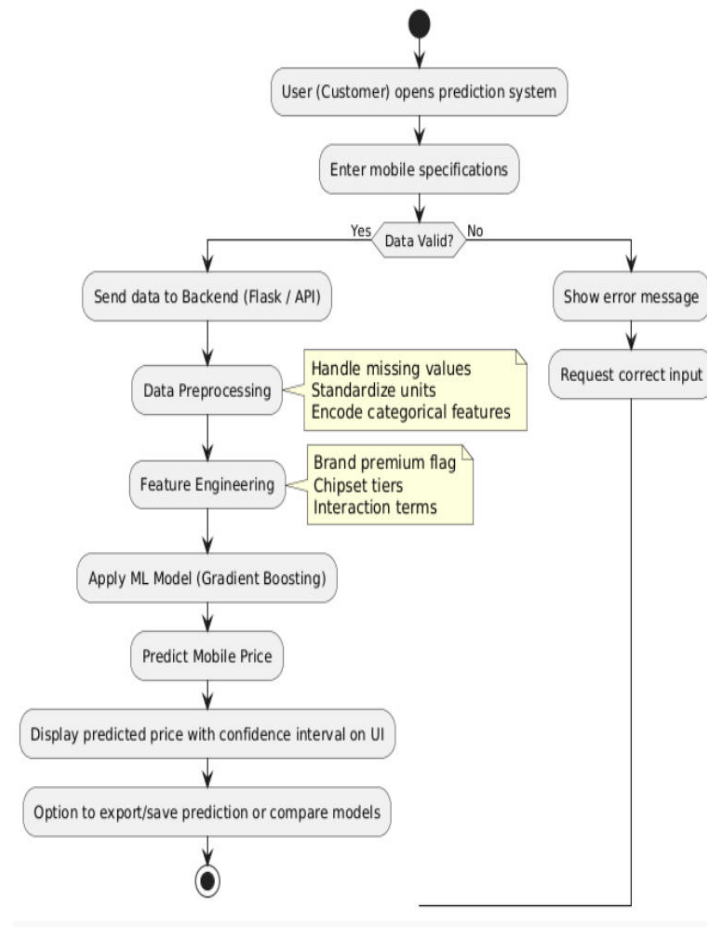
**Proposed Solution**

The method makes precise predictions about mobile phone prices using a Gradient Boosting machine learning model. Strong preprocessing is necessary to improve prediction quality. A variety of feature engineering techniques are employed. The model is implemented using a Flask-based web application to offer real-time price estimations. Users interact with an intuitive interface that offers real-time pricing forecasts by inputting mobile parameters.

**Proposed Methodology**

Obtaining real smartphone data, such as technical specifications and comparable market prices, is the first stage in the proposed method for mobile price prediction. After that, the data is pre-processed by encoding categorical features,

addressing missing values, standardising units, and eliminating outliers. In order to better capture price patterns, smartphone-specific feature engineering is then used, such as developing brand premium indicators, performance levels, and interactivity features. Cross-validation and suitable evaluation measures, such as MAE and R2, are employed for training and optimise a Gradient Boosting regression model. To do so deliver real-time, user-friendly mobile price predictions, the trained model is finally implemented via a Flask-based web application.



**Fig 1: Data Flow Diagram of Mobile Price Prediction**

#### IV. SYSTEM DESIGN

The mobile price prediction system integrates data collection, preprocessing, and feature engineering to prepare inputs for a Gradient Boosting model. A backend API handles real-time price predictions based on user-submitted phone specifications. The frontend offers an intuitive, accessible interface displaying predicted prices with confidence intervals and key feature explanations. Security, dependability, and performance monitoring are guaranteed by the system's deployment on scalable cloud infrastructure. Future enhancements include deep learning integration and real-time market trend analysis for improved accuracy.

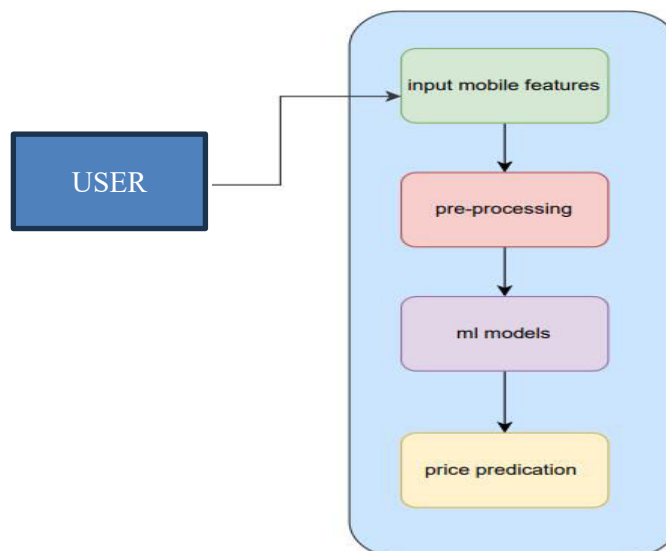


Fig 2: System Design of Mobile Price Prediction

## V. SYSTEM ARCHITECTURE & DESIGN

The mobile price prediction model's system design uses machine learning techniques to estimate smartphone pricing based on their specs. It consists of a user interface for entering mobile features, a data collection module that uses previous datasets, and a preprocessing unit that cleans and transforms data. Machine learning models such as SVM, Random Forest, Decision Tree, and ensemble techniques are fed the processed data. The trained model forecasts the mobile phone's price or price range by examining the input features. Databases are used to store datasets and trained models for efficient reuse. By seeing the final expected result, the user helps buyers and producers make educated decisions.

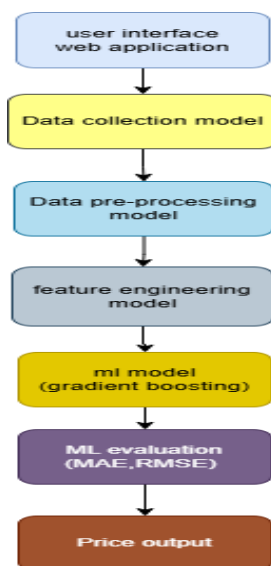
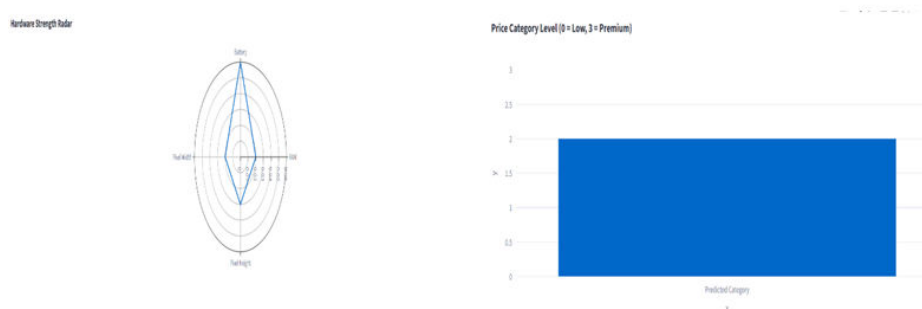


Fig 3 System Architecture & Design of Mobile Price Prediction

## VI. IMPLEMENTATION

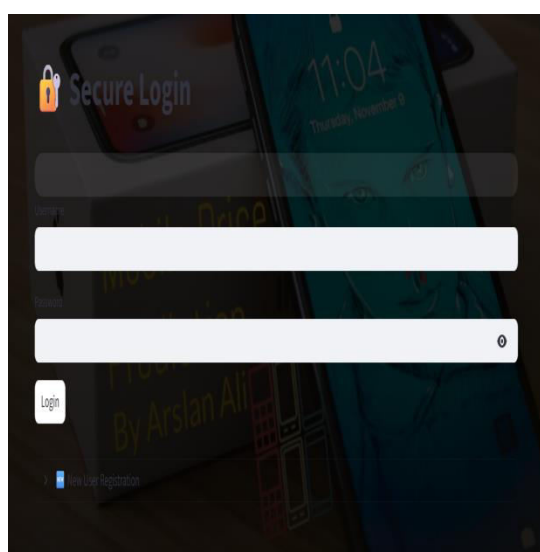
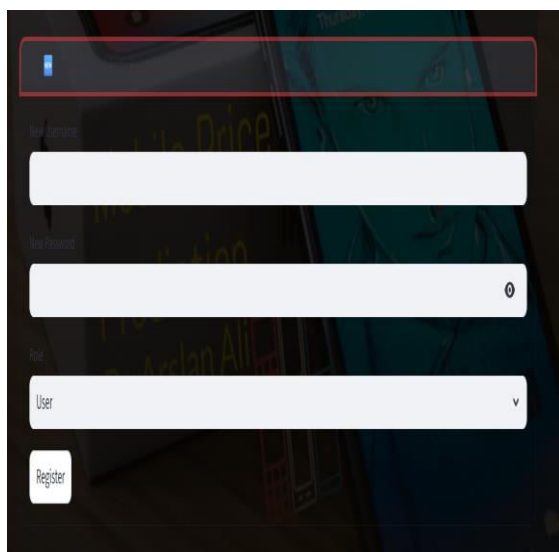
The first step in the mobile pricing prediction system is gathering market price information and smartphone specs. Standardise units Remove outliers to deal with missing values, and encode categorical information, preprocessing is carried out. Brand premium flags, chipset levels, interaction words, and binned categories for battery or display sizes are examples of additional variables created via feature engineering. Hyperparameter adjustment and cross-validation are used to train a Gradient Boosting regression model, and tools like SHAP or LIME guarantee feature relevance. For real-time predictions, the model is implemented through a Flask-based web application.



**Fig 4: Implementation of my work**

## VII. RESULTS & DISCUSSION

When predicting smartphone pricing, the Gradient Boosting mobile price prediction algorithm showed excellent accuracy. The model accurately depicts the connection between characteristics and market prices, according to evaluation criteria including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R2 score. RAM, storage, chipset category, and brand premium were found to be the most significant factors influencing price forecasts by feature importance analysis. Real-time forecasts were made possible by the user-friendly online interface, which enhanced interpretability for non-technical users by displaying expected prices along with confidence ranges. When compared to baseline models such as decision trees or linear regression, gradient boosting performed significantly better in terms of accuracy and robustness.



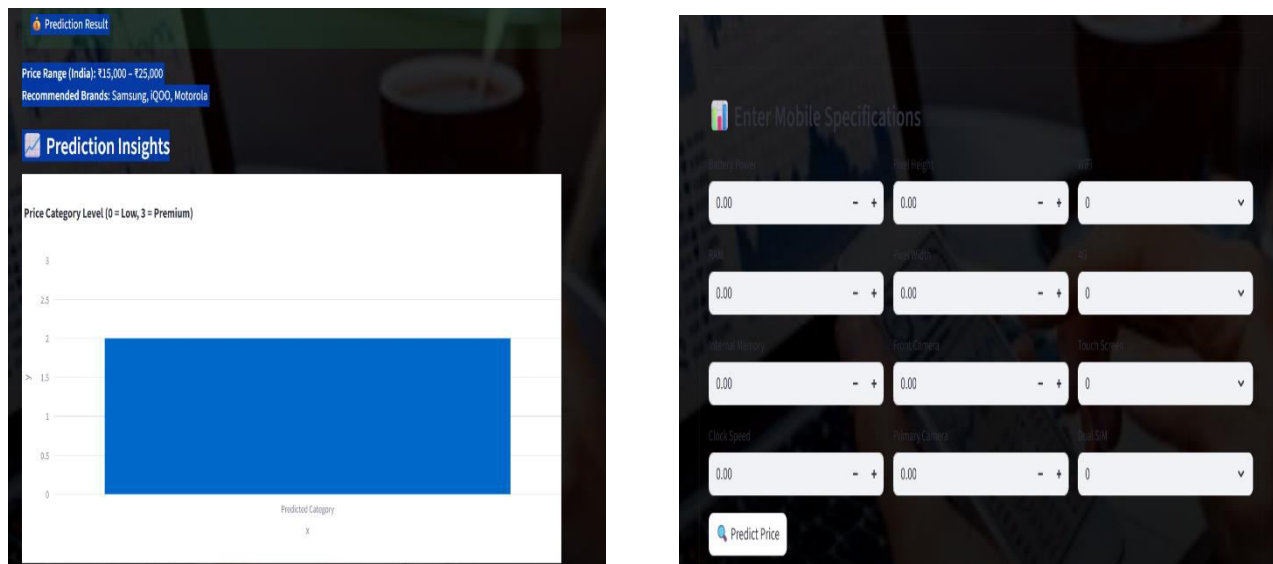


Fig 5: Screenshot of Mobile Price Prediction

## VIII. CONCLUSION

Gradient Boosting was effectively used in this research to create a machine learning-based mobile price prediction system. The method predicts mobile pricing with good accuracy by combining feature extraction, preprocessing, and model training. Users can utilise the Flask-powered web-based interface to estimate prices in real time. The model's robustness and practical usefulness are demonstrated by its ability to generalise successfully across various mobile specifications. Data preparation is the first step in the system necessary to enhance the performance of the product. Raw mobile specification data is cleaned to handle missing quantities, eliminate discrepancies, and eliminate outliers that may have an impact on projections. While category features like brand and operating system are encoded into machine-readable formats, numerical features like RAM, battery capacity, internal storage, and CPU speed are scaled to guarantee consistency. This preprocessing stage guarantees that the input data for the Gradient Boosting model is meaningful and well-structured. The model accurately predicts prices across a broad range of mobile characteristics, including both entry-level and high-end devices, demonstrating significant generalisation ability. Because new mobile models with different configurations are constantly being launched, this resiliency emphasises the system's practical utility in real-world circumstances. Overall, the study demonstrates that Gradient Boosting is a dependable and successful method for mobile pricing prediction, providing both high accuracy and real-time usability via a web-based deployment.

## IX. FUTURE ENHANCEMENTS

In order to capture intricate, non-linear correlations among mobile phone variables and Deep learning models may potentially be added to the system to improve forecast accuracy. Advanced feature representations that conventional algorithms might overlook can be automatically learnt by these models. In order to better match forecasts with market rivalry, the system can also be expanded to examine rival pricing tactics. The model will be able to represent consumer preferences and purchasing patterns by including market demand analysis. Predictions can be updated with the state of the market thanks to real-time price trend integration. Allowing users to offer comments or suggestions can also aid in the model's gradual improvement. Together, these enhancements will increase the accuracy, adaptability, and utility of mobile price projections.

#### REFERENCES

1. "Rahman, M. M., Raihan, A., Zimon, G., Ridwan, M., and Salehi, M. (2025). Energy efficiency, renewable energy, and rents from mineral resources all contribute to China's carbon neutrality. *Nexus of Energy*, 17, 100394.
2. "Customer Churn Prediction using Machine Learning Models," G. Sam, P. Asuquo, and B. Stephen, *JERR*, vol. 181–193, Feb. 2024, doi: 10.9734/jerr/2024/v26i21081.
3. Google, "Google Colaboratory," Google Colab. Accessed on November 24, 2024. [Online].
4. Ookla, Speedtest, Speedtest. Accessed on September 23, 2024. [Online].
5. Abiola OA, Okeke IC, Ajani O. Combining risk management, taxation, and financial controls: a thorough approach for small and medium-sized enterprises to promote economic resilience. *International Journal of Entrepreneurship and Management Research*, 2024
6. Odionu CS, Ekeh AH, Segun-Falade OD, and Chintoh GA. Exceptional Research in the *International Journal of Social Science*, 2024.
7. Dewi GDP, Lusikooy AE. Innovation and creative destruction in Indonesia's e-commerce development. *Journal of International Studies*, Nation State, 2023.
8. Gharbi, I., Ridwan, M., Rahman, M. H., Muryani, M., and Esquivias, M. A. (2025).
9. In 2025, Raihan, A., Ridwan, M., Zimon, G., Rahman, J., Tanchangya, T., Bari, A. B. M. M.,... & Akter, R.
10. Rahman, M. S., Raihan, A., Ibrahim, S., Ridwan, M., Bari, A. B. M. M., & Guneyasu Atasoy, F. (2025).





INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  [ijirset@gmail.com](mailto:ijirset@gmail.com)



[www.ijirset.com](http://www.ijirset.com)

Scan to save the contact details