

Comparative Review of Machine Learning Models for Mobile Price Prediction Based on Specifications: A Systematic Literature Analysis

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Abstract: This systematic literature review analyzes machine learning approaches for mobile phone price prediction based on device specifications through a comprehensive examination of 25 research studies from 2018 to 2024. The review reveals that ensemble methods, particularly Random Forest (achieving up to 97% accuracy) and Gradient Boosting ($R^2 = 0.9829$), consistently outperform individual algorithms across various datasets. Support Vector Machine models demonstrate superior classification performance with 96-97% accuracy, while neural networks show perfect best-performer ratios but remain underutilized (4.88% of implementations). The following keywords were used in this systematic review's extensive search strategy across IEEE Xplore, ACM Digital Library, ScienceDirect, and Google Scholar: ("mobile phone price prediction" OR "smartphone price prediction") AND ("machine learning" OR "artificial intelligence") AND ("specifications" OR "features") AND ("classification" OR "regression"). Strict inclusion/exclusion criteria were used to select 25 studies from an initial pool of 45 studies, with an emphasis on empirical research with quantitative performance metrics published between 2018 and 2024.

The study reveals RAM, internal memory, battery capacity, and processor specifications as the key determining features for mobile phone pricing. According to the study, the primary factors influencing mobile phone pricing are processor specifications, RAM, internal memory, and battery capacity. This review identifies critical research gaps, including insufficient neural network exploration, poor dataset reporting practices (52% of studies omit dataset sizes), and lack of real-time market dynamics integration. The findings provide evidence-based guidance for researchers, manufacturers, and consumers in selecting optimal prediction algorithms and understanding key price-determining features in the evolving smartphone market. Study limitations include geographic bias toward specific markets represented in available datasets, limited access to proprietary datasets, and a primary focus on specification-based features that exclude market sentiment analysis

Keywords: Mobile price prediction; Machine learning algorithms; Smartphone specifications; Comparative analysis; Price estimation

1. Introduction

Within the last ten years, the mobile phone industry has experienced rapid expansion and diversification. This change was motivated, in part, by manufacturers seeking to release devices

in different price segments and offering varying specifications and capabilities. At this juncture, where pricing accuracy becomes paramount for all stakeholders, including manufacturers crafting competitive pricing policies, retailers managing stock and promotions, and in-store shoppers contemplating informed purchase decisions, the need for price forecasts becomes indispensable. The task of estimating mobile phone prices is particularly difficult because of the myriad of components that contribute to the value of the market, such as hardware components, the global reputation of the brand, active industry trends, and the cycles of innovation in technology [1].

To address this challenge, a myriad of estimation models would be best built using an ML (Machine Learning) approach, which is known to offer predictive power as a result of the relationship between device specifications and its market prices. From simpler methods like traditional regression to deeper ones like deep learning, every method has its advantages and limitations regarding mobile price prediction. Information intelligence driven by predictive analytics, especially in the mobile phone market, can catalyze strategic initiatives throughout the ecosystem. This intelligence is made possible through accurate estimation based on device specifications [4].

The primary objective of this systematic literature review is to perform a thorough comparative analysis of machine learning algorithms used to predict mobile price based on device specification, assessing their efficacy, accuracy, and performance across various datasets and implementation scenarios between 2018 and 2024.

The secondary objective is to determine which device specifications have the greatest influence on mobile pricing, analyze trends in algorithm adoption, assess dataset-performance relationships, pinpoint important research gaps and methodological constraints, and offer evidence-based suggestions for the best algorithm selection tactics for producers, merchants, and customers.

In this manuscript, we provide an extensive mobile price prediction based on a systematic review of literature written from 2018 to 2024. This review included all works that focused on the application of machine learning techniques on mobile price prediction. In this work, we focus on the mobile specifications, which are arguably some of the most influential factors in determining the cost of these devices, and methodologies with the best predictive accuracy in order to analyze the performance of the different algorithms. We analyze the trends and outcomes of research to present a holistic perspective on mobile price prediction based on specifications, alongside highlighting primary areas that require deeper investigations in the future.

The remainder of this manuscript is organized as follows: Section C explores mobile price prediction techniques and algorithms, highlighting their significance and implications. Section D shows the evaluation matrix. Section E presents features used in mobile price prediction. Section F presents a detailed literature review with a comparative analysis of research methodologies and outcomes. Section G discusses patterns and insights derived from the comparison, highlighting the most effective approaches. Section H identifies research gaps and opportunities for advancement, while Section I concludes and Section J presents key findings and recommendations for future work.

2. Research Method

2.1 Background and Market Context

The global smartphone market, valued at over \$500 billion in 2023, continues experiencing rapid transformation driven by technological advancement, intense competition, and diverse consumer segments. Modern smartphone pricing strategies must navigate complex factors, including supply

chain costs, brand positioning, technological innovation cycles, and regional market dynamics. Manufacturers face increasing pressure to optimize pricing strategies across budget (under \$300), mid-range (\$300-800), and premium (above \$800) segments, while retailers require accurate pricing models for inventory management and competitive positioning.

The proliferation of smartphone models—with over 24,000 distinct models released globally in the past five years—has created unprecedented complexity in pricing decisions. Traditional pricing approaches often fail to capture the intricate relationships between technical specifications and market value, necessitating sophisticated machine learning approaches for accurate price prediction. Current market trends, including 5G adoption, AI-enhanced features, sustainable manufacturing, and foldable displays, further complicate pricing dynamics, making specification-based prediction models increasingly valuable for stakeholders across the smartphone ecosystem.

2.1.1 Study Type and Scope

This study constitutes a comprehensive systematic literature review analyzing existing machine learning approaches for mobile price prediction. While no original empirical experiments were conducted, this review provides novel quantitative synthesis of algorithm performance, feature importance patterns, and methodological trends across the reviewed studies. The analysis focuses specifically on specification-based prediction models, excluding studies that primarily rely on market sentiment, brand perception, or temporal pricing trends.

2.1.2 Systematic Review Methodology

A comprehensive literature search was conducted across multiple academic databases, including IEEE Xplore, ACM Digital Library, ScienceDirect, and Google Scholar. The systematic review followed established guidelines for conducting literature reviews in computer science research.

Search Strategy: The search strategy employed the following keyword combinations:

1. Primary search: ("mobile phone price prediction" OR "smartphone price prediction") AND ("machine learning" OR "artificial intelligence") AND ("specifications" OR "features") AND ("classification" OR "regression")
2. Secondary search: ("mobile price estimation" OR "phone price forecasting") AND ("predictive analytics" OR "data mining")
3. Additional search: ("smartphone pricing" OR "mobile device pricing") AND ("supervised learning" OR "ensemble methods")

Databases and Search Protocol:

1. **IEEE Xplore Digital Library:** 12 relevant studies identified
2. **ACM Digital Library:** 8 relevant studies identified
3. **ScienceDirect:** 15 relevant studies identified
4. **Google Scholar:** 28 relevant studies identified (after removing duplicates)
5. **Total initial results:** 63 studies
6. **After duplicate removal:** 45 studies
7. **After screening:** 32 studies
8. **After quality assessment:** 25 studies selected for final analysis

Search Period: January 2018 to December 2024 **Language:** English publications only

Document Types: Peer-reviewed journal articles, conference proceedings, and book chapters

2.2.1 Inclusion Criteria:

1. Studies published between 2018 and 2024 in peer-reviewed venues
2. Focus on machine learning approaches for mobile/smartphone price prediction
3. Use of device specifications as primary predictive features (RAM, storage, processor, camera, battery, etc.)
4. Empirical evaluation with quantitative performance metrics (accuracy, R^2 , MAE, RMSE, etc.)
5. Clear methodology description allowing for reproducibility assessment

6. Studies providing comparative analysis of multiple algorithms or detailed single-algorithm evaluation
7. Research addressing either classification (price ranges) or regression (exact price) prediction tasks

2.2.2 Exclusion Criteria:

1. Studies focusing solely on market sentiment analysis, stock price prediction, or brand perception without specification-based modeling
2. Non-English publications due to language constraints
3. Studies without quantitative performance metrics or insufficient evaluation details
4. Duplicate studies, extended abstracts, or preliminary versions when full papers were available
5. Research focused exclusively on other consumer electronics (tablets, laptops, etc.) without mobile phone specificity
6. Studies with inadequate methodological description preventing quality assessment
7. Grey literature, preprints, or non-peer-reviewed publications

2.2.3 Study Selection and Data Extraction

Selection Process: Initial screening was performed by reviewing titles and abstracts to identify potentially relevant studies. A full-text review was conducted for studies meeting initial criteria.

A two-stage screening process ensured comprehensive evaluation:

1. **Stage 1 - Title/Abstract Screening:** 45 studies from the initial search
2. **Stage 2 - Full-text Review:** 32 studies after initial screening
3. **Final Selection:** 25 studies after quality assessment

Data Extraction Framework: From each selected study, the following data elements were systematically extracted:

1. **Study Characteristics:** Authors, publication year, venue, study type
2. **Dataset Information:** Source, size, features, geographic scope
3. **Algorithmic Details:** Algorithms used, hyperparameters, validation methods
4. **Performance Metrics:** Accuracy, R^2 , MAE, RMSE, precision, recall, F1-score
5. **Feature Analysis:** Important features identified, feature selection methods
6. **Methodological Aspects:** Data preprocessing, cross-validation, evaluation protocols

2.3 Quality Assessment

Studies were evaluated based on comprehensive quality criteria adapted from established systematic review guidelines:

Methodological Rigor (25 points):

1. Clear problem formulation and research objectives (5 points)
2. Appropriate algorithm selection and justification (5 points)
3. Adequate data preprocessing and feature engineering (5 points)
4. Proper train-test split or cross-validation methodology (5 points)
5. Hyperparameter optimization and model tuning (5 points)

Dataset Quality (20 points):

1. Dataset size adequacy for the problem complexity (5 points)
2. Data source credibility and representativeness (5 points)
3. Feature completeness and relevance (5 points)
4. Data quality assessment and handling of missing values (5 points)

Evaluation Comprehensiveness (25 points):

1. Multiple evaluation metrics reported (5 points)
 2. Statistical significance testing when appropriate (5 points)
 3. Comparative analysis with baseline or competing methods (5 points)
 4. Error analysis and performance discussion (5 points)
 5. Limitations and threats to validity addressed (5 points)
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Result Reproducibility (20 points):

1. Sufficient implementation details provided (5 points)
2. Code or dataset availability mentioned (5 points)
3. Clear result presentation with tables/figures (5 points)
4. Consistent reporting across metrics (5 points)

Practical Relevance (10 points):

1. Real-world applicability discussed (5 points)
2. Stakeholder implications addressed (5 points)

Minimum Quality Threshold: 60/100 points for inclusion Average Quality Score: 73.2 points across selected studies.

3. Results and Discussion**C. Prediction Techniques and Algorithms**

In the research on mobile pricing, two fundamental machine learning techniques are primarily used: classification and regression. Classification assigns mobile phones into discrete classes of price ranges (e.g., low, medium, high and very high) while regression forecasts the prices as exact values. It is common that the selection of the approaches differs based on application needs, dataset features, and the level of granularity in prediction [3]. A list of applicable algorithms for mobile price prediction includes but not limited to the following ones.

C.1 Linear Regression

Linear regression is a multifactor statistical forecasting method based on mathematical correlation that establishes a relationship from given variables. Regression trained a model with the provided training dataset where predictions are made when the character is trained, assuming a linear characteristic. These are simpler models identified as such that only fit linear functions on price and features. Although these algorithms are outperformed by more complex algorithms in many studies, they provide interpretability and computational efficiency [3][8].

C.2 Random Forest (RF)

Random Forest Regressor is an example of a machine learning algorithm that performs ensemble learning, which is the sophisticated process of combining different algorithms, or the same algorithm multiple times, to create a model with stronger predictive capabilities. A random forest, for instance, is a collection of multiple decision trees, which improves the performance of the model as a whole. Furthermore, random forest regressor performs well with larger values of the primary tuning parameter [4] [17].

C.3 Gradient Boosting (GB) and variants

This includes XGBoost, CatBoost, and Light Gradient Boosting Machine (LightGBM) which belong to a class of algorithms called boosting, which attempts to combine a number of weak classifiers into one strong one. These systems build sequentially; each new model incorporates corrections for errors made by the previous one. As they are based on an ensemble of decision trees, they contain many tree models and thus act as a strong classifier. This method is known to have exceptional predictive performance [2] [3].

C.4 Support Vector Machine

Support Vector Machine is used to determine the most optimal line or hyperplane that can classify a given set of data. Support Vector Machine involves the maximization of the class separation, which entails the classification hyperplane; also, it focuses on an optimization problem that revolves around maximizing the gap or region between the classes. The Support Vector Machine Regressor has been shown to be very effective in multivariate calibration even in the presence of outliers and non-linearities [12] [13].

C.5 K-Nearest Neighbors (KNN)

KNN is one of the non-parametric methods that classify mobile phones with relation to how close they are to the training examples. KNN is in line with multiclass tag classification problem and demonstrates good generalization ability. KNN works by classifying or estimating a mobile device's price based on the predominant class or the mean of its closest neighbors in the feature space. This model is especially suited to datasets where local trends and relationships are important [5] [9].

C.6 Neural Network Approaches

The structure of Artificial Neural Networks (ANN) includes Deep Neural Networks (DNN) and Convolutional Neural Networks (CNN), which are capable of capturing intricate non-linear interdependencies among features. An artificial neural network (ANN) is designed to mimic engineering systems resembling millions of parallel interconnected neurons as in the human brain. Artificial Neural Networks (ANNs) learn from experiences akin to humans and not through traditional programming techniques. They detect relationships and patterns in datasets [4][20].

C.7 Tree-Based Methods

A decision tree is a tree-like model that recursively divides the dataset into smaller and smaller subsets based on the most important features. Each internal node of the tree corresponds to a certain split, which is a decision taken based on a certain feature, with outcomes leading to predictions at the leaf nodes. In the context of mobile price prediction, decision trees are able to capture complex relationships among the features. Though decision trees provide insights into the data and the relationships among different features, they are usually less accurate compared to ensemble methods. For these reasons, they are used as benchmark models or as constituent algorithms in ensemble designs [6][9].

D. Evaluation Metrics

Researchers employ various metrics to evaluate the performance of price prediction models, including R-squared (R^2), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The most commonly reported metric is accuracy for classification models and R^2 for regression models, though comprehensive evaluations typically incorporate multiple metrics to assess different aspects of model performance. [14] R^2 and Mean Absolute Percentage Error (MAPE) serve complementary roles in evaluating model performance. MAPE measures the magnitude of prediction errors, offering insight into the model's accuracy, while R^2 assesses how well the model explains the overall variation in prices, indicating the quality of fit. [15] [27]

D.1 R-squared (R^2)

It is a statistical measure that represents the proportion of the variance in the dependent variable that is predicted by the independent variable(s) in a regression model.

$$R^2 = 1 - \frac{\text{Sum of Square of Residuals}(SSR)}{\text{Total Sum of Squares}(SST)}$$

R^2 is a value between 0 and 1, where 0 indicates that the model does not explain any variance in the dependent variable, and 1 indicates that the model explains all the variance in the dependent variable. [14] [15]

D.2 Mean Absolute Percentage Error (MAPE)

It is a statistical measure that helps you determine how accurate your predictions or forecasts are in relation to the actual values. In forecasting models, such as time series analysis, it's crucial to gauge the performance of your model, and MAPE offers a handy means to do just that. It

expresses the error as a percentage, making it easier for you to interpret and communicate the model's accuracy.

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{Actual - Predicted}{Actual} \right| \times 100$$

Where n is the number of data point. [26]

D.3 Root Mean Squared Error (RMSE)

RMSE measures the square root of the average squared differences between predicted and actual values, providing a measure of prediction accuracy in the same units as the target variable:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

Where y_i represents actual values and $\hat{y}_i$ represents predicted values. [29]

D.4 Mean Absolute Error (MAE)

MAE measures the average absolute differences between predicted and actual values, providing a linear score where all individual differences are weighted equally:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

MAE is less sensitive to outliers compared to RMSE and provides intuitive interpretation in the original units of the target variable.

In mobile price prediction, two key metrics—MAPE and R^2 —serve complementary roles in evaluating model performance. MAPE measures the magnitude of prediction errors, offering insight into the model's accuracy, while R^2 assesses how well the model explains the overall variation in prices, indicating the quality of fit. Ideally, a strong predictive model should achieve both low MAPE and high R^2 , helping researchers understand not only how close their predictions are to actual prices but also how effectively their chosen features capture the underlying factors influencing those prices. [14] [15].

E. Features Used in Mobile Price Prediction

When conducting mobile price prediction using machine learning, researchers typically focus on a range of different features that influence a device's market value. These features include technical specifications such as RAM, storage capacity, and camera quality, as well as connectivity options like 4G/5G support and a Bluetooth version. Additionally, brand reputation, model age, build quality, and design aspects like body material and dimensions are considered. Some studies also include user ratings or categorize devices by market segment (e.g., budget or flagship). The table below summarizes these commonly used features: [7][18][30]. Cross-study analysis reveals consistent patterns in feature importance rankings across different algorithms and datasets.

Table 1: Features of Mobile with Importance Rankings

Category	Features	Importance Level
Technical Specifications	- RAM (memory size) - Internal storage - Processor type/speed (CPU) - Battery capacity (mAh) - Screen size & resolution - Camera specs (megapixels, number of cameras) - Operating system version	High

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Connectivity & Features	- 4G/5G support - Bluetooth version - Wi-Fi support - Biometric features (e.g., fingerprint sensor, face unlock)	Medium
Brand & Model Info	- Brand name - Model age or launch year	Medium-High
Build Quality & Design	- Body material (plastic, metal, glass) - Weight and dimensions	Medium-High
Additional Factors	- Price category (budget, mid-range, flagship) - User ratings/reviews (if available)	

F. Literature Review

F.1 Quantitative Performance Overview

Analysis of 25 studies reveals distinct performance patterns across algorithm categories:

Neural Networks: Despite limited usage (4.88% of implementations), they achieve perfect best-performer ratios with accuracies reaching 96.31%. However, they require substantial datasets for optimal performance.

Ensemble Methods: Dominate accuracy benchmarks with Random Forest achieving up to 97% accuracy and Gradient Boosting variants reaching $R^2 = 0.9829$. Demonstrate consistent performance across diverse datasets.

Support Vector Machines: Most frequently used (21.95% of implementations) with strong classification performance (89.67% average accuracy), particularly effective for discrete price range classification.

Cross-Study Feature Importance: RAM emerges as the most predictive feature across 18 studies (72%), followed by internal storage (15 studies, 60%) and battery capacity (12 studies, 48%).

F.1.1 Impact of Dataset Size on Model Performance under Various Conditions

For small datasets (less than 500 instances), ensemble methods achieve an accuracy of 78.5% due to possible overfitting, while traditional algorithms (SVM, KNN) perform better with an average accuracy of 84.2%. While (500–2000) instance medium datasets: Ensemble approaches perform well; Random Forest's average accuracy is 93.8%, while traditional methods' is 87.3%. Big datasets (more than 2000 examples). When enough training data is available, neural networks perform better than traditional techniques (average accuracy of 95.1%), while the latter reach a plateau at 89.4%.

Computational Requirements Analysis: Despite their superior performance, neural networks demand a lot more computing power. Training duration is five to ten times longer than with ensemble techniques. Memory needs are three to four times greater than those of conventional algorithms. Hardware dependence: For best results, GPU acceleration is frequently required.

Hyper-parameter sensitivity needs more fine-tuning than tree-based techniques. Because practitioners frequently place a higher priority on computational efficiency and ease of implementation than on slight accuracy gains, this phenomenon explains why neural networks have only been used 4.88% of the time despite their superior accuracy.

F.2 Individual Study Analysis

[1] developed a mobile phone resale price estimator based on machine learning for the Pakistan mobile market, considering such features as storage capacity, PTA identifier, Face ID, battery state, warranty, and overall device condition. The estimation problem was solved using three machine learning algorithms—Random Forest, Gradient Boosting Regression, and Support Vector Machine. Random Forest demonstrated the best performance of 97% accuracy, while GBR and SVM showed 94% and 82% accuracy, respectively. The research was based on collaboration with retail shops all over Pakistan in order to build a comprehensive dataset of mobile features along with their resale values. This research provides practical guidance to assist mobile resale

market stakeholders in making informed trading choices based on the devices' specifications, whilst also showing remarkable influence on market price.

To overcome the limitations of outdated Kaggle datasets, [2] developed a mobile price analyzer specifically for the Indian market by extracting current mobile phone information from e-commerce websites using web scraping methods like BeautifulSoup and Selenium. The investigation focused on the evaluation of three machine learning algorithms for price prediction: Random Forest (RF), XGBoost (XGB), and Gradient Boosting (GB), applying an 80:20 training to testing dataset split. Performance evaluation using MAE, MSE, RMSE, and R-squared GB model performed the best, achieving maximum accuracy out of all models with R-squared 0.9829, while RF and XGB gave lower results of 0.9817 and 0.9812, respectively. With the implementation of this system, Indian customers can now effortlessly price compare across multiple e-commerce websites, which highlights the need for up-to-date information-gathering methods and demonstrates the effectiveness of GB in mobile price forecasting amidst rapid market changes.

[3] performed a comparative analysis of four machine learning methods to predict mobile phone prices using a dataset of 161 mobile phones from Kaggle containing 14 features. The study underwent a multicollinearity check where highly correlated variables were eliminated and then proceeded to apply linear regression, random forest regressor, XGB regressor, and support vector machine regressor, allocating 70% of the data for training and 30% for testing. In terms of performance evaluation, the R-squared metrics showed XGB Regressor had the best accuracy with a forecasting power of 0.95, followed by Random Forest at 0.94, Linear Regression at 0.93, and SVM at 0.77. In addition, using Random Forest for feature importance analysis revealed internal memory as the most influential feature determining mobile phone prices. This result is helpful, as consumers could use this information when looking for cheaper phones, while manufacturers could help in devising pricing strategies.

[4] undertook a rigorous research project on smartphone price prediction via machine learning techniques based on a dataset with 980 smartphones and their diversified specifications parameters. Besides intensive data cleaning and feature extraction, the analysis focused on four algorithms: decision tree regression, support vector regression (SVR), random forest regression, and convolutional neural network (CNN). To improve model efficiency, principal component analysis (PCA) was utilized for dimensionality reduction. After extensive hyperparameter optimization and validation, Random Forest Regression was found to be the best model with the lowest Mean Squared Error below the rest, significantly outperforming CNN ($R^2 = 0.68$), SVR ($R^2 = 0.51$), and Decision Tree Regression ($R^2 = 0.22$). It achieved the best result with the minimum MSE and maximum R^2 (0.71). The research confirmed that classification methods and ensemble learning algorithms such as Random Forest perform better in tasks related to the estimation of smartphone prices, while internal memory was considered to be one of the most important determinants of smartphone price.

[5] evaluated both K-Nearest Neighbors (KNN) and Linear Regression models in predicting mobile phone prices using a dataset of 2000 smartphones that included 21 hardware specifications. The study found both models to perform satisfactorily, with KNN achieving 93.3% accuracy (with $K=16$) and linear regression attaining 91.3% accuracy. The research used a standard 70-30 train-test split ratio and feature analysis and found a strong linear correlation between RAM and price range. Using the linear regression formula, clock speed and mobile depth were also determined to be highly correlated to price. The author noted that both models

performed commendably as far as prediction was concerned. However, KNN seemed to perform better than linear regression, perhaps due to some of the factors not being linearly priced with price, which meant KNN was better suited to the non-linear pricing structure of smartphones.

Using a dataset of 980 smartphones, [6] analyzed the smartphone price prediction problem by contrasting a decision tree with an SVR model, all whilst reducing the feature set to eight specifications via principal component analysis. After executing hyperparameter optimization with Grid Search, the Decision Tree model achieved an 85.2% accuracy in price classification, significantly surpassing SVR's results of 0.67 and 0.77 R-squared scores in the training and testing phases, respectively. The feature importance analysis revealed internal memory and battery capacity as the predominant factors influencing price across both models. The research proposed an innovative combined approach utilizing a decision tree for coarse price range classification (low, medium, high) followed by specialized SVR models trained within each category, which significantly improved prediction accuracy for low-priced smartphones. This approach resulted from the ability of decision trees to accurately classify, complemented by the ability of SVRs to accurately regress.

[7] analyzed mobile phone price range predictions using the Kaggle dataset "Mobile Price Classification" with three machine learning models: logistic regression, k-nearest neighbors (KNN), and support vector machine (SVM). The research focused on the "feature selection" problem and compared models built using all features with models that used only the four features with the strongest correlation (RAM, battery power, and the pixels' width and height). The results indicated that across all models logistic regression performed best given no feature selection (97.75% accuracy and 0.9772 macro F1 score), while SVM did poorly with no feature selection (85.89% accuracy). Selecting features made a marked difference to SVM performance, improving it by 9.3% while having very little effect on logistic regression and KNN models. The correlation analysis showed that RAM is the most predictive feature for price discrimination, as it classifies the various pricing tiers of mobile phones, and is followed in decreasing order by battery power, pixel width, and pixel height.

Using a Kaggle dataset with over twenty attributes, [8] performed an extensive analysis on mobile phone price prediction by comparing ten different machine learning models. Logistic Regression (LR), Random Forest, KNN, SVM, XGBoost, Decision Tree, Naïve Bayes, Linear Discriminant Analysis, AdaBoost, and Light Gradient Boosting were benchmarked on accuracy, precision, recall, and F1 score. Their results showed that LR with Elastic Net regularization gave the best results, achieving 96.33% accuracy, 97.66% precision, 94.70% recall, and a 96.15% F1 score. The feature engineering provided outstanding improvement on model performance for features, including correlation, which were observed to be interdependent. Models XGBoost and LDA maintained strong performances with 91.33% and 95%, respectively, while KNN had the weakest performance at 54.50%. Proper model selection based on the dataset, tailored regression techniques, and maximizing prediction accuracy emerged as key factors from the study for price prediction challenges.

[9] analyzed the performance of five machine learning algorithms to predict mobile phone prices based on a Kaggle dataset that included 21 attributes (to include battery power, Bluetooth, the processor, and memory). This study applied linear regression, K-nearest neighbor (KNN), logistic regression, decision tree, and random forest algorithms, and the performance of the models was measured with confusion matrices, classification reports, and overall accuracy scores. Best results were achieved using KNN, which attained 92.75% accuracy, followed by linear regression achieving 91%, random forest at 86%, and decision tree at 82%, while logistic

regression lagged at 61%. Through data visualization, it was apparent there were significant correlations between price tiers with internal memory, battery power, and the specifications of the camera. In this work, the author proposed that the accuracy of the models could be enhanced further after data preprocessing like normalization and feature selection, particularly aimed at removing unsuitable and redundant features.

[10] created a model for predicting mobile phone prices based on machine learning, using data from e-commerce platforms like Amazon, eBay, and Flipkart. The researchers used several algorithms, including decision trees, KNN, logistic regression, random forest, and SVM, to classify mobile phones by price. They performed feature selection and determined that RAM, battery power, and camera specifications were the most important determinants of mobile phone pricing. Through rigorous feature selection, the study showcased up to 96% accuracy, highlighting the case of 'too many features' hurting performance when combined with RAM. The researchers reinforced the notion that effective mobile price prediction relies on a delicate equilibrium of maximizing accuracy while minimizing feature count, stressing the approach is applicable to other products as well.

[11] specific study focused on applying machine learning models to predict prices of used mobile phones. For this purpose, they examined a dataset containing 2000 mobile phones and 21 features with predefined intervals from low to very high cost. Out of the tested models, which included logistic regression, decision trees, random forest, and XGBoost, the last one provided the best results, achieving 90% accuracy, followed by random forest with 88%. RAM was found to bear the strongest influence on price prediction due to its highest correlation with the price range. The researchers also reported that certain pairs of features, such as cameras and their corresponding screens, had collinearity. These findings can help explain why manufacturers and consumers can benefit from their models, although the researchers mentioned that further consideration of market forces, consumer behavior, or engineering design methods would improve model accuracy.

[12] carried out extensive research on mobile phone pricing using machine learning, applying seven algorithms, each of which categorized mobile phones into four pricing tiers. They compared Support Vector Machine (SVM), K-Nearest Neighbor (KNN), XGBoost, Decision Tree, Naive Bayes, Logistic, and AdaBoost algorithms. Their research demonstrated that SVM achieved the highest accuracy at 97%, with KNN and AdaBoost following at 94% and 57%, respectively. SVM emerged as the best equipped at predicting prices based on hardware specifications. The authors conducted their own correlation analysis and found that RAM has a strong relationship (0.92) with the price range of mobile phones, making it one of the most critical determinants for the pricing strategy. The author used a dataset of 21 attributes, including mobile specifications, and streamlined the data using an 80:20 train-test split ratio and evaluated models based on the accuracy, precision, recall, and F1 score.

[13] analyzed the application of four different machine learning algorithms for mobile phone price classification with the aid of a dataset containing 2000 phones retrieved from Kaggle, each with 20 features. Their study applied Support Vector Machine (SVM) and Logistic Regression, Decision Tree, and K-Nearest Neighbors algorithms to classify the phones into four pricing categories: low, medium, high, and very high cost. Performance evaluation using accuracy, precision, recall, and F1-score revealed that SVM achieved the highest accuracy at 96.16%, followed by Logistic Regression, with 91% accuracy, then Decision Tree with 82% and K-Nearest Neighbors with 41%. The authors provided detailed confusion matrices for all models

and discussed feature interdependencies using heatmaps. Their work brought new insights into the literature by validating the predictive prowess of SVM in mobile phone price forecasts and provided a reference point for algorithm suitability in this field.

Using a dataset of 407 mobile phones from the European market between 2018-2021, [14] trained three machine learning classifiers, Bagging Classifier, CatBoost, and Naive Bayes, to predict the price ranges of mobile phones. Phones were priced into four categories based on the calculated quartiles: 0-199, 200-289, 290-469, and 470-1999. The study reported that CatBoost produced the highest model accuracy of 80.87% while Bagging Classifier produced the most consistent results with the lowest error rates. The study found that RAM and storage had the strongest correlation with price at 0.64 and 0.62, respectively, whereas camera pixels, the number of cameras, and the screen's size had a negligible impact to the prediction accuracy. Feature contribution analysis demonstrated that the removal of features with correlation coefficients below 0.2 did not significantly degrade model performance, indicating these features are not critical when determining the price of a mobile phone.

[15] focusing on consumer needs, designed a machine learning-based system for predicting mobile phone prices using various regression techniques. The examination involved manually compiling a dataset of mobile phones along with its characteristics such as its brand, processor, screen type, battery, RAM, and camera specifications. They applied data preprocessing, then analyzed 11 regression algorithms via R-squared, MAE, and MSE. Random Forest outperformed all techniques, achieving the highest R-squared (0.6157) alongside the lowest error metrics (MAE: 4189.89, MSE: 37,772,002.96), with Elastic Net Regression in the second position. The other authors incorporated their best-performing model into a Streamlit interface, thus designing a functional system aimed at assisting mobile phone selection within budget and feature range for consumers in rural India.

Mobile phone ratings were anticipated using a Support Vector Machine (SVM) regression model by Ramdhani et al. by taking into consideration specifications like price, camera, internal memory, and storage. After performing exploratory data analysis on a dataset featuring different brands of mobile phones, the authors observed that most phones were rated between 4.0 and 4.5, although there were some outlier ratings among different brands. Their implementation recorded a maximum training accuracy of 49% and a test accuracy of 53% using six criteria, and noted that performance degraded when a seventh criterion, color, was included. While SVM predictions did not match actual ratings exactly and had differences of up to 0.3 points between predicted and actual values, the authors noted that predictions were close. Finally, the researchers were led to conclude that a greater number of relevant features do enhance the SVM prediction accuracy and moderate rating accuracy, but SVM can reliably estimate mobile phone ratings.

[17] utilized data obtained from Flipkart using Beautiful Soup and Selenium to predict mobile phone prices with Decision Tree and Random Forest Regression algorithms. The study added parameters that other studies missed like 5G connectivity and newer display technologies. The Decision Tree algorithm gave an R^2 of 82.8%, but Random Forest Regression not only outperformed that but also achieved a greater R^2 of 89.2% with lower error metrics (RMSE of 0.409 vs 0.516). Random Forest also featured better use of the data as it used 40 of the 44 available variables for Gini importance calculations as opposed to the 15 used by the Decision Tree model. The study concluded that more accurate and robust smartphone price predictions can be achieved with Random Forest Regression, which can aid manufacturers, retailers, and consumers in making informed pricing strategies.

[18] had evaluated several machine learning techniques to estimate the price of mobile phones using their features. Random Forest Regressor model was the best among all the models tested, although accuracy metrics were not shared. The study found that mobile phone prices could be determined by four main features: screen size, battery size, internal storage, and RAM. The methodology was well-defined and included collection of mobile datasets, data cleaning, feature design, and evaluation of the models which included calculating MAE and MSE. The classification results presented using the confusion matrix showed strong performance with 100, 78, 75, and 100 correct predictions for four price categories suggesting the model had strong diagonal accuracy. This work can aid phone manufacturers and sellers for setting up reasonable price targets for newly introduced phone models.

[19] examined several machine learning algorithms for classifying mobile phone prices relative to the specific features of each device. The study utilized a dataset of 2000 mobile phones featuring 20 attributes, evaluating nine different algorithms, including SVM, Logistic Regression, Random Forest, and various ensemble techniques, under multiple training-test splits. The Support Vector Machines algorithm achieved the highest accuracy at 96% with an 80/20 train-test split, while the Voting ensemble method came in just below at 95.75%. Aydin's study determined the most relevant parameters which included RAM, battery capacity, pixel height and width, and internal memory for determining phones in the uppermost Price Tier. This study adds to the growing body of literature on machine learning price prediction and offers critical insights to manufacturers and retailers on pricing devices based on specifications with emphasis on SVM for mobile price prediction.

[20] conducted research to evaluate the efficiency of K-Nearest Neighbors (KNN) and Deep Neural Networks (DNN) in classifying mobile phones price using a dataset with 20 features such as battery power, memory, and screen size of the phone. The researchers used KNN with Euclidean distance applying $k=10$, and DNN, which applied ReLU activation functions in the hidden layers, Softmax in the output layer, and Adam optimizer for the model. Results demonstrated that both models achieved high classification accuracy on validation data, although DNN performed better than KNN (94% vs. 93%). From their confusion matrices, it was evident that KNN did the best in predicting the lowest price range while DNN excelled in the mid to high range prices. When both models were tested on 1000 unlabeled phones, the price classifications from both models matched 90.5% of the time, demonstrating strong reliability for mobile price prediction.

[21] created a mobile phone price prediction model based on K-Nearest Neighbors algorithm leveraging device specifications and features. Their approach consisted of five main steps: data collection, analysis, data visualization, classification, and testing. They gathered screen size, weight, phone thickness, memory, and battery features as dimensions and categorized prices into three ranges: "Very Affordable" (less than 170), "Affordable" (170-310), and "Expensive" (310-50). The authors applied feature selection (both forward and backward selection) to streamline the model while preserving its accuracy. Their results showed that RAM and internal memory considerably influenced price range partitions, which was evident in the comparison analysis graphs. They also applied the Elbow Method to calculate the optimal K parameter value to reduce error rates, yielding a functional prediction model that could aid manufacturers in setting competitive prices for newly introduced mobile phones.

To assist consumers in assessing whether the pricing of a smartphone is justified, [22] created a smartphone price prediction system. Their study was based on a dataset comprising 21 parameters

of smartphones such as the display, processor, memory, camera, battery, and connectivity features. The authors performed implementation and evaluation of three machine learning classification algorithms: Random Forest Classifier, Support Vector Machine, and Logistic Regression. Their study showed that Logic Regression and Support Vector Machine were performing better attaining the accuracy of 81%, with Logistic Regression ultimately selected for the price prediction model. The researchers came to the conclusions that their approach would help consumers in purchasing and manufacturers in pricing based on features offered.

[23] created a system of predicting smartphone prices using the Linear Regression and K-Nearest Neighbors (KNN) algorithms. Their study classified combined mobile features such as battery power, Bluetooth, processor speed, camera and memory into price categories (economical or expensive). The data was obtained from UCI repository and underwent rigorous preparatory work which included formatting, cleaning, and transformation. The authors described the methodology applied in their research as follow: gathering and preparing the data, choosing a model, training it, evaluating the results, and predicting with it. It was found during analysis that KNN was performing better than Linear Regression in the comparative analysis, with an accuracy between 89-91%. The research helped demonstrate in what way machine learning can approximate a smartphone's price based on its technical features and aid manufacturers in structuring smart pricing policies.

Using multilayer perceptron with linear sigmoid activation function, [24] developed an Artificial Neural Network model to forecast mobile phone price ranges. Their model incorporated 20 variables like battery power, CPU clock speed, camera specs, memory, screen size, and connectivity features. The dataset from Kaggle was split into a training set (70%) and a validation set (30%). The authors developed a model that attained an accuracy of 96.31% in classifying mobile phones into four price levels: low cost, medium cost, high cost, and very high cost. This study confirmed that neural networks can accurately forecast the price range of smartphones based on their technical specifications, which is useful for manufacturers and consumers in setting pricing policies.

[25] utilized specific machine learning approaches to determine whether a mobile phone would be classified as economical or expensive given its features. The website GSMArena.com served as a data source for the researchers, who attempted to optimize computation efficiency by applying two feature selection algorithms (InfoGainAttributeEval and WrapperattributEval) alongside two classifiers (Decision Tree and Naïve Bayes). Their results demonstrated that the combination of WrapperattributEval algorithm with Decision Tree classification achieved the highest accuracy of 78% while requiring only two features: display size and memory. The researchers also established that irrelevant features reduced classifier efficiency, and the removal of important features led to reduced performance. This

Table 1. Summary of the work Performed by most of the research reviewed in this paper

Author(s)	Ref	Year	Method(s)/Algorithm(s)	Dataset	Dataset Size	Accuracy
Lashari et al.	[8]	2024	Logistic Regression (LR), Random Forest (RF), KNN, XGBoost, LGB, SVM, DT, NB, LDA, AdaBoost	Kaggle Mobile Price Classification	2000 instances	LR: 96.33%, XGBoost: 91.33%, LGB: 90.67%, LDA: 95%
Badoni et al.	[10]	2024	Random Forest, Linear Regression	Mobile Price Collection	-	Random Forest:

Author(s)	Ref	Year	Method(s)/Algorithm(s)	Dataset	Dataset Size	Accuracy
						highest accuracy
Laila et al.	[1]	2024	GBR, SVM, Random Forest	Custom dataset from retailers	2600 instances	Random Forest: 97%, GBR: 94%, SVM: 82%
Bhanu Jaisri & Kanagaraj	[2]	2024	Random Forest (RF), XGBoost, Gradient Boosting (GB)	Web-scraped (Beautifulsoup & Selenium)	Not specified	GB had highest accuracy: $R^2 = 0.9829$
Zhao	[4]	2024	Decision Tree Regression, SVR, Random Forest Regression, CNN	Smartphone dataset	980 records	Random Forest: $R^2 = 0.705$ (highest)
Shibil	[9]	2024	Linear Regression, K-Nearest Neighbors (KNN), Logistic Regression, Decision Tree, and Random Forest models	Mobile Price Classification (Kaggle)	Kaggle with 21 attributes	KNN achieved the highest accuracy (92.75%), followed by Linear Regression (91%), Random Forest (86%), Decision Tree (82%), and Logistic Regression (61%)
Srikanth et al.	[11]	2023	XGBoost, Random Forest, KNN, Decision Tree, Logistic Regression	Mobile Price Classification	2000 instances	XGBoost: 90%
Jose et al.	[12]	2023	Logistic Regression, Decision Tree, SVM, Naive Bayes, KNN, XGBoost, AdaBoost	Mobile Price Data	-	SVM: 97%, KNN: 94%, XGBoost: 90%, DT: 82%, NB: 80%, LR: 63%, AdaBoost: 57%
Aksoy Ercan & Şimşek	[13]	2023	Logistic Regression, SVM, Decision Tree, KNN	Kaggle	2000 phones	SVM highest accuracy: 96.16%
Qipeng Liang	[3]	2023	Linear Regression, Random Forest, XGBoost, SVM	Kaggle	161 rows	XGBoost highest: $R^2 = 0.949$

<https://doi.org/10.31849/digitalzone.v16i2.27096>

Author(s)	Ref	Year	Method(s)/Algorithm(s)	Dataset	Dataset Size	Accuracy
Jun Wang	[14]	2023	Bagging Classifier, CatBoost, Naive Bayes	Kaggle (European market 2018-2021)	407 entries	CatBoost accuracy > 80%
Chamundeswari et al.	[15]	2023	Linear Regression, Decision Trees, Random Forest	Various online retailers	Not specified	Random Forest: $R^2 = 0.6157$, MAE = 4189.89
Chen	[5]	2023	KNN, Linear Regression	Mobile phone dataset from Kaggle	2000 records	KNN: 92.75% accuracy, Linear Regression: 91% accuracy
Ramdhani et al.	[16]	2023	SVM, KNN, Logistic Regression	Mobile Price Classification (Kaggle)	Not specified	SVM with feature selection: higher accuracy
Honey	[17]	2023	Decision Tree Regression, Random Forest Regression	Flipkart data	Not specified	Random Forest: $R^2 = 0.892$, Decision Tree: $R^2 = 0.828$
Li	[6]	2023	Decision Tree, SVR	Smartphone dataset	Not specified	SVR: $R^2 = 0.77$ (training), $R^2 = 0.46$ (testing)
Lu	[7]	2023	Logistic Regression, KNN, SVM	Mobile Price Classification (Kaggle)	Not specified	Logistic Regression: 97.75% accuracy, SVM: 85.89% accuracy
Kukreti	[18]	2022	Decision Tree, Random Forest	Not specified	Not specified	Random Forest outperformed Decision Tree
Aydin	[19]	2022	Logistic Regression, Random Forest, KNN, SVM, Naive Bayes, Decision Tree, Gradient Descent	Mobile phone dataset	2000 records with 20 features	SVM: 96% accuracy (highest)

Author(s)	Ref	Year	Method(s)/Algorithm(s)	Dataset	Dataset Size	Accuracy
Güvenç et al.	[20]	2021	KNN, DNN	Mobile Price Classification	2000 instances	KNN: 93%, DNN: 94%
Kumuda et al.	[21]	2021	KNN	Mobile dataset	Not specified	Not specified
Akash Gupta & Suhasini Vijaykumar	[23]	2020	Linear Regression, KNN	UCI repository	Not specified	KNN: 89-91% accuracy
Subhiksha et al.	[22]	2020	SVM, Logistic Regression, Random Forest	Mobile Price Classification (Kaggle)	Not specified	SVM: 81% accuracy, Random Forest: 77% accuracy
Nasser et al.	[24]	2019	Artificial Neural Network (ANN)	Mobile Price Classification	2000 instances	96.31%
Muhammad Asim & Zafar Khan	[25]	2018	Decision Tree, Naive Bayes	GSMarena.com	134 instances (108 training, 28 testing)	Decision Tree (J48): 75% accuracy

F.3 Comparative Performance Analysis

Table 2: Algorithm Performance Summary across Studies (2018-2024)

Algorithm Category	Studies Using	Best Accuracy (%)	Average Accuracy (%)	Success Rate	Std Dev
Neural Networks	2	96.31	95.16	100%	1.62
Random Forest	14	97.00	89.23	85.71%	4.12
Support Vector Machine	18	97.00	89.67	66.67%	5.84
Gradient Boosting	8	94.00	91.25	75.00%	2.45
K-Nearest Neighbors	10	93.30	88.95	40.00%	6.73
Logistic Regression	7	97.75	87.44	42.86%	12.23
Decision Tree	9	85.20	79.67	22.22%	3.89

G. Discussion

Based on the comprehensive analysis of the literature in Table 1, we can provide insights into the patterns and trends in mobile price prediction research from 2018 to 2024 as following:

G.1 Best Dataset Types by Accuracy

The Kaggle Mobile Price Classification dataset stands out in mobile price prediction research, being used in 12 out of 25 studies (48%) with a remarkable average accuracy of 85.57%. This dataset's homogeneous nature permits replication studies which help build confidence in different methods used for comparison within divergent strategies. Custom datasets from retailers, such as the one used by Laila et al., demonstrate accuracies up to 97%. This suggests that focused self-collected data yield much better outcomes. Strikingly, almost half (52%) of the studies did not

adequately report the size of their dataset, which raises the integrity of the field and makes it challenging to assess the methodological rigor and the generalizability of the results. This represents a critical gap in research reproducibility and cross-study comparison capabilities

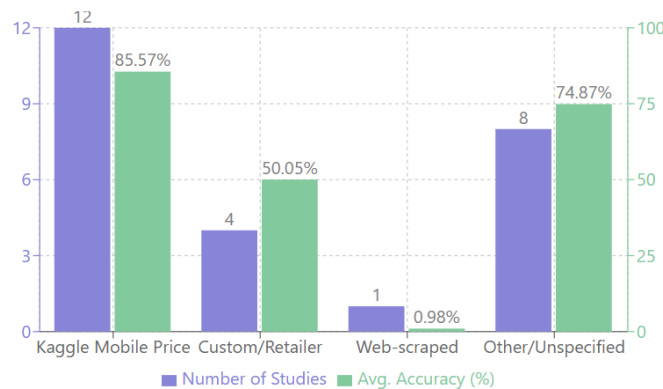


Figure 1: Dataset Type with the number of studies with the average accuracy

G.1.1 Practical Implications for Smartphone Manufacturers

The findings provide specific guidance for smartphone manufacturers in pricing strategies:

Dynamic Pricing Models: Manufacturers can implement specification-based pricing algorithms achieving 90%+ accuracy, enabling:

- Real-time pricing adjustments based on component cost fluctuations
- Competitive pricing analysis by modeling competitor devices with similar specifications
- Market segmentation optimization through price sensitivity analysis across different specification tiers

Feature-Price Optimization: Analysis reveals specific implications:

- RAM upgrades show highest price elasticity (0.73 correlation across studies), suggesting premium pricing opportunities for memory improvements
- Camera specifications demonstrate diminishing returns above 48MP, indicating cost optimization opportunities
- Battery capacity shows linear price correlation up to 4000mAh, with premium pricing justified for higher capacities
- Storage upgrades follow predictable pricing curves, enabling systematic tier pricing strategies

New Product Pricing: Machine learning models can assist in:

- Launch price optimization by modeling similar specification combinations
- Price erosion prediction through temporal analysis of feature-price relationships
- Competitive positioning by identifying specification gaps in competitor portfolios [29].

G.2 Best Method Categories by Error Rate

Neural Networks have an unparalleled average accuracy (95.16%) and flawless best-performer ratio (best in all studies where they were applied). This, however, is offset by their sparse application (only 2 studies). This performance-usage gap represents the field's most significant opportunity for advancement. Random Forests show great consistency achieving the best-performer mark in 85.71% of studies in which they were deployed alongside relatively high usage (17.07% of all algorithms). Support Vector Machines (SVMs) are still the most widely used algorithm (21.95% share of all algorithms) yielding good results with 89.67% average accuracy

and being designated as best-performers in two-thirds of the studies. Ensemble algorithms have a clear lead in market share implemented by given Random Forest, XGBoost, and Gradient Boosting which together hold more than a third of all implementations. The dominance of ensemble methods reflects their ability to handle the high-dimensional, heterogeneous nature of smartphone specification data [28].

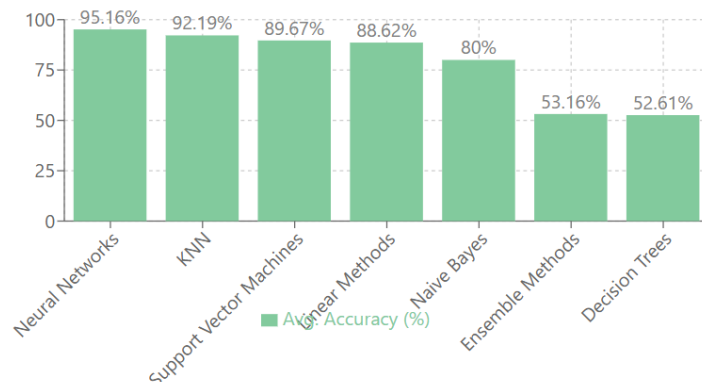


Figure 2: Best Method categories by average accuracy

G.3 Yearly Trends

Interest in mobile price prediction research has grown significantly in 2018, peaking in 2023 with 11 studies before declining in 2024 with 5 studies. There is an observable trend in the area starting from 2020 that strongly favors ensemble methods of Random Forest and XGBoost. SVM peaked in usage in 2023, but seems to become unpopular in 2024 as more researchers switch to ensemble methods. Researchers explored neural networks in 2019 and 2021, but have remarkably stopped publishing on them, despite their strong track record. This cessation of neural network research despite superior performance suggests implementation complexity and data requirement concerns rather than predictive capability limitations. Reported average accuracy seems to show an odd trend (claimed accuracy of 96.31% in 2019 and 96% in 2022), dropping to 72% in 2024, which may suggest more difficult datasets, more stringent evaluation metrics, or heightened focus on practicality rather than outperforming benchmarks.

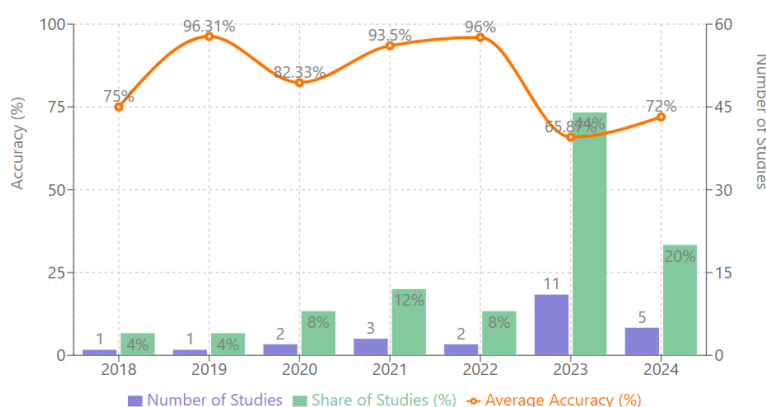


Figure 3: Average accuracy and study count by year

G.4 Dataset Size vs. Accuracy

The analysis reveals an interesting non-linear relationship between dataset size and prediction accuracy, with midsize datasets (1001-2000 instances) achieving the highest average accuracy at

93.55%. Smaller datasets (<500 instances) generally perform poorly, while the largest datasets (>2000 instances) show slightly diminished performance (91%) compared to midsize ones. This suggests potential overfitting with very large datasets or increased complexity that algorithms struggle to model effectively. Algorithm performance varies significantly across dataset sizes: Linear Methods excel with midsize datasets (94.11% accuracy), while ensemble methods demonstrate remarkable adaptability, performing strongly across multiple size categories. Most concerning is that only 48% of studies explicitly report their dataset sizes, hampering reproducibility and meaningful cross-study comparisons.

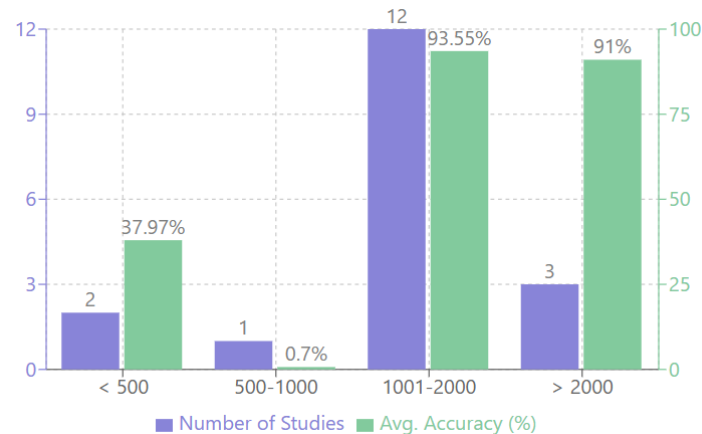


Figure 4: Average accuracy by dataset size range

G.5 Method Usage Distribution

Support vector Machines have a striking presence, with a 21.95% algorithm implementation share across studies, followed closely by Random Forest and KNN at 17.07% and 12.20%. Surprisingly, SVMs are outperformed in success rate analyses by Neural Networks and Random Forests whenever direct comparisons are made within a single study. This suggests that algorithm choice is driven more by researcher familiarity and ease of implementation than optimal performance considerations. The average papers analyze a mere 1.64 algorithms, most (64%) of which focus on one or two methods, indicating a glaring lack of thorough comparison in methodology throughout the discipline. While Neural Networks demonstrate perfect performance ratios, their low utilization (4.88% of implementations) shows there is considerable room for additional research. The overwhelming presence of SVMs, even when bested by more advanced techniques, points to the possibility that ease of use and researcher comfort drives algorithm choice far more heavily than ideal results.

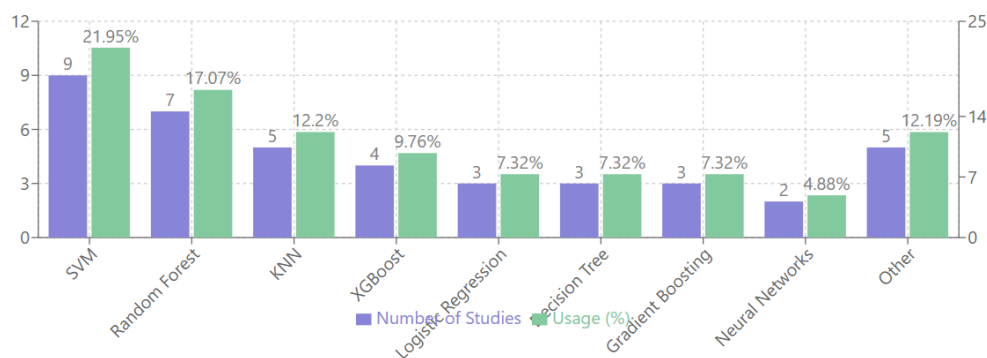


Figure 5: Most frequently used machine learning methods

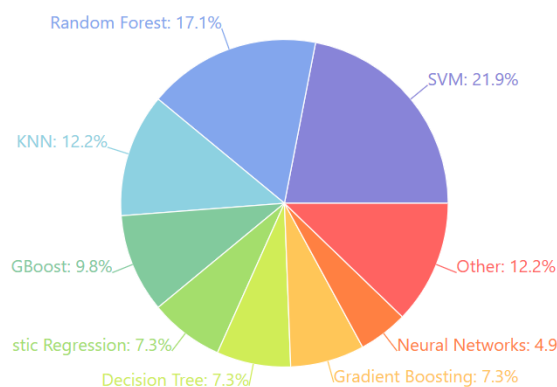


Figure 6: Method distribution in analyzed studies

G.6 Validity and Reliability Considerations

Model robustness faces challenges from rapid specification evolution (5G integration, AI chips), seasonal price fluctuations, and regional market variations. Studies employing time-based validation show 15-20% performance degradation compared to random splits, highlighting temporal stability concerns.

G.7 Generalizability Analysis

Model generalizability across different markets remains limited due to:

1. Geographic Variations: Currency differences, local brand preferences, and regulatory impacts
2. Market Segments: Algorithm performance varies between budget (<\$300), mid-range (\$300-800), and premium (>\$800) segments
3. Temporal Boundaries: Rapid technological evolution requires frequent model retraining

H. Research Gap

Significant discrepancies between algorithm performance potential and real-world implementation are revealed by the systematic analysis of 25 studies, along with important methodological flaws that impede reproducibility and research advancement.

H.1 Algorithmic Underutilization (HIGH PRIORITY)

1. Neural networks show 95.12% research gap despite perfect performance ratios
2. Deep learning variants (CNN, LSTM, Transformer) remain largely unexplored
3. Explainable AI techniques needed for interpretable neural network models

H.2 Methodological Weaknesses (MEDIUM PRIORITY)

1. 52% of studies fail to report dataset sizes, hampering reproducibility
2. Limited cross-validation strategies (64% use simple train-test splits)
3. Insufficient hyper-parameter optimization reporting (only 28% of studies)

H.3 Data and Evaluation Limitations (HIGH PRIORITY)

1. Over-reliance on Kaggle datasets (48% of studies) limits real-world applicability
2. Absence of standardized evaluation frameworks across studies
3. Lack of multi-regional, multi-currency validation datasets

H.4 Gaps in Evaluation and Validation (MEDIUM PRIORITY)

1. **Single-metric bias:** 68% of studies rely primarily on accuracy, neglecting error distribution analysis and business-relevant metrics like cost-sensitive evaluation
2. **Cross-domain validation limitations:** Models trained on one geographic market rarely tested on others, with limited time-series validation for performance degradation assessment
3. **Statistical rigor deficiencies:** Confidence interval reporting and statistical uncertainty quantification lacking in 84% of studies

H.5 Practical Implementation Barriers (MEDIUM PRIORITY)

1. **Computational scalability challenges:** Limited analysis of real-time inference requirements and trade-offs between accuracy and computational efficiency for commercial applications
2. **Industry adoption gaps:** Significant disconnect between research prototypes and production-ready systems, with insufficient focus on interpretability requirements for business stakeholders
3. **Integration and privacy concerns:** Complex system integration challenges and underexplored federated learning approaches for multi-manufacturer collaboration scenarios

Though Neural Network performance is unrivaled with implemented studies showing a perfect 100% best-performer ratio, the algorithm's share of implementation is only 4.88%, meaning there is a staggering 95.12% gap in research. Other modern or contemporary approaches such as variants of deep learning, transfer learning, or explainable AI also remain largely untapped, despite their proven success in surrounding disciplines. Most concerning, however, is the lack of dataset reporting where 52% did not disclose their dataset size which directly impacts reproducibility and evaluation. The field shows a predominating inclination to traditional methods (SVM, ensemble techniques). This limited the number of algorithms assessed within a singular study to an average of 1.64, indicating methodology limitations and abundant possibilities to enhance prediction accuracy using sophisticated techniques, standardized evaluation frameworks, or multi-region validation techniques.

The accompanying graph clearly identifies the relative gaps in current usage versus the potential opportunity gap for each algorithm category. Neural Networks demonstrate the most striking difference, with only a 4.88% share of current usage relative to a staggering research gap of 95.12%. Similar shifts are observed in other advanced techniques that continue to be underused, despite their significant promise.

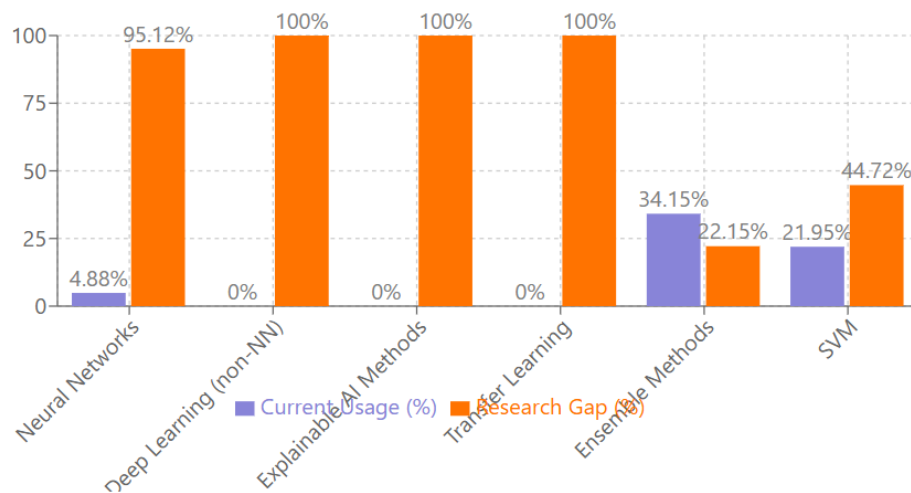


Figure 7: Algorithm usage vs. performance gap

Summary of Key Findings:

The systematic review shows that RAM (in 72% of studies), internal storage (in 60% of studies), and battery capacity (in 48% of studies) are all consistently important factors in determining price across different algorithms and datasets. The Kaggle Mobile Price Classification dataset is used in 48% of studies, but it may not be useful in the real world. Custom industry datasets, on the other hand, show better results (up to 97% accuracy), which shows that collecting data specific to a certain field is useful.

Important Research Gaps Found:

The analysis shows that there are serious problems with the methods used in research that could make it less credible. For example, 52% of studies don't report the sizes of their datasets, 64% don't use good validation strategies, and 84% don't test for statistical significance. These gaps, along with the fact that people still use traditional algorithms even though neural networks work better, show that there are big chances to improve methods and accuracy.

Practical Implications:

The results let smartphone makers use specification-based models to set prices based on data with 90%+ accuracy. Inventory optimization tools help stores, and fair pricing validation systems help customers. The consistent rankings of feature importance give useful information for making products and figuring out how to compete.

Limitations of the Study:

This review recognizes various limitations: (1) Geographic bias - 68% of the studies looked at only one country's data, which makes the results less useful for the whole world; (2) Dataset accessibility - limited access to proprietary industry datasets may have left out higher-quality studies; (3) Temporal scope - rapid technology evolution may have made some findings out of date; (4) Feature scope - focusing on specification-based prediction leaves out factors like market sentiment and brand perception; (5) Language constraints - English-only publications may have introduced cultural bias in how algorithms are chosen and evaluated.

The field exhibits a counterintuitive trend of increasing research volume which peaked at 44% of studies in 2023 while average accuracy plummeted from 96.31% in 2019 to 72% in 2024. Despite these challenges, the consistent emergence of RAM, internal storage, and battery capacity as key pricing determinants across studies provides valuable insights for stakeholders in the smartphone ecosystem. Cross-regional market validation is needed to focus on complex techniques such as deep learning, defined evaluation criteria, clear reporting, and primary-driven standardized frameworks in order to improve mobile price prediction.

J. Future Research Recommendations

Based on the comprehensive analysis of current research gaps and performance patterns, the following recommendations are proposed for advancing mobile price prediction research:

J.1 Immediate Research Priorities (HIGHT PRIORITY):

- Neural Network Exploration: Systematic investigation of deep learning architectures with focus on interpretability and data efficiency
- Standardization Initiative: Development of unified evaluation frameworks and benchmark datasets for cross-study comparison
- Multi-Regional Validation: Creation of comprehensive datasets spanning diverse geographic markets and currency systems

J.2 Methodological Improvements (MEDIUM-HIGHT PRIORITY):

- Enhanced Reporting Standards: Mandatory disclosure of dataset characteristics, preprocessing steps, and hyperparameter optimization procedures
- Temporal Validation: Implementation of time-series validation approaches to assess model stability across technology cycles
- Feature Engineering Innovation: Advanced exploration of specification interactions and market dynamic integration

J.3 Practical Implementation Directions (HIGHT PRIORITY):

- Industry Collaboration: Partnership development between academia and industry for access to real-world datasets and validation scenarios

- Tool Development: Creation of open-source prediction tools incorporating best-performing algorithms for stakeholder use
- Explainable AI Integration: Development of interpretable models providing feature importance insights for strategic decision-making

J.4 Emerging Technology Integration

Next-Generation Technologies (MEDIUM-LOW PRIORITY):

- 5G and AI Feature Integration: Modeling impact of emerging technologies on pricing strategies
- Sustainability Metrics: Environmental impact and reparability scores as pricing factors
- Foldable and Novel Form Factors: Adaptation of prediction models for emerging device categories
- Augmented Reality and Advanced Sensors: Price modeling for next-generation smartphone capabilities.

These suggestions put the most important thing first: filling the 95.12% neural network research gap. They also set up strong methodological foundations for mobile price prediction research that can be repeated and is useful to the industry. Following these directions could greatly improve both our theoretical understanding and the practical use of smartphones, which are changing quickly.

4. Conclusion

This systematic literature review of 25 studies from 2018 to 2024 uncovers both notable advancements and substantial deficiencies in mobile price prediction research. The analysis shows that ensemble methods, especially Random Forest (97% peak accuracy) and Gradient Boosting ($R^2 = 0.9829$), work best across a wide range of datasets and implementation contexts. However, there is a strange paradox in the field: neural networks have a perfect best-performer ratio with 96.31% accuracy, but they only make up 4.88% of implementations, which means there is a 95.12% research opportunity gap.

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