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Analysing the Refurbished Smart Phone Market with Machine Learning

Yenilenmiş Akıllı Telefon Pazarının Makine Öğrenmesi ile Analizi

Berrin Beyza ÖZEN[1]
[1]Mus Alparslan University, Information Systems and Technologies, Muş, Türkiye

Muhammed Fatih ALAEDDİNOĞLU[2]
[2]Department of Business Administration, Open Education Faculty, Atatürk University, Erzurum, Türkiye

Tolga AYDIN[3]
[3]Computer Engineering, Faculty of Engineering, Atatürk University, Erzurum, Türkiye

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Sorumlu Yazar/Corresponding author: Berrin Beyza ÖZEN
E-mail: bb.ozen@alparslan.edu.tr

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ABSTRACT

The refurbished smartphone market has recently attracted attention because of its economic and environmental benefits. In particular, rising environmental awareness and the search for cost-effective alternatives have increased demand for refurbished products. However, the dynamics of this market and its pricing practices differ from those of the new-device market.

Price formation depends on several product-specific factors, including device condition and model. Yet, analysing this multi-factor structure and producing accurate price estimates remains challenging for consumers, sellers, and remanufacturers. In this context, machine learning can support high-accuracy price prediction. Developing feature-based price prediction models for refurbished smartphones helps to explain price fluctuations and to estimate a device's value by considering usage and post-refurbishment condition. In this study, both traditional machine learning and deep learning methods are used to improve prediction accuracy. Model performance is evaluated using MSE, MAE, RMSE, and the R^2 score. The XGB Regressor achieved the best result among the traditional machine learning algorithms, with an R^2 of 0.9902. Among the deep learning models, LSTM also performed strongly, reaching an R^2 of 0.9870.

JEL Codes: C61, E37, L17

Keywords: Refurbished Market, Smartphone Price, Regression, Price Prediction, Sustainability

ÖZ

Yenilenmiş akıllı telefon pazarı, ekonomik ve çevresel faydaları nedeniyle son zamanlarda dikkat çekmektedir. Özellikle, artan çevre bilinci ve uygun maliyetli alternatiflerin aranması, yenilenmiş ürünlere olan talebi artırmıştır. Ancak, bu pazarın dinamikleri ve fiyatlandırma uygulamaları, yeni cihaz pazarından farklıdır.

Fiyat oluşumu, cihazın durumu ve modeli gibi ürüne özgü çeşitli faktörlere bağlıdır. Ancak, bu çok faktörlü yapıyı analiz etmek ve doğru fiyat tahminleri yapmak tüketiciler, satıcılar ve yeniden üreticiler için hala zorlu bir görevdir. Bu bağlamda, makine öğrenimi yüksek doğrulukta fiyat tahmini yapılmasına destek olabilir.

Yenilenmiş akıllı telefonlar için özellik tabanlı fiyat tahmin modelleri geliştirmek, fiyat dalgalanmalarını açıklamaya ve kullanım ve yenileme sonrası durumu dikkate alarak cihazın değerini tahmin etmeye yardımcı olur. Bu çalışmada, tahmin doğruluğunu artırmak için hem geleneksel makine öğrenimi hem de derin öğrenme yöntemleri kullanılmıştır. Model performansı MSE, MAE, RMSE ve R^2 puanı kullanılarak değerlendirilmiştir. XGB Regressor, geleneksel makine öğrenimi algoritmaları arasında 0,9902 R^2 ile en iyi sonucu elde etmiştir. Derin öğrenme modelleri arasında LSTM de 0,9870 R^2 ile güçlü bir performans göstermiştir.

JEL Kodları: C61, E37, L17

Anahtar Kelimeler: Yenilenmiş Pazar, Akıllı Telefon Fiyatı, Fiyat Tahmini, Sürdürebilirlik

Introduction

The refurbished mobile handset market represents an important segment of the mobile handset industry, focussing on bringing previously used, returned or faulty devices back into working order through refurbishment processes prior to re-launch (Mhatre & Srivatsa, 2019; Van Weelden et al., 2016). The market for refurbished smartphones has grown a lot around the world in the last few years. This is because of new technology and more people wanting these phones (Halim et al., 2022). Another important reason more people are buying refurbished items is that they are cheaper and help the economy reach its sustainability goals (Rientjes & Denis, 2024). More and more people are interested in using refurbished devices and how they affect the market. The appeal of refurbished devices is growing, and their impact on the market is becoming increasingly apparent. More people are aware of refurbished equipment, driving up prices based on how much the equipment was used previously. Knowing this historical trend is vital for assessing the current market and predicting the future of the market (Srikanth et al., 2023).

As technology continues to evolve, devices continue to shorten their lifespan and increase their negative environmental impact. When the environmental issues surrounding the increased manufacturing of electronic devices and their cheaper prices started to attract users in the1990s, users began using refurbished electronics. When the number of internet users continued to grow towards the end of 2000's, it enabled refurbished electronic products to be readily available due to the increasing access to online retailers (Plan, 2020). In addition, many large IT corporations are now making used devices more appealing to potential buyers through the refurbishment and resale of their products. As people became more concerned of the environment in the 2010s, they became more confident in reconditioned gadgets and more people began to recognise them. Previous studies have shown that electronic waste is very bad for the environment and that it is important to utilise less resources (Hossain et al., 2015).

Young people are becoming more interested in sustainable consumption because of money problems and the fact that reconditioned products are sometimes 30–50% less than new ones (Hazelwood & Pecht, 2021). By putting more money into selling refurbished products, big tech firms like Apple and Samsung are making their products seem more reliable and trustworthy to users. Quality concerns are going down, while access through online stores and platforms is going up (Barros & Dimla, 2021).

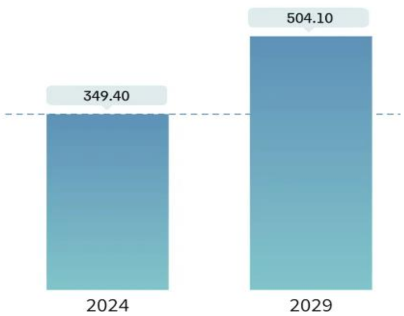
The industry has evolved very swiftly, which has caused reconditioned cell phones to have widely different features, tech specs, and prices. Intelligence (2023) argues that being able to properly guess costs based on the qualities of a device would assist producers, merchants, and customers make better choices, enhance marketing strategies, and come up with profitable pricing models (see Figure 1). There are a lot of people that work in the industry of selling refurbished phones. These include manufacturers, merchants, firms that make phones again, and those who buy phones. It is a very intricate structure, and brands that have a lot of market share have a large effect on it.

The next part of the research looked at the problems that come up when trying to figure out how much old cell phones are worth when they are sold again. The price of a reconditioned item is different from that of a new one. The price of a refurbished device depends on its model, condition, and the quality of the refurbishment. With increasing global emphasis on sustainability and economic issues, this research will address the use of pricing strategies as they relate to refurbished devices. The major challenge in developing pricing strategies for refurbished devices involves the complexity of the marketplace and the associated problems experienced by consumers, sellers, and manufacturers in accurately understanding the true value of refurbished products. In this respect, machine learning will be applied in this research through the development of predictive pricing models so that all interested parties can better understand the current pricing scenario and take better and more informed decisions with increased pricing transparency and financial accountability. Traditional machine learning and deep learning methods will contribute to the models developed by this research.

Fair and ethical pricing is one mechanism that allows consumers to buy refurbished products so that it is possible to continue using them rather than disposing of them in landfills. Enhancements in pricing and techniques to ensure consistent and correct pricing for refurbished products bring forward an increase in the total refurbished market and ultimately help in making the marketplace more efficient. Fair pricing is also another way through which consumers are able to purchase refurbished products, hence allowing there to be a way through which the products are not disposed of in a landfill, but are rather used. Improvements in price as well as methods to provide consistent prices for the refurbishment of products lead to advancements in the overall market for refurbished products, hence making the marketplace more efficient.

Figure 1.

Global Used and Refurbished Smartphone Market Growth (2018-2023) in Million Units.



The process of renewals in the consumer sector provides a different set of dynamics. Research on the circle of consumption indicates that the public is in favor of refurbished phones. This is due to environmental advantages, affordability, and the promotion of sustainable consumption patterns (Van Weelden et al., 2016). The increasing use of environmental certification for the product indicates an emerging reality: refurbished phones are becoming widely used, and the market shared by refurbished phones is increasing progressively.

This is especially true for phones that are environmentally certified (Harms & Linton, 2016).

The refurbished smartphone market is performing well because all stakeholders are collaborating together. This collaboration ensures that cheap and good-quality products, along with environmentally responsible ones, are available to the public. For example, a game theory concept was applied to the competitive dynamics created by mobile phone corporations, analyzing how competitive dynamics influence the market in its entirety. These pieces of research demonstrate the significant role played by key players in the development of the refurbished mobile phone markets, including the need to cooperate to achieve the market goals as demonstrated in the researched materials (Polat & Akan, 2020). You can purchase refurbished phones in a variety of options available to the public. The refurbished phones are available in stores, both on online platforms and specific pages solely centred on refurbished phones.

A key driver for this trend is the price-sensitive nature of consumers in developing countries, who prefer cheap cell phones (see fig 2). The reconditioned mobile phone becoming more popular with people is the awareness of environmental issues. Giving used electronics a new lease of life by repairing and reselling them makes them last longer, reduces electronic waste, and promotes the use of greener products (Pachange, 04 September 2023).

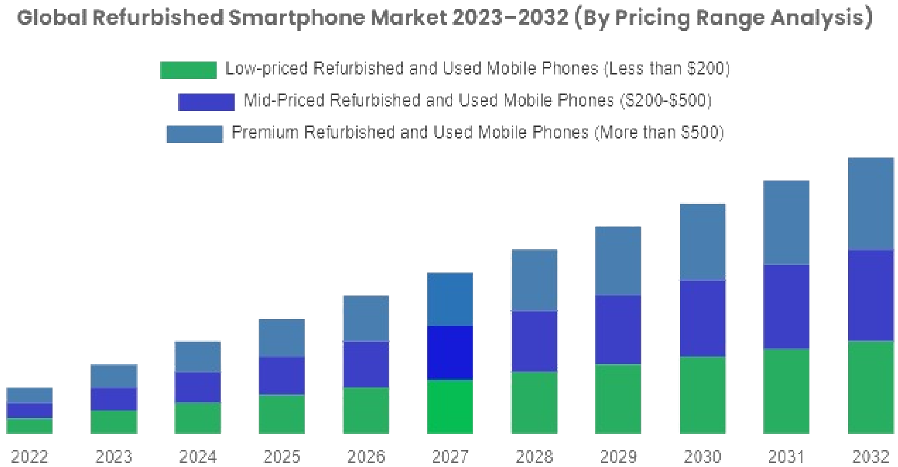
The customers' demands, preferences and behaviour also influence the changes in the industries. According to Future Market Insights, the market for refurbished smartphones is anticipated to grow at a compound annual growth rate (CAGR) of 11.2% between 2023 and 2032. It is expected to grow from a valuation of US$76.45 billion in 2023 to US$185.89 billion by 2032. When the price is the same and warrant is offered, consumers would rather buy a refurbished smartphone than a new one (Vorasayan & Ryan, 2006) When shopping for refurbished phones, items such as the brand's credibility, quality, warranty period all directly affect the how people make their purchase. The origin and authenticity of these aspects hold significant importance in decision-making. Purchasing a refurbished smartphone, brand trust and product quality play an important role. The warranty period positively influences buying behaviour because customers feel more confident (Agostini et al., 2021). Research shows that reliability is very important for consumers seeking to purchase refurbished mobiles.

In the last few years, more attention has been driven by the refurbished smartphone market, with its increasing environmental and economic benefits. Growing consumers' environmental awareness and search for cheap solutions further drive demand for refurbished products (Bigliardi et al., 2022).

Price setting for recycled devices can be a complex and potentially problematic process for companies operating within this area. Infrastructure and planning and auditing on a stringent level for the industry as a whole are a must. Repair charges usually will not exceed the amount for the repair itself. ssOn the other hand, for a licensed refurbished business to assess the charges properly, several factors need to be taken into consideration. These factors include the device's state and condition, whether any replacements have to be made to the device, how long the device will last in the market, the value it holds in the market currently, the feasibility of the device on the whole, variations in exchange rates, the feasibility of spare parts for the device, the time taken for the sales process to happen, the purchasing habits of the customers, and the evolving technology on the whole.

Figure 2.

Price Range Analysis of the Global Refurbished Smartphone Market (2023-2032) Based on Market Segments.



Spare parts are produced by calculating their lifetime and can be out of use at any time. Companies supply spare parts for devices, but this can lead to losses in storage and evaluation processes. Refurbished devices demand top-notch parts. Furthermore, any replacements during the warranty phase must also adhere to these quality benchmarks to avoid future problems. Having a constant supply of necessary spare parts is essential in maintaining satisfied customers and a smoothly operating business. This scenario is also attuned to the needs related to the delivery times of devices and sourcing spare parts (Richter et al., 2021). It is also essential to estimate the time required to repair a defective device.

This includes a number of essential considerations, such as the frequency with which replacements should be made, the needs pertaining to the movement of data, and the compatibility levels with hardware. All such assessments may be difficult for persons lacking expertise in the subject.

Refurbished device market pricing strategies are different from new device market pricing strategies. Pricing of products is directly affected by factors such as its condition, model, age, and warranties. Yet, predicting accurately the pricing based on the above-mentioned complex parameters is a challenge.

In this regard, machine learning algorithms have been shown to be useful tools for making accurate price forecasts for used smartphones. For people who are trying to buy or sell used smartphones, having accurate price prediction algorithms could be a useful tool.

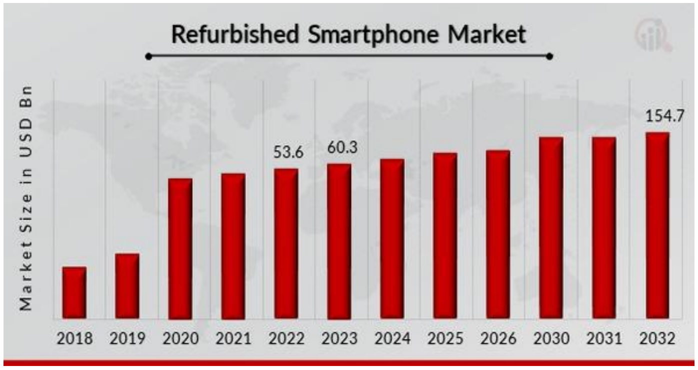
There have been studies undertaken by previous researchers that have taken a look at the consumer behavior of refurbished goods, challenges of formulating a pricing plan, and utilizing machine learning and pricing forecast tools. Some studies have also observed the approach of consumers within the Dutch market towards refurbished phones and what influences them towards expecting a particular pricing approach. Similarly, studies using machine learning practices for anticipating the value of refurbished mobile phones have shown that a good degree of precision is possible with the use of previous sales and product details (Gülmez & Kulluk, 2023). The results of these studies indicate that pricing predictions within the refurbished smartphone market can be a distinct tool for both vendors and consumers.

The refurbished smartphone market is forecast to register substantial growth with an anticipated CAGR of 12.50% from 2023 to 2032, from USD 60.3 billion to USD 154.7 billion, as depicted in Figure 3 above.One of the reasons why the refurbished smartphone market is gaining traction and experiencing substantial growth is the increased cost of new smartphones with minimal to no features upgrade.

The consumers find refurbished smartphones to be more economical compared to the old mobile phones used for an extended time period and possibly malfunctioning. Smartphone preferences among consumers are driven by the development of the renewal process, the launch of new products, and the vision for Circular Economy and Sustainability (Russell & Nasr, 2023). The Asia-Pacific region, with its huge customer base and penetration of smartphones, is forecast to have an impressive market share due to an understanding of the economical and environmental advantage of refurbished smartphones (Dhapte, October 2024).

Figure 3.

Projected Growth of the Refurbished Smartphone Market (2018-2032) in USD Billion.



There is much potential in machine learning (ML) methods to analyze large amounts of data and model complicated prediction tasks by identifying unknown patterns. Machine learning algorithms can be applied to forecast the price of a renovated mobile phone. It requires analysis of varied technical parameters such as screen size, battery life, processor model, memory, and storage. It is essential to design a strong prediction model of the market worth of the product. Companies can enhance their product range by adopting appropriate pricing predictions. This research seeks to examine machine learning models to determine their effectiveness to accurately forecast the price of renovated smartphones.

This project proposes developing a price forecasting model. The project proposes the use of machine learning algorithms in forecasting the prices of refurbished smartphones taking into consideration the following factors. It evaluates the effectiveness of different approaches in predicting refurbished smartphone prices by utilising both deep learning algorithms and traditional machine learning algorithms. The study also investigates the importance of attributes and identifies which attributes have the most significant impact on pricing. Furthermore, by enhancing pricing transparency and supporting competitive market strategies, the findings of this study can offer producers and customers useful information.

In this paper, regression algorithms for forecasting refurbished smartphones are analysed and discussed in detail to make an effective progress in the field of price forecasting. This paper's contribution can be summed up as follows:

1. Developing an effective approach to predict the price of refurbished smartphones.

2. This paper is based on an original dataset that has been cleaned and prepared for machine learning prediction models and feature engineering has been used.

3. To choose the best strategy for the refurbished smartphone market, the performance of the used algorithms is examined and assessed.

This approach focused on the refurbished smartphones due to their contribution to reduce electronic waste, increase customer cost-effectiveness, and support the preservation of both the environment and the economy.

Related Works

Recently, price prediction using machine learning has attracted considerable interest due to its potential to provide accurate and dynamic pricing models across a variety of industries, including property, automobiles and consumer electronics. Forecasting prices in the refurbished smartphone market is a tough nut to crack. The sheer volume of variables, coupled with the fast-paced evolution of technology, makes it a complex undertaking.

Machine Learning-Based Price Prediction in Consumer Markets

Patel and his group developed a stock market prediction system using common techniques in machine learning processes like support vector machine and random forests. In their study, it was found that the support vector machine algorithm was more accurate compared with other algorithms, achieving an accuracy of more than 95% (Patel et al., 2015). Random forests and artificial neural networks were found to be highly accurate, achieving 92% and 90% accuracy, respectively.

Wang et al. have also predicted car prices based on car parameters by means of ensemble methods such as random forests and support vector machines. These examples illustrate the capability of machine learning to process huge datasets and make extremely accurate predictions for prices within several disciplines (Weng, 2017).

Wen Long et al. built a stock price forecasting model through the integration of LSTM (Long Short Term Memory) and statistical models, along with traditional machine learning algorithms. As per the findings presented in the study, the output or prediction accuracy of the Multilayer Feed Forward Neural Network (MFNN) was the highest, outperforming the best machine learning algorithm and statistical method by a margin of 11.47% and 19.75%, respectively (Wen Long et al., 2019).

In their study, Paraskevi Nousi et al. assessed three classifiers employing a mix of manual feature design based on investment expertise and financial market understanding and machine learning techniques, with feature vectors having dimensions that varied greatly. This underscores how feature representation aggregation with manual features leads to better prediction outcomes and that valuable insights may be gleaned from feature extraction models (Nousi et al., 2019).

Smartphone Price Prediction Using Machine Learning

A study utilizing machine learning prediction models to forecast mobile phone prices was presented by Srikanth et al. Additionally, they focused on phone aspects that affect cost, including memory capacity or Bluetooth availability. As stated by Srikanth et al., Random Forests and XGBoosting outperformed the rest of the classification algorithms, scoring 90% and 88%, respectively.

Jinsi Jose and his colleagues are involved in predicting the price of smartphones. They are utilizing the past data and key features to achieve this. We have applied multiple machine learning algorithms: XGBoost, AdaBoost, logistic regression, decision tree, support vector machine, naive Bayes, and K-Nearest Neighbor algorithms. The accuracy of 94% of the K-Nearest Neighbor algorithm is comparable to the accuracy of 97% of the support vector machine, which is the maximum accuracy obtained. Utilizing the data decreases human intervention in day-to-day tasks, especially in the field of mobile technology (Jose et al., 2023).

Deepak Singh Rana and his team Smartphones have become an essential daily item with multiple uses. They're essential tools nowadays for activities like web-surfing and managing your email box. This research proposes the usage of machine learning to make predictions on smartphone retail price based on specific attributes of every smartphone model. The price-performance ratio determines how specific phone attributes correlate with smartphone performance. This research work can be applied in running businesses to aid consumers in making informed decisions regarding smartphones with new attributes and lower costs. This work aims to assist people in making informed decisions about what to purchase. The precision of this price prediction machine learning system has been tested on 20% of the total data to ensure reliability, with 95% accuracy (Rana et al., 2024). Linear Discriminant Analysis has proven to be most precise with 95% accuracy rate (Rana et al., 2024).

Feature Selection and Importance in Price Forecasting

Xiangzhou Zhang and his group of researchers have created an algorithm that is capable of recognizing causality that can be used to accurately determine predictions of stock prices. Their findings indicate that the use of the algorithm is more effective compared to other methods. The experiment was carried out using data obtained from the Shanghai Stock Exchange for a period of thirteen years, and the results were accurate and precise compared to other feature selection methods that are widely applicable. Despite correlation analysis, the paper emphasizes that causality is a superior method of making predictions about stock market trends (Zhang et al., 2014).

Ruth Mugge and her team did an online survey involving 250 people to establish the viability of selling refurbished smartphones. From the survey, three out of six groups of customers (46%) liked refurbished phones. Customers are more comfortable purchasing an item if they believe it benefits the environment and they are familiar with the process. One major benefit of purchasing this refurbished smartphone is that its battery life may be longer. Additionally, software updates are guaranteed. It is a major advantage. Performance is also much improved. This empirical evidence helps in making sense of consumers' response in relation to refurbished phones by providing information on overall consumer attitudes toward refurbished phones, including their overall sentiments, perceptions, and buying behavior as well as those specific attributes they are interested in (Mugge et al., 2017).

The Life Cycle Analysis (LCA) of an refurbished high-end smartphone in Chile by Pia Wiche et al. (2022) proves the potential advantage of the refurbished smartphone compared to the newly bought smartphone and the modular version, as well as the environmental aspect. The utilisation and production stages have the greatest impact, with refurbished smartphones producing 71% and 60% less greenhouse gases during the stages, respectively. By avoiding the mining and manufacture processes, refurbishment can lessen its negative effects on the environment. Determining the importance of these changes is challenging, though, because uncertainty has not been examined in other investigations. Comparison of cyclic models requires the assessment and communication of uncertainty in LCA results (Wiche et al., 2022).

Fadhil M. Basysyar et al. conducted research to predict house prices based on house characteristics. In particular, it was used to examine the differences in house prices and to predict future prices. Feature selection was done using machine learning models (Linear Regression, Ridge Regression, Lasso Regression, and Elastic Net Regression). In this way, the most effective variables on house prices were determined. The Lasso regression model was found to give better results than the other models. This model performs better in forecasting house prices and selects the most important variables more efficiently (Basysyar & Dwilestari, 2022).

Even with the increasing amount of research on machine learning-based price prediction, there are still certain gaps in the literature, particularly with regard to the market for refurbished smartphones. With little investigation of more sophisticated approaches like deep learning and ensemble methods, the majority of research have concentrated on using conventional machine learning algorithms like linear regression, decision trees, and random forests. The renovated smartphone market is yet to be properly researched in terms of the dynamics of the market. The pricing for the market is further affected by factors such as market trends and technology. In addition to that, the use of past information in conjunction with current market information for price estimation is an area yet to be fully researched. While most research focusses on predicting prices based only on technical specifications, including external factors like brand loyalty, consumer reviews, and market demand can improve the accuracy and usefulness of predictions for refurbished smartphone prices.

Material and Methods

The following sections provide a detailed explanation of the methods and techniques used to predict the prices of refurbished smartphones. The steps followed for price prediction, starting from the collection of the dataset, pre-processing, performance evaluation and the algorithms used are explained in depth in this section. The steps used in the methodology of this study are shown in Figure 4.

Collecting the Data Set

The data was extracted and analysed with the help of a bot using Python programming language and related SQL queries. The collected data was transferred to the AKILLICIHAZ database. SQL Server database named AKILLICIHAZ was used as data source. This database contains tables containing model, category and asset information of smart devices. Python language and pyodbc and sqlalchemy libraries were used to access the data. The bot developed for this study automatically extracted data from category, model, entity, and category-entity relationship tables using SQL queries. This data was made ready for analysis. The dataset contains characteristics of different refurbished smartphone models. These attributes include brand, model, battery capacity, memory, colour, cosmetic condition, degree of refurbishment and data transfer capacity.

The dataset used in this study consists of 36130 data with 11 attributes. These attributes are shown in Table 1.

Figure 4.

Methodology steps used to predict smartphone processes.

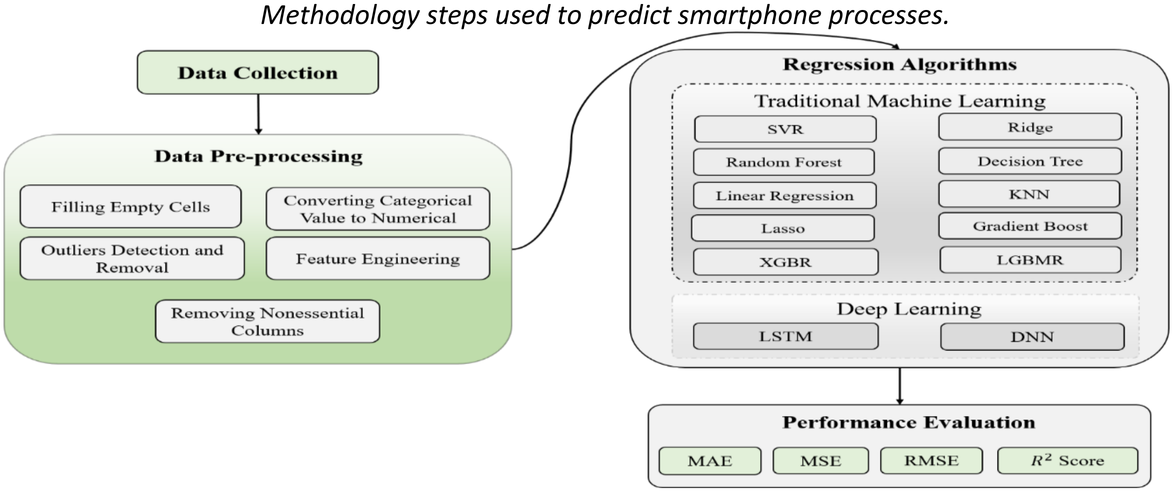


Table 1.

Features available in the data set.

No	Features	Type	Description
1	Brand	Categorical	This column includes categories for smartphone brands such as Apple, Samsung and Xiaomi.
2	Model	Categorical	This column includes subcategories of smartphone brands such as Apple 11, Samsung Galaxy S23 Ultra and Xiaomi Redmi Note 10 Pro.
3	Title	Categorical	It refers to the advertisement title of the product.
4	device	Categorical	It contains a detailed description of the device.
5	Price	Numerical	It contains the price information of the device.
6	Battery	Categorical	It refers to the power of the device.
7	memory	Categorical	Indicates the storage capacity and accessory status of the device.
8	Color	Categorical	Refers to the colour of the device.
9	cosmetics	Numerical	It shows the cosmetic condition of the device. It makes an assessment of the physical appearance of the device.
10	refurbished	Numerically coded categorical	It covers whether the device has been refurbished or not.
11	DataTransfer	Numerical	It refers to the data transfer rate or capacity of the device.

Data Preprocessing

Firstly, data cleaning operations were performed on the data set and rows containing missing data were removed from the data set. Then, categorical variables were converted into numerical values and made suitable for machine learning algorithms. Categorical features such as brand, model, color, and memory weight standardization were digitized using Label Encoder. Features such as battery capacity and cosmetic condition were also converted into numerical format.

Data Cleaning Process: In the process of filling in the missing values, missing values in some features were completed with the SimpleImputer method by using the mean, median or mode values of the columns. Outliers in numerical variables were identified by z-score or IQR (Interquartile Range) methods and these values were limited or removed from the data set. Moreover, non-relevant attributes involving the modeling procedure and performance degradation, for instance, the product descriptions, were eliminated from the dataset. Redundant information from the dataset was also cleaned. Categorical attributes were transformed to numeric attributes for improved usefulness during the analysis and modeling process by utilizing the LabelEncoder. Lastly, the StandardScaler technique was employed to scale the numerical attributes to improve the performance of models including KNN and SVR.

Handling Outliers: A methodical approach is used in the preprocessing phase to eliminate the effects of the outliers. The first step is to group the data according to the brands and models, considering the context of the data. The interquartile range is then used to set the boundaries within each group. Data points that fall outside these defined limits are considered outliers. After the outliers have been discovered, they can be replaced by the boundary values and recorded. Maintaining an auditable trail is a key aspect of this process.

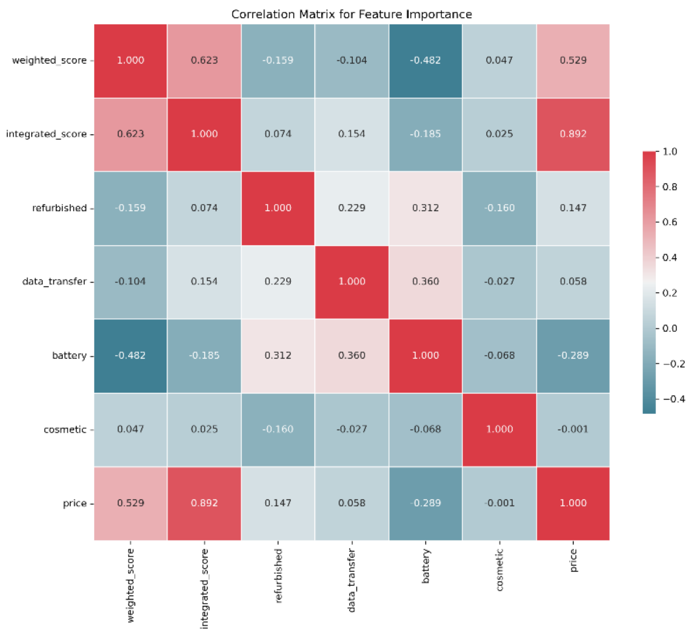
Feature Selection

In addition to the implementation of the KBest algorithm, feature engineering was also employed with the aim of improving the predictive ability of the model. Creating informative variables from the datasets, such as brand density and scores, was a key part of feature engineering. The resulting metrics were then combined into a weighted score, called agirlikli_skoru, which was calculated by multiplying the price and density scores. Moreover, the popularity score of brands (marka_populerligi_skoru) is used to measure how often a brand appears in the dataset.

The price position score, or fiyat_konum_skoru, was also created to illustrate the pricing strategies employed by different brands. Later, these scores are combined to create a new composite score, called "entegre_skor," which considers brand popularity and the resulting price changes. The combined score, which showed the connection between brands and their pricing strategies, led to a statistically significant change in the model's overall performance. These combined scores provide a detailed view of a brand's market position and pricing strategies. Figure 5 shows the correlation matrix for the variables we chose.

Figure 5.

The correlation matrix of the selected features.



In the last step of the feature engineering process, eight prominent features were selected and considered for the prediction of the prices of the smartphone, including agirlikli_skor (weighted score), entegre_skor (integrated score), yenilenmis (indicative of refurbished status), VeriAktarim (data transfer ability), Batarya (battery capacity), kozmetik (cosmetic details), hafiza (memory capacity), and renk (color). The selection of the features took into consideration the significance values provided by SelectKBest. To determine generalizability, the data was split into a training data set (80%) and a test data set (20%).

Modelling

The price of refurbished smartphones is predicted in this study using both conventional machine learning methods and deep learning algorithms. The following subheadings provide descriptions of both deep learning algorithms and conventional machine learning techniques.

Traditional Machine Learning Algorithms

Linear Regression: Linear regression analysis allows the value of one variable to be predicted from another variable values as illustrated in formula (1). This process is employed to forecast the dependent variable. Predicting the value of the other variable is done using the independent variable. assumes that the target variable and the independent variables have a linear relationship (Montgomery et al., 2021).

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 . + .. \ \beta_n x_n + \varepsilon \quad (1)$$

Y: The estimated dependent variable, β_0: Value of Y when the independent variables are zero, β_1, β_2, ..., β_n: Coefficients showing the effect of independent variables, x_1, x_2, ..., x_n: Independent variables and ε: Difference between forecast and actual value.

Ridge and Lasso Regression: These are penalized regression types used to prevent overfitting in linear regression models and to improve the generalization performance of the model. These methods control the size of the parameters by applying certain penalties to the coefficients of the model. It aims to prevent overfitting by reducing complexity. While Lasso eliminates the effect of redundant features, Ridge applies a more balanced penalty as shown in formula (2).

$$\mathrm{J}(\beta) = \mathrm{RSS} + \lambda \mathrm{j} = 1 \sum \mathrm{n} \beta_j^2 \quad (2)$$

Where RSS: Sum of error squares, λ: Regularisation parameter (determines the weight of the penalty term), $\boldsymbol{\beta_j^2}$: Squares of the coefficients.

Decision Tree Regression: It is a useful and effective machine learning method for predicting a dependent variable by splitting the data into branches. This approach uses step-by-step splits to understand the complex structure of the data. Reducing the variance of the dependent variable is the primary goal of each split. In the tree structure, a specific independent variable (feature) and threshold value are selected at each node using either Entropy or Gini methods as in formulas (3) and (4). This selection is usually based on a loss function such as the mean square error (MSE). The aim is to create more homogeneous groups by splitting the data into branches and use the averages of these groups to estimate the target variable at leaf nodes (Charbuty & Abdulazeez, 2021).

$$\text{Gini Index: } G = 1 - \Sigma(p_i^2) \quad (3)$$

$$\text{Entropy: } H = -\Sigma(p_i * \log_2(p_i)) \quad (4)$$

p_i: the proportion of samples in the i-th class.

Random Forest Regression: It makes more accurate predictions by combining the predictions of more than one decision tree.

Support Vector Regression (SVR): It determines boundaries by decomposing the data using hyperplane and makes predictions over these boundaries.

Ensemble Algorithms (Gradient Boosting, AdaBoost, Bagging Regressor): It creates strong prediction models by combining more than one weak model.

XGBoost and LightGBM: They are advanced machine learning methods and give successful results on large datasets.

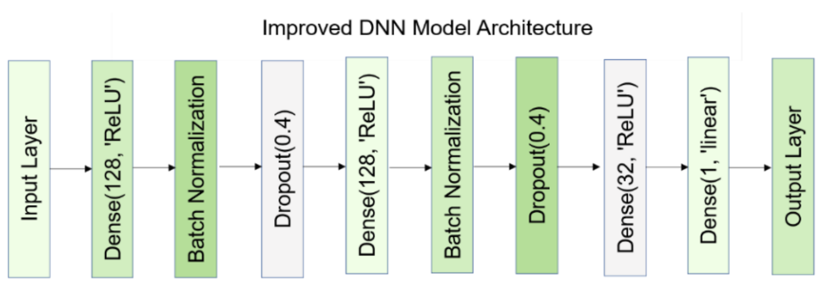
Deep Learning Algorithms

Deep learning methods make sense of complex data structures using multilayer neural networks. The methods used in this study:

Deep Neural Networks (DNN): DNN refers to deep learning models with a multilayer architecture, which is a subtype of artificial neural networks. DNNs contain multiple hidden layers to learn complex patterns and relationships in data. These networks can operate particularly effectively on large datasets (Chen & Lin, 2004).

Figure 6.

DNN Model Architecture.

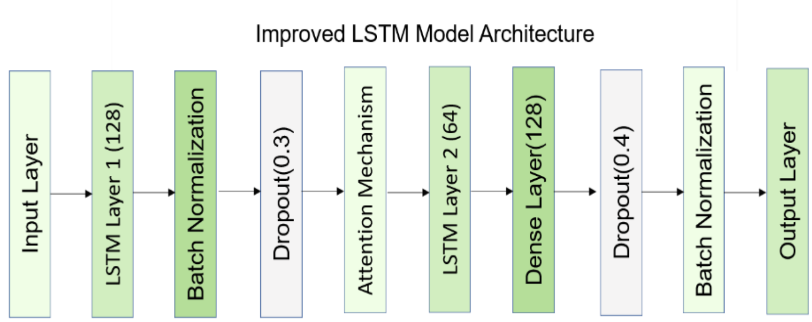


1.

LSTM (Long Short-Term Memory): This kind of recurrent neural network (RNN) architecture is used to represent and learn from sequential input. Unlike traditional RNNs, LSTMs are designed to efficiently learn long-term dependencies. Specifically developed to solve the vanishing gradient problem (Sherstinsky, 2020).

Figure 7.

Improved LSTM Model Architecture.



Hyperparameter Optimisation

The hyperparameters of the Random Forest model are optimised with RandomizedSearchCV. Experimentally tested as shown in Table 2.

Table 2 shows the hyperparameters investigated using each model. For the various regression models the hyperparameter tuning process yielded the best parameters that optimised their performance. For Linear Regression, no additional hyperparameters needed to be tuned as it runs without tunable parameters in its basic implementation. The Ridge regression model achieved its best performance with an alpha value of 1, striking a balance between bias and variance. The Lasso model performed best with an alpha of 0.01, emphasizing minimum feature selection while maintaining prediction accuracy.

Decision Tree Regressor performed better when the tree was un-restricted in its depth (max_depth=None) and samples were minimized to splits of 10, hence able to grow without overfitting. For Random Forest Regressor, the optimal parameters included a tree depth of 20 and the number of predictors set to 200, hence keeping it complex for accurate estimations. The Kneighbors Regressor required a depth of 7 neighbors, hence adding precision by considering proximity. The SVR performed better using the linear kernel, along with a penalty parameter C of 10, hence favoring a linear relation while over-penalizing for accurate estimations.

The Gradient Boosting Regressor performed better using a learning rate of 0.2, along with predictors of 200, hence enabling it to make precise estimations by learning. The AdaBoostRegressionr also required a learning rate of 0.2, along with predictors of 200, hence making it prone to effective boosting. The BaggingRegressor performed better when it had predictors of 100, hence requiring a balance between fast processing and precise estimations.

Table 2.

Hyperparameters used for each model.

Model	Hyperparameter	Value
Ridge	Alpha	[0.1, 1, 10]
Lasso	Alpha	[0.01, 0.1, 1]
Decision Tree Regressor	max_depth	[10, 20, None]
	min_samples_split	[2, 10]
Random Forest Regressor	n_estimators	[100, 200]
	max_depth	[None, 20]
Kneighbours Regressor	n_neighbors	[3, 5, 7]
	Weights	['uniform', 'distance']
SVR	Kernel	['linear', 'rbf']
	C	[1, 10]
Gradient Boosting Regressor	n_estimators	[100, 200]
	learning_rate	[0.1, 0.2]
AdaBoost Regressor	n_estimators	[100, 200]
	learning_rate	[0.1, 0.2]
Bagging Regressor	n_estimators	[50, 100]
XGB Regressor	n_estimators	[100, 200]
	learning_rate	[0.1, 0.2]
LGBM Regressor	n_estimators	[100, 200]
	learning_rate	[0.1, 0.2]

The XGB Regressor model, using gradient boosting, made refined predictions. It performed best with a learning rate of 0.1 and 200 predictors. The LGBMRegressor performed best with a learning rate of 0.2 and 200 predictors, indicating it was efficient when handling larger datasets. The best values found for each regressor show their different needs for adjusting hyperparameters. This highlights the importance of carefully tuning them when making predictions.

Model Performance Measures

Model performance was evaluated using the Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R2) metrics.

Mean Absolute Error (MAE): The Mean Absolute Error (MAE) is calculated by averaging the absolute differences between the predicted and actual values, as shown in equations (5). This value represents the average size of the prediction errors, regardless of whether they are positive or negative.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y - \tilde{y}| \qquad (5)$$

Where MSE is the mean absolute error, y is the actual target value and ỳ is the predicted value.

Mean Square Error (MSE): It is the mean of the squared differences between predicted and actual values as in equation (6). MSE penalises larger errors more than MAE, making it sensitive to outliers.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y - \grave{y})^2 \qquad (6)$$

Where MSE is the mean squared error, y is the actual target value, ỳ is the predicted value.

Root Mean Square Error (RMSE): RMSE gives an indication of error in the same units as the target variable, making it easier to understand as a gauge of the precision of predictions as in formula (7).

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \grave{y}_i)^2}{n}} \qquad (7)$$

Where RMSE is Root Mean Square Error, y_i actual target value, $\grave{y}_i$ is its estimated value.

R² Score: The percentage of the dependent variable's variation that can be anticipated from the independent variable is shown by the R2 score, often referred to as the coefficient of determination. used often in regression analysis to evaluate a model's quality of fit.
The R^2 score formula is given as follows:

$$R^2 = 1 - (\Sigma(y_i - \hat{y}_i)^2 / \Sigma(y_i - \bar{y})^2) \qquad (8)$$

yi: Actual value of the target variable, ŷi: Predicted value of the target variable, ȳ: Average of the true target values and Σ: Means the sum of all data points.

While traditional machine learning algorithms have simpler and clearer models, deep learning methods have more complex and powerful prediction capabilities. In this study, various traditional and deep learning methods are compared to determine the best performing model in price prediction, and the performance evaluation is performed with MAE, MSE, RMSE and R^2 Score metrics.

Results and Discussion

Deep learning and machine learning algorithms are compared to predict the prices of refurbished smartphones. The models were evaluated by MSE, MAE, RMSE and R^2 and the performance of traditional machine learning models is presented in Table 3. The presented metrics help to assess the precision and reliability of each model in price forecasting. Decision tree-based models such as Decision Tree Regressor, XGB Regressor, Bagging Regressor, and LGBM Regressor stand out among the analyzed models as they exhibit a good balance among low MAE, MSE, and high R^2 values. This indicates that they effectively capture the correlations between input characteristics and prices. XGB Regressor shows the best performance with an R^2 of 0.9902 and an RMSE of 2403.13. The variance explained by the model is approximately 99.02%, meaning that the model is highly predictive. The XGB Regressor, from the list of machine learning models, performs best, with an R^2 value of 0.9902, making this the best-performing model. The gradient boosting optimization technique used in the XGB Regressor helps to learn from past errors, making the model efficient at performing the non-linear relationship that exists in the pricing of the refurbished smartphone. Additionally, the technique is able to avoid the problem of overfitting by using the concept of L1 and L2 regularization. The XGB Regressor is able to rank features, making the model more efficient. From the list of deep learning models, the Long Short-Term Memory (LSTM) model is the best-performing model, with an R^2 value of 0.9870. This is due to the ability of the model to tackle the sequential relationship and the inclusion of the attention method. However, the XGB Regressor model is the most accurate and efficient method of determining the refurbished smartphone. The performance of the model can be attributed to the ability of the model to handle the data that is not linear. Additionally, the complexity of the features is captured. The results of Decision TreeRegressor, Bagging Regressor, and LGBM Regressor are also similar, with RMSE and R^2 values very close to the XGB Regressor model. This supports the idea that boosted tree models work very well for regression problems involving such complex data.

Table 3.

Performance Comparison of Traditional Machine Learning Models in Refurbished Smartphone Price Prediction.

Model	MAE	MSE	RMSE	R^2 Score
Linear Regression	6570.192	85145117	9227.411	0.8549
Ridge	6570.192	85145172	9227.414	0.8549
Lasso	6570.19	85145118	9227.411	0.8549
Decision Tree Regressor	1416.018	5844262	2417.491	0.9900
Random Forest Regressor	1415.412	5882173	2425.319	0.9900
K-Neighbours Regressor	1483.512	6499357	2549.384	0.9889
SVR	6145.156	1,12*10^8	10568.86	0.8096
Gradient Boosting Regressor	1495.856	6089078	2467.606	0.9896
AdaBoost Regressor	4124.871	29072638	5391.905	0.9505
Bagging Regressor	1415.012	5870130	2422.835	0.9900
XGB Regressor	1421.62	5775036	2403.13	0.9902
LGBM Regressor	1417.594	5791753	2406.606	0.9901

Vividly, linear models such as Ridge, Lasso, and Linear Regression perform much worse, especially the basic linear regression model with an R^2 of 0.8549 and RMSE of 9227.41. Ridge and Lasso's R^2 value of 0.8549 suggests that although they use regularisation to reduce overfitting and improve accuracy, they do not adequately capture the more complex relationships in the data. This result is expected given that linear models are inherently less adaptive and have difficulty dealing with non-linear models on the prediction of smartphones' price tasks.

Among the non-tree-based models, Kneighbors Regressor performs well with an RMSE of 2549.38 and an R^2 of 0.9889. This shows that a proximity-based strategy can give competitive results in this case, but the SVR model performed the worst with an R^2 of 0.8096 and an RMSE of 10568.86. This may be due to the sensitivity of SVR to hyperparameter settings and suggests that it is not suitable for this dataset. AdaBoost Regressor performed moderately with an R^2 of 0.9505 and RMSE of 5391.91, suggesting that the model struggles to capture certain complex interactions compared to LGBM and XGB Regressors.

In the general context, the use of tree-based algorithms, including XGBoost (XGB), decision trees, bagging methods, LightGBM (LGBM), etc., are currently considered the most practical solutions for the price estimation of second-hand smartphones. These algorithms are able to identify complex interactions between the variables and achieve a high level of accuracy in the modeling task while producing the price estimations. Conversely, linear models and support vector regression methods seem less appropriate for this specific dataset, due to the insufficient capability to identify the non-linear relations. Thus, in this context, it is required to use even more sophisticated methods for the price estimation of smartphones.

The performance of deep learning algorithms such as Improved Long Short-Term Memory (ILSTM) networks and Deep Neural Networks (DNNs) is given below in Table 4.

Table 4.

Performance of Deep Learning Models for Refurbished Smartphone Price Estimation.

Model	MAE	MSE	RMSE	R^2 Score
LSTM	1639.89	7505594.15	2739.63	0.9870
DNN (Fully Connected)	5101.92	54770560.08	7400.71	0.9060

For evaluating the performance of a model, a combination of important metrics such as MAE, MSE, RMSE, and R^2 is considered. Based on these factors, it can be seen in the results that the Proposed Improved LSTM model is better than a more conventional model such as Ridge Regression in this particular problem. To be more precise, the best results are obtained by the Proposed Improved LSTM model when MAE is 1639.89, RMSE is 2739.63, and R^2 is 0.9872. These results highlight a significant improvement made by the induction of the attention layer in these experiments. Additionally, the sequential relationships nature of this network helps on achieving better results. This shows that the model is highly successful in predicting refurbished phone prices and accurately captures the relationships between input characteristics and prices.

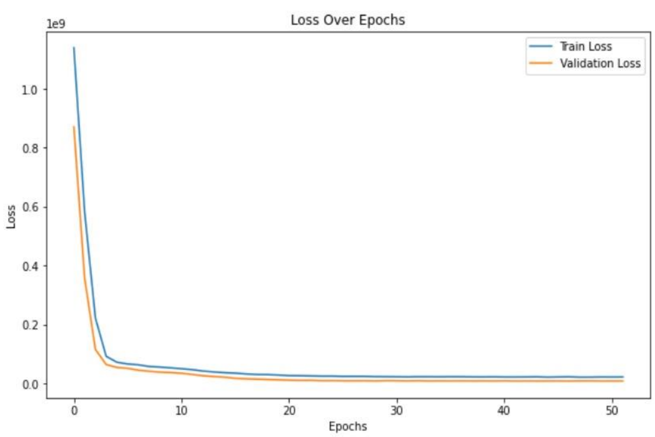
The DNN (Fully Connected) model showed lower performance than the Improved LSTM model with 5101.92 MAE and 7400.71 RMSE. This result shows that the DNN model is not as successful as the improved LSTM in capturing complex relationships in the data. However, the high error rates observed in the DNN model indicate that the model should be improved in terms of accuracy.

The loss of LSTM during the training and validation phases is shown in Figure 8.

Figure 8 illustrates that although the model was configured for 100 epochs, the early stopping mechanism terminated training after 35 epochs. During this period, the training loss decreased from about 1.510^9 to about 0.1 10^9, while the validation loss dropped from approximately 0.8510^9 in the first epoch to around 0.0510^9 by the 35th epoch. This pattern confirms that training was halted before overfitting occurred. The concurrent decline in both training and validation losses indicates effective learning, and the utilization of early stopping along with a Dropout layer further ensured that overfitting was mitigated.

Figure 8.

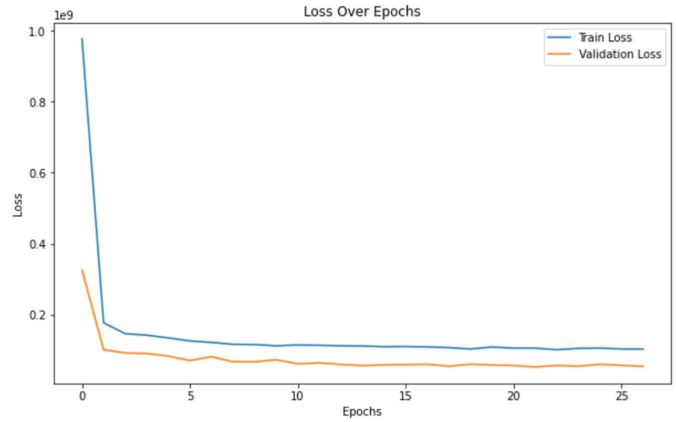
LSTM Loss Curve.



The loss of DNN during training and validation phases is shown in Figure 9.

Figure 9.

DNN Loss Curve.



As in Figure 9, the DNN performed well during the training phase. The values of training loss and validation loss are comparable. The number of epochs was set to 100. However, the model was automatically stopped after 25 epochs with the early stopping technique. The loss of the model for training and validation decreases from about 0.9*10^9 to about 0.15*10^9 in terms of training loss during the first 25 epochs. Similarly, in terms of validation loss, it decreased from 0.35*10^9 in the first epoch to about 0.1*10^9 in the 25th epoch.

Conclusion and Recommendations

This work seeks to predict the cost of refurbished smartphones using both deep and conventional machine learning methods. Experimental results show that deep methods, most specifically the Improved LSTM Model, outperformed in terms of error and accuracy metrics. It is observed that this Improved LSTM Model has an RMSE of 2739.63, an MAE of 1639.89, and an R^2 value of 0.9870, clearly outperforming in prediction. These results prove the ability of deep machine learning models in uncovering hidden patterns in structured data.

On the other hand, traditional machine learning algorithms, particularly the Random Forest Regressor, XGB Regressor, and LGBM Regressor, also performed well on all parameters. The XGB Regressor was found to be the best model with MAE = 1421.62, MSE = 5775036, RMSE = 2403.13, and R^2 = 0.9902. The LGBM Regressor was second best with R^2 of 0.9901. Though the Random Forest Regressor gave a commendable MAE of 1415.412 and RMSE value of 2425.319, it was outperformed by LGBM and XGB Regressors.

In conclusion, the outcome of the study clearly suggests that both deep and traditional machine learning models can be used for the prediction of the refurbished smartphone prices, and that the traditional models of XGB Regressor and LGBM Regressor have slightly better performance, exceeding an R^2 of 0.99.

In its efforts to improve prediction accuracy within the refurbished electronics market, this research proposes the integration of extra variables such as smartphone status indicators and past pricing trends to improve the prediction ability of the models. This research has implications for the e-commerce industry, second-hand phone sellers, refurbishing companies, and consumers alike. The e-commerce industry can take advantage of this machine learning model to provide automatic price suggestions, thus eliminating price disparities and ensuring that consumers and sellers get equal marketplace value in respect of price. Others can also take advantage of this model to provide accurate resale estimates and set۱۴market strategic pricing based on optimum margin targets. Large-scale refurbishment companies can make use of this model to determine just and reasonable marketplace value for refurbished phones, thus improving profitability and prediction accuracy of marketplace prices. Consumers can take advantage of this model to develop an AI-based application that provides on-time price estimates, thus improving marketplace transparency for consumers to make informed buying and selling decisions. This research model has the potential to improve marketplace efficiency in terms of fairness, timeliness, and marketplace reliance on facts in the refurbished smartphone marketplace. Deep learning models can also be fine-tuned by leveraging the use of more data, hyperparameter optimization, and sophisticated methods. Additionally, optimizing the interpretability of the models may offer greater insight into the underlying drivers influencing the price of smartphones. Using other data sources, including market demand and consumer reviews, may offer an enhanced framework for forecasting. This set of approaches may also find an application in other fields, including refurbished product pricing forecasting or the prediction of the second-hand price of a product. Implementation of the models in pricing systems would help to authenticate the benefits for practical applications while simultaneously identifying the potential pitfalls.

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Genişletilmiş Özet

Yenilenmiş akıllı telefon pazarı, teknolojik gelişmelerin hızlanması, sürdürülebilirlik arayışı ve ekonomik zorluklar nedeniyle son yıllarda önemli bir büyüme göstermektedir. Bu büyümeyle birlikte, ürünlerin doğru fiyatlandırılması hem satıcılar hem de tüketiciler için kritik hale gelmiştir ancak bu pazarda ürünlerin marka, model, kozmetik durumu, batarya kapasitesi, bellek boyutu gibi birçok değişkenle fiyat ilişkisinin kurulması, geleneksel fiyatlandırma yaklaşımlarını yetersiz kılmaktadır. Bu çalışma, yenilenmiş akıllı telefon pazarında makine öğrenmesi ve derin öğrenme tekniklerini kullanarak ürün özelliklerine dayalı fiyat tahmin modelleri geliştirmeyi amaçlamaktadır. Araştırmada, Türkiye'deki yenilenmiş telefon pazarına ait 36.130 satırlık gerçek satış verisinden oluşan özgün bir veri seti kullanılmıştır. Veri seti; cihaz markası, modeli, batarya gücü, bellek miktarı, kozmetik durumu, renk, yenilenmişlik durumu gibi toplam 11 özelliği içermektedir. Veri ön işleme aşamasında eksik veriler temizlenmiş, etiketleme (Label Encoding), aykırı değer yönetimi (IQR yöntemiyle), ölçekleme (StandardScaler) ve öznitelik mühendisliği uygulanmıştır. Özellikle ağırlıklı skor, entegre skor, fiyat konum skoru ve marka popülarite skoru gibi türetilmiş değişkenler, modelin tahmin gücünü artırmıştır. Çalışmada regresyon temelli 10'dan fazla geleneksel makine öğrenimi modeli (Linear, Ridge, Lasso, Decision Tree, Random Forest, KNN, SVR, Gradient Boosting, XGBoost, LGBM) ile derin öğrenme algoritmaları (DNN ve LSTM) karşılaştırmalı olarak değerlendirilmiştir. Modellerin performansı, Ortalama Mutlak Hata (MAE), Ortalama Karesel Hata (MSE), Kök Ortalama Karesel Hata (RMSE) ve Determinasyon Katsayısı (R^2) metrikleri ile ölçülmüştür. XGBoost Regressor modeli, 0.9902 R^2 skoru ve 2403.13 RMSE değeri ile en başarılı sonuçları vermiştir. Derin öğrenme modelleri arasında LSTM ağı, özellikle dikkat mekanizması ve zaman serisi ilişkilerini öğrenme kabiliyeti sayesinde 0.9870 R^2 skoru ile öne çıkmıştır. Elde edilen bulgular, geleneksel yöntemlerin özellikle karar ağaçlarına dayalı modellerle yüksek doğruluk sağladığını; derin öğrenme yöntemlerinin ise daha karmaşık ilişkileri başarılı şekilde temsil ettiğini göstermektedir. Çalışma, sadece bir tahmin sistemi geliştirmekle kalmayıp, aynı zamanda yenilenmiş cihaz piyasasında fiyatlandırma süreçlerinin veri temelli ve dinamik olarak nasıl optimize edilebileceğine dair bir çerçeve sunmaktadır. Gelecekteki çalışmalarda, kullanıcı yorumları, bölgesel fiyat farklılıkları, mevsimsel değişkenlikler gibi dışsal verilerin entegrasyonu ile modellerin daha yüksek genelleme başarısı göstermesi hedeflenmektedir. Bu çalışma, hem e-ticaret platformları hem de yenileme firmaları için adil ve şeffaf fiyatlandırma stratejileri geliştirmeye katkı sağlamaktadır. Sonuçlar, sürdürülebilir tüketimin desteklenmesine, elektronik atıkların azaltılmasına ve ekonomik erişilebilirliğin artırılmasına yönelik politika geliştirme süreçlerine de ışık tutmaktadır.