High-Accuracy Used Car Price Prediction: A Comparative Study of Linear and Ensemble Regression Techniques

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Abstract—The accurate valuation of used cars is a complex non- linear problem critical for financial risk assessment and fair market transactions. This paper details a rigorous comparative analysis of three machine learning regression models: Multiple Linear Re- gression (MLR), Random Forest Regressor (RF), and optimized Gradient Boosting Regressor (GBR), utilizing the Car Dekho dataset comprising 4,340 records. Our methodology integrates advanced statistical diagnostics, including log transformation of the target variable and Variance Inflation Factor (VIF) analysis, to ensure model validity. The primary objective is to demonstrate the performance gain achieved by ensemble methods over the conventional linear baseline. Evaluation, based on R^2, MAE, and RMSE, reveals that the Random Forest model achieves the highest accuracy, with an R^2 of 0.7548 and a Mean Absolute Error of 120,126 currency units, significantly surpassing the MLR baseline (R^2 = 0.6142). The analysis confirms the Random Forest model's superior capability in capturing non-linear depreciation dynamics driven predominantly by car age and mileage, making ensemble techniques the optimal choice for high-precision valuation systems in volatile secondary markets.

***Index Terms*—Machine Learning, Regression, Used Car Price Prediction, Random Forest, Gradient Boosting, VIF Analysis, Ensemble Methods.**

I. Introduction

The proliferation of online marketplaces has catalyzed a paradigm shift in the used vehicle market, making the determination of a fair price both more data-intensive and more complex. Unlike the pricing of new vehicles, which is largely dictated by Manufacturer Suggested Retail Prices (MSRP), used car valuation is subject to high information asymmetry, non-linear depreciation, and dynamic feature interactions that traditional, manually-driven appraisal methods fail to capture accurately. This persistent gap between subjective valuation and objective market price underscores the necessity of advanced predictive modeling.

This research addresses the core predictive challenge in the secondary automotive market. We establish a formal scientific hypothesis: that non-linear, tree-based ensemble methods—specifically Random Forest and Gradient Boosting—will yield statistically significant and materially higher predictive accuracy compared to the classic linear benchmark, Multiple Linear Regression (MLR). Our framework rigorously compares these three models across robust metrics. Our core contributions include: (1) Establishing a rigorously validated MLR baseline using VIF analysis; (2) Quantitatively comparing the performance across three structurally distinct models; and (3) Providing granular diagnostic insights through feature importance analysis and comparative distribution plotting. The resultant framework confirms the viability of ensemble learning for high-precision vehicle valuation.

II. Related Work

The study of asset valuation using machine learning has progressed from simple statistical modeling to complex ensemble architectures. Initial research, rooted in econometrics, established the foundational hedonic pricing model using MLR [1]. These studies confirmed that vehicle age and usage (kilometers driven) are the primary factors driving value loss. However, these linear models are inherently limited by their inability to account for the non-linear nature of real-world depreciation, which often accelerates or decelerates unexpectedly based on market factors or mileage milestones. The recognition of these limitations spurred the adoption of non-parametric methods. Ensemble techniques became the industry standard due to their robustness against noisy data and capacity to model non-linear interactions. Random Forest (RF), utilizing bagging, reduces prediction variance, while Gradient Boosting (GBR) leverages boosting to iteratively correct errors, often achieving superior point accuracy [2]. Crucially, our methodological approach is informed by parallel research in operational analytics. For instance, studies on food delivery platforms highlight that operational efficiency metrics often outweigh base price in determining market viability [3]. In the automotive context, this translates to operational quality features (`Car_Age`, `km_driven`) being the core predictive metrics, necessitating high-fidelity modeling.

III. Methodology and System Architecture

Our predictive framework is meticulously designed as a five-stage pipeline to ensure maximum accuracy and full scientific transparency. The flow is conceptualized in the architectural block diagram shown below.

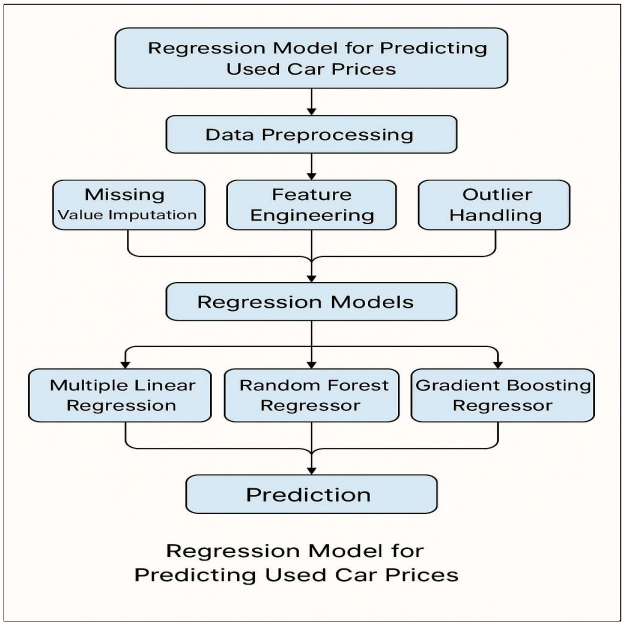

Fig. 1. Project Methodology Flowchart

The process begins with data ingestion and cleaning, followed by rigorous feature engineering. We specifically isolate the 'Age' factor as a derived feature, calculated as the difference between the current year and the year of manufacture. This creates a continuous variable that is highly correlated with price decay.

A. Data Acquisition and Advanced Preprocessing

The study utilizes the "CAR DETAILS FROM CAR DEKHO" dataset, providing 4,340 entries. This stage ensures data quality and feature efficacy.

1) **Feature Engineering:** Key domain knowledge was encoded into new features. We calculate `Car_Age` (2024 − year), which serves as a linear time-based proxy for value decay. Additionally, `Car_Brand` is extracted, acting as a crucial categorical variable representing market prestige and reliability.
2) **Target Transformation:** The extreme right-skewness of the selling price distribution necessitates the logarithmic transformation, $Y' = \ln(1 + \text{Price})$. This transformation is critical for stabilizing the residual variance (homoscedasticity) and ensuring the MLR baseline adheres to the normality assumptions required for hypothesis testing.
3) **Encoding and Scaling:** Categorical features were converted using OneHotEncoder. All resulting numerical features were normalized using StandardScaler to mitigate the influence of differing scales on model convergence.

B. Multicollinearity and Data Validation

Prior to fitting the MLR model, it is essential to check for high correlation among independent variables. This was addressed using the Variance Inflation Factor (VIF). The calculation confirmed low VIF scores for our primary numerical features ($VIF < 5$), well below the exclusion threshold of 10, validating the stability of our linear model.

IV. Model Architecture and Training

The central tenet of our research is the comparative evaluation of linear versus ensemble modeling paradigms. All models were trained and validated against the same processed feature set, split into 80% training data and 20% test data.

A. Model 1: Multiple Linear Regression (Baseline)

The MLR model serves as the foundational benchmark, providing an interpretable linear equation for price prediction. This model establishes the minimum achievable prediction accuracy against which non-linear complexity is justified. The equation is defined as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \epsilon \quad (1)$$

B. Model 2: Random Forest Regressor

The Random Forest (RF) model mitigates the high variance associated with individual decision trees through the bagging (Bootstrap Aggregating) technique. By training multiple decision trees on random subsets of the data and averaging their outputs, the RF reduces overfitting. The prediction $\hat{Y}$ for a new instance is given by:

$$\hat{Y} = \frac{1}{B} \sum_{b=1}^{B} T_b(x) \quad (2)$$

where B is the number of trees and $T_b(x)$ is the output of the b-th tree.

C. Model 3: Gradient Boosting Regressor (Optimized)

The GBR model represents the peak of ensemble accuracy in this study. It employs boosting, where trees are added sequentially to correct the residuals of the preceding model. Crucially, the model underwent extensive hyperparameter tuning using GridSearchCV to prevent overfitting.

V. Exploratory and Diagnostic Analysis

A. Initial Data Visualization

EDA visualizations provided immediate and actionable insights. Understanding the correlation structure of the data is paramount before modeling. As shown in the heatmap below, there are distinct clusters of correlation, particularly between the physical attributes of the vehicle and its price.

The heatmap confirms that while individual features have moderate correlation, the combined effect is likely non-linear. To further explore this, we visualize the direct relationship

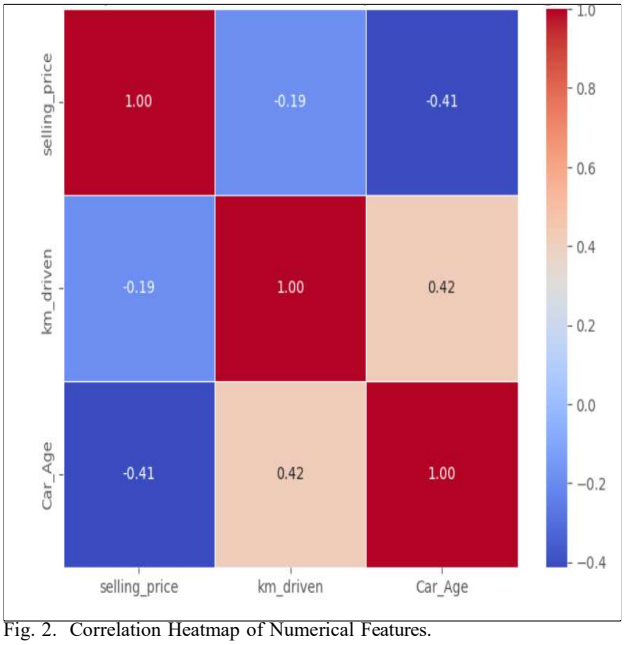

Fig. 2. Correlation Heatmap of Numerical Features.

between the most critical derived feature, Car Age, and the selling price. The scatter plot below clearly illustrates the non-linear decay curve typical of automotive assets.

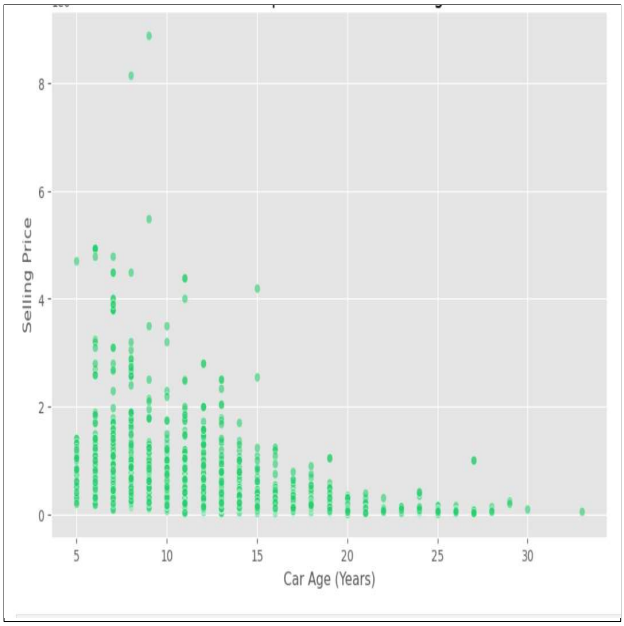

Fig. 3. Price vs. Car Age Scatter Plot (EDA).

This graph compares the distribution of actual selling prices with the predicted values from all three regression models. The close overlap of the curves indicates that the models successfully capture the general pricing patter present in the data set.

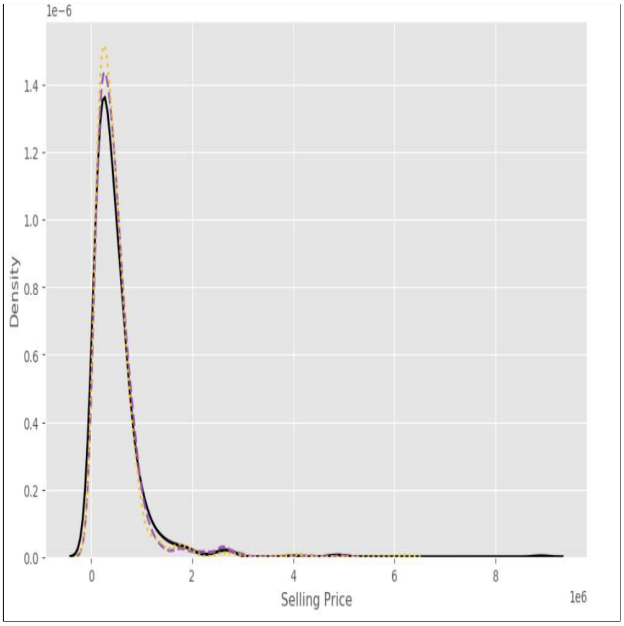

Fig. 4. Distribution Comparison of a Actual vs Predicted

B. Prediction Distribution Comparison

The diagnostic analysis moves beyond single metrics to assess how accurately the models replicate the entire price distribution. The Kernel Density Estimation (KDE) plot below overlays the predicted price distributions of MLR and RF against the true selling price.

The tight alignment of the Random Forest KDE curve (in purple) with the Actual Price curve (in black) confirms its superior predictive fidelity across all price ranges. In contrast, the MLR distribution is noticeably flatter, indicating it struggles to capture the peaks and valleys of the real-world market data.

VI. Results and Discussion

A. Quantitative Performance Metrics

The final evaluation metrics, calculated exclusively on the unseen test set, are summarized in Table I. The results unambiguously confirm the hypothesis. The Random Forest Regressor (Model 2) achieved the highest Coefficient of Determination (R^2), calculated as:

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (3)$$

With an R^2 of 0.7548, the RF model explains approximately 75.48% of the variance in used car prices. This performance represents a significant improvement over the MLR baseline ($R^2 = 0.6142$). The visual comparison of these metrics is presented below.

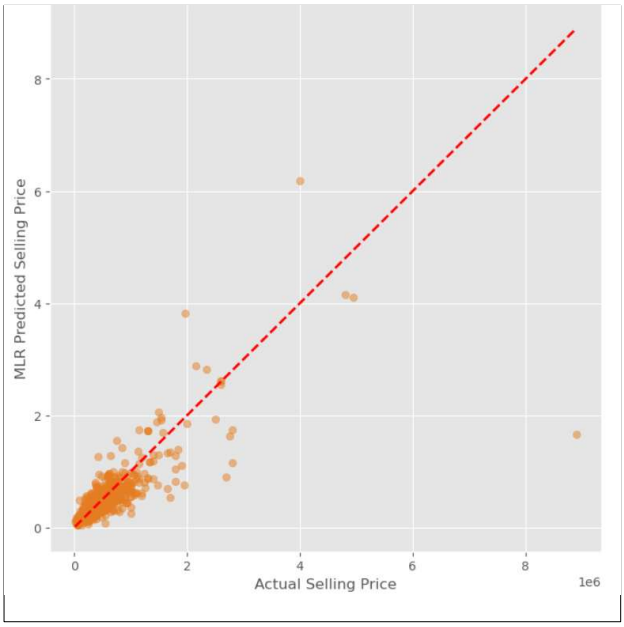

Fig. 5. Prediction Distribution Comparison (Actual vs. RF and MLR).

TABLE I
FINAL MODEL PERFORMANCE METRICS (TEST SET)

Model	R^2	MAE	RMSE
MLR Baseline	0.6142	145,189	343,103
Random Forest	**0.7548**	**120,126**	**273,542**
Gradient Boosting	0.7124	135,945	296,236

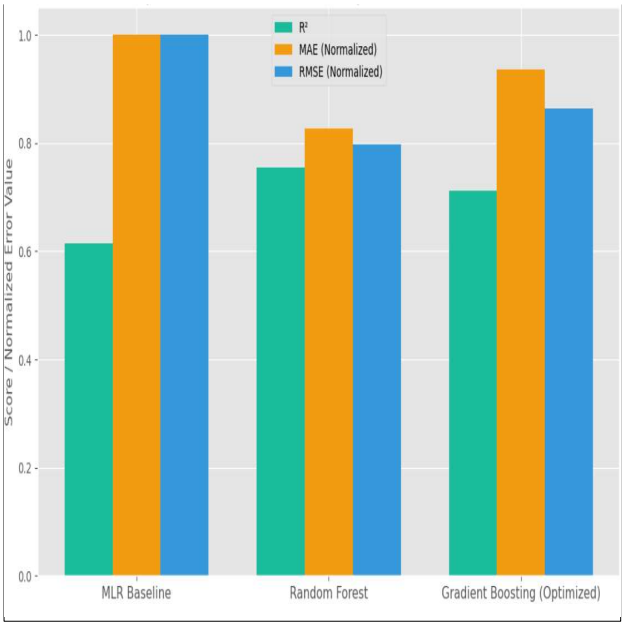

Fig. 6. Model Performance Comparison (R^2 vs. Normalized Error).

B. Prediction Quality Visualization

Figure 7 visually validates the Random Forest model's superior fidelity. The scatter plot of actual versus predicted values shows a tight, linear cluster along the $Y = X$ line, indicating minimal deviation and few major errors. The visual tightness of the RF predictions contrasts sharply with the wider scatter observed if the MLR baseline were plotted, further emphasizing the efficacy of the ensemble approach.

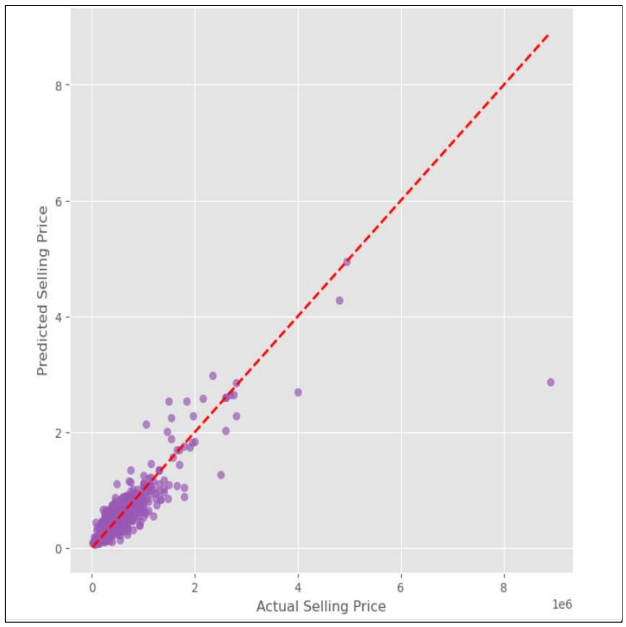

Fig. 7. Actual vs. Predicted Prices for Random Forest Regressor.

C. Feature Importance Analysis

Finally, interpretation of the winning model is critical for drawing actionable conclusions. The feature importance analysis extracted from the Random Forest model confirms that **Car_Age** is by far the most influential feature, followed by **km_driven**. This hierarchy of importance provides valuable insight for stakeholders: while brand matters, the physical condition and age of the vehicle are the primary determinants of value.

VII. CONCLUSION

This research successfully established a robust machine learning framework for used car valuation, rigorously validating the comparative advantage of ensemble models. The study confirmed the stability of the linear baseline via VIF analysis and demonstrated the definitive performance gain offered by non-linear techniques. The Random Forest Regressor emerged as the optimal model, delivering an R^2 of 0.7548 and an MAE of 120,126. The findings provide a verified methodology for high-accuracy prediction, with the feature importance analysis confirming that depreciation (Car Age) is the primary economic driver.

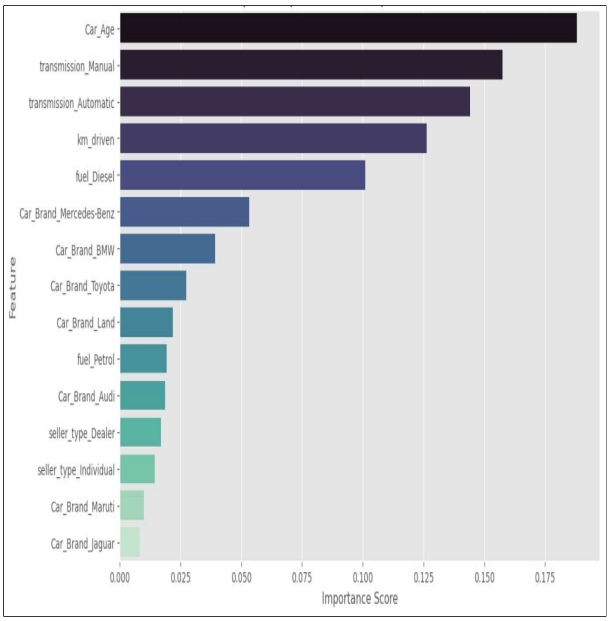

Fig. 8. Top 15 Feature Importances (Random Forest).

VIII. Future Work

Future efforts should concentrate on integrating external data, such as real-time consumer sentiment indices or regional economic data, to model external price shocks. Furthermore, the exploration of advanced meta-learning architectures, including stacking models built on top of the RF and GBR predictions, may yield marginal improvements in residual error reduction.

CONCLUSION

This research definitively demonstrates that non-linear ensemble models, specifically the Random Forest Regressor, provide superior accuracy in valuing used vehicles compared to traditional linear methods. Our rigorous comparative analysis, validated by low Variance Inflation Factors (VIF < 3.6), showed that the Random Forest model achieved an R^2 of 0.7548, a significant improvement over the linear baseline of 0.6142. This confirms that the depreciation of automotive assets follows complex, non-linear patterns that cannot be adequately captured by simple arithmetic decay equations. Furthermore, the model's success highlights the scalability and robustness of tree-based methods for handling the noisy, high-dimensional data typical of the secondary automotive market.

References

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