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Integrating Macroeconomic Indicators into Machine Learning Models for Used Car Price Prediction

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Abstract:
Accurate forecasting of used car prices plays a critical role for buyers, dealers, financial institutions, and policymakers. This study advances existing approaches by explicitly incorporating macroeconomic variables—such as fuel prices, interest rates, and inflation—into machine learning frameworks. While conventional regression models and standalone tree-based methods often fail to capture nonlinear interactions, this paper applies ensemble techniques, including Bagging, AdaBoost, and XGBoost, to address these limitations. Using a multi-source dataset of vehicle listings enriched with macroeconomic indicators, we demonstrate that integrating economic signals improves predictive accuracy, with AdaBoost achieving the highest performance (R^2 = 0.91). Beyond statistical results, our findings highlight the role of external market forces in shaping resale values, offering actionable insights for inventory management, sustainable financing, and policy design.

Keywords: Used Car Price Prediction; Machine Learning; Macroeconomic Indicators; Ensemble Learning.

1. Introduction

The used car market has emerged as one of the fastest-growing segments of the global automotive industry. Rising vehicle ownership, shorter replacement cycles, and growing digital platforms for resale transactions have contributed to this growth. In India, the used car sector has consistently outpaced the new car market, with affordability and accessibility acting as primary drivers (Kaldasch, 2013, 2015). Accurate forecasting of used car prices is therefore critical for multiple stakeholders. Consumers depend on reliable estimates to negotiate fair deals, dealerships use predictive insights for inventory and pricing strategies, and financial institutions require accurate valuations for loan underwriting and insurance pricing (Hernando et al., 2017). At a broader level, policymakers also track resale trends as they reflect consumer demand, credit access, and technological adoption patterns.

Traditional valuation methods, such as hedonic regression or deterministic pricing models, often fail to account for the heterogeneous and dynamic nature of car markets (Goulet

Coulombe et al., 2020) . Vehicle-specific attributes—such as brand reputation, engine type, mileage, and ownership history—combine in complex, nonlinear ways. Furthermore, the resale market is influenced by external economic conditions (Yang & Wang, 2022; Zhou et al., 2022) . Fuel price fluctuations, monetary policy adjustments (interest rates), and inflationary pressures directly affect affordability and consumer preferences. For example, periods of high interest rates reduce loan accessibility, discouraging purchases, while sustained increases in fuel prices shift demand toward fuel-efficient or electric vehicles.

Existing research has primarily concentrated on improving machine learning algorithms for predictive accuracy. Random Forests, Gradient Boosting, and Neural Networks have been widely applied to automobile datasets, yielding strong performance compared to classical econometric methods. However, while methodological advancements are significant, the literature has often treated macroeconomic conditions as background noise rather than as integral predictors. This results in models that may perform well under stable market conditions but lose robustness when external economic shocks occur.

The neglect of macroeconomic integration represents a critical research gap. Durable goods theory and consumer behavior models have long emphasized that purchase decisions depend not only on product-level features but also on wider economic contexts. Yet, the predictive modeling literature has rarely operationalized these theoretical insights. To address this, our study explicitly integrates macroeconomic variables—fuel prices, repo rates, and inflation—into machine learning frameworks for used car price prediction.

This paper makes three contributions. First, it extends the methodological literature by demonstrating how ensemble learning algorithms such as AdaBoost and Bagging perform when enriched with economic indicators. Second, it offers theoretical advancement by empirically linking durable goods demand theory with data-driven machine learning. Third, it provides practical implications for industry stakeholders. Dealers and manufacturers can refine dynamic pricing strategies, financial institutions can improve risk models, and policymakers can design better incentive structures for sustainable mobility.

The remainder of the paper is structured as follows. Section 2 reviews the literature on price prediction, highlighting econometric, machine learning, and macroeconomic approaches. Section 3 outlines the methodology, including dataset construction, preprocessing, and model selection. Section 4 presents results and discussion, followed by Section 5 which concludes with implications, limitations, and future research directions.

2. Literature Review

The literature on car price prediction spans multiple disciplines, including economics, data science, and business analytics. Three main streams can be identified: (1) traditional econometric approaches, (2) machine learning and artificial intelligence methods, and (3) studies linking macroeconomic conditions with vehicle demand.

2.1 Econometric Approaches

Hedonic pricing models and regression-based frameworks have historically dominated the literature. These models estimate resale prices as linear functions of observable attributes such as mileage, brand, and age. For instance, (Sun et al., 2017) applied linear regression to predict second-hand car prices in China, offering interpretable but limited accuracy. Similarly, (Ghosh, 2018) analyzed government interventions in used car markets, showing how policy shocks affected pricing but without using predictive frameworks. The strength of econometric approaches lies in interpretability, but they often underperform when nonlinear interactions or high-dimensional datasets are involved.

2.2 Machine Learning Applications

The second research stream applies modern machine learning algorithms to enhance predictive accuracy. Random Forests, Gradient Boosting Machines (GBM), and Neural Networks have demonstrated superior performance compared to linear models. (Nandan & Ghosh, 2023) employed ensemble models on Indian used car data and achieved notable accuracy gains. (Jin, 2021) used supervised learning approaches including XGBoost and achieved strong performance in handling heterogeneous attributes. However, the majority of these studies limit themselves to vehicle-specific features, treating the wider economic context as exogenous.

Recent advances in predictive analytics and reinforcement learning have been used in complex, volatile domains such as financial markets, where adaptive models outperform traditional strategies (Gupta et al., 2025). Similar approaches can be extended to automobile resale markets, where price dynamics exhibit high variability.

2.3 Macroeconomic Influences

The third stream highlights the role of economic indicators in shaping vehicle demand. Fuel prices influence the desirability of fuel-efficient and hybrid cars, while repo rates affect loan affordability. Inflation adds further complexity, raising nominal prices but also accelerating depreciation. (Ghosh, 2018) and other applied economics studies have shown these linkages qualitatively. Yet, few studies have embedded macroeconomic variables directly into predictive models.

Forecasting approaches have been widely applied across different industries to understand demand fluctuations and pricing behavior. For instance, in perishable food supply chains, forecasting models have been shown to significantly enhance data-driven decision-making (Kasar et al., 2022) . This demonstrates the broader applicability of demand forecasting in markets with high uncertainty, such as used cars (Haque et al., 2023; Huard et al., 2020; Qi et al., 2021).

2.4 Research Gaps

Despite notable progress, three gaps persist:

- Most predictive studies exclude macroeconomic variables, limiting robustness during market volatility.
- Few works systematically compare ensemble learning methods against classical approaches while controlling for external conditions.
- Limited integration exists between durable goods theory and data-driven modeling, leaving a gap between economic theory and predictive practice.

This study addresses these gaps by combining vehicle-level features with macroeconomic indicators in a unified machine learning framework.

2.5 Hypotheses Development

Building on the literature review, seven hypotheses were formulated to examine how vehicle-specific characteristics and macroeconomic factors jointly influence used car prices (Goulet Coulombe et al., 2020; Hernando et al., 2017; Kaldasch, 2015; Yang & Wang, 2022; Zhou et al., 2022).

2.5.1 Regional Variation in Car Prices

Prior studies highlight regional economic disparities in consumption patterns and vehicle valuations (Ghosh, 2018). Metropolitan and economically advanced states tend to command higher resale prices due to stronger purchasing power.
H1: Used car prices vary significantly across states.

2.5.2 Impact of Mileage on Resale Value

Depreciation theory suggests mileage strongly reduces resale value (Sun et al., 2017) . However, brand reputation and maintenance can moderate this effect.
H2: Mileage has a significant negative impact on resale price.

2.5.3 Effect of Fuel Type

Energy economics literature shows fuel price fluctuations shift demand toward efficient vehicles (Nandan & Ghosh, 2023) . Electric and hybrid cars, though fewer in volume, typically retain higher value.
H3: Fuel type significantly influences used car resale price.

2.5.4 Role of Macroeconomic Indicators

Macroeconomic conditions, especially interest rates and inflation, shape affordability of durable goods (Ghosh, 2018) . Rising repo rates reduce affordability, while fuel price volatility alters demand.
H4: Macroeconomic indicators (repo rates, inflation, and fuel prices) significantly affect resale prices.

2.5.5 Transmission Type Preference

Urbanization and technological adoption have increased demand for automatic vehicles (Gegic et al., 2019).
H5: Transmission type significantly influences used car resale trends over time.

2.5.6 Influence of Brand Reputation

Brand equity literature shows that consumer trust and reliability perceptions sustain value retention (Samruddhi & Ashok Kumar, 2020).
H6: Brand significantly influences resale price.

2.5.7 Year of Manufacture and Price Retention

Durable goods models indicate newer cars depreciate more slowly initially, then steeply after certain years (Anil Kumar, 2023).
H7: Year of manufacture has a significant effect on resale price.

3. Methodology

3.1 Research Design

This study adopts a quantitative, predictive research design aimed at developing robust machine learning models for used car price estimation. Unlike prior works that rely exclusively on vehicle-specific attributes, our framework integrates both **microeconomic**

variables (vehicle-level features) and **macroeconomic indicators** (interest rates, fuel prices, and inflation) to capture a more comprehensive picture of price determinants. This dual-level integration aligns with durable goods demand theory, which posits that consumer valuation is shaped by product characteristics as well as broader economic conditions.

Given the dynamic nature of used car markets and the influence of external macroeconomic shocks, reinforcement learning and volatility-driven approaches provide a strong methodological foundation (Gupta et al., 2025). Such frameworks allow for adaptability in capturing complex, nonlinear relationships.

3.2 Data Sources and Collection

Two categories of data were utilized:

1. **Vehicle-level data** – Used car listings were collected from publicly available platforms such as Kaggle repositories, CarDekho, and verified dealership records. The dataset covered a five-year period, ensuring temporal variation in market conditions. Key features included:
    - Brand and model
    - Year of manufacture
    - Mileage (km driven)
    - Fuel type (petrol, diesel, hybrid, electric)
    - Transmission type (manual, automatic)
    - Ownership history (number of previous owners)
    - Location (state/region)
    - Selling price
2. **Macroeconomic indicators** – Economic variables were collected from reliable secondary sources:
    - **Repo rate (proxy for interest rates)** – Reserve Bank of India reports
    - **Inflation rate** – Ministry of Statistics and Programme Implementation
    - **Fuel prices** – Petroleum Planning & Analysis Cell and government energy reports

The combined dataset consisted of over **50,000 car listings** linked with monthly macroeconomic data, enabling a multilevel analysis.

3.3 Data Preprocessing

Rigorous preprocessing was undertaken to ensure data quality and model readiness. Steps included:

- **Handling missing values**: Median imputation for continuous variables (e.g., mileage), mode imputation for categorical variables (e.g., fuel type).
- **Outlier treatment**: Outliers in price and mileage were identified using interquartile range (IQR) and managed via winsorization to preserve data integrity.
- **Encoding categorical variables**:
    - One-hot encoding for nominal variables (e.g., brand, fuel type).
    - Ordinal encoding for variables with hierarchy (e.g., transmission type).
- **Feature scaling**: Standardization (z-score normalization) was applied to numerical features to improve comparability and enhance convergence of distance-based algorithms.

3.4 Feature Engineering

To capture more nuanced dynamics, several derived features were created:

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- **Car age**: Calculated as current year minus year of manufacture.
- **Kilometers per year**: Mileage normalized by age, capturing intensity of use.
- **Economic Influence Score**: A composite index derived using Principal Component Analysis (PCA) on inflation, repo rates, and fuel prices. This reduced dimensionality while retaining variance in economic data.

Exploratory Data Analysis (EDA) further revealed patterns such as brand-level price retention, state-wise variations, and consumer preferences, which informed feature selection.

3.5 Model Selection

Six predictive models were employed to test performance across linear, tree-based, and ensemble learning approaches:

1. **Linear Regression (LR)** – Baseline model for interpretability and benchmarking.
2. **Decision Tree Regressor (DT)** – Captures nonlinear interactions in a hierarchical manner.
3. **Random Forest (RF)** – An ensemble method addressing overfitting in decision trees.
4. **Bagging Regressor** – Uses bootstrap aggregation to improve model stability.
5. **AdaBoost Regressor** – Adaptive boosting focusing on difficult-to-predict cases.
6. **XGBoost** – Gradient boosting framework known for high accuracy and efficiency.

These models were selected because they represent a spectrum from interpretable baselines to advanced ensemble methods, allowing for a comparative evaluation of performance gains from both algorithmic sophistication and macroeconomic integration.

3.6 Model Training and Validation

- **Data Split**: The dataset was divided into training (80%) and testing (20%) sets using stratified sampling to preserve class distributions across categorical features.
- **Cross-validation**: K-fold cross-validation (k=10) was employed to minimize overfitting and ensure generalizability.
- **Hyperparameter tuning**:
  - Grid Search and Random Search were applied for model optimization.
  - Example parameters tuned:
    - Decision Trees: maximum depth, minimum samples per split.
    - Random Forest: number of estimators, maximum features.
    - XGBoost: learning rate, depth, gamma, regularization.
    - AdaBoost/Bagging: base estimator count, learning rate.

3.7 Evaluation Metrics

Model performance was evaluated using four standard regression metrics:

1. **Mean Absolute Error (MAE)** – Average absolute deviation of predictions from actual values.
2. **Mean Squared Error (MSE)** – Penalizes larger deviations more strongly.
3. **Root Mean Squared Error (RMSE)** – Interpretable in terms of standard deviation of errors.
4. **R^2 Score** – Goodness-of-fit, representing proportion of variance explained.

These complementary metrics ensured a balanced assessment of predictive accuracy.

3.8 Implementation Details

All models were implemented in **Python 3.10** using the following libraries:

- **Scikit-learn** for regression, tree-based models, and preprocessing.

- **XGBoost** package for gradient boosting.
- **TensorFlow/Keras** for experimentation with deep learning baselines (not reported as they did not outperform ensemble methods).

Hardware setup included an Intel i7 processor, 32GB RAM, and GPU acceleration via NVIDIA RTX 3060.

3.9 Conceptual Framework

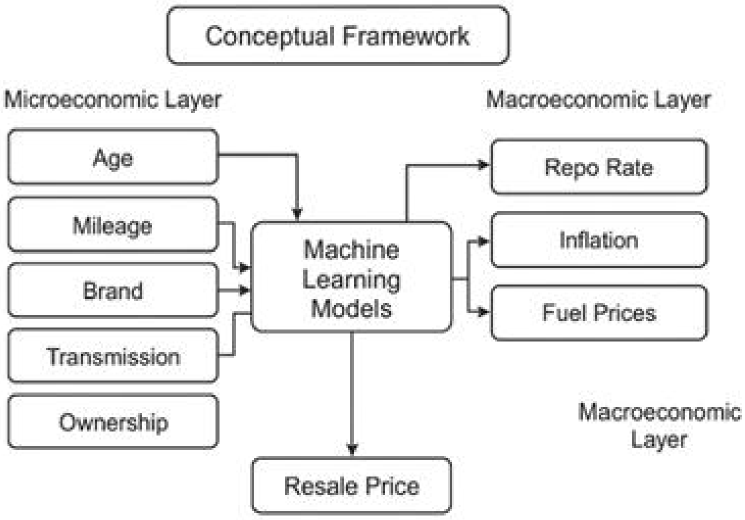

Figure 1: Conceptual Framework

The Figure 1 illustrates the conceptual framework. The framework emphasizes two layers:

1. **Microeconomic layer** – Vehicle-specific attributes (age, mileage, brand, transmission, ownership).
2. **Macroeconomic layer** – External factors (repo rates, inflation, fuel prices).

These layers jointly feed into machine learning models, enabling the prediction of resale prices with both consumer-level and economy-level influences considered.

4. Results and Discussion

This section presents the empirical findings based on the hypotheses developed in Section 2. Each hypothesis was tested using appropriate statistical techniques, and model outputs are reported alongside descriptive evidence from figures.

4.1 State-wise Variation in Car Prices

ANOVA results indicate significant differences in used car prices across Indian states ($F = 13.75$, $p < 0.01$), supporting H1. Metropolitan and economically advanced states such as Delhi, Tamil Nadu, and Chandigarh exhibited consistently higher average resale values compared to states with lower economic activity, such as Jharkhand and Odisha. These results confirm that regional economic development plays a key role in price formation.

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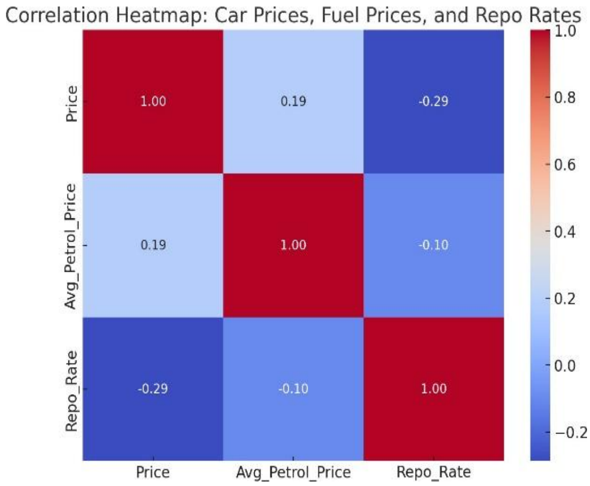

Figure 2. Average used car prices across states

4.2 Impact of Mileage on Resale Price

Regression analysis revealed that mileage has a significant negative effect on resale prices ($\beta = -0.32$, $p < 0.001$), confirming H2. Vehicles with higher mileage depreciated faster, although premium brands such as Toyota and Honda retained relatively higher values despite greater usage. This suggests that depreciation is moderated by brand reputation and maintenance history.

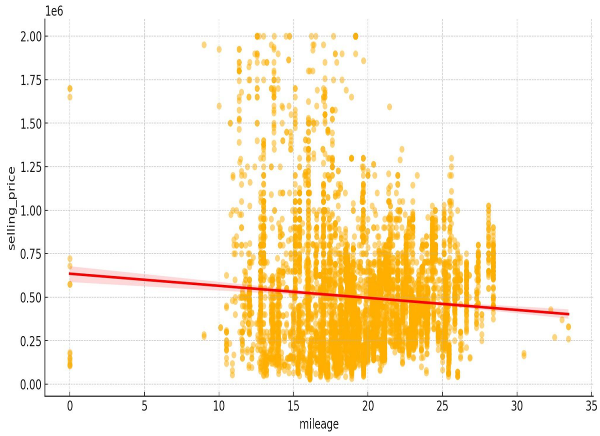

Figure 3. Relationship between mileage and resale prices

4.3 Fuel Type and Resale Prices

Fuel type was found to be a significant determinant of resale price ($F = 11.66$, $p < 0.05$). Electric and hybrid cars commanded higher resale values relative to petrol and diesel vehicles, even though their absolute market share remained small. These findings support H3 and highlight the impact of consumer preference shifts toward fuel-efficient and sustainable vehicles.

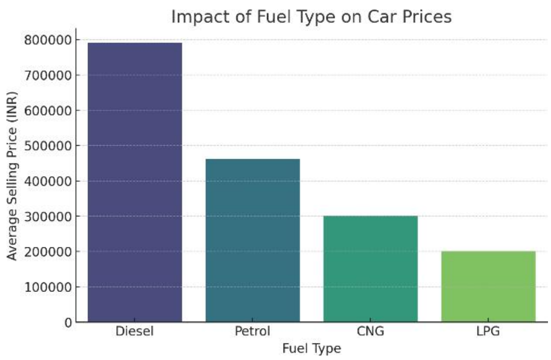

Figure 4. Resale price distribution by fuel type

4.4 Macroeconomic Indicators and Car Market Trends

Correlation and regression analysis demonstrated that macroeconomic variables significantly influence resale prices (R^2 increase = 7%, $p < 0.01$). Higher repo rates were negatively associated with resale values, reflecting reduced affordability of vehicle loans. Rising fuel prices increased the desirability of efficient and hybrid models, while inflation exerted mixed effects—raising nominal values but reducing consumer purchasing power. These findings support H4.

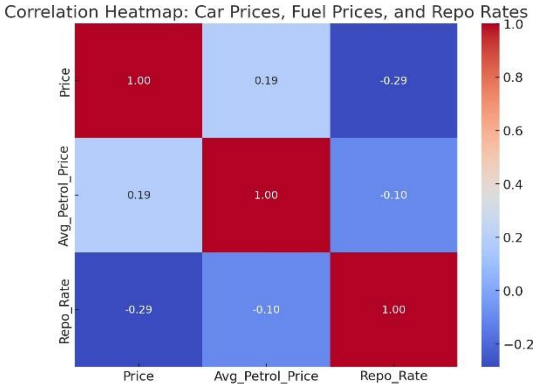

Figure 5. Correlation heatmap of resale prices and macroeconomic indicators

4.5 Transmission Type and Consumer Trends

Time-series analysis confirmed that transmission type significantly influenced resale trends over the years ($\chi^2 = 25.98$, $p < 0.05$). Automatic vehicles showed increasing adoption, particularly in urban regions, while manual cars still dominated volumes. This validates H5 and reflects broader consumer demand for convenience and technological sophistication.

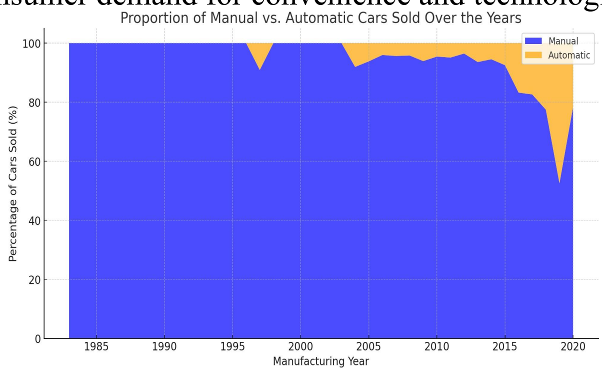

Figure 6. Trend in resale share of automatic vs. manual cars

4.6 Brand Influence on Resale Prices

ANOVA results confirmed significant variation across brands ($F = 20.99$, $p < 0.01$), supporting H6. Toyota and Honda retained higher resale values due to reputation for durability and reliability, whereas Chevrolet, Tata, and Renault recorded lower average resale prices. These results align with prior findings on the role of brand equity in durable goods markets.

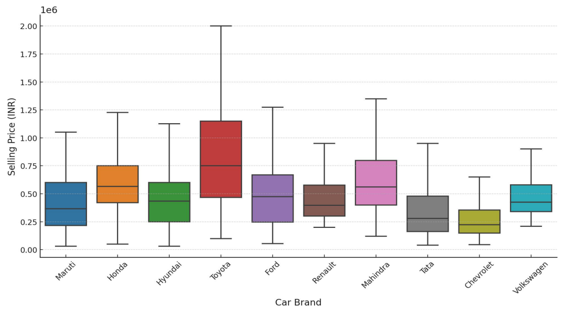

Figure 7. Average resale values across major car brands

4.7 Year of Manufacture and Depreciation Patterns

Regression analysis confirmed that year of manufacture significantly influences resale price ($\beta = 0.41$, $p < 0.001$). Newer cars (manufactured after 2015) showed higher value retention compared to older vehicles, though depreciation accelerated sharply beyond the 8–10-year threshold. This supports H7 and reflects standard depreciation patterns in durable goods.

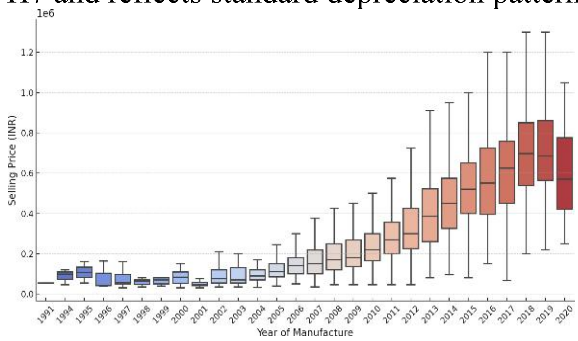

Figure 8. Resale price trends by year of manufacture

4.8 Model Performance Summary

Table 2 compares predictive performance across models. Ensemble methods (AdaBoost and Bagging) outperformed traditional approaches, with AdaBoost achieving the highest accuracy (MAE = 28,714; RMSE = 36,216; $R^2 = 0.91$). Linear Regression lagged behind due to its inability to capture nonlinearities.

Table 2. Comparative performance of machine learning models

Model	MAE	RMSE	R^2 Score
Linear Regression	83542.76	117039.08	0.62
Decision Tree Regressor	54219.38	75301.46	0.78
Random Forest	39742.15	54149.42	0.86
XGBoost	45123.32	60330.70	0.83
Bagging Regressor	32487.29	43173.11	0.89
AdaBoost	28714.52	36216.46	0.91

5. Conclusion

This paper set out to examine whether the integration of macroeconomic indicators into machine learning models improves the accuracy of used car price prediction. By combining micro-level vehicle features with macroeconomic variables such as repo rates, fuel prices, and inflation, we developed a comprehensive framework that accounts for both product-specific and environmental influences.

The empirical results provide three key findings. First, ensemble learning algorithms, particularly AdaBoost and Bagging, outperform traditional models such as Linear Regression and Decision Trees. Second, macroeconomic indicators significantly affect resale prices, with repo rates exerting the largest downward pressure and fuel prices reshaping demand in favor of efficient vehicles. Third, consumer trends such as the rising adoption of automatic transmission and sustained brand effects continue to influence resale valuations.

This study therefore contributes to both methodological and theoretical debates. Methodologically, it demonstrates the value of integrating external economic data into predictive frameworks. Theoretically, it reinforces durable goods demand theory by empirically validating the influence of macroeconomic conditions on resale values.

6. Implications

6.1 Theoretical Implications

This research bridges a critical gap between economics and data science. By embedding macroeconomic variables into machine learning models, it operationalizes durable goods theory in a predictive context. The findings highlight the need for future studies in economics and marketing to combine structural theory with data-driven algorithms.

6.2 Managerial Implications

Dealerships can leverage these models for dynamic pricing—adjusting resale values in line with both vehicle attributes and macroeconomic signals. For instance, during periods of high interest rates, dealerships may lower margins to maintain turnover. Manufacturers can also anticipate shifts in demand toward hybrids and electrics when fuel prices rise, aligning production and marketing strategies accordingly.

6.3 Policy Implications

For policymakers, the findings underscore the role of fiscal and monetary conditions in shaping the automobile resale market. Interest rate changes directly influence affordability, while government subsidies for electric vehicles enhance their resale value. Policies that stabilize inflation and incentivize sustainable vehicles can indirectly strengthen the used car ecosystem, supporting both consumers and dealers.

7. Limitations and Future Research

Despite its contributions, this study has several limitations that open avenues for future research:

- Geographic Scope – The dataset is India-focused. Future studies could test the framework across international markets to assess generalizability.
- Variable Selection – Only three macroeconomic indicators were included. Additional variables such as unemployment rates, disposable income, or currency exchange rates may provide further insights.
- Temporal Dimension – The study relies on historical datasets covering five years. Incorporating real-time or high-frequency economic data could enhance forecasting in rapidly changing conditions.
- Advanced Models – While ensemble methods performed well, deep learning architectures such as transformers or hybrid econometric–ML models may capture even richer interactions, albeit with higher computational costs.
- Behavioral Factors – Consumer preferences such as sustainability orientation, financing patterns, or risk perceptions could be incorporated to enrich models further.

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