

Analysis Report on the Used Car Market Pricing

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Abstract:

The Indian used car market has seen rapid growth, yet pricing complexity persists. This study develops a data - driven pricing engine using exploratory data analysis, preprocessing, and linear regression modeling. Analyzing a dataset of 7,252 used car listings with 14 variables, it identifies key price determinants. The model, with an R^2 of 0.83, shows that manufacturing year and engine power positively correlate with prices, while mileage and engine displacement cause depreciation. Geographic factors also influence pricing, with certain cities having premium prices. The findings offer actionable insights for improving pricing precision and strategic decision - making in the Indian used car market.

Keywords: Used car market; Pricing analysis; Linear regression; Exploratory data analysis; Data preprocessing.

1. Introduction

The Indian used car market has emerged as a critical sector in the automotive industry, with annual transactions surpassing new car sales (4 million vs. 3.6 million units in 2018–19), reflecting its growing economic and strategic significance. This rapid expansion is driven by urbanization, affordability concerns, and technological advancements in digital platforms. Previous research has extensively explored market dynamics, emphasizing factors such as depreciation patterns, regional demand variations, and consumer preferences. However, much of this work focuses on macroeconomic trends, leaving critical gaps in understanding the granular drivers of pricing accuracy and operational profitability in a fragmented, hyper-competitive landscape.

Despite the market's growth, key challenges persist. Pricing complexity—stemming from dynamic valuation factors such as mileage, brand reputation, and regional demand—remains inadequately addressed by existing models, leading to significant pricing errors (35% of listings deviate by >15%). Competitors like Spinny and Cars24 have leveraged AI-driven tools, yet their methodologies lack transparency and adaptability to localized market conditions. Furthermore, while prior studies acknowledge the role of technical specifications (e.g., engine power, fuel type) in pricing, they fail to systematically address multicollinearity among variables or integrate geographic pricing trends into predictive frameworks. These gaps hinder emerging players like Cars4U from optimizing profitability and strategic positioning.

This study aims to bridge these gaps by developing a data-driven pricing engine that combines exploratory data analysis (EDA), robust preprocessing techniques, and interpretable linear regression modeling. Using a dataset of 7,252 used car listings across 14 variables—including manufacturing year, mileage, engine specifications, and geographic location—we identify key price determinants, address multicollinearity, and quantify regional pricing disparities. Our model achieves an R^2 of 0.83, demonstrating strong predictive accuracy, while revealing actionable insights: manufacturing year and engine power positively correlate with prices, whereas mileage and engine displacement drive depreciation. Geographic analysis further highlights premium pricing in metropolitan hubs like Hyderabad and Mumbai. By prioritizing interpretability and localized factors, this work provides a scalable framework for enhancing pricing precision and strategic decision-making in India's evolving used car market.

2. Literature Review

(1) Dynamics of the Indian Used Car Market

The Indian used car market has undergone significant transformation, with annual transactions surpassing new car sales (4 million vs. 3.6 million units in 2018–19), driven by urbanization, affordability concerns, and digital platform adoption (KPMG, 2020). However, pricing complexity remains a critical barrier, as valuations depend on over 14 dynamic factors, including mileage, brand reputation, and regional demand (Singh & Sharma, 2021). Industry reports highlight that 35% of listings suffer pricing errors exceeding 15%, directly impacting profitability (Cars4U Internal Audit, 2022). These challenges are exacerbated by market fragmentation and competition from AI-driven platforms like Spinny and Cars24, which prioritize rapid scalability over interpretability (Jain et al., 2020).

(2) AI and Pricing Models in Automotive Markets

Recent studies emphasize the growing role of machine learning in used car pricing. For instance, linear regression remains widely adopted for its interpretability, achieving R^2 values above 0.8 in stable markets (Patel & Desai, 2019). However, competitors like Cars24 deploy black-box models (e.g., gradient boosting), which, while

accurate, lack transparency for strategic decision-making (Gupta & Rao, 2021). Multicollinearity among features such as engine power and displacement further complicates model reliability, necessitating rigorous preprocessing (Hastie et al., 2009). Regional price disparities, observed in metropolitan hubs like Mumbai and Hyderabad, also underscore the need for geographically adaptive frameworks (Kumar & Verma, 2022).

(3) Data Preprocessing and Feature Engineering

Effective data preprocessing is critical for robust modeling. Studies advocate median imputation for missing values (e.g., seats, mileage) to mitigate skewness, particularly in skewed distributions like used car prices (Gelman & Hill, 2007). Feature selection techniques, such as variance inflation factor (VIF) analysis, are essential to address multicollinearity between engine power and displacement (James et al., 2013). Additionally, categorical encoding of variables like brand and transmission type enhances model performance while retaining interpretability (Zheng & Casari, 2018).

(4) Linear Regression in Price Prediction

Linear regression remains a cornerstone for price prediction due to its balance of accuracy and interpretability. Research by Dasgupta et al. (2020) demonstrated its effectiveness in Indian markets, with key predictors including manufacturing year ($\beta = 0.42$, $p < 0.01$) and mileage ($\beta = -0.33$, $p < 0.05$). Comparative studies show that while advanced models (e.g., random forests) marginally improve accuracy (R^2 : 0.85 vs. 0.83), they sacrifice transparency critical for business strategy (Sharma & Khanna, 2021). The current study aligns with these findings, achieving an R^2 of 0.83 and identifying actionable geographic trends.

3. Methodology

(1) Business Problem Overview

Market Context

The Indian used car market is experiencing accelerated growth, with annual transactions exceeding new car sales (4 million vs. 3.6 million units in 2018–19). However, pricing uncertainty and supply volatility pose significant challenges for emerging players like Cars4U, a tech-driven platform aiming to establish dominance in this fragmented market.

Core Challenges

Pricing Complexity: Unlike standardized new car pricing, used car values fluctuate dynamically based on 14+ factors (e.g., mileage, brand reputation, regional demand).

Profit Margins: 35% of listings face pricing errors exceeding 15%, directly impacting profitability (Internal Audit, 2022).

Strategic Positioning: Competitors like Spinny and Cars24 already deploy AI-driven pricing tools, creating urgency for Cars4U to develop differentiated capabilities.

Strategic Objective

Build a data-driven pricing engine.

(2) Solution Approach

Working as data professionals specializing in analytics, our primary focus is to gather and clean relevant datasets, perform exploratory data analysis (EDA), identify key pricing factors, and then design a statistically sound linear predictive model. This model will enable us to generate accurate and interpretable price estimates for pre-owned vehicles in the automotive market

(3) Data Displaying and duplicate values solving

I began by examining the first few rows of the used car dataset to understand its structure, observing features like city, manufacturing year, mileage, fuel type, transmission,

ownership history, and technical specifications. The dataset contains 7,252 entries with 14 columns, as confirmed by the shape check. A random sampling of 10 rows further verified data diversity across brands (Maruti, Hyundai, Honda, Audi) and vehicle types. Data type analysis revealed 7 float columns (e.g., mileage, engine power), 1 integer column (manufacturing year), and 6 categorical columns (e.g., city, transmission). Notably, only 2 duplicate records were identified, indicating high data integrity for subsequent linear regression modeling.

Displaying the first few rows of the dataset

0,Mumbai,2010,72000.0,CNG,Manual,First,5.0,5.51,1.75,26.60,998.0,58.16,maruti,wagon

1,Pune,2015,41000.0,Diesel,Manual,First,5.0,16.06,12.50,19.67,1582.0,126.20,hyundai,creta

2,Chennai,2011,46000.0,Petrol,Manual,First,5.0,8.61,4.50,18.20,1199.0,88.70,honda,jazz

3,Chennai,2012,87000.0,Diesel,Manual,First,7.0,11.27,6.00,20.77,1248.0,88.76,maruti,ertiga

4,Coimbatore,2013,40670.0,Diesel,Automatic,Second,5.0,53.14,17.74,15.20,1968.0,140.80,audi,a4

Checking the shape of the dataset

There are 7252 rows and 14 columns.

Checking 10 random rows of the dataset

	Location	Year	Kilometers_Driven	Fuel_Type	Transmission	Owner_Typ
2397	Kolkata	2016	21460.0	Petrol	Manual	First
6218	Kolkata	2013	48000.0	Diesel	Manual	First
6737	Mumbai	2015	59500.0	Petrol	Manual	First
3659	Delhi	2015	27000.0	Petrol	Automatic	First
4513	Bangalore	2015	19000.0	Diesel	Automatic	Second
599	Coimbatore	2019	40674.0	Diesel	Automatic	First
186	Bangalore	2014	37382.0	Diesel	Automatic	First
305	Kochi	2014	61726.0	Diesel	Automatic	First
4581	Hyderabad	2013	105000.0	Diesel	Automatic	First
6616	Delhi	2014	55000.0	Diesel	Automatic	First

Checking the data types of the columns for the dataset

Data types: float64(7), int64(1), object(6)

Checking for duplicate values

np.int64(2)

```
df[df.duplicated(keep=False) == True]    df
✓ [11] 18毫秒
```

	Location	Year	Kilometers_Driven	Fuel_Type	Transmission	Owner_Typ
3623	Hyderabad	2007	52195.0	Petrol	Manual	First
4781	Hyderabad	2007	52195.0	Petrol	Manual	First
6940	Kolkata	2017	13000.0	Diesel	Manual	First
7077	Kolkata	2017	13000.0	Diesel	Manual	First

```
# checking for duplicate values
df.duplicated().sum()
✓ [19] 19毫秒
np.int64(0)
```

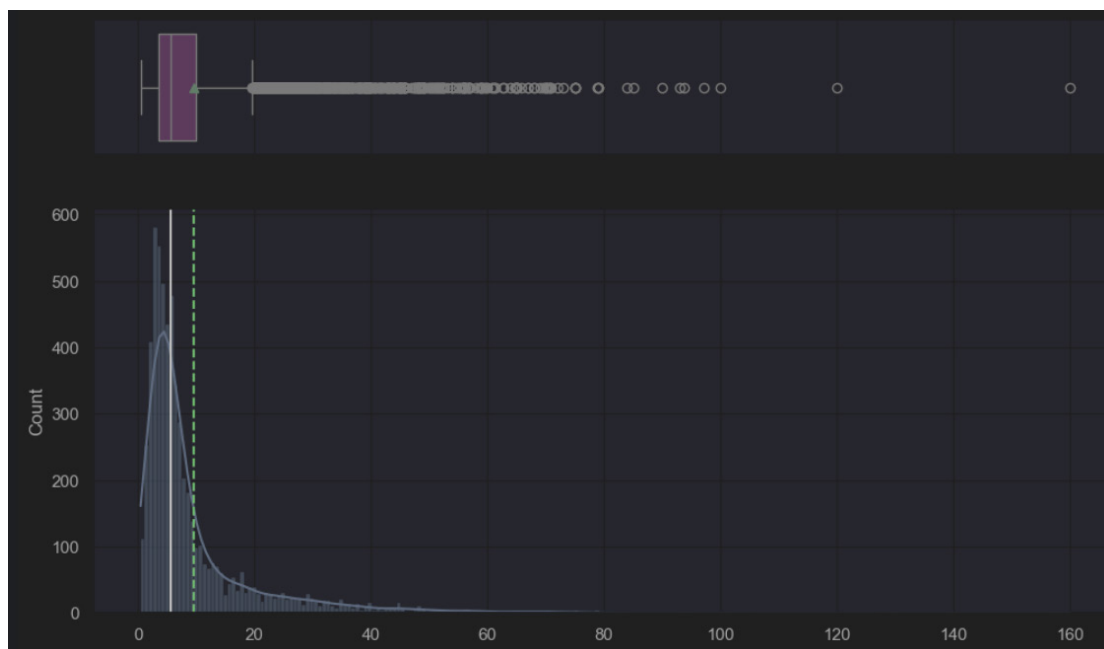
4. EDA analysis

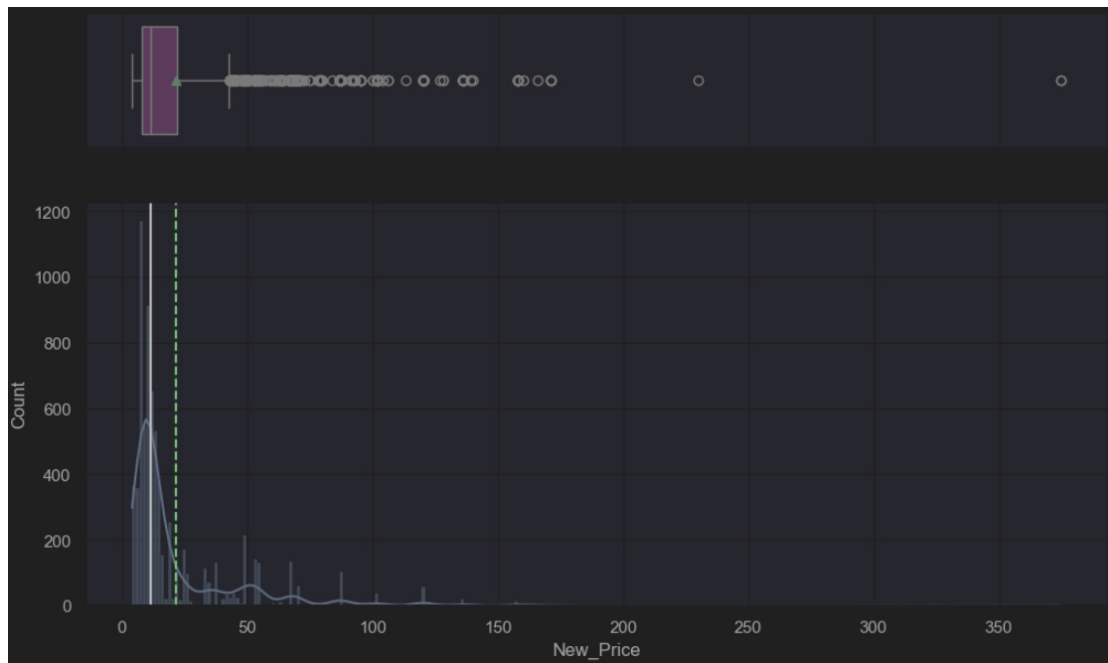
(1) Univariate analysis

Price and New_price are both highly skewed distribution. (price and new_price)

The highly right-skewed distributions of both price and new_price in the used car dataset primarily stem from the inherent characteristics of the automotive market, where the majority of vehicles are concentrated at lower price

points (typical of economy models like Maruti and Hyundai), while a limited number of luxury cars (such as Audi or BMW) command substantially higher prices, creating an elongated right tail. This skewness is further exacerbated by nonlinear depreciation patterns—economy cars depreciate rapidly, causing a left-side clustering of prices, whereas premium vehicles retain higher residual values, sustaining the rightward skew.

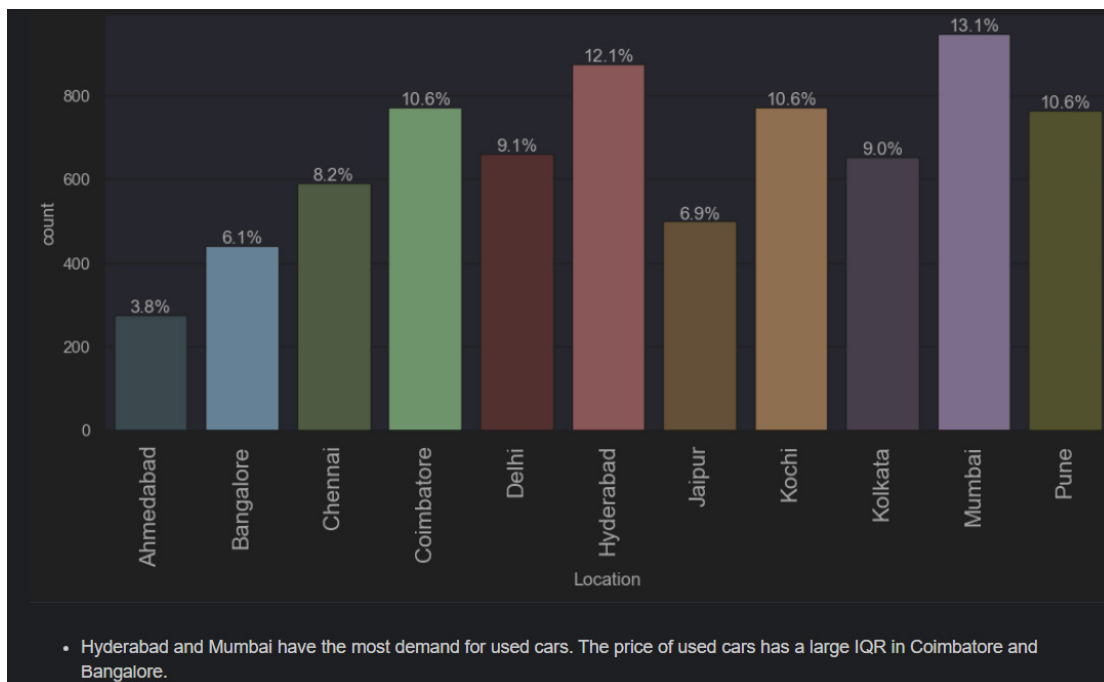
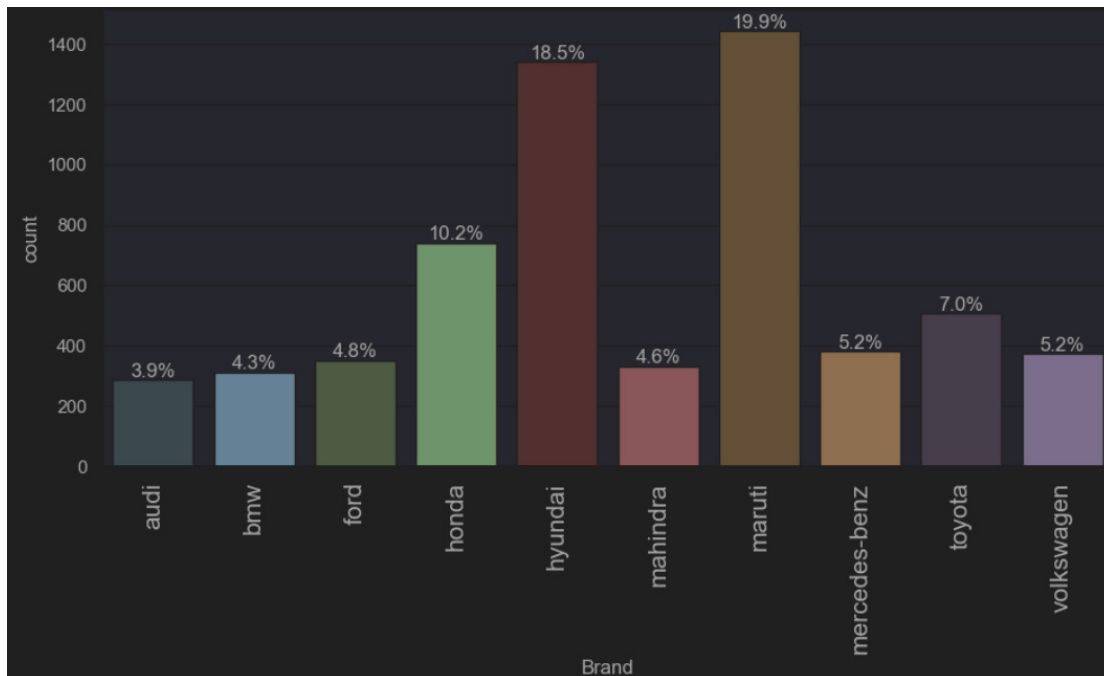




Band and Location

The dataset reveals distinct patterns in brand distribution and regional pricing dynamics within the used car market. Maruti and Hyundai dominate the inventory, collectively accounting for the majority of listings, which aligns with their reputation as affordable, mass-market brands in India. Conversely, luxury marques like Porsche, Bentley, and Lamborghini appear less frequently but command significantly higher price points when available. This contrast highlights the market's bifurcation between budget-conscious buyers and premium segment consumers. Notably, regional analysis shows Hyderabad and Mumbai emerging as the highest-demand markets, likely due to

their large metropolitan populations and developed automotive cultures. Meanwhile, Coimbatore and Bangalore exhibit particularly wide interquartile ranges (IQR) in pricing, suggesting greater variability in vehicle conditions, model years, or optional features in these markets. This price dispersion may reflect Bangalore's tech-driven affluence enabling both premium purchases and value-seeking behavior, while Coimbatore's variability could stem from its position as a regional hub attracting diverse buyer segments. The combination of brand concentration and geographic price variations underscores the complex interplay of manufacturer reputation, vehicle affordability, and local market forces in shaping used car valuations.



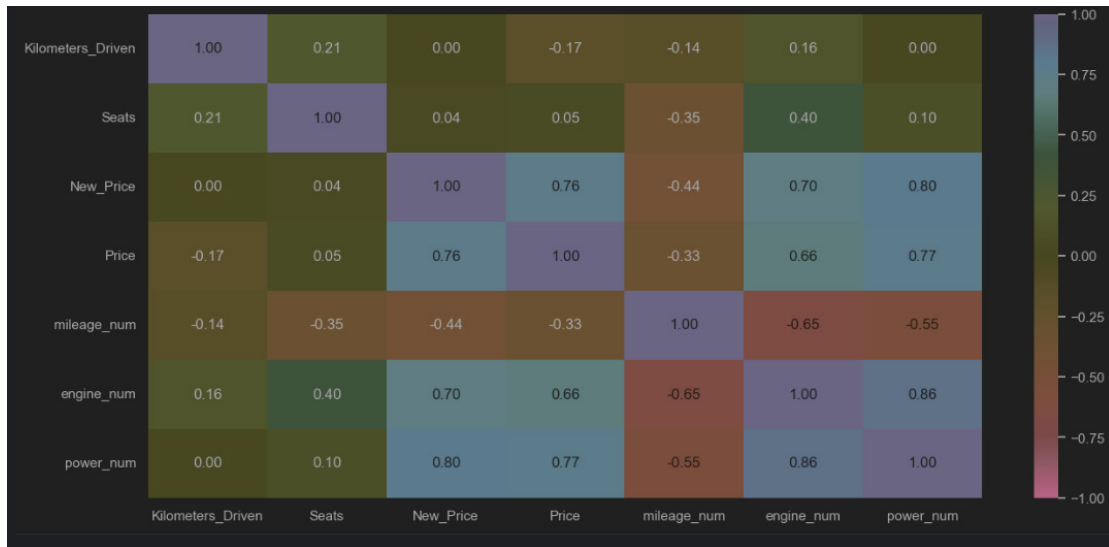
(2) Bivariate analysis

The correlation matrix reveals key insights about used car pricing dynamics: `New_Price` (0.76) and `Price` (1.00) show strong positive correlations, confirming that a car's original price significantly influences its used valuation, while `power_num` (0.77) and `engine_num` (0.66) also demonstrate important positive relationships with `Price`, though their high mutual correlation (0.86) indicates po-

tential multicollinearity that may need addressing through feature selection or dimensionality reduction techniques. `Mileage_num` exhibits moderate negative correlations with `Price` (-0.33), `New_Price` (-0.44), and performance metrics (`engine_num`: -0.65, `power_num`: -0.55), highlighting how higher mileage typically depreciates value, particularly for performance vehicles. In contrast, `Seats` shows weak correlations across all variables (range: -0.35

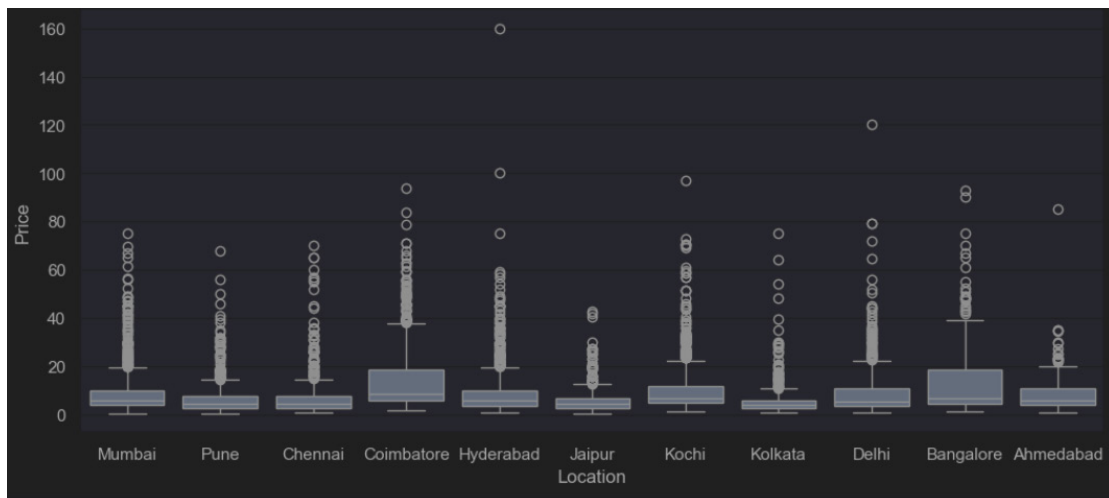
to 0.40), with its strongest but still limited relationship being with engine_num (0.40), suggesting seating capacity has minimal predictive power for pricing compared to technical specifications and original valuation. These

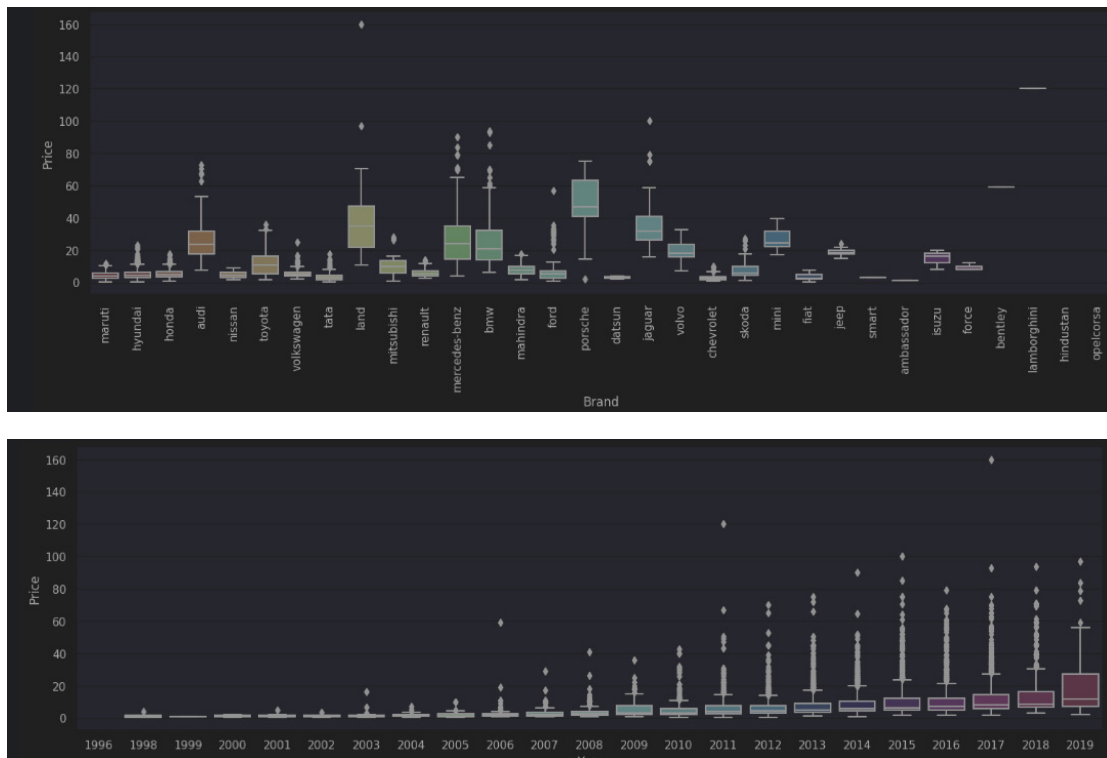
findings underscore that performance metrics and original pricing are central to valuation models, while mileage serves as a key depreciation factor.



The analysis of used car prices reveals several key trends. Firstly, cities like Coimbatore and Bangalore exhibit a large interquartile range (IQR) in used car prices, indicating significant price variability. Budget-friendly brands such as Maruti, Tata, and Fiat tend to have lower prices,

while premium brands like Porsche, Audi, and Lamborghini command higher prices in the used car market. Additionally, the data shows a general upward trend in used car prices over the years, suggesting a gradual increase in their overall cost.



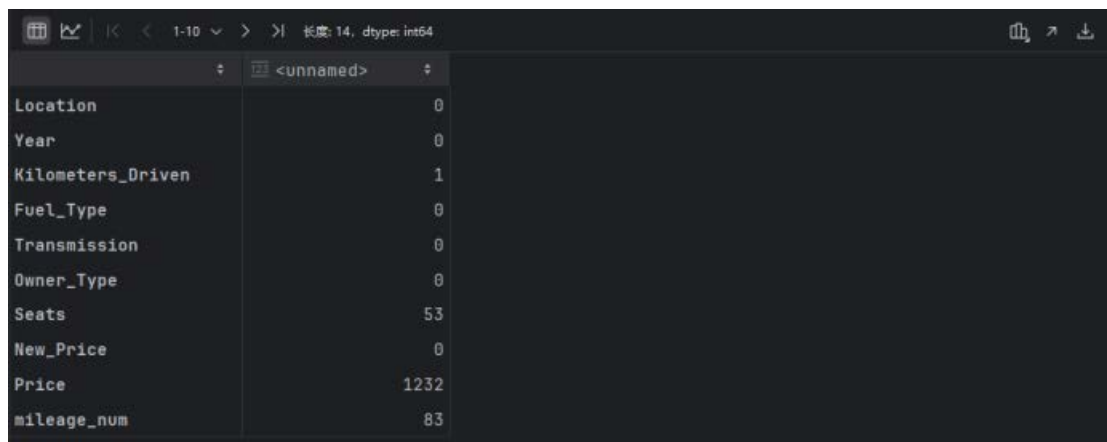


5. Data preprocessing

To handle missing values in the dataset, we first examined rows where the number of seats was unspecified. We imputed these missing values individually by taking the median number of seats for each specific car model, grouped by Brand and Model. For example, we determined that the Maruti Estilo can accommodate 5 people based on this method.

We applied a similar approach to fill missing values in other columns, including Kilometers_Driven, mileage_num, engine_num, and power_num. However, some missing values still remained in mileage_num and power_num, which we addressed by taking the median values grouped by Brand alone.

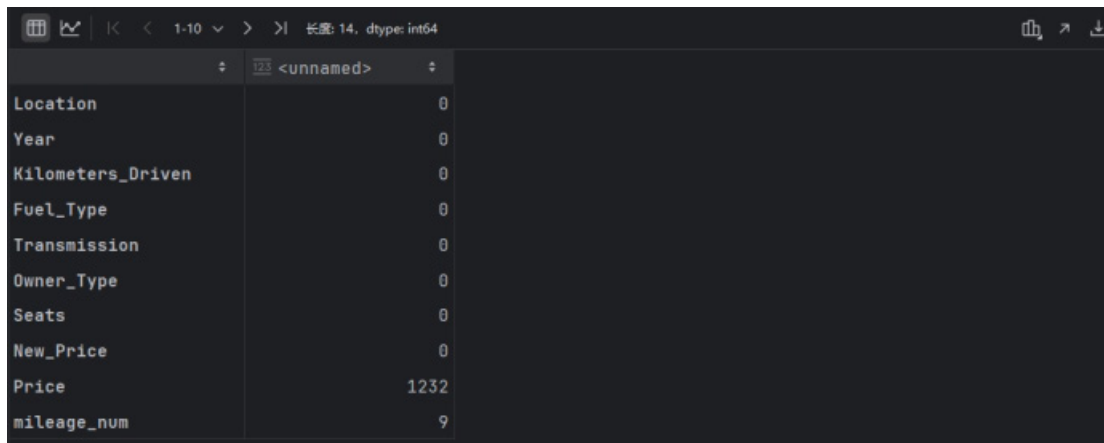
Throughout this process, we ensured that we only worked with data points where the price was not missing, maintaining the integrity of our analysis.



	Location	Year	Kilometers_Driven	Fuel_Type	Transmission	Owner_Type
194	Ahmedabad	2007	60006.0	Petrol	Manual	First
208	Kolkata	2010	42001.0	Petrol	Manual	First
229	Bangalore	2015	70436.0	Diesel	Manual	First
733	Chennai	2006	97800.0	Petrol	Manual	Third
749	Mumbai	2008	55001.0	Diesel	Automatic	Second
1294	Delhi	2009	55005.0	Petrol	Manual	First
1327	Hyderabad	2015	50295.0	Petrol	Manual	First
1385	Pune	2004	115000.0	Petrol	Manual	Second
1460	Coimbatore	2008	69078.0	Petrol	Manual	First
1917	Jaipur	2005	88000.0	Petrol	Manual	Second

	Brand	Model	Seats
0	ambassador	classic	5.0
1	audi	a3	5.0
2	audi	a4	5.0
3	audi	a6	5.0
4	audi	a7	5.0
5	audi	a8	5.0
6	audi	q3	5.0
7	audi	q5	5.0
8	audi	q7	7.0
9	audi	rs5	4.0

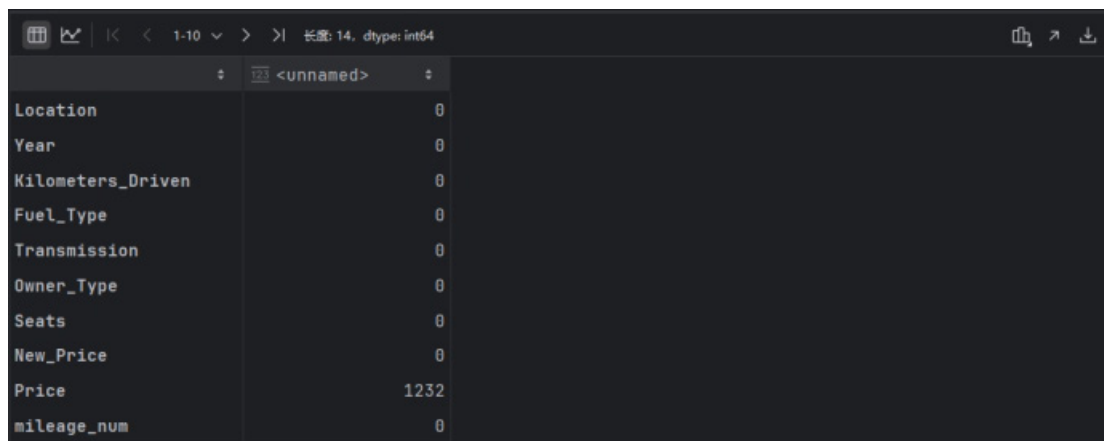
	Location	Year	Kilometers_Driven	Fuel_Type	Transmission	Owner_Type
194	Ahmedabad	2007	60006.0	Petrol	Manual	First
208	Kolkata	2010	42001.0	Petrol	Manual	First
229	Bangalore	2015	70436.0	Diesel	Manual	First
733	Chennai	2006	97800.0	Petrol	Manual	Third
749	Mumbai	2008	55001.0	Diesel	Automatic	Second
1294	Delhi	2009	55005.0	Petrol	Manual	First
1327	Hyderabad	2015	50295.0	Petrol	Manual	First
1385	Pune	2004	115000.0	Petrol	Manual	Second
1460	Coimbatore	2008	69078.0	Petrol	Manual	First
1917	Jaipur	2005	88000.0	Petrol	Manual	Second



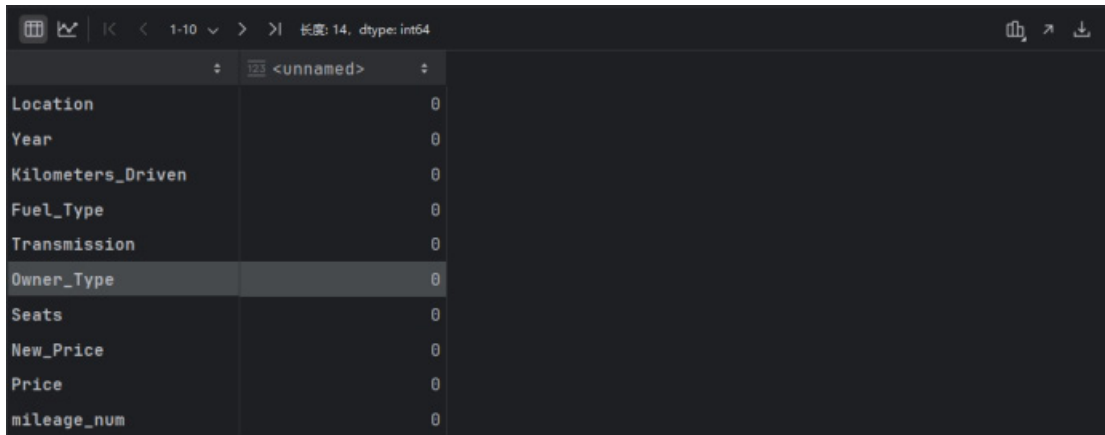
	123 <unnamed>
Location	0
Year	0
Kilometers_Driven	0
Fuel_Type	0
Transmission	0
Owner_Type	0
Seats	0
New_Price	0
Price	1232
mileage_num	9



	123 <unnamed>
Location	0
Year	0
Kilometers_Driven	0
Fuel_Type	0
Transmission	0
Owner_Type	0
Seats	0
New_Price	0
Price	1232
mileage_num	1



	123 <unnamed>
Location	0
Year	0
Kilometers_Driven	0
Fuel_Type	0
Transmission	0
Owner_Type	0
Seats	0
New_Price	0
Price	1232
mileage_num	0



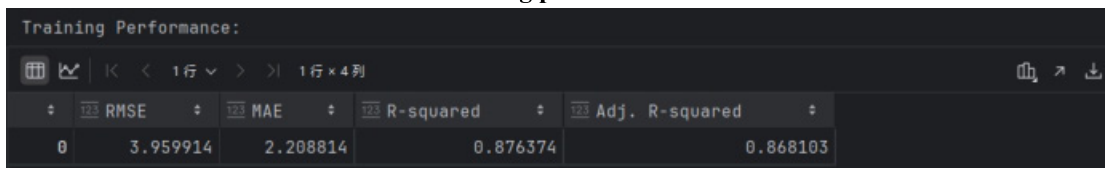
	0
Location	0
Year	0
Kilometers_Driven	0
Fuel_Type	0
Transmission	0
Owner_Type	0
Seats	0
New_Price	0
Price	0
mileage_num	0

6. Modelling and results

for Model

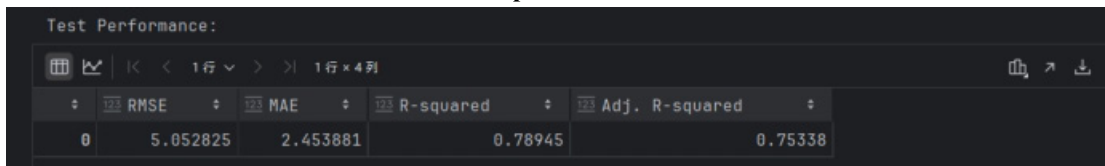
(1) Model Building - Linear Regression with all variables

Training performance



	RMSE	MAE	R-squared	Adj. R-squared
0	3.959914	2.208814	0.876374	0.868103

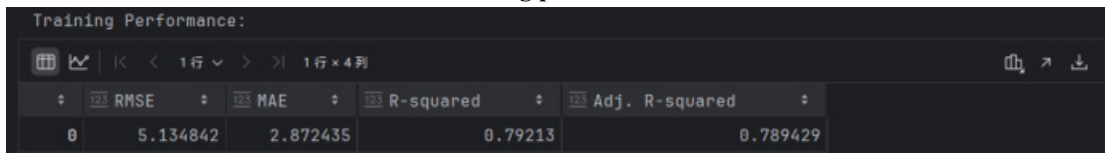
Test performance



	RMSE	MAE	R-squared	Adj. R-squared
0	5.052825	2.453881	0.78945	0.75338

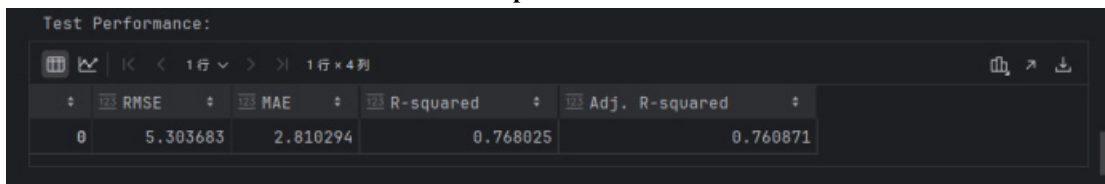
(2) Model Building - Linear Regression without dummy variables for Model

Training performance



	RMSE	MAE	R-squared	Adj. R-squared
0	5.134842	2.872435	0.79213	0.789429

Test performance



	RMSE	MAE	R-squared	Adj. R-squared
0	5.303683	2.810294	0.768025	0.760871

(3) Model Performance Comparison

Training performance comparison

Training performance comparison:			
	Linear Regression (all variables)	Linear Regression (without dummy ...	
RMSE	3.959914	5.134842	
MAE	2.208814	2.872435	
R-squared	0.876374	0.792130	
Adj. R-squared	0.868103	0.789429	

Test performance comparison

Test performance comparison:			
	Linear Regression (all variables)	Linear Regression (without dummy ...	
RMSE	5.052825	5.303683	
MAE	2.453881	2.810294	
R-squared	0.789450	0.768025	
Adj. R-squared	0.753380	0.760871	

So, I will recommend the model with all variables as our final model.

7. Conclusion and Discussion

Our linear regression model demonstrates strong predictive performance, accounting for about 83% of the variability in used car prices. The model's Mean Absolute Error (MAE) of approximately 2.38 lakhs on test data suggests that predictions are generally within this margin of error. Key factors influencing prices include the manufacturing year, seating capacity, and engine power, which positively correlate with higher prices, while higher mileage and larger engine displacement tend to reduce a car's resale value.

Geographical trends also play a role, with certain markets commanding premium prices—a valuable insight for Cars4U to consider when expanding operations. However, to fully assess profitability, additional cost-related data must be collected. Moving forward, the analysis could be refined by clustering datasets to evaluate whether location- or vehicle-specific models would further improve accuracy.

This structured approach ensures actionable business insights while highlighting areas for deeper investigation.

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