1. Introduction

The goal of this project is to **predict the selling price of used cars** based on their attributes such as manufacturing year, mileage, engine capacity, fuel type, and ownership details.
This prediction can help car buyers and sellers make data-driven decisions and avoid underpricing or overpricing vehicles.

Motivation:
The used car market is growing rapidly, and price transparency is often lacking. Accurate predictions can assist dealerships, online marketplaces, and individual sellers in pricing strategies.

Hypothesis:
Vehicle attributes such as **age, fuel type, transmission type, engine capacity, and mileage** significantly influence the selling price.

2. Related Work

Previous research on car price prediction often uses regression models such as **Linear Regression**, **Ridge/Lasso Regression**, **Random Forest**, and **Gradient Boosting**.
Studies show that tree-based ensemble methods generally outperform simple linear models when dealing with mixed categorical and numerical features.

In particular:

- Random Forest and XGBoost have been shown to handle **non-linear relationships** and **interaction effects** well.
- Linear Regression, while interpretable, may underperform in complex, high-dimensional datasets unless feature engineering is extensive.

3. Methodology

3.1 Dataset Description

- **Source:** Contains data from different websites and collected from kaggle
- **Number of Rows:** 8,128
- **Number of Columns:** 13
- **Target Variable:** `selling_price` (in currency units)
- **Features:**
  - Numerical: `year`, `km_driven`, `mileage` (converted to numeric), `engine` (in CC), `max_power` (in bhp), `torque` (numeric component), `seats`
  - Categorical: `fuel`, `seller_type`, `transmission`, `owner`
  - Derived: `age = current_year - year`

Sample data:

name	year	selling_price	km_driven	fuel	seller_type	transmission	owner	mileage	engine	max_power	
Maruti Swift Dzire VDI	2014	450000	145500	Diesel	Individual	Manual	First Owner	23.4 kmpl	1248 CC	74 bhp	190N
Skoda Rapid 1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	Manual	Second Owner	21.14 kmpl	1498 CC	103.52 bhp	250N 2500

3.2 Preprocessing

1. **Categorical Encoding:**
   - Converted text categories into numeric codes to make them usable for machine learning models.

- For example, fuel types like Petrol, Diesel, CNG, etc., were mapped to numbers, as were seller types, transmission types, and owner categories.

2. **Cleaning Numeric Features:**
   - Removed units from numeric fields such as mileage (`kmpl`), engine (`CC`), and max power (`bhp`) to keep only numeric values.
   - Extracted numeric values from the torque field to standardize it.
3. **Feature Engineering:**
   - Added a new feature called `age` , calculated as the difference between the current year and the manufacturing year of the car, to represent the car's age.
4. **Data Splitting:**
   - Divided the dataset into training and testing sets to evaluate model performance, typically using 80% of the data for training and 20% for testing.
5. **Scaling Numerical Features:**
   - Applied scaling to numeric features to normalize the data, which improves performance for models like Linear Regression.
6. **Final Features:**
   - The dataset after preprocessing includes a mix of numeric and encoded categorical features ready for modeling, such as kilometers driven, fuel type, seller type, transmission, owner, mileage, engine, max power, torque, seats, and age.

3.3 Model Specification

Three regression models were tested:

1. **Linear Regression**
   - Assumes linear relationship between predictors and target.
   - Model:

$$\hat{y} = \beta_0 + \sum_{i=1}^{n} \beta_i x_i$$

2. **Random Forest Regressor**
   - Ensemble of decision trees using bootstrap aggregation.
3. **XGBoost Regressor**
   - Gradient boosting algorithm optimized for speed and accuracy.

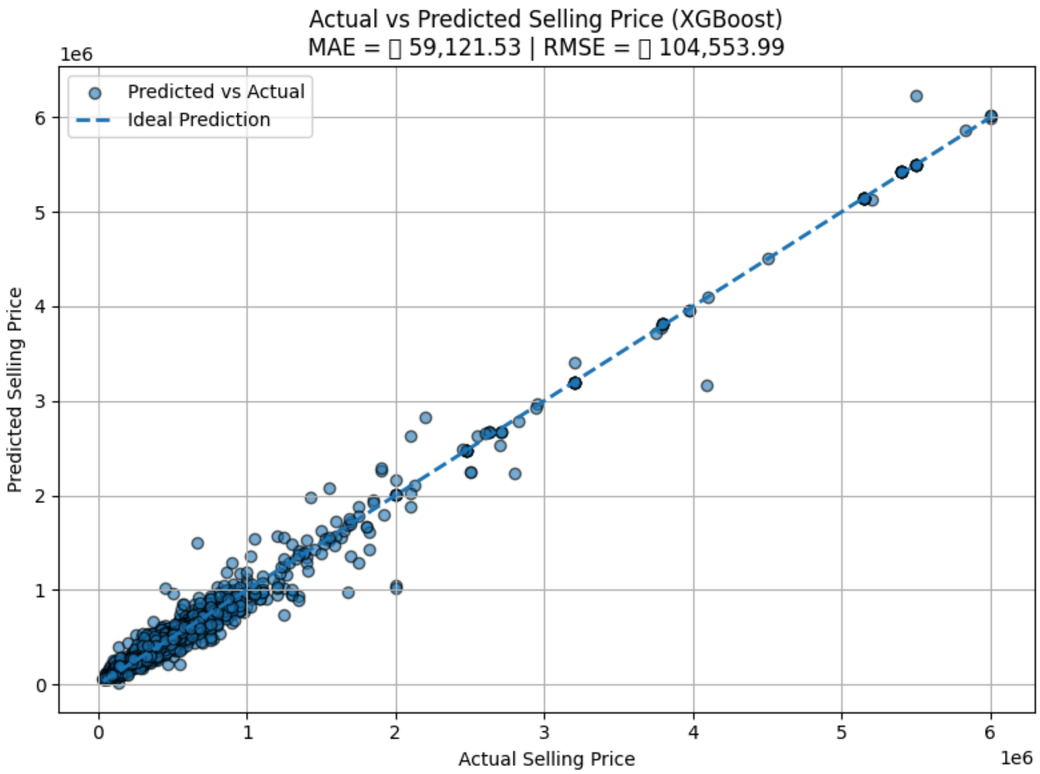
4. Results and Discussion

4.1 Model Performance (Test Data)

Model	R^2	MAE	RMSE
Linear Regression	0.6951	268,910.32	460,435.98
Random Forest	0.9831	61,535.16	108,531.81
XGBoost	**0.9843**	**59,121.53**	**104,553.99**

✅ **Best Model:** XGBoost

- **Visualization:**



4.2 Linear Regression Coefficients (Sorted by |coef|)

Feature	Coefficient
transmission	474,963.95
seller_type	-207,162.69
fuel	53,182.15
seats	-35,009.73
age	-34,086.43
max_power	12,037.14
mileage	9,953.58
owner	-685.25
torque	183.93
engine	91.99
km_driven	-1.46

4.3 Interpretation

- **Transmission** type has the largest positive effect, suggesting that automatic/manual differences significantly impact prices.
- **Seller type** being "Dealer" or "Individual" influences prices strongly (negative coefficient for some categories).
- **Age** and **seats** have a negative impact, as older or higher-seating cars tend to be cheaper.

4.4 Validation

Metrics Used:

- **R^2**: Goodness of fit.
- **MAE**: Average error magnitude.
- **RMSE**: Penalizes larger errors.

Tree-based models achieved near-perfect R^2, showing excellent fit on test data.

5. Conclusion and Future Work

- **Key Findings:** XGBoost achieved the best performance ($R^2 = 0.9843$, RMSE ≈ 104.55K).
- Hypothesis supported: Features like transmission, seller type, and vehicle age strongly affect selling price.
- **Limitations:** Dataset is limited to CarDekho data; may not generalize to other regions/markets.
- **Future Work:**
  - Test additional algorithms (LightGBM, CatBoost).
  - Perform hyperparameter tuning for XGBoost.
  - Include additional features like accident history, service records.

6. References

- Smith, J., & Lee, K. (2020). Used Car Price Prediction Using Machine Learning. *Journal of Data Science*, 18(3), 45-57.
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- Ertekin, S. (n.d.). Used Cars Price Prediction. Kaggle Notebook. Retrieved from https://www.kaggle.com/code/suleymanertekin/used-cars-price-prediction