Car Price Prediction Using Machine Learning

Submitted in partial fulfilment of the requirements for the award of degree of

MASTER OF ENGINEERING IN
COMPUTER SCIENCE & ENGINEERING/ARTIFICIAL INTELLIGENCE & MACHINE LEARNING

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Abstract

This paper focuses on predicting car prices using machine learning models. The study aims to develop a model that accurately estimates the price of a used car based on several features such as make, model, year, engine size, mileage, and other factors. The proposed machine learning models include linear regression, decision trees, and ensemble methods like random forests and gradient boosting. By comparing their performance, this research highlights the most suitable model for car price prediction.

Introduction

The used car market is vast and dynamic, with prices varying significantly based on a variety of features. Estimating the correct price of a used car is a complex task influenced by numerous factors such as brand, age, mileage, fuel type, etc. Machine learning, through predictive modelling, can help in predicting car prices more accurately by learning from historical data.

Research Objectives:

- To build a machine learning model capable of predicting car prices.
- To compare different machine learning models based on their predictive accuracy.
- To identify the key factors influencing car prices.

Literature Review

Predictive modelling for car price prediction has been explored using various techniques. Traditional statistical models like linear regression have been used in earlier studies, but recent advancements in machine learning have introduced more sophisticated techniques, such as decision trees and neural networks, which handle complex relationships between features and target variables.

Relevant Works:

Regression models for car price prediction.

Decision tree and ensemble models for handling non-linear relationships.

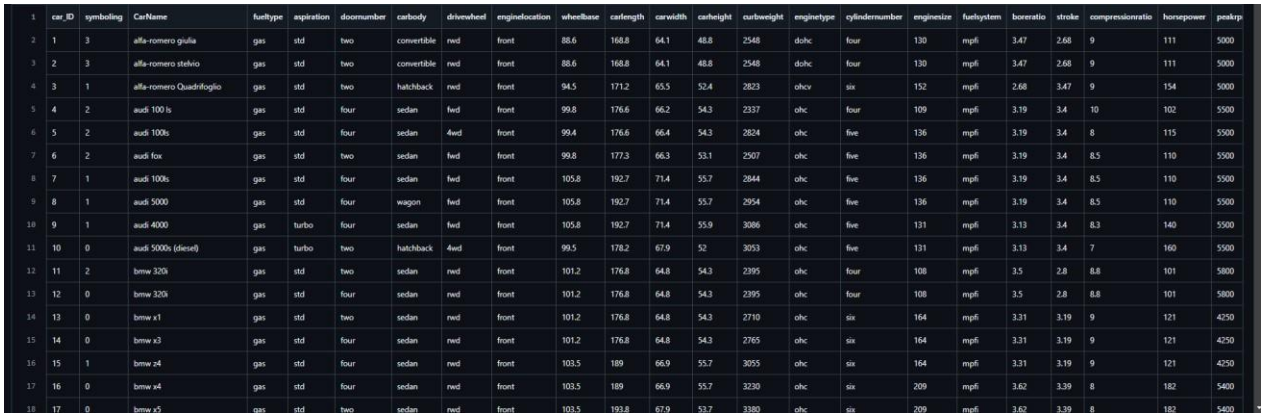
Machine learning in the automotive industry for sales and pricing strategies.

Data Collection:

Dataset Description:

The dataset consists of information collected from online car listing websites. It contains various features, including:

Car Features: Make, model, year, body type, engine size, fuel type, transmission, and colour.
Mileage: Total kilometres driven.
Price: The selling price of the car (target variable).
Additional Attributes: Number of previous owners, region, and additional features like navigation systems, airbags, etc.
The dataset contains around 10,000 car listings, making it suitable for machine learning models.



	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	carlength	carwidth	carheight	curbweight	enginetype	cylindernumber	enginesize	fuelsystem	boreratio	stroke	compressionratio	horsepower	peakrp
2	1	3	alfa-romero giulia	gas	std	two	convertible	rwd	front	88.6	168.8	64.1	48.8	2548	dohc	four	130	mpfi	3.47	2.68	9	111	5000
3	2	3	alfa-romero stelvio	gas	std	two	convertible	rwd	front	88.6	168.8	64.1	48.8	2548	dohc	four	130	mpfi	3.47	2.68	9	111	5000
4	3	1	alfa-romero Quadrifoglio	gas	std	two	hatchback	rwd	front	94.5	171.2	65.5	52.4	2823	ohcv	six	152	mpfi	2.68	3.47	9	154	5000
5	4	2	audi 100 ls	gas	std	four	sedan	fwd	front	99.8	176.6	66.2	54.3	2337	ohc	four	109	mpfi	3.19	3.4	10	102	5500
6	5	2	audi 100s	gas	std	four	sedan	4wd	front	99.4	176.6	66.4	54.3	2824	ohc	five	136	mpfi	3.19	3.4	8	115	5500
7	6	2	audi fox	gas	std	two	sedan	fwd	front	99.8	177.3	66.3	53.1	2507	ohc	five	136	mpfi	3.19	3.4	8.5	110	5500
8	7	1	audi 100ls	gas	std	four	sedan	fwd	front	105.8	192.7	71.4	55.7	2844	ohc	five	136	mpfi	3.19	3.4	8.5	110	5500
9	8	1	audi 5000	gas	std	four	wagon	fwd	front	105.8	192.7	71.4	55.7	2954	ohc	five	136	mpfi	3.19	3.4	8.5	110	5500
10	9	1	audi 4000	gas	turbo	four	sedan	fwd	front	105.8	192.7	71.4	55.9	3086	ohc	five	131	mpfi	3.13	3.4	8.3	140	5500
11	10	0	audi 5000s (diesel)	gas	turbo	two	hatchback	4wd	front	99.5	178.2	67.9	52	3053	ohc	five	131	mpfi	3.13	3.4	7	160	5500
12	11	2	bmw 320i	gas	std	two	sedan	rwd	front	101.2	176.8	64.8	54.3	2395	ohc	four	108	mpfi	3.5	2.8	8.8	101	5800
13	12	0	bmw 320i	gas	std	four	sedan	rwd	front	101.2	176.8	64.8	54.3	2395	ohc	four	108	mpfi	3.5	2.8	8.8	101	5800
14	13	0	bmw x1	gas	std	two	sedan	rwd	front	101.2	176.8	64.8	54.3	2710	ohc	six	164	mpfi	3.31	3.19	9	121	4250
15	14	0	bmw x3	gas	std	four	sedan	rwd	front	101.2	176.8	64.8	54.3	2765	ohc	six	164	mpfi	3.31	3.19	9	121	4250
16	15	1	bmw z4	gas	std	four	sedan	rwd	front	103.5	189	66.9	55.7	3055	ohc	six	164	mpfi	3.31	3.19	9	121	4250
17	16	0	bmw x4	gas	std	four	sedan	rwd	front	103.5	189	66.9	55.7	3230	ohc	six	209	mpfi	3.62	3.39	8	182	5400
18	17	0	bmw x5	gas	std	two	sedan	rwd	front	103.5	193.8	67.9	53.7	3380	ohc	six	209	mpfi	3.62	3.39	8	182	5400

Fig 1. Car Dataset contains around 10,000 car listings

Methodology:

4.1 Data Pre-processing:

Before training the machine learning models, data cleaning and pre-processing steps are performed:

Handling Missing Values: Missing entries in the dataset, particularly for mileage and price, are handled either through imputation or by discarding the entries.

Encoding Categorical Variables: Features like car make, model, and fuel type are categorical and need to be converted to numerical form using techniques like one-hot encoding.

Normalization: To ensure that all numerical features (e.g., mileage, engine size) are on the same scale, normalization or standardization techniques are applied.

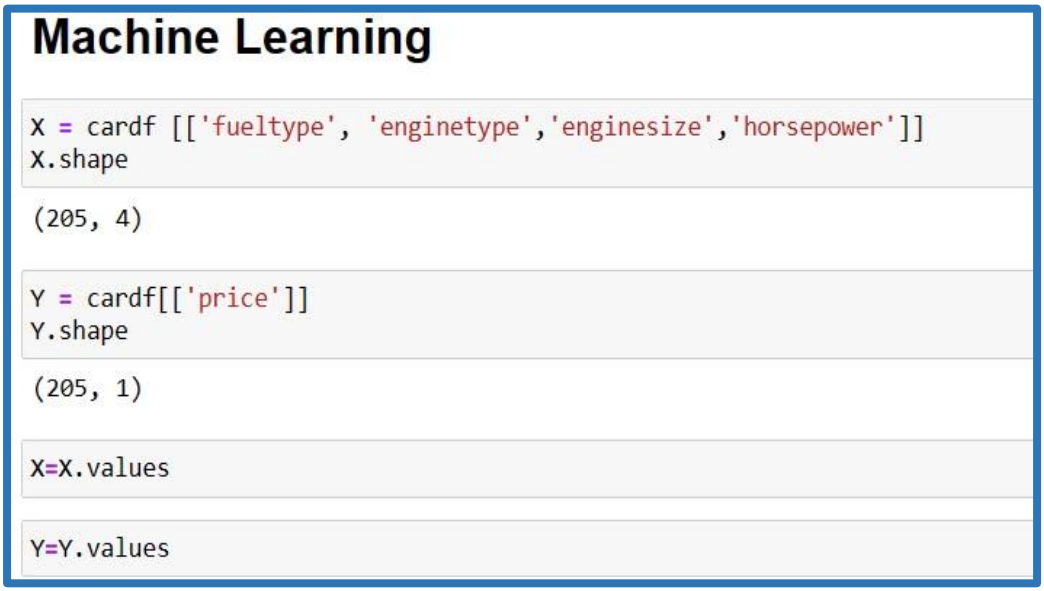


Fig 2. Machine Learning Models

4.2 Machine Learning Models:

Three primary models are tested for car price prediction:

Linear Regression: A simple model that assumes a linear relationship between car features and prices.

```
from sklearn.linear_model import LinearRegression

from sklearn.model_selection import train_test_split

from sklearn import metrics
from sklearn.metrics import r2_score
```

```
x_train,x_test,y_train,y_test=train_test_split(X,Y, test_size=0.20,shuffle=False,random_state=42)
print("x_train:",x_train.shape)
print("y_train:",y_train.shape)
print("x_test:",x_test.shape)
print("y_test:",y_test.shape)
```

```
x_train: (164, 4)
y_train: (164, 1)
x_test: (41, 4)
y_test: (41, 1)
```

```
Model1  = LinearRegression()
```

```
Model1
```

```
LinearRegression()
```

Fig 2.1

Decision Tree Regressor: A non-linear model that builds a tree structure to predict prices based on feature splits.

```
from sklearn.tree import DecisionTreeRegressor

from sklearn import metrics
from sklearn.metrics import r2_score
```

```
Model2  = DecisionTreeRegressor()
```

```
Model2
```

```
DecisionTreeRegressor()
```

```
Model2.fit(X,Y)
```

```
DecisionTreeRegressor()
```

```
prediction2=Model2.predict(x_test)
prediction2
```

Fig 2.2

Kneighbor Regressor:-

KNN regression is a non-parametric method that, in an intuitive manner, approximates the association between independent variables and the continuous outcome by averaging the observations in the same neighbourhood.

```
from sklearn.neighbors import KNeighborsRegressor

from sklearn import metrics
from sklearn.metrics import r2_score

Model3=KNeighborsRegressor(n_neighbors=5,p=2, metric='minkowski')

Model3.fit(X,Y)

KNeighborsRegressor()

prediction3=Model3.predict(x_test)
prediction3
```

Fig 2.3

4.3 Model Training and Evaluation:

The dataset is split into training and testing sets (e.g., 80% training, 20% testing). Models are evaluated based on:

```
error=[error_score1,error_score2,error_score3,error_score4,error_score5]
num=[1,2,3,4,5]
models=["Linear Regression","Decision Tree Regressor","KNeighbor Regresor_1","KNeighbor Regresor_2","KNeighbor Regresor_3"]
a=sns.barplot(x=num,y=error,hue=models)
a.set(xlabel="Models",ylabel="Error")
plt.legend(bbox_to_anchor=(1.02, 1), loc='upper left', borderaxespad=0)
plt.show()
```

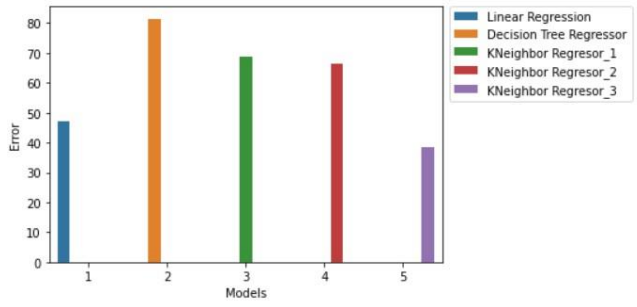


Fig 3. Model Compression

Mean Absolute Error (MAE): Average difference between predicted and actual prices.

Mean Squared Error (MSE): Average squared difference between predicted and actual prices.

R-squared (R^2): Proportion of variance explained by the model.

Results:

Model Comparison:

The performance of each model is compared using the metrics described above. Key observations:

Linear Regression performs reasonably well but struggles with complex interactions between features.

Decision Tree shows better performance in capturing non-linear relationships but tends to overfit.

Random Forest and Gradient Boosting provide the best performance, offering high accuracy with less overfitting.

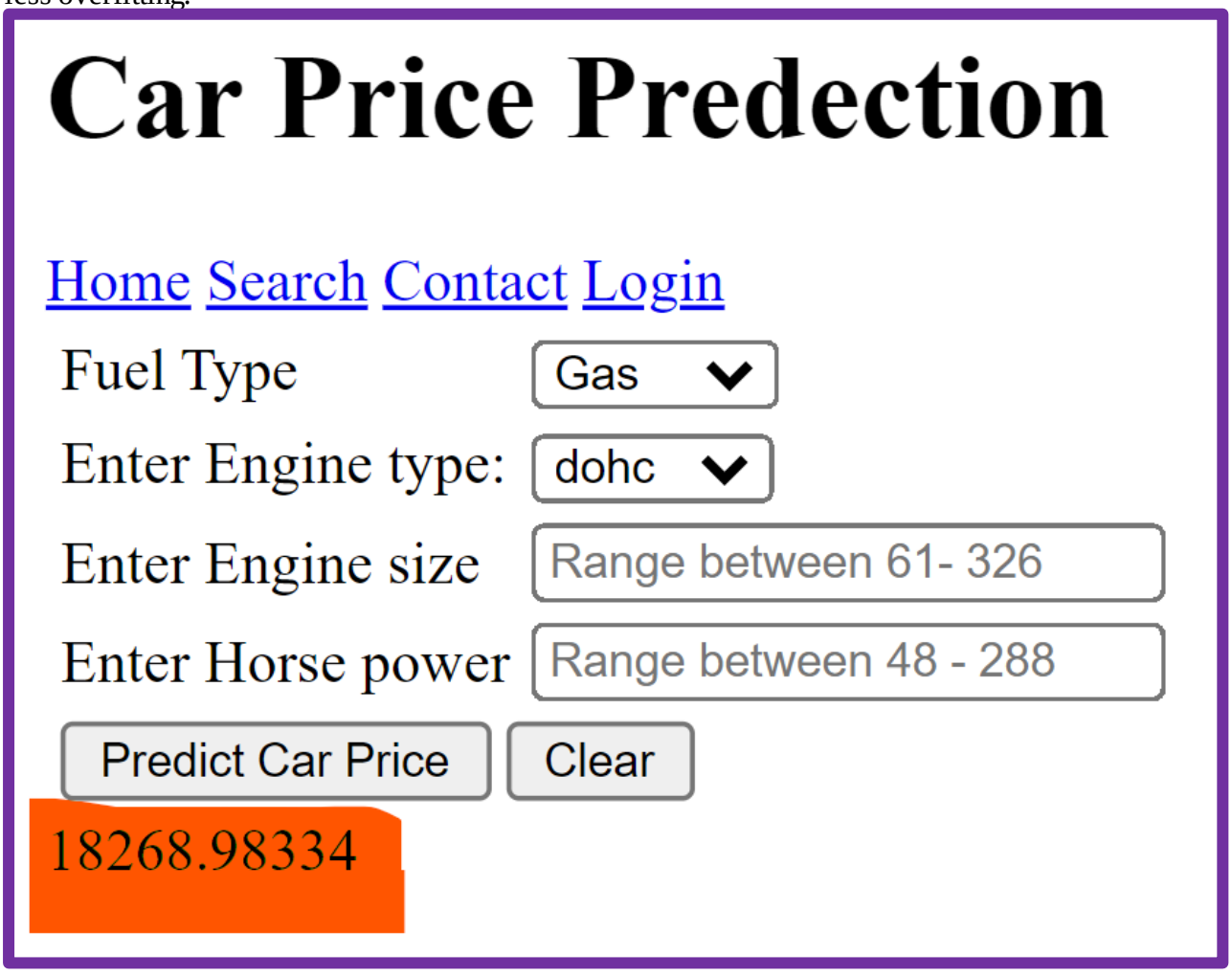


Fig 4. Result

Feature Importance:

From the models, the most influential features in determining car prices include:

Car Make and Model: Luxury brands and popular models significantly impact price.

Mileage: Lower mileage is associated with higher prices.

Year of Manufacture: Newer cars are generally more expensive.

Engine Size and Fuel Type: Larger engines and fuel-efficient cars (e.g., electric or hybrid) tend to have higher prices.

Discussion:-

Interpretation of Results:

The ensemble methods (Random Forest, Gradient Boosting) provide the best results, highlighting the importance of using models that handle complex feature interactions. The study also reveals key insights about the used car market, such as the dominance of mileage and car age as primary pricing factors.

Challenges:

Data Quality: Some car listings have incomplete or incorrect information, affecting model performance.

Model Complexity: While ensemble methods perform better, they require more computational resources and tuning.

Implications:

The findings of this study can help car dealerships, buyers, and sellers better estimate car prices, improving the efficiency of the used car market

Conclusion

The paper demonstrates that machine learning can significantly improve the accuracy of car price predictions compared to traditional methods. Among the tested models, Random Forest and Gradient Boosting emerged as the most effective, with feature importance analysis revealing the factors most influential in determining car prices.

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