

# PREDICT CAR PRICES

A Machine Learning Approach to Car Price Prediction  
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# Introduction

## ▣ Problem Statement:

Traditional Car Pricing: Many traditional methods fail to account for the complex interaction of variables like engine size, vehicle dimensions, fuel efficiency, etc. Need for Accurate Pricing: Proper car price prediction is crucial for manufacturers, dealerships, and consumers to make informed decisions.

## Objective:

Develop a predictive model for car prices using a comprehensive dataset. Predict car prices based on features such as engine size, horsepower, fuel efficiency, and more.

# Dataset Overview

## ▣ Dataset Details:

Total Number of Features: 10Sample

Features : Engine Size (Numeric)Horsepower (Numeric)Year of Manufacture (Categorical)Car Make (Categorical)Fuel Efficiency (Numeric - MPG)

Dataset Source: Google Drive CSV file Link:

<https://drive.google.com/file/d/1JT-pWgT4iIThbC8DqGzSJ2Wv0wfpO0WW/view?usp=drivesdk>

# Data Preprocessing

## ▣ Steps Performed:

Missing Data Handling: Replaced missing values with the average value for features like horsepower and fuel efficiency. Categorical Encoding: Converted categorical features (e.g., car make, model) into numerical values using one-hot encoding. Data Normalization: Applied log transformation to the 'Price' variable to reduce skewness and improve model performance. Why Preprocessing is Important: Ensures that data is clean and machine-learning models can interpret it effectively.

# Feature Engineering

- ▣ Engineered Features:

Car Age: 2023 minus the year of manufacture. Fuel Efficiency Group: Grouped cars based on their MPG (High, Medium, Low). Power-to-Weight Ratio: Created a new feature that represents the vehicle's performance by dividing horsepower by the car's weight. Purpose: Improve prediction accuracy by adding more meaningful features to the model.

# Machine Learning Model

## ▣ Model Selection:

Ridge Regression was chosen to handle multicollinearity and to prevent overfitting.

Training Process:

Dataset Split:

Training Set: 60%

Validation Set: 20%

Test Set: 20%

Why Ridge Regression:

Penalizes large coefficients, handles numeric and categorical features, and helps generalize well on unseen data.

# Model Performance

▣ Evaluation Metric:

RMSE (Root Mean Squared Error)

Training RMSE: 0.45

Validation RMSE: 0.55

Graph: Show a line graph comparing Predicted vs Actual Prices for the validation set.

# code

- ▣ [https://colab.research.google.com/drive/1o62rSUC\\_E6VA1TGc5vYEuKp1sNLrqhAC?usp=sharing](https://colab.research.google.com/drive/1o62rSUC_E6VA1TGc5vYEuKp1sNLrqhAC?usp=sharing)



# Multiple Model Evaluation

- ▣ Models Used:
  - ▣ - Ridge Regression (original)
  - ▣ - Linear Regression
  - ▣ - Random Forest Regressor
- ▣ Data Split: Training: 60% , Validation: 20% , Test: 20%
- ▣ Evaluation Metric: Root Mean Squared Error (RMSE)
- ▣ Why Multiple Models:
  - ▣ - To compare performance and choose the most accurate model.

# Actual vs Predicted Price (Validation Set)

- ▣ Visualization:
  - ▣ - Scatter plots comparing actual vs predicted prices.
  - ▣ - Diagonal line shows perfect prediction.
- ▣ Insight:
  - ▣ - Random Forest shows better fit with less scatter.
  - ▣ - Linear and Ridge Regression models show more variance.

# Model Accuracy (RMSE Comparison)

- ▣ RMSE Results:
  - ▣ - Ridge Regression:  $\sim 0.51$
  - ▣ - Linear Regression:  $\sim 0.51$
  - ▣ - Random Forest:  $\sim 0.13$
- ▣ Insight:
  - ▣ - Lower RMSE means better performance.
  - ▣ - Random Forest performed best for this dataset.

# Results & Insights

## ▣ Key Findings:

Engine Size and Car Age have a significant impact on price predictions. The model performs well with an RMSE of 0.55, indicating accurate predictions.

## Applications:

For Dealerships: Optimizes pricing strategies based on vehicle specifications.

For Consumers: Provides insights on market prices for various car models and types.

# Challenges

- ▣ Challenges Faced:

Data Availability: Some features had missing values, which required careful handling.

Feature Selection: Balancing between including enough features for accuracy and avoiding overfitting.

Interpreting Results: Ensuring that the model's output is understandable for non-technical stakeholders.

# Conclusion

- ▣ Summary:

Developed an accurate predictive model for car prices using a robust dataset. The model can inform decisions for car manufacturers, dealerships, and consumers. Final Thoughts: Future improvements and additional data can make the model even more accurate and useful for various sectors of the automotive industry.

Thankyou