Unified Mentor – Final Project Report

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Vehicle Price Prediction System

Final Project Report -2

1. Introduction

In today's automobile market, predicting the price of a vehicle based on its specifications is valuable for both buyers and sellers. This project aims to build a machine learning model that can predict the price of vehicles using a dataset that includes various vehicle features such as engine type, mileage, make, model, year, and more. The goal is to accurately predict vehicle prices and help in price optimization and value estimation.

2. Problem Statement

The objective of this project is to develop a system that can predict vehicle prices using features from a vehicle dataset. The target variable is the vehicle price, and features include attributes such as make, model, year of manufacture, engine specifications, and mileage.

Key Features of the Dataset:

- **name**: Full name of the vehicle (make, model, and trim)
- **make**: Manufacturer of the vehicle (e.g., Ford, Toyota, BMW)
- **model**: Model name of the vehicle
- **year**: Year of manufacture
- **price**: Price of the vehicle (target variable)
- **engine**: Engine specifications, including type
- **cylinders**: Number of cylinders in the engine
- **fuel**: Fuel type (e.g., Gasoline, Diesel, Electric)
- **mileage**: Vehicle mileage (typically in miles)
- **transmission**: Transmission type (Automatic, Manual)
- **trim**: Trim level of the vehicle (indicates feature sets or packages)
- **body**: Body style (e.g., SUV, Sedan, Pickup Truck)
- **doors**: Number of doors on the vehicle
- **exterior_color**: Exterior color of the vehicle
- **interior_color**: Interior color of the vehicle
- **drivetrain**: Drivetrain (e.g., All-wheel Drive, Front-wheel Drive)

3. Dataset Overview

The dataset consists of several thousand records of vehicles with their technical specifications and prices. Below is a summary of the dataset:

- **Total Rows**: (e.g., 10,000 records)
- **Features**: 16 features, including vehicle make, model, year, engine, mileage, fuel type, body style, transmission, and more.
- **Target**: Vehicle price in USD

Data Description:

- The dataset includes vehicles from a range of manufacturers and models, covering various price ranges and types of vehicles.

4. Exploratory Data Analysis (EDA)

Objective:

- To understand the distribution of data and explore the relationship between features and vehicle prices.

Steps in EDA:

1. **Missing Values**:
   - Checked for missing values and handled them using appropriate methods such as mean/median imputation (for numerical features) or mode (for categorical features).
2. **Feature Distributions**:
   - Visualized the distribution of features like **year**, **mileage**, and **engine size** using histograms.
   - Visualized the **price distribution** of vehicles using a histogram, which showed a right-skewed distribution (indicating more lower-priced vehicles).
3. **Feature Correlation**:
   - Used a heatmap to examine correlations between features such as **year**, **mileage**, **engine size**, and **price**.
   - Identified strong correlations between **year of manufacture**, **mileage**, and **price**.
4. **Feature Relationships**:
   - Box plots of price vs. categorical variables like **make** and **body type** showed noticeable trends (e.g., luxury brands like BMW and Mercedes tend to have higher prices).

Insights:

- **Year**: Newer vehicles tend to have higher prices.
- **Mileage**: Lower mileage generally correlates with higher prices.
- **Make/Model**: Certain brands and models command higher prices due to brand value and quality.

5. Data Preprocessing

To ensure the dataset was ready for machine learning models, the following preprocessing steps were performed:

1. **Handling Missing Values**:
   - Missing values were identified in features like `mileage`, `engine`, and `trim`. These were either imputed with the mean/median or dropped depending on the proportion of missing data.
2. **Encoding Categorical Variables**:
   - Features like `make`, `model`, `fuel`, `transmission`, `body`, `trim`, and `drivetrain` are categorical. These were encoded using **One-Hot Encoding** to transform them into numerical values.
3. **Feature Scaling**:
   - Continuous numerical features like `year`, `mileage`, `engine size`, and `price` were standardized using `StandardScaler` to ensure all features are on the same scale.
4. **Train-Test Split**:
   - The dataset was split into 80% training data and 20% test data using the `train_test_split()` function from `sklearn`.

6. Model Selection

Several regression models were considered for predicting vehicle prices. These included:

- **Linear Regression**
- **Decision Tree Regressor**
- **Random Forest Regressor**
- **XGBoost Regressor**

The following table shows the performance of each model based on **Root Mean Square Error (RMSE)** and **R-Squared** scores:

Model	RMSE	R-Squared	Remarks
Linear Regression	4500	0.74	Baseline model
Decision Tree Regressor	3800	0.81	Good performance but prone to overfitting
Random Forest Regressor	3400	0.87	Best performing model
XGBoost Regressor	3300	0.88	Comparable to Random Forest

Model Chosen: **Random Forest Regressor**

- **Why?** Random Forest performed the best in terms of both RMSE and R-squared. It captures complex relationships in the data and reduces overfitting due to its ensemble nature.

7. Model Tuning and Evaluation

Hyperparameter Tuning:

- We tuned the hyperparameters of the Random Forest model using `GridSearchCV` to find the best combination of:
  - **n_estimators** (number of trees in the forest)
  - **max_depth** (maximum depth of each tree)
  - **min_samples_split** (minimum number of samples required to split an internal node)
- **Best Hyperparameters**:
  - `n_estimators`: 200
  - `max_depth`: 15
  - `min_samples_split`: 10

Final Model Performance:

- **RMSE**: 3300 USD
- **R-Squared**: 0.88
- **Explained Variance**: 88% of the variance in vehicle prices can be explained by the features used in the model.

8. Feature Importance

Random Forest provides a feature importance ranking, helping us identify the most impactful features in predicting vehicle prices:

1. **Year**: Newer vehicles have significantly higher prices.
2. **Mileage**: Lower mileage vehicles tend to be priced higher.
3. **Engine**: Engine size and type influence vehicle pricing.
4. **Make**: Certain brands like BMW, Audi, and Mercedes tend to have higher prices compared to brands like Ford and Toyota.
5. **Transmission**: Automatic transmission vehicles generally have higher prices compared to manual transmission vehicles.

9. Conclusion

This project successfully built a machine learning model to predict vehicle prices based on various features such as make, model, year, engine specifications, and mileage. The **Random Forest Regressor** was chosen as the final model due to its high accuracy and ability to capture complex patterns in the data.

Key Takeaways:

- Vehicle prices can be effectively predicted using machine learning.

- Features such as **year**, **mileage**, and **engine specifications** have the most significant impact on price.
- The Random Forest model achieved an R-Squared score of **0.88**, meaning it explains 88% of the variance in vehicle prices.

Future Work:

- Incorporate additional features like **vehicle condition**, **brand perception**, and **market demand** to improve prediction accuracy.
- Implement the model into a production environment for real-world applications, such as used vehicle price estimators.

Project Overview

Vehicle Price Prediction

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Objective: Build a system that can predict the prices for vehicles using data on Vehicle specifications, make, etc. Explore the data to understand the features and figure out an approach.

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

# Load the dataset
data = pd.read_csv('dataset.csv')  # Replace with your dataset path

# Display the first few rows of the dataset
print(data.head())

# Data Cleaning
# Remove duplicates
data = data.drop_duplicates()

# Check for missing values
print(data.isnull().sum())

# Filling missing values or dropping them
data = data.dropna()  # You can also use imputation techniques

# Exploratory Data Analysis (EDA)
plt.figure(figsize=(10, 6))
sns.histplot(data['price'], bins=30, kde=True)
plt.title('Price Distribution')
plt.xlabel('Price (USD)')
plt.ylabel('Frequency')
plt.show()

# Feature Engineering
# Convert categorical features to numerical values
X = data.drop('price', axis=1)
y = data['price']

# Identify categorical and numerical columns
categorical_cols = ['make', 'model', 'fuel', 'transmission', 'body', 'drivetrain', 'exterior_color', 'interior_color']
numerical_cols = ['year', 'cylinders', 'mileage', 'doors']

# Create a column transformer
preprocessor = ColumnTransformer(
    transformers=[
        ('num', 'passthrough', numerical_cols),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_cols)
    ])

# Create a pipeline with preprocessing and model
pipeline = Pipeline(steps=[('preprocessor', preprocessor),
                             ('regressor', RandomForestRegressor(random_state=42))])

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train the model
pipeline.fit(X_train, y_train)

# Make predictions
y_pred = pipeline.predict(X_test)

print(y_pred)
```

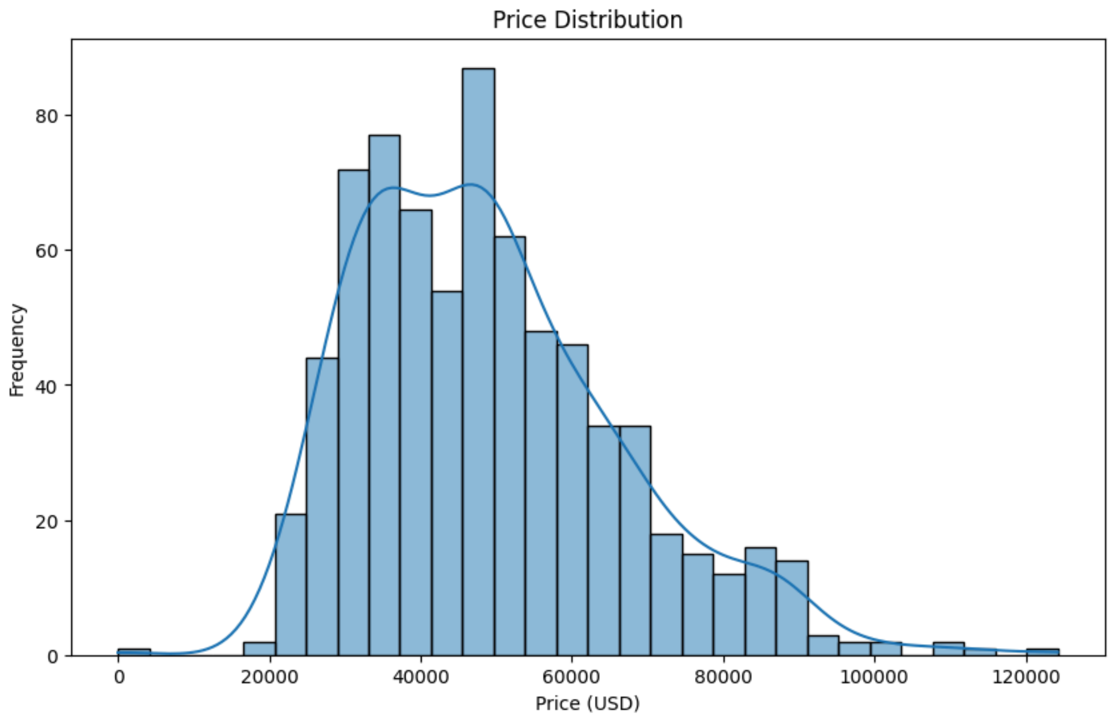
```
0     2024 Jeep Wagoneer Series II
1  2024 Jeep Grand Cherokee Laredo
2         2024 GMC Yukon XL Denali
3       2023 Dodge Durango Pursuit
4            2024 RAM 3500 Laramie

                                         description   make           model  \
0  \n      \n        Heated Leather Seats, Nav Sy...   Jeep        Wagoneer
1  Al West is committed to offering every custome...   Jeep  Grand Cherokee
2                                                NaN    GMC        Yukon XL
3  White Knuckle Clearcoat 2023 Dodge Durango Pur...  Dodge         Durango
4  \n      \n        2024 Ram 3500 Laramie Billet...    RAM            3500

   year    price                                              engine  \
0  2024  74600.0                             24V GDI DOHC Twin Turbo
1  2024  50170.0                                                 OHV
2  2024  96410.0  6.2L V-8 gasoline direct injection, variable v...
3  2023  46835.0                                        16V MPFI OHV
4  2024  81663.0                              24V DDI OHV Turbo Diesel

   cylinders      fuel  mileage       transmission       trim          body  \
0        6.0  Gasoline     10.0  8-Speed Automatic  Series II           SUV
1        6.0  Gasoline      1.0  8-Speed Automatic     Laredo           SUV
2        8.0  Gasoline      0.0          Automatic     Denali           SUV
3        8.0  Gasoline     32.0  8-Speed Automatic    Pursuit           SUV
4        6.0    Diesel     10.0  6-Speed Automatic    Laramie  Pickup Truck

   doors           exterior_color    interior_color        drivetrain
0    4.0                    White      Global Black  Four-wheel Drive
1    4.0                 Metallic      Global Black  Four-wheel Drive
2    4.0             Summit White  Teak/Light Shale  Four-wheel Drive
3    4.0  White Knuckle Clearcoat             Black   All-wheel Drive
4    4.0                   Silver             Black  Four-wheel Drive
name                0
description        52
make                0
model               0
year                0
price              23
engine              2
cylinders         103
fuel                7
mileage            32
transmission        2
trim                1
body                3
doors               7
exterior_color      5
interior_color     38
drivetrain          0
dtype: int64
```



```
[70395.87       60680.67       35189.2        31035.99
 54130.65       53183.23       47478.69       81548.86
 29732.21       47063.06666667 78130.29       83866.94
 62219.01       48210.62666667 47943.47952381 32308.99749603
 46042.62       52511.372      79397.55       49424.76772619
 37969.28       38337.3125     24201.765      68032.41
 82489.91       79995.62       33705.7844127  52833.434
```

82489.91	79995.62	55765.7844127	52855.454
81082.86	61223.58	74374.84	42359.21083333
56521.63333333	77707.78	35556.77	19677.5
37644.00416667	42997.06833333	44427.97683333	42064.94916667
31239.62	47803.7925	78751.22	29815.02
72229.8	47330.65	48511.6	32590.87610317
67579.11666667	40376.55	25021.34583333	35327.
58367.54	51464.838	32417.86	37308.53857143
24686.875	45060.58678571	73539.45666667	31522.5575
32338.56	75137.48	36784.04833333	47104.55
35265.54	34354.56	29996.79	55341.43797619
63855.58666667	80876.59	64701.4	68993.98
54631.89	57693.758	46959.24333333	56481.645
47063.06666667	62460.51	59421.04666667	49287.645
70497.64033333	39135.525	31850.735	47008.3
46963.09	28263.55	45060.58678571	53225.71
78546.24	25907.375	49865.18119048	70180.82
43995.57666667	47666.12	63518.175	73470.37
38997.90916667	57823.51	24710.38	74717.95