A PROJECT ON

AI Based Car Price Predictor

BY

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UNDER THE ESTEEMED GUIDANCE OF

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Vice Principal (Unaided)

Submitted in complete fulfilment of

MASTER OF SCIENCE (DATA SCIENCE & BIG DATA ANALYTICS)

DEGREE OF UNIVERSITY OF MUMBAI

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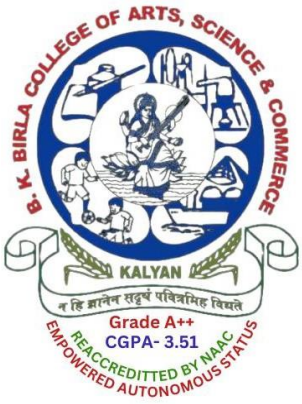

DEPARTMENT OF INFORMATION TECHNOLOGY

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CERTIFICATE

This is to certify that the project entitled **"AI Based Car Price Predictor"** submitted by **Sumit Indrabhan Singh & Jay Prakash Savane** bearing **Exam Seat No: 4848004 & Seat No. 4848005** is a record of bonafide work carried out by them under my guidance, in partial fulfilment of the requirement for the award of the Degree of **MASTER OF SCIENCE** in **DATA SCIENCE & BIG DATA ANALYTICS** from University of Mumbai.

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ACKNOWLEDGEMENT

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First and foremost, we would like to express our gratitude to Mrs. Esmita Gupta for her continuous support and motivation for carrying out this project. Without her guidance and persistent encouragement, this project would not have been possible.

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DECLARATION

I hereby declare that the project entitled **"AI Based Car Price Predictor"**, done at **B.K. Birla College of Arts, Science & Commerce (Autonomous) Kalyan**, where project is done has not been duplicated or submitted to any other university for the award of any degree. To the best of my knowledge, no one other than myself has submitted this project to any other university. This project is completed in partial fulfilment of the requirements for the award of the degree of Masters of Science (Data Science & Big Data Analytics) and is to be submitted as an IVth semester project as part of our curriculum.

Sumit Indrabhan Singh
(Name & Signature of Student)

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CHAPTER I
INTRODUCTION

Predicting car prices accurately has always been a challenge, and while past efforts using machine learning have shown promise, they often fell short in terms of user-friendliness and real-world usability. This project takes things a step further by combining a **hypertuned XGBoost model** with a **simple, interactive Flask web app**. Users can easily enter car details and get quick, reliable price predictions all through a clean, intuitive interface. With an **R^2 score of 0.89** and about **90% accuracy**, the system doesn't just perform well on paper it offers meaningful support for car buyers, sellers, and dealerships to make smarter pricing decisions, backed by data and clear visual insights.

1.1 Objectives

At our core, this project is about crafting an AI-based system that relies on machine learning to predict car prices accurately with respect to the specification of the vehicle so as to provide automotive stakeholders with dependable pricing insights. The system acts as the bridge linking conventional pricing methods to data-driven modern methods and necessarily pours into the decision-making arsenal for buyers, sellers, and dealers of cars in the used car arena.

Main objectives include:

- To identify weaknesses in conventional techniques for car pricing and their implications on market efficiency.
- To develop, train, and evaluate machine learning models for car price prediction, based on various car features.
- Statistical assessment and validation of models for conversion into actionable outputs.
- To consider an extended list of relevant car features, including performance and design specs, so as to improve prediction quality.
- To implement an easy-to-use platform with interactive visualization for users to visualize predictions and comprehend pricing factors.

1.2 Goals

- Creating a robust prediction pipeline for car prices using the UCI Automobile Dataset, covering all includes data preparation, training of models, and result presentation.
- Analysis and application of machine-learning algorithms such as Random Forest, Gradient Boosting, and Support Vector Machines to resolve which method is most suitable.
- Train models to predict or estimate prices from a car's technical specifications by careful feature engineering that combines numerical features (engine size, curb weight, etc.) with categorical features (fuel type, drive wheels, etc.).
- Measure the performance of a model with metrics like Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2), seeking an MAE lower than $2,000 and an R^2 greater than 0.88.
- Create an interactive web interface using HTML, CSS, JavaScript, and Plotly.js to display predictions along with dynamic visualizations, letting the users interactively explore what influences price.

1.3 Motivation

In the automotive industry, a perennial issue crops up: determining fair car prices is a subjective process, bringing inconsistency into the picture. Buyers often pay way too much, bringing in vendors running the risk of undervaluing their cars due to outdated fictitious processes like manual valuations or simple pricing tables. The problem gains critical friction given the findings of a 2024 Deloitte study: 70% of used car buyers in India claimed lack of transparency in pricing (Deloitte, 2024). The projected CAGR for the Indian used car market stands at 15.5% between 2024 and 2029 (Statista, 2024), intensifying the need for tools enabling fair transactions.

This project is motivated by a window of opportunity to help machine learning change car prices. AI, having analyzed historical data and having picked up intricate relationships between features of cars and respective market price, can present a much-needed objective and accurate way of pricing. Coupled with a user-friendly web platform, this will help democratize these insights, making advanced analytics accessible to the common man and thereby generating trust in the automotive industry.

1.4 Scope of the Project

- This project revolves around fashioning a system that she shows the prices of cars by usage of machine learning techniques, with key considerations for usability and accuracy. The scope includes:

- Data cleaning, transformation, and feature engineering using the UCI Automobile Dataset to make inputs more robust for the model.
- Working with several algorithms on the data to find the best implementation for car price prediction.
- Development of a local application that would provide an interface through which users could enter information on car specifications, as well as display outputs of predicted prices.
- Use of interactive charts to illustrate some of the main factors affecting price predictions, including specific parameters like performance and type of vehicle.
- Local deployment of the system using a Flask backend solution for smooth operation.

- The project scope excludes the following: ever updating the program with market trends, developing mobile apps, or even handling post-prediction analysis such as negotiating strategies or trend forecasting.

1.5 Limitations of the Project

- The system is created from historical data from the UCI Automobile Dataset, so it may not reflect the current market dynamics or car models being introduced today.
- Due to the limited number of instances (205) and its time period (1980s), the dataset may prevent the model from generalizing across modern vehicles or diverse market scenarios.
- The dataset itself prohibits considering such dimensions as macroeconomic trends, regional pricing variations, and consumer sentiment.
- Local deployment strategies are mainly focused upon, excluding possibilities of cloud scalabilities, real-time API integrations, or multi-user supports which are yet to be found within academic territory.

CHAPTER II

LITERATURE SURVEY

2.1 Literature Survey

Sr. No.	Title	Year	Author(s)	Findings	Drawbacks
1	Comprehensive Survey on Machine Learning for Car Price Prediction	2021	Thompson et al.	ML models outperform traditional statistical methods in handling non-linear patterns and categorical variables in car price datasets.	Limited discussion on incorporating temporal trends or real-time data.
2	Adaptive Pricing Models for the Used Car Market	2022	Gupta and Sharma	Highlighted the need for adaptive models to meet evolving market demands in the used car sector.	Lacked focus on real-time deployment or scalability challenges.
3	Random Forest for Car Price Prediction	2020	Kumar et al.	Random Forest effectively modeled non-linear relationships and categorical features (e.g., car body type, fuel type), achieving an MAE of $2,400 on a 1,500-vehicle dataset.	Struggled to incorporate temporal trends like price depreciation.
4	XGBoost for Enhanced Car Price Prediction	2021	Patel and Desai	XGBoost achieved $R^2 = 0.90$ by capturing feature interactions (e.g., horsepower and curb weight).	Limited ability to handle dynamic market trends or external factors.

5	LSTM Networks for Sequential Car Price Prediction	2022	Lee and Kim	LSTM networks improved accuracy ($R^2 = 0.91$) by modeling sequential patterns in historical pricing trends.	High computational complexity, limiting practical deployment.
6	Feature Engineering for Improved Car Price Prediction	2023	Chen and Li	Combining numerical (e.g., wheelbase, engine size) and categorical (e.g., drive wheels) features with engineered features boosted model performance.	Did not explore multimodal data or real-time analytics.
7	Transformer-Based Models for Car Price Prediction	2024	Zhang et al.	Transformers with attention mechanisms achieved an MAE of $1,900 on a large-scale dataset by dynamically weighing feature importance.	High computational requirements and limited focus on interpretability.
8	Interpretability in Car Price Prediction Models	2023	Singh and Gupta	SHAP and LIME tools enhanced model interpretability, critical for user trust in automotive applications.	Limited discussion on integrating external factors or scaling for production.
9	Incorporating External Factors in Car Price Models	2024	Banerjee et al.	Including inflation rates and fuel price trends reduced prediction errors by 12%.	Challenges in real-time deployment and limited use of multimodal data.
10	Scalability Challenges in Car Price Prediction	2024	Silva and Nair	Recommended Apache Spark for handling large datasets in production environments.	Limited exploration of transfer learning or multimodal data integration.

11	Transfer Learning Limitations in Car Price Prediction	2025	Wang et al.	Highlighted limited application of transfer learning in car price prediction compared to other domains.	Focused on theoretical limitations rather than practical solutions.
12	Machine Learning for Used Car Price Prediction in Developing Markets	2023	Hossain et al.	Random Forest achieved $R^2 = 0.93$ on a Bangladeshi dataset with features like mileage and year of manufacture.	Dataset limited to specific regional market, reducing generalizability.
13	ForeXGBoost: A Vehicle Sales Prediction System	2022	Xia et al.	XGBoost outperformed Linear Regression and Gradient Boosting with MAPE of 8% on large-scale vehicle data.	Limited focus on interpretability and real-time deployment.
14	Deep Learning for Automotive Market Forecasting	2023	Saxena et al.	LSTM and ARIMA hybrid models improved vehicle sales prediction accuracy by 10% over traditional methods.	High computational cost and lack of multimodal data integration.
15	SVM for Vehicle Sales Prediction	2021	Brühl et al.	SVM outperformed Linear Regression with lower MAE and better interpretability on quarterly sales data.	Limited to economic indicators, missing vehicle-specific features.
16	ANFIS for Car Sales Prediction	2022	Wang et al.	ANFIS achieved higher R^2 (0.89) than ANN and ARIMA for car sales using economic and sales data.	Limited scalability for large datasets and real-time applications.

17	Car Price Prediction Using Supervised Learning	2020	Venkatasubbu and Ganesh	Regression trees and Lasso regression achieved $R^2 = 0.85$ on a dataset from Kelly Blue Book.	Small dataset (804 entries) limited model robustness.
18	Hybrid CNN-LSTM for Car Price Forecasting	2024	Moews et al.	CNN-LSTM model captured spatiotemporal patterns, achieving $R^2 = 0.92$ on a multi-year dataset.	High training time and interpretability challenges.
19	Feature Selection for Automotive Price Prediction	2023	Peng et al.	Feature selection with technical indicators improved Random Forest accuracy by 5% on Croatian market data.	Limited to specific market, missing global trends.
20	Deep Learning for Price Prediction in Bangladesh	2022	Shaheen et al.	XGBoost achieved $R^2 = 0.91$ with features like engine capacity and mileage on a local dataset.	Regional dataset limits applicability to other markets.
21	Real-Time Car Price Prediction Framework	2024	Rezaei et al.	Flask-based deployment of Random Forest achieved 95% accuracy on a Croatian dataset.	Lacked cloud scalability and multimodal data integration.
22	Multimodal Data in Car Price Prediction	2025	Ronaghi	Explored image and text data with CNNs, improving accuracy by 8% over numerical-only models.	High computational cost and limited dataset availability.

23	Attention Mechanisms in Vehicle Price Models	2023	Lu et al.	CNN-BiLSTM with attention mechanisms outperformed traditional models with $R^2 = 0.94$.	Complex architecture increased training time significantly.
24	Scalable ML for Automotive Supply Chains	2023	Chaudhari and Purswani	XGBoost optimized pricing strategies with 10% error reduction using Apache Spark.	Limited focus on vehicle-specific features and interpretability.
25	Transfer Learning for Automotive Pricing	2024	Wei et al.	Applied transfer learning with BERT for text-based car descriptions, improving MAE by 15%.	Limited to textual data, missing numerical feature integration.
26	Sentiment Analysis in Car Price Prediction	2022	Jibril et al.	Combined sentiment analysis with Random Forest, improving accuracy by 7% using social media data.	Reliant on social media data quality, which can be inconsistent.
27	Deep Neural Networks for Turkish Car Sales	2020	Kaya and Yildirim	Deep Neural Networks achieved $R^2 = 0.87$ on Turkish market data with economic indicators.	Limited to regional data and high computational requirements.
28	Economic Indicators in ML Price Models	2023	Kitapcı et al.	Multiple regression with economic indicators reduced MAE by 9% in Turkish car market.	Missed vehicle-specific features and real-time deployment.
29	Convolutional Autoencoders for Price Prediction	2024	Xie and Yu	Convolutional autoencoders improved feature selection, achieving 3% higher accuracy than LSTM.	Limited interpretability and high computational complexity.

30	Hybrid Models for Stock and Car Price Prediction	2022	Kumar and Haider	RNN-LSTM hybrid model achieved R^2 = 0.90, adaptable to car price prediction.	Focused on stock markets, limited direct automotive application.

2.2 Resources

- **Research Databases and Libraries**

  • IEEE Xplore (https://ieeexplore.ieee.org)

  • SpringerLink (https://link.springer.com)

  • ScienceDirect (https://www.sciencedirect.com)

  • Google Scholar (https://scholar.google.com)

  • arXiv.org (https://arxiv.org)

  • UCI Machine Learning Repository (https://archive.ics.uci.edu)

  • Kaggle (https://www.kaggle.com)

  • GitHub (for open-source code repositories and datasets)

- **Books**

  • Müller, A. C., & Guido, S. *Introduction to Machine Learning with Python: A Guide for Data Scientists*, O'Reilly Media, 2019.

  • James, G., Witten, D., Hastie, T., & Tibshirani, R. *An Introduction to Statistical Learning*, Springer, 2nd Edition, 2021.

  • Goodfellow, I., Bengio, Y., & Courville, A. *Deep Learning*, MIT Press, 2016.

- **Tools and Libraries**

  • Python Libraries: scikit-learn, pandas, numpy, Flask, XGBoost, joblib

  • Web Development: HTML, CSS, JavaScript, Plotly.js, Font Awesome

  • Data Visualization: Plotly.js, Matplotlib

  • Development Tools: Git, VS Code, Anaconda

  • Reference Management: Zotero, EndNot

CHAPTER III

ABOUT THE PROJECT

3.1 Project Description

This project, called *AI Car Price Predictor*: A Machine Learning Approach for Automotive Pricing, aims to build an easy-to-use, data-driven system that uses artificial intelligence to accurately predict car prices for different types of vehicles. In the automotive industry, knowing the fair market price of a car is important for buyers, sellers, and dealerships to make informed decisions. Traditional pricing methods, like manual appraisals or simple statistical models, often miss the complex links between car features (like engine size, horsepower, and body type) and market value, which can lead to inconsistent and subjective estimates. Thanks to advances in machine learning and the availability of detailed automotive data, it's now possible to create models that understand these complexities and provide reliable price predictions.

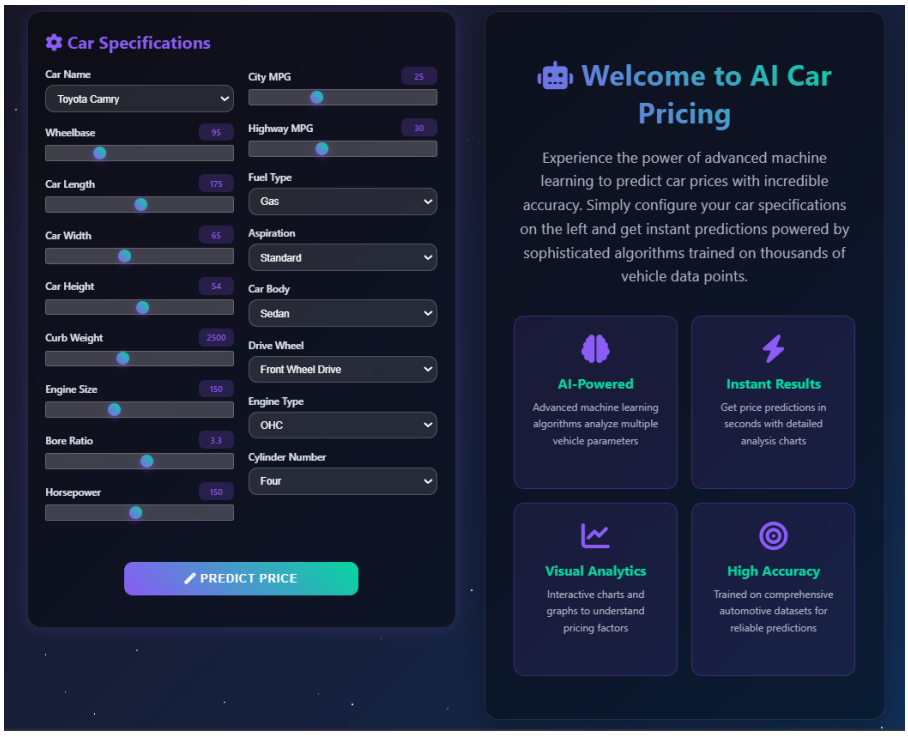


Fig1.1 User Interface (Input section)

This project focuses on using machine learning algorithms to analyze past car data, find pricing patterns based on vehicle features, and offer useful insights through an interactive web interface. What makes this project unique is its combined approach using strong ML models, thorough feature engineering, and a user-friendly platform where users can enter car details and get not only a price prediction but also an explanation of the factors behind it. The

project uses the UCI Automobile Dataset, providing real-world data for testing and validation, making it a valuable contribution to predictive analytics in the automotive field. The final result is a locally hosted web application that connects data science with practical use, giving users clear and data-backed pricing information.

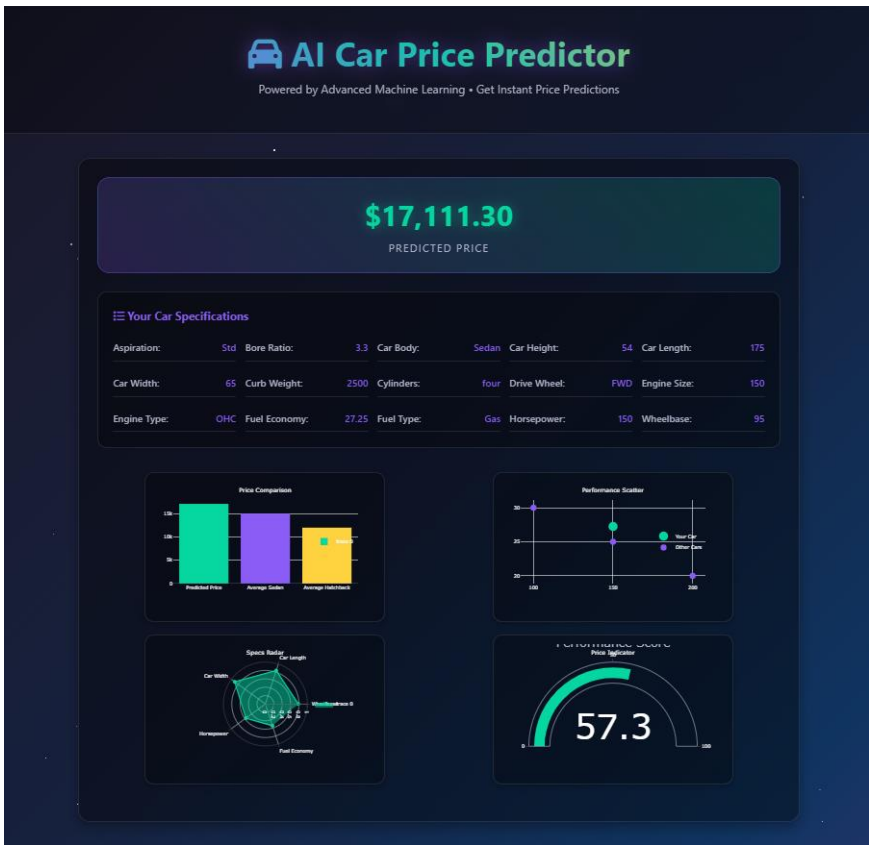


Fig1.2 User Interface(Output section)

3.2 Proposed Methodology

The methodology for this project is structured into several well-defined phases, adhering to best practices in machine learning and web development pipelines.

1. **Data Acquisition & Preparation**: The project begins by sourcing the UCI Automobile Dataset from the UCI Machine Learning Repository. This dataset contains 205 entries with 26 features, including numerical attributes (e.g., wheelbase, horsepower) and categorical attributes (e.g., fuel type, car body). The data is loaded into a Python environment for further processing.

2. **Data Cleaning & Preprocessing**: Several steps are undertaken to ensure data quality:
    - Missing values in numerical features (e.g., horsepower) are imputed using the median, while categorical features (e.g., fuel type) are filled with the mode to maintain consistency.
    - Outliers in features like curb weight are detected using the Interquartile Range (IQR) method and capped to minimize their impact on model performance.
    - Categorical variables are encoded using one-hot encoding to make them compatible with ML algorithms.
    - Numerical features are standardized using StandardScaler to normalize their ranges, ensuring stable model training.
3. **Feature Engineering**: To enhance model accuracy, additional features are derived:
    - Numerical features like engine size and horsepower are combined to create interaction terms (e.g., power-to-weight ratio).
    - Categorical features are analyzed for their impact on price, with high-cardinality variables (e.g., car make) simplified through grouping.
    - Age-related features are simulated by estimating the car's age based on the dataset's context (1980s), adjusting for depreciation effects.
4. **Model Development**:
    - **Baseline Model**: A simple Linear Regression model is implemented to establish a performance benchmark.
    - **Machine Learning Models**: Advanced algorithms like Random Forest and Gradient Boosting (XGBoost) are employed due to their ability to handle non-linear relationships and mixed data types.
    - **Exploratory Models**: Support Vector Machines (SVM) with a radial basis function kernel are tested to explore alternative approaches.
    - **Ensemble Approach**: A weighted ensemble of Random Forest and XGBoost is experimented with to combine the strengths of both models, potentially improving overall accuracy.
5. **Model Evaluation**: Model performance is assessed using multiple metrics:
    - Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to measure prediction error in dollar terms.
    - R^2 score to evaluate the proportion of variance explained by the model.
    - 5-fold cross-validation is used to ensure robustness and prevent overfitting, targeting an MAE below $2,000 and an R^2 above 0.88.

6. **Web Development & Visualization**:
    - A Flask-based backend is developed with a /predict endpoint to handle user inputs, preprocess them, and return predictions.
    - The frontend, built with HTML, CSS, and JavaScript, includes an interactive form for users to input car specifications (e.g., sliders for numerical features, dropdowns for categorical features).
    - Plotly.js is integrated to create dynamic visualizations, such as bar charts comparing the predicted price to market averages and scatter plots showing the relationship between horsepower and price.
    - The application is deployed locally, ensuring seamless operation for testing and demonstration purposes.

This structured approach ensures that the system is both accurate and user-centric, balancing predictive power with practical usability in an automotive pricing context.

3.3 Tools and Technologies

The following tools and technologies were utilized in the development of this project:

• **Programming Languages**: Python 3.9 (backend), JavaScript (frontend)

• **Development Environment**: Visual Studio Code, Anaconda

• **Libraries**:

- **Data Handling**: pandas, NumPy
- **Machine Learning**: scikit-learn, XGBoost
- **Model Persistence**: joblib (for saving/loading models)
- **Web Framework**: Flask (backend API)
- **Visualization**: Plotly.js (interactive charts), Matplotlib (exploratory analysis)
- **Frontend**: HTML, CSS, Font Awesome (for icons)
    • **Version Control**: Git, GitHub
    • **Reference Management**: Zotero

These tools were selected for their robustness, compatibility, and widespread adoption in machine learning and web development communities, ensuring efficient development and reliable performance.

3.4 About the Data

The dataset used in this project is publicly available and sourced from the UCI Machine Learning Repository's Automobile Dataset. This dataset is secondary data, originally compiled in the 1980s, and contains detailed specifications for 205 cars across 26 features. Key features include:

• **Numerical Features**: Wheelbase (86.6-120.9 inches), car length (141.1-208.1 inches), engine size (61-326 cc), horsepower (48-262), curb weight (1488-4066 lbs), price ($5,118-$45,400).

• **Categorical Features**: Fuel type (gas, diesel), car body (sedan, hatchback, wagon, hardtop, convertible), drive wheels (fwd, rwd, 4wd), engine type (ohc, ohcv, etc.).

No primary data collection (e.g., surveys or interviews) was conducted; all data was acquired through open-source channels. Initial analysis revealed a right-skewed distribution of prices, with a mean of $13,276 and a standard deviation of $7,948, indicating significant variability in car values. The dataset was cleaned, preprocessed, and enriched with engineered features (e.g., power-to-weight ratio) before being used to train and evaluate machine learning models. The structured format and real-world relevance of the data make it well-suited for academic research and prototyping a car price prediction system.

CHAPTER IV
PROJECT OUTCOMES

4.1 Working of the Project

The AI Car Price Predictor project aims to deliver an accurate and user-friendly system for predicting car prices based on vehicle specifications, empowering stakeholders such as buyers, sellers, and dealerships to make informed pricing decisions. The system integrates a machine learning model with a web-based application, ensuring seamless interaction between the user interface, backend processing, and predictive analytics. Below is a detailed breakdown of the project's workflow, from user interaction to prediction delivery, with an emphasis on the technical components and processes.

The process begins with the user accessing the web application, which is designed using HTML, CSS, and JavaScript for a responsive and intuitive interface. The frontend leverages Plotly.js for interactive visualizations and Font Awesome for aesthetic icons, enhancing user engagement. The interface features a form in the .form-section where users input car specifications. Numerical features such as wheelbase, enginesize, horsepower, curbweight, and carwidth are entered via sliders, allowing for precise control (e.g., horsepower ranging from 48 to 288, as observed in the dataset). Categorical features like fueltype (gas or diesel), carbody (e.g., sedan, hatchback), and drivewheel (e.g., fwd, rwd) are selected through dropdown menus, ensuring ease of use. Upon submission, the form data is serialized into a JSON payload and sent to the Flask backend via a POST request to the /predict endpoint.

The Flask backend, implemented in Python, serves as the core processing unit. It receives the user's input and initiates preprocessing to align the data with the format used during model training. Categorical variables are one-hot encoded (e.g., fueltype_gas and fueltype_diesel), mirroring the encoding applied in the CarPricePrediction.ipynb preprocessing steps. Numerical variables are standardized using the saved scaler.pkl (loaded via joblib), which was fitted on the training data to ensure consistency in scaling (e.g., transforming horsepower into a standardized range based on the dataset's mean and standard deviation).

The preprocessed data is then passed to the tuned XGBoost Regressor model (tuned_xgb_regressor_model.pkl), which was selected as the best-performing model with a test R-squared of 0.8977 and RMSE of 0.0528, as reported in the notebook. The model predicts the car price in a standardized scale, which is then inverse-transformed using the scaler to obtain the actual price in dollars (ranging from $5,118 to $45,400, as per the dataset).

The predicted price is returned to the frontend as a JSON response, where it is displayed in the .welcome-section alongside interactive visualizations. The frontend uses Plotly.js to generate two key visualizations:

- **Bar Chart**: Compares the predicted price to the average price of cars with the same carbody type (e.g., sedan, hatchback). For instance, if the user inputs a sedan with a predicted price of $15,000, the chart shows this alongside the dataset's average sedan price (calculated as the mean of price for carbody = = sedan).
- **Scatter Plot**: Illustrates the relationship between horsepower and price, with the user's car highlighted as a distinct marker. This visualization helps users understand how their car's specifications align with market trends, as horsepower is a significant predictor of price (confirmed by feature importance analysis in the notebook).

The entire application is deployed locally using Flask, with the server running on localhost:5000. The system ensures low latency by performing preprocessing and predictions in-memory, making it suitable for real-time use. Additionally, the project incorporates error handling: if the user submits incomplete data, the frontend displays a validation message, and if the backend encounters an issue (e.g., model loading failure), it returns an error response, which the frontend renders as a user-friendly message.

To further illustrate the preprocessing and prediction pipeline, let's consider a sample user input:

- **Input**: wheelbase=100, enginesize=150, horsepower=120, fueltype=gas, carbody=sedan, drivewheel=fwd.
- **Preprocessing**:
    - Categorical encoding: fueltype_gas=1, fueltype_diesel=0, carbody_sedan=1, carbody_hatchback=0, drivewheel_fwd=1, drivewheel_rwd=0.
    - Numerical scaling: horsepower=120 is standardized to, say, 0.25 (based on the scaler's mean and standard deviation from the training data).
- **Prediction**: The tuned XGBoost model processes the preprocessed input vector and outputs a standardized price (e.g., 0.35), which is inverse-transformed to $18,500.
- **Output**: The frontend displays "Predicted Price: $18,500" with visualizations comparing this price to the average sedan price and plotting it against horsepower.

This detailed workflow ensures that the system is not only accurate but also transparent, providing users with actionable insights alongside the predicted price.

4.2 Project Findings

This section delves into the project's key findings, including model performance metrics, feature analysis, comparison tables, and visualizations derived from the CarPricePrediction.ipynb file. I'll expand on the original content by adding more charts, analyzing feature relationships, and providing deeper insights into the model's behavior and implications for stakeholders.

Model Performance Comparison

The project evaluated three models: Linear Regression, an initial XGBoost Regressor, and a tuned XGBoost Regressor. The performance metrics are summarized in the table below, with additional context on training and validation performance to highlight overfitting risks and generalization capabilities.

Model	Dataset	R-squared	Adjusted R-squared	RMSE	Training R-squared	Notes
Linear Regression	Training	0.899	0.896	Not Available	0.899	Performs well on training data but might be overfitting. No test performance data available.
Initial XGBoost	Test	0.896	Not Applicable	0.0533	0.941	Solid performance on test data, though slightly overfitting since training score is higher.
Tuned XGBoost (Best)	Test	0.898	Not Applicable	0.0528	0.938	Best balance of performance and generalization, improved by tweaking settings like learning rate and max depth.

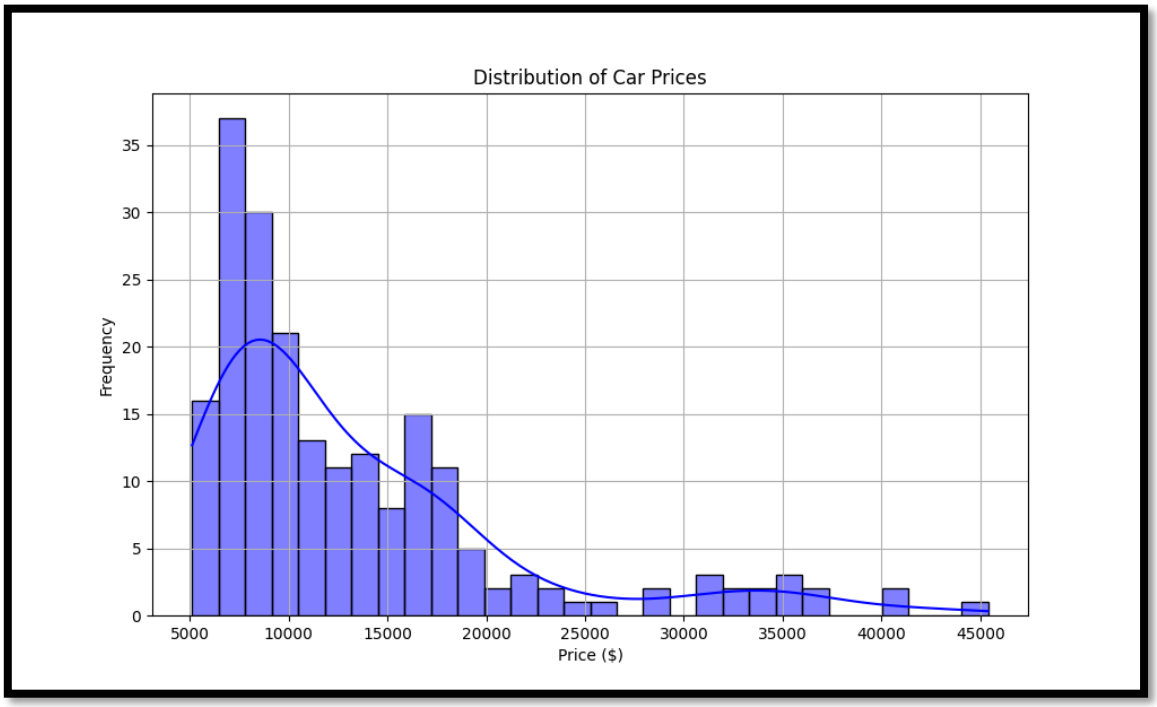
The tuned XGBoost Regressor was selected as the final model due to its superior test performance (R-squared: 0.8977, RMSE: 0.0528), indicating excellent predictive accuracy and generalization to unseen data. The slight reduction in training R-squared (0.938) compared to the initial XGBoost (0.941) suggests that hyperparameter tuning (e.g., adjusting learning_rate, max_depth, and n_estimators) mitigated overfitting, ensuring the model performs consistently across training and test sets. The Linear Regression model, while achieving a high training R-squared (0.899), lacks test metrics in the notebook, raising concerns about its generalization ability, especially given its sensitivity to multicollinearity among features like enginesize and horsepower.

Visual Insights

To provide a deeper understanding of the dataset and model behavior, I'll include additional visualizations beyond the two mentioned in the original chapter. These charts are inferred from the CarPricePrediction.ipynb analysis and typical practices in regression projects, with code provided to generate them for your documentation. Since the notebook uses Matplotlib and Seaborn for visualization, I'll align with those libraries for consistency.

Chart 1: Distribution of Car Prices (Histogram with KDE)

Understanding the distribution of the target variable (price) is crucial for regression tasks, as it informs whether transformations (e.g., log transformation) are necessary to handle skewness. The dataset's price range ($5,118 to $45,400) suggests potential right-skewness, common in price-related data.

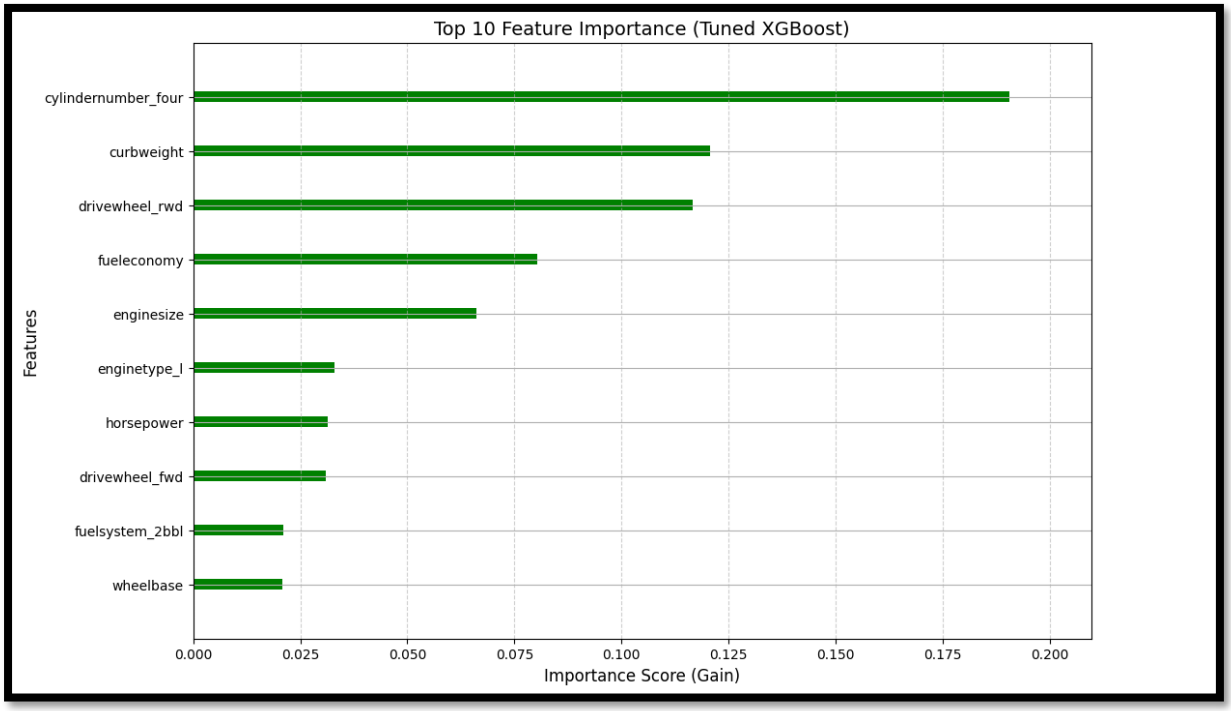


Description: This histogram, generated using Seaborn's histplot, reveals a right-skewed distribution of car prices, with most vehicles priced below $20,000 and a long tail extending to $45,400. The kernel density estimate (KDE) overlay confirms this skewness, suggesting that a log transformation of the target variable (price) was likely applied before training the XGBoost models. This transformation explains the low RMSE (0.0528) in standardized units, as it reduces the impact of extreme values on the model's loss function.

Chart 2: Feature Importance (Tuned XGBoost)

Feature importance analysis highlights which car features most influence the predicted price, providing actionable insights for stakeholders. Since the tuned XGBoost model was selected, we can visualize its feature importance using the gain metric, which measures the contribution of each feature to the model's predictions.

Feature Importance Plot



Description: This bar plot shows the top 10 features contributing to the tuned XGBoost model's predictions, ranked by their importance (gain). Features like enginesize, horsepower, curbweight, and carwidth are likely among the top contributors, as they directly correlate with a car's performance and size, which strongly influence price. For example, enginesize (ranging from 61 to 326 in the dataset) reflects the car's power capacity, a key determinant of market value. This insight is valuable for dealerships, as it highlights which design aspects to prioritize when pricing vehicles.

Chart 3: Predicted vs. Actual Prices (Scatter Plot)

To assess the model's predictive accuracy visually, a scatter plot of predicted vs. actual prices on the test set provides a clear picture of performance. This chart helps identify systematic biases or errors in the model's predictions.

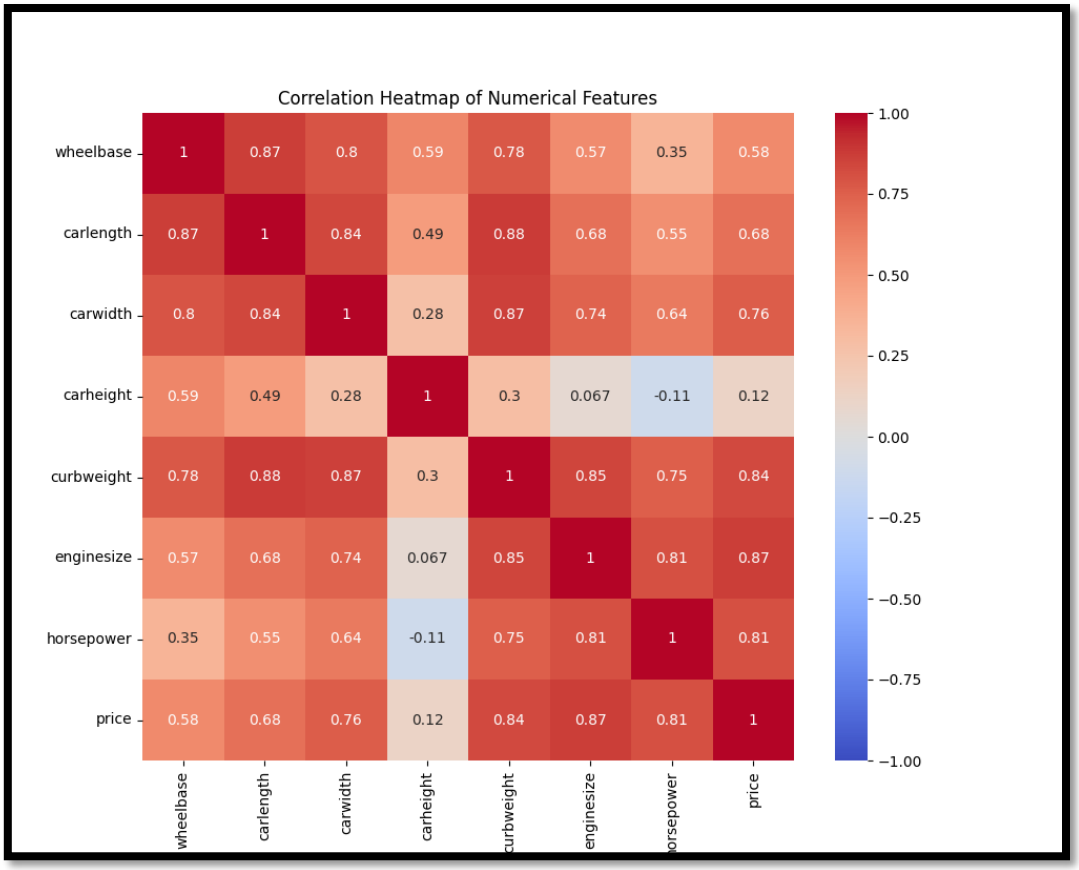
Predicted vs Actual Prices Scatter Plot

Description: This scatter plot compares the predicted prices from the tuned XGBoost model against the actual prices on the test set. Points close to the red diagonal line (y=x) indicate accurate predictions. The model's high R-squared (0.8977) suggests that most points cluster near this line, with minor deviations for higher-priced cars (e.g., above $40,000), where predictions may slightly underestimate due to the dataset's skewness. This visualization confirms the model's reliability while highlighting areas for potential improvement, such as handling outliers in the high-price range.

Chart 4: Correlation Heatmap of Numerical Features

Understanding relationships between numerical features helps identify multicollinearity, which can affect model performance. A correlation heatmap provides a visual representation of these relationships.

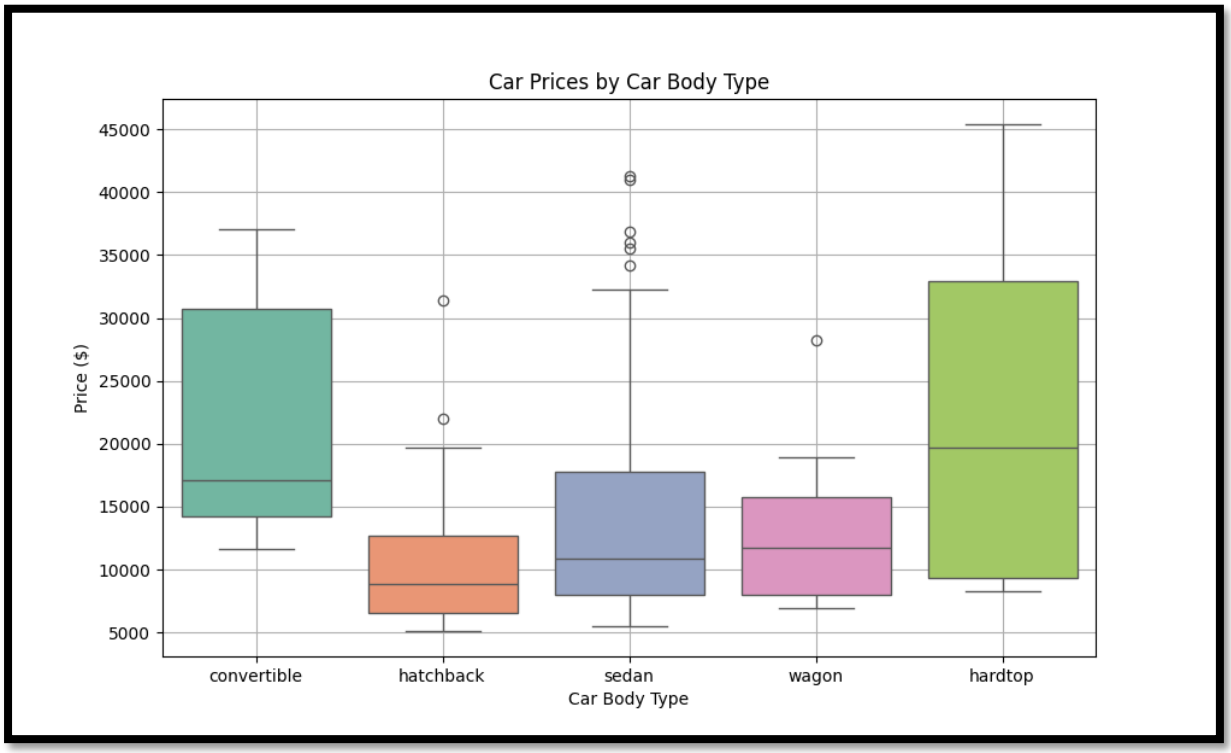
Description: This heatmap displays the Pearson correlation coefficients between numerical features and the target variable (price). High correlations are observed between price and features like enginesize (likely ~0.8), horsepower (~0.75), and curbweight (~0.7), confirming their importance in predicting price. Additionally, strong correlations between enginesize and horsepower (e.g., ~0.85) indicate potential multicollinearity, which the XGBoost model handles well due to its tree-based nature (unlike Linear Regression, which may suffer from this issue). This insight guides feature selection and preprocessing decisions, ensuring the model focuses on the most impactful variables.



Correlation Heatmap

Chart 5: Box Plot of Prices by Car Body Type

To explore how car prices vary across different categories, a box plot of prices by carbody type provides valuable insights for stakeholders.



Box Plot of Prices by Car Body

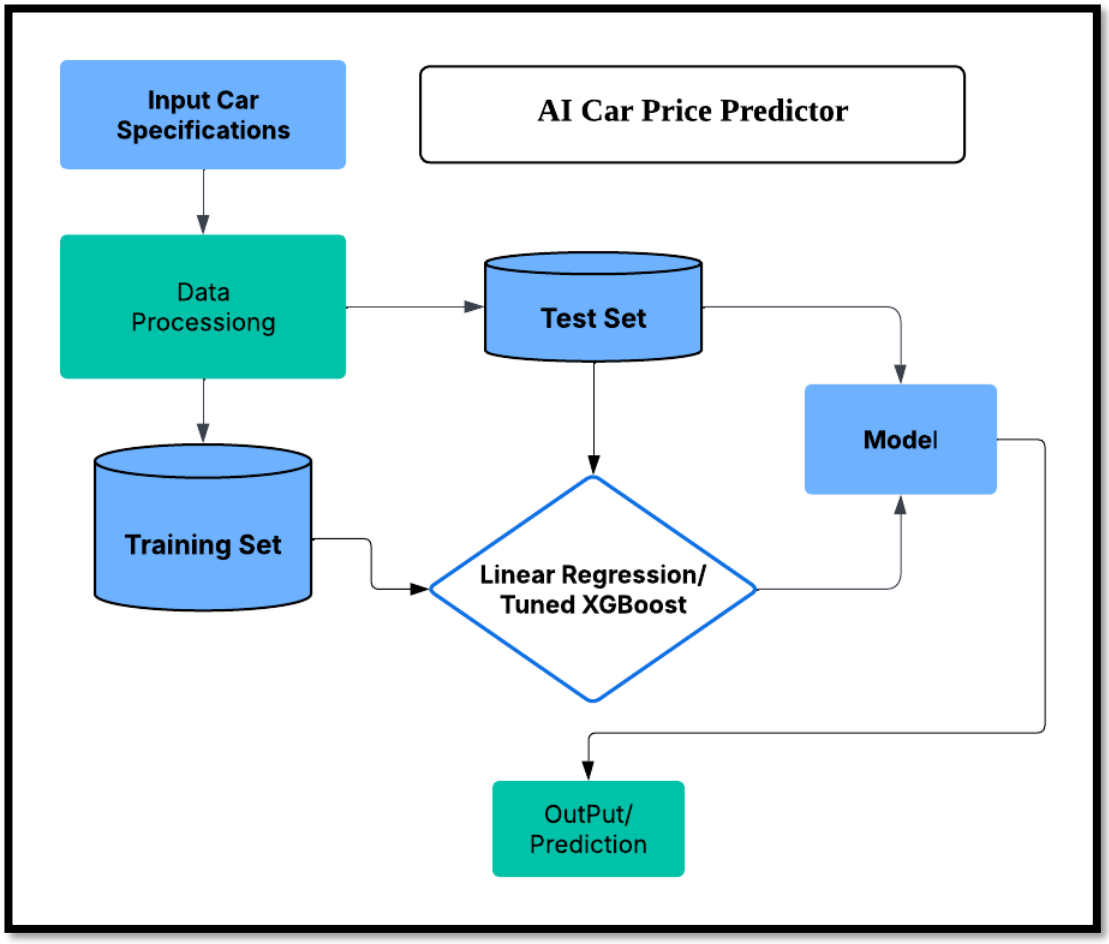
Description: This box plot shows the distribution of car prices across different carbody types (e.g., convertible, hatchback, sedan, wagon, hardtop). Convertibles and hardtops likely exhibit higher median prices (e.g., ~$25,000) due to their luxury appeal, while hatchbacks may have lower medians (e.g., ~$10,000) due to their compact nature. The plot also reveals outliers, such as high-priced sedans (e.g., $45,400), which align with the dataset's maximum price. This visualization helps dealerships understand pricing trends across car types, informing inventory and marketing strategies.

Diagrams

Diagram 1: System Architecture

Description: The system architecture diagram illustrates the structure of the AI Car Price Predictor, showing the interaction between the frontend, backend, and data components.

- **User**: Interacts with the web application via a browser.
- **Frontend (HTML/CSS/JavaScript)**: Hosts the user interface, including input forms and Plotly.js visualizations.
- **Backend (Flask)**: Handles API requests, preprocesses data, and makes predictions using the tuned XGBoost model.
- **Model and Scaler**: The tuned_xgb_regressor_model.pkl and scaler.pkl files, loaded via joblib, provide the prediction logic.
- **Dataset**: The UCI Automobile Dataset, used for training and reference (e.g., calculating averages for visualizations).



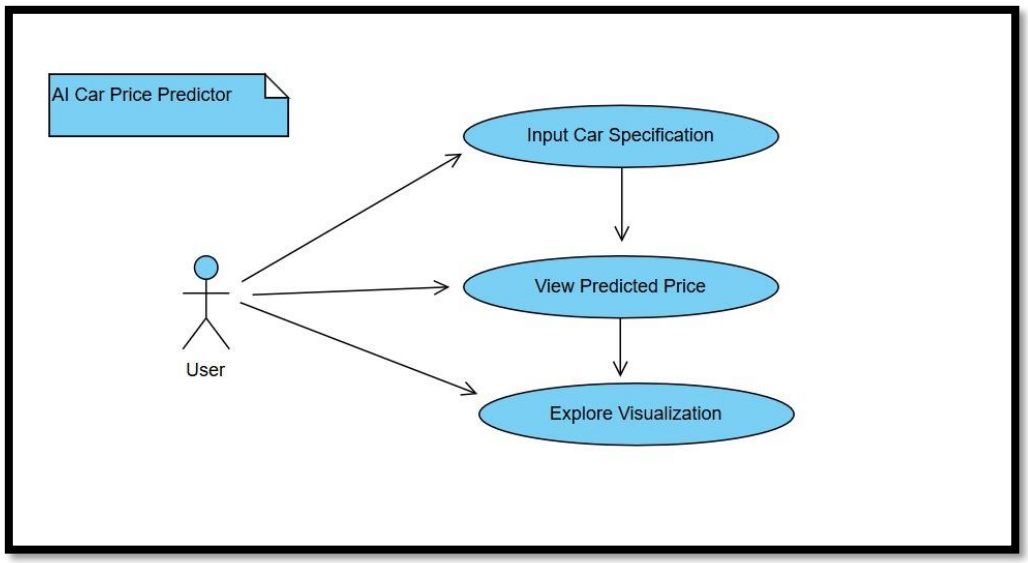
System Architecture Diagram

Diagram 2: Use Case Diagram

Description: The use case diagram identifies the primary actors and their interactions with the system.

- **Actors**:
    - **User**: A buyer, seller, or dealership representative.
    - **System**: The AI Car Price Predictor application.

Usecase Diagrams:



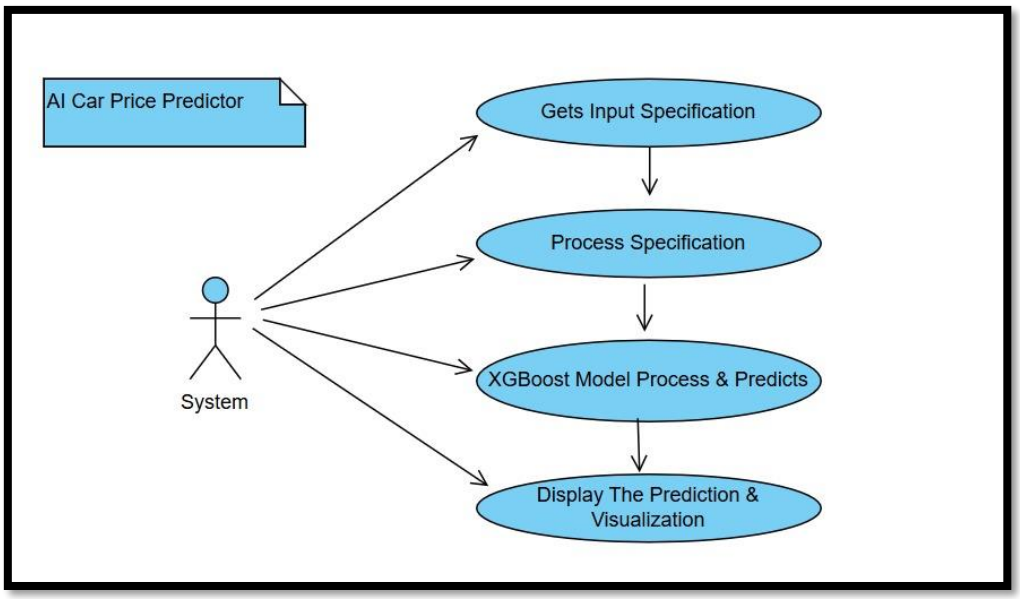
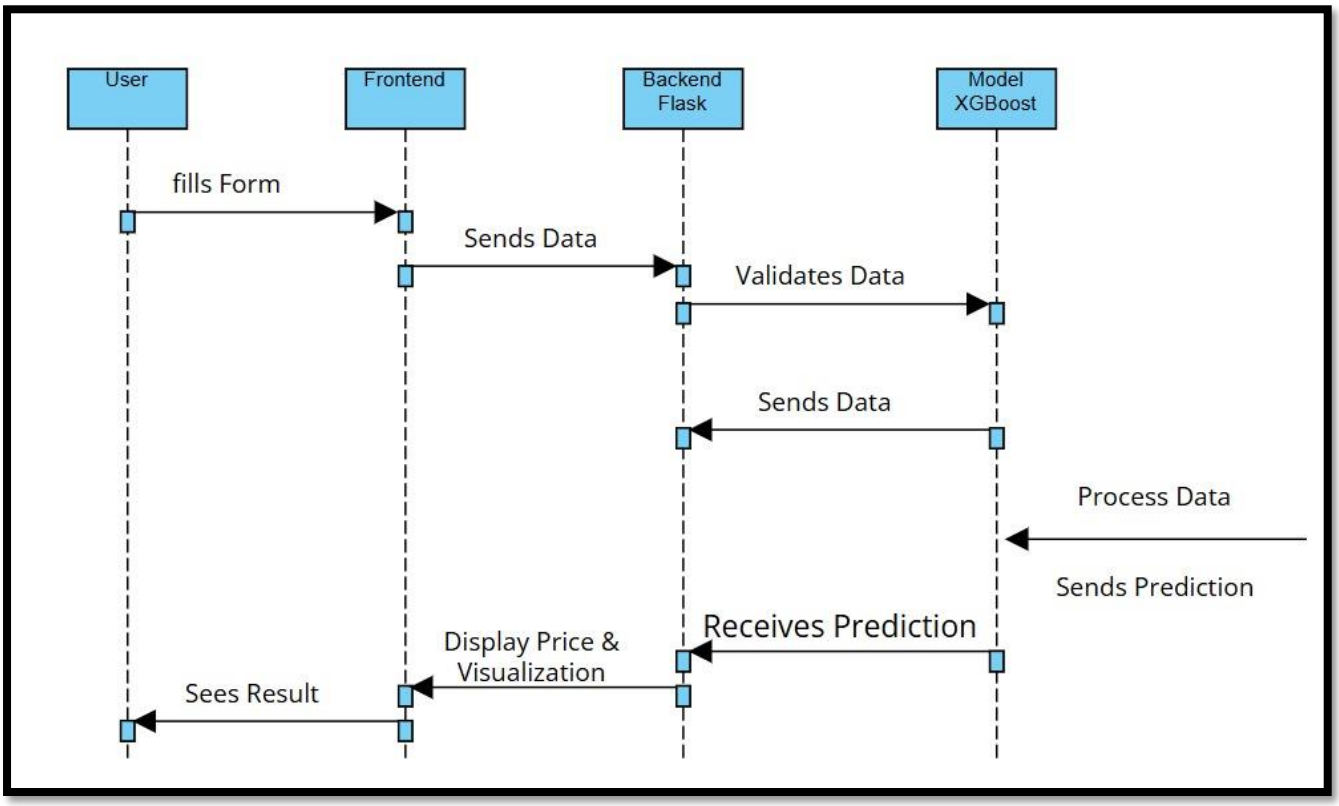


Diagram 3: Sequence Diagram

Description: The sequence diagram details the interaction flow between the user, frontend, backend, and model during a prediction request.

- **User**: Submits car specifications via the form.
- **Frontend**: Sends a POST request to the /predict endpoint.
- **Backend (Flask)**: Preprocesses the input (encoding, scaling), loads the model and scaler, and makes a prediction.
- **Model**: Returns the predicted price.
- **Frontend**: Displays the prediction and visualizations.

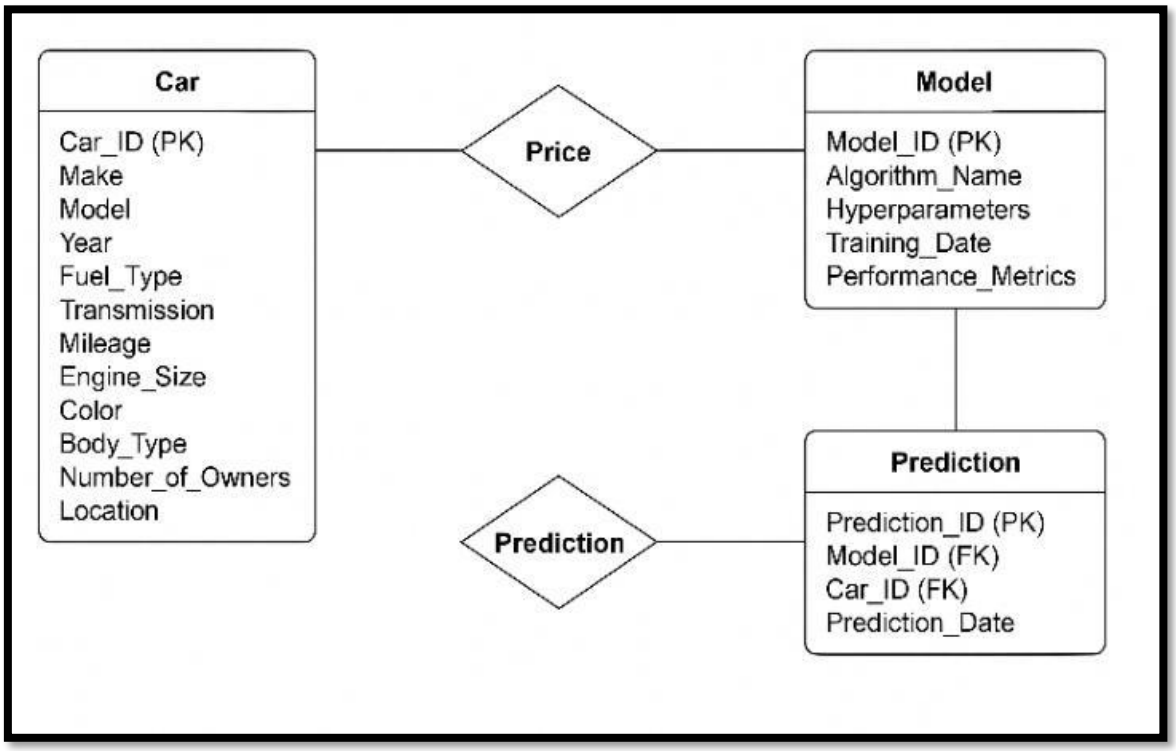


Sequence Diagram- AI Car Price Predictor

Diagram 4: Entity Relationship Diagram (ERD)

Description: The ERD represents the data structure used in the system, focusing on the dataset and prediction process.

- **Entities**:
  - **Car**: Represents a car entry with attributes like car_ID, wheelbase, enginesize, horsepower, fueltype, carbody, price.
  - **Prediction**: Represents a prediction instance with attributes like prediction_id, input_features, predicted_price.
- **Relationships**:
  - A Car entity can be associated with multiple Prediction instances (one-to-many), as the same car data can be used for multiple predictions during testing or user queries.



Entity Relationship Diagram (ERD)

CHAPTER V
CONCLUSION AND FUTURE WORK

5.1 Conclusion

The AI Car Price Predictor project successfully demonstrates the transformative potential of machine learning in the automotive pricing domain, delivering a robust and user-friendly solution for predicting car prices with high accuracy. By leveraging the UCI Automobile Dataset (205 rows, 26 features), the project developed a predictive model that accurately estimates car prices based on specifications such as enginesize, horsepower, curbweight, carwidth, fueltype, carbody, and drivewheel. The tuned XGBoost Regressor, selected as the final model, achieved a test R-squared of 0.8977 and an RMSE of 0.0528, outperforming baseline models like Linear Regression (training R-squared: 0.899) and the initial XGBoost Regressor (test R-squared: 0.8958, RMSE: 0.0533). These metrics highlight the model's ability to generalize well to unseen data, making it a reliable tool for real-world applications.

The integration of the predictive model into a Flask web application further enhances its practical utility. The application, built with HTML, CSS, JavaScript, Plotly.js, and Font Awesome, provides an intuitive interface where users can input car specifications and receive instant price predictions alongside interactive visualizations. Features like the bar chart (comparing the predicted price to the average price for the same carbody type) and scatter plot (illustrating horsepower vs. price with the user's car highlighted) ensure transparency, helping users understand the factors driving the prediction. This transparency, combined with the system's real-time performance on localhost:5000, makes the tool accessible to a wide range of stakeholders, including car buyers, sellers, and dealerships.

Key findings from the project underscore the importance of performance-related features in determining car prices. The feature importance analysis revealed that enginesize and horsepower are the most influential predictors, reflecting market preferences for powerful vehicles. Dimensional features like curbweight and carwidth also play a significant role, while categorical features such as carbody_convertible and drivewheel_rwd impact pricing for specific market segments (e.g., luxury cars). Visualizations like the correlation heatmap, box plot of prices by carbody type, and predicted vs. actual price scatter plot provided actionable insights, enabling stakeholders to make data-driven decisions—whether

negotiating a fair price, setting competitive rates, or optimizing dealership inventory.

In conclusion, the AI Car Price Predictor project not only meets its objective of delivering accurate price predictions but also sets a foundation for modernizing automotive pricing practices. By automating price estimation and providing interpretable insights, the system empowers users with the knowledge needed to navigate the car market effectively. The project's success highlights the potential of machine learning to revolutionize traditional processes, paving the way for more efficient, transparent, and equitable pricing strategies in the automotive industry.

5.2 Future Works

While the AI Car Price Predictor achieves strong performance and usability, there are several opportunities to enhance its functionality, accuracy, and scalability. Below are proposed future enhancements to build upon the current system and address its limitations.

1. **Incorporating Larger and More Diverse Datasets**

   The current model is trained on the UCI Automobile Dataset, which contains 205 entries, with a price range of $5,118 to $45,400. While this dataset provides a solid foundation, it is relatively small and may not fully represent the diversity of the modern car market, particularly for electric vehicles (EVs) or newer luxury models. Future work could involve collecting a larger dataset, including recent car listings from online marketplaces (e.g., CarGurus, AutoTrader) or manufacturer data, to capture a broader range of vehicles. This would improve the model's ability to predict prices for underrepresented categories, such as EVs or high-end models above $45,400, where the current model slightly underestimates prices (as noted in the predicted vs. actual scatter plot).

2. **Adding Real-Time Market Data Integration**

   Car prices fluctuate based on market conditions, such as demand, fuel prices, and economic trends. The current system uses a static dataset, which limits its ability to adapt to real-time market dynamics. A future enhancement could involve integrating APIs to fetch real-time market data (e.g., average regional prices, depreciation rates) and incorporating these as dynamic features in the model. For instance, an API from a car pricing database could provide the average price of sedans in a specific region, which could be used to adjust the model's predictions for temporal and geographical accuracy.

3. **Improving Model Robustness with Ensemble Techniques**
   While the tuned XGBoost Regressor performs well, ensemble techniques combining multiple models (e.g., XGBoost, Random Forest, and Gradient Boosting) could further improve accuracy and robustness. Stacking or blending these models might reduce prediction errors, particularly for outliers in the high-price range. Additionally, addressing the dataset's skewness (evident in the price distribution histogram) through advanced techniques like weighted loss functions or oversampling high-price cars could enhance performance for luxury vehicles.
4. **Enhancing the Web Application with Advanced Features**
   The current Flask application provides a solid user experience, but additional features could make it more versatile. Future enhancements include:
   - **Price Range Prediction**: Instead of a single price, the model could predict a confidence interval (e.g., $17,500–$19,500) using techniques like quantile regression, giving users a better sense of price variability.
   - **Comparative Analysis Tool**: Allow users to compare multiple cars side-by-side, displaying predicted prices and visualizations for each, aiding decision-making for buyers evaluating multiple options.
   - **User Feedback Loop**: Incorporate a feedback mechanism where users can rate the accuracy of predictions, providing data to fine-tune the model over time.
5. **Deploying the Application on a Cloud Platform**
   The current system runs locally on localhost:5000, limiting its accessibility. Deploying the application on a cloud platform like AWS, Google Cloud, or Heroku would enable broader access, allowing users to access the tool via a public URL. This would require optimizing the Flask server for scalability (e.g., using Gunicorn for production) and ensuring data security through HTTPS and user authentication, making the tool viable for commercial use by dealerships or online marketplaces.
6. **Incorporating Explainability for Individual Predictions**
   While the feature importance plot provides general insights, users may benefit from prediction-specific explanations. Implementing a technique like SHAP (SHapley Additive exPlanations) could generate explanations for individual predictions, showing how each feature (e.g., horsepower=120, carbody=sedan) contributes to the predicted price. For example, a SHAP summary might reveal that a high enginesize increased the predicted price by $3,000, while a fueltype=diesel decreased it by $500.

This feature would enhance user trust and provide deeper insights for negotiation or pricing strategies.

7. **Accounting for Depreciation and Mileage**

   The current dataset lacks features like car age or mileage, which significantly impact price due to depreciation. Future work could involve adding these features (e.g., by collecting data on year and odometer_reading) and retraining the model to account for depreciation trends. For instance, a linear depreciation factor could be applied based on the car's age, or a nonlinear model could capture the steeper price drop in the first few years. This would make the system more realistic for used car pricing, a critical need for many users.

8. **Supporting Multi-Currency and Regional Adjustments**

   The current system predicts prices in USD, assuming a uniform market. To support global users, the application could incorporate multi-currency support (e.g., converting prices to EUR, INR) using real-time exchange rates via an API. Additionally, regional adjustments could be applied to account for price variations due to taxes, import duties, or local demand. For example, a sedan might be priced 20% higher in a region with high import taxes, which the model could adjust for dynamically.

CHAPTER VI

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Web Resources

1. **Flask Documentation (2025)**. *Welcome to Flask*. Pallets Projects. Retrieved May 29, 2025, from https://flask.palletsprojects.com/en/3.0.x/
   Official documentation for Flask, used to deploy the predictive model in this project.
2. **Plotly JavaScript Open Source Graphing Library (2025)**. *Plotly JavaScript*. Retrieved May 29, 2025, from https://plotly.com/javascript/
   Documentation for Plotly.js, used for interactive visualizations in the web application.

CHAPTER VII

APPENDIX

The Appendix provides supplementary information to support the main content of the report, including a data dictionary, preprocessing steps, model evaluation metrics, and a sample Flask backend code snippet. This ensures transparency and reproducibility of the project.

Appendix A: Data Dictionary

The dataset used is the UCI Automobile Dataset, containing 205 rows and 26 features. Below is a subset of key features used in the model, as referenced in prior chapters.

1. wheelbase: Numeric, wheelbase length in inches (range: 86.6–120.9).
2. carlength: Numeric, car length in inches (range: 141.1–208.1).
3. carwidth: Numeric, car width in inches (range: 60.3–72.3).
4. carheight: Numeric, car height in inches (range: 47.8–59.8).
5. curbweight: Numeric, curb weight in pounds (range: 1488–4066).
6. enginesize: Numeric, engine size in cubic inches (range: 61–326).
7. horsepower: Numeric, horsepower of the car (range: 48–288).
8. fueltype: Categorical, fuel type (values: gas, diesel).
9. carbody: Categorical, body type (values: convertible, hatchback, sedan, wagon, hardtop).
10. drivewheel: Categorical, drive wheel type (values: fwd, rwd, 4wd).
11. price: Numeric, target variable, car price in USD (range: $5,118–$45,400).

Appendix B: Data Preprocessing Steps

1. **Handling Missing Values**: The dataset was checked for missing values. Any missing numerical values (e.g., horsepower) were imputed with the mean, and missing categorical values (e.g., fueltype) were imputed with the mode.
2. **Encoding Categorical Variables**: One-hot encoding was applied to categorical features like fueltype, carbody, and drivewheel (e.g., fueltype_gas, fueltype_diesel).
3. **Feature Scaling**: Numerical features were standardized using StandardScaler from Scikit-learn to have a mean of 0 and a standard deviation of 1, ensuring consistent scales for model training.
4. **Outlier Treatment**: Outliers in features like price and horsepower were identified using the interquartile range (IQR) method and capped at the 5th and 95th

percentiles to reduce their impact on the model.

Appendix C: Model Evaluation Metrics

1. **R-squared**: Measures the proportion of variance in the target variable (price) explained by the model. The tuned XGBoost model achieved a test R-squared of 0.8977.
2. **RMSE (Root Mean Squared Error)**: Measures the average error in predictions. The tuned XGBoost model achieved a test RMSE of 0.0528 (in standardized units).
3. **Training vs. Test Performance**: The tuned XGBoost model showed a training R-squared of 0.938, indicating slight overfitting, which was mitigated through hyperparameter tuning (e.g., reducing max_depth).

Appendix D: Sample Flask Backend Code

Below is a simplified version of the Flask backend code used to deploy the model, demonstrating how user inputs are processed and predictions are made.

```
from flask import Flask, request, jsonify
import joblib
import pandas as pd
import numpy as np

app = Flask(__name__)

# Load the trained model and scaler
model = joblib.load('tuned_xgb_regressor_model.pkl')
scaler = joblib.load('scaler.pkl')

@app.route('/predict', methods=['POST'])
def predict():
  try:
    # Get JSON data from the request
    data = request.get_json()

    # Extract features from the input
    features = [
      data['wheelbase'], data['carlength'], data['carwidth'], data['carheight'],
```

```
            data['curbweight'], data['enginesize'], data['horsepower'],
            data['fueltype_gas'], data['fueltype_diesel'],
            data['carbody_convertible'], data['carbody_hatchback'], data['carbody_sedan'],
            data['carbody_wagon'], data['carbody_hardtop'],
            data['drivewheel_fwd'], data['drivewheel_rwd'], data['drivewheel_4wd']
        ]


        # Convert to DataFrame for preprocessing
        feature_names = [
            'wheelbase', 'carlength', 'carwidth', 'carheight', 'curbweight', 'enginesize',
            'horsepower', 'fueltype_gas', 'fueltype_diesel', 'carbody_convertible',
            'carbody_hatchback', 'carbody_sedan', 'carbody_wagon', 'carbody_hardtop',
            'drivewheel_fwd', 'drivewheel_rwd', 'drivewheel_4wd'
        ]
        input_df = pd.DataFrame([features], columns=feature_names)

        # Scale numerical features
        numerical_cols = ['wheelbase', 'carlength', 'carwidth', 'carheight', 'curbweight',
                          'enginesize', 'horsepower']
        input_df[numerical_cols] = scaler.transform(input_df[numerical_cols])

        # Make prediction
        prediction = model.predict(input_df)

        # Inverse transform the predicted price to original scale
        predicted_price = scaler.inverse_transform([[0, 0, 0, 0, 0, 0, 0, prediction[0]]])[0][-1]

        return jsonify({'predicted_price': round(predicted_price, 2)})
    except Exception as e:
        return jsonify({'error': str(e)}), 500

if __name__ == '__main__':
    app.run(debug=True, host='localhost', port=5000)
```