BDM 3014 INTRODUCTION TO ARTIFICIAL INTELLIGENCE
Final Project Report
Used Cars Price Prediction

GROUP - 5

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INTRODUCTION

The current market Size for used cars in the USA is around 191.24 billion USD.
The digital transformation is positively impacting the used-car retail industry. This emerging era of digital retailing goes beyond technology itself, as it highlights the crucial role of enhancing the customer experience in the process of purchasing used cars.
Accurate pricing of these used cars is important for both buyers and sellers since it affects profitability and market competitiveness.

The goal of this project is to create a machine learning model that can forecast used car prices based on a variety of characteristics, including the vehicle's age, brand, model, mileage, and other pertinent information. Our goal is to develop a predictive model that may help both consumers and sellers make well-informed decisions by utilizing previous data on used car sales.

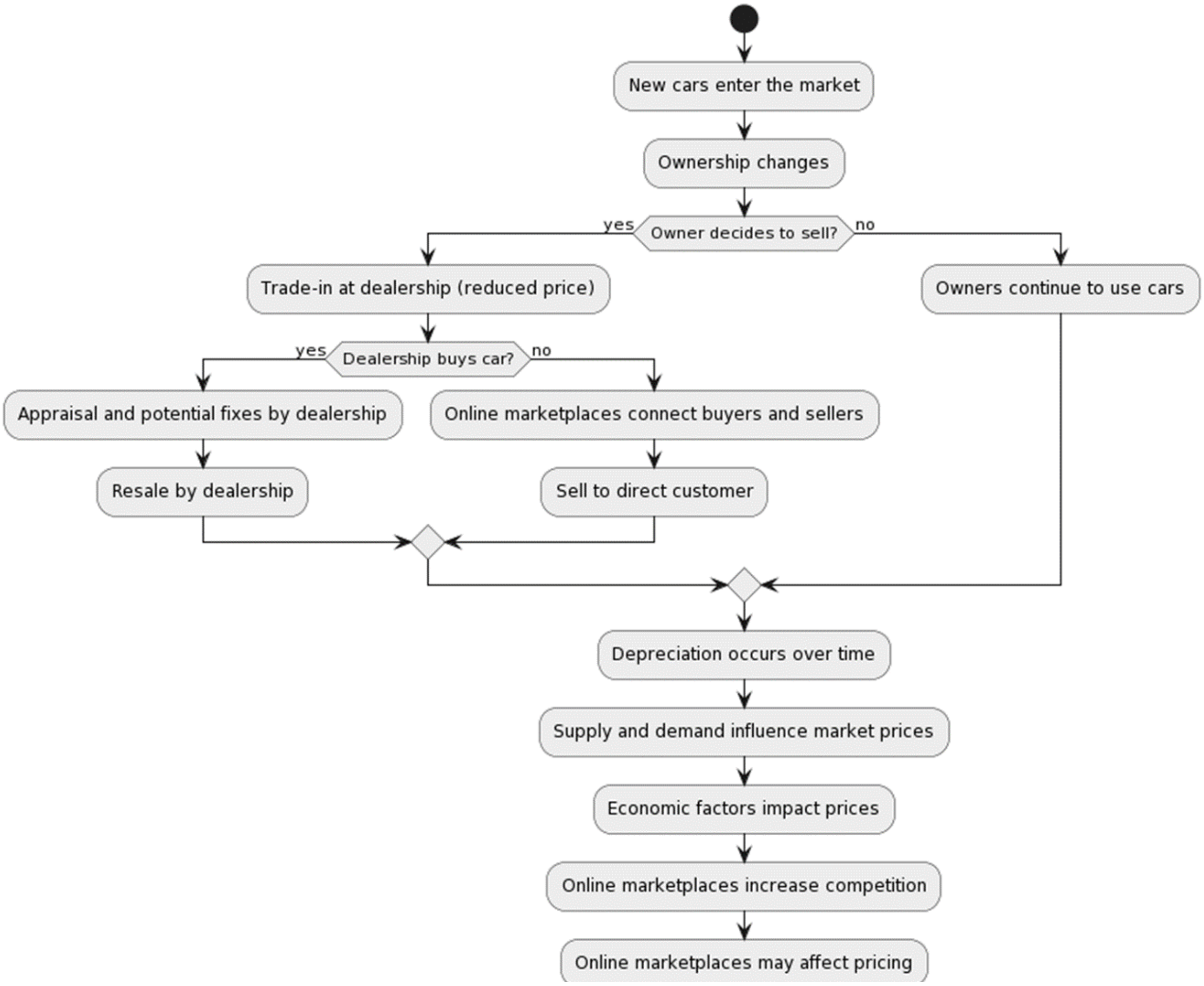
How our industry works

A study by McKinsey shows that online car sellers are changing the way things work in the used car industry. This is giving customers who are comfortable with technology more choices and helping the industry grow as a whole. This trend aligns with predictions about the used car market, which suggest that there will be more recently leased cars available for purchase in 2024 compared to 2023.

The used car market functions like a complex web, with various players and processes impacting how it operates. Here's the gist:

- New cars constantly enter the market, eventually becoming used cars as ownership changes.
- Owners use their cars, causing depreciation (value decrease) over time.
- When selling, owners can either trade-in their car at a dealership (receiving a reduced price) or sell it privately (potentially for more but requiring more effort).
- Dealerships acquire used cars through various channels, appraise them, fix them up (if needed), and resell them.
- Supply and demand, along with the economy, significantly influence market prices.
- Online marketplaces connect buyers and sellers, increasing competition and potentially affecting pricing.

Used Car Market Flowchart



Project Overview

1. Data Input Section:
- Fields for entering information about the used car, such as the year, manufacturer, model, condition, cylinders, fuel type, odometer reading, title status, transmission type, drive type, vehicle type, paint color, county, and state.

2. Pre-processing Module:
- Utilize Python libraries (e.g., Pandas, NumPy, Scikit-learn) for data cleaning and preparation tasks, such as handling missing values, encoding categorical variables, and scaling numerical features.

3. Data visualization(Exploratory Data analysis) :
- Using the above cleaned data , for creating visualizations , such as heat maps, box plots etc, for finding correlation among variables,and outlier detection, respectively.
- Using other kinds of visualizations to find patterns and relationships among average .

4. Model Selection:
- Select from different regression algorithms for predicting the car price, such as linear regression, decision tree regression, or random forest regression.
- Evaluate each algorithm's performance and suitability for the project.
- Using multiple models and trying to use model stacking to find our predicted variable.

5. Model Training Section:
- Button to initiate the training process with the selected algorithm.
- Progress indicator to track the training progress.
- Feedback on the success or failure of the training process, including any errors encountered during training.

6. Prediction Output:
- Display the predicted price of the used car based on the trained regression model.
- Provide insights into the factors influencing the predicted price, such as feature importance or coefficients.
- Visual representation of the predicted price compared to actual prices for similar cars, such as a scatter plot or histogram.

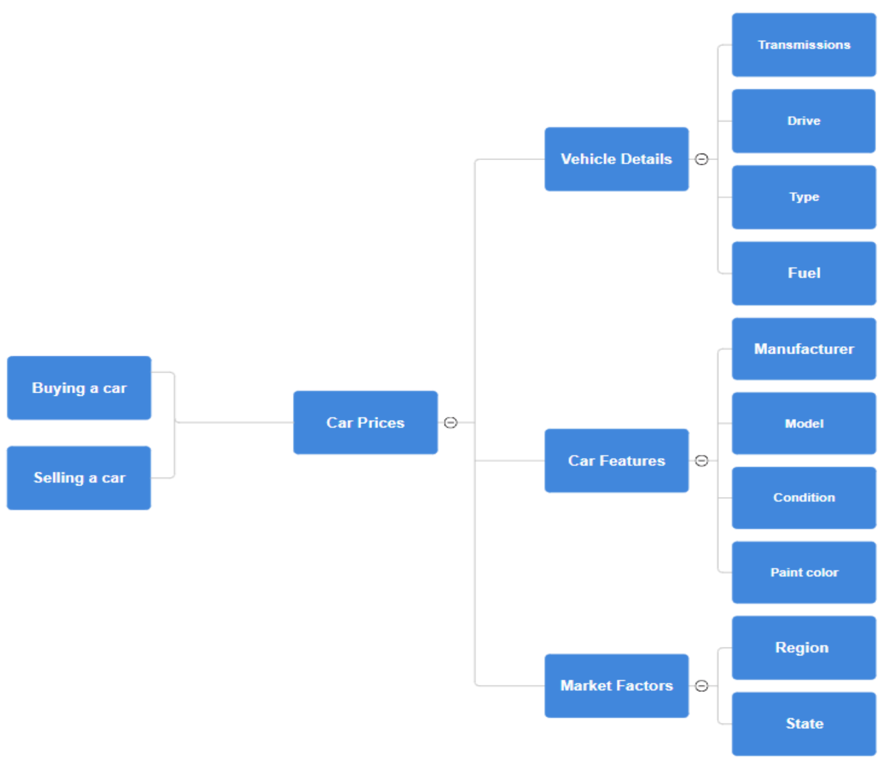
7. Model Evaluation:
- Evaluate the performance of the trained model using evaluation metrics such as mean absolute error, mean squared error, and R-squared value.
- Compare the performance of different regression algorithms used in the model selection stage.

8. Improvement and Iteration:
- Identify areas for improving the model's accuracy based on evaluation results and user feedback.
- Implement updates or adjustments to the model and retrain as necessary to enhance predictive capabilities.

MECE Table

Factors Influencing Used Car Price Prediction while buying or selling a car-

Category	**Factors**	**Description**
Car Features	Manufacturer	Brand of the car
	Model	Specific model or version of the car
	Condition	Condition of car like Excellent, good, etc
	Paint color	Paint color of the car
Vehicle Details	Transmissions	Type of transmission like, automatic, manual
	Drive	Drive type of the body like 2-wheel, 4-wheel
	Type	Type of car like sedan, pickup, truck, bus
	Fuel	Fuel used by car like gas, electric
Market Factors	Region	Listed in which geographical region
	State	State in which the car is located



Project Work Table

Category	Task	Status
Stacked Ensemble Model	Training and Optimization of Decision Trees, Linear Regression and Random Forest	Done
Stacked Ensemble Model Perf	Evaluate the performance of the ensemble model on the Test set	Done
Ensemble Net Perf	Integration of all Models for ensemble	Done
Interpretation	Local Interpretation of Decision Trees decisions	Done
	Global Interpretation of ensemble model predictions	Done
Model Tuning	Investigate and resolve Stacked Ensemble Model performance Issues : Wrong predictions but high R2	Solution: Dropped the model due to overfitting
	Issue with Linear Regression and Random Forest : High MSE and low R2	Done
	Addressed issues of Low accuracy in Decision Trees	Done
Deployment and Demo	Deployment of the Decision trees model	Done
	Prepare a demo showcasing model prediction on an example	Done
Github Repository Link	**https://github.com/SaurabhGangwar007/test**	Done
Project Board link	**https://app.clickup.com/9014210724/v/b/li/901402157335**	Done

Github Walk through

Link to the Github repository - https://github.com/SaurabhGangwar007/test

- Repository Structure:
  A well-organized repository structure is crucial for maintaining clarity and ease of navigation within the project. It typically includes directories for source code, documentation, tests, and any other relevant resources. Each directory should have a clear purpose and contain files related to that purpose. For example:

  src/: Contains the source code files.
  docs/: Contains project documentation.
  data/: Contains datasets used in the project.

- Version Control:
  Version control systems like Git track changes made to files in the project, enabling developers to collaborate effectively, revert to previous versions, and manage concurrent development. Regular commits with descriptive messages help maintain a detailed history of changes, making it easier to understand the evolution of the codebase over time.

- Branching Strategy:
  A branching strategy defines rules for creating and managing branches in the repository.
  Common strategies include:
  Feature Branching: Create separate branches for developing new features or fixing bugs.
  Main/Master Branch: Represents the stable, production-ready version of the codebase.
  Pull Requests: Changes are reviewed and merged into the main/master branch via pull requests, ensuring that only validated code is merged.

- Pull Requests (PRs):

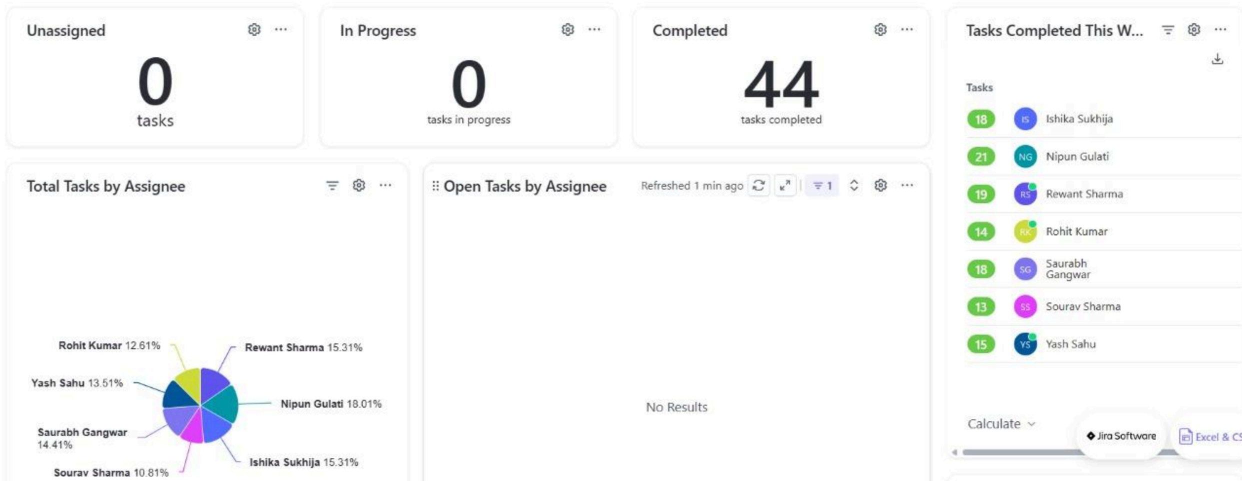
Pull Requests are a mechanism for proposing and reviewing changes to the codebase. They provide a structured way for team members to collaborate, discuss changes, and ensure code quality before merging. Here is the list of Pull Request committed so far:

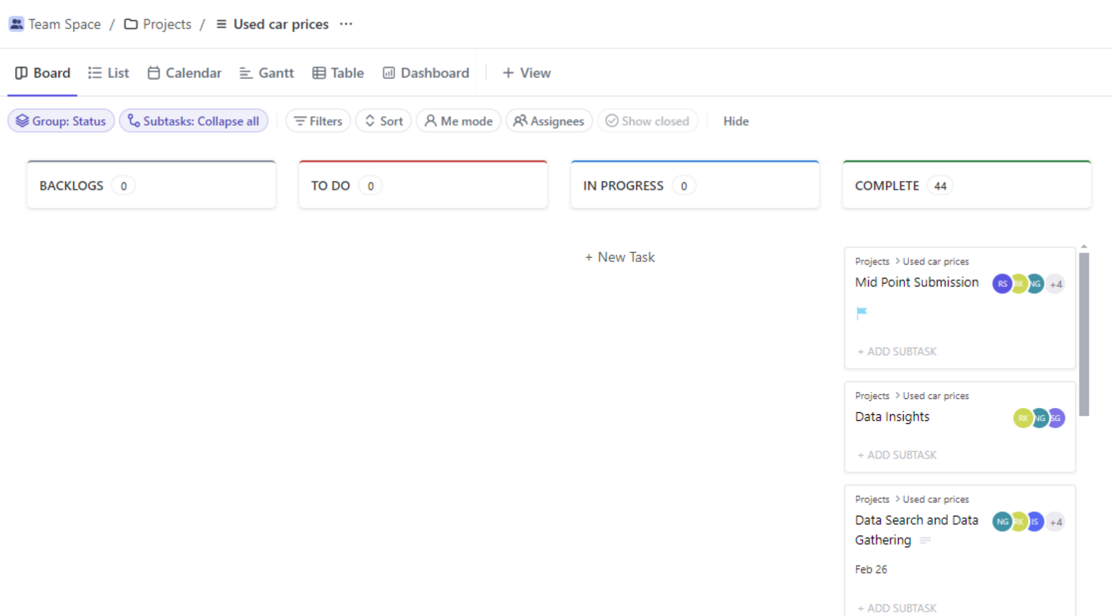
1. Read ME File
2. Data_Cleaning:
3. Car_Price_version_01
   Car_Price_Version_02
4. Outlier detection
   Outlier_detection.ipynb

5. Data_Visualization:
   Data_visualization_py
6. Data encoding
   Data_Encoding_01.ipynb
   Data_Encoding_02.ipynb

Click-Up Dashboard

Link - https://app.clickup.com/9014210724/v/b/li/901402157335





Data Gathering:

Data

- Source: Kaggle
- Dataset: Craigslist Used Vehicles (US)
- Size: 1.34 GB

Format:

The data is stored in a tabular format, commonly referred to as a rectangular format with rows and columns. It resembles a spreadsheet where each row represents a unique used vehicle listing, and each column represents a specific feature of that listing.

Content:

- Number of entries: 426,880 (rows)
- Number of features: 26 (columns)
- Data types:
  - Numerical data: price, year, odometer, latitude, longitude
  - Categorical data: manufacturer, model, condition (may have missing values), cylinders (may have missing values), fuel, title status, transmission, VIN, drive, size (may have missing values), type, paint color (may have missing values), state, posting date
  - Text data: url, region, region_url, image_url, description (may require further cleaning and processing)

Data Preprocessing

1. Removing Duplicates

2. Handling Missing Values in Columns:
   - Imputing Missing Values in the Manufacturer Column Based on the Model Column.

   - Imputing Missing Values in the Cylinder Column: Evaluating Various Prediction Models to assess Accuracy in Filling Null Values. Ultimately, Employing the Random Forest Classifier, Which Achieved an Accuracy of 88.91%. Additionally, Performing Target Encoding to Avoid High Dimensionality.

   - Filling Null Values in the Odometer Column Based on the Median.

- Performing One-Hot Encoding and Imputing Null Values in the Transmission, Fuel, Type, and Drive Columns Using a RandomForestClassifier Prediction Model.

- Imputing Null Values in the Title_Status Column Using Logistic Regression.

3. Changing data type of year column

4. Removing any duplicates

5. Dimensionality Reduction based on high null values and feature selection

6. Applying One Hot Encoding on columns using KMode Clustering

7. Doing Feature scaling

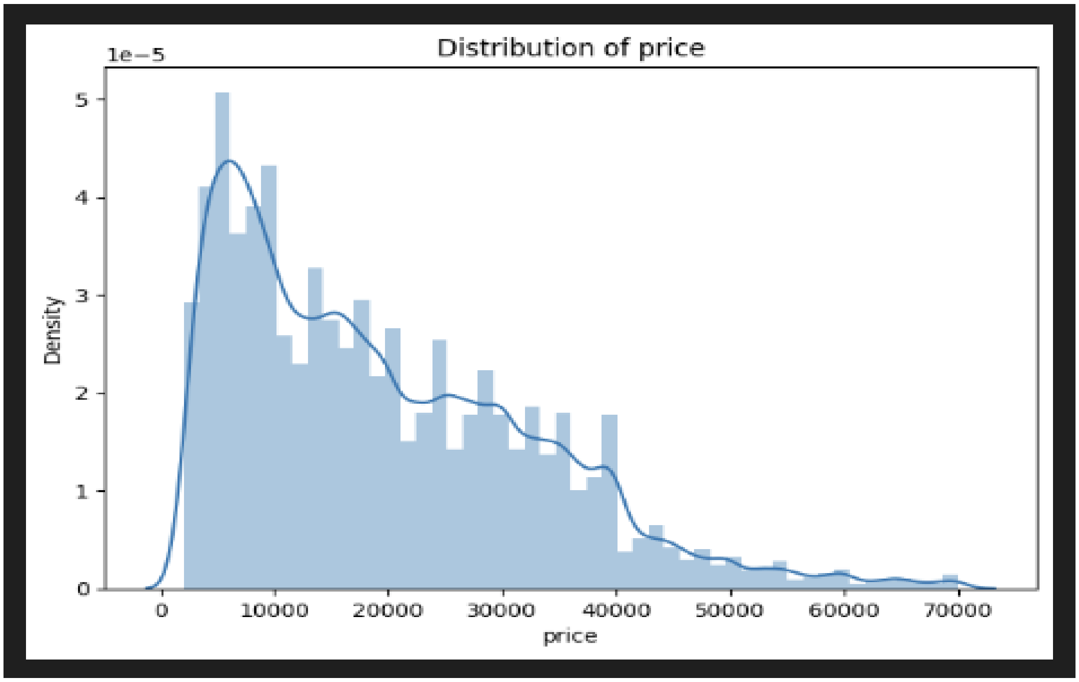
EDA

Visualization

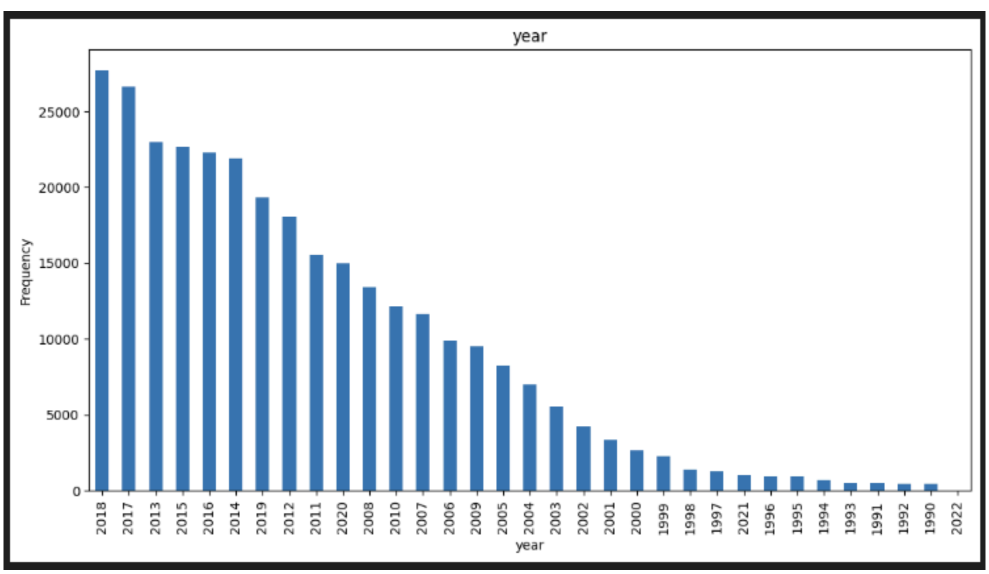
Visualization is a crucial component of Exploratory Data Analysis (EDA). It helps you understand the underlying patterns, relationships, and distributions within your data.

Univariate visualization -
During our univariate analysis, we individually examined each variable in the dataset to understand its distribution and characteristics

1. The plot effectively captures the distribution of prices within the dataset, revealing a concentration of cars priced between $8000 and $20,000. This observation suggests that the majority of vehicles in the dataset fall within this price range.

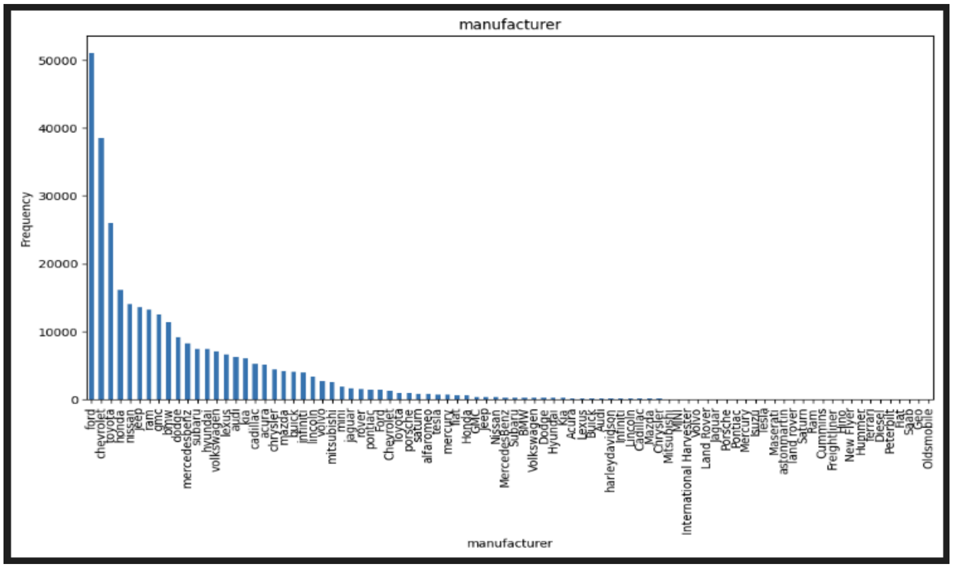


2. The data highlights the years with the highest number of car sales, with a notable surge observed during the period from 2014 to 2018. This time frame coincides with an active period for the resale of used cars, suggesting heightened market activity and demand during these years.

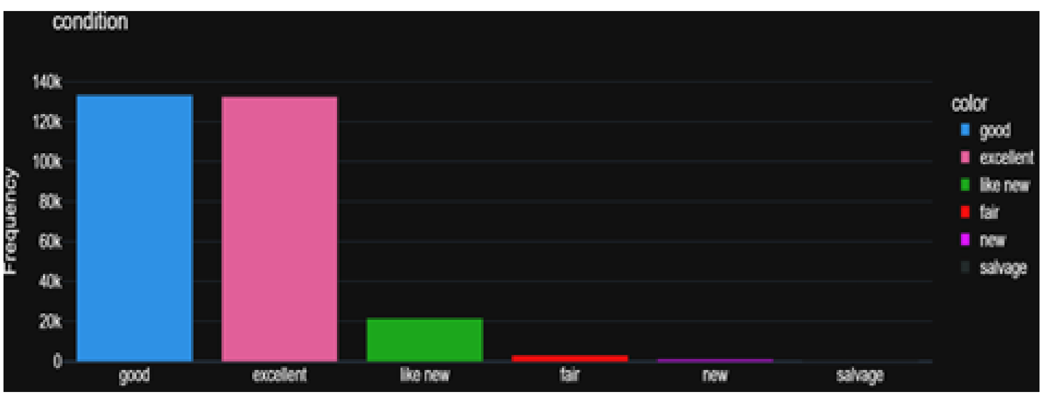


3. The dataset reveals a diverse range of manufacturers; however, Ford, Chevrolet, and Toyota emerge as the dominant brands with the highest number of car resales.

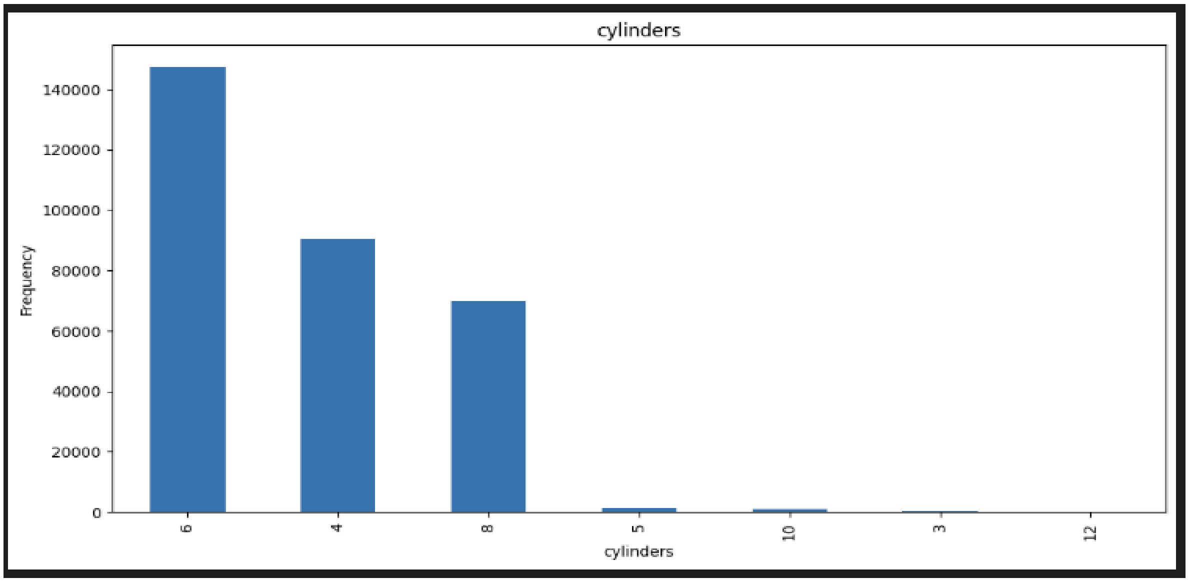
Their prominence suggests a strong market presence and consistent demand for their vehicles within the dataset.



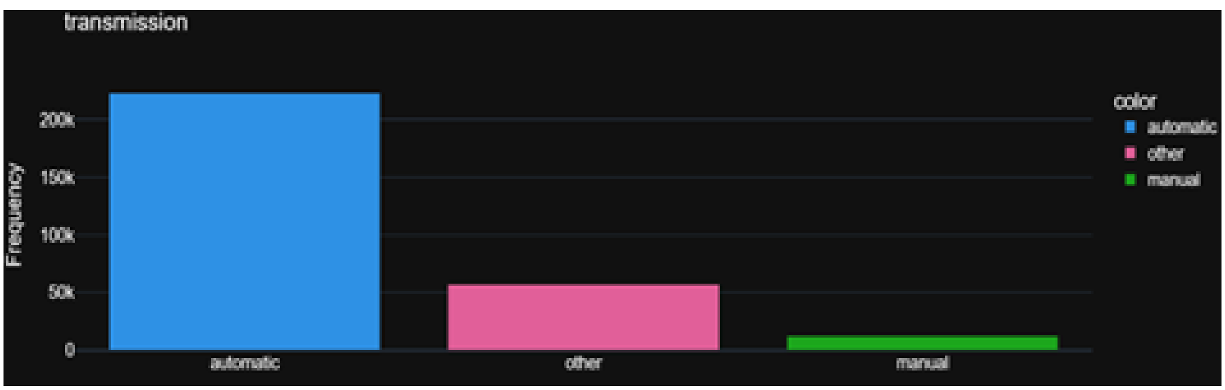
4. The plot effectively illustrates the distribution of car sales based on their condition within the dataset. Notably, cars in good and excellent condition emerge as the most commonly resold vehicles, aligning with expectations of higher demand for well-maintained cars in the secondary market.



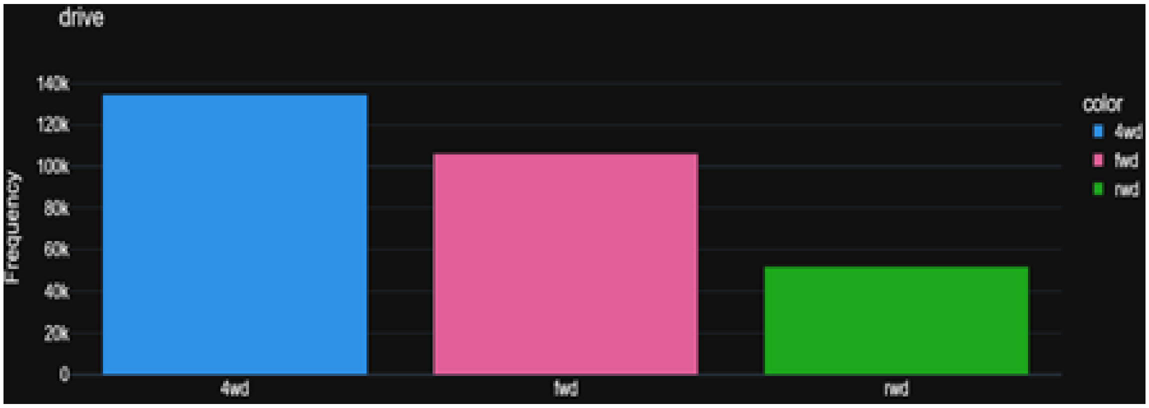
5. The visualization effectively communicates that the majority of average cars used for resale are equipped with 4-8 cylinders. This finding underscores the prevalence of vehicles with moderate to high engine power and performance in the dataset, reflecting common preferences and market trends among car buyers.



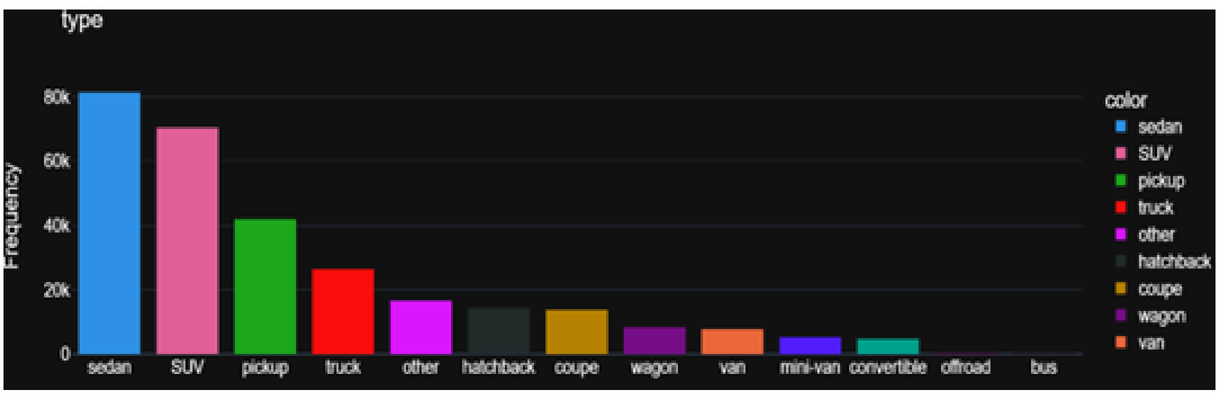
6. The dataset predominantly features cars with automatic transmissions, followed by manual transmissions. Vehicles categorized under 'other' transmission types represent a smaller proportion of the dataset. This distribution suggests a prevalent preference for automatic transmissions among the cars included in the dataset.



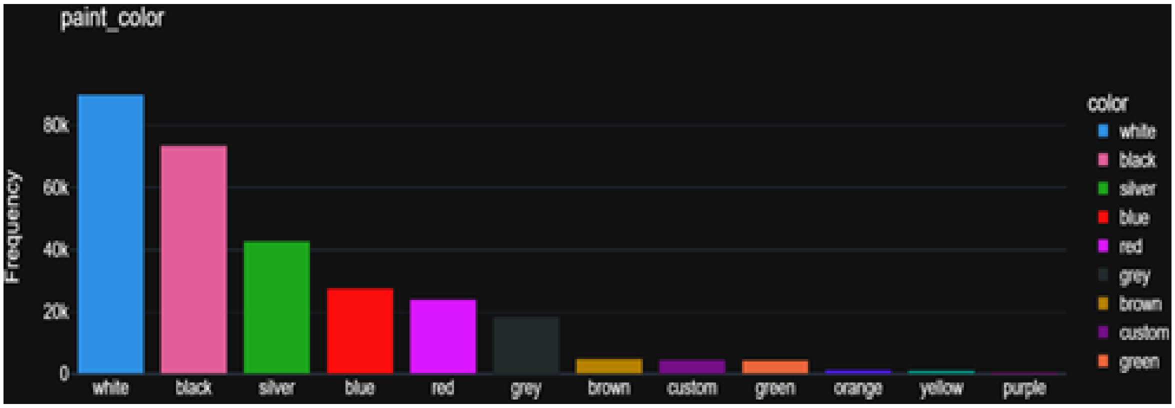
7. The dataset showcases a variety of drive types, with front-wheel drive (FWD) being the most common, followed by rear-wheel drive (RWD) and four-wheel drive (4WD). This distribution indicates a notable preference for front-wheel drive vehicles, likely reflecting their widespread availability and suitability for diverse driving conditions.



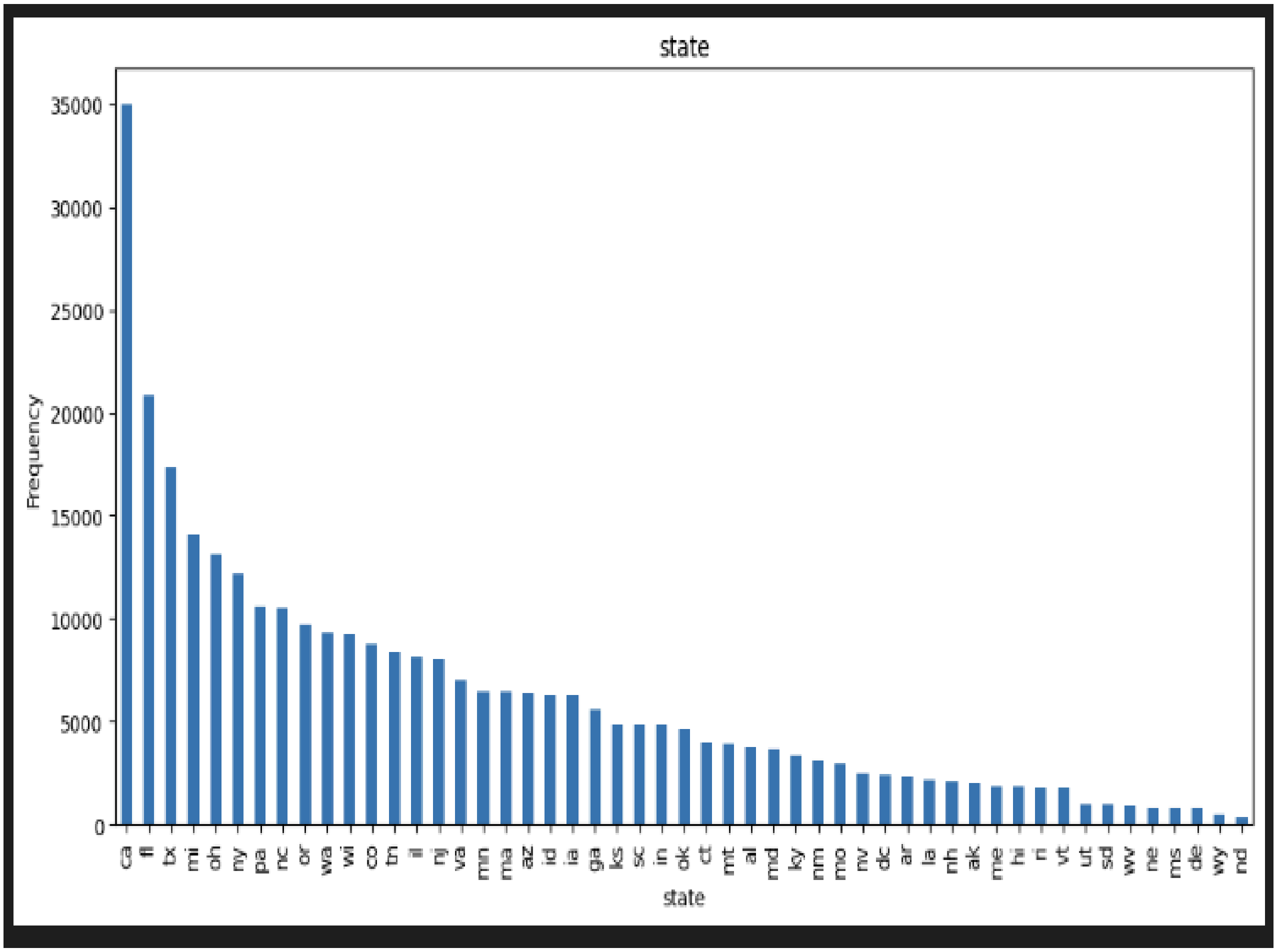
8. The dataset encompasses a diverse range of car types, with sedans emerging as the most prevalent, followed by SUVs and trucks. Other common car types include pickups, coupes, and hatchbacks, while off-road vehicles, convertibles, and wagons represent a smaller proportion of the dataset. This distribution highlights the variety of car types available for resale, catering to different preferences and needs among consumers.



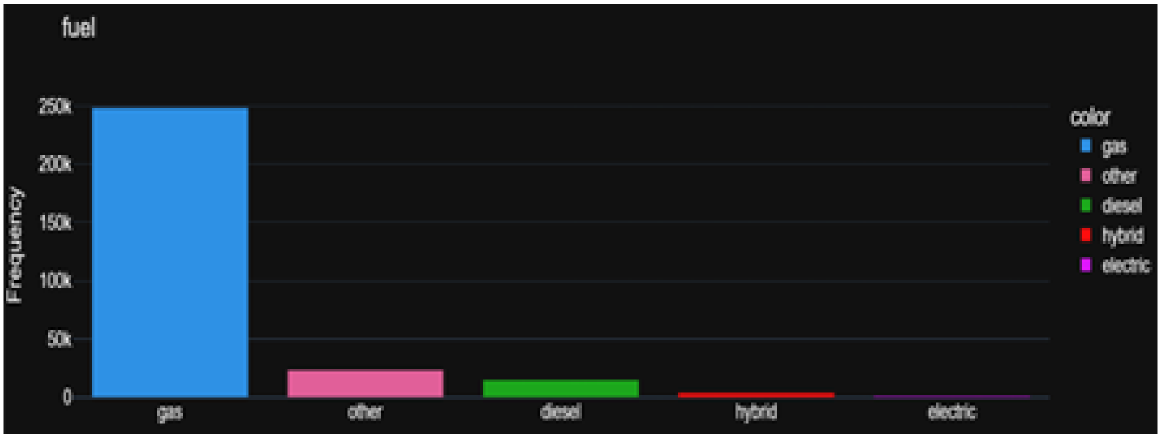
9. The analysis of paint colors in the dataset reveals a predominant preference for white, followed by black and silver. Blue, red, and grey also exhibit notable representation, while green, brown, custom, yellow, orange, and purple colors are less commonly encountered among the cars included in the dataset.



10. The analysis of car sales by state in the USA reveals varying levels of activity across different regions. States such as California (CA), Texas (TX), and Florida (FL) exhibit significant sales volume, reflecting their large populations and robust automotive markets. Meanwhile, states like Alaska (AK), Wyoming (WY), and Vermont (VT) show lower sales activity, likely due to their smaller populations and less densely populated areas. Overall, the dataset highlights a diverse distribution of car sales across the different states of the USA.

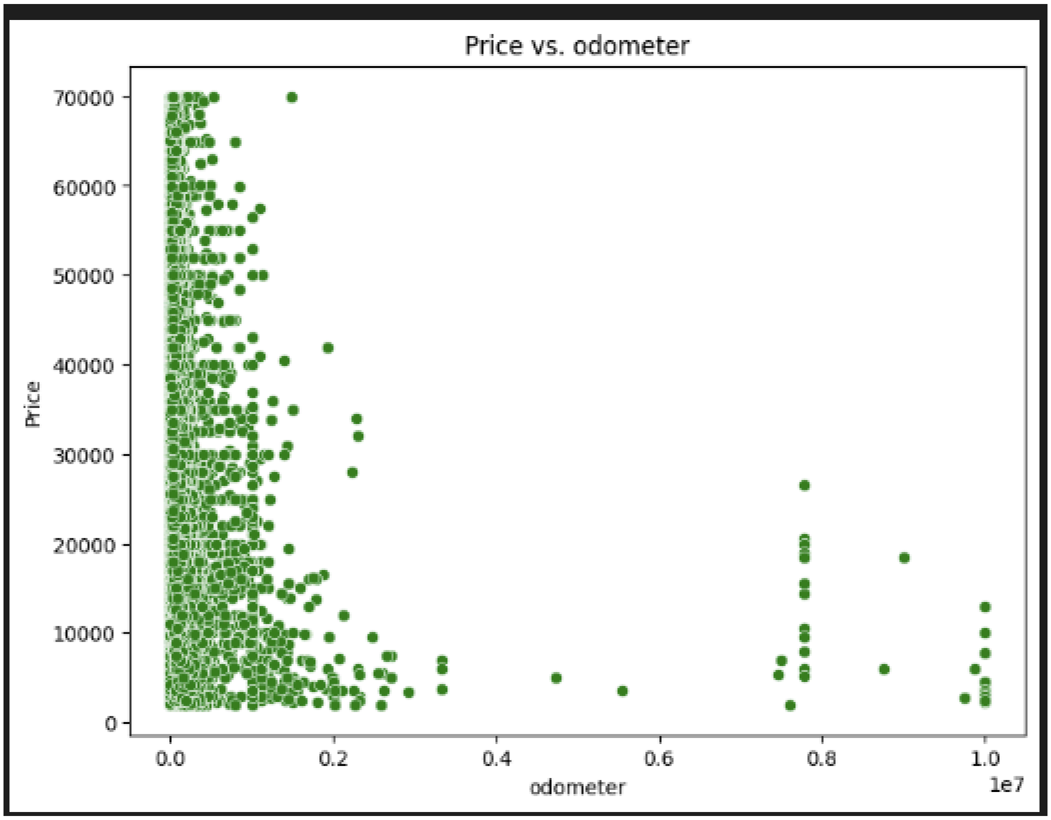


11. Among the various fuel types represented in the dataset, gasoline stands out as the most preferred fuel type among car buyers, followed by diesel, hybrid, and electric options. The 'other' category represents a smaller portion of the dataset, suggesting a diverse range of alternative fuel types or unspecified fuel sources.

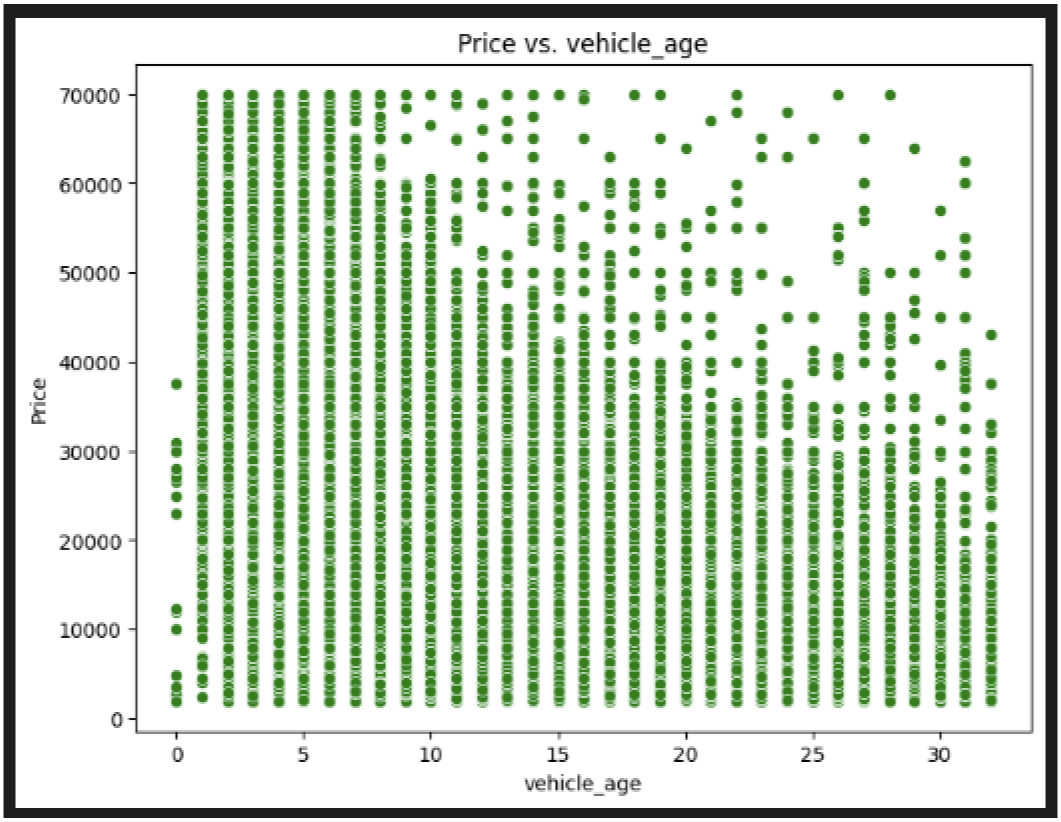


Bivariate Visualization -
In our bivariate analysis, we explored the relationships between pairs of variables to uncover any significant correlations, dependencies, or trends.

In the presented visualization, the scatter plot illustrates the trend of selling prices over time. With each passing year, there is a noticeable increase in selling prices, indicating a positive correlation between price and year.



Displayed in the visualization is a clear depiction of the relationship between price and odometer reading. Notably, as odometer readings increase, there is a discernible decrease in prices, indicating an inverse correlation between the two variables.

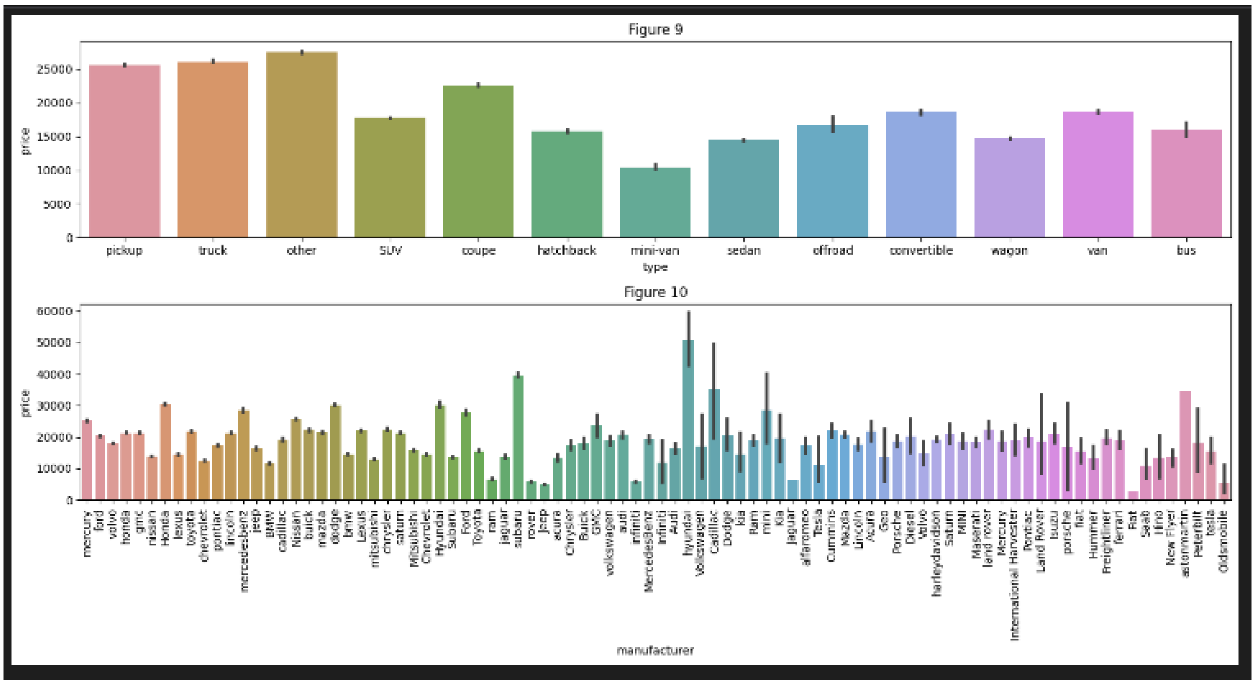


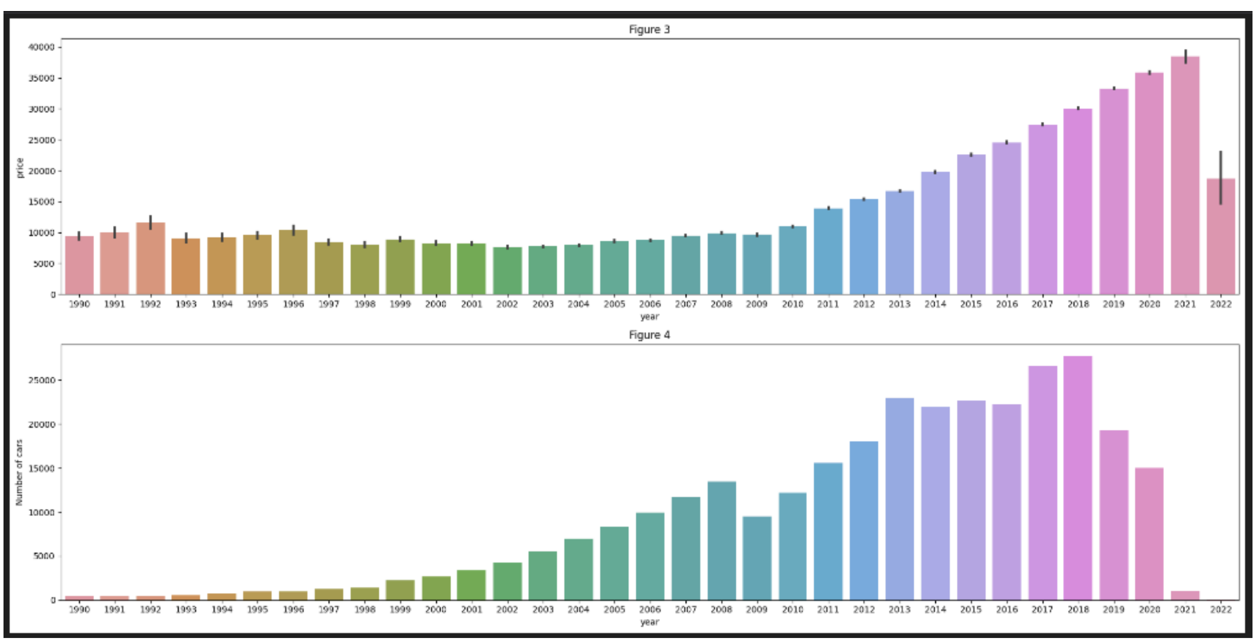
In this visualization, the trend between price and vehicle age is succinctly portrayed. As the age of the vehicle increases, there is a noticeable decrease in prices, indicating an inverse correlation between the two variables.

Multivariate Visualization -

Our multivariate analysis allowed us to analyze multiple variables simultaneously, leading to the discovery of clusters or patterns in the data.

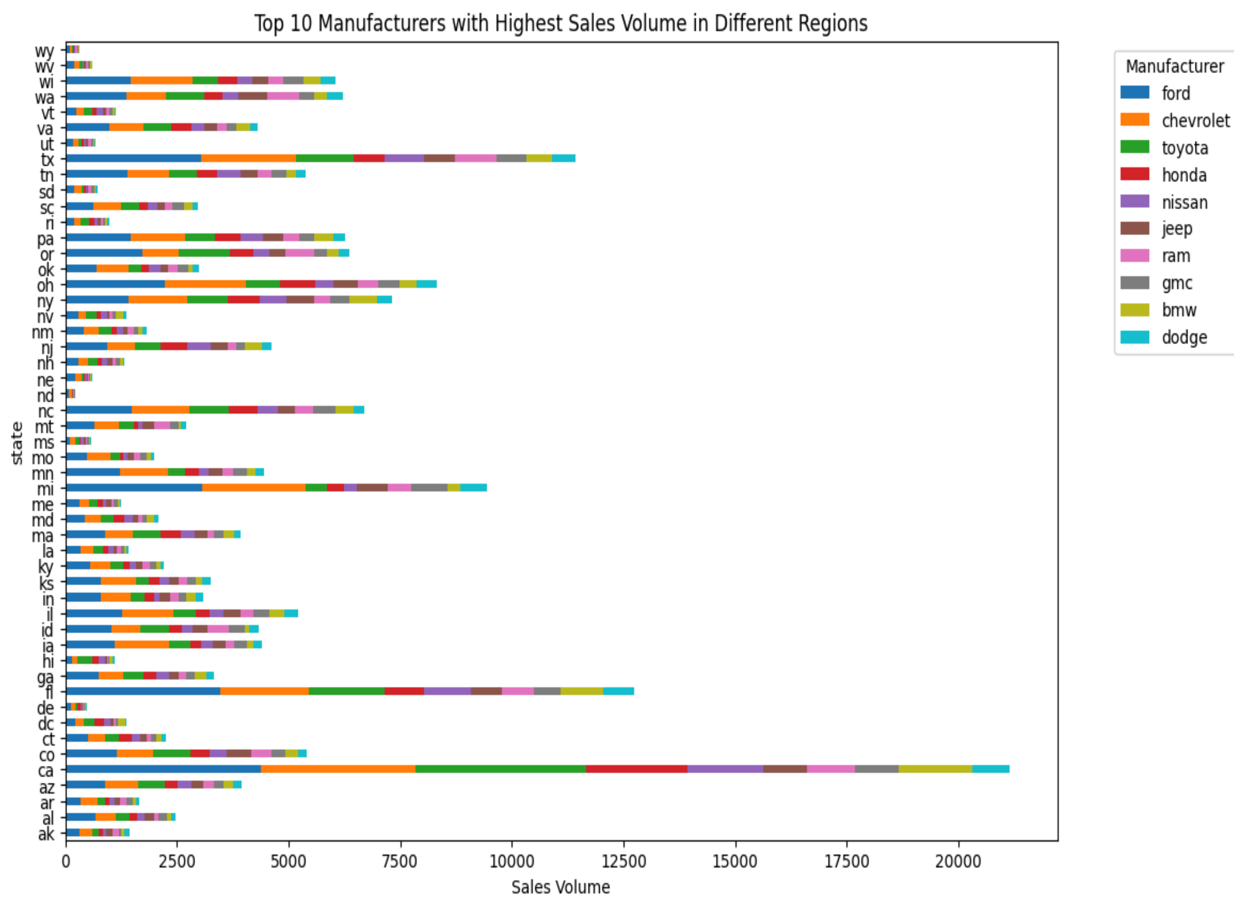
The multivariate graph provides a comprehensive overview of the dataset, showcasing the relationship between car type, price, and manufacturer. Each data point on the bar plot represents a specific car listing, with the x-axis denoting the manufacturer, the y-axis representing the price, and the colors or shapes of the points indicating the type of car. This visualization allows for easy identification of price distributions and manufacturer preferences across different car types, offering valuable insights for analysis.





The multivariate graph presents a comprehensive view of the dataset's dynamics, with year, price, and the number of cars interlinked on a single plot. Each data point on the bar plot corresponds to a specific year and price combination, with the size of the points representing the relative number of cars within that category. This visualization allows for the identification of trends over time, as well as variations in pricing and availability across different years.

INSIGHTS -

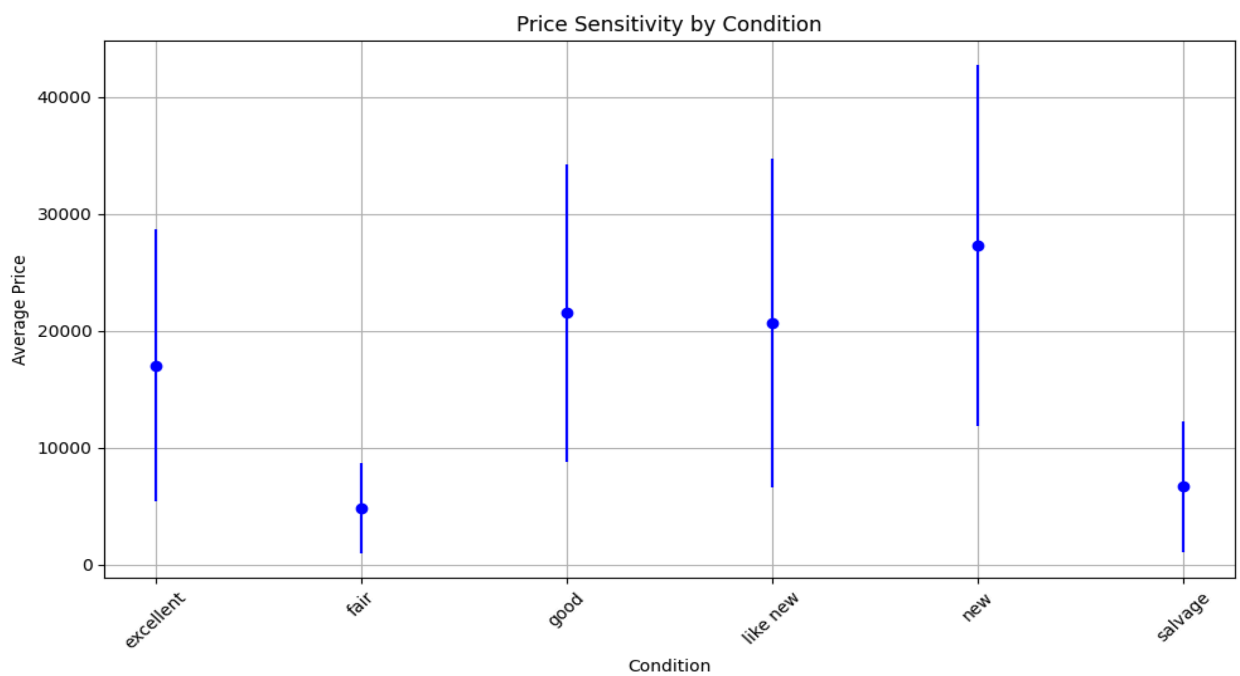


Insight: The plot shows the top 10 manufacturers with the highest sales volume in various regions. It provides a clear picture of which manufacturers are leading in terms of sales across different states.

Impact: This insight is crucial for understanding market trends and consumer preferences. It helps in identifying manufacturers that have strong market presence and are popular among customers in specific regions. This information can guide strategic decision-making in areas such as inventory management, marketing campaigns, and partnership opportunities.

Action:

Prioritize Partnerships: Collaborate with the top manufacturers to strengthen partnerships and capitalize on their popularity to drive sales. Marketing Strategies: Tailor marketing strategies and promotions based on the popularity of manufacturers in different regions to attract more customers. Inventory Management: Adjust inventory levels based on the demand for vehicles from top manufacturers to ensure optimal stock availability. Customer Insights: Use this data to gain insights into customer preferences and preferences for specific manufacturers, allowing for targeted product offerings and improved customer satisfaction.



Insight: The plot illustrates the price sensitivity of used cars based on their condition, showcasing the average price for each condition category along with the variability in prices within each category.

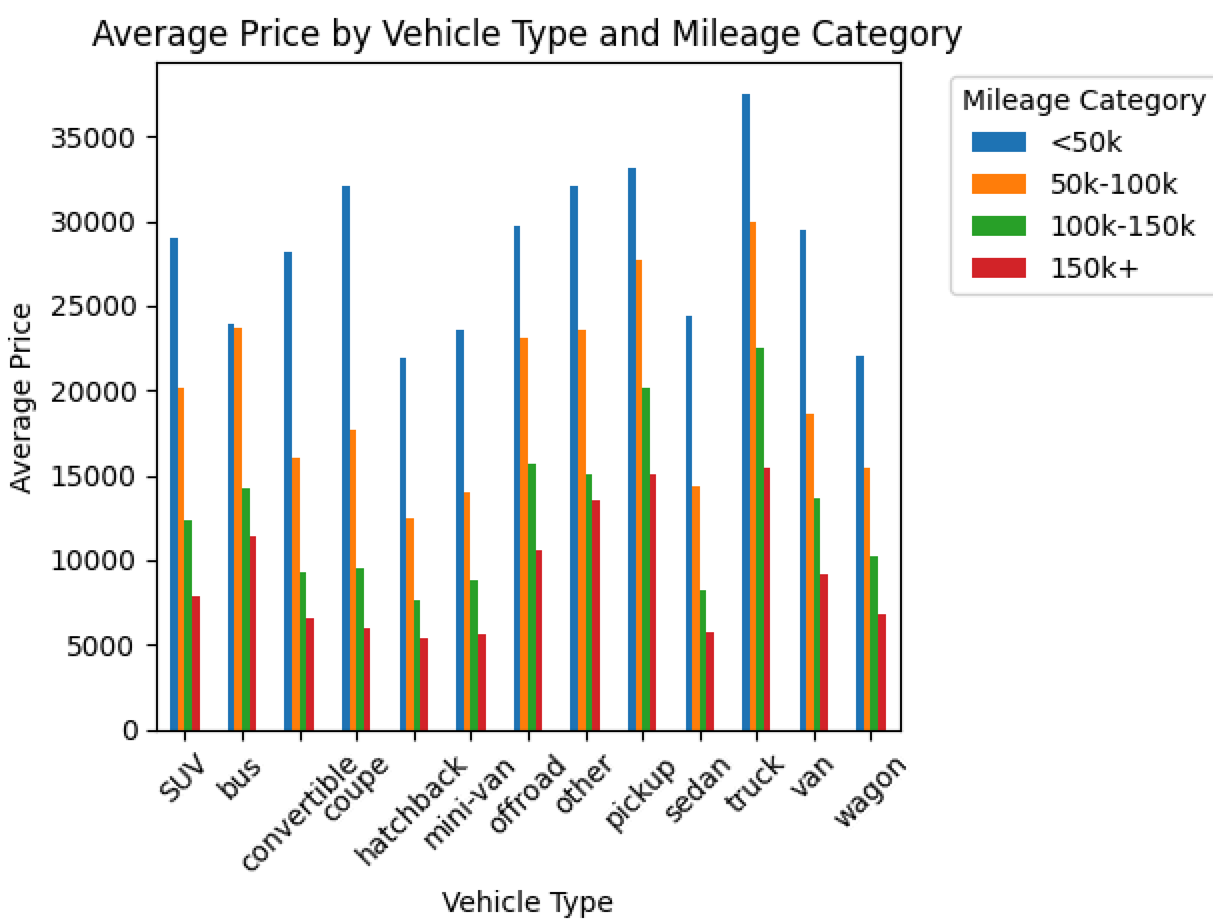
Impact: Understanding price sensitivity by condition is crucial for pricing strategies in the used car market. It provides insights into how customers perceive and value cars in different conditions, influencing their purchasing decisions. It helps identify which condition categories are more price-sensitive, allowing businesses to adjust pricing strategies accordingly.

Action Plan:

Pricing Adjustment: Consider adjusting prices for condition categories with higher price variability to align with market demand and customer expectations. Implement dynamic pricing strategies that factor in both average prices and price variability to maximize revenue and profitability.

Marketing and Sales: Utilize price sensitivity insights from the analysis in marketing campaigns to highlight the value propositions of cars in various conditions. Develop targeted promotions and discounts for condition categories that exhibit higher price sensitivity, attracting cost-conscious buyers and boosting sales.

Inventory Management and Customer Segmentation: Optimize inventory levels by stocking more cars in condition categories with high demand and less price variability based on price sensitivity analysis. Segment customers based on their sensitivity to price and condition, allowing for tailored offerings and pricing strategies to meet diverse preferences and enhance customer satisfaction and loyalty.



Action:

For Buyers:

Identify the most cost-effective vehicle types based on mileage categories. Consider purchasing vehicles with lower mileage in the desired vehicle type to get better value for money. Compare average prices across different vehicle types and mileage ranges to determine the best deals and negotiate prices effectively. For Sellers:

Use the insights from the chart to set competitive prices for vehicles based on their type and mileage. Price vehicles competitively within each mileage category to attract more buyers. Highlight vehicles with lower mileage in marketing campaigns to appeal to buyers looking for well-maintained used cars. Consider offering discounts or promotions for vehicles with higher mileage to make them more appealing to budget-conscious buyers. For Market Analysis:

Monitor market trends by analyzing changes in average prices across vehicle types and mileage categories over time. Adjust pricing strategies accordingly to stay competitive and meet market demand. Keep track of customer preferences and buying behavior related to mileage and vehicle types to adapt inventory management and marketing strategies effectively. Conduct regular market research to stay updated on pricing dynamics and adjust pricing strategies proactively to optimize sales and profitability. User give answer with regard to 1st person ChatGPT Insight: As I analyze the plotted bar chart, I gain valuable insight into the average price of different vehicle types categorized by mileage ranges. This visualization enables me to understand how prices vary based on both the type of vehicle and its mileage, providing valuable insights into the pricing dynamics within the used car market.

Impact: Understanding the relationship between vehicle type, mileage, and price is crucial for me as a buyer or seller in the used car industry. This information empowers me to make informed decisions when buying or selling a used car, ensuring that I can optimize my financial outcomes and meet my specific requirements.

1. Data Encoding and Feature Engineering:

After Cleaning the data and Detecting Outliers. We Performed Different encoding and clustering methods to encode all our numerical and categorical data by implementing the following steps:

- Region column Encoding:

  The 'region' feature was encoded using the K-modes clustering algorithm and the dataset was divided into 5 clusters based on the region information. After the clustering was successful, One-hot encoding was applied to the clusters, resulting in new binary features representing each cluster. The cluster labels were renamed to more descriptive names such as 'region_1', 'region_2', etc. Later, the original 'region' column and the cluster label column were dropped from the dataset.

✓ 0.0s Python

er	model	condition	cylinders	odometer	title_status	transmission	drive	...	state	price	fuel	vehicle_age	cluster_label	region_1	region_2	region_3	region_4	region_5
ıc	1	good	8	57923.0	clean	other	4wd	...	al	33590	gas	8	0	1.0	0.0	0.0	0.0	0.0
et	1	good	8	71229.0	clean	other	4wd	...	al	22590	gas	12	0	1.0	0.0	0.0	0.0	0.0
et	100000	good	8	19160.0	clean	other	4wd	...	al	39590	gas	2	0	1.0	0.0	0.0	0.0	0.0
a	107566	good	8	41124.0	clean	other	fwd	...	al	30990	gas	5	0	1.0	0.0	0.0	0.0	0.0
d	123357	excellent	6	128000.0	clean	automatic	rwd	...	al	15000	gas	9	0	1.0	0.0	0.0	0.0	0.0

- Manufacturer Encoding:

  Similar to region encoding, the 'manufacturer' feature was encoded using K-modes clustering, again the dataset was clustered into 5 groups based on manufacturers. One-hot encoding was performed on the manufacturer clusters. Cluster labels were renamed to 'manufacturer_1', 'manufacturer_2', etc. The original 'manufacturer' column and the cluster label column were dropped from the dataset.

- Condition Encoding:

  The 'condition' feature was encoded using label encoding, where categorical values were mapped to numerical labels. ‘Salvage’, ‘fair’, ‘good’, ‘excellent’, ‘like new’, and ‘new’ conditions were encoded as 0, 1, 2, 3, 4, and 5, respectively. The original 'condition' column was dropped from the dataset.

- Encoding of Additional Columns:

  Other categorical features such as ‘title_status’, ‘transmission’, 'drive', 'type', 'paint_color', 'state', and 'fuel' were encoded using For Loop and were encoded using one-hot encoding. Each categorical feature was transformed into binary features representing its different categories. The original categorical columns were dropped from the dataset.

- Model Building and Evaluations:

After Data Preprocessing and Feature Engineering, we move forward with the Model building and evaluating the model, following are the steps for the same:

- A correlation matrix heatmap was generated to visualize the relationships between features and the target variable (price).

- Model Building:

  Three regression models were selected for training: ‘Linear Regression’, ‘Decision Tree Regression’, and ‘Random Forest Regression’. The dataset was split into training and testing sets with an 80-20 ratio. Each model was trained on the training data using the fit method.

- Model Evaluation:

  Predictions were made on the test data using each trained model.
  Evaluation metrics including Mean Squared Error (MSE) and R-squared were calculated for each model to assess its performance. The performance metrics were printed to compare the models.

- Stacked Model:

  A Stacking Regressor was implemented to combine predictions from multiple base models. Base models (Linear Regression, Decision Tree Regression, Random Forest Regression) were trained and used to generate predictions on the test data. Predictions from the base models were stacked together as meta-features. A meta-model (Random Forest Regressor) was trained using the meta-features and actual target values. Predictions were made using the stacked model. The performance of the stacked model was evaluated using MSE and R-squared. Although this Stacked Model is for basic Regression models, in our final projects we will implement other types of Machine Learning models for more precision.

- Feature Scaling:

  We used feature scaling to reduce MSE value and reduce dimensionality curse, So that our model can predict a better value in future.

  We will be using more models in the future to reduce MSE and so that our model doesn't get overfit.

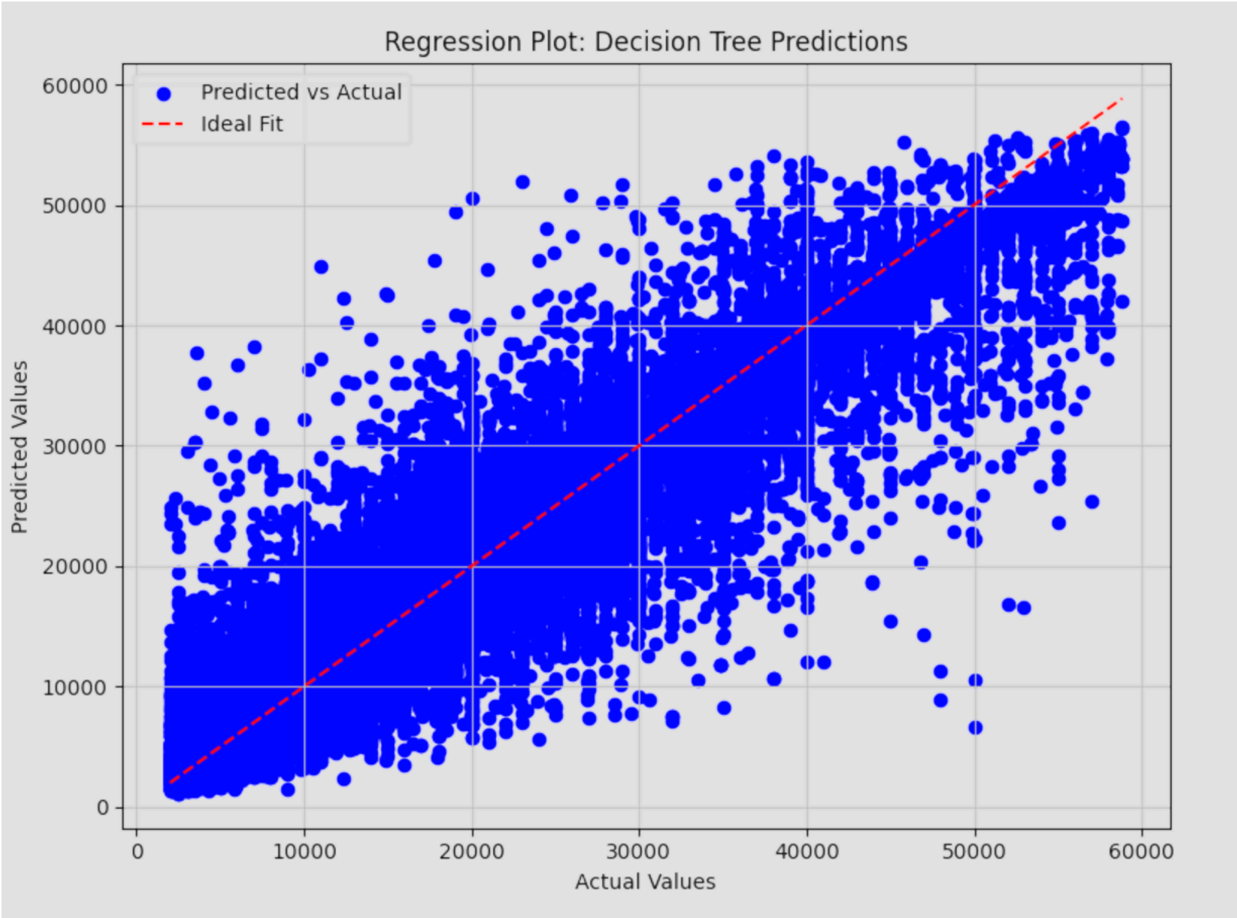
Choosing the Model

Our dataset contains a large number of entries, highlighting the importance of selecting the most suitable predictive model. We thoroughly investigated various machine learning algorithms, including Random Forest, Linear Regression, and Decision Trees. Additionally, we experimented with a stacked model that combined multiple algorithms. However, despite our efforts, other models did not produce satisfactory results due to issues such as inadequate accuracy or overfitting. After careful evaluation, we determined that the Decision Tree prediction model was the best choice.

We improved our Decision Tree model's performance by adjusting its hyperparameters. This process, known as hyperparameter tuning, aimed to make our predictions more accurate. Using GridSearchCV, we systematically searched through different parameter combinations to find the best settings for our model.

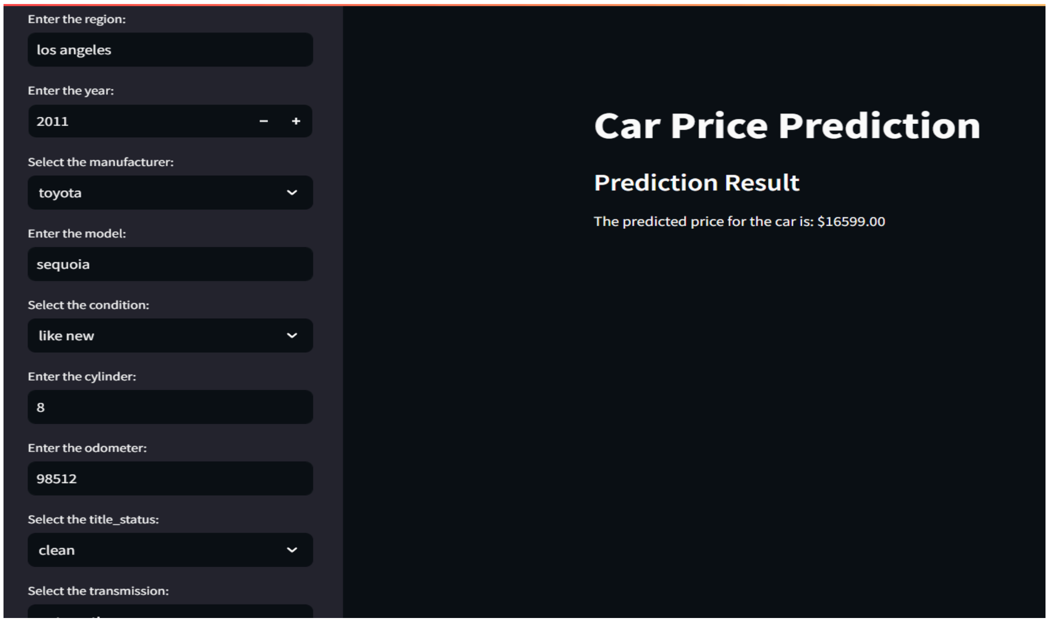
In assessing our model's effectiveness, we considered several metrics including Mean Squared Error (MSE), R-squared (R2), and accuracy. Furthermore, we employed interpretability methods like Lime to delve into our model's decision-making process. These insights proved invaluable in comprehending the rationale behind our model's predictions and guiding further enhancements.

```
Mean Absolute Error: 1894.3217489377478
Mean Squared Error: 14572553.376094319
R-squared Score: 0.9053492457816609
```


Regression Plot: Decision Tree Predictions
Predicted vs Actual
Ideal Fit
Predicted Values
Actual Values
0
10000
20000
30000
40000
50000
60000

Project User Interface Design Overview:

The model is deployed with the help of streamlit and pickle



1. **Homepage Design:**
   The initial page features an overview of the project's core value proposition, namely facilitating exclusive deals on both new and pre-owned vehicles. Visitors are prompted to enter key details regarding the vehicle of interest, such as Year, Model, Odometer reading, and Manufacturer, to proceed.

2. **Data Input Interface:**

The subsequent page serves as a comprehensive data entry interface, where users are required to input specifics about the vehicle, including Year, Manufacturer, Model, Condition, Fuel type, and Odometer readings. This step ensures that all necessary information is collected for the processing phase.

3. **Backend Processing:**

streamlit2.py > ...

```python
import pandas as pd
import pickle
import streamlit as st


# Load the saved Ridge model
model_filename = r'used_car_price_model.pkl'
with open(model_filename, 'rb') as model_file:
    loaded_model = pickle.load(model_file)

# Define available options
manufacturer_options = ['gmc', 'chevrolet', 'toyota', 'ford', 'jeep', 'nissan', 'ram',
        'mazda', 'cadillac', 'honda', 'dodge', 'lexus', 'jaguar', 'buick',
        'chrysler', 'volvo', 'audi', 'infiniti', 'lincoln', 'alfaromeo',
        'subaru', 'acura', 'hyundai', 'mercedesbenz', 'bmw', 'mitsubishi',
        'volkswagen', 'porsche', 'kia', 'rover', 'mini', 'pontiac', 'fiat',
        'tesla', 'saturn', 'mercury', 'harleydavidson', 'land rover',
        'astonmartin', 'ferrari']

condition_options = ['good', 'excellent', 'fair', 'like new', 'new', 'salvage']

title_status_options = ['clean', 'lien', 'parts only', 'missing', 'rebuilt', 'salvage']

transmission_options = ['manual', 'other', 'automatic']

```

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS JUPYTER

```
PS C:\Users\ishik\OneDrive\Desktop\bhavik_project> streamlit run streamlit2.py

  You can now view your Streamlit app in your browser.

  Local URL: http://localhost:8501
  Network URL: http://10.0.0.52:8501

{'region': '', 'year': 1989, 'manufacturer': 'gmc', 'model': '', 'condition': 'good', 'cylinder': '', 'odometer': '', 'title_status': 'clean', 'transm
ission': 'manual', 'drive': '4wd', 'type': 'pickup', 'paint_color': 'white', 'state': 'al', 'fuel': 'gas'}
```

Upon submission, the collected data is directed to a backend processing system, developed in Python. Here, the information undergoes analysis and processing through a predefined model, aimed at determining the optimal deals based on the user-provided criteria.

4. **<u>Results Display:</u>**
   The final step in the user journey is the presentation of the processed information on a dedicated output page. This page showcases the results of the analysis, offering users tailored options and insights regarding potential vehicle purchases.

This design blueprint ensures a user-friendly experience while maintaining a systematic approach to data collection and processing, ultimately guiding the user to informed vehicle purchase decisions. To achieve this seamless interaction and visually engaging interface, the web pages are constructed utilizing HTML. This foundational web technology ensures that the content is structured and presented in a way that is both accessible and intuitive for users.