

Car Prediction Model

Mini-Project





Introduction

Our project involves implementing a Neural Network to suggest consumers a car based on their preferences such as price, mileage, transmission type and fuel type. We have developed a model using a rich dataset.



Scope




01 Dataset 

02 Data Cleaning and Visualisation 

03 A.I. Model 

04 Testing 

05 Conclusion 



Dataset

Dataset Overview

A comprehensive dataset of car listings which includes features like make, model, year, mileage, engine size, and price.

Data Source

The data was sourced from kaggle.

Objective

To develop a model capable of suggesting cars based on a buyers needs.



Data Cleaning

Common Issues

Initial data inspection showed missing values, duplicate entries, and inconsistent formats, especially in the 'year' and 'price' fields.

Data Quality

Significant outliers were found in 'price' and 'mileage', which skewed the data distribution and needed addressing.



Handling Missing Values

Missing values in critical fields like 'engine size' and 'mileage' were added using median values based on the car's make and model.



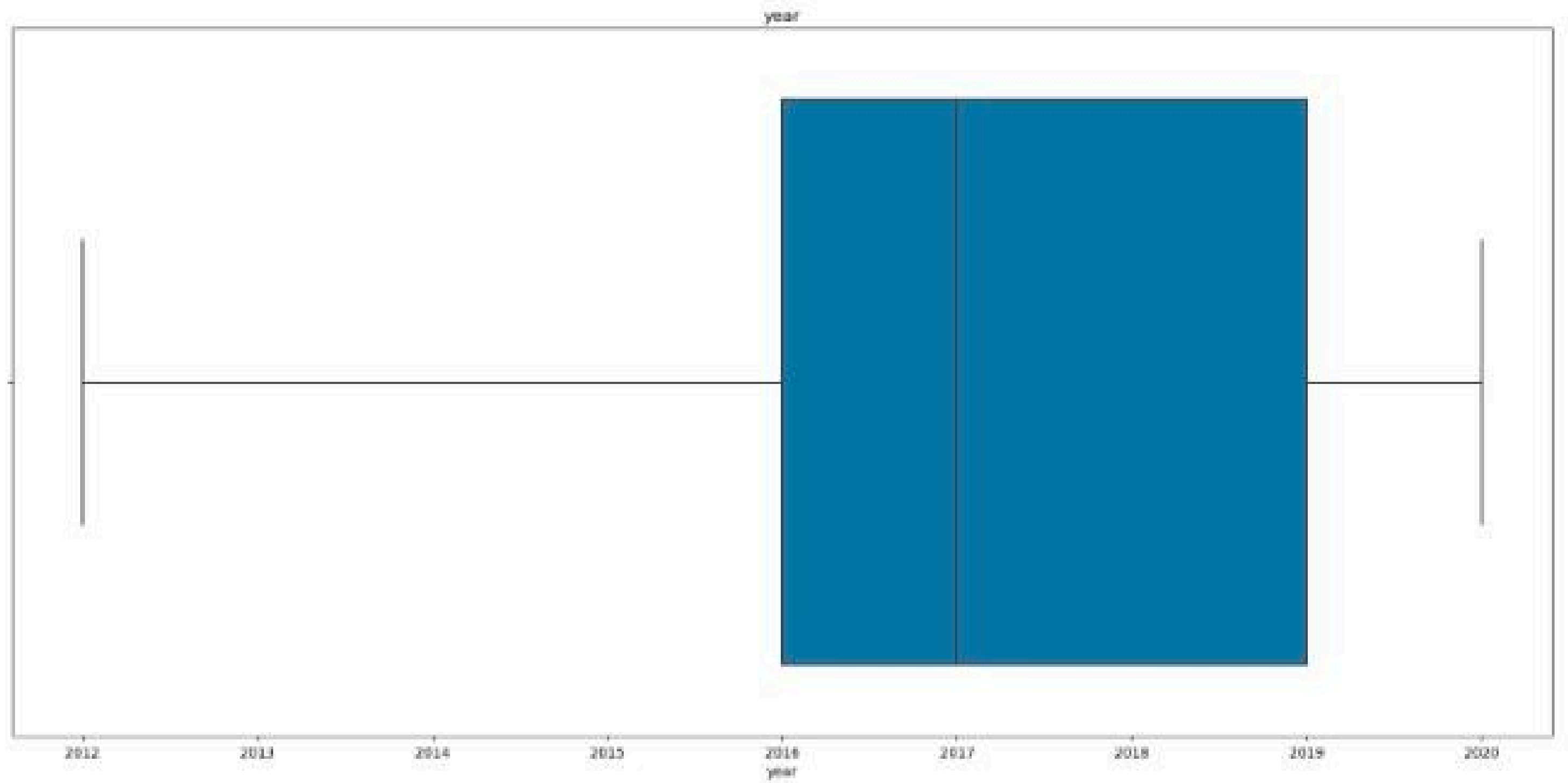
Standardising Formats

All date fields were standardised to YYYY format, and categorical data was encoded for model compatibility.

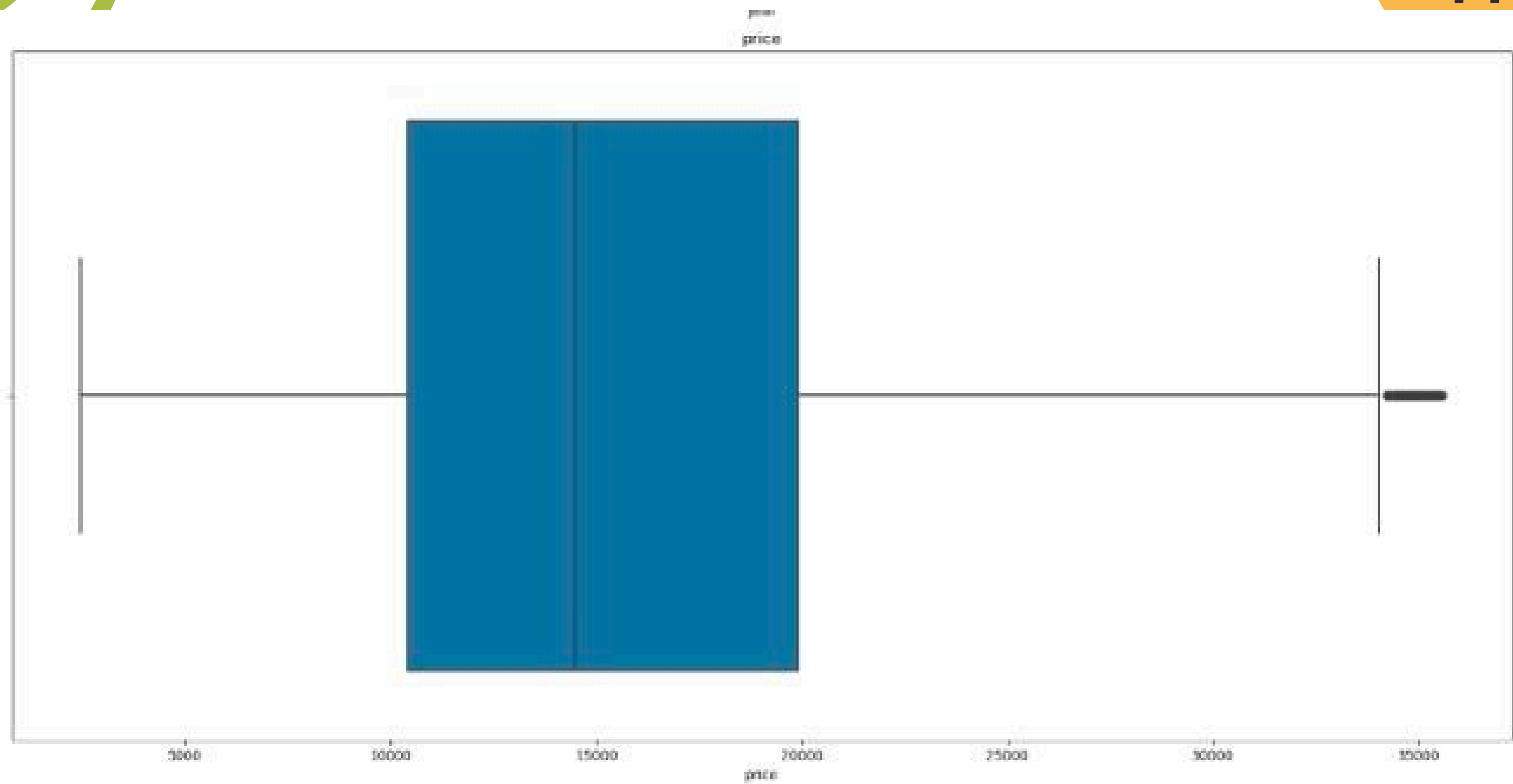


Removing Outliers

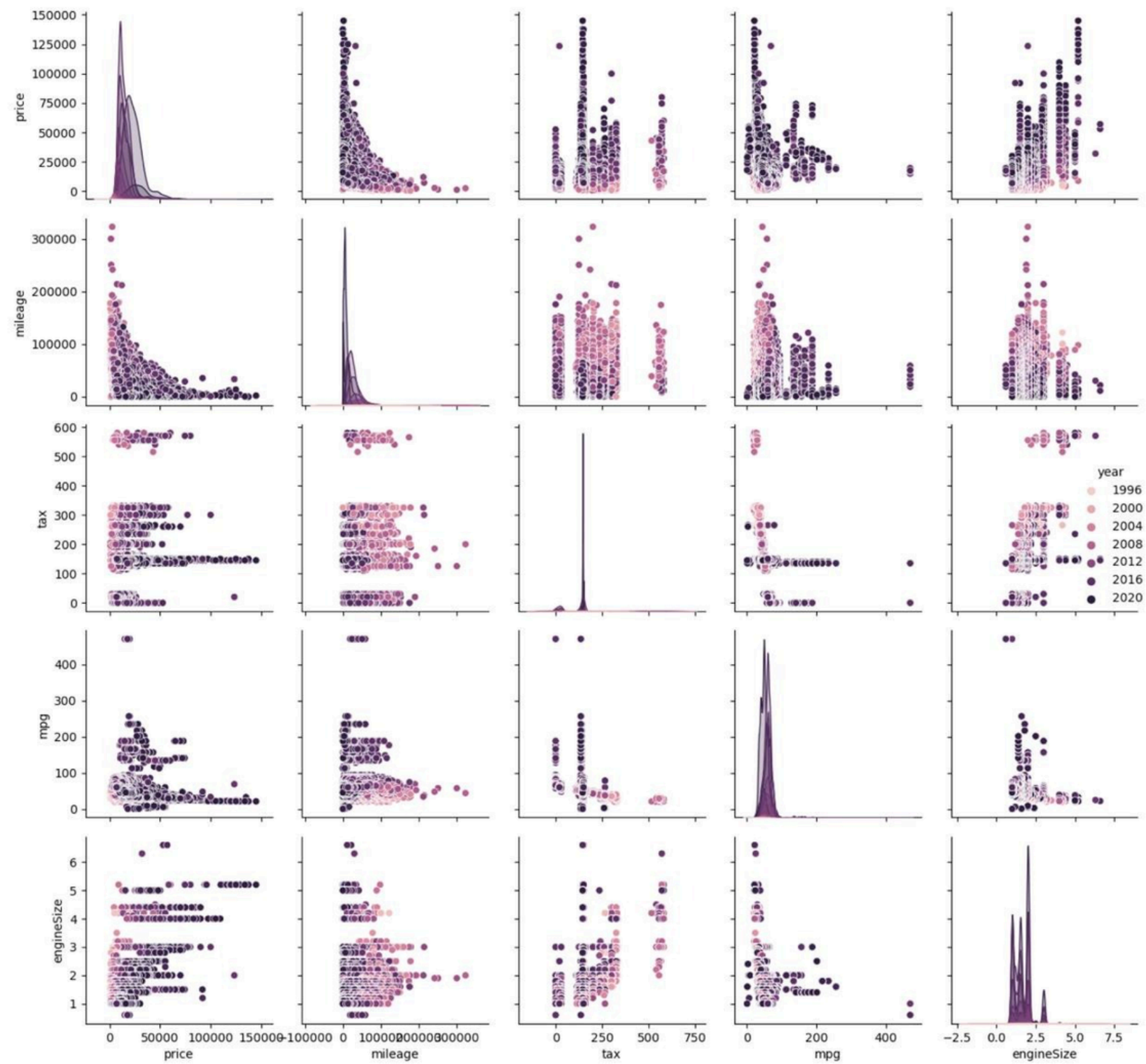
Price and mileage outliers were identified and removed using IQR scores to normalize the data distribution.



Year Box Plot



Price Box Plot



Pair Plot



Visualizing Data Distribution (EDA)

Box Plots

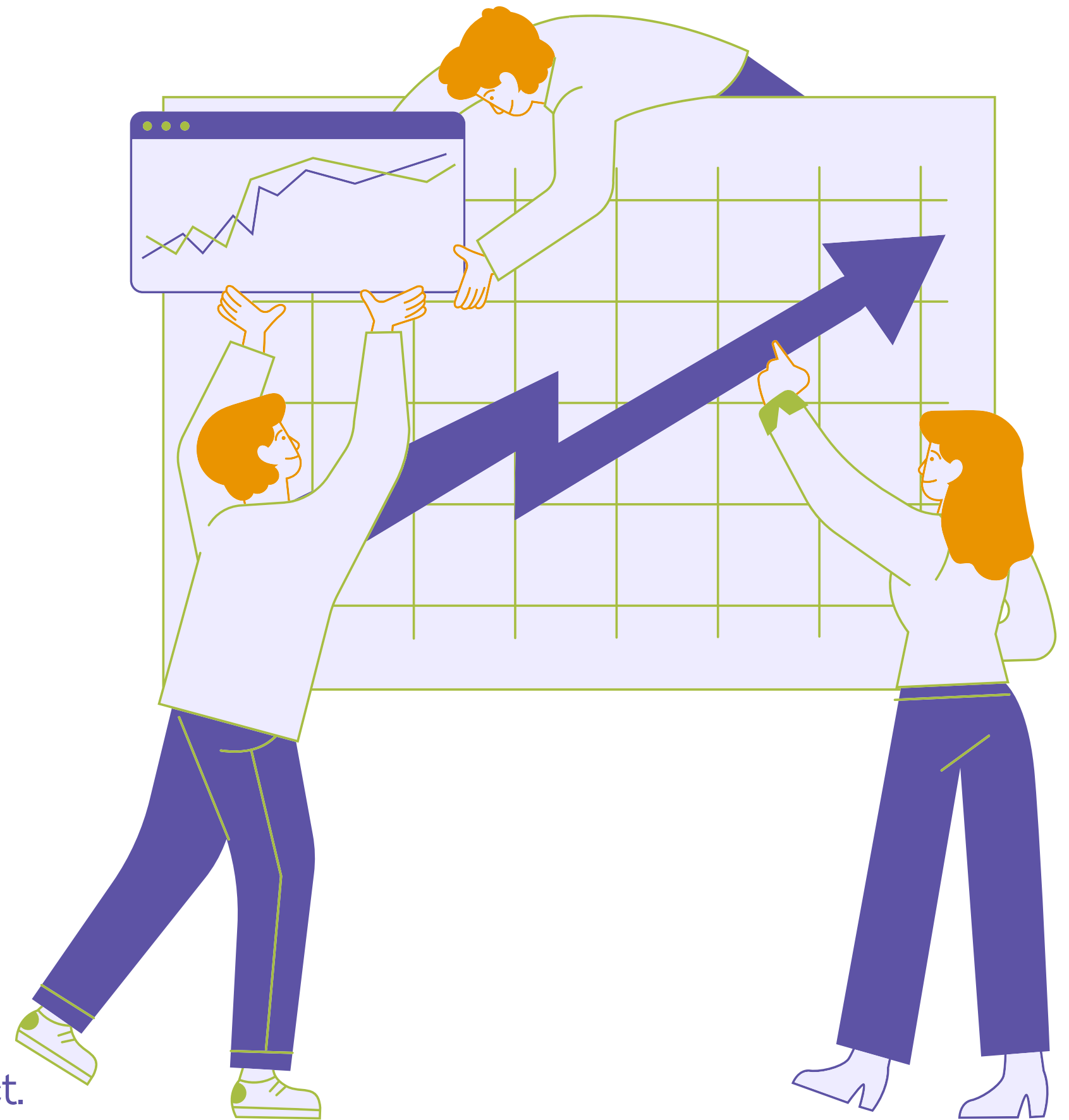
Used to assess the distribution of prices and mileage, identifying skewness and the impact of outlier removal.

Correlation Heatmap

A heatmap was employed to visualise the correlation between numerical features, highlighting the strong predictors for car pricing.

Pair Plot

Plotting engine size against price showed patterns and trends, aiding in hypothesis generation about feature impact.



A.I. Model

Autoencoder

Autoencoders are a type of neural network used to learn efficient codings of unlabeled data. They work by compressing the input into a latent-space representation and then reconstructing the output from this representation.

Autoencoder is used to reduce the dimensionality of the data, enhancing the neural network's ability to capture essential features without overfitting.

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Testing & Optimisation

Methods

01

Loss Function

Mean Squared Error (MSE) was used as the loss function to measure how well the autoencoder reconstructed the data, with the aim being to minimize the difference between the original input and the reconstructed output

02

Reconstruction Accuracy

Additionally, reconstruction accuracy helps in identifying potential shortcomings or limitations of the model, guiding further refinement or adaptation strategies.



Testing & Optimisation

Methods

03 Optimizer
The Adam optimizer was utilised for its efficient computation and adaptive learning rate properties, which help in converging to the minimum loss faster.

04 Training Process
The autoencoder was trained on the entire dataset without labels, focusing on learning the most salient features. We utilised early stopping to prevent overtraining and ensure the model generalized well.



In [24]:

```
1 # Define the function that will be called when the button is clicked
2 def on_button_clicked(b):
3     with output:
4         output.clear_output()
5         recommend_similar_cars()
6 button = widgets.Button(description="Recommend Cars")
7 button.on_click(on_button_clicked)
8
9 # Display widgets for user input
10 output = widgets.Output()
11 display(price_input, mileage_input, transmission_input, fuel_type_input, button, output)
```

Price:

Mileage:

Transmission:

Fuel Type:

Recommend Cars

Based on your input, here are suggested cars:

| | model | year | price | transmission | mileage | fuelType | tax | mpg | \ |
|-------|----------|------|-------|--------------|---------|----------|-------|------|---|
| 45550 | A5 | 2019 | 25000 | Automatic | 100 | Petrol | 145.0 | 53.3 | |
| 15271 | 2 Series | 2020 | 25000 | Automatic | 101 | Petrol | 145.0 | 47.9 | |
| 15267 | 2 Series | 2019 | 25000 | Automatic | 4000 | Petrol | 145.0 | 47.9 | |
| 37631 | X1 | 2019 | 25000 | Automatic | 4534 | Petrol | 145.0 | 46.3 | |
| 10340 | A5 | 2017 | 25000 | Automatic | 19000 | Petrol | 145.0 | 45.6 | |

| | engineSize | Make |
|-------|------------|------|
| 45550 | 1.4 | audi |
| 15271 | 2.0 | BMW |
| 15267 | 2.0 | BMW |
| 37631 | 1.5 | BMW |
| 10340 | 2.0 | audi |

Pair Plot



Conclusion

Our project successfully uses a neural network to address a real-world need in the automotive industry. By integrating data cleaning, visualisations, and innovative AI modelling, we've developed a tool that not only predicts but also understands consumer preferences.





Thanks

