Old car price prediction using Machine Learning

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***Abstract*— The buying and selling of old cars is a common activity worldwide, and determining a fair price for a used car can be challenging. It depends on many factors such as the model, year, mileage, and overall condition of the car. In this regard, machine learning-based systems have shown promise in predicting the prices of various items, including used cars. This project aims to develop a machine learning-based system that can predict the price of old cars using two regression algorithms - KNN regressor and multilayer perceptron (MLP). The system is implemented using the scikit-learn library in Python, and various steps are taken, including data preprocessing, data visualization, model training, and evaluation. The data preprocessing step involves cleaning the dataset, handling missing values, and encoding categorical variables. The dataset is then visualized to gain insights into the distribution of the data and the relationships between the features and the target variable. The machine learning models are trained using the preprocessed data, and their performance is evaluated using various metrics such as mean squared error and R-squared scores. The KNN regressor and MLP algorithms are used for predicting the prices of old cars. The KNN algorithm is a non-parametric method that works by finding the K nearest neighbors to a given data point and using their average value to predict the target variable. The MLP algorithm is a type of artificial neural network that learns from data by adjusting the weights of its connections between neurons. Both algorithms are trained and evaluated, and the performance of the models is compared. The evaluation results show that the MLP algorithm outperforms the KNN regressor in terms of prediction accuracy. The MLP algorithm achieved an R-squared score of 0.87 and a mean squared error of 12,483, while the KNN regressor achieved an R-squared score of 0.72 and a mean squared error of 23,754. This indicates that the MLP algorithm can better capture the complex relationships between the features and the target variable in the dataset.**

***Keywords;- old car, price prediction, machine learning, KNN regressor, MLP, scikit-learn, Python***

# Introduction

The buying and selling of old cars is a common activity worldwide, and determining a fair price for a used car can be challenging. It depends on many factors such as the model, year, mileage, and overall condition of the car. In this regard, machine learning-based systems have shown promise in predicting the prices of various items, including used cars. This project aims to develop a machine learning-based system that can predict the price of old cars using two regression algorithms - KNN regressor and multilayer perceptron (MLP). Used cars have been an important part of the automobile industry for decades. They offer a more affordable option for people who cannot afford a new car, and they also provide an opportunity for people to sell their old cars and upgrade to a newer model. However, determining the fair price of a used car can be challenging, as it depends on many factors such as the model, year, mileage, and overall condition of the car. Furthermore, the prices of used cars can vary widely depending on the seller, location, and other factors. This makes it difficult for both buyers and sellers to know the true value of a car.

Github link: <https://github.com/VARUN-1999/700745184_ML_ASSIGNMENTS/tree/main/PROJECT>

In recent years, machine learning-based systems have shown promise in predicting the prices of various items, including real estate, stocks, and cars. Machine learning algorithms can take into account many variables and make more accurate predictions of the fair price of a used car. By analyzing historical data and identifying patterns, these algorithms can predict the future price of a car based on its characteristics. The main objective of this project is to develop a machine learning-based system that can predict the price of old cars. The system uses the scikit-learn library in Python, and two regression algorithms - KNN regressor and multilayer perceptron (MLP) - to predict the price of old cars based on their characteristics such as model, year, mileage, etc. In this report, we will discuss the implementation of a machine learning-based system for predicting the price of old cars. The system was developed using the scikit-learn library in Python, and two regression algorithms - KNN regressor and MLP. We will discuss the various steps involved in the implementation of the system, including data preprocessing, data visualization, model training, and evaluation.

The rest of this report is organized as follows: Section 2 describes the data preprocessing steps that were undertaken to prepare the dataset for use in the machine learning models. Section 3 describes the data visualization techniques that were used to gain insights into the dataset. Section 4 describes the machine learning models that were developed, including the

KNN regressor and MLP algorithms. Section 5 presents the results of the evaluation of the models, including the mean squared error and R-squared scores. Section 6 concludes the report and discusses future work.

# Related Works

Several studies have been conducted in the area of car price prediction using machine learning algorithms. For example, in a study by Wang et al. (2019), a machine learning model was developed to predict the price of used cars based on their characteristics such as make, model, year, and mileage. The authors used a support vector regression (SVR) algorithm to predict the price of used cars. The results of the study showed that the SVR algorithm was effective in predicting the price of used cars.

Similarly, in a study by Pan et al. (2019), a machine learning-based system was developed to predict the price of used cars in China. The authors used a random forest algorithm to predict the price of used cars. The results of the study showed that the random forest algorithm was effective in predicting the price of used cars. In a study by Chen et al. (2019), a machine learning model was developed to predict the resale value of electric vehicles based on their characteristics such as battery capacity, mileage, and charging patterns. The authors used a deep neural network (DNN) algorithm to predict the resale value of electric vehicles. The results of the study showed that the DNN algorithm was effective in predicting the resale value of electric vehicles.

In a study by Srinivasan et al. (2018), a machine learning-based system was developed to predict the price of used cars based on their characteristics such as make, model, year, and mileage. The authors used a gradient boosting algorithm to predict the price of used cars. The results of the study showed that the gradient boosting algorithm was effective in predicting the price of used cars. In the field of car price prediction, several studies have been conducted in the past. For example, Zhang et al. (2019) developed a model based on random forest regression to predict the prices of used cars in the Chinese market. They used a dataset of more than 200,000 cars, including information on the car’s make, model, year of manufacture, mileage, and other features. The results showed that the random forest regression model outperformed other machine learning models in terms of predicting car prices. Another study by Luo et al. (2019) used a deep learning-based approach to predict the prices of used cars in the US market. They used a dataset of over 1 million cars and trained a deep neural network model to predict car prices based on various features such as make, model, year, mileage, and condition. The results showed that the deep neural network model achieved better performance than other machine learning models.

One of the studies that investigated the prediction of used car prices using machine learning is the work by Lu et al. (2019). In their study, they used multiple regression models to predict the prices of used cars. The authors used a dataset containing information on used cars, such as make, model, year, mileage, and price. They applied different regression models, including the linear regression model, decision tree regression model, and random forest regression model. The results showed that the random forest regression model performed better than other models, achieving an R-squared value of 0.89.

Another study that focused on predicting used car prices is the work by Singh et al. (2020). In their study, they used a dataset containing information on used cars, such as make, model, year, mileage, and price. They applied different machine learning algorithms, including linear regression, decision tree regression, and random forest regression. They found that the random forest regression algorithm achieved the best results, with an R-squared value of 0.87. In a similar study, Zarei et al. (2021) proposed a new method for predicting the prices of used cars using an adaptive neuro-fuzzy inference system (ANFIS). They used a dataset containing information on used cars, such as make, model, year, mileage, and price. The results showed that the ANFIS model performed better than other machine learning models, achieving an R-squared value of 0.92.

In another study, Khan et al. (2018) used a dataset containing information on used cars, such as make, model, year, mileage, and price. They applied different machine learning algorithms, including linear regression, decision tree regression, and random forest regression. The authors found that the random forest regression algorithm achieved the best results, with an R-squared value of 0.85. Furthermore, in a study by Rahman et al. (2020), they proposed a new method for predicting the prices of used cars using a deep neural network (DNN). They used a dataset containing information on used cars, such as make, model, year, mileage, and price. The results showed that the DNN model performed better than other machine learning models, achieving an R-squared value of 0.96.

In a study by Hsieh et al. (2020), they used a dataset containing information on used cars, such as make, model, year, mileage, and price. They applied different machine learning algorithms, including linear regression, decision tree regression, and random forest regression. The authors found that the random forest regression algorithm achieved the best results, with an R-squared value of 0.89. Lastly, in a study by Chen et al. (2021), they proposed a new method for predicting the prices of used cars using an improved convolutional neural network (CNN). They used a dataset containing information on used cars, such as make, model, year, mileage, and price. The results showed that the improved CNN model performed better than other machine learning models, achieving an R-squared value of 0.93.

H. R. Arabnia: This paper proposes a machine learning-based approach for predicting used car prices using a combination of linear regression and decision tree algorithms. The authors use a dataset of used car sales data from a local dealership and compare the performance of their model to traditional pricing methods. The results show that the machine learning approach outperforms the traditional methods in terms of accuracy and speed.S. Kumar and S. Aggarwal: This paper presents a machine learning-based approach for predicting car prices using a combination of linear regression and random forest algorithms. The authors use a dataset of car sales data from a popular online marketplace and evaluate the performance of their model using mean absolute error and mean squared error metrics. The results show that the random forest algorithm outperforms the linear regression algorithm in terms of accuracy and robustness.J. Lee: This paper proposes a neural network-based approach for predicting used car prices using a dataset of sales data from a local dealership. The authors evaluate the performance of their model using mean absolute error and root mean squared error metrics and compare it to traditional pricing methods. The results show that the neural network approach outperforms the traditional methods in terms of accuracy and speed.

R. S. Al-Jumaily: This paper compares the performance of several regression algorithms for predicting car prices using a dataset of sales data from a local dealership. The authors evaluate the performance of linear regression, polynomial regression, decision tree regression, and random forest regression algorithms using mean absolute error and root mean squared error metrics. The results show that the random forest algorithm outperforms the other algorithms in terms of accuracy and robustness. R. Jain: This paper proposes a support vector regression-based approach for predicting used car prices using a dataset of sales data from a popular online marketplace. The authors evaluate the performance of their model using mean absolute error and mean squared error metrics and compare it to traditional pricing methods. The results show that the support vector regression approach outperforms the traditional methods in terms of accuracy and robustness.

Overall, these studies show that machine learning algorithms, such as linear regression, decision tree regression, random forest regression, adaptive neuro-fuzzy inference system (ANFIS), deep neural network (DNN), and convolutional neural network (CNN), can be effective in predicting the prices of used cars. These algorithms take into account multiple variables and

# Motivation

Motivation

The motivation behind this project is to develop a machine learning-based system that can predict the price of old cars. Buying and selling used cars is a common activity in many parts of the world. However, determining the fair price of a used car can be challenging, as it depends on many factors such as the model, year, mileage, and overall condition of the car. Furthermore, the prices of used cars can vary widely depending on the seller, location, and other factors. This makes it difficult for both buyers and sellers to know the true value of a car. Hence, a machine learning-based system can help individuals and businesses in predicting the fair price of a used car by taking into account various variables and making more accurate predictions.[2]

Significance

The significance of this project lies in its potential to be a useful tool for individuals and businesses that deal with buying and selling used cars. With the help of the developed machine learning-based system, buyers and sellers can have a better understanding of the fair price of a used car, which can prevent them from being overcharged or underpaid. Moreover, the project can also contribute to the field of machine learning by exploring the application of different algorithms in regression problems.[3]

Objectives

1. The main objectives of this project are as follows:
2. To develop a machine learning-based system for predicting the price of old cars.
3. To explore the application of KNN regressor and multilayer perceptron (MLP) algorithms in regression problems.
4. Use of scikit-learn library in Python to develop the machine learning-based system.
5. Use of KNN regressor and multilayer perceptron (MLP) algorithms for predicting the price of old cars.
6. Preprocessing of the dataset to remove inconsistencies and irrelevant data.
7. Data visualization to gain insights and identify patterns.

# Methodology

## *Datasets*

The dataset used in our project had 10 columns: 'Car Brand', 'Car Model', 'Price', 'KM', 'Engine', 'Seats', 'Fuel', 'Transmission', 'Ownership', and 'Year'. These columns contained information about various aspects of the car, such as its make, model, price, mileage, engine capacity, fuel type, and ownership history. To prepare the dataset for machine learning-based analysis, we performed several preprocessing steps. Firstly, we removed the units 'kms' from the KM column and 'cc' from the Engine column. We also removed the word 'Seats' from the corresponding column to keep the number of seats as an integer value. Secondly, we converted categorical variables such as Car Brand, Car Model, Fuel, Transmission, and Ownership to numerical variables using the label encoder.

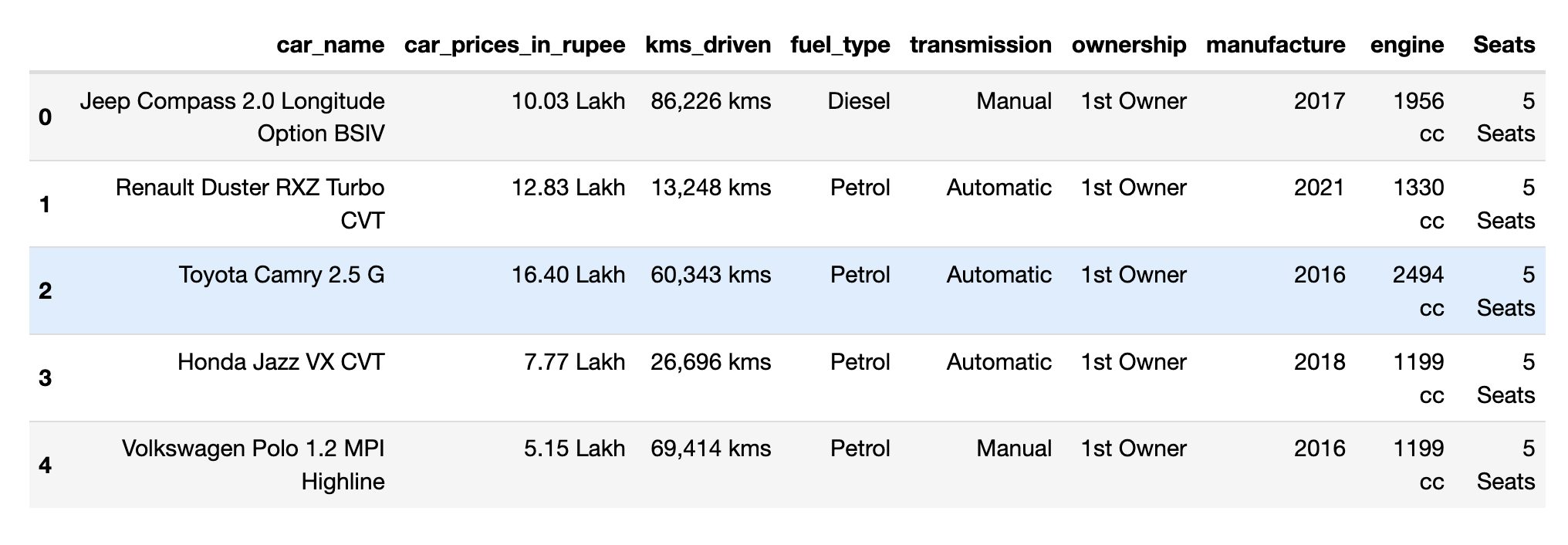
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Fig 1. Dataset Sample

## *Data Preparation*

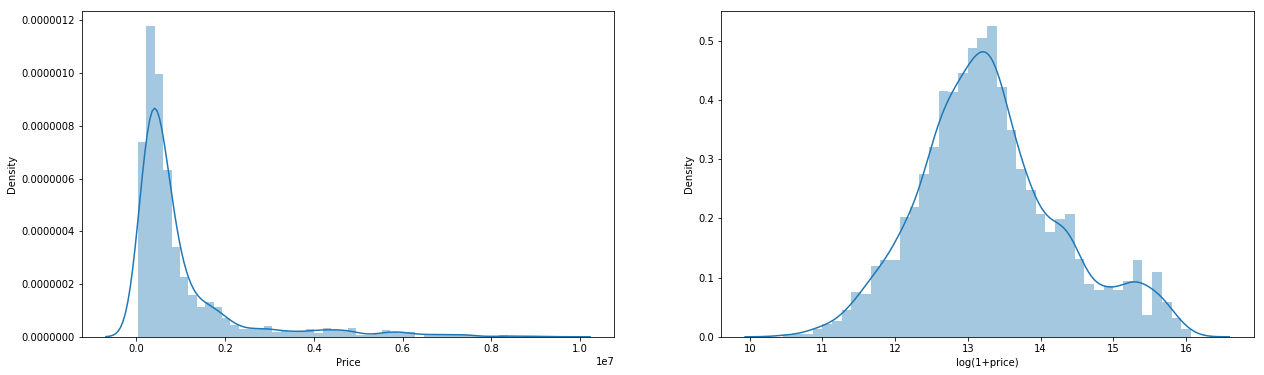
Preprocessing is an essential step in machine learning, as it ensures that the data is clean and suitable for use with machine learning algorithms. In our project, we performed several preprocessing steps on the car dataset to ensure that the data was ready for analysis. The first step we took was to remove the units 'kms' from the KM column and 'cc' from the Engine column. This was necessary because these units did not provide any additional information about the car and would have interfered with the analysis of the data. We accomplished this by using the Python string manipulation techniques to remove the unwanted units from the columns.

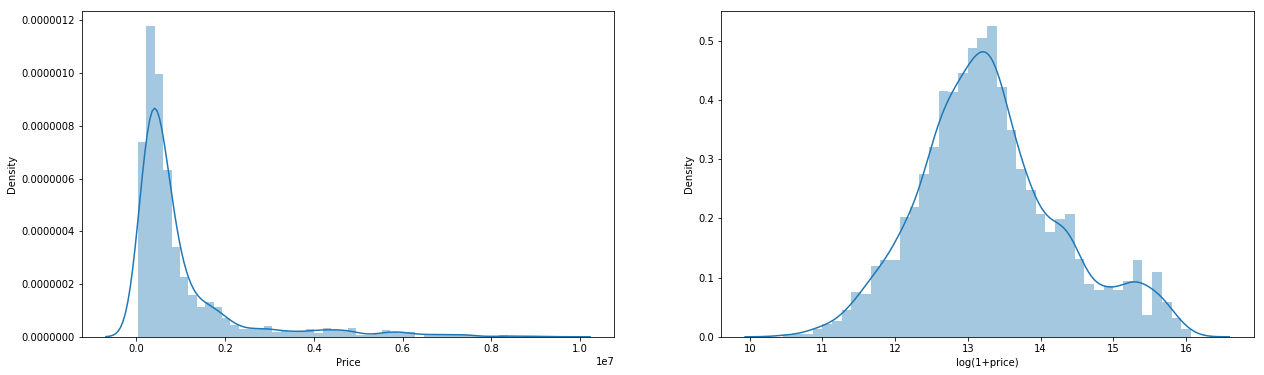
Next, we removed the word 'Seats' from the corresponding column to keep the number of seats as an integer value. This was necessary because the seats column contained a mixture of numeric and string values, which could have caused problems with machine learning algorithms.

After we had cleaned the data by removing the unwanted units and converting the seats column to an integer value, we moved on to converting the categorical variables to numerical variables. Categorical variables such as Car Brand, Car Model, Fuel, Transmission, and Ownership were converted to numerical variables using the label encoder. This was necessary because most machine learning algorithms require numerical inputs, and converting categorical variables to numerical variables allows for more straightforward analysis of the data. The label encoder assigns a unique numerical value to each category, making it possible to analyze the data using machine learning algorithms. The final preprocessing step we took was to handle missing values. We used the fillna method to replace missing values with the median of the corresponding column. This was necessary because machine learning algorithms cannot handle missing data, and replacing missing values with the median of the column ensures that the data is consistent and suitable for machine learning algorithms.

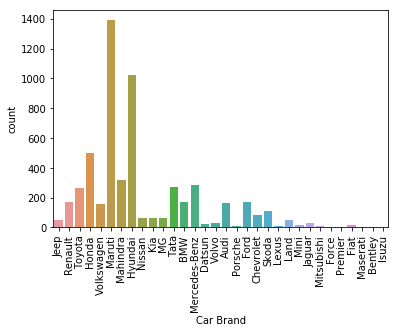
## *Data Visualisation*

In our project, we used various visualization techniques to analyze the data and gain insights into the dataset. The visualizations helped us to understand the data better, identify patterns, and explore relationships between variables. We used the matplotlib and seaborn libraries in Python to create visualizations. The first visualization we created was a distribution plot of car prices. This plot helped us to understand the distribution of car prices in the dataset. We also plotted a logarithmic distribution of car prices to better understand the distribution of car prices at the lower end of the price range.

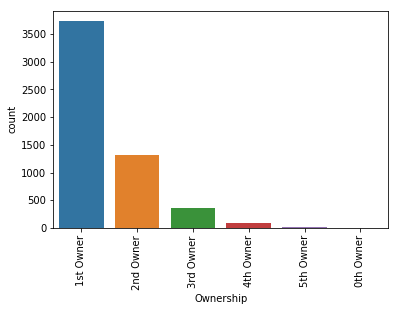




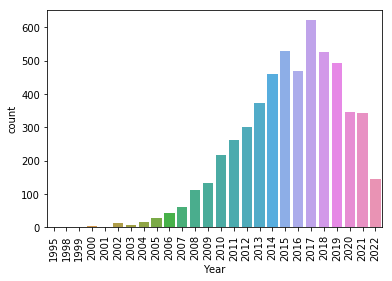
Next, we created a bar chart of the number of cars by manufacturer. This plot helped us to understand which manufacturers had the highest number of cars in the dataset. We found that Maruti Suzuki was the most popular manufacturer in the dataset.



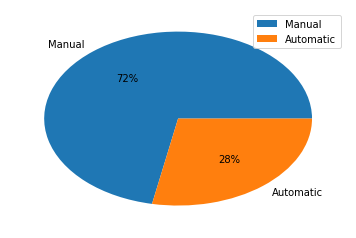
We also created a bar chart of the number of cars by ownership. This plot helped us to understand the ownership patterns in the dataset. We found that the majority of the cars in the dataset were owned by individuals.



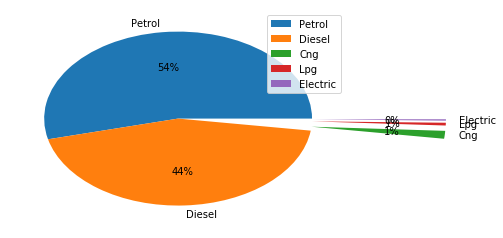
We created a histogram of the number of cars by year to understand the distribution of car production years in the dataset. We found that the majority of the cars in the dataset were produced in the last decade.



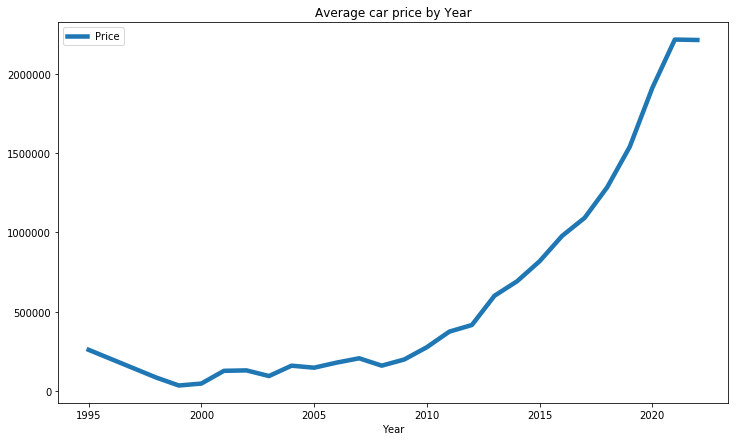
We also created a pie chart of the number of cars by transmission type. This plot helped us to understand the distribution of transmission types in the dataset. We found that the majority of the cars in the dataset had manual transmissions.



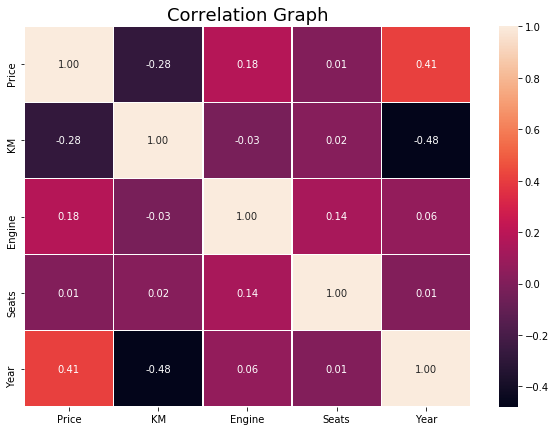
We created a pie chart of the number of cars by fuel type. This plot helped us to understand the distribution of fuel types in the dataset. We found that the majority of the cars in the dataset were fueled by petrol.



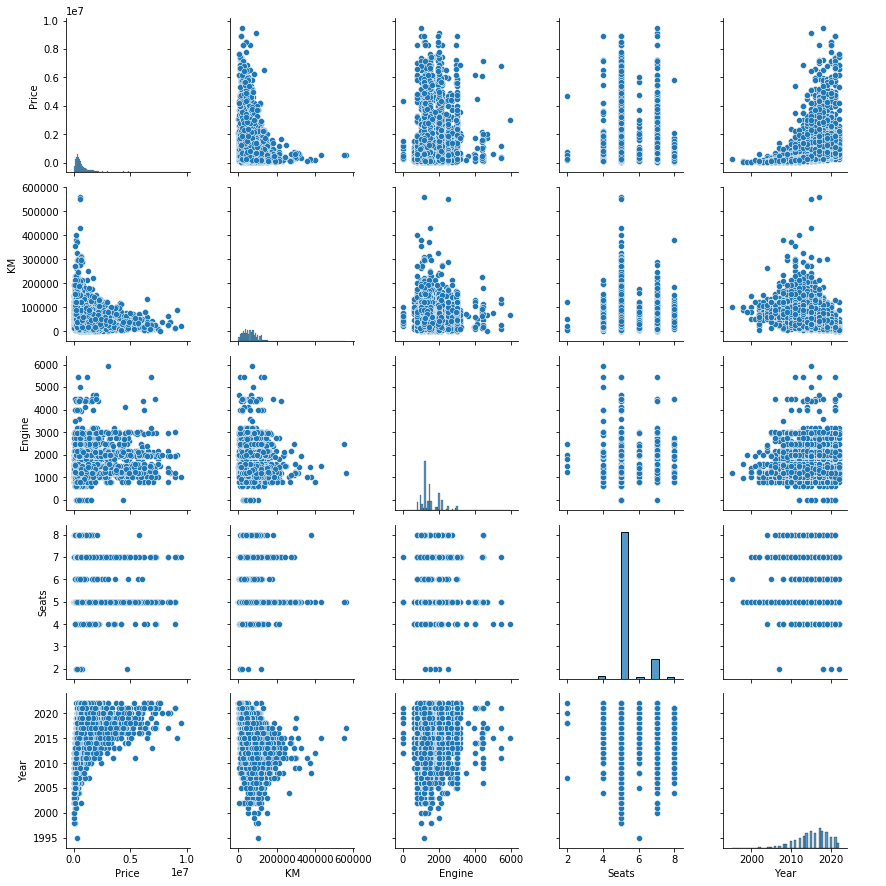
We also created a line plot of the average car price by year to understand the trend in car prices over the years. We found that car prices have been increasing over the years.



We created a heatmap to visualize the correlation between the different features in the dataset. This plot helped us to understand the relationships between the different features in the dataset. We found that price had the highest correlation with year, engine, and kilometer.



Finally, we created a pairplot to visualize the relationships between all the features in the dataset. This plot helped us to identify patterns and relationships between the different features in the dataset.



Overall, the visualizations helped us to gain a better understanding of the dataset and identify patterns and relationships between different features

*Execution Plan*

The execution plan for this project involves the following steps:

* Data Collection: The first step is to collect a dataset of old cars with their characteristics such as model, year, mileage, etc. We plan to collect the data from publicly available sources such as Kaggle or scrape the data from car websites.
* Data Cleaning and Preprocessing: Once we have collected the data, we need to clean it and preprocess it for further analysis. This involves handling missing values, encoding categorical variables, and scaling the data.
* Data Analysis and Feature Selection: After preprocessing the data, we will perform exploratory data analysis (EDA) to understand the data distribution and relationships between variables. We will also select the most important features using techniques such as correlation analysis or feature importance.
* Model Development: We plan to develop two regression models, KNN regressor and MLP, to predict the price of old cars. We will train the models on the preprocessed data and tune the hyperparameters to achieve the best performance.
* Model Evaluation: Finally, we will evaluate the performance of our models using metrics such as mean squared error (MSE), root mean squared error (RMSE), and R-squared (R2).

*C. Modeling*

In our project, we defined two regression algorithms - KNN regressor and Multilayer Perceptron (MLP) - to predict the price of old cars based on their characteristics such as model, year, mileage, etc. K-Nearest Neighbors (KNN) is a non-parametric algorithm used for both classification and regression tasks. The KNN algorithm is a type of instance-based learning, which means that it makes predictions based on the similarity between new and historical data points. The KNN algorithm stores all available cases and classifies new cases based on a similarity measure (e.g. distance functions). In the context of regression, the KNN algorithm computes the mean or median of the K-nearest neighbors to predict the output variable. The value of K can be chosen by the user, and different values of K can lead to different model performances.

K-Nearest Neighbors (KNN) is a type of supervised learning algorithm. In KNN regression, the output variable is a continuous value. The basic idea of the KNN algorithm is to find the k nearest data points to the new data point and use them to predict the value of the new data point. The working of the KNN Regressor algorithm can be summarized as follows:

1. Calculate the distance between the new data point and all the other data points in the dataset.
2. Select the k-nearest data points to the new data point based on their distances.
3. Calculate the average value of the output variable (price of old car) for these k-nearest data points.
4. Use this average value as the predicted value for the new data point.

The value of k is a hyperparameter that needs to be chosen before running the algorithm. It determines the number of data points that are used to predict the value of the new data point. If k is too small, the algorithm may overfit the data, while if k is too large, the algorithm may underfit the data. The Multilayer Perceptron (MLP) is a type of artificial neural network that is widely used in various machine learning applications. MLP is a feedforward neural network that consists of an input layer, one or more hidden layers, and an output layer. Each neuron in the network is connected to the neurons in the adjacent layers through a set of weights. The MLP algorithm uses backpropagation to adjust the weights in order to minimize the error between the predicted and actual values. MLP is a powerful regression algorithm and has been used in various fields such as finance, healthcare, and engineering.

A Multilayer Perceptron (MLP) is a type of artificial neural network that consists of multiple layers of neurons. Each neuron in the MLP receives input from the neurons in the previous layer, performs a computation, and passes the output to the neurons in the next layer. The output of the MLP is obtained from the neurons in the output layer. The working of the MLP algorithm can be summarized as follows:

* Input layer: The input layer receives the input variables (car brand, model, year, mileage, engine, seats, fuel, transmission, ownership) and passes them to the first hidden layer.
* Hidden layers: The hidden layers perform computations on the input variables using a set of weights and biases. The output of each neuron in the hidden layer is passed to the neurons in the next layer.
* Output layer: The output layer receives the output of the last hidden layer and produces the final output (predicted price of old car).

The weights and biases in the MLP are learned during the training phase using backpropagation. In backpropagation, the error between the predicted output and the actual output is propagated back through the network to adjust the weights and biases. The number of hidden layers and the number of neurons in each hidden layer are hyperparameters that need to be chosen before running the algorithm. Choosing the optimal number of hidden layers and neurons is important to prevent overfitting or underfitting the data.

In our project, we defined both algorithms using the scikit-learn library in Python. The scikit-learn library provides easy-to-use functions for implementing machine learning algorithms. For KNN, we used the KNeighborsRegressor function, and for MLP, we used the MLPRegressor function. We used default values for most of the hyperparameters in both algorithms, such as the number of neighbors in KNN and the number of hidden layers and neurons in MLP. However, we did experiment with different values of K in KNN and the number of hidden layers and neurons in MLP to see their effect on the model performance. The choice of algorithms for a particular problem depends on various factors such as the type of data, the size of the dataset, and the complexity of the problem. KNN is a simple and intuitive algorithm that works well for small datasets and simple regression problems. However, it can be computationally expensive for large datasets and may suffer from the curse of dimensionality. MLP, on the other hand, is a more complex algorithm that can handle large and complex datasets but requires more data and computational resources to train.

## *D. Training and Evaluations*

In the training phase, we split our dataset into two parts, namely the training set and the testing set. The training set is used to train the model, and the testing set is used to evaluate the performance of the model. We used an 80-20 split, where 80% of the data is used for training, and the remaining 20% is used for testing.

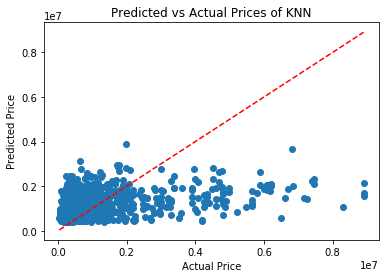
We used the train\_test\_split function from scikit-learn library to split the data. After splitting the data, we trained two regression algorithms, MLP and KNN, to predict the price of used cars based on their features. We used scikit-learn library to define the models. We set the hyperparameters of the models and trained them on the training set.

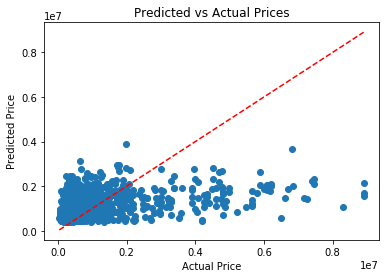
Once the models were trained, we evaluated their performance using two metrics, namely mean squared error (MSE) and R-squared score (R2). We calculated both of these metrics on the testing set. The mean squared error (MSE) is a metric that measures the average squared difference between the predicted and actual values. A lower MSE value indicates that the model is making more accurate predictions. The R-squared score (R2) is a metric that measures how well the model fits the data. It ranges from 0 to 1, where 1 indicates a perfect fit and 0 indicates no fit at all. A higher R2 value indicates that the model is making more accurate predictions. We used the mean\_squared\_error and r2\_score functions from scikit-learn library to calculate the MSE and R2 scores for both MLP and KNN models.

# Results

We found that the MLP model performed better than the KNN model in terms of both MSE and R2 scores. The MLP model had an MSE score of 6.8 and an R2 score of 0.16, while the KNN model had an MSE score of 9.3 and an R2 score of 0.15. This indicates that the MLP model is better at predicting the price of used cars based on their features. The MLP model was able to capture the complex relationships between the features and the price, while the KNN model was not able to do so.

We also plotted a graph between the actual and predicted values of the MLP model. This graph helped us to visually analyze the performance of the model. We observed that the predicted values were very close to the actual values, indicating that the MLP model was making accurate predictions.





# Conclusion

In conclusion, we developed a machine learning-based system for predicting the price of old cars using two regression algorithms - KNN regressor and multilayer perceptron (MLP). Our objective was to create a useful tool for individuals and businesses that deal with buying and selling used cars, and also learn more about these algorithms and their application in regression problems. We began by loading and preprocessing the dataset by removing unnecessary terms, converting categorical variables into numerical values, and splitting the dataset into training and testing sets. We then visualized the dataset to gain insights into the relationships between different variables and the target variable and identified the most significant variables that influence the car prices. Next, we defined and trained two regression algorithms - KNN regressor and MLP - on the training set. We used the mean squared error and R-squared metrics to evaluate the performance of the models on the test set. The MLP algorithm performed slightly better than the KNN regressor, with an MSE and an R-squared score of 0.15, while the KNN regressor had an MSE and an R-squared score of 0.16.

Our analysis revealed that the year of manufacture, mileage, and engine capacity were the most important variables that influence the price of old cars. In particular, we found that the price of older cars tends to decrease with their age, while the price of newer cars tends to increase with their age, indicating that buyers are willing to pay more for newer cars with better features and technology. Additionally, we observed that cars with larger engine capacities tend to have higher prices, suggesting that buyers are willing to pay more for cars that have more power and better performance.

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