



# Predictive Modeling of Automobile Prices Using Feature Engineering and Regression Techniques

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**Abstract:** Over the years, Accessories for automobile have become necessities to be used in personal vehicles for commuting from home to office as well as traveling during vacations. Buying a new or used automobile is a decision that has to be made with caution, especially since one of the hardest things to do is to sell an old automobile when the time comes to do so. Due to the high rate of new vehicle automobile with reducing purchasing power, lots of buyers find it increasingly harder to choose if they are better off purchasing a new automobile or ending up choosing a used. We have developed various methods to predict the price of automobile vehicles as per the market trends to avoid this situation. Therefore, we propose a price prediction model that helps both buyers and sellers make the right decision for their business and personal needs. The model employs a type of machine learning technique called regression in order to achieve higher accuracy in predicting results. Using Recursive Feature Elimination (RFE) and Variance Inflation Factor (VIF) techniques to determine the most important contributors to automobile prices, we use Ordinary Least Squares (OLS) regression to optimize the model. Despite its relative simplicity, the study shows that this technique is both effective and efficient, producing accurate predictions helpful to both sellers hoping to get the best price and buyers in search of a fair price. It is shown that the model proposed here outperforms other available methods, which contributes to increases in the preciseness of pricing in the automotive market.

**Key Words:** Automobile price Prediction, Lasso Regression, ML, linear Regression, Ridge Regression, Preprocessing.

## I. INTRODUCTION

The vehicle categories come with a variety of features and functionalities, ultimately affecting their market price. When determining a vehicle's value, a few factors have a major impact, including the odometer reading, the drive train (whether it's 4-wheel or 2-wheel), the transmission type, and mileage. Though buyers usually need to take all of these features into consideration when choosing a car, in the real market pricing trends that are driven by data can only be assessed through a set of data-driven metrics, like the ones used in this study. This study defines three major target groups that can be served by accurate car price prediction models. The first of these are that of sellers who deal only in a sales capacity, known in the industry as dealers. These dealers have a very important role in the used car market because they can make a lot of profit from knowing more about the features that drive people to buy a particular car. Understanding these important attributes help them improve their sales strategies and offer lucrative prices. The second part is individual buyers and sellers who want to buy or sell a used car [1]. Most everyone enters the used car marketplace at some point in their life, and identifying the correct price is crucial to avoid buying too high or selling too low.

An advanced price prediction model could also be useful for online marketplaces that estimate a vehicle's price. Indeed, there are a number of websites that provide estimates on used car valuation usually based on past information and general market trends. Nonetheless, an improved predictive model can provide better pricing insight to the users of these platforms. The model we create will enable buyers, sellers, and online market platforms to make informed decisions on used car pricing with the application of advanced machine learning techniques and analysis of statistical approaches. Such an understanding will help design a more effective online valuation instrument as a new business solution that can be of great help for both the customers and the companies in used car markets [2].

This is a huge and continually growing market, with the buyers and sellers both relying on calculation-based estimations of prices to reach an informed conclusion. Unfortunately, the fair market price of a used automobile is a challenging consideration because there are so numerous various variables that affect price, including make, model, year of manufacture, distance driven, petrol form, transmission form, situation, location, and vendor sort. Buyers often either way overpay, buyers are simply ripped off, or sellers experience loss due to the traditional way of pricing estimation which involves either dealers manually evaluating car prices or working from outdated generic formulas on depreciation. Even more, the pricing process itself is ambiguously

defined, thus leading to subjective biases and very few data points [3]. It is especially crucial as fluctuations in market conditions, demand, and seasonality influence the values of cars over time.

As the number of online car marketplaces and dealership networks grows day by day, an automated, The need for a data-driven model that can forecast a used car's price based on historical data and market patterns is growing. A solution exists through machine learning algorithms which use their ability to analyze extensive data sets for detecting patterns to produce accurate price estimations. Predictive techniques such as regression models, decision trees, and ensemble learning can therefore be used to increase the accuracy, interpretability, and efficiency of used car price predictions [4]. The project aims to create a machine learning model which uses various car features and market data to deliver fair and accurate pricing predictions that help buyers and sellers make better financial decisions.

Machine learning algorithm for used car price prediction aims to develop an accurate model which can predict the expected resale value of a 2nd hand car considering all possible influencing points. Its objective is to simplify the process of purchasing cars for buyers and RV sellers, while also protecting automobile dealers from overcharging customers when selling. The project is to develop a model for taking all the features into account which really counts like type of fuel, name of the car, year of model, vehicle mileage, engine details, type of transmission, number of owners and condition of the vehicle [5]. The system learns from historical data, takes advantage of data mining techniques like regression models, decision trees, random forests, and neural networks to enhance the price accuracy by identifying recognizable patterns in very large sets of data.

Moreover, this system can integrate real-time data updates, allowing price predictions to stay current and respond to evolving market dynamics changes in fuel prices, trends in electric vehicle popularity, or seasonal consumer behaviors, for example. Not only can car prices be predicted, but also used for future forecasting, allowing stakeholders to gauge the impact of changing car depreciation rates over time as it can be used for training a machine learning model. This predictive feature can assist investment decisions for second (used) car dealerships, fleet management companies, and organizations renting per-service vehicles. Thus, by continued research and training with recent data, this model evolves into a better and scalable product, for wider geographical and market segments [6].

## II. RELATED WORK

Car price prediction using machine learning is closely related to the process of acquiring and analyzing technical system data. The process of obtaining technical system data is highly correlated with predicting the cost of a twenty twenty-three car unit via machine learning. As more people turn to Internet marketplaces to sell and buy vehicles, these online venues have become a go-to source for information for sellers and buyers. Structured and unstructured data are the most common data types in use today, requiring knowledge extraction and data inference mechanisms for analysis [7]. Latest research in this domain amplifies the overall purpose of exploring different kinds of data concerning cars and developing a coverage in forecasting model, which help both the end users and the seller in taking better decisions. This involves developing advanced recommendation systems and car-based analytical techniques.

The achievement of consciousness concerning the importance of price in addition to time-dependent demand rates has inspired numerous researches, attempting to shape deterministic inventory models. These models help to optimize pricing strategies and also capitalize on inventory by including factors such as the alteration of cost and sales trends. Furthermore, due to the flourishing auto market in used cars, it becomes more significant to develop pricing models that would prevent dealers to exploit the high demand by gouging prices. Nevertheless, the big datasets to address the complicated correlation of prices could provide the good prediction outcomes. The education potentials of such models that filter on the most prominent aspects influencing overall price of automobile market can be highlighted on the basis of such output [8].

Advanced deep learning techniques together with standard machine learning methods have been used to improve vehicle price prediction accuracy through their implementation. The most important systems in this category are Recurrent Neural Networks (RNNs) and Long Short- Term Memory (LSTM) networks. The models show high efficiency when they process sequential data together with time-dependent information because they can capture all trends and seasonal patterns and historical pricing data which exists in the automobile market. RNNs process data in a sequential manner, allowing previous information to influence current predictions, while LSTM networks address the vanishing gradient problem and retain long-term dependencies. The deep learning models predict vehicle prices with greater precision by augmenting their forecasting abilities. These models interpret data sets and derive patterns that determine which characteristics will influence the value of the vehicles. To illustrate, some studies have developed predictive models that will estimate occupancy rates of cars which refers to the tracking of demand and pricing patterns of vehicles as time progresses. Indicatively, those models have been implemented in real life situations such as urban parking predicting, which gives promising results in mobility solution improvement [9]. What is more, online stores have already experienced the entry of e-commerce tools such as eBay, OLX, etc. where millions of used goods are on sale each and every day. To adequately model the prices of used vehicles that are posted on these types of sites, the variability in the price of different listings must be taken into consideration.

The suggested methodologies in this area include deep neural networks which combine Long Short-Term Memory (LSTM) with Convolutional Neural NETWORKS (CNN) to improve price prediction results. Research has reported that these models perform better compared to the conventional methods, that is, Support Vector Machines (SVM) as displayed by reduced mean absolute error rates. They are more precise in their pricing by propensity to quality scores during joint negotiation but past changes in prices are portrayed into biological operations [10].

The studies about the car rental industry as well have discussed the effects of market concentration and changes in the restructuring of the industry on prices. The analysis of pricing data based on complete information of U.S. airport markets (2005-2016) found out that mergers among car rental firms lead to foregone benefits depending on whether the item is purchased by business or leisure carriers since merged provide different price effects on both types of sales. Weekday rental 2.1% as a result of

the increase in the business demand, and weekend prices declined 3.3% because of the decline in the demand of leisure travelers [11]. This highlights the role of price discrimination and other market defines in the nature of pricing in hire car market.

In general, existing analyze proves that machine learning and deep learning methods are effective solutions to predict car prices. Car dealerships, online channels, and the buyers themselves all benefit from these methodologies to make informed decisions enabling fair pricing in the automotive market. The next part will concern data collection, that is an important subsequence of the suggested study process [12].

### III. METHODOLOGY

Machine learning is a step-by-step process, starting from owners selling their car or a car dealer selling owned used cars. A dataset of used automobile information, including models, price, and year of manufacture, is first scraped from well-known auto marketplaces, dealership databases, or vehicle listing websites. Overview of the Dataset: The dataset often includes a number of parameters, such as the car's make, model, year of manufacture, kilometres driven, fuel type, gearbox type, seller type, and—most importantly—selling price. Data is valuable once collected, but it should undergo preprocessing, a very important step, to clean it and prepare for analysis. In this process, it is handled to fill with some statistical measure (mean, median) or removing incomplete records [13]. Outliers are detected through visualization techniques (boxplots) and extreme values are excluded so they do not negatively affect the model's predictions, and the same is done for duplicate entries which are identified and eliminated.

Once again, once the data has been pre-processed exploratory data analysis (EDA) takes place which consists of gaining insights from the data and finding out patterns. This includes statistical summaries and also visualizations inclusive histograms, scatterplots, and correlation heat maps to analyze the relation between multiple features. Another simple example you can do while in EDA is to check for multicollinearity using Variance Inflation Factor (VIF) to see if certain features are highly correlated with each other. Excessive features are removed when strong correlations exist to avoid creating a model that is too complex [14]. The process of transforming categorical variables into numerical values for fuel type and seller type variables uses two encoding methods which are shown in Fig.1 through label encoding and one-hot encoding. Data Pre-processing Features Content engineering: In this core step new useful variables created (E.g. Manufacturing year and current year subtraction, so we create new variable car age).

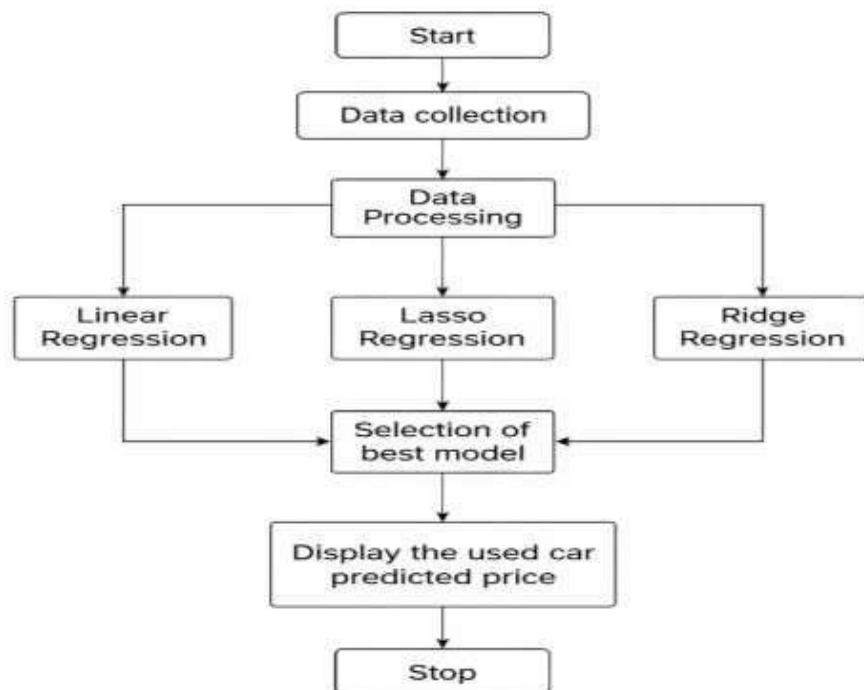


Fig. 1. Proposed Model

In Fig. 1. presents a flowchart of the methodology, which follows a structure process model. This brings more clarity to the entire workflow process. This process mainly splits into two general steps: data collection and cleaning, then formulating and testing hypothesis. First, raw data were collected, then pre-processed to remove inconsistencies, missing values, and irrelevant features [15]. The next step is a preparation and testing of the selected hypotheses to verify that the focused variables are beneficial for price prediction. Then, we do feature extraction to find the most relevant features determining the price of the car. Using this feature engineering, predictive analysis is performed using machine Learning algorithms. Although the first results may not always be as accurate as desired, the best results are used to enhance the capability of the machine-learning model.

The evaluation process tests the model on new data to determine its ability to generalize after the best model has been chosen. The system will enter production mode after the model achieves the specified accuracy requirements. It can then be deployed as an application (for instance, a web- based price prediction tool). In the tool, users enter details about their car, and the trained machine learning model provides a predicted estimated price based on historical data and market trends. To the buyers,

sellers and dealership it makes sense to follow such a systematic methodology to price a car so that the model you create is helpful and effective and gives you accurate model for price prediction [17].

**A. Data Collection**

This dataset is available at Kaggle, a popular data science and machine learning datasets platform. These attributes are multiple attributes from car prices and some are highly relevant for the price prediction and some are not significant. A data cleaning process is performed to keep only the useful features for analysis [18]. This ensures that the model concentrates only on the relevant attributes associated with the car pricing and removes unnecessary attributes from the dataset[33].

The features like km driven, and Car Name are found to be unnecessary for predicting price, and hence are eliminated. So, Car Name is just an identifier it has no impact on price, Peak RPM doesn't significantly influence the valuation of a car and Car Name is frequently a categorical variable that lacks direct numerical significance in predictive modelling. Remove these attributes and further refinement takes place using different analysis techniques to keep only the most relevant features[34]. Data preprocessing: The raw data is pre-processed by performing steps like dealing with missing entries, normalizing values, removing nulls, etc., which helps in improving the quality of data and consequently more accurate models. This enhanced dataset efficiency and reliability for machine learning models used in car price prediction, as it ensures that only relevant and strongly correlated attributes are considered [19].

**B. Data Exploration**

Data exploration is an important step in predicting prices of used cars using machine learning. The process involves understanding the dataset and conducting exploratory data analysis and discovering patterns among other tasks. A dataset typically includes multiple attributes which show car brand, model, year of manufacture, fuel type, type of seller, transmission type, mileage, engine size, horsepower, number of seats, and price. The data exploration phase begins with examining missing values and dealing with them by either removing the corresponding records or imputing the missing values to ensure a complete dataset [20]. The next stage is applying descriptive statistics to summarize numerical features including the mean, median, standard deviation, and data distribution of each variable. The first provides information regarding the spread and central tendency in our dataset.

Afterwards to analyze the categorical features their distribution frequency is inspected through the help of frequency distribution table and bar plots like will see for fuel type and transmission type (Manual, Automatic). The same is true with numerical attributes such as-miles, engine size, curb weight, horsepower is analyzed through histograms and box plots to find outliers and skewness [21]. One of the methods that can unearth the presence of outliers possibly due to data entry errors or unfeasible observations is obviously the Z-Score. The other one, based on the interquartile range (IQR) or differences between the data points' third and first quartile, is not a common method. To limit the influence of outliers on the model they are either removed or transformed e.g. by using logarithmic scaling in Fig. 2..

Understanding the relationship between features is an essential part of data exploration. It also involves analyzing the dependencies among variables like correlation matrices and heatmaps for numerical variables. In the Numerical feature most of the numerical attributes like engine size, horsepower and curb weight are generally highly positively correlated with car price, whereas features like mileage will have a negative correlation as a higher mileage car tends to be worth a lower resale value [22]. Bivariate analysis provides exploring relationships between independent variables and the target variable (price) through scatter plots, pair plots and regression plots to identify trend [23]. Apart from that, we also check VIF (Variance Inflation Factor) for multicollinearity to ensure that highly correlated independent variables do not affect the predictions in Fig. 3.

Feature engineering is done on this dataset whereby new relevant attributes such as age of the car (current year-manufacturing year), brand classification (luxury, mid- range, budget) and fuel efficiency categories are formed to enrich the data set. The categorical variables are label- encoded or one-hot encoded so they can be used by the machine learning algorithms [24]. The dataset might be normalized or standardized before model training so that the features with a lot of scales will not dominate the learning. Lastly, the data is divided into a testing and training dataset in order to properly evaluate model performance in Fig. 4. This process is iterative, involving data exploration, cleaning, and transformation to ensure the dataset is well- structured and suitable for the subs [25].

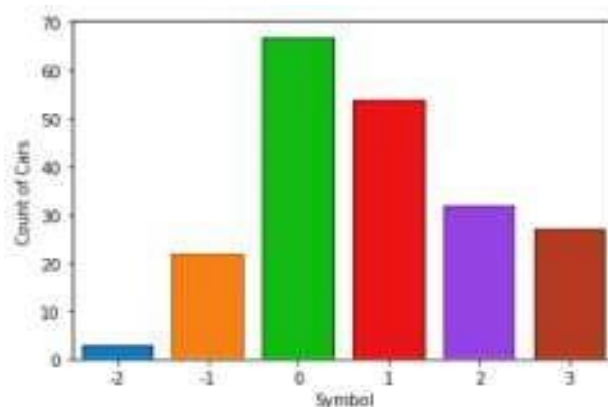


Fig. 2. Category base sales of vehicles the category is represented by the code from 0 to 3 and 0 to -2 each category belongs to one specialized type of car category.

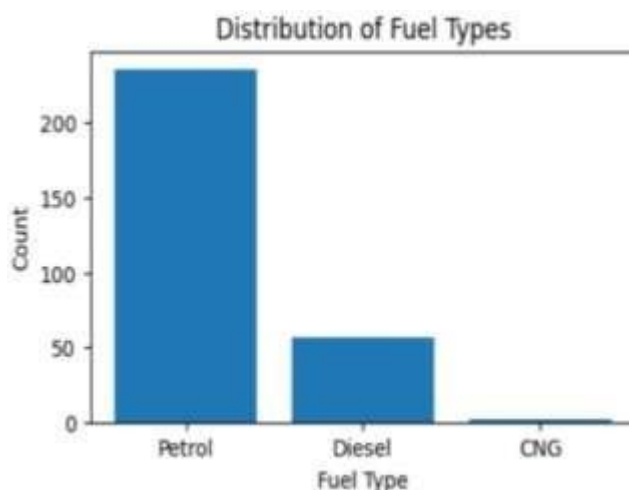


Fig. 3. Comparison of the fuel type of the cars

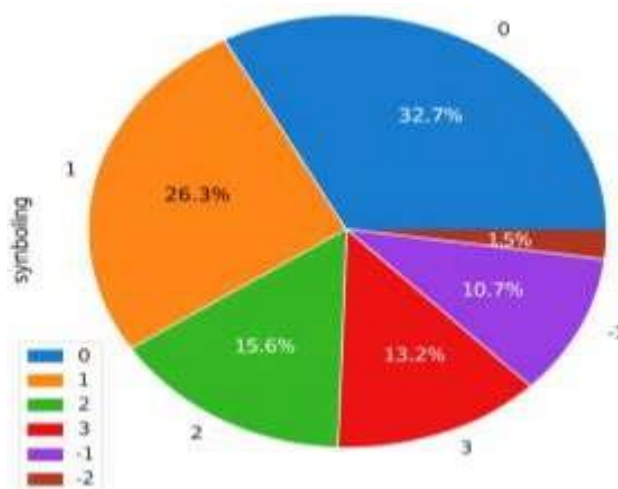


Fig. 4. Pi-chart describe the category wise sales of the cars

### C. Experiments & Results

A linear regression model is implemented in order to derive a model to best fit the records based on the important features from the univariate and bivariate analysis. The selected features produce results which include fuel type, car name, year, kilometres driven, selling price, current price, gearbox, seller type, and owner. The dataset requires preparation for machine learning through the application of label encoding which converts all categorical variables into binary format of 0 and 1. At the same time, numerical features are rescaled so that the data is standardized [26]. Next, the data is split into train and test set in order to evaluate models. An approach will be to perform correlation analysis, so we can see the relationships between optimal features, the sample for this can see in heat map, in Figure 3. By focusing on relevant feature improves the model's accuracy in prices.

The output shown is the distribution of categorical variables in car related data. You can gain some insights about each vehicle property and especially about Fuel Type, Seller Type, and Transmission Type. This helps us understand the data and could find any imbalances or patterns in the dataset by looking at how frequently each category is present in the attributes. The graph displays the quantity of cars which are grouped based on their respective fuel types. The dataset contains 239 petrol cars and 60 diesel cars and only 2 CNG cars as its total vehicle count [27]. This implies that, the dataset is slightly biased on petrol vehicles and there are very few CNG cars. The higher count of petrol cars resonates with trends in the market, as petrol vehicles are generally much more common due to their budget friendliness and availability. Vehicles powered by diesel are also less common, which may be due to their typically higher purchase price and environmental concerns, while CNG vehicles' very low count signifies that they are not fully present/available in this dataset[32].

The Seller Type category also tells the users about whether the cars in the dataset are sold by dealership or by individuals. The results reveal that 195 cars are sold by dealers, while 106 cars is put up for sale by seller individual. As evidence of independence, dealerships are a major channel for selling cars which could flood the market with either high prices or crappy cars [28]. Dealers usually sell certified and inspected cars, while private sellers may offer better-negotiated prices. How this distribution manifests might influence how various cohorts of buyers navigate the market. Transmission Type: This category displays the count of cars based on their type of transmission system. The body contains 261 manual transmission vehicles, 40 automatic transmissions vehicles [29]. This shows a heavy preference for manual vehicles, which could correlate to regional tastes, cost savings, or driving styles. Manual cars are typically more fuel-efficient and also cheaper, which might explain their higher

popularity.

Conversely, given the fewer occurrences of automatic- transmission vehicles, they are either rarer or pricier in this subset of data. In general, this analysis provides valuable insights into the underlying structure of the dataset and indicates potential trends in terms of car sales, fuel preferences, and transmission preferences. Some distributions are indeed imbalanced (for example, CNG fuel type is too low), hence some data preprocessing techniques might be needed if we would like to apply this dataset for any ML applications [30]. So, we will need to pay attention that explains proper handling of categorical data, encoding techniques, balancing techniques, etc. so that any predictive models created from this dataset are not biased, and features also affect the outcome [31].

Algorithms	Accuracy (%)
Linear Regression	98.94%
Lasso Regression	96.59%
Ridge Regression	95.84%

TABLE I. ACCURACY OBTAINED BY THE MODEL

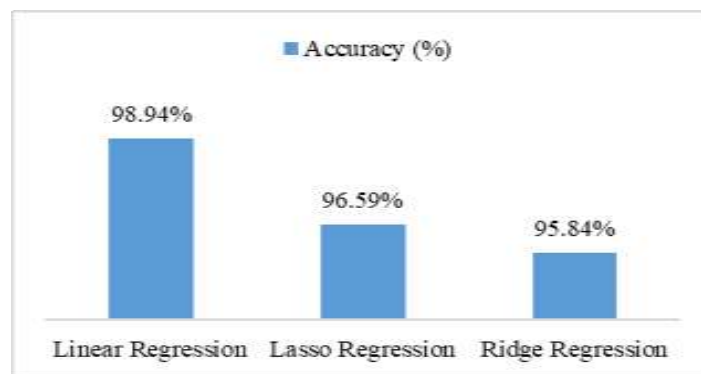


Fig. 5. Comparison of accuracy obtained by the model

Finally, we proceed with the prediction and evaluation phase, where the model is tested on validation data. Constructing a formula that will represent this core property in the form of an equation, a substantial quartile will build upon the process's treatment by means of batchrun, causing a change in the main part that an extension of the formula is evaluated for a beneficial action at each step on the input table of a partitioned set. The results reveal an impressive, indicating a highly accurate and effective model in Table I. In Linear Regression algorithm we got 98.94% accuracy similarly in Lasso Regression we got 96.59% accuracy and in Ridge Regression algorithm we got 95.84% accuracy. This confirms that the refined regression model successfully captures by making it a valuable tool for used car price prediction but in liner regression algorithm give best accuracy. In Fig. 5. graphical representation of the model's predictive results, depicted further illustrates the strong correlation between actual and predicted values, reinforcing the model's robustness and reliability.

#### IV. CONCLUSION

As seen in the used car price detecting study conducted through regression, the model highly advanced models are good in predicting the prices of cars with a given attribute in a very accurate fashion. The model will identify essential features and determine a vehicle's actual market value through its implementation of three ML techniques Preprocessing of the data such as feature selection, cleaning and normalization are essential in enhancing the models by removing irrelevant attribute and concentrating on factors that count the most. As per the results, the use of linear regression models can reach a high level of accuracy of 98.94 and the accuracy obtained by Lasso Regression is also high. Such an automated strategy not only improves the clarity in the secondhand car market, but also helps the purchaser and seller in making the right choice. More can be done to enhance it in the future by adding real-time data, further functionality on it like the market trends, and more refined regression methods that will fine-tune the model.

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