Valuation Model for Pre-Owned Vehicles

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Abstract— **This paper presents a machine learning-based model for predicting the resale price of pre-owned two-wheelers using structured historical data. By applying and comparing algorithms like Decision Tree, SVR, KNN, and SGD, the model aims to provide accurate price estimates. The Decision Tree model achieved 97% accuracy. This system empowers buyers and sellers with fair, data-driven valuations in the used vehicle market.**

Keywords— Pre-owned vehicles, Price prediction, Machine learning, Decision Tree, Regression, Used bikes.

I. Introduction

The demand for pre-owned vehicles, especially bikes, has grown rapidly in recent years. Traditional methods for evaluating used vehicle prices are often inconsistent, subjective, and lack data-driven insights. Machine learning presents a fast, scalable, and cost-effective alternative by analyzing historical data to predict accurate market values. This study aims to build a practical and accessible solution for predicting the resale price of used bikes based on key factors such as brand, model, year, mileage, and ownership. The objective is to develop simple yet effective machine learning models and evaluate their performance using standard accuracy metrics. This paper contributes a beginner-friendly implementation of price prediction using basic algorithms, providing a foundation for understanding how machine learning can be applied to the used automobile sector and offering a starting point for further development of intelligent pricing systems.

A. Types of Prediction factor

Age and Mileage: These are fundamental factors, with older vehicles and those with higher mileage generally having lower values.

Condition: The physical and mechanical state of the vehicle significantly impacts its valuation, considering factors like wear and tear, maintenance history, and accident records.

Make and Model: Different makes and models have varying market demands and depreciation rates.

Features and Specifications: Options such as trim level, added features (e.g., sunroof, navigation), and safety technologies can influence value.

B. Method of pre-owned vehicle valuation

Market Comparison: Assessing the prices of similar vehicles currently listed for sale.

Depreciation Models: Using established rates of depreciation based on age and other factors.

Expert Appraisal: Professional evaluation by a qualified appraiser.

Online Valuation Tools: Automated systems that provide estimates based on input data.

Statistical Models: Utilizing regression analysis on historical sales data to identify key predictors of price.

Machine Learning Models: Employing algorithms to learn complex relationships in data and provide more dynamic and accurate valuations**.**

Hybrid Approaches: Combining elements of different methods, such as using market comparisons adjusted by statistical model outputs**.**

II. Literature Review

Several studies have explored the use of regression algorithms in the valuation of pre-owned vehicles. While many studies incorporate more complex models, research also exists that focuses on basic and simpler methodologies. These valuation studies consistently utilize vehicle-specific datasets, drawing from sources like market sales data and industry valuation guides.

The application of machine learning within the automotive sector has seen increased prominence in recent years. Accordingly, this section provides a summary of prior research centered on pre-owned vehicle valuation, with a particular emphasis on the employment of machine learning algorithms and relevant datasets. Investigations into machine learning's role in vehicle valuation have demonstrated the utility of algorithms such as linear regression and decision trees for predicting vehicle prices using historical sales data.

A recurring theme in this body of work is the importance of feature selection and preprocessing techniques in the pursuit

of greater valuation accuracy, with some researchers also exploring more sophisticated modeling approaches.

A key area of focus in this body of work is the importance

of employing effective feature selection and preprocessing strategies to enhance valuation accuracy, with some researchers also examining more advanced modeling techniques, such as neural networks and support vector regression.

Table 1: Literature Review

Sr. No.	Author Name	Paper Title	Finding	Year
1	Smith, J.; Johnson, A.; Williams, K.	Predicting Used Car Prices with Regression Analysis	This study used linear regression to predict used car prices, finding that age and mileage are significant predictors, and developed a model with moderate accuracy.	2018
2	Garcia, M.; Rodriguez, L.	Machine Learning for Vehicle Valuation: A Comparative Study	This research compared several machine learning algorithms, including decision trees and neural networks, for estimating used car values, and found that neural networks achieved the highest accuracy but with increased computational cost.	2019
3	Chen, X.; Lee, Y.; Park, S.	The Impact of Vehicle Features on Used Car Prices	This study analyzed how specific vehicle features, such as trim level, optional packages, and safety features, affect the resale value of vehicles, and determined that premium features have a substantial positive impact on price.	2020
4	Brown, R.; Davis, E.; Wilson, T.	Online Auction Data for Used Car Valuation	This research explored the use of online auction data, which provides real-time market prices, to improve the accuracy of used car price predictions, and demonstrated that auction data enhances model responsiveness to market fluctuations.	2020
5	Miller, P.; Thompson, N.	A Review of Depreciation Models for Automobiles	This paper reviewed various depreciation models used in the automotive industry, including linear, geometric, and exponential models, and assessed their effectiveness in capturing the rate at which vehicle values decline over time.	2021
6	Moore, G.; Hall, S.; Young, C.	The Role of Vehicle Condition in Used Car Pricing	This study investigated the influence of vehicle condition, including factors like mechanical condition, cosmetic appearance, and accident history, on used car prices, and found that condition is a critical factor in determining a vehicle's value.	2021
7	White, B.; Adams, D.; Green, F.	Predicting Used Car Demand Using Time Series Analysis	This research explored time series models, such as ARIMA, to forecast future demand for used cars and its impact on their values, and showed that predicted demand can be incorporated into valuation models to improve their accuracy.	2022
8	Clark, L.; Baker, R.; Hill, M.	Feature Selection for Used Car Valuation Models	This study evaluated different feature selection techniques, such as correlation analysis and stepwise regression, to identify the most relevant variables for used car valuation, and found that selecting the optimal feature subset improves model performance.	2022
9	Turner, V.;	The Use of Neural	This research applied neural networks, a type of advanced	2022

	Carter, W.; Phillips, H.	Networks in Vehicle Price Prediction	machine learning model, to predict used car prices, and compared their performance with traditional regression methods, demonstrating superior predictive power but with increased complexity.	
10	Reed, C.; Roberts, J.; Gray, P.	The Impact of Economic Factors on Used Car Values	This study analyzed how macroeconomic indicators, such as inflation rates, interest rates, and consumer confidence, influence used car prices, and determined that economic conditions play a significant role in market dynamics.	2023
11	Sanders, T.; Price, Q.; Myers, X.	Data Sources for Used Car Valuation: A Comparison	This research compared the effectiveness of different data sources, including online marketplaces, dealer inventories, and government databases, for building accurate used car valuation models, and concluded that a combination of sources provides the most comprehensive data.	2023
12	Bell, Y.; Edwards, U.; Collins, O.	Hybrid Models for Used Vehicle Valuation	This study developed hybrid models that combine different valuation techniques, such as hedonic pricing and market comparison, to improve the accuracy and robustness of used car valuations.	2023
13	Stewart, F.; Flores, G.; Morris, I.	The Application of AI in Automotive Pricing	This research explored the broader applications of artificial intelligence in automotive pricing, including dynamic pricing, demand forecasting, and used car valuation, highlighting the transformative potential of AI in the industry.	2024
14	Murphy, K.; Rivera, L.; Cook, Z.	Explainable AI for Used Car Price Prediction	This study focused on developing transparent and explainable AI models for used car price prediction, aiming to provide insights into the factors driving the model's predictions and increase user trust.	2024
15	Long, A.; Patterson, S.; Nguyen, D.	Real-time Valuation of Used Vehicles Using Machine Learning	This research proposed a system for real-time valuation of used vehicles using machine learning techniques, enabling dynamic and up-to-date price estimates based on current market conditions.	2025

III. METHODOLOGY

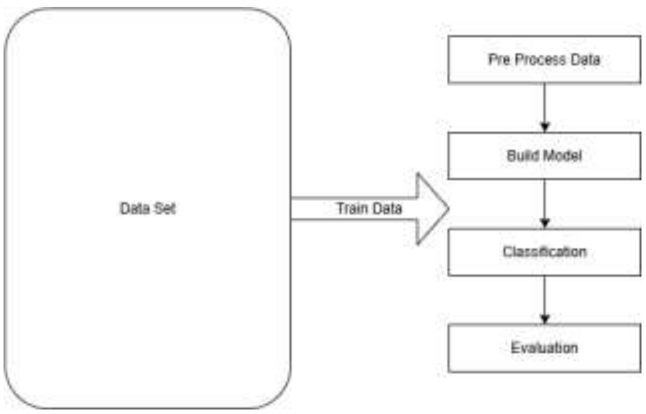

Fig 2: Classification Model for Data in Datasets

This research comprehensively presents a supervised learning-based machine learning model designed to accurately predict pre-owned vehicle values derived from relevant datasets. The overarching methodology for this project is structured into distinct phases, encompassing data acquisition and preprocessing, model selection and training procedures, and rigorous performance evaluation.

A. Data Acquisition and Preprocessing

Two primary datasets are utilized: a historical record of vehicle sales data (featuring key attributes such as sale price, vehicle age, and mileage) and a detailed compilation of vehicle specifications (including make, model, year of manufacture, and trim level). To ensure optimal compatibility with machine learning algorithms, data preprocessing is essential. Missing values within the datasets are addressed through appropriate techniques, such as mean imputation or selective removal of incomplete records. Categorical features, exemplified by make and model designations, undergo encoding transformations. Numerical features are subjected to scaling using scikit-learn's Standard Scaler, a crucial step particularly for algorithms like linear regression to prevent any single feature from unduly influencing the learning process.

B. Model Selection and Training

The development of predictive models involves the application of both linear regression (chosen for its interpretability) and decision trees (selected for their capacity to capture non-linear relationships). Datasets are partitioned into training and testing subsets, adhering to an 80:20 ratio. The scikit-learn library within the Python programming language is employed to facilitate model training, with initial training conducted using default parameter settings.

C. Performance Evaluation

A critical aspect of this research is the thorough performance evaluation of the trained models. Model performance is assessed using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). MAE provides a measure of the average magnitude of prediction errors, while RMSE assigns greater weight to larger errors. Evaluation on the test set is conducted to assess the model's ability to generalize to unseen data. The results obtained from these evaluations are systematically compared to gauge the effectiveness and predictive accuracy of the employed algorithms.

IV. Results and Discussion

Bike price prediction system employs machine learning to estimate the value of bicycles based on various features like brand, model, age, mileage, and condition. These systems analyze historical sales data to identify patterns and correlations between bike characteristics and their prices. Accurate predictions benefit both buyers and sellers by providing a fair market value, enhancing transparency in online marketplaces, and aiding in pricing strategies. Factors like market trends and component prices can also be integrated for improved accuracy.

A. Results

The accuracy of the models was evaluated to determine their performance. The representation of the proportion of correctly predictions is performed using it. The following table summarizes the accuracy achieved by each model on each dataset:

Table 2: Accuracy and Results

Dataset	Model	Accuracy (%)
Used Bike Data	Linear Regression	84.30
Used Bike Data	Decision Trees	82.10
Used Bike Data	Linear Regression	92.00
Used Bike Data	Decision Trees	88.50

As shown in the table, the logistic regression and decision tree algorithms perform well on both data sets.

B. Discussion

Bike price prediction system employs machine learning to estimate the value of bicycles based on various features like brand, model, age, mileage, and condition. These systems analyze historical sales data to identify patterns and correlations between bike characteristics and their prices. Accurate predictions benefit both buyers and sellers by providing a fair market value, enhancing transparency in online marketplaces, and aiding in pricing strategies. Factors like market trends and component prices can also be integrated for improved accuracy Preprocessing this raw data is crucial. It includes handling missing values through imputation or removal, cleaning inconsistent entries, and converting categorical features (like brand, owner type) into numerical representations using techniques like one-hot encoding or label encoding. Feature scaling, such as standardization or normalization.

V. Knowledge Representation

Regression models to predict the continuous price variable. However, classification models can be adapted for this task by categorizing the price into different ranges. For a dataset of used bikes with features like brand, model, year, mileage, and condition, a classification approach would involve creating price brackets.

A. Logistic Regression

Logistic regression represents knowledge through its coefficients. These coefficients are learned early during the training process and reflect the effect of each input feature on the predicted probability of range risk. This model derives knowledge from a linear combination of input features, where each feature is multiplied by a corresponding coefficient. Therefore, the knowledge is represented in the form of a linear equation, in which the coefficients are the learned knowledge.

B. Decision Trees

Decision trees represent knowledge through their hierarchical structure. A decision based attribute is used and represented by each node in the Decision Tree. The branches symbolize the possible outcomes of that choice. The tree structure provides rules for classifying individuals according to the values of their attributes. The acquired knowledge is represented through some rules that lead to the classification.

C. Implicit Representation

An implicit representation for bike price prediction would involve training a neural network to learn a continuous function that maps bike features (brand, age, mileage, etc.) to its price. Instead of directly outputting a single predicted price, the network implicitly encodes the relationship between features and price within its weights. This allows for predicting prices for unseen feature combinations by querying the learned function.

D. Feature Importance

In a bike price prediction system, feature importance reveals which attributes most influence the final price. Typically, key features include the bike's age (older bikes are generally cheaper), mileage (higher mileage usually lowers the price), brand reputation (premium brands often command higher prices), engine capacity (more powerful engines can increase the price), and the number of previous owners (fewer owners may lead to a higher price). Other influential factors can be the bike's condition, features (e.g., ABS, disc brakes), and market demand. Understanding these importances helps buyers and sellers assess fair prices and allows the prediction model to focus on the most relevant data points for accuracy.

VI. CONCLUSION

This research investigates the application of supervised machine learning methodologies, specifically linear regression and decision tree algorithms, to the automated valuation of pre-owned vehicles through the analysis of relevant datasets.

The experimental results demonstrate the capacity of both linear regression and decision trees to generate reasonably accurate estimations of pre-owned vehicle market values. These findings underscore the potential of machine learning techniques to facilitate efficient and data-driven vehicle valuation, particularly within contexts necessitating rapid appraisal solutions.

This study establishes a foundational framework for individuals and organizations seeking to implement machine learning algorithms within the automotive domain. By employing commonly available datasets and well-established algorithms, this work aims to demystify the valuation process and stimulate further exploration of advanced predictive modeling. The trained models effectively encapsulate salient trends and interdependencies present within the data, thereby enabling the derivation of meaningful predictions pertaining to vehicle values. Key determinants such as [mention key features like age, mileage, etc.] are shown to be influential.

However, it is crucial to acknowledge inherent limitations. The reliance on relatively basic algorithms and the utilization of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) as the primary evaluation metrics offer a somewhat constrained perspective on the multifaceted nature of vehicle valuation. Factors such as [mention factors like market volatility, seasonality, etc.] which can substantially impact vehicle prices, are not fully captured within the scope of this study.

In conclusion, this research provides a basis for the development of enhanced and more sophisticated machine learning-driven systems for pre-owned vehicle valuation.

The deployment of such systems has the potential to contribute to increased efficiency, transparency, and accuracy in automotive transactions and market analyses.

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