Machine Learning Powered Chatbot for Prediction of Used Car Price

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ABSTRACT
The used car market is a complex ecosystem influenced by various factors such as vehicle make, model, year, mileage, and condition. Predicting the price of a used car accurately requires a comprehensive understanding of these factors.

In this paper, a machine learning-based approach is proposed to develop a chatbot that can predict the prices of used cars in India. To achieve this, three machine learning techniques namely Gradient Boosting, Random Forest, and Cat Boost have been used. The data for prediction is collected from reputable used car marketplaces such as OLX and Cars24, using web scraping tools like Scrapy and Selenium. The aforementioned techniques have been applied and compared on their respective performance to find the one that best suits the available dataset. Additionally, the model has been evaluated using test data and an accuracy of over 80% has been achieved. The chatbot interface has been provided which allows users to input car details and get real-time price estimates, helping them make informed decisions in the used car market.

Keywords
Machine Learning, used vehicles, catboost, gradient boosting, random forest, regression, prediction, chatbot

1. INTRODUCTION
The market for used cars is a dynamic space where buyers and sellers come together based on their individual needs and preferences. Unlike the new car market, which is more predictable, the used car market involves several factors such as the age of the vehicle, mileage, condition, and ownership history [15]. These factors make it difficult to determine pricing.

It is really important to know the right price when buying or selling used cars. This helps both the buyer and the seller make fair deals and avoid any misunderstandings. Predicting the accurate price for a used car is a very important skill that helps to deal with uncertainties in the market. By doing this, we can make sure that everyone is treated fairly and we can trust each other when we make these deals.

In recent years, the application of machine learning techniques has greatly impacted the used car market by providing innovative solutions for complex predictive tasks. Machine learning methods utilize large datasets and advanced algorithms to help stakeholders make effective predictive insights based on historical transactions and patterns. This has led to improved accuracy and efficiency in price prediction [18].

This paper is organized as follows. Section 2 provides overview of related work. Section 3 discusses the methodology. The implementation and results are explained in Section 4. Section 5 provides a conclusion.

2. RELATED WORK
In recent years, predicting the prices of used cars has become a significant area of interest for researchers and practitioners alike. Various machine learning and data-driven approaches have been proposed to address this problem, leveraging different algorithms and datasets from diverse geographical locations. This frame related work section provides a comprehensive overview of the methodologies, datasets, and findings from multiple research studies on predicting used car prices which is indicated in Table 1.

The study conducted by Anamika Das Mou et al. [1] focuses on predicting the probability of buying a car based on several features such as price, spare part availability, customer review, cylinder volume, and resale price. The researchers employed machine learning algorithms including Naive Bayes, Support Vector Machine (SVM), Random Forest, and K-nearest neighbor (KNN) to compare their predictive accuracy. SVM emerged as the most accurate model with 87.6% accuracy.

Bukvi´c et al. [2] proposed a supervised machine learning model to predict used-car prices in the Croatian market. They utilized features like year of car production, motor type, condition, kilometers traveled, horsepower, number of doors, and mass of the car. Models such as Linear Regression, Random Forest, and SVM were employed, with R2 values ranging from 0.24 to 0.95.

Fathalla et al. [3] introduced a deep learning architecture for predicting the price of second-hand items based on image and textual descriptions. Their model combined long short-term memory (LSTM) and convolutional neural networks (CNN) for price prediction, achieving promising results. The dataset consisted of second-hand item attributes collected from various websites.

Longani et al. [4] developed a system using ensemble machine learning techniques to predict prices for used cars in the Mumbai region. They compared the performance of Random Forest and eXtreme gradient boosting (XGBoost) algorithms. Attributes such as year of purchase, mileage, showroom price, mileage, engine capacity, seating capacity, and power capacity of the car battery were considered.

Liu et al. [5] proposed the PSO-GRA-BPNN method for predicting used car prices in the onlinemarket. They utilized variables like new car price, displacement, mileage, gearbox, fuel consumption, registration time, drive mode, region, engine power, emission standard, body structure, and brand. Their model outperformed traditional BPNN and GRA-BPNN models in terms of accuracy.

Salim and Abu [6] proposed a model for estimating used car prices in the Malaysian market, addressing the limitations of linear regression. They considered variables such as mileage, color, and sale location, and compared the performance of simple linear regression, cubic regression, and S-curve model.

Pudaruth [7] applied supervised machine learning techniques to predict the price of used cars in Mauritius. He experimented with Multiple Linear Regression, K-Nearest Neighbors, Decision Trees (J48 and Random Forest), and Naïve Bayes algorithms. Factors like make, model, cylinder volume, year, mileage, and price were considered.

Gegic et al. [8] applied Support Vector Machine (SVM), Artificial Neural Network (ANN), and Random Forest (RF) to predict used car prices. Attributes such as brand, model, car condition, fuel, year of manufacturing, power, transmission type, mileage, color, city, state, and number of doors were used. ANN exhibited the highest accuracy among the models tested.

Monburinon et al. [9] conducted a comparative study on regression-based supervised machine learning models for predicting used car prices using data from a German e-commerce website. They considered variables like seller information, offer type, and A/B testing variables, with gradient boosted regression trees performing the best.

Venkatasubbu and Ganesh [10] proposed deep end-to-end learning models for predicting the retail price of used cars. They compared the accuracy of Lasso Regression, Multiple Regression, and Regression Trees using data from the Kelly Blue Book. Their results indicated varying levels of accuracy among the models tested.

Table No: 1. Literature review of existing techniques

Ref. No.	DATASET	METHODOLOGY	ADVANTAGES	DISADVANTAGES	ALGORITHM USED	ACCURACY	ATTRIBUTES
[1]	Collected data from different shops in Bangladesh and social media.	Analyses the accuracy of different predictive algorithms that can predict the probability of purchasing a car.	Considers customer reviews, an essential factor in the decision-making process.	Dataset contains only 50 data points.	Naive Bayes, Support Vector Machine (SVM), K-nearest neighbor , and Random Forest tree.	Support Vector Machine (SVM) achieved the highest accuracy of 86.7%.	Price, spare parts, cylinder volume, resale price, customer reviews, and decision to buy or not.
[2]	Dataset collected from "Njuškalo, " a used car in Croatia.	Provides an overview of data-driven models using attributes production year and kilometres travelled.	Accurate price predictions of used cars.	Specific to the Croatian market and may not generalize well to other markets.	Support Vector Machine, Random Forest trees, linear regression, and decision trees.	Linear regression achieved a highest accuracy of 95%.	Manufacturer, kilometres travelled, selling price, and year of production.
[3]	Data collected from advertisements for second-hand item	Involves price prediction and price forecasting, uses visual features.	Combines textual and visual features.	Dataset size is not very large.	Linear Regression, LSTM-DNN, ARIMA/ SARIMA.	BI-LSTM-CNN price prediction model, accuracy of 77.14	Date, product description (textual data), image,price.
[4]	Dataset contains used cars data in the Mumbai with 2454 records.	Ensemble machine learning using Bagging (Random Forest) and Boosting (XGBoost) methods.	It enhances prediction accuracy.	Dataset may vary by region.	Random Forest & XGBoost.	XGBoost outperforms Random Forest.	Year, seller type, mileage, owner type, fuel type, gear type,various technical specification

[5]	Uses web crawler technolog y to collect used car data.	Predict used car prices accurately by selecting relevant features, constructing and optimizing prediction models, and evaluating their performance.	Grey Relation Analysis (GRA) effectively reduced the training time and improved model's accuracy.	Use of multiple models and optimization methods increased the complexity of the approach.	BP Neural Network (BPNN) Grey Relation Analysis (GRA) Particle Swarm Optimization (PSO)	PSO-GRA-BPNN model achieves the best accuracy with a MAPE of 3.936% and a MAE of 0.475	Brand, drive mode, gearbox, engine power, body structure, mileage, usage time, displacement, fuel consumption, emission standard, region, new car price.
[6]	Data is collected from the Mudah. my website.	provides a more accurate pricing model for used cars,acknowledgi ng the limitations of linear models in capturing real-world price trends	S-Curve is more realistic, better forecast and dynamic. S-Curve has improved accuracy.	limited dataset, and the findings may not be universally applicable to all used car markets	Linear Regression, Cubic Regression, S-Curve Model, Mean Squared Error (MSE).	S-curve model shows a slightly higher MSE	Mileage, colour, and sale location.
[7]	Dataset consisted of 97 records of Toyota, Nissan, and Honda cars collected from daily newspaper	systematic process of data collection, preprocessing, application of diverse machine learning techniques, and evaluation metrics.	ML techniques, feature insights, model comparisons, data normalization, and advanced algorithms in predicting car prices.	Small dataset, challenges in handling nominal and numeric attributes.	Multiple Linear Regression, K-Nearest Neighbors (KNN), Decision Trees (J48 and Random Forest), and Naïve Bayes	Random Forest exhibited enhanced performance when applied to the entire training dataset.	Model, cylinder volume, year of manufacture, and price.
[8]	Data was collected from autopijaca .ba.	Data was pre-processed by removing sparse attributes and converting numeric attributes like mileage and year into categorical values.	SVM was used both as a standalone classifier and to categorize the car samples into price categories.	consumes much more computational resources than single machine learning algorithm	Support Vector Machine (SVM) Artificial Neural Network, Random Forest (RF)	RF achieved 85.82% accuracy (ANN)- 83.91% SVM- 86.96%.	Brand, model, condition, fuel type, age, power, mileage, colour, and various features.
[9]	Dataset was collected from www.kagg le.com.	Compares the performance of multiple linear regression, random forest regression, and gradient boosted regression trees for predicting used car prices.	High predictive accuracy, robust to nonlinear relationships, ensemble strength, and sequential learning capabilities.	Computational intensity, interpretability challenges, overfitting risk, hyper parameter tuning sensitivity, and maintenance complexity in production.	Multiple Linear Regression, Random Forest Regression, Gradient Boosted Regression Trees	Gradient boosted regression MAE of 0.28, RF regression MAE of 0.35, multiple linear regression MAE of 0.55	Seller information, offer type, A/B testing variables, and others.
[10]	Data was taken from GM cars.	Used Lasso Regression, Multiple Regression, and Regression Trees on car data for price prediction, validated with ANOVA.	Uses ANOVA and Tukey's test to ensure the robustness of the results.	Focused on a narrow dataset of 2005 GM cars.	Lasso Regression, Multiple Regression, Regression Tree.	Error rates : Lasso Regression 3.581% , Multiple Regression 3.468% , Regression Tree 3.512%	mileage, make, model, trim, type, cylinder, litre, doors, cruise control, sound system, and leather interiors.

The techniques and approaches used in predicting used car prices are diverse and varied. Data collection methods range from web crawling to newspaper ads, and datasets originate from different regions. Various algorithms such as Support Vector Machine, Random Forest, Gradient Boosted Regression Trees, and different regression techniques are employed with their own advantages and disadvantages. Although some models achieve high accuracies, concerns remain regarding dataset size, regional specificity, computational resources, and interpretability.

Commonly used attributes for prediction include mileage, brand, year of production, and customer reviews.

Despite varying complexities and accuracies, these studies contribute to the development of more accurate and robust pricing models for the used car market.

3. METHODOLOGY

The purpose of this research is to assess the precision of different predictive algorithms in determining the likelihood of purchasing a car. The main goal is to recognize the algorithm that yields the most accurate results and incorporate it into the chatbot. Figure 1 illustrates the system block diagram of the proposed methodology.

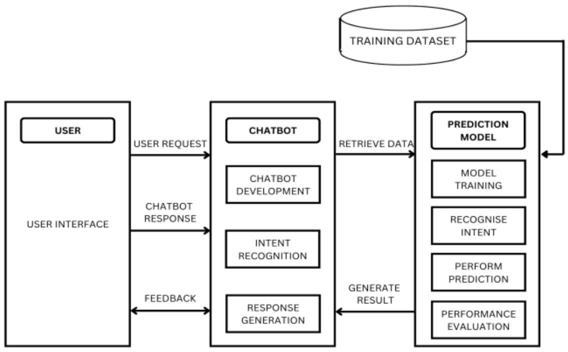

Fig 1: System diagram for proposed methodology

The methodology for developing the Used Car Price Prediction Chatbot involves a seamless integration of machine learning models, including Gradient Boosting [9], CatBoost [4] and Random Forest [9], coupled with an interactive interface powered by Dialogflow [18]. The objective is to create a user-friendly system that accurately predicts used car prices based on relevant features provided by the user.

Dataset Collection: A diverse and comprehensive dataset is collected from various sources, encompassing historical used car data with corresponding prices. This dataset serves as the foundation for training and evaluating the machine learning models.

Data Preprocessing: The collected dataset undergoes thorough preprocessing to handle missing values, outliers, and ensure uniformity in the format. Features such as car model, mileage, and other relevant attributes are carefully selected and encoded for model training.

Model Selection: Three distinct machine learning models are chosen for their efficacy in regression tasks: Gradient Boosting, Random Forest, and CatBoost. These models are preferred for their ability to handle both non-linear relationships within the data and effectively capture complex patterns, making them suitable for retail price prediction tasks.

Model Training: The models are trained using the preprocessed dataset. Gradient Boosting excels in capturing complex relationships and iteratively improves predictive accuracy. Random Forest provides an ensemble approach for robust predictions by constructing multiple decision trees. CatBoost specifically designed for categorical features, enhances model performance by handling categorical variables efficiently. The training process involves optimizing model parameters to maximize predictive accuracy and generalization capability.

Dialogflow Integration: Dialogflow, a natural language processing (NLP) [18] tool, is seamlessly integrated to facilitate user interactions. Intent recognition in Dialogflow identifies user queries related to used car price predictions, ensuring a user-friendly conversational interface.

User Interaction Flow: The chatbot engages users in a natural language conversation, extracting relevant information such as car model, mileage, and other features crucial for price prediction. Dialogflow processes user inputs, mapping them to specific intents and entities.

Prediction Phase: Upon gathering user details, the chatbot triggers the trained machine learning models (GBT, CB, RF) to predict the used car price. The models run in parallel, contributing to a comprehensive prediction.

Result Aggregation: The individual predictions from GBT, CB, and RF are aggregated using techniques like averaging to provide a consolidated and more robust prediction.

User Feedback Loop: Optionally, the chatbot incorporates a feedback loop, allowing users to provide feedback on the predicted price. This feedback is invaluable for continuous improvement of both the chatbot's interaction capabilities and the predictive models.

3.1 MODELS USED

The supervised learning algorithms specifically, Gradient Boost, Random Forest Tree, and CatBoost have been used.

Gradient Boosting: is an ensemble learning technique used for classification and regression tasks. It builds multiple decision trees sequentially, where each tree corrects the errors of the previous one. The algorithm works by fitting new models to the residuals of the previous models, thereby gradually reducing the errors. The general formula for Gradient Boosting can be represented as follows:

$$F_m(x)=F_{m-1}(x)+\lambda h_m(x) \tag{1}$$

Where:

- $F_m(x)$ is the current ensemble model at iteration m,
- $F_{m-1}(x)$ is the ensemble model from the previous iteration,
- λ is the learning rate which controls the contribution of each tree to the ensemble,
- $h_m(x)$ is the base learner (usually a decision tree) added to the ensemble at iteration m.

Random Forest: is a powerful ensemble learning method commonly used for classification and regression tasks. It operates by constructing multiple decision trees during training and outputs the mode of the classes (classification) or the mean prediction (regression) of the individual trees. The core idea involves the aggregation of predictions from multiple decision trees. In classification tasks, the final prediction of the Random Forest is often determined by a majority vote among the trees.

In regression tasks, it's typically the average prediction of all the trees.

CatBoost: is a state-of-the-art gradient boosting algorithm that is particularly effective for categorical data. Developed by Yandex, CatBoost stands out due to its ability to handle categorical features efficiently without requiring prior preprocessing or one-hot encoding. It automatically deals with categorical variables by implementing an efficient computation scheme and feature combination method. Its functionality is similar to other gradient boosting algorithms, where each new tree is trained to minimize the loss function, which includes regularization terms to control model complexity and overfitting.

4. IMPLEMENATION

To implement the car prediction algorithm, we utilized VScode and Google Colab with several Python libraries. The hardware specifications we used were an Intel Core i5-10500H processor with a clock rate of 2.50GHz and 8GB of RAM. We carried out the development on a Windows 11 (64-bit) operating system.

Data Extraction:
A parameterization mechanism has been implemented to effectively manage NaN (Not a Number) values within the dataset. This parameter ensures a systematic approach to dealing with missing or undefined data points. During the data refinement process, we meticulously segregated merged data into distinct values based on their corresponding attributes. This segregation facilitated a more granular analysis and manipulation of the dataset, enabling us to derive meaningful insights and conclusions from it. The program takes into account several factors, including the car's make and model, year, mileage, ownership status, fuel type, transmission, and location. In the example shown, the program predicts that a 2015 Maruti Suzuki Baleno with 50,000 kilometers driven, owned by its first owner, and located in Punjab, India, would be worth ₹497,323.27.

The collected dataset has been preprocessed to handle missing values, outliers, and ensure uniformity in the format. The preprocessed dataset sample is indicated in Figure 2.

1	Brands	CarName	Year	KmDriven	OwnerStatu	FuelType	Transmissio	Location	Price
2	Audi	Audi Q7	2011	76000	First owner	Diesel	Manual	Punjab	1850000
3	Audi	Audi Q7	2013	120000	First owner	Diesel	Manual	Punjab	2200000
4	Audi	Audi Q7	2017	65000	First owner	Diesel	Automatic	Uttar Prade	2250000
5	Audi	Audi Q3	2015	73656	First owner	Diesel	Manual	Punjab	1656999
6	Audi	Audi Q5	2014	75000	First owner	Diesel	Manual	Rajasthan	1850000
7	Audi	Audi A4	2013	40670	Second owr	Diesel	Automatic	Gujarat	1773999
8	Audi	Audi A6	2015	55985	First owner	Petrol	Automatic	Karnataka	2350000
9	Audi	Audi A6	2010	35000	First owner	Diesel	Automatic	Goa	1150000
10	Audi	Audi A4	2015	13648	First owner	Diesel	Automatic	Chhattisgarl	2143000
11	Audi	Audi A4	2012	65664	First owner	Diesel	Automatic	Uttarakhan	1350000
12	Audi	Audi A6	2014	56000	Second owr	Diesel	Automatic	Punjab	2950000
13	Audi	Audi A6	2018	48367	First owner	Diesel	Automatic	Jammu and	3958000
14	Audi	Audi A4	2010	30000	First owner	Diesel	Automatic	Andhra Prac	980000
15	Audi	Audi RS5	2013	23000	First owner	Petrol	Automatic	Haryana	3700000

Fig 2: Processed dataset sample in CSV format

Evaluation Dataset

We obtained our data from reliable used car marketplaces such as OLX [15] and Cars24 [14] using web-scraping tools like Scrapy and Selenium. We used 80% of the data for training and 20% for testing. A summary of the dataset can be found in Table 2 below.

Table 2: Simple Statistics of Dataset

Attributes	Number of Count
Data Collected	24348
Training Data	19,478
Testing Data	4,870

Evaluation Measurement

To evaluate the results, R2 score and accuracy measurement of the algorithms have been used as indicated in Table 3.

i. R2 score: R2 score [18] represents the proportion of the variance in the dependent variable that is predictable from the independent variables, indicating the goodness of fit of a regression model.

ii. Accuracy of algorithms: Accuracy [18] is a measurement of how a model predicts correctly to the total number of input samples. In our proposed method, the dataset is split into 80% for training and 20% for testing.

Table 3: Performance evaluation of model on algorithms.

Algorithm used	R2 score	Accuracy
Gradient Boosting	0.69	78.05%
Random Forest	0.78	78.63%
CatBoost	0.72	80.03%

According to the analysis, among the three algorithms considered, Gradient Boosting seems to be the least accurate with an accuracy rate of approximately 78.05%. Random Forest is more accurate than Gradient Boosting, with an accuracy rate of about 78.63%. Finally, CatBoost stands out as the most accurate of the three algorithms, with an accuracy rate of around 80.03% as shown in Figure 3.

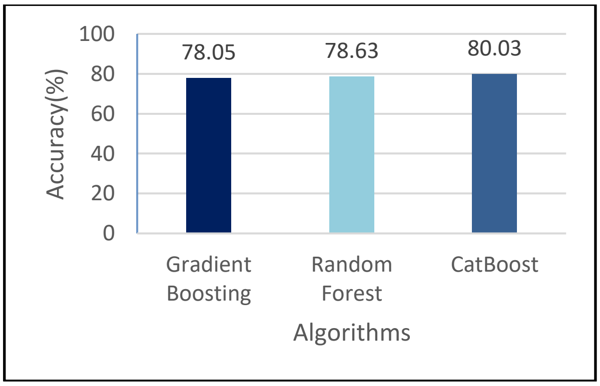

Fig. 3: Accuracy of model on various algorithms

The final prediction chatbot as shown in Figure 4 has been incorporated using the Dialogflow application, with a webhook connected to the server and integrated into the front end.

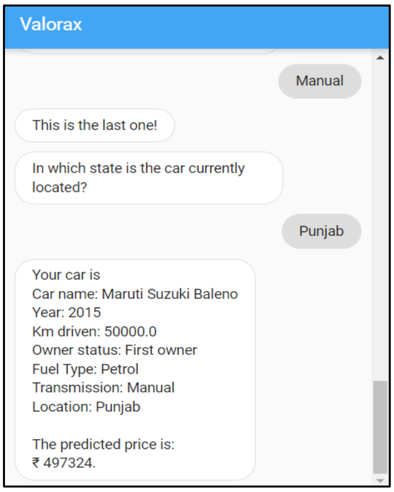

Fig. 4: GUI of the car price prediction chatbot

5. CONCLUSION

Estimating the resale value of a car is a complex task that requires expert knowledge. The price of a car depends on several distinctive features and factors, making it difficult to predict accurately. Furthermore, different preferences among buyers can lead to bias when attempting to predict the resale price of a car.

A chatbot named 'VALORAX' has been developed that can predict the price of used cars in India using machine learning. A user interface which is created allows users to input car details and receive real-time price estimates, helping them make informed decisions. The dataset was collected from reputable websites such as OLX and Cars24. A machine-learning model using the Catboost technique was trained for predicting the resale value of the car. The Catboost model achieved an accuracy of 80.03% when trained with the dataset. Using this model, the chatbot can successfully predict the price of the car based on the user's input.

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