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Measuring the Effectiveness of AI-Powered Training in Luxury Automotive Retail Sales Networks

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***Abstract*—The vehicle valuation process in the dynamic secondary automotive market is a challenging task because the vehicle value depends on condition, mileage, and the constantly changing market in a non-linear relationship. The objective of this study is to create a very accurate, scalable predictive model of vehicle selling prices that combines institutional market benchmarks with vehicle physical characteristics. For this purpose, a comprehensive end-to-end pipeline is designed based on automatic column transformations that convert high-dimensional categorical features into continuous numerical features. In this study, three advanced ensemble learning models XGBoost (XGB) Random Forest (RF) and Gradient Boosting (GB), were considered and compared to the traditional models. The results show that ensemble architectures outperform individual architectures at predicting accuracy. The Gradient Boosting model had the best empirical performance with a score of 0.976, MSE of 2161666.55 and a RMSE of 1,470.26, followed closely by Random Forest and XGBoost with an score of 0.975. The proposed models were rigorously validated against existing models such as Support Vector Regression, LSTM, KNN, Linear Regression, and Prophet, where the results presented that the proposed models significantly outperform the traditional models. Results from the feature importance mapping confirmed that the Manheim Market Report (MMR) remains most useful as a predictive indicator, and the results from the residual diagnostics showed performance boundaries in the premium asset segments. The overall contribution of this research is a validated data-driven methodology that improves the accuracy of valuing assets in real-time, and offers a solid framework for structured data prediction in the secondary markets.**

Keywords—Automotive industry, Sales forecasting, Digital transformation, Machine learning, Production planning, vehicle sales data.

I. INTRODUCTION

The automotive sector, like other aspects of urban economies and consumerism, is undergoing a tremendous digital transformation. This change encompasses new consumer habits and business models, especially in the realm of online car buying, and extends beyond the mere digitization of manual processes. New digital platforms and the sharing economy changed the way consumers interacted with goods and services, particularly commodities with significant value additions like cars [1][2]. Accurate predicting vehicle sales can assist manufacturers in effective production and inventory planning[3], eliminate waste of resources, enhance market competitiveness and support companies to create effective marketing strategies [4]. Moreover, accurate predictions can be utilized to support the government and industry decision making and to develop scientific policies and measures [5][6]. Forecasting the sales for an investor offers them a reliable analysis of the market trend, helps optimize the allocation of resources, and boosts the investor's investment returns [7][8].

In the automotive industry, car retail prediction has a significant effect on production planning, inventory management, and optimization of market strategies. Historically, the car sales prediction problem was approached with typical statistical methods, and more recently, with AI methods [9][10][11]. Advanced technologies like AI and big data have transformed sales forecasting, producing unprecedentedly accurate sales estimates [12]. Modern artificial intelligence (AI) algorithms and ML models sift through mountains of data in search of hidden trends and patterns [13][14]. With the complexity of consumer behaviour and market trends, the traditional sales forecasting method based on statistical techniques is already outdated[15]. An accurate forecast of car retail is essential for good manufacturing planning, product management, marketing planning and policies, government decisions and investment allocation[16]. The aim of this study is to utilize machine learning and AI for accurate insights and predictions, culminating in competitiveness and sustainability in the evolving automotive industry. This study makes some key contributions:

- High-performance ensemble learning models that substantially surpass traditional baselines for automotive pricing were deployed and validated.
- To improve interpretability, key variables like odometer reading, MMR, condition score, and brand distribution are included.
- The findings offer valuable information for dealerships and organizations regarding pricing, inventory management, and strategic planning.
- The study extends prior work by demonstrating how ensemble learning with heterogeneous automotive data improves scalability, accuracy, and applicability in real-world contexts.

The study is further extended to demonstrate that the ensemble learning with different automotive data has superior scalability, accuracy and applicability in practical applications. In this work, they provide an ensemble method with high performance which can be used in a beneficial manner to combine the market benchmarks and categorially distributed data with a high complexity. This method is more suited to capturing the non-linear relationships between vehicle condition, mileage and price, as compared to previous methods, which are based on simple linear models or basic time-series forecasting. Advanced forest and boosting based architectures do significantly better than the standard baseline architectures, and the results validate the use of these advanced architectures. In this study, a methodology is presented which is more accurate and scalable for automotive valuation. This predictive ability gives an invaluable resource to deal with the intricacies of the secondary vehicle market.

A. *Paper Layout*

This paper is structured as follows. A literature review of previous forecasting studies of used-car sale values is presented in Section II. The approach presented in this work is introduced in Section III by providing some specific preprocessing methodologies. Section IV provides the results and comparative analysis. Finally, in section V, limitations and future work is discussed.

II. Literature Review

In this section, discuss the relevant studies that focus on sales price forecasting in the industry. Mazur et al. (2025) assesses the efficacy of four ML algorithms in predicting sales, represented by the binary variable Success: GBM, RF, SVM and XGBoost with an RBF kernel. The results showed that RF had the best capacity to differentiate between successful and unsuccessful transactions, with an AUC of 0.90, F1-score of 0.73 and accuracy of 84.3% outperforming all of the other models that were examined [17]. Du, Feng and He (2025) use data on vehicle retail and production from 2004–2023, together with suggestions for a hybrid deep learning model that combines XGBoost, LSTNet, and CNN. The experimental results demonstrate that the suggested model offers more trustworthy decision support for businesses compared to conventional methods in terms of prediction accuracy. Model predictions show that by 2030, China's automobile sales will reach 26.77 million units, with BYD, Volkswagen, and Toyota expected to lead the market [18].

Bergmann and Feuerriegel (2025) utilize ML with a large-scale dataset derived from the actual world. Incorporating data on the equipment leads to a 3.27 percent improvement in prediction performance (mean absolute error), which is a statistically significant improvement. In sum, auto dealerships may improve their used-car pricing predictions by using data pertaining to the precise vehicle configuration [19]. Golderzahi and Pao (2024) incorporate a range of machine learning methods, including Support Vector Regression and Random Forest to generate models. They test these models with respect to three main prediction tasks: product amount, customer evaluation device count, and coffee shop revenue. Maximizing MAPE by 6-10% is possible when they use both group data and weather conditions in their predictions [20]. Sajawal et al. (2023) analyzed the Citadel POS dataset for retail sales predictions using several machine learning methods. In order to estimate sales, they used various time series models (ARIMA LSTM) and regression techniques (Gradient Boosting, Random Forest, and Linear Regression) and offered in-depth analysis and assessment. With an MAE of 0.516 and an RMSE of 0.63, Xgboost outperformed other regression models and time series in terms of overall performance [21].

A. *Research Gap*

Although there are promising advances in ML and DL for forecasting sales in the automobile industry, some critical issues have yet to be addressed. Most models focus on the accuracy while ignoring a wide range of market differences and external shocks at a dealership level. Usually, there are few features and no links between consumer behavior, macro-economic data and events within the supply chain. Certain contextual variables and equipment have proven to be helpful in other sectors, but few have adopted a systematic approach to automotive forecasting. Overall, it is needed to develop a more comprehensive and comprehensible model or framework that combines multiple data sources and provides powerful and practical forecast for actual car sales and pricing in the market.

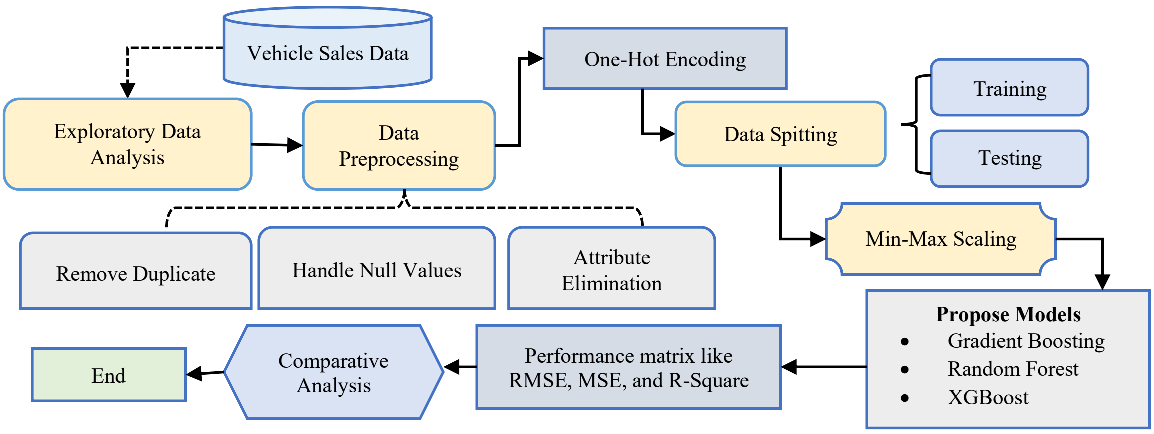

Fig. 1. Proposed Flowchart of the Vehicle Price Prediction Framework

III. Methodology

This flowchart shows the whole of the process to predict the selling price of a vehicle, as shown in Fig. 1. It begins with raw data, followed by an extensive data preprocessing stage which involves eliminating duplicates, dealing with missing values and attributes, and then Exploratory Data Analysis (EDA). The Data Splitting phase includes one-hot coding the categorical features and dividing the data set into two equal parts: a training set and a testing set. The continuous features are normalized using Min-Max Scaling and the three proposed models (Gradient Boosting, Random Forest, and XGBoost) are trained on the processed data. Last, it is considered extensively and compared with baseline methods with the Performance Matrix: (RMSE, MSE and R^2).

Discuss each steps of proposed framework are given in below:

A. Data Collection and Visualization

The vehicle sales data comes from the Kaggle open-source database. It contained 558,837 records and 16 attributes, and after pre-processing, it is reduced to 472,310 records and 8 features. The dataset showed distinct patterns when viewed in a visual format: selling price dropped as odometer reading increased; there is a strong correlation between MMR and price accuracy; and the more favorable the product condition, the higher the resale value. Some of the visualisation of the datasets are given in below:

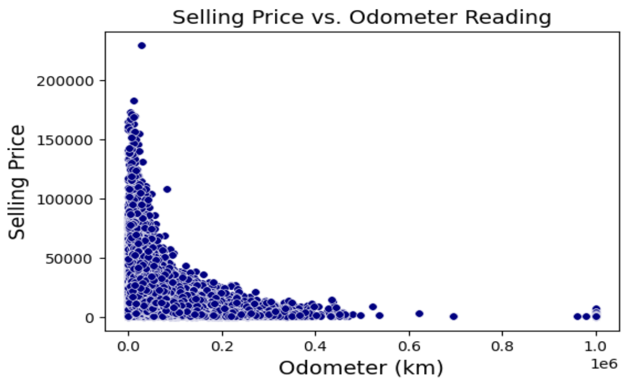

Fig. 2. Scatter plot for Selling Price and Odometer Reading

Fig. 2 is a scatter plot showing the correlation between odometer readings and sales prices of vehicles. The number of kilometers driven is shown on the x-axis, while the selling price of the vehicles is revealed on the y-axis. As the plot reveals, there is a strong negative correlation; as the vehicle's mileage decreases, its selling price increases, and as the vehicle's mileage increases, its resale value decreases. Since most of the information is located toward the lower end of the odometer range, a large portion of the cars in the dataset have moderate to low mileage.

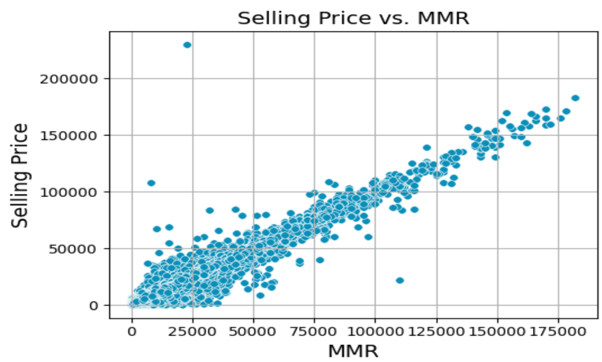

Fig. 3. Scatter plot for Relationship Between MMR and Selling Price

Fig. 3 shows that the correlation among MMR and selling price is positive and close to one, with a higher value for MMR indicating a higher value for selling price. The distribution of high density at lower values eventually gets linear upward, which shows the predictive consistency. Selling prices for outliers are high, indicating that there are occasional deviations from market estimates. The figure overall is indicative of MMR's success as a valuation benchmark for pricing accuracy.

Fig. 4 illustrates the relationship among product condition and selling price. The graph shows the selling prices, which start off with some variation, but then increases quickly at moderate percentages of condition, and decreases marginally at the highest percentages. After level 20, the price of selling the product gradually rises, suggesting that as the condition of the product increases, the market price increases. The results of this investigation revealed positive associations between product condition and selling price.

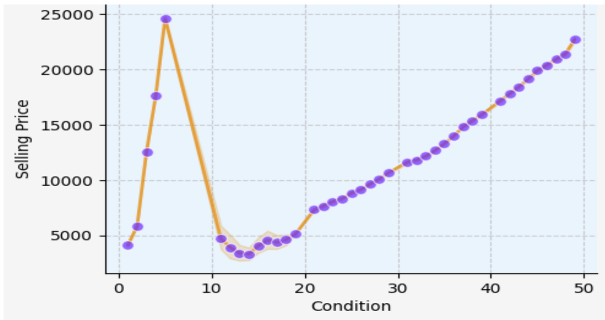

Fig. 4. Selling Price and Condition Analysis

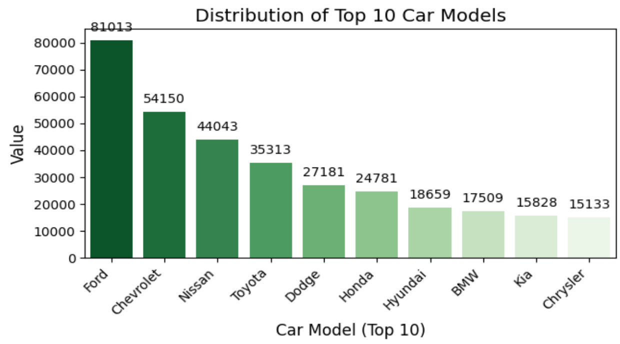

Fig. 5. Distribution of Top 10 Car Models

The top 10 cars by Frequency/Count in the data are shown in Fig. 5. Ford is the most represented with 81,013 records, followed by Chevrolet and Nissan. The most cars that are not in the top 10 models are Chrysler. The figure emphasizes that some of the cars in the data set are more dominant than others and gives an idea of the most common vehicle models listed.

B. Data pre-processing

To make sure the data is consistent, of high quality, and compatible with the machine learning models, the automobile sales dataset is pre-processed. To enhance the efficiency of the model, irrelevance and redundancy of attributes like unique identifiers and non-predictive columns were eliminated first. Data is checked for missing values and records are duplicated and removed accordingly to preserves the integrity of the data set. Last, the features are classified as either numerical or categorical and are further pre-processed and used to train the model. The following pre-processing steps are given in below:

C. Data Encoding and Splitting

To enable machine learning algorithms to process categorical variables numerically, they are often transformed into numerical values using a technique called One-Hot Encoding. Categorical features like vehicle make, model, transmission, body style, and color are features in the vehicle sales dataset that do not contain numbers, and cannot be directly used by predictive models. Each unique category is represented by a new column that One Hot Encoder generates using a binary coding technique, where 1 indicates the presence of a category and 0 indicates its absence. This method ensures that the model does not make any ordinal assumption about the categories, and allows for better prediction accuracy since it is able to represent the categorical data in a machine-readable format. All the preprocessing steps are then combined into a machine learning Pipeline for uniform data transformation in training and testing. The final stage in effectively testing models and limiting data leaks is partitioning data into training and test sets. The dataset is split into 80% training data and 20% testing data to train and test models on unseen data.

D. Feature Scaling

As a normalization technique, Min-Max Scaling converts a range of numerical values to a set range, usually between zero and one. It scales all the numeric attributes to a comparable range and helps avoid that the feature with the largest range dominating the machine learning model. For numerical features like odometer reading, MMR, and condition, Min-Max Scaling is used to normalize the data prior to training the model. Equation (1) of the Min-Max Scaling is:

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

Where X_{min}= Minimum value of the feature, X_{scaled}= Normalized value after scaling, X= Original feature value,X_{max}= Maximum value of the feature.

E. Model Building

This study chose Gradient Boosting (GB), Random Forest (RF), and XGBoost models for predicting vehicle sales prices because of their excellent performance on structured datasets and ability to capture nonlinear correlations.

1) Gradient Boost (GB)

This study chose XGBoost models, Random Forest (RF), and Gradient Boosting (GB), for predicting vehicle sales prices because of their high performance on structured datasets and ability to capture nonlinear correlations. Common parameters include learning_rate = 0.1, n_estimators = 200 (number of boosting stages), max_depth = 5 (tree depth) and subsample = 0.8 (fraction of samples per tree). For accurate predictions with minimal overfitting, these numbers provide a happy medium between bias and variance. GB's great accuracy and interpretability make it a popular choice for regression and classification problems.

2) Random Forest (RF)

Gradient Boosting constructs trees in a progressive manner, with each rectifying past errors [22]. It employs the gradient descent method to minimize loss functions, which is helpful for challenging tasks. Typical parameters include learning_rate = 0.1, n_estimators = 200, subsample = 0.8 (fraction of samples per tree) and max_depth = 5 (tree depth). Strong predictive performance and less overfitting are achieved by balancing variance and bias with these parameters. GB is often used for classification and regression problems due to its high accuracy and interpretability.

3) XGboost

XGBoost is an improved and scalable gradient boosting system. Rarely overfits, regularizes and optimizes via parallelization. The most important training parameters are max depth, the number of estimators (n estimators), the learning rate, subsample, colsample by tree, and minimal loss reduction to produce a split. It is guaranteed that the accuracy of XGBoost will be outstanding in structured data prediction tasks, and the parameters can be finely adjusted to the complexity and performance of the XGBoost model.

F. Performance Measurements

The suitability of the proposed model is measured based on several measures of multiple regression, including Root i.e., Root Mean Square Error (RMSE) and Mean Square Error (MSE), Coefficient of Determination(R^2). These measures give a comprehensive evaluation of accuracy of prediction as well as the behavior of errors. These measures of evaluation have mathematical formulations as indicated by Equations (2)-(4):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i)^2 \tag{3}$$

$$R^2 = 1 - \frac{\Sigma(y_i - \hat{y}_i)^2}{\Sigma(y_i - \bar{y})^2} \tag{4}$$

RMSE is used to measure the standard deviation of the prediction errors with an emphasis to bigger errors. The R^2 value is used to show the extent to which the model accounts the variation in the variable of interest. The variance among the predicted and actual values are squared, averaged, and then calculated with MSE.

IV. Results and Discussion

This study made use of an experimental system that ran on Windows 10 and featured a 32 GB RAM, 3.90 GHz Intel Core i9-13900HX desktop computer. For even quicker processing, it made use of the NVIDIA GeForce RTX 4070 GPU. It made extensive use of several Python packages, including Pandas, NumPy, TensorFlow, and Keras. All three ensemble models had a prediction accuracy of high level with R^2 of 0.975–0.976, as presented in the experimental results shown in Table I. Gradient Boosting had a slightly better performance with the minimum MSE and RMSE, which means it performed better in minimizing errors and predicting vehicle sales with good precision. Both the Random Forest and XGBoost models achieved good performance with only slight variations in the number of errors. Overall, the findings confirm that the ensemble learning approaches are extremely effective for the prediction of structured data in the automobile field.

TABLE I. Experiment Results of Propose Models for Automotive Sales Prediction

Model	R^2 Score	MSE	RMSE
GB	0.976	2161666.55	1470.260708
RF	0.975	2246630.89	1498.876543
XGB	0.975	2278402.02	1509.437650

Actual and predicting prices of selling vehicles are shown in Fig. 6. The subplots consist of comparing the actual selling price on the x-axis of each one with the predicted selling price on the y-axis of each one. In each of the graphs the dashed red diagonal line is the ideal prediction line on which x and y values are exactly equal to each other. In all three models, scatter points are tightly grouped around the reference line, suggesting that the models have good predictive power and accuracy. Within the models, Gradient Boosting and Random Forest show tighter clusters around the diagonal line indicating slight consistency and less prediction error. XGBoost also shows a good predictive power, with some outliers suggesting slight deviations in some instances. In overall, the figure shows the effectiveness of ensemble learning models in achieving an accurate selling price prediction for vehicles.

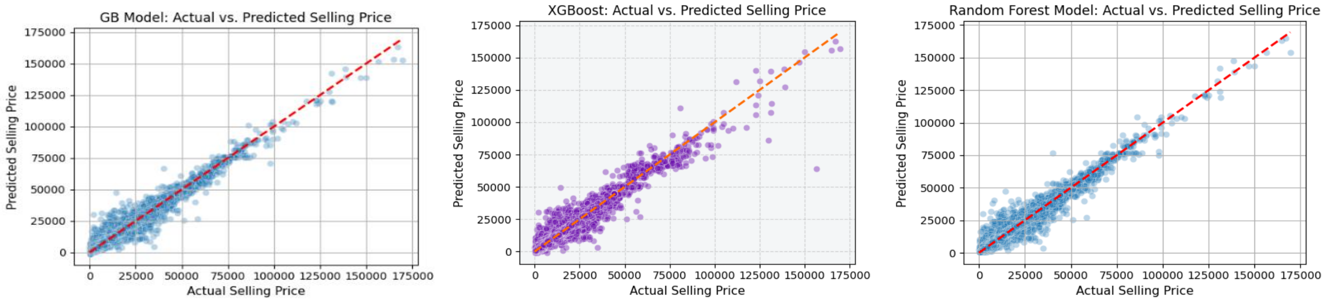

Fig. 6. Actual and Predicted Selling Price prediction with GB, XGB, and RF Models

Fig. 7. Residual Analysis for Proposed Models

The prediction errors of the three machine learning models are shown in Fig. 7. The y-axis is the residual values and x axis is the predicted selling prices. The red dashed horizontal line represents the reference for zero residual, where predictions match actual data. If the points are clustered near the zero line, the forecasts are correct; if the points are positioned far from the zero line, the prediction errors are significant. The overall pattern of the residuals indicates that the models are reasonably accurate, with some variation and outliers present at higher predicted prices.

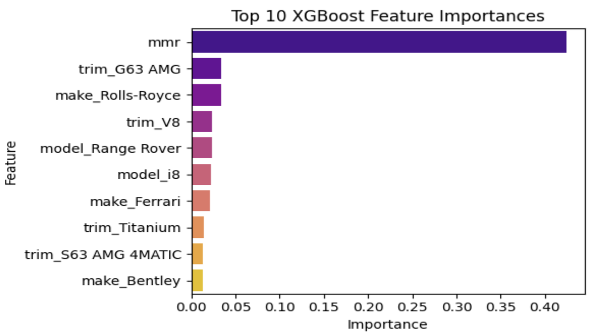

Fig. 8. Top 10 Feature Importance Score with XGBoost

The top 10 most important features for the XGBoost model to predict selling prices are shown in Fig. 8. The x-axis is a score of the importance of each feature, and the y-axis is a list of the features. The MMR variable has the largest value indicating that it is the most important variable with respect to the other variables in the model. Other important features are specific trims, makes, models, etc., such as trim_G63 AMG, make Rolls-Royce, and model Range Rover. The chart shows the relative importance of car value indicators and luxury car attributes in the performance of the XGBoost model.

Comparative study of numerous models predicts sell price of vehicles based on performance evaluation metrics is given in Table II. The Gradient Boosting model outperformed the others in terms of both predictive ability and model accuracy, as evidenced by its high R^2 of 0.976 and relatively low prediction error. With R^2 values more than 0.97, Random Forest and XGBoost also did admirably. Prophet and KNN, on the other hand, had comparatively poor predicting efficacy. In terms of predicting the automobiles' selling prices, ensemble learning models outperformed both classic machine learning and time-series forecasting methods.

TABLE II. COMPARATIVE ANALYSIS BETWEEN BASE AND PROPOSED MODELS

Model	R^2 Score	MSE	RMSE
LR[23]	50.4	-	1162.441
LSTM [24]	0.93	34.64	5.89
KNN [25]	0.5757	-	1073.83
Prophet [26]	0.0014	-	27.38
SVR [27]	0.9398	0.063279	0.2515
GB	0.976	2161666.55	1470.260708
RF	0.975	2246630.89	1498.876543
XGB	0.975	2278402.02	1509.437650

This work offers several benefits as a result of the combination of big automotive data and sophisticated ensemble learning techniques. This solution is able to deliver predictive quality levels that exceed those of traditional statistical methods, thanks to the usage of GB, RF and XGBoost. Balanced data sets minimize bias and SHAP provides transparency by interpreting feature importance. The framework can be expanded to support a large number of records, is efficient for processing large quantities of data and offers useful applications in production planning, inventory management and strategic decision making. Together, these strengths demonstrate the rigorous methodological approach and industry relevance of the study, which contribute to the improvement of forecasting techniques in the automotive sector.

V. CONCLUSION AND FUTURE WORK

In this research, a high-performance ML model has been developed and validated for the accurate prediction of the selling price of an automobile in the secondary automotive market. The experimental assessment showed that the ensemble learning architectures based on advanced algorithms clearly outperform traditional linear, non-parametric and time-series based models. In particular, Gradient Boosting attained the highest predictive accuracy with an R^2 score of 0.976, while Random Forest and XGBoost were at an R^2 of 0.975. The outcomes of the comparative analysis show that there is a significant difference among the methods of ensemble and the known baseline methods. Models such as SVC and LSTM achieved high accuracy, but failed to outperform the reduction in error that could be obtained by the boosting frameworks. In contrast, traditional methods such as Linear Regression and Prophet failed to adequately model the non-linearities of the automotive data set. Finally, the study demonstrates that MMR-type institutional market indexes are essential to predictive consistency, but in different degrees, depending on luxury vehicle segments. These outcomes will enable stakeholders to adopt an automated and data-driven pricing strategy.

A. Research Limitations and Future Work

The primary limitations of this study include a heavy reliance on a MMR, which may introduce bias, and a noticeable increase in residual variance for high-value vehicle segments. Also, the staticness of the data does not capture the dynamics of the macro-economic and the seasonal demand changes. Future research is needed to fill these gaps in the study, including through the use of unstructured data sources (such as VHRs and regional economic indicators), and to explore hybrid designs that better represent temporal dynamics. Continuing with the use of an online learning framework would also allow the model to be flexible in adapting to the fast-changing automotive market and to be generalized to other segments of the automotive market.

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