Suggesting Product Prices in Automotive E-Commerce: A Study Assessing Regression Models and Explicability

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Abstract: E-commerce pricing may involve complex processes, including various factors such as cost, perceived value, and market demand. Exploring machine learning (ML) for informing pricing in the automotive sector presents significant open research challenges that require innovative solutions. This investigation examines a real-world Brazilian e-commerce dataset to train, test, and compare several state-of-the-art regression models to understand their applicability. Our study originally includes how SHapley Additive exPlanations (SHAP) help to interpret the most influential features for price prediction. Results indicate that Light GBM and XGBoost performed best, combining high predictive accuracy with computational efficiency, and reveal features such as product weight, stock levels, and physical dimensions as the most influential on final pricing. This study outcome paves the way for novel data-driven pricing strategies in Brazilian automotive e-commerce.

1 INTRODUCTION

The advancement of technology and the widespread adoption of e-commerce have increased the volume and variety of data generated in retail environments. Unlike in-person shopping, online platforms enable simultaneous interactions with numerous customers while facilitating the systematic collection and storage of consumer information. This transformation has expanded data availability and reshaped several business processes, from customer acquisition (Patel, 2023) to fraud detection (Mutemi and Bacao, 2024), demanding intelligent tools to support decision-making and operational efficiency.

Pricing in e-commerce is a strategic decision that directly affects a company's profitability and competitiveness (Kotler and Keller, 2022). Even small price changes in high-volume retail can impact overall revenue, especially in a low-margin market. Mispricing can result in financial losses and, in extreme cases, business failure (Xuming, 2024). Effective pricing strategies aim to maximize revenue, increase market share, and enhance customer satisfaction, balancing production costs, consumer demand, and competition.

Traditional pricing methods like mark-up or competition-based pricing are often inadequate in digital commerce scenarios where pricing dynamics are complex. Online markets demand real-time price adjustments informed by large-scale and heterogeneous datasets. These may include historical pricing trends, user behavior patterns, and competitor promotions. Dynamic pricing, powered by algorithmic models, addresses these needs (El Youbi et al., 2023) but poses challenges like data integration, continuous competitor tracking, and adapting to fast-changing market conditions.

Research into data-driven pricing models is essential for competitiveness and financial sustainability in digital markets. In the same direction, Artificial

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Intelligence (AI) and Machine Learning (ML) help businesses analyze large volumes of data, detect demand patterns, adjust prices in real-time, and anticipate market trends (El Youbi et al., 2023). These technologies enable more dynamic and data-driven pricing strategies (Aparicio and Misra, 2023).

Automatically determining the optimal price remains complex and challenging due to factors like seasonality, competition, and production costs. These variables are often interdependent and can change rapidly, introducing high levels of volatility and uncertainty into pricing strategies. As a result, companies struggle to understand the rationale behind pricing recommendations, which can hinder trust in automated systems and limit their adoption in dynamic markets.

This article investigates regression models for the pricing task. These models offer a practical balance between simplicity, precision, and performance. They may enable interpretation of how input variables – such as product weight, dimensions, and stock levels– affect pricing outcomes. In particular, our investigation considers the Brazilian automotive sector as the context of our data-driven pricing models. This context presents high production costs, fluctuating demands, and a strong influence on perceived values. Such context was poorly studied in the literature and motivates novel analyses and contributions.

Our investigation introduces the following contributions:

- Original analyses leveraging real-world dataset from the Brazilian automotive e-commerce sector.
- Evaluation of nine well-studied ML models with default and fine-tuned hyperparameters, including linear, tree-based, and neural network models: Linear Regression, Random Forest, Lasso, Ridge, Support Vector Machine (SVM), XGBoost, Light GBM, Long Short Term Memory (LSTM), and Feed Forward.
- Interpretation of the model predictions using SHapley Additive exPlanations (SHAP) (Lundberg and Lee, 2017), chosen for its ability to provide consistent local explanations. SHAP highlights the most influential features in pricing, making it easier to understand how each variable impacts predictions in the automotive sector.

Our study found that LightGBM and XGBoost offered the best balance between accuracy and efficiency for price prediction tasks. Hyperparameter optimisation further enhanced model performance, consistently reducing prediction errors. SHAP analysis revealed that key factors influencing product price include weight, stock quantity, sales volume, and physical dimensions.

The remaining of this article is organized as follows. Section 2 reviews related work. Section 3 describes the overall methodology, including data collection, exploratory analysis, preprocessing, model development, training, and assessment. Section 4 presents the results whereas Section 5 discusses them. Section 6 concludes the article and highlights future investigations.

2 RELATED WORK

The study presented by (Bhaskar et al., 2022) addresses the issue of consumer deception in the used car market through price manipulation. To mitigate this problem, three regression models are developed to predict the selling price of used vehicles based on features such as listed price and mileage. The models evaluated include Linear Regression, Lasso Regression, and an ensemble approach combining both. The dataset, obtained from Kaggle, underwent preprocessing steps like removing missing values and categorical encoding. Among the evaluated models, the ensemble regression achieved the highest predictive accuracy (94%), indicating its effectiveness in estimating used car prices. In contrast to this approach, our study explores the pricing problem within a different context—namely, the Brazilian automotive e-commerce sector—where pricing dynamics are influenced by additional factors such as inventory levels, product dimensions, and temporal variables like the date of sale. We expand the methodological scope by evaluating nine distinct regression models, encompassing linear, tree-based, and neural network models. While both studies share the goal of price prediction in the automotive sector, our work addresses a broader, more complex set of variable.

(Chowdhury et al., 2024) explored the use of supervised ML models to optimize pricing strategies in e-commerce, with a focus on predicting customer satisfaction. Using a dataset with features such as historical prices, customer demographics, and transaction data, the authors compare the performance of Linear Regression, Decision Trees, Random Forest, SVM, and Neural Networks models, to predict customer satisfaction based on price prediction. The main contribution of the study is in the comparative evaluation of the models regarding their predictive capacity, where Neural Networks presented the best overall performance. However, the high computational cost of the Neural Network may be a barrier to practical use. Random Forest emerged as a viable alternative, balancing accuracy (MAE 0.130, R^2 0.82) with interpretability and lower resource demands. In contrast to this general-purpose approach, our study focuses on pricing in the Brazilian automotive e-commerce sector.

The work described by (Akash et al., 2024) investigated the price of the "Toyota" cars based on the customer's requirement. The dataset, obtained from Kaggle, contained 1442 examples. ML training used 80% of the data, while 20% was used for testing. Ridge was used to predict the sales price, and the model showed results with almost 93% accuracy. In contrast, our study focuses on the automotive parts and materials, instead of the whole car. Furthermore, we are not limited to just one ML model and provide model explainability, highlighting the most impactful features.

(Das et al., 2024) investigated real-time dynamic pricing strategies in the context of retail and e-commerce, benchmarking Linear Regression, Random Forest, and Gradient Boosting Machines (GBM) algorithms to predict optimal prices. The dataset, composed of records from different sectors (e.g., electronics and apparel), included variables such as price history, competitor prices, promotional status, inventory levels, and consumer demographics. The results indicated that GBM achieved the best performance in all evaluated metrics, reaching MAE of 1.73, RMSE of 2.01, and R^2 of 0.94, demonstrating a greater ability to capture nonlinear patterns and complex interactions between variables. In addition to predictive evaluation, the authors highlight the relevance of attribute engineering, class balancing, and simulation of real scenarios to validate the applicability of the proposed strategies. In contrast, our work focuses specifically on the automotive domain and also seeks to promote the explainability of the best model used.

Table 1 compares the related studies regarding the models employed. To the best of our knowledge, our study is the first to investigate how these models behave experimentally and are relevant to apply to the *Brazilian automotive e-commerce context*.

3 INVESTIGATING PRODUCT PRICES THROUGH REGRESSION METHODS

This section describes the methodology employed to investigate the problem of product prices in Brazilian automotive e-commerce. The methodology is structured into six main stages: data acquisition (Section 3.1), exploratory analysis and cleaning (Section 3.2), model selection (Section 3.3), algorithm execution (Section 3.4), result evaluation (Section 3.5), and model explainability (Section 3.6) as illustrated in Figure 1.

3.1 Data Collection

We employed a dataset provided by GoBots[1], a Brazilian startup offering AI-based services for e-commerce platforms. The dataset contains detailed information about products, pricing, and sales history. Data extraction was performed using MongoDB.

Filters: To ensure data quality and relevance, we applied the following filters:

1. *Sample Size:* A maximum of 100,000 products were selected to ensure analytical feasibility while maintaining representative diversity. This sample was drawn from a larger pool of 4.5 million products.
2. *Time Range:* Data spanned from January to December 2023, covering seasonal events such as Black Friday.
3. *Automotive Sector:* Chosen based on GoBots' expertise and the strategic importance of automotive parts within e-commerce, a segment associated with heightened consumer urgency. Observations indicate that consumers searching for automotive products tend to exhibit stronger purchase intent and greater immediacy than in other sectors. For instance, a customer searching for a replacement tire must substitute a worn-out tire to maintain the vehicle's operability promptly.
4. *Status:* Only products sold and active (i.e., not out of stock) were considered.

Collected Fields: We collected the following attributes (summarized in Table 2):

- *orderCreated:* A timestamp indicating when the purchase was registered. This temporal field enables derivation of features such as month, week of the year, or even position within the month (e.g., begin, end). These derived features allow the models to capture temporal price variation patterns, such as consumer behavior around salary periods or promotional events like Black Friday and Christmas.
- *initialQuantity:* Represents the initial inventory available at the start of a product's sales cycle. This value serves as a proxy for the product's supply conditions and potential market expectations. A higher initial quantity may indicate widespread availability or popularity, which can influence pricing strategies;

[1] Available at: https://gobots.ai/

Table 1: Comparison of our work and related studies. The ML models considered are: Linear Regression (LR); Decision Tree (DT); Lasso (La); Ridge (Ri); Random Forest (RF); Gradient Boosting Machines (GBM); XGBoost (XG); LightGBM (Li); Support Vector Machine (SVM); Feedforward Neural Network (FF); and Long Short-Term Memory Neural Network (LSTM). The ✓symbol indicates the ML models addressed by each study.

Study	Domain	LR	DT	La	Ri	RF	GBM	XG	Li	SVM	FF	LSTM
(Bhaskar et al., 2022)	Automobilistic	✓		✓								
(Chowdhury et al., 2024)	Not defined	✓	✓			✓				✓	✓	✓
(Akash et al., 2024)	Automobilistic				✓							
(Das et al., 2024)	Not defined	✓				✓	✓					
This study	Automobilistic	✓		✓	✓	✓		✓	✓	✓	✓	✓

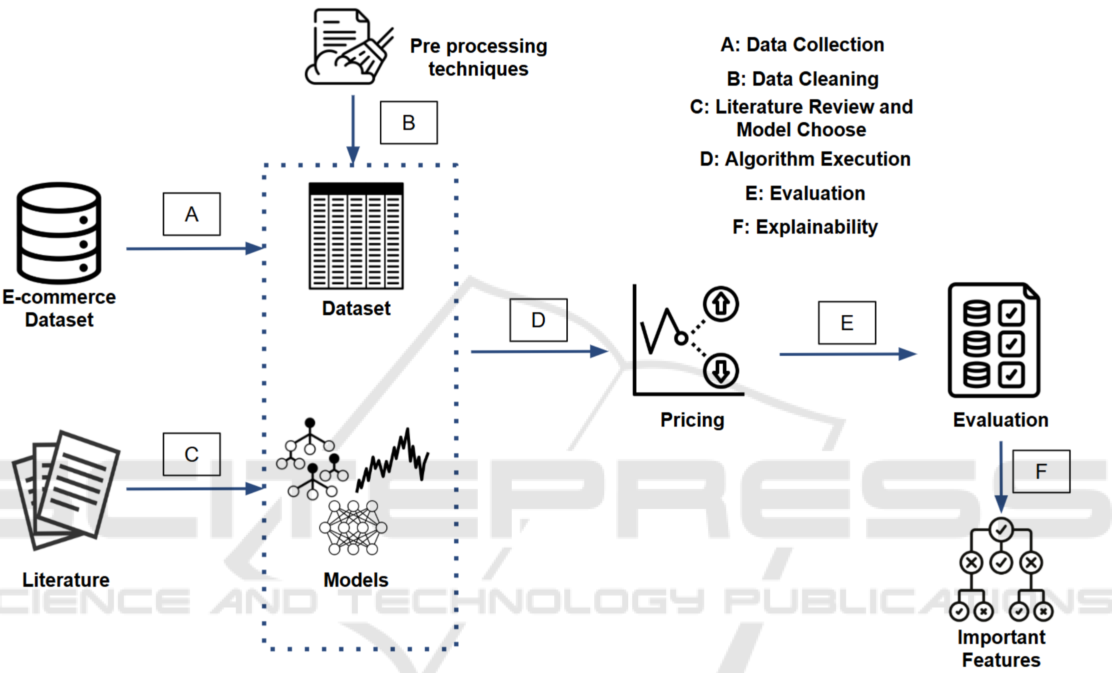


Figure 1: Methodology: A) Data Collection; B) Data Analysis and Cleaning; C) Model Selection; D) Algorithm Execution; E) Evaluation; F) Explainability.

- *availableQuantity:* Number of units in stock during data collection. This dynamic attribute provides insights into stock pressure. A low value suggests scarcity, justifying higher prices, while a high value may indicate overstock, encouraging discounts to boost demand.
- *soldQuantity:* Cumulative number of units sold. This variable indicates product demand. High sales volumes may be associated with stronger pricing power, while low sales could trigger price reductions or promotional activity.
- *domain:* Denotes the market vertical of the product. In this study, the dataset is constrained to the automotive domain, where consumers are often driven by necessity and urgency, which can influence willingness to pay.
- *category:* Indicates the product subcategory (e.g., “brake light”, “air filter”). Different categories may reflect different levels of urgency, elasticity, and competition. Safety-critical parts may command premium prices and faster purchase decisions, while others are more discretionary.
- *condition:* Describes the state of the product (e.g., new, used, refurbished). Product condition directly impacts consumer expectations and acceptable pricing. New items generally have higher perceived value, whereas used items may require price adjustments to remain competitive.
- *weight and dimensions:* The logistical attributes (*width*, *height*, *length* and *weight*) can indirectly affect pricing, especially when shipping costs or storage constraints are factored into the pricing strategy.
- *price:* The target variable for the regression models. It reflects the final listed price at the time of sale and encapsulates the combined effect of all

Table 2: Summary of the Collected Fields.

Field	Data Type	Example
orderCreated	datetime	"2024-06-07T23:59:59.000Z"
initialQuantity	number	1392
availableQuantity	number	86
soldQuantity	number	1306
domain	string	"MLB-AUTOMOTIVE_TIRES"
category	string	"Luz de Freio"
condition	string	"new"
weight	number	47.0
height	number	2.0
width	number	14.0
length	number	19.0
price	number	105

other features. The primary objective of the predictive model is to estimate this value based on the available product and contextual attributes.

3.2 Exploratory Analysis and Data Cleaning

Initial Exploratory Analysis: After data collection, we performed an initial exploratory analysis by examining the numerical features using descriptive statistics. Table 3 summarizes these statistics.

The variable *price* revealed great variability, with prices ranging from R$5 to approximately R$109,000. The variable *initialQuantity*, which represents the initial quantity of products in stock, presented an average of 2,372.88 units and a high standard deviation (6,503.62), indicating wide variation in stock capacity among products and retailers. The same dispersion pattern was observed in *availableQuantity* and *soldQuantity*, which varied from 1 to 99,999 available products (average of 873.56) and from 0 to 45,056 products sold (average of 1,500.13), respectively.

Next, we investigated missing values. About 27.1% of the rows had null values in the fields *weight*, *height*, *width*, and *length*. These rows were removed from the dataset. The analysis of unique values was applied to the categorical variables. We observed that the variable *domain* contained 329 unique values, *category* had 375 distinct categories, and *condition* presented only three variations. Next, a correlation analysis, based on Pearson's correlation coefficient, was constructed among the numerical variables[2]. We identified a strong positive correlation between the variables *initialQuantity* and *availableQuantity* (coefficient of 0.91), indicating that these variables tend to increase or decrease together. We also observed a moderate correlation between *initialQuantity* and *soldQuantity* (0.51), suggesting that products with larger initial stock tend to have higher sales volumes. Further, the variables *dimension* and *weight* exhibited moderate correlations both among themselves and with the target variable price, supporting their inclusion as relevant features in the predictive modeling process. The diversity of categories is illustrated in Figure 2, which shows a word cloud featuring the most frequent terms in the category variable, including items such as "tires", "filters" and "speakers".

Figure 2: *Category* word cloud.

Finally, we examined the behavior of the variable *price*, which revealed a pronounced skewness. The calculated skewness value was 2003.62, suggesting the presence of a long right tail in the distribution. This observation is supported by the descriptive statistics presented in Table 3, which indicate a mean of R$ 257.34 contrasted with a significantly higher maximum value of R$ 109,097.10. Such skewness highlights the need for standardization to prevent extreme values from negatively impacting the performance of certain machine learning algorithms.

Data Cleaning and Transformation: We executed the data cleaning and transformation, focusing on preparing data for predictive modeling.

- *Timestamp transformation:* The *orderCreated* timestamp was split into components (month, day, weekday, week, and hour), enabling finer-grained temporal analysis;
- *Categorical encoding:* All categorical columns were one-hot encoded. In particular, the *category* and *domain* fields generated numerous new binary columns due to their high cardinality. However, given the dataset size (100,000 rows), the added dimensionality did not introduce sparsity-related issues;
- *Numeric standardization:* All numerical features were standardized using z-score normalization. This standardization adjusts the data to have a mean of zero and a standard deviation of one, contributing to the performance and convergence of various machine learning models employed during the predictive modeling phase.

[2] Available at: https://github.com/andreregino/pricing/blob/main/matriz-correlacao.png

Table 3: Descriptive Statistics for the Numeric Features.

Variable	Mean	Std	Min	25%	50%	75%	Max
initialQuantity	2,372.88	6,503.62	1.00	81.00	301.00	1,536.00	101,401.00
availableQuantity	873.56	4,653.38	1.00	9.00	345.00	1,520.00	99,999.00
soldQuantity	1,500.13	4,347.25	1.00	26.00	125.00	713.00	45,056.00
weight	3,148.53	7,476.56	1.00	340.00	840.00	2,295.00	900,000.00
height	15.86	25.24	1.00	7.00	11.00	18.00	419.00
width	24.20	15.51	1.00	14.00	20.00	29.00	348.00
length	41.91	42.04	1.00	19.00	30.00	47.00	2,720.00
price	257.34	354.10	5.53	70.12	155.24	309.53	109,097.10

3.3 Techniques and Model Choice

The techniques were selected according to a previous literature review on dynamic pricing and the application of machine learning in this context. The following ML techniques were selected for evaluation: Linear Regression, Lasso Regression, Ridge Regression, Support Vector Machines (SVM), XGBoost, LightGBM, Feedforward Neural Networks, and LSTM Neural Network. Cross-validation techniques were used to ensure robust and generalizable models.

3.4 Algorithm Execution

The next step involved developing the models using popular ML frameworks (e.g. Scikit-learn[3] and TensorFlow[4]). Two executions were performed for each ML technique: the baseline model training (using the default hyperparameters provided by the libraries) and the tuned model training (hyperparameters from grid search).

The dataset was split into training, validation, and test sets using a 70/15/15 ratio. All experiments were carried out on Google Colab[5], using a cloud server with the following configuration: 100 GB storage, 12 GB system RAM, and 15 GB GPU RAM (T4 GPU). Further details regarding model configurations, hyperparameters, and experimental setup are provided in Section 4.

3.5 Evaluation

In this step, we evaluated the models' results. Efficiency metrics such as MSE, RMSE, MAE, and R^2 were employed. These metrics allow for assessing the model's accuracy in terms of the difference between the predicted price and the actual price. We further measured the total training and prediction times — *i.e.*, the time required to run the models on the training and test sets. These metrics are important for assessing the practical feasibility of the models, particularly in pricing systems that require fast responses for large volumes of data.

3.6 Explainability

Once the best model and configuration were identified, the SHAP explainability algorithm was applied to the test set to understand which product features most significantly contribute to the final price.

4 RESULTS

This section presents our outcomes. Section 4.1 discusses the results of the baseline models, *i.e.*, models trained using default hyperparameters. Section 4.2 presents the results of the refined models, where hyperparameters were tuned. Section 4.3 describes the results related to the model's performance, focusing on the time required to execute them. Section 4.4 addresses aspects related to model explainability.

4.1 Baseline Models

Table 4 presents the obtained results sorted in ascending order based on the R^2 values for the test set. These values provide an initial assessment of each model's predictive performance.

The Lasso regression model yielded the poorest results, with a R^2 of 0% on the test set. This suggests that when trained using default hyperparameters, the model could not learn meaningful patterns from the data and failed to generalize appropriately.

The LSTM and XGBoost models presented competitive effectiveness. The LSTM model achieved an MAE of 0.264 and an R^2 of 64.12% on the test set. Similarly, the XGBoost model showed strong results,

[3] Available at: https://scikit-learn.org/
[4] Available at: https://www.tensorflow.org/
[5] Available at: https://colab.research.google.com/

Table 4: Evaluation of Results for the Baseline Models. Training and testing times were measured in seconds. The best results for each metric are shown in bold. SVM values are not reported in the table as the model did not complete execution within a reasonable time (< 9,999 seconds). The values are displayed in ascending order by R^2.

Model	Validation				Test				Time (s)	
	MAE	MSE	RMSE	R²	MAE	MSE	RMSE	R²	Train	Test
SVM	-	-	-	-	-	-	-	-	-	-
Lasso	0.570	0.845	0.919	0.00%	0.583	1.030	1.014	0.00%	2.040	**0.089**
Ridge	0.354	0.431	0.656	49.03%	0.363	0.557	0.747	45.88%	**1.826**	**0.089**
Linear Regression	0.351	0.428	0.654	48.90%	0.362	0.497	0.705	48.50%	9.400	0.159
Feed Forward	0.290	0.315	0.561	62.43%	0.299	0.378	0.615	60.78%	215.345	1.510
Light GBM	0.274	0.273	0.523	67.68%	0.278	0.399	0.632	61.24%	3.093	0.181
XGBoost	0.260	0.258	0.508	69.45%	0.264	0.370	0.608	64.12%	35.503	1.017
LSTM	0.279	0.280	0.529	66.58%	0.287	0.346	0.588	64.13%	176.017	1.466
Random Forest	**0.207**	**0.222**	**0.471**	**73.78%**	**0.212**	**0.334**	**0.578**	**67.54%**	734.724	0.851

followed closely by the LightGBM, which also performed well under default settings. These models stand out due to their ability to model complex, non-linear relationships and temporal dependencies.

The Feedforward Neural Network, while outperforming the linear models in terms of MAE, still fell short of the results exhibited by the tree-based models. This result reflects the model's capacity to handle non-linearities, with some limitations compared to ensemble-based approaches.

Both Linear Regression and Ridge Regression presented similar outcomes. As relatively interpretable and straightforward models, they serve as useful baselines, yet their inability to capture non-linear patterns limits their effectiveness. It is worth noting that the SVM model could not be evaluated due to excessive training time. The model exceeded $9,999$ seconds without completing the training phase, prompting the decision to abort its execution to ensure computational feasibility. The Random Forest model exhibited the longest training time among all models whose execution duration did not exceed $9,999$ seconds.

4.2 Tuned Models

Table 5 presents the obtained results from the regression models after hyperparameter tuning. We chose the best hyperparameter configurations[6] for each model using a grid search strategy. The evaluation was conducted on both the validation and test sets using the same performance metrics employed in the baseline evaluation, namely MAE, MSE, RMSE, and R^2.

The tuned models showed notable improvements, significantly varying across different approaches. Among them, the tuned LightGBM model stood out as the most effective. It achieved the lowest absolute and squared errors on validation and test sets, along with R^2 scores exceeding 72%. This consistent performance highlights its strong ability to generalize to unseen data, making it a robust choice for price prediction tasks. The tuned XGBoost model was followed closely, delivering slightly lower metrics than LightGBM and maintaining solid overall performance.

These results suggest that XGBoost remains a viable and competitive alternative, particularly in scenarios where interpretability and efficiency are also valued. The tuned Random Forest showed competitive results, though marginally below the top two models. Meanwhile, the Feedforward Neural Network showed more modest performance, with a lower ability to explain the variance in the data, indicating some limitations in capturing complex relationships under the tested configuration.

Despite hyperparameter tuning, linear models such as Ridge and Lasso remained limited in accuracy and explanatory power, with R^2 scores around 48%. These findings underscore the importance of fine-tuning in more complex models—especially those based on decision trees and gradient boosting frameworks — as a way to maximize predictive performance in tasks involving multiple, potentially non-linear features.

4.3 Computational Performance Results

Regarding computational performance, Figure 3a illustrates the training time across all models[7]. The models were trained on $75,000$ products and validated on an additional $15,000$ products.

The training time analysis (Figure 3a) distinguishes between base (green) and tuned (blue) models. The tuned Feed Forward network required the

[6] Available at: https://github.com/andreregino/pricing

[7] Prediction inference time available at: https://github.com/andreregino/pricing/blob/main/prediction-time.png

Table 5: Evaluation of the Results for the Tuned Models. Training and test times were measured in seconds. The best results for each metric are shown in bold. The values are displayed in ascending order by R^2.

Model	Validation				Test				Time (s)	
	MAE	MSE	RMSE	R²	MAE	MSE	RMSE	R²	Train	Test
SVM	0.427	0.548	0.740	34.57%	0.441	0.624	0.790	35.26%	999.99+	139.215
Lasso	0.351	0.427	0.654	49.00%	0.363	0.500	0.708	48.07%	88.272	0.095
Linear Regression	0.351	0.428	0.654	48.90%	0.362	0.497	0.705	48.50%	9.400	0.159
Ridge	0.351	0.428	0.654	48.90%	0.362	0.497	0.705	48.50%	**9.052**	**0.092**
Feed Forward	0.286	0.317	0.563	62.21%	0.291	0.354	0.595	63.26%	999.99+	1.467
LSTM	0.276	0.275	0.525	67.14%	0.282	0.325	0.702	66.26%	360.400	1.170
Random Forest	0.243	0.219	0.468	73.85%	0.249	0.282	0.531	70.73%	637.962	0.383
XGBoost	0.241	0.211	0.459	74.87%	0.247	0.273	0.523	71.67%	169.045	0.505
Light GBM	**0.227**	**0.203**	**0.450**	**75.79%**	**0.235**	**0.268**	**0.517**	**72.23%**	21.386	0.768

longest training time (1274.8 seconds, approximately 21 minutes), more than double of the tuned Random Forest model (637.9 seconds). These results highlight the computational cost associated with hyperparameter tuning in neural networks, particularly with respect to parameters such as the number of layers, regularization techniques, and optimization strategies. Conversely, Ridge and Lasso regression models — both in base and tuned versions — were the fastest to train, taking less than 10 seconds, reflecting their algorithmic simplicity. Most of the linear models (e.g., Ridge, Lasso, and Linear Regression) had low computational overhead, while tuned neural networks and tree-based models required substantially more training time, as expected.

Figure 3b reports the prediction time for 10,000 data entries. The tuned Feed Forward model was again the slowest (1.510 seconds), closely followed by its base version (1.467 seconds). LSTM models, both base and tuned, also recorded relatively long prediction times due to their complex internal structure. Although Random Forest demonstrated high predictive accuracy, it lagged behind in inference efficiency. Notably, LightGBM (both base and tuned) showed exceptional prediction speed, with execution times under 0.2 seconds, confirming its suitability for real-time pricing tasks.

4.4 Explainability

Figure 4 presents the results regarding explainability. We identified which features contribute to the final predicted price and how much they influence the model's output.

The LightGBM model was chosen for this analysis, as it achieved the best performance. The test set (unseen during training) assessed the model's ability to generalize to new data. The SHAP summary plot in Figure 4 presents the explainability results. The feature weight stands out as the most influential variable in the model (cf. the top of the figure). The impact of weight on price is substantial, with higher values generally increasing the predicted price. Heavier products tend to be more expensive due to higher manufacturing, shipping, and material costs.

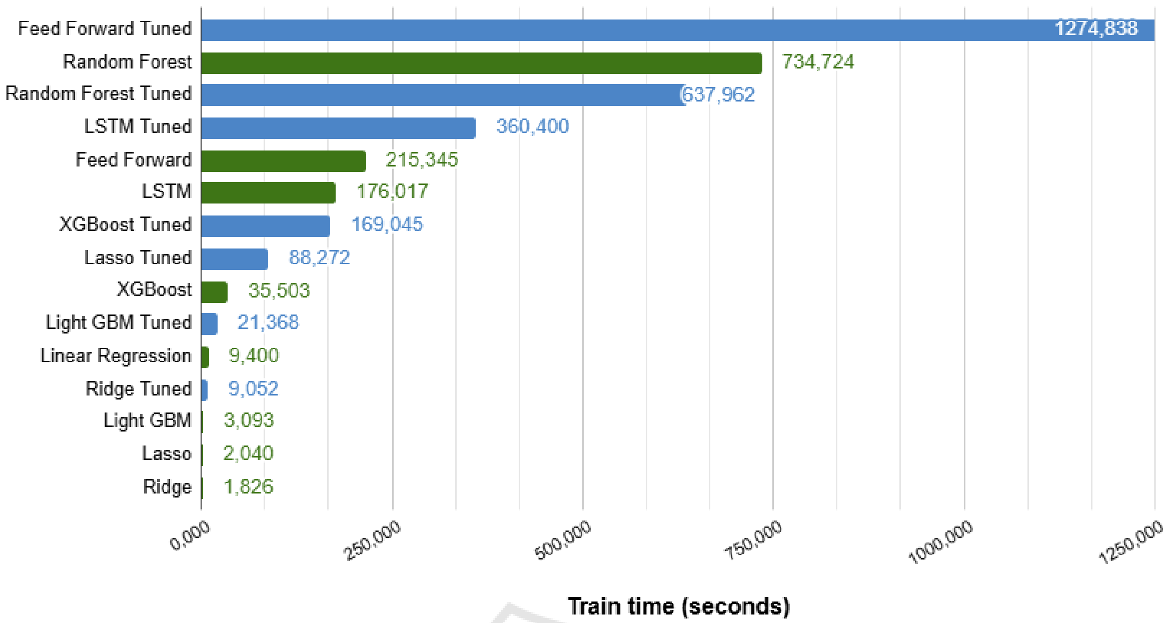
The *soldQuantity* feature, representing the number of units sold, also plays a key role. Products with higher sales volume are associated with higher prices, likely reflecting their popularity and market demand. This relationship suggests that the model captures demand as a key factor in pricing. Similarly, the *initialQuantity*, the initial stock level of a product, directly affects the predicted price.

The presence of specific categories, such as VEHICLE_AMPLIFIERS, indicates that the model can capture nuanced market segments and their corresponding price ranges, suggesting a degree of granularity in how the model incorporates categorical product information.

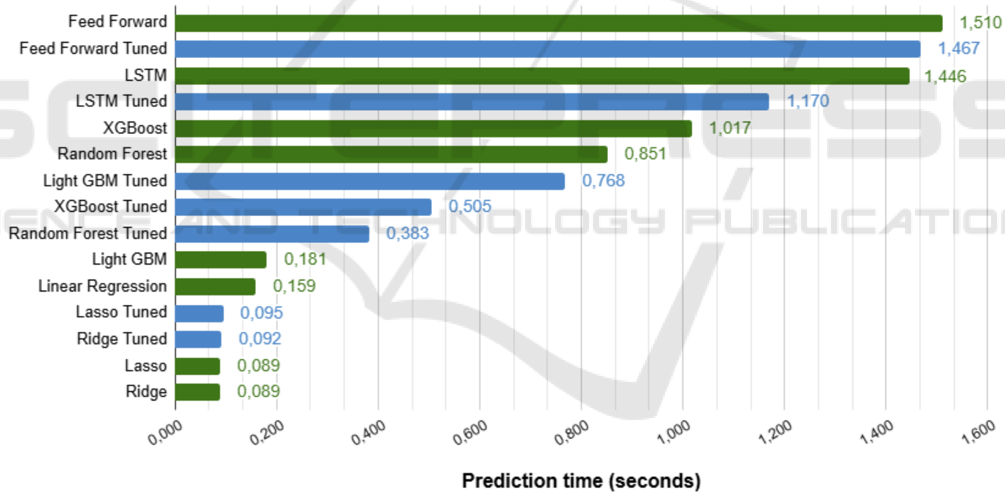
5 DISCUSSION

Figure 5 presents a comparative analysis of the R^2 scores across the evaluated regression models, highlighting the impact of hyperparameter tuning. The top-performing models in terms of R^2 (cf. top of the Figure 5) were LightGBM, XGBoost, and Random Forest. In contrast, neural network-based models such as LSTM and Feed Forward exhibited R^2 values below 0.7, although still comparable to the top-tier models. Linear models—including Linear Regression, Ridge, Lasso, and SVM—yielded the lowest R^2 scores.

Tree-based models, particularly LightGBM and XGBoost, benefited from hyperparameter optimization, achieving improvements in R^2 and demonstrating enhanced explanatory power regarding the variance in the dataset. The tuned LightGBM model achieved the best overall effectiveness, with an increase of nearly 18% in R^2 compared to its base ver-



(a) Training times of base and tuned regression models for product pricing. Values are shown in seconds.



(b) Prediction times of base and tuned regression models for pricing 10,000 products. Values are shown in seconds.

Figure 3: Training and prediction times for regression models evaluated in the product pricing task.

sion. This result underscores its robustness in the pricing task. Similarly, the tuned XGBoost model presented a notable increase of approximately 12% in R^2, confirming its effectiveness when fine-tuned appropriately.

We analyzed the trade-off between predictive effectiveness (measured by R^2 – Figure 5) and computational efficiency (in terms of training and time – Figure 3a). Linear models such as Linear Regression and Ridge showed negligible or marginal improvements in R^2 after hyperparameter tuning (+0.00% and +5.70%, respectively). Nevertheless, these models were the fastest in both training and prediction phases. While this low computational cost could be advantageous for applications requiring rapid responses, their limited predictive accuracy renders them inadequate for effective pricing tasks. Tree-based models, in contrast, achieved higher R^2 scores at the cost of increased computational time.

The tuned LightGBM model was the best-performing option because it combined the highest R^2 score with fast prediction time (0.181 seconds) and

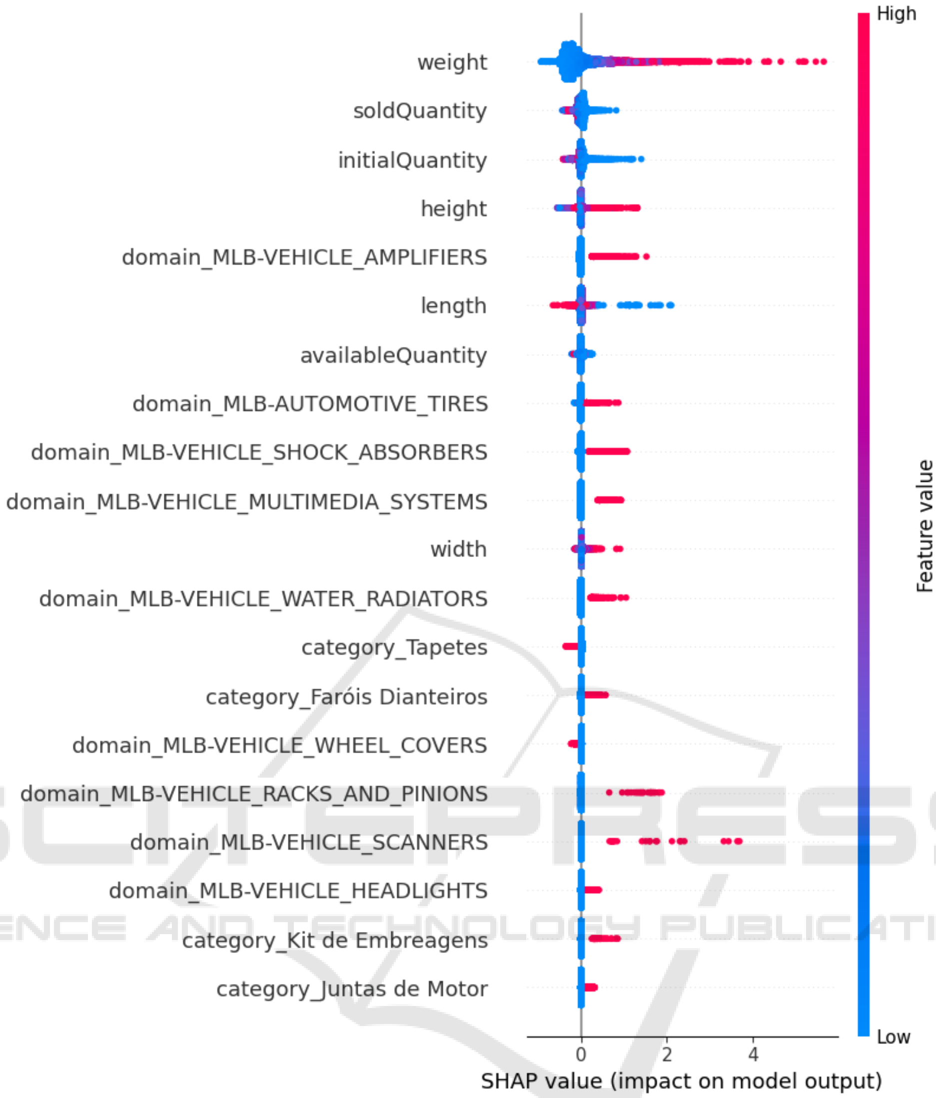


Figure 4: SHAP Summary Plot illustrating the explainability of the LightGBM regression model on the test set. Each row in the plot corresponds to a model feature, ordered from the most influential (at the top) to the least influential (at the bottom). The SHAP values (horizontal axis) indicate the impact of each feature on the model's prediction: positive values increase the prediction, while negative values decrease it. The spread of the points along the horizontal axis reflects the variation in the impact of each feature across different predictions.

relatively low training time (21.4 seconds), making it particularly well-suited for the pricing domain. Similarly, the tuned XGBoost model showed strong effectiveness improvements with acceptable training and prediction times. Although Random Forest yielded competitive accuracy, its excessively long training time (637 seconds) makes it less practical for frequent retraining scenarios.

Lasso and SVM improved slightly with hyperparameter tuning among the underperforming base models. Their overall R^2 outcome remained uncompetitive. Furthermore, SVM incurred higher training and inference times, reducing its practical utility. Neural network-based models (LSTM and Feed Forward) exhibited high computational costs for training and prediction, despite achieving moderate R^2 values. Although their effectiveness improved after tuning, the associated resource requirements limit their applicability in pricing systems where rapid retraining is necessary. In summary, the tuned LightGBM and XGBoost models were revealed as the most viable choices for this pricing task, offering an optimal balance between accuracy and computational efficiency.

In terms of explainability, the results indicate that

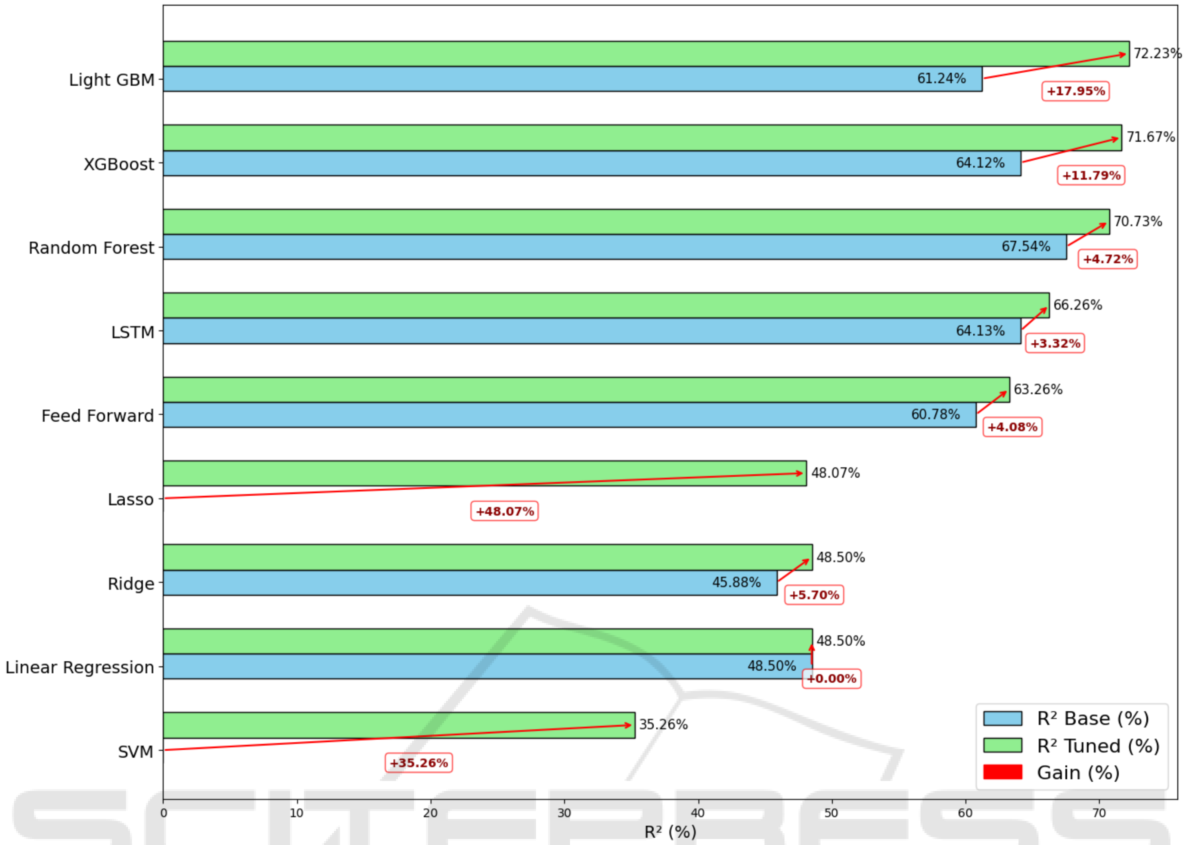


Figure 5: Comparison of R^2 scores for base and tuned regression models. The x-axis represents the R^2, while the y-axis lists the regression models. Red bars indicate the percentage increase in R^2 for the tuned models relative to their base versions.

higher initial availability is associated with higher prices. This could reflect a pricing strategy based on inventory management and the availability of automotive products. Physical product characteristics such as height and length significantly influence the model's predictions. In an e-commerce context, these variables may relate to the product's size, which affects production and transportation costs. Larger products typically require more materials and resources, resulting in higher prices.

In summary, the results show that tree-based models, especially LightGBM and XGBoost, are suitable for production use in our automobile e-commerce pricing context, combining high predictive accuracy with low latency. Their explainability highlights key pricing drivers that automotive e-commerce sellers should monitor to make informed, data-driven decisions.

Future work may explore the following directions: **(a) System Integration:** Embedding the model into GoBots' systems to support automated, explainable price recommendations for e-commerce vendors; **(b) Advanced Categorical Encoding:** Using embedding techniques to replace one-hot encoding, capturing semantic relationships between categories and enhancing multilingual applications; **(c) Temporal Price Analysis:** Incorporating time series models (e.g., SARIMA, Prophet) to detect seasonal trends and price fluctuations over time; **(d) Scalable Data Processing:** Utilizing high-performance or cloud-based infrastructure to process the complete dataset and evaluate model scalability; **(e) Cross-Domain Application:** Adapting the model to other pricing domains, such as real estate, involving various data characteristics and influencing factors.

6 CONCLUSION

The accurate pricing in online commerce plays a strategic role for businesses. This study explored and compared the effectiveness of several regression models applied to product pricing in the Brazilian automotive e-commerce sector. Our study evaluated how various ML techniques contribute to this task, balancing prediction accuracy with computational efficiency. Analysing a dataset comprising $100,000$ product records, we handled missing values, generated derived variables from temporal features, encoded categorical attributes, and standardized numerical features. Our experimental results highlighted the value of base and optimized models in the pricing task. The comparative evaluation of nine regression algorithms, including hyperparameter tuning, revealed that tree-based ensemble methods such as LightGBM and XGBoost offer a substantial tradeoff between predictive accuracy and training/prediction time. The RMSE, MSE, and R^2 metrics were used to quantify effectiveness, while runtime metrics supported the analysis of each model's practical feasibility in real-world scenarios. This study contributed with methodological and original practical assessment by systematically comparing regression models in Brazilian automotive e-commerce. Our investigation contributed to the application of SHAP to interpret model outputs. This analysis provided insights into the most influential features for price prediction, such as product weight, inventory levels, and units sold. This investigation established a foundation for future studies and is a reference for new researchers and practitioners seeking to implement data-driven pricing strategies.

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