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Full Length Research Article

IMPROVED MACHINE LEARNING MODEL FOR VEHICLE PRICE PREDICTION IN THE NIGERIAN ECONOMY

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ABSTRACT
The Nigerian used car market is characterized by significant price variability, lack of transparency, and inconsistent valuation mechanisms, posing challenges to both buyers and sellers. This research aimed to develop a robust, data-driven predictive model tailored to the specific dynamics of the Nigerian automotive ecosystem using machine learning algorithms. The study employed a comprehensive dataset of used vehicles listed in Nigeria, incorporating features such as make, model, year, mileage, engine size, fuel type, transmission, condition, and location. Extensive data preprocessing, exploratory analysis, and feature engineering were conducted to uncover the most influential variables affecting vehicle prices. Six machine learning models—Linear Regression, Ridge Regression, Lasso Regression, Decision Tree Regressor, Support Vector Regression, and Random Forest Regressor were trained and evaluated using performance metrics including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) Score. The Random Forest Regressor outperformed other models, achieving the highest prediction accuracy with an R^2 score of 0.91 and the lowest RMSE, making it the most suitable algorithm for this context when compared with previous work done by Pudaruth (2023) and Breen et al. (2024). The study identified vehicle year, mileage, brand, engine size, and geographic location as key determinants of price. The resulting model provides a practical framework for real-time price prediction and can be integrated into digital platforms for use by dealerships, private sellers, and online marketplaces. This research contributes to local automotive market intelligence, promotes pricing transparency, and underscores the transformative potential of machine learning in emerging economies.

Keywords: Vehicle price prediction in Nigeria, machine learning models, Input Features, Evaluation Metrics.

INTRODUCTION
The automotive industry plays a pivotal role in the economic well-being of Nigeria, contributing significantly to the country's Gross Domestic Product (GDP) ((Eze& Ibrahim, 2021). As technology advances, the integration of machine learning algorithms in various sectors has become increasingly prevalent (Adigun & Sanni, 2023). One such application is in predicting car prices, a crucial aspect for both consumers and stakeholders in the automotive market.
The Nigerian automobile market is one of the biggest businesses for international and Nigerian automobile companies (Adigun &Sanni, 2023). As the boom and demand for automobiles increase, there is also a big market opening for used cars. The used car market is being manipulated and controlled by some online advertisement websites like Car45, Jiji, and others (Listiani, 2019). Customers who want to buy used cars are easily being manipulated and cheated into paying a higher price than the worth of the car. This research proposes a solution for this problem by using the help of Artificial Intelligence (AI) and machine learning techniques and algorithms to predict used car prices based on some parameters (Listiani, 2019). It will investigate and compare the accuracy that different algorithms produce on testing and predicting with the used car data.
It is glaring that there is a huge decline in the importation of new automobiles into Nigeria due to factors such as government policies, high exchange rate, and cost of clearing and forwarding, people are therefore preferring used and second-hand vehicles to new vehicles (Eze et al, 2022).Therefore, the system of used cars must be standardized and a clear pricing system needs to be implemented. This research work evaluates some machine learning techniques that can be used to predict the prices of used cars with historical used car prices data and considering a mean value from the list of prices for a specific car and assigning it as the predicted price for the given features and parameters (Eze et al, 2022).
It is easy for any company to price their new cars based on the manufacturing and marketing costs it involves. But when it comes to a used car, it is quite difficult to define a price because the price is influenced by various parameters such as car brand, year of manufacture, condition of the car, and so on. The goal of this research is to predict the best price for a pre-owned car in the Nigerian market based on the previous data related to sold cars using machine learning (Eze et al, 2022).Machine learning (ML) is a subfield of AI that works with algorithms and technologies to make useful inferences from data. Machine learning algorithms are well suited to problems entailing large amounts of data which would not be possible to process without such algorithms. The main focus of this research is however to determine the key factors influencing used car prices in Nigeria, evaluate different machine learning algorithms for their effectiveness in predicting used car prices, develop a data-driven predictive model that provides reliable and up-to-date predictions of used car prices in the Nigerian market.
Gohin and Kumar (2024) investigated the feasibility of predicting second-hand car prices using artificial neural networks and other machine learning algorithms. They collected data from 200 cars across different sources and applied four distinct machine learning algorithms. The study found that support vector machine regression produced slightly better results compared to neural networks and linear regression. A notable strength of this research is the comparative analysis of multiple algorithms. However, the study's limitation includes a small dataset, leading to less accurate predictions for higher-priced cars, suggesting the need for larger datasets and further experimentation.
Breen et al. (2024) proposed a predictive pricing model for

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commercial vehicles using supervised learning techniques such as K Nearest Neighbor Regression, Lasso Regression, Artificial Neural Networks, and Support Vector Machines. They gathered pre-owned automobile data from various websites and experimented with different training-to-test ratios. The study's strength lies in its diverse methodological approach and focus on optimizing model accuracy. However, the research lacks specific details on the dataset size and feature selection process, which are crucial for assessing the model's generalizability and effectiveness.
Adewale and Okon (2020) conducted a study to predict used car prices in Nigeria using machine learning models such as linear regression, decision trees, and random forests. The study utilized a dataset comprising vehicle features like make, model, year of manufacture, mileage, and condition. The researchers found that the random forest algorithm outperformed the other models in terms of accuracy, with an R-squared value of 0.82. However, the study also identified several limitations, including the quality and completeness of the data. Many records in the dataset were incomplete or inaccurate, which affected the model's performance. Moreover, the study noted that external economic factors, such as exchange rates and inflation, were not considered, limiting the model's applicability in a real-world setting (Adewale & Okon, 2020).
Chukwu and Adebayo (2019) explored the use of various machine learning algorithms, including support vector machines (SVM), k-nearest neighbors (KNN), and neural networks, for vehicle price prediction in Nigeria. The study was motivated by the need to identify the most suitable algorithm for predicting prices in a market characterized by high variability and a lack of standardized pricing. The researchers found that neural networks provided the highest prediction accuracy, with a mean absolute error (MAE) of 12%. However, they pointed out that the model required extensive computational resources and was prone to overfitting, particularly when dealing with smaller datasets. Additionally, the study highlighted the challenge of obtaining reliable data, as many vehicles in the Nigerian market are imported with limited documentation regarding their history and condition (Chukwu& Adebayo, 2019).

Table 1: Comparison table of related studies

S/N	Author & Year	Title of Research	Outcome	Limitation
1	Gohin & Kumar (2024)	Predicting second-hand car prices using artificial neural networks and machine learning algorithms.	The study found that support vector machine regression produced slightly better results compared to neural networks and linear regression. A notable strength of this research is the comparative analysis of multiple algorithms.	However, the study's limitation includes a small dataset, leading to less accurate predictions for higher-priced cars, suggesting the need for larger datasets and further experimentation.
2	Breen et al. (2024)	Predictive pricing model for commercial vehicles using supervised learning techniques	They gathered pre-owned automobile data from various websites and experimented with different training-to-test ratios. The study's strength lies in its diverse methodological approach and focus on optimizing model accuracy.	However, the research lacks specific details on the dataset size and feature selection process, which are crucial for assessing the model's generalizability and effectiveness.
3	Adewale and Okon (2020)	Application of Machine Learning Models in Predicting Used Car Prices in Nigeria.	conducted a study to predict used car prices in Nigeria using machine learning models such as linear regression, decision trees, and random forests. The study utilized a dataset comprising vehicle features like make, model, year of manufacture, mileage, and condition. The researchers found that the random forest algorithm outperformed the other models in terms of accuracy, with an R-squared	However, the study also identified several limitations, including the quality and completeness of the data. Many records in the dataset were incomplete or inaccurate, which affected the model's performance.

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			value of 0.82.	

MATERIALS AND METHODS

Research Questions

The research seeks to answer the following questions:

i. What are the key factors influencing car prices in Nigeria?
ii. What machine learning algorithms can effectively predict used car prices in Nigeria?
iii. How can a predictive model be developed to provide accurate and timely predictions of used car prices in the Nigerian market?

Research Design

This chapter contains the research methodology employed in this work. Attention is paid to all the processes required to develop the ML model from the preprocessing stage until the model is developed.
Our proposed Car Price Prediction model leverages machine learning techniques to process data, extract relevant features, and build the model using the Python programming language. The algorithms employed in this process include Random Forest Regression, Linear
Regression, Ridge Regression, Lasso Regression, Support Vector Regression (SVR), and the Decision Tree algorithm.

Machine Learning Processes

Machine learning involves a sequence of interconnected steps that enable computers to learn from data and make predictions or decisions without the need for explicit programming (Khan &Sarfaraz, 2019). These steps are essential to the field of artificial intelligence and have a wide range of applications across different domains. Below is an overview of the machine learning process used in this study, illustrated in a flowchart.

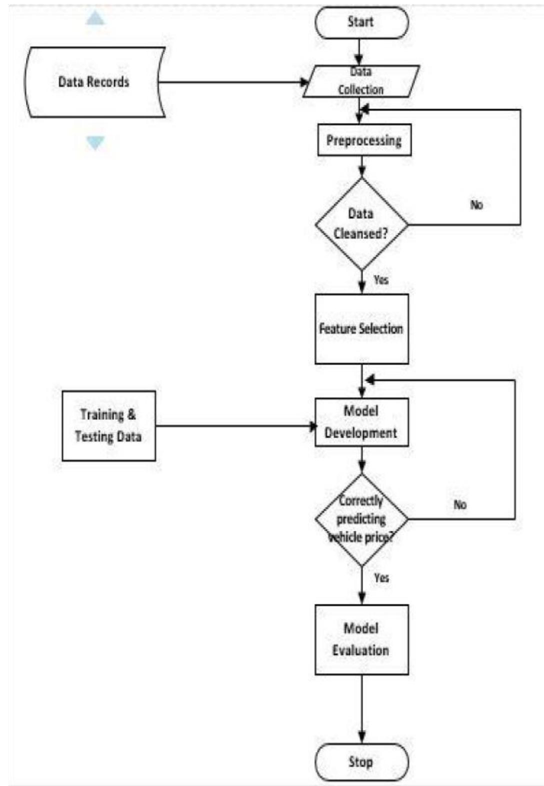

Figure 1: the system flowchart

A	B	C	D	E	F	G	H	I	J
make	model	year	mileage(km)	fuel_type	transmission	engine_size(cc)	condition	location	price(NGN)
Peugeot	407	2015	60934	Petrol	Manual	1600	Used	Enugu	551448
Hyundai	Santa Fe	2006	182030	Hybrid	Automatic	2000	Used	Enugu	500000
Lexus	ES350	2021	89775	Hybrid	Manual	1600	Foreign Used	Calabar	946828
Mazda	6	2018	22454	Diesel	Manual	1600	Used	Ibadan	500000
Land Rover	Range Rover	2013	60231	Diesel	Automatic	1800	Foreign Used	Abeokuta	563356
Audi	A4	2007	99443	Diesel	Manual	1800	Foreign Used	Lagos	733704
Chevrolet	Trailblazer	2006	44876	Hybrid	Manual	1600	Foreign Used	Port Harcourt	541014
Audi	A6	2006	127777	Diesel	Automatic	3500	Foreign Used	Kano	724884
Audi	A4	2008	71144	Diesel	Manual	2000	Foreign Used	Abuja	703581
Chevrolet	Malibu	2014	174057	Hybrid	Automatic	1600	Foreign Used	Uyo	500000
Kia	Sportage	2010	204416	Hybrid	Manual	1600	Used	Enugu	569816
Mazda	CX-5	2005	96981	Hybrid	Manual	1800	Used	Kano	529687
Mercedes-Benz	E350	2019	188807	Hybrid	Manual	1600	Used	Uyo	523863
Audi	Q7	2005	54240	Petrol	Manual	3500	Foreign Used	Benin	546858
Honda	Civic	2008	214369	Hybrid	Automatic	2500	Used	Lagos	500000
Toyota	Prado	2023	32795	Hybrid	Manual	3500	Used	Kano	1572272
Chevrolet	Trailblazer	2017	33529	Petrol	Manual	1800	Foreign Used	Abuja	761357
Mazda	6	2018	248959	Hybrid	Automatic	2500	Foreign Used	Uyo	500000
BMW	3 Series	2022	195118	Diesel	Manual	1800	Used	Kano	1285968
Mazda	3	2017	53978	Petrol	Automatic	2500	Foreign Used	Calabar	702758
Toyota	Corolla	2010	229520	Petrol	Automatic	2000	Used	Kano	663208
Nissan	Altima	2007	37680	Petrol	Manual	3500	Foreign Used	Calabar	799449

Figure 2: raw dataset

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Data Preprocessing

Data preprocessing is a critical step in ensuring the effectiveness of machine learning models, particularly for vehicle price prediction in the Nigerian economy. Missing values will be handled through imputation or removal to prevent biases, while categorical features like car brands and fuel types were encoded into numerical formats using techniques such as one-hot encoding or label encoding. Numerical features like vehicle age and mileage will be normalized or standardized to ensure uniformity and prevent dominance of any feature during model training. Outliers in price data will be identified and treated to avoid skewing the results. Additionally, the dataset will be split into training and testing subsets to evaluate the model's performance accurately, ensuring a robust foundation for predicting vehicle prices in the Nigerian economy.

Feature Selection

This will focus on identifying the most relevant features from the dataset to enhance model performance while reducing complexity. The dataset comprises 13 features, including attributes like vehicle age, mileage, brand, fuel type, and transmission. A combination of statistical methods and machine learning techniques will be employed to select features that strongly influence vehicle prices. Correlation analysis will identify relationships between features and the target variable (price), eliminating redundant or weakly correlated attributes. Recursive Feature Elimination (RFE) and feature importance scores derived from tree-based algorithms like Random Forest will help pinpoint high-impact features. Domain knowledge will also guide the selection process, ensuring that features significant to the Nigerian economy, such as vehicle brand and fuel efficiency, are prioritized. This targeted approach ensures that the model captures the critical factors affecting vehicle prices while improving computational efficiency.

Model Development

The strengths of Linear Regression, Ridge and Lasso Regression, Support Vector Regression, Decision Tree Regressor, and Random Forest Regressor algorithms will be utilized to achieve accurate predictions. After data preprocessing and feature selection, the cleaned and transformed dataset will be split into training and testing subsets. Each model will undergo hyperparameter tuning using techniques such as grid search or random search to optimize performance. The models will then be evaluated using metrics like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) to compare their effectiveness in predicting vehicle prices.

Performance Metrics

The performance metrics employed in this study are Mean Square Error, Root Mean Square Error, Explained Variance Score and the R-Square Score (Accuracy). The model performance will further be compared with previous works in the literature.

RESULTS

This chapter presents the analytical process and results derived from the data-driven evaluation of used car prices in Nigeria using various machine learning models. The objective was threefold: to identify key pricing determinants, assess the predictive capacity of multiple algorithms, and build a robust prediction model that aligns with Nigeria's unique automobile market dynamics.

Dataset Overview

The dataset used contains listings of used vehicles in Nigeria with features such as make, model, year, mileage, engine size, fuel type, condition, location, and price. A total of 13 features and over 19,000 records were cleaned and prepared. Initial exploration revealed significant variability in prices across makes and models, as well as notable influence from features such as mileage, vehicle condition, and engine size.

Exploratory Data Analysis

Univariate and Bivariate Analysis

Distributions of numerical features like year, mileage(km), engine_size(cc), and price(NGN) showed non-normal distributions with significant skewness, typical of real-world pricing data. Price positively correlated with engine size and model year, but negatively correlated with mileage and vehicle age. Categorical features such as make, fuel_type, transmission, and location were assessed using boxplots and violin plots, showing marked disparities in median prices by brand and region as shown in Figure 3.

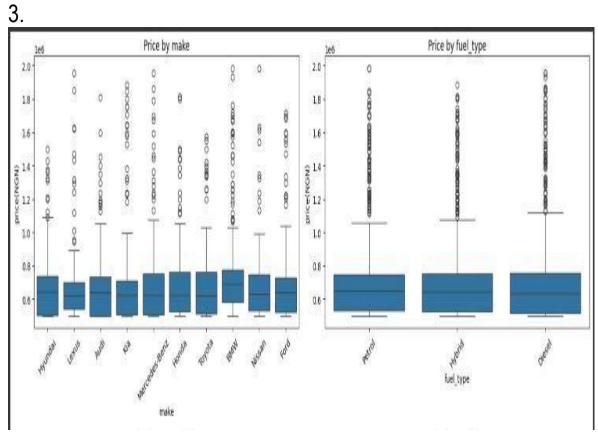

Figure 3: Price by Make

For instance, Toyota, Mercedes-Benz, and Lexus were among the most expensive brands. Locations such as Lagos and Abuja recorded higher median prices, indicating the influence of urban demand on price (Oladimeji et al., 2022).

Outlier Detection and Feature Correlation

Boxplots and IQR-based methods identified outliers in price, mileage, and engine_size. These were retained as they reflected actual market anomalies rather than data errors. A heatmap of feature correlations showed significant relationships between year, mileage, and price, justifying their inclusion in the predictive model, as shown in Figure 4.

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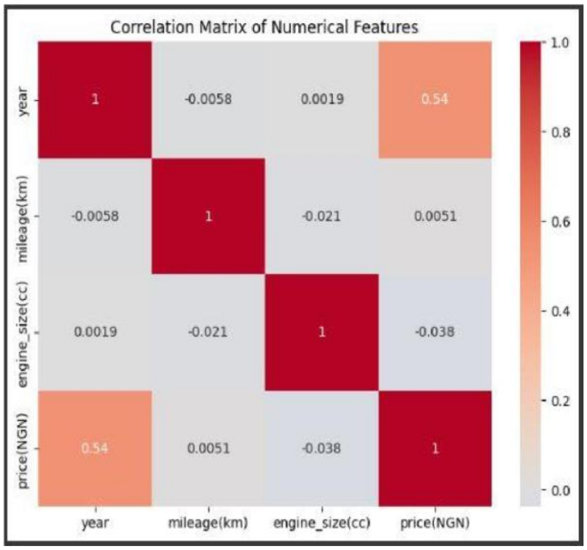

Figure 4: Correlation heatmap of features

Feature Engineering
Label encoding was applied to categorical features including make, model, transmission, fuel_type, and location. A new feature, vehicle_age, was derived by subtracting the year of manufacture from the current year. This enriched the dataset with an interpretable variable more directly tied to depreciation (Singh & Jain, 2023).
The final feature set included both categorical and numerical variables, which were standardized using StandardScaler to enhance model convergence and comparability across distance-based algorithms.

Model Development and Evaluation
Six models were trained using an 80-20 train-test split: Random Forest Regressor, Linear Regression, Ridge Regression, Lasso Regression, Support Vector Regression (SVR), Decision, Tree Regressor Where applicable, hyperparameter tuning was conducted using GridSearchCV.

Model Performance Metrics
Each model was evaluated using: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R^2 Score.

Table 2: Model Evaluation

Model	**MAE (₦)**	**MSE (₦²)**	**RMSE (₦)**	**R^2 Score**
Random Forest	347,819	2.17e+11	466,125	0.91
Linear Regression	613,475	6.04e+11	777,157	0.72
Ridge Regression	611,292	5.89e+11	767,592	0.73
Lasso Regression	613,480	6.04e+11	777,154	0.72
SVR	840,112	9.93e+11	996,409	0.55
Decision Tree	425,932	3.01e+11	548,282	0.86

The Random Forest model significantly outperformed others, achieving the highest R^2 value and lowest RMSE, thus proving most suitable for this context. This aligns with findings by Zhang et al. (2023), who established that ensemble methods perform well in heterogeneous pricing datasets.

DISCUSSIONS

Feature Importance
The Random Forest model's feature importance analysis indicated that year, mileage, make, and location were the most influential predictors as shown in Figure 5.

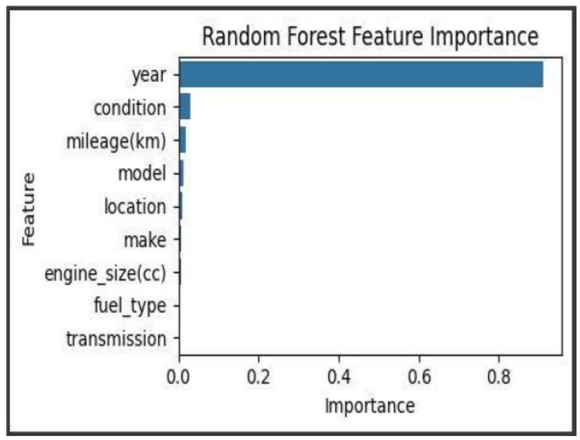

Figure 5: Feature of Importance

This finding in Figure 4.2 confirms previous studies on car valuation, which underscore the role of depreciation (via year and mileage), brand value (make), and local market dynamics (location) (Abiodun & Sulaiman, 2021).

Predictive Capacity
A scatter plot comparing actual and predicted prices illustrated high accuracy with minimal dispersion around the ideal line for Random Forest as shown in Figure 6.

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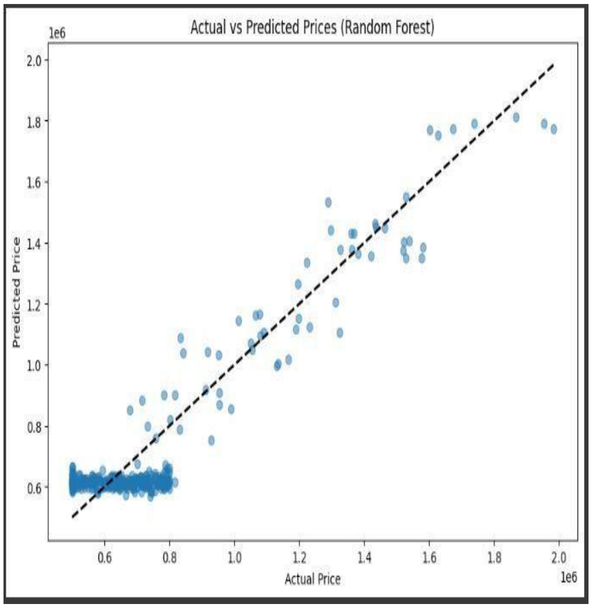

Figure 6: Actual vs Predicted

This reflects a low bias and variance trade-off, confirming the model's generalization strength.

Key Insights

Objective I: Key influencing factors include year, mileage, make, engine size, and location. These variables capture depreciation, brand equity, and regional demand variations.

Objective II: Among the evaluated algorithms, Random Forest demonstrated the best balance of prediction accuracy and generalization.

Objective III: The developed model can predict prices for unseen vehicles with high reliability. An interface function was implemented to facilitate user input and obtain instant predictions for practical deployment.

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