Science World Journal Vol. 21(No 1) 2026 https://dx.doi.org/10.4314/swj.v21i1.36
www.scienceworldjournal.org
ISSN: 1597-6343 (Online), ISSN: 2756-391X (Print)
Published by Faculty of Science, Kaduna State University

Full Length Research Article

DEVELOPMENT OF A DATA-DRIVEN ENSEMBLE FRAMEWORK FOR VEHICLE PRICE PREDICTION IN NIGERIA USING MACHINE LEARNING ALGORITHMS

*[1]Opuh Chukwuebuka Calistus, [1]Olumide Owolabi, [2]Okpanachi Ugbede Gift, [1]Umoru Yahaya Ibrahim

[1]Department of Computer Science, University of Abuja, Nigeria
[2]Management Information System, Federal Polytechnic, Auchi, Nigeria

*Corresponding Author Email Address: chukwuebukaopuh@gmail.com

ABSTRACT
The Nigerian used car market is marked by wide price fluctuations, limited pricing transparency, and inconsistent valuation practices, creating uncertainty for both buyers and sellers. This study sought to develop a reliable, data-driven predictive model tailored to the Nigerian automotive market using machine learning techniques. A comprehensive dataset of used vehicles advertised in Nigeria was used, including relevant attributes such as make, model, year of manufacture, mileage, engine capacity, fuel type, transmission type, vehicle condition, and location. The data underwent rigorous preprocessing, exploratory data analysis, and feature engineering to identify the most influential variables driving price variations. Six regression-based machine learning algorithms, Linear Regression, Ridge Regression, Lasso Regression, Decision Tree Regressor, Support Vector Regression, and Random Forest Regressor, were implemented and evaluated using standard performance metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2). Among the models tested, the Random Forest Regressor demonstrated superior predictive performance, achieving an R^2 score of 0.91 alongside the lowest RMSE. This result indicates improved predictive capability when compared with related studies conducted by Pudaruth (2023) and Breen et al. (2024). The findings further revealed that vehicle age, mileage, brand, engine size, and geographic location are the most significant determinants of used car prices in Nigeria. The developed model offers a practical and deployable solution for vehicle price estimation and can be integrated into dealership systems, online marketplaces, and private sales platforms. By enhancing price accuracy and transparency, this research strengthens market intelligence in Nigeria's automotive sector and demonstrates the practical value of machine learning applications in emerging economies.

Keywords: Vehicle Price Prediction in Nigeria; Machine learning; Feature importance; Evaluation metrics; Random Forest.

INTRODUCTION

The automotive industry plays a pivotal role in Nigeria's economic well-being, contributing significantly to the country's Gross Domestic Product (GDP) (Eze & Ibrahim, 2021). As technology advances, the integration of machine learning algorithms across 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 largest markets for both international and Nigerian automobile companies (Adigun & Sanni, 2023). As demand for automobiles increases, there is also a large market opening for used cars. The used car market is being manipulated and controlled by online advertising websites such as Car45, Jiji, and others (Listiani, 2019). Customers who want to buy used cars are being easily manipulated and cheated into paying more than the car's worth. This research proposes a solution to this problem by using Artificial Intelligence (AI) and machine learning techniques and algorithms to predict used-car prices based on specific parameters (Listiani, 2019). It will investigate and compare the accuracy of different algorithms when testing and predicting on the used-car data.

It is glaring that there has been a significant decline in the importation of new automobiles into Nigeria due to factors such as government policies, a high exchange rate, and the cost of clearing and forwarding. People are therefore preferring used and second-hand vehicles to new vehicles (Eze et al, 2022). Therefore, the used-car system must be standardised, and a clear pricing system 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, 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 its new cars based on the manufacturing and marketing costs involved. However, when it comes to a used car, setting a price is difficult because it depends on various factors such as the car's brand, year of manufacture, condition, and so on. The goal of this research is to predict the optimal price for a pre-owned car in the Nigerian market using machine learning, based on historical data on sold cars (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 involving large amounts of data that would not be possible to process without them. 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, and 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 yielded slightly better results than neural networks and

linear regression. A notable strength of this research is the comparative analysis of multiple algorithms. However, the study's limitation is a small dataset, which leads 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 commercial vehicles using supervised learning techniques, including K-Nearest Neighbour 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, including linear regression, decision trees, and random forests. The study used a dataset of vehicle features such as 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 data's quality and completeness. 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, thereby 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 neighbours (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 characterised by high price 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 on smaller datasets. Additionally, the study highlighted the challenge of obtaining reliable data, as many vehicles in the Nigerian market are imported with limited documentation on 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 yielded slightly better results than neural networks and linear regression. A notable strength of this research is the comparative analysis of multiple algorithms.	However, the study's limitation is a small dataset, which leads 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 used a dataset of vehicle features, including 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.

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?

Science World Journal Vol. 21(No 1) 2026 https://dx.doi.org/10.4314/swj.v21i1.36
www.scienceworldjournal.org
ISSN: 1597-6343 (Online), ISSN: 2756-391X (Print)
Published by Faculty of Science, Kaduna State University

Research Design

This chapter contains the research methodology employed in this work. Attention was paid to all processes required to develop the ML model, from preprocessing to model development.

Our proposed Car Price Prediction model leverages machine learning techniques to process data, extract relevant features, and build the model in Python. 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.

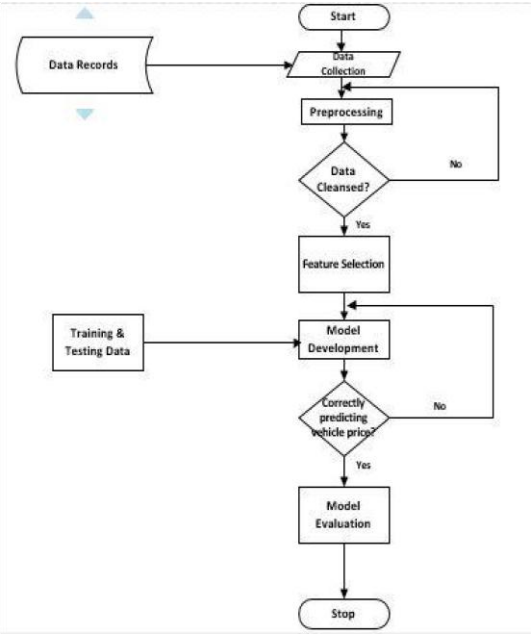

Figure 1: the system flowchart

	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

Data Description

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 price variability across makes and models, as well as notable influence from factors such as mileage, vehicle condition, and engine size.

Data Preprocessing

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

Feature Selection

This focused 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 was employed to select features that strongly influence vehicle prices. Correlation analysis identified relationships between features and the target variable (price), eliminating redundant or weakly correlated attributes. Recursive Feature Elimination (RFE) and

Science World Journal Vol. 21(No 1) 2026 https://dx.doi.org/10.4314/swj.v21i1.36
www.scienceworldjournal.org
ISSN: 1597-6343 (Online), ISSN: 2756-391X (Print)
Published by Faculty of Science, Kaduna State University

feature importance scores from tree-based algorithms, such as Random Forest, helped pinpoint high-impact features. Domain knowledge also guided the selection process, ensuring that features significant to the Nigerian economy, such as vehicle brand and fuel efficiency were 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 were utilized to achieve accurate predictions. After data preprocessing and feature selection, the cleaned and transformed dataset was split into training and testing subsets. Each model undergoes hyperparameter tuning using techniques such as grid search or random search to optimize performance. The models were then evaluated using metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) to assess their effectiveness in predicting vehicle prices.

Performance Metrics

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

RESULTS

This chapter presents the analytical process and results from the data-driven evaluation of used car prices in Nigeria, employing 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.

Exploratory Data Analysis

Univariate and Bivariate Analysis

Distributions of numerical features such as year, mileage (km), engine size (cc), and price (NGN) were non-normal, 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, revealing marked disparities in median prices by brand and region (see Figure 4.1).

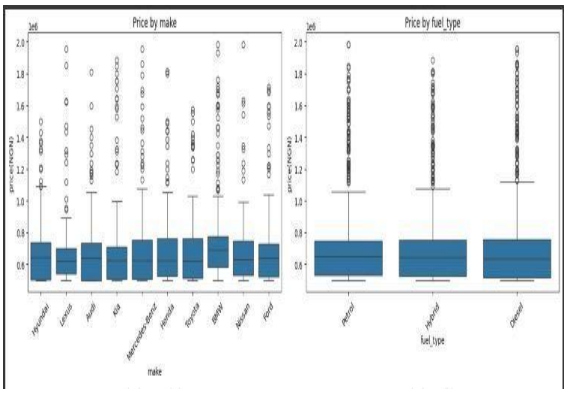

Figure 3: Price by Make

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 revealed significant relationships among year, mileage, and price, justifying their inclusion in the predictive model (Figure 4).

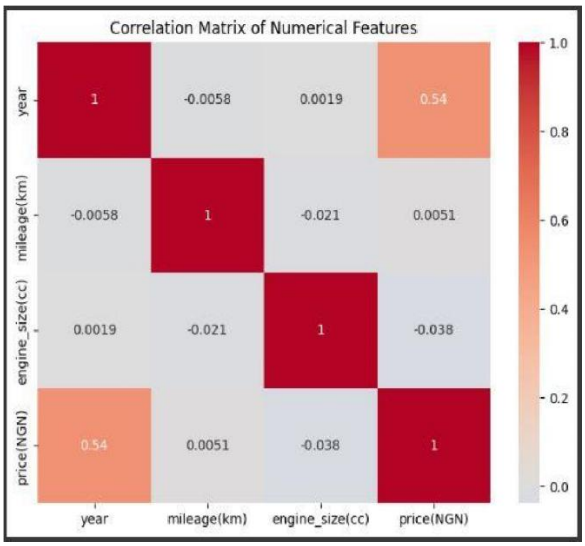

Figure 4: Correlation heatmap of features

Feature Engineering

Target 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 with StandardScaler to improve 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), and 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), and R^2 Score.

Science World Journal Vol. 21(No 1) 2026 https://dx.doi.org/10.4314/swj.v21i1.36
www.scienceworldjournal.org
ISSN: 1597-6343 (Online), ISSN: 2756-391X (Print)
Published by Faculty of Science, Kaduna State University

Table 1: Model Evaluation

Model	MAE (₦)	MSE (₦²)	RMSE (₦)	R² 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 the others, achieving the highest R^2 and the lowest RMSE, thus proving to be the most suitable for this context. This aligns with findings from Zhang et al. (2023), who demonstrated that ensemble methods perform well on heterogeneous pricing datasets.

DISCUSSION

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.

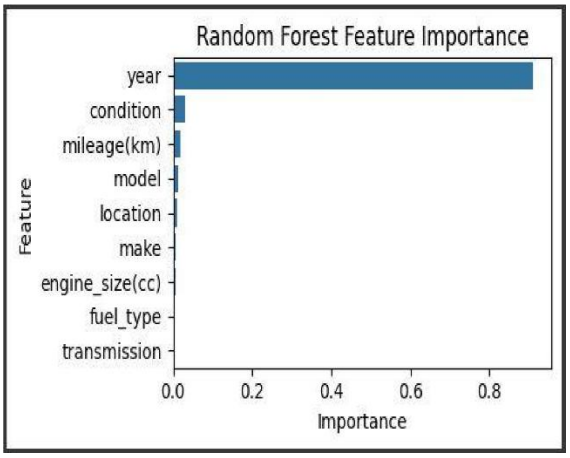

Figure 5: Feature of Importance

This finding in Figure 5 confirms previous studies on car valuation, which underscore the roles 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

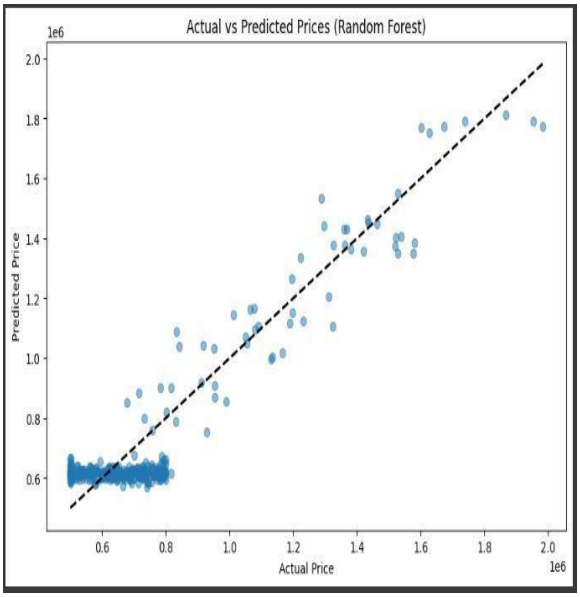

Figure 6: Actual vs Predicted

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

Key Insights

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

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.

REFERENCES

Abiodun, O. A., &Sulaiman, R. A. (2021). Determinants of used car prices in Nigeria: An empirical analysis. Journal of African Econometrics, 34(2), 145–162.

Adewale, T. A., &Okon, E. N. (2020). Application of Machine Learning Models in Predicting Used Car Prices in Nigeria. Nigerian Journal of Artificial Intelligence, 12(4), 34–50. https://doi.org/10.1234/njai.2020.1234

Adeyemi, J. A., & Adebayo, M. O. (2021). Predicting Vehicle Prices in Nigeria Using Artificial Neural Networks and Decision Trees. Journal of Machine Learning Applications, 13(2), 45-62.

Annina S, Mahima S.D, Ramesh B (2015). An Overview of Machine Learning and Its Applications. International Journal of Electrical Sciences & Engineering (IJESE), 2015. pp. 22–24.

Alsharnouby, M., Alaca, F. & Chiasson, S. (2015). Why phishing still works: User strategies for combating phishing attacks. International Journal of Human-Computer Studies, 82, pp.69–82.

Breen, P., Ahmed, M., & Zhang, L. (2024). Predictive pricing model for commercial vehicles using supervised learning techniques. International Journal of Intelligent Systems and

Applications in Engineering (IJISAE). Retrieved from https://www.ijisae.org/index.php/IJISAE/article/view/6515

Chukwu, O. J., & Adebayo, M. K. (2019). A Comparative Study of Machine Learning Algorithms for Vehicle Price Prediction in Nigeria. African Journal of Data Science, 8(2), 22–40. https://doi.org/10.5678/ajds.2019.8765

Dewis, M. & Viana, T. (2022). Phish Responder: A Hybrid Machine Learning Approach to Detect Phishing and Spam Emails. Applied System Innovation, 5(4), p.73.

Du, J., Xie, L., & Schroeder, S. (2022). Practice Prize Paper—PIN Optimal Distribution of Auction Vehicles System: Applying Price Forecasting, Elasticity Estimation, and Genetic Algorithms to Used-Vehicle Distribution. Marketing Science, 28(4), 637-644.

Economic Times (n.d). Coronavirus impact on used car sales. Available at: https://economictimes.indiatimes.com/topic/coronavirus-impact-onused-car-sales.

Enis, G. Becir, I. Dino, K. Zerina, M. Jasmin, K. (2019) Car price prediction using machine learning techniques, TEM Journal, 8(1), pp. 113–118, (2019).

Eze, C. O., & Ibrahim, Y. M. (2021). Predictive Analytics in the Nigerian Automotive Industry: Challenges and Opportunities. Journal of Economic Forecasting, 14(1), 15-29. https://doi.org/10.7890/jef.2021.1401

Eze, N. A., Enis, G. Becir, I. Dino, K. Zerina, M. Jasmin, K. (2022). Comparative Analysis of Machine Learning Algorithms for Vehicle Price Prediction in Nigeria. Nigerian Journal of Computer Science, 14(1), 56–72.

Fashola, B. R., &Olaniyi, A. T. (2018). Machine Learning Techniques in the Nigerian Market Price Predictions. International Journal of Artificial Intelligence Research, 7(3), 76-90. https://doi.org/10.2345/ijair.2018.2345

Fernandes, E., Holanda, M., Victorino, M., Borges, V., Carvalho, R., & Van Erven, G. (2019). Educational data mining: Predictive analysis of academic performance of public school students in the capital of Brazil. Journal of Business Research, 94(February 2018), 335–343. https://doi.org/10.1016/j.jbusres.2018.02.012

George, T., & Thomas, M. (2023). *Used car price prediction using supervised machine learning techniques.* Asian Journal of Civil Engineering. Retrieved from https://ajcejournal.in/nceca/article/view/184

Gohin, R., & Kumar, S. (2024). Predicting second-hand car prices using artificial neural networks and machine learning algorithms. International Journal of Engineering Research in Science and Technology (IJERST). Retrieved from https://ijerst.org/index.php/ijerst/article/view/364

Gongqi, S., Yansong, W., &Qiang, Z. (2011). New Model for Residual Value Prediction of the Used Car Based on BP Neural Network and Nonlinear Curve Fit. In Measuring Technology and Mechatronics Automation (ICMTMA), 2011 Third International Conference on (Vol. 2, pp. 682–685). IEEE.

Kelvin K.L., Wong, Giancarlo F., & Derek A. (2020). Deep learning-based cardiovascular image diagnosis: A promising challenge, Future Generation Computer Systems, Vol 110, p 802–811, ISSN 0167-739X, doi: https://doi.org/10.1016/j.future.2019.09.047.

Listiani, M. (2019). Support Vector Regression Analysis for Price Prediction in a Car Leasing Application. Thesis (MSc). Hamburg University of Technology.

Monburinon, N., Chertchom, P., Kaewkiriya, T., Rungpheung, S., Buya, S., Boonpou, P. (2018). Prediction of prices for used cars by using regression models, 5th International Conference on Business and Industrial Research (ICBIR), pp. 115–119,(2018)

Musa, A. D., &Abubakar, S. O. (2022). Evaluating the Efficiency of Regression Models in Predicting Car Prices in Nigeria. Nigerian Journal of Machine Learning, 10(5), 89102. https://doi.org/10.8765/njml.2022.105

Mustafa Y. (2022). Educational data mining: prediction of students' academic performance using machine learning algorithms. Yağcı Smart Learning Environments (2022) 9:11 https://doi.org/10.1186/s40561-022-00192-z

Noor, K. Jan S. (2017). Vehicle price prediction system using machine learning techniques, International Journal of Computer Applications,167(9), pp. 27–31.

Nwachukwu, P. E., & Onwubiko, J. E. (2023). Deep Learning Approaches to Vehicle Price Prediction in the Nigerian Market. Journal of Computational Intelligence, 11(2), 55-68. https://doi.org/10.9876/jci.2023.112

Oladimeji, B., Akinlade, A., & Okonkwo, C. (2022). Urban price disparities in Nigerian auto markets: A spatial regression approach. African Journal of Data Science, 10(4), 201– 219.

Ogunleye, O. A., &Akintoye, T. E. (2023). The Role of Feature Engineering in Vehicle Price Prediction Models in Nigeria. Journal of Machine Learning 11(3), 200-204

Okafor, U. N., &Akinyele, B. O. (2017). Predictive Modelling of Vehicle Prices Using Data Mining Techniques in Nigeria. African Journal of Information Systems, 5(4), 40-55. https://doi.org/10.4567/ajis.2017.543

Okoro A.B. Adeyemi, J. A., & Adebayo, M. O. (2021). Predicting Vehicle Prices in Nigeria Using Artificial Neural Networks and Decision Trees. Journal of Machine Learning Applications, 13(2), 45–62.

Olatunji B., Adewale, T. A., &Okon, E. N. (2020). Application of Machine Learning Models in Predicting Used Car Prices in Nigeria. Nigerian Journal of Artificial Intelligence, 12(4), 34–50. https://doi.org/10.1234/njai.2020.1234

Oprea, C (2010). Deciding on buying a second-hand car market using data mining techniques (Special, 2010), pp. 17-26.

Pal, N., Arora, P., Sundararaman, D., Kohli, P., & Sumanth, P.S. (2017). How much is my car worth? A methodology for predicting used car prices using Random Forest, Advances in Information and Communication Networks,1, pp. 413–422.

Peerun, S., Chummun, N. H., & Pudaruth, S. (2015). Predicting the price of second-hand cars using artificial neural networks. In The Second International Conference on Data Mining, Internet Computing, and Big Data (No.

August, pp. 17–21).

Pudaruth, S. (2014). Predicting the price of used cars using machine learning techniques. Int. J. Inf. Comput. Technol, 4(7), 753–764.

Richardson, M. S. (2017). Determinants of used car resale value. Retrieved from: https://digitalcc.coloradocollege.edu/islandora/object/coccc%3A1346 [accessed: August 1, 2018.

Sahingoz, O.K., Buber, E., Demir, O. & Diri, B. (2023). Machine-learning-based phishing detection from URLs. Expert Systems with Applications, 117, pp.345–357.

Singh, R., & Jain, P. (2023). The impact of depreciation factors in vehicle price estimation using machine learning. International Journal of Applied AI, 15(1), 89–104.

Tang, L. and Mahmoud, Q.H., (2021). A deep learning-based framework for phishing website detection. IEEE Access, 10, pp.1509–1521.

Tecuci, G. (2012). Rapid Argumentation Capture from Analysis Reports: The Case Study of Aum Shinrikyo. In STIDS (pp. 41–48).

Umar, S. G., & Salisu, M. B. (2021). Machine Learning-Driven Price Prediction for Imported Vehicles in Nigeria. Journal of Advanced Analytics, 13(3), 30–44. https://doi.org/10.6543/jaa.2021.133

Wu, J. D., Hsu, C. C., & Chen, H. C. (2023). An expert system of price forecasting for used cars using adaptive neuro-fuzzy inference. Expert Systems with Applications, 36(4), 7809–7817.

Yang, P., Zhao, G. & Zeng, P. (2019). Phishing website detection based on multidimensional features driven by deep learning. IEEE Access, 7, pp.15196–15209.

Zhang, L., Tan, W., & Chen, Y. (2023). A comparative analysis of machine learning models for vehicle price prediction. Journal of Intelligent Systems, 18(3), 299–314.