Predictive Sales Analytics: A Novel Deer Hunting Optimization and Machine Learning Approaches

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Predictive sales analytics encompasses data analysis and machine learning (ML) techniques to anticipate forthcoming sales patterns. This practice empowers firms to make well-informed judgments and optimize strategies to enhance sales performance. This research presents a new Deer hunting optimization-tuned XGBoost (DHO-XGB) methodology to enhance the accuracy of diagnostic sales analytics. To assess the effectiveness of the suggested approach for predicting sales of furnishings, an open data set encompassing the store's revenue record is acquired. The experimental results obtained inside the Python 3.11-based simulation environment demonstrate important performance metrics, including Accuracy (85%), Precision (83%), Recall (87%), and F1-Score (89%). Additionally, the Mean Absolute Error (MAE) is measured at 1669.10, while the Root Mean Square Error (RMSE) is calculated to be 3696.59. Our findings resultsmake a great contribution to the expanding domain of predictive analytics and provide significant insights for firms seeking to improve their sales forecasting abilities in dynamic market conditions. It is advisable to do additional study in order to investigate the applicability of the suggested methodology in various industries and to tackle unique obstacles related to the integration of real-time data and external environmental factors.

Keywords: Predictive Sales, Sales Performance, Market Conditions; Environmental Factors, Industries, Deer Hunting Optimization-Tuned XGboost (DHO-XGB).

1. Introduction

Predictive sales analytics represents a groundbreaking methodology within the domain of business strategy, empowering firms with the necessary resources to anticipate forthcoming sales patterns and formulate assessments based on empirical data [1]. In an era characterized by the proliferation of information and the inherent difficulties in interpreting its effects, predictive sales analytics has emerged as a crucial tool for effectively navigating the intricacies of the market and fostering long-term growth [2]. Predictive sales analytics, fundamentally, involves a comprehensive examination of past sales data, which includes client engagements and purchasing records [3]. This analysis provides significant insights into historical performance, serving as the basis for predictive modeling. Client segmentation is a crucial element that enables firms to customize their marketing and sales strategies according to the distinct tastes, behaviors, and demographics exhibited by various client segments [4]. Lead assessment is a crucial element that allows for the prioritization of leads by considering their engagement levels, tradition purchasing behavior, and other relatable data [5]. This enables sales teams to concentrate their efforts on leads that have the greatest probability of conversion, thus enhancing both efficiency and effectiveness [6]. In addition, Predictive sales analytics does not function independently; it takes into account external variables such as market trends, economic data, and industry advancements [7]. By integrating this wider context into the analysis, organizations have the ability to adapt their plans to conform to evolving circumstances and developing possibilities. There are numerous advantages associated with the utilization of Predictive sales analytics [8]. The utilization of data-driven insights boosts decision-making, while reducing procedures and automating operations increases operational efficiency [9]. Additionally, individualized interactions contribute to an improved overall customer experience. In essence, this method serves as a catalyst for revenue expansion as it empowers firms to execute focused strategies that are in line with market dynamics and client demands [10]. The current study introduces a novel approach called Deer hunting optimization-tuned XGBoost (DHO-XGB) for the purpose of Predictive sales analytics.

The remaining sections of this study are structured as follows: The paper is structured into four main sections: Related work (Part 2), Methodology (Part 3), Results (Part 4), and Conclusion (Part 5).

2. Related works

According to the author of,[11] utilized a Naive Bayes model to analyze a dataset consisting of sales data during a span of three years. The objective was to categorize each salesperson based on their performance in an international logistics organization.The business offers pre-established categories. The outcome of the Performance Evaluation was a categorization accompanied by strategies for enhancing performance in areas requiring improvement.The study[12] observed that plants utilizing predictive analytics demonstrate a noteworthy increase in production, resulting in sales figures that are up to $918,000 greater when contrasted with comparable competitors. Moreover, the evidence from both the instrumental parameter assessments and the temporal sequence of benefits indicates a causal association. The results of their study provide empirical evidence in favor of the assertion that the utilization of predictive analytics has the potential to significantly enhance performance.In presented a data analytics-driven methodology for forecasting sales information by utilizing the previous 12 months' data [13]. The proposed strategy generated a comprehensive report that highlights the goods with the highest sales profits for each month. The system was capable of performing a range of tasks. These tasks include identifying the most profitable months for business, calculating the monthly revenue generated from various products, determining the city with the highest product sales, identifying the optimal time for advertising to maximize customer purchases, generating reports, identifying frequently purchased items to ensure adequate stock for future years, and ultimately increasing the profitability of a retail store companies.

To present a comprehensive analysis of several strategies employed in “retail Supply Chain Management (SCM)” and assesses the efficacy of two specific methodologies [14]. They proposed the utilization of hybrid methodologies, wherein SARIMA(X) and “Long short-term memory (LSTM)” models are trained on comparable store groups that have been pre-clustered. In general terms, it was seen that LSTM had superior performance when applied to products characterized by consistent demand patterns, but SARIMA demonstrated more favorable outcomes for products exhibiting seasonal behavior. To presented the applicability of their suggested solution methods, which draw inspiration to a diverse array of decision problems [15]. They demonstrated the computational tractability and temporal optimality of the proposed methods, despite moderate circumstances. The present study aims to broaden the scope of their findings by considering scenarios in which some choice variables have the potential to directly influence uncertainty in unpredictable manners.The supply chain demand forecasting was investigated in [16]. Their recommended goals were to categorize those programs, clear to any shortages in the available information, and provide suggestions for further research in the field. The analysis also indicates that there was a significant gap in the existing literature about the utilization of BDA for the purpose of demand forecasting in “closed-loop supply chains (CLSCs)”. Consequently, it emphasizes potential directions for future studies in this domain.

Author[17], examined the randomized forest classification algorithm to categorize employees depending on the amount they receive each month. Additionally, they are utilizing an informal data analytics. Moreover, they apply clustering methodologies that rely on the similarity of performance data to examine employee performance. The study examined a method of analysis for the purpose of determining optimal development sites for stores that specialize in providing supplementary services, the requirement for which was contingent upon the desire for a primary business [18]. The study utilizes data obtained from a business partner specializing in the sale of add-on products. The findings of their study suggested that the predictions exhibit a high level of efficacy in forecasting add-on goods sales. It demonstrated that the integration of predictive analytical models can significantly enhance corporate operations, particularly by facilitating the decision-making process [19]. Predictive analytics was a systematic procedure employed by firms to leverage statistical methodologies and advanced technologies in order to examine their past data, thereby generating novel insights and formulating new approaches based on these findings.

3. Methodology

Figure 1 depicts the flow of predictive sales analytics, focusing significant focus on the utilization of real-time datasets. The evaluation of Predictive Sales is conducted using the Deer hunting optimization-tuned XGBoost (DHO-XGB) technique.

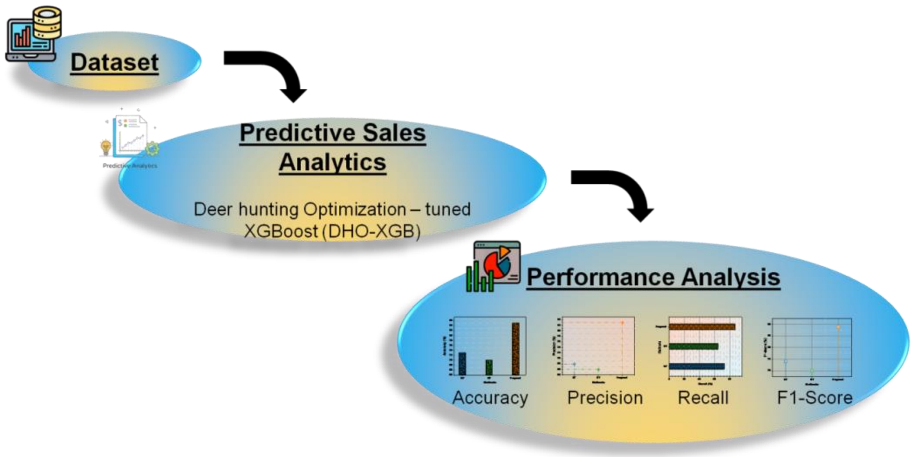


Figure 1:Systemic Structure (Source: Author)

3.1. Data collection

The dataset utilized in research pertains to the sales of a retail store spanning from 2014 to the conclusion of 2017. It encompasses around 11,000 data points and encompasses 23 distinct attributes. Furthermore, the dataset encompasses sales information pertaining to three distinct categories, especially household items, technological items, and office materials.

3.2 Deer hunting optimization-tuned XGBoost (DHO-XGB)

3.2.1 Deer hunting optimization (DHO)

DHO optimizes algorithms for more accurate forecasting, boosting sales strategies in Predictive sales analytics. DHO's clever technique improves models' adaptability to dynamic market situations, improving sales estimates. This dynamic connection helps firms make educated decisions, boosting predictive analytics potential.The traditional deer hunting optimization algorithm, or DHOA, was created with inspiration or an idea derived from human hunting techniques. A few of the unique characteristics of deer are their keen sense of vision, their exceptional sense of smell, and their capacity to detect ultra-high frequency sounds. Mathematically, the traditional DHOA is expressed in four phases.

Step 1: Initialization of population

The population of hunters is initialized and given in Equation (1) in the traditional DHOA.

$$S = \{S_1, S_2, \dots, S_n\}\,; 1 < o \leq r \qquad (1)$$

Here, S is the population of hunters, and r is the amount number of hunters.

Step 2: Initialization of wind and position angle

Equation (2) displays the mathematical formula for calculating the wind angle depending on the radius of the circle.

$$\phi_s = 2\pi g \tag{2}$$

The wind angle is expressed using the symbol ϕ. The range of the random number denoted by gis [0, 1]. s indicates the current iteration. Equation (3) provides a mathematical formulation of the position angle. The symbol θ represents the position angle.

$$\theta_s = \phi + \pi \tag{3}$$

Step 3: Propagation of position

There are two positions in general: leader position (S^{lead}) and successor position ($S^{successor}$).

3.2.1.1 Propagation method is carried out using the location of leader

To locate the best answer, the hunters begin changing their positions as soon as they believe they are in the ideal location in equation (4).

$$S_{s+1} = S^{lead} - J.a.\left|R \times S^{lead} - S_s\right| \tag{4}$$

The hunter's position in the current iteration is represented by S_s in equation (4), and their updated position in the next iteration is represented by S_{s+1}. The wind speed introduces a random variablea, which ranges from 0 to 2, and the coefficient vectors denoted by the notations J and R, are computed using the mathematical formulas provided in Equations (5) and (6), respectively.

$$J = \frac{1}{4}\log\left(s + \frac{1}{s_{max}}\right) d \tag{5}$$

$$R = 2.a \tag{6}$$

The algorithm for computing the coefficient vectors J uses a parameter d, whose value ranges between -1 and 1. In Equation (4), the maximum number of iterations is indicated by s_{max}. The random number in Equation (5) falls into the range [0, 1].

3.2.1.2 Propagation method is carried out using the position angle

Equation (7) provides the difference between the wind angle and the angle of visualization, which is used to update the position angle by adding a new parameter c_s. Using the mathematical method found in Equation (8), one can ascertain the angle of visualization l_s of the target.

$$c_s = \phi_s - l_s \tag{7}$$

$$l_s = \frac{\pi}{8} \times g \tag{8}$$

The search agent's S^{lead} role was assigned as the successor. Equation (9) provides the algebraic formula for updating the position angle, and Equation (10) updates the hunter's position while taking the position angle into consideration.

$$\theta_{s+1} = \theta_s + c_s \quad (9)$$

$$S_{s+1} = S^{lead} - a.\left|\cos(x) \times S^{lead} - S_s\right| \quad (10)$$

3.2.1.3 Propagation method is carried out using the successor's position

Here, the exploration stage's vector R has been modified to reflect the concept of the encircling process. The value of vector R is regarded as smaller than 1, even though random search is assumed at the beginning. Equation (11) shows the hunter's location as it was modified based on the position of the successor.

$$S_{s+1} = S^{successor} - J.a.\left|R \times S^{Successor} - S_s\right| \quad (11)$$

The search agent will be selected randomly if R is less than 1, and the best solution will be chosen to update the search agent's position if R is greater than or equal to 1.

Step 4: Terminating the process

In the traditional DHOA, closing the process is the last step. Here, the location is updated until the optimal position is reached.

3.2.2 XGBoost Algorithm

Predictive sales analytics is a field in which XGBoost is applied. It does this by using an ensemble of decision trees to analyze historical sales data, improve forecast accuracy, and identify complex patterns that lead to more effective sales projections.The algorithm has the important property of distributed computing, which allows it to process large and complex models efficiently. The examination of extensive and varied datasets defines it as an out-of-core computing. This analytical technique is used to control resource use in an efficient manner. With every iteration, a new model must be incorporated in order to reduce errors. Equation (12) is the objective of the XGBoost function at iteration t.

$$K(s) = \sum_{j=1} K(y_{out_i}, y_{out_j^{(s-1)}} + e_s(w_j) + h(g_s) \quad (12)$$

Let us consider the most basic linear approximate of the function f(x) as in Equation (13):

$$e(w) = e(a) + e(a(w-a)dw = f_s(w_j) \quad (13)$$

In this context, the loss Equation (14) and (15)K, denoted ase(w), is being evaluated. The variablearepresents the expected outcome from the previous procedure $(s-1)$, while dx refers to the additional

$$e(w) = e(a) + e(a)(w-a) + 0.5e'(a)(x-a)^2 \quad (14)$$

$$K(s) = \sum_{j=1}[K\left(y_{out_i}, y_{out_j^{(s-1)}}\right) + g_j e_s(w_j) + 0.5 l_j e_s\ ^2(w_j)] + h(e_s) \quad (15)$$

Equation (16) are left with the eliminated objectives that needs to be minimized at step s.

$$K1(s) = \sum_{j=1}[g_j e_s(w_j) + 0.5 l_j e_s\ ^2(w_j)] + h(e_s) \quad (16)$$

3.2.3 Deer hunting optimization-tuned XGBoost (DHO-XGB)

The DHO-XGB model, which combines the Hybrid Deer Hunting Optimization (DHO) technique with the XGBoost algorithm, is designed to enhance Predictive sales analytics by leveraging the respective advantages of both methods. The DHO algorithm performs optimal fine-tuning of XGBoost hyper parameters, so ensuring that the model is finely tailored to the specific properties of the sales dataset. The integration of evolutionary optimization and ensemble learning yields a predictive analytics tool that effectively handles the complexities of sales data while also demonstrating adaptability, so offering enterprises a robust solution for precise and agile sales projections.The DHO-XGB is shown in Algorithm 1:

Algorithm 1: Deer hunting optimization-tuned XGBoost (DHO-XGB)

Step:1import DHO

Step:2import XGBoost as xgb

Step:3defobjective_function(params):

Step:4xgb_model = xgb.train(params, train_data)

Step:5predictions = xgb_model.predict(validation_data)

Step:6error = calculate_error(predictions, actual_values)

Step:7return error

Step:8dho_params = {

Step:9'population_size': 50,

Step:10'max_generations': 100,

Step:11 'mutation_rate': 0.2,

}

Step:12initial_xgb_params = {

Step:13'max_depth': 3,

Step:14'learning_rate': 0.1,

Step:15'n_estimators': 100,

}

Step:16best_xgb_params = DHO.optimize(objective_function, initial_xgb_params, dho_params)

Step:17final_xgb_model = xgb.train(best_xgb_params, full_train_data)

Step:18test_predictions = final_xgb_model.predict(test_data)

4. Results

In this paper, the Python platform has been used to implement the proposed method. We need a laptop with 32 GB of RAM, a 100 GB hard drive, an Intel i7 processor, and Windows 10. This section examines the metrics of accuracy, precision, recall, F1-score, RMSE, and MAE. The existing techniques, such as RF [20], DT [20], Bayesian linear regression [21], and linear regression[21] are used for comparison.

Figure 2 depicts the sales forecasting outcomes of the most optimal models derived from each respective forecasting technique. The sales projection outcomes for the beginning of the year have yielded varied results. Nevertheless, each of these methods was able to accurately reflect the increase in sales during the final quarter of 2017.Figure 2 illustrates the sales forecasting graph of the DHO-XGB (Proposed) model.

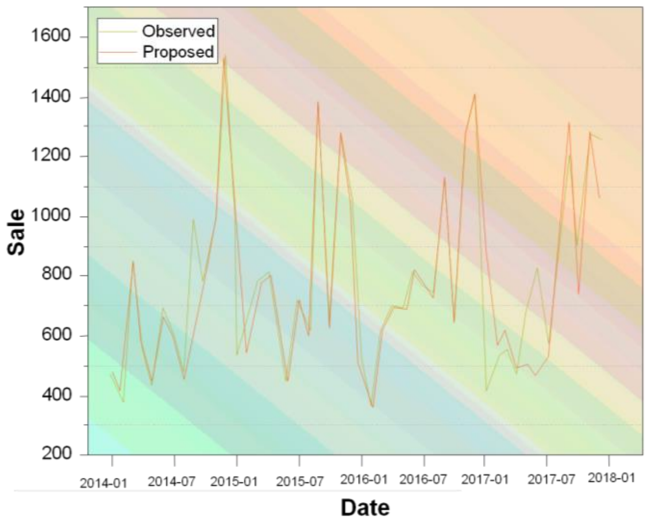


Figure 2: DHO-XGB sales forecasting [Source: Author]

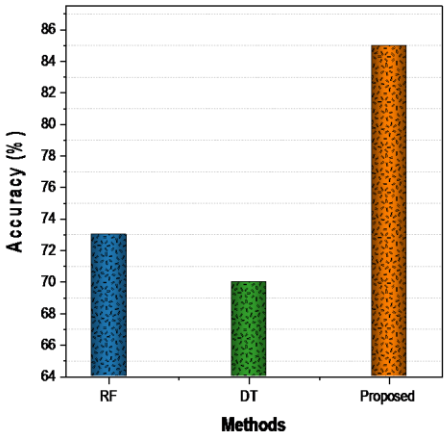
Accuracy is a statistical measure that quantifies the proportion of accurate predictions relative to the total number of predictions generated by a model for prediction.Equation (17) can be represented as:

$$\text{Accuracy} = \frac{\text{Numberofcorrectpredictions}}{\text{Totalnumberofpredictions}} \times 100 \tag{17}$$

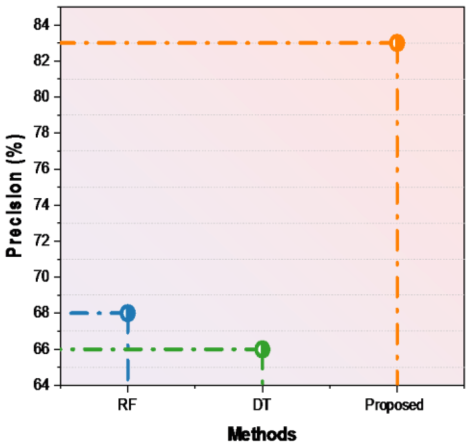
Precision in the context of predictive sales pertains to the proportion of accurate positive predictions in relation to the overall number of forecasted positive outcomes. The calculation is performed

Utilizing the prescribed Equation (18):

$$\frac{[\text{TP}]}{[\text{TP+FP}]} \tag{18}$$



(a) Accuracy



(b) precision

Figure 3:Results of (a) accuracy and (b) precision

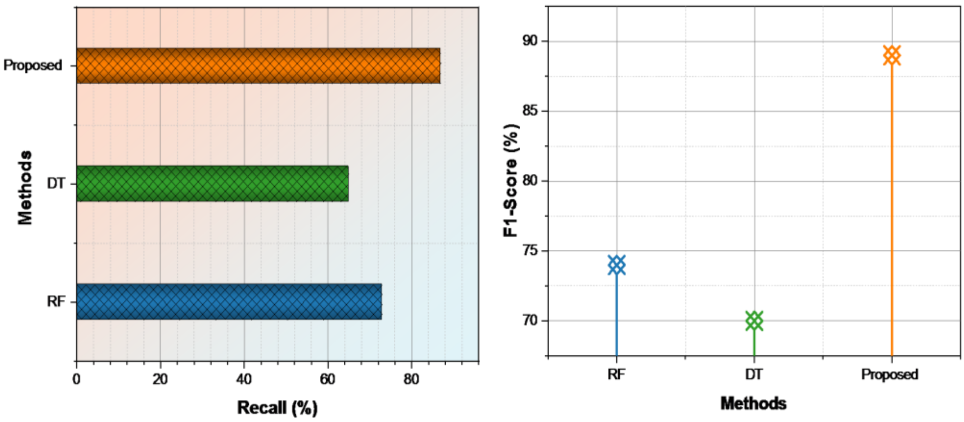
Figure 3 illustrates the relationship between accuracy and precision. The DHO-XGB technique exhibited superior performance in terms of accuracy and precision compared to the RF and DT approaches. Specifically, it achieved an accuracy score of 85% and a precision score of83%, while the RF and DT approaches achieved accuracy scores of 73% and 70%, and precision scores of 68% and 66%, respectively. It demonstrates that our suggested approach is better than the current techniques for Predictive sales analytics.

The term of recall pertains to the ability of a prediction model to accurately identify positive events, as quantified by a mathematical Equation (19).

$$\frac{[TP]}{[TP+FN]} \quad (19)$$

The F1 score is a statistical measure that computes the harmonic mean of precision and recall to quantify their balance. Equation (20) can be expressed as follows:

$$F1 - \text{score} = \frac{2 * (\text{precision} * \text{recall})}{(\text{precision} + \text{recall})} \quad (20)$$



(c) Recall (d) F1-score

Figure 4:Results of (c) Recall and (d) F1-score

Table 1: Values of parameters

Methods	Accuracy	Precision	Recall	F1-score
RF	73	68	73	74
DT	70	66	65	70
Proposed	85	83	87	89

Figure 4 illustrates a comparison between the recall and f1-score. RF and DT models achieved accuracy ratings of 73% and 65% respectively, along with f1-scores of 74% and 70%. The DHO-XGB technique was recommended due to its superior recall score of 87% and f1-score of 89%. This finding contributes to the enhanced effectiveness of the methodology that we have presented.

Table 1 shows the values of, recall, precision, accuracy and F1-score.

MAE calculates the average of absolute errors. The calculation of this parameter is determined by Equation (21). Figure 5 displays a comparison of the MAE. The algorithms employed, namely DHO-XGB, Bayesian linear regression, and Linear Regression, yield MAE values of 1669.10, 2469.54 and 2480.12, respectively. The DHO-XGB algorithms that are recommended exhibit a decreased MAE value in comparison to the existing approaches. This demonstrates that the proposed technique is more efficient.

$$\mathrm{MAE} = \frac{1}{n}\sum_{j=1}^{m}|f_s| \tag{21}$$

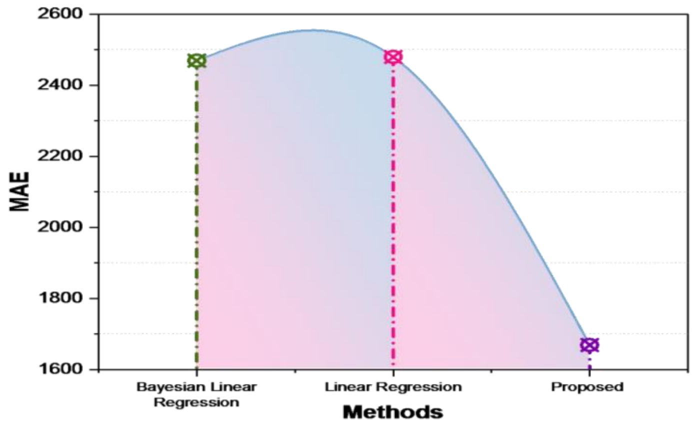


Figure 5: Results of MAE

The RMSE is calculated as the square root of the average error. The RMSE is represented by Equation (22).Figure 6 displays a comparative analysis of RMSE between the proposed approach and the standard approach. The proposed methodologies, namely DHO-XGB, Bayesian linear regression, and Linear Regression, exhibit root mean square error (RMSE) values of 3696.59, 4361.40, and 4365.04, respectively. The proposed DHO-XGB algorithms exhibit a RMSE value compared to the currently employed methodologies. This indicates that the proposed methodology is more effective.Table 2 shows the value of MAE and RMSE.

$$RMSE = \sqrt{\frac{\sum_{j=1}^{n}(\mathrm{Wobs,j}-\mathrm{wmodel,j})}{n}} \quad (22)$$

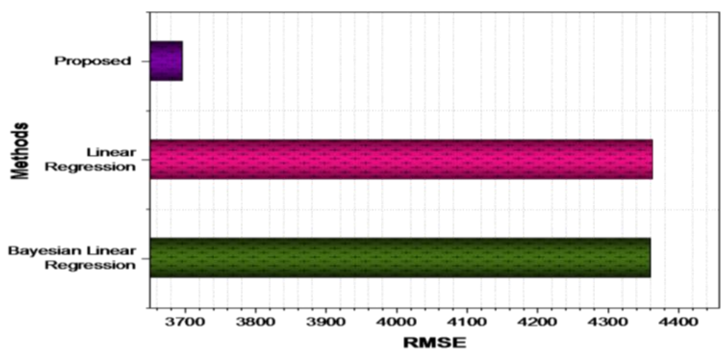


Figure 6: Results of RMSE

Table 2: Values of parameters

Methods	MAE	RMSE
BLR	2469.54	4361.4
LR	2480.12	4365.04
Proposed	1669.1	3696.59

5. Conclusion

Predictive sales analytics encompasses the application of data analysis and ML techniques to forecast forthcoming sales trends, hence facilitating well-informed decision-making to optimize sales performance. This study presents an innovative approach that integrates Deer Hunting Optimization-tuned XGBoost (DHO-XGB) with real-time datasets and digital humanities to enhance the accuracy of Predictive sales analytics. The simulation environment based on Python 3.11 was used for the research, and the incredible outcomes include Accuracy (85%), Precision (83%), Recall (87%), and F1-Score (89%). The MAE and RMSE were found to be 1669.10 and 3696.59, respectively. The aforementioned findings make a substantial contribution to the field of predictive analytics, providing vital insights for companies aiming to enhance their sales forecasting capabilities in dynamic market environments. The responsible implementation of algorithms necessitates careful navigation of ethical factors, such as privacy and algorithmic bias, in order to maintain trust and openness over time. The combination of emerging technologies, along with advancements in artificial intelligence and ML, presents promising prospects for the improvement of predictive sales analytics.

References

1. Morande, Swapnil, TahseenArshi, Kanwal Gul, and MitraAmini. "Harnessing the Power of Artificial Intelligence to Forecast Startup Success: An Empirical Evaluation of the SECURE AI Model." (2023).10.31235/osf.io/p3gyb.
2. Talaat, Fatma M., AbdussalamAljadani, BshairAlharthi, Mohammed A. Farsi, Mahmoud Badawy, and Mostafa Elhosseini. "A Mathematical Model for Customer Segmentation Leveraging Deep Learning, Explainable AI, and RFM Analysis in Targeted Marketing." Mathematics 11, no. 18 (2023): 3930.https://doi.org/10.3390/math11183930
3. PraveenaSri, Perini, Vaddi Naga Padma Prasuna, R. Murugesan, and S. P. Usha. "Business Challenges of Forecasting Sales in Bakery Industry: Applications of Machine Learning Algorithms." In Proceedings of the International Conference on Emerging Trends in Business & Management (ICETBM 2023), vol. 242, p. 335. Springer Nature, 2023.https://doi.org/10.3390/math11183930
4. Zulaikha, Siti, Hazik Mohamed, MasmiraKurniawati, SulistyaRusgianto, and Sylva AlifRusmita. "Customer predictive analytics using artificial intelligence." The Singapore Economic Review (2020): 1-12.https://dx.doi.org/10.1142/S0217590820480021
5. Punia, Sushil, and Sonali Shankar. "Predictive analytics for demand forecasting: A deep learning-based decision support system." Knowledge-Based Systems 258 (2022): 109956.https://doi.org/10.1016/j.knosys.2022.109956
6. Chou, Ping, Howard Hao-Chun Chuang, Yen-Chun Chou, and Ting-Peng Liang. "Predictive analytics for customer repurchase: Interdisciplinary integration of buy till you die modeling and machine learning." European Journal of Operational Research 296, no. 2 (2022): 635-651.https://doi.org/10.1016/j.ejor.2021.04.021
7. Bajaj, Purvika, Renesa Ray, ShivaniShedge, ShravaniVidhate, and NikhilkumarShardoor. "Sales prediction using machine learning algorithms." International Research Journal of Engineering and Technology (IRJET) 7, no. 6 (2020): 3619-3625.
8. Özemre, Murat, and OzgurKabadurmus. "A big data analytics based methodology for strategic decision making." Journal of Enterprise Information Management 33, no. 6 (2020): 1467-1490.https://doi.org/10.1108/JEIM-08-2019-0222
9. Awan, Usama, SaqibShamim, Zaheer Khan, NajamUl Zia, Syed Muhammad Shariq, and

Muhammad Naveed Khan. "Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance." Technological Forecasting and Social Change 168 (2021): 120766.https://doi.org/10.1016/j.techfore.2021.120766

10. Gupta, Shivam, Vinayak A. Drave, Yogesh K. Dwivedi, Abdullah M. Baabdullah, and Elvira Ismagilova. "Achieving superior organizational performance via big data predictive analytics: A dynamic capability view." Industrial Marketing Management 90 (2020): 581-592.https://doi.org/10.1108/EMJB-07-2021-0105
11. Calixto, Nelito, and João Ferreira. "Salespeople performance evaluation with predictive analytics in B2B." Applied Sciences 10, no. 11 (2020): 4036.https://doi.org/10.3390/app10114036
12. Brynjolfsson, Erik, Wang Jin, and Kristina McElheran. "The power of prediction: predictive analytics, workplace complements, and business performance." Business Economics 56 (2021): 217-239.https://doi.org/10.1057/s11369-021-00224-5
13. Vengatesan, K., E. Visuvanathan, A. Kumar, S. Yuvaraj, and P. ShivkumarTanesh. "An approach of sales prediction system of customers using data analytics techniques." Advances in Mathematics: Scientific Journal 9, no. 7 (2020): 5049-5056.https://doi.org/10.37418/amsj.9.7.70
14. Falatouri, Taha, FarzanehDarbanian, Patrick Brandtner, and ChibuzorUdokwu. "Predictive analytics for demand forecasting–a comparison of SARIMA and LSTM in retail SCM." Procedia Computer Science 200 (2022): 993-1003.https://doi.org/10.1016/j.procs.2022.01.298
15. Bertsimas, Dimitris, and Nathan Kallus. "From predictive to prescriptive analytics." Management Science 66, no. 3 (2020): 1025-1044.https://doi.org/10.1287/mnsc.2018.3253
16. Seyedan, Mahya, and FereshtehMafakheri. "Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities." Journal of Big Data 7, no. 1 (2020): 1-22.https://doi.org/10.1186/s40537-020-00329-2
17. Kakulapati, Vijayalakshmi, Kalluri Krishna Chaitanya, KolliVamsi Guru Chaitanya, and PonugotiAkshay. "Predictive analytics of HR-A machine learning approach." Journal of Statistics and Management Systems 23, no. 6 (2020): 959-969.https://doi.org/10.1080/09720510.2020.1799497
18. Huang, Teng, David Bergman, and Ram Gopal. "Predictive and prescriptive analytics for location selection of add-on retail products." Production and Operations Management 28, no. 7 (2019): 1858-1877.https://doi.org/10.1111/poms.13018
19. Narayana, ChejarlaVenkat, Chinta Lakshmi Likhitha, Syed Bademiya, and KarreKusumanjali. "Machine learning techniques to predict the price of used cars: predictive analytics in retail business." In 2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC), pp. 1680-1687. IEEE, (2021).https://doi.org/10.1109/ICESC51422.2021.9532845
20. Akbulut, Akhan. "Benchmarking of Regression Algorithms and Time Series Analysis Techniques for Sales Forecasting." (2019).
21. Zhao, Xian, and PanteaKeikhosrokiani. "Sales Prediction and Product Recommendation Model Through User Behavior Analytics." Computers, Materials & Continua 70, no. 2 (2022).10.32604/cmc.2022.019750