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| RESEARCH ARTICLE

Optimizing E-Commerce Profits: A Comprehensive Machine Learning Framework for Dynamic Pricing and Predicting Online Purchases

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| ABSTRACT

In the online realm, pricing transparency is crucial in influencing consumer decisions and driving online purchases. While dynamic pricing is not a novel concept and is widely employed to boost sales and profit margins, its significance for online retailers is substantial. The current study is an outcome of an ongoing project that aims to construct a comprehensive framework and deploy effective techniques, leveraging robust machine learning algorithms. The objective is to optimize the pricing strategy on e-commerce platforms, emphasizing the importance of selecting the right purchase price rather than merely offering the cheapest option. Although the study primarily targets inventory-led e-commerce companies, the model's applicability can be extended to online marketplaces that operate without maintaining inventories. The study endeavors to forecast purchase decisions based on adaptive or dynamic pricing strategies for individual products by integrating statistical and machine learning models. Various data sources capturing visit attributes, visitor details, purchase history, web data, and contextual insights form the robust foundation for this framework. Notably, the study specifically emphasizes predicting purchases within customer segments rather than focusing on individual buyers. The logical progression of this research involves the personalization of adaptive pricing and purchase prediction, with future extensions planned once the outcomes of the current study are presented. The solution landscape for this study encompasses web mining, big data technologies, and the implementation of machine learning algorithms.

| KEYWORDS

E-Commerce Profits; Machine Learning Framework; Online Purchases

| ARTICLE INFORMATION

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1. Introduction

Dynamic pricing, also known as price optimization, has emerged as a strategic tool in the business landscape, revolutionizing how goods and services are offered in response to the ever-changing dynamics of consumer demand, market competition, and external factors. This concept involves the flexible adjustment of prices based on a myriad of factors, such as competitors' pricing, supply and demand dynamics, conversion rates, and sales goals. Often referred to as individual-level price discrimination, revenue

management, or yield management, dynamic pricing has become a pervasive phenomenon across various industries, including retail, automotive, mobile communication, electricity, air travel, and more.
The prevalence of dynamic pricing is attributed to advancements in technology, particularly the increased availability of customer demand data, sophisticated decision support tools, and the influence of emerging technologies. In the retail sector (khan, 2023, 2022,2021,20219), the surge in demand data availability has empowered businesses to study consumer patterns efficiently, enabling more informed pricing decisions. Similarly, in mobile communication, reduced call rates, heightened competition, and improved network infrastructure have all been influenced by dynamic pricing strategies.

The automotive industry has experienced the impact of dynamic pricing through enhanced coordination in production processes, inventory decisions, and the adoption of direct-to-customer business models. The intensification of network connections, facilitated by the proliferation of the internet, has played a pivotal role in the success of dynamic pricing, benefiting both consumers and sellers by reducing menu costs and providing an integrated customer information database.

This article explores the multifaceted applications of dynamic pricing and its impact on various industries globally. The integration of web technology and automation has streamlined processes for vendors, eliminating the need for a physical presence, lowering input costs, and centralizing customer information. The reciprocal nature of dynamic pricing fosters open communication between consumers and sellers, creating a platform for reviews and feedback to enhance services.

Implementing dynamic pricing requires considerations such as customers' willingness to pay varying prices, segmented market availability, fair play rules, and ensuring that revenue costs outweigh the expenses associated with segmentation and policing. This strategy is particularly effective in industries characterized by fixed high costs and low variable costs.

Dynamic pricing strategies can be executed through methods such as re-pricing based on competitors' prices, adjusting prices during high and low-demand scenarios, and implementing short-term cycles like temporary and permanent markdowns. The flexibility offered by dynamic pricing has permeated industries such as airlines, hotels, electric utilities, retail, mobile communication systems, automotive, sporting events, car rentals, and insurance.

In-depth applications of dynamic pricing, such as yield management in the airline industry and enhanced coordination in the automotive sector, underscore its versatility. Determining dynamic pricing involves various methods, including surveys, observations, and experimental auctions, each tailored to the characteristics of mass or niche markets. Magloff's pricing strategies, including segmented pricing, peak use pricing, service time pricing, time of purchase pricing, and changing conditions pricing, provide frameworks for understanding and implementing dynamic pricing.

This paper proposes a new framework for dynamic pricing in retail organizations, combining mining, statistical, and machine learning techniques. The central question driving this research is whether this combination can predict better pricing for customers, defined by their purchase decisions. The subsequent sections delve into existing models, the proposed model, data description, results, and a comparative analysis with other dynamic pricing techniques for retail stores, culminating in conclusions, recommendations, and future avenues for exploration. As dynamic pricing continues to evolve, this study contributes to the ongoing discourse on optimizing pricing strategies for the benefit of both consumers and businesses.

2. Literature Review

The study by Namburu et al. (2022) emphasizes the pressing need for effective pricing strategies, particularly in the dynamically evolving landscape exacerbated by the surge in online shopping during the COVID-19 pandemic. Through an extensive literature review, the paper explores existing research on pricing strategies and market analysis, highlighting the role of machine learning models in personalized dynamic pricing and market trend prediction. The study's objectives are clearly defined, aiming to provide scalable pricing solutions, assist retailers in making swift decisions, and offer repeatable pricing strategies. The methodology encompasses meticulous data preprocessing and feature engineering steps, including exploratory data analysis and the creation of novel features to enhance machine learning model performance. The introduction of ensemble learning techniques, such as XGBoost, LightGBM, and CatBoost, sets the stage for the innovative X-NGBoost algorithm—a hybrid approach integrating XGBoost with natural gradient boosting, demonstrating superior speed and accuracy. The paper thoroughly compares existing algorithms based on various criteria and concludes that X-NGBoost outperforms its counterparts, as evidenced by lower root-mean-square error (RMSE). The significance of the proposed methodology for small-scale retailers is underscored in conclusion, with a forward-looking approach suggesting future work involving the extension of ensemble techniques to predict pricing solutions across multiple e-commerce platforms. In essence, the paper provides a comprehensive and promising avenue for addressing pricing challenges in online retail through the application of advanced machine learning algorithms, notably the novel X-NGBoost.

Gupta et al. (2014) The ongoing project represents an endeavor to create a comprehensive framework and effective methodologies utilizing robust machine learning algorithms to optimize customer decision-making regarding the right-priced purchases on e-commerce platforms. While the primary focus is on inventory-centric e-commerce companies, the proposed model exhibits adaptability for application in online marketplaces without physical inventories. Leveraging statistical and machine learning models, the study aims to forecast purchase decisions through the implementation of adaptive or dynamic pricing strategies. Various data sources, encompassing visit attributes, visitor characteristics, purchase history, web data, and context understanding, form the bedrock of this framework. Unlike concentrating on individual buyers, the study places emphasis on customer segments to enhance the accuracy of purchase predictions. Subsequent stages of the research involve the personalization of adaptive pricing and purchase forecasting. The study integrates web mining, big data technologies, and machine learning algorithms into a cohesive solution landscape to address the complexities of optimizing pricing decisions in the realm of e-commerce.

Peiseler et al. (2022) research delves into the viability of firms maintaining collusion in a scenario where horizontally differentiated firms possess the ability to engage in price discrimination based on private information. These firms receive private signals that are subject to noise, reflecting customer preferences. The study identifies a non-linear relationship between the precision of signals and the sustainability of collusion. Initially, from a lower level, an improvement in signal accuracy facilitates collusion. However, there exists a threshold beyond which further enhancements in signal precision diminish the sustainability of collusion. The findings offer significant implications for competition policy, especially given the increasing reliance of firms on sophisticated algorithms for consumer data analysis and pricing decisions. In contrast to prior conclusions, the research suggests that prohibiting price discrimination can be effective in curbing collusive behavior, particularly when the signals are adequately noisy.

Ho et al. (2021) research employs three distinct machine learning algorithms—support vector machine (SVM), random forest (RF), and gradient boosting machine (GBM)—to evaluate property prices. The study applies these methodologies to analyze a dataset comprising approximately 40,000 housing transactions spanning over 18 years in Hong Kong, subsequently comparing the outcomes of these algorithms. In terms of predictive accuracy, both RF and GBM demonstrate superior performance compared to SVM. Evaluation metrics, namely mean squared error (MSE), root mean squared error (RMSE), and mean absolute percentage error (MAPE), associated with RF and GBM consistently outperform those of SVM. Despite this, the study identifies SVM as a valuable algorithm for data fitting, particularly when precise predictions are required within a constrained timeframe. The overarching conclusion is that machine learning presents a promising and alternative approach to property valuation and appraisal research, especially concerning property price prediction.

Li et al. (2021) research paper constructs a game theoretical model to explore the issue of pricing cause-related products. It takes into account the customer's prosociality level and reference behavior, with the overall utility of a regular product serving as a reference point. The study specifically examines pricing strategies for cause-related products in scenarios with and without a competitive response. The analytical findings highlight the substantial impact of consumers' purchasing behaviors, such as varying levels of prosociality and recognition of reference points, on decisions related to the pricing of cause-related products. In the presence of consumers exhibiting diverse purchasing behaviors, the pricing strategies for cause-related products should be adapted accordingly.

3. Methodology

The proposed model considers the amalgamation of three different techniques - to identify the customer segments, appropriate pricing for them, and the prediction for their likely purchase within that price range. The framework is shown in Figure 1.

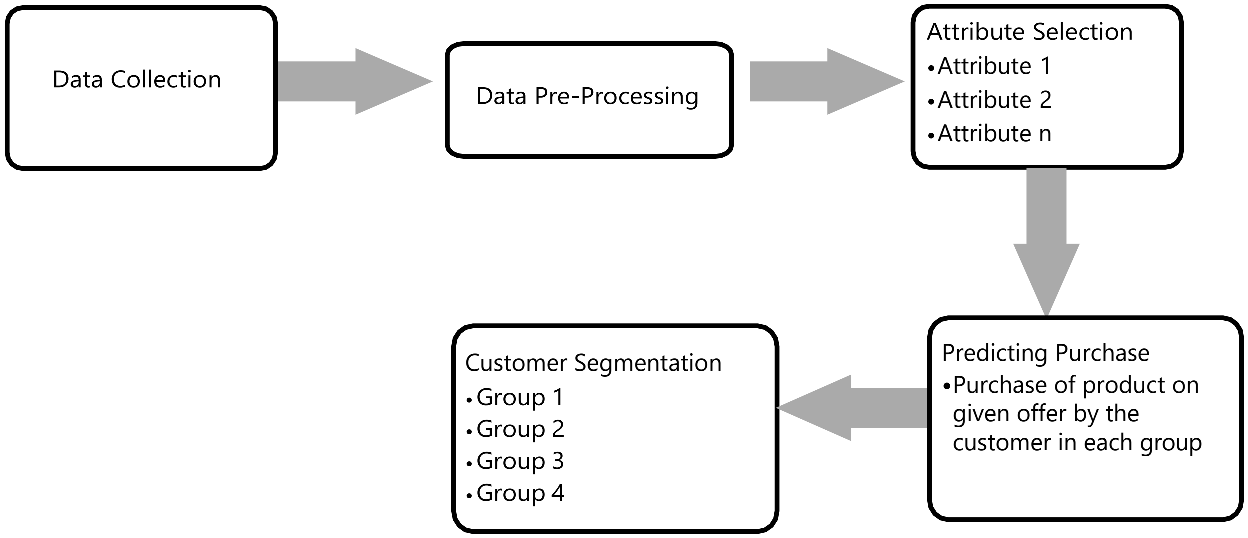


Figure 1. The proposed framework for predicting online purchases by a customer is based on Dynamic Pricing for online.

3.1 Data Collection

The initial and pivotal stage in the framework process is the gathering of data from diverse data points consolidated within an integrated database. For our research, we utilized a subset of data from an online marketplace. Figure 2 illustrates the schema of the two datasets employed in the study.

Customer ID	Store Chain	Store Department	Product Category	Product Company	Product Brand	Purchase Date	Product Size	Product Measure	Purchase Quantity	Purchase Amount

Offer ID	Product Category	Product Quantity	Product Company	Offer/price Value	Product Brand

Figure 2. The first schema corresponds to the transaction database, which contains all the customer's transaction records, while the second schema corresponds to the offer database, where different offers in terms of price deductions were mentioned concerning products, categories, and companies.

The transaction database primarily consisted of categorical data for numerous variables, with various IDs corresponding to elements such as customer, chain, department, category, company, brand, size, and measure. Notably, purchase quantity and amount emerged as continuous variables within this dataset. Similarly, in the offers database, only offer value and product quantity were continuous, while other variables were categorical. The database documented a total of 350 million transactions involving approximately 2.4 million distinct customers. For our analysis, we focused on customers who were offered and utilized promotions, resulting in a dataset comprising all customers with varied price ranges when purchasing products from specific categories, companies, and brands.

3.2 Data Pre-Processing

This stage involves processing all the gathered data based on its relevance to the prediction of prices. Additionally, preprocessing is essential to structure data sheets for specific analytical tools used in the study, including R, SAS, and Excel. Since the data was not initially in a continuous form, new variables were created to enhance its meaningfulness. The derived variables include purchase by offer (POR), purchase by category (PCT), purchase by quantity (PQT), purchase by company (PCY), purchase by brand (PBD), and purchase by channel (PCN). These variables were computed by aggregating the total purchase amount of a specific customer and tallying the total number of offers, categories, quantities, companies, brands, and channels considered for the customer's purchased products. The resulting values were obtained by dividing the two respective totals. To ensure data accuracy, outliers were eliminated, and the data was aggregated for various analytical tests.

3.3. Attribute Selection

In this phase, the selection of attributes is crucial for conducting customer segmentation. For a new customer, various attributes such as visit attributes, demographic profiles, context, purchase history, and purchase intentions should be utilized from the selected data. However, in the current study, the focus is solely on repeat customers chosen to provide a specific case for the project. Among repeat customers, the primary variables considered include POR, PCT, PQT, PCY, PBD, PCN, purchase amount, and purchase quantity. These attributes are employed to identify similarities among different customers, facilitating the grouping of users with similar characteristics.

3.4 Customer Grouping

Customer grouping is achieved by leveraging selected attributes and utilizing the K-means clustering algorithm to ascertain similarity among users. The resulting clusters are presented in Table 1 and Figure 2. The overall coefficient of variation is determined to be 83%, encapsulating a significant portion of the dataset.

Table 1 Clusters formed for the various customers.

Variables	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Frequency	5000	223455	86903	**94565**
RMS-SD	1.33	0.40	0.60	**0.93**
Variable 1 - POR	1.34	0.34	0.44	**0.92**
Variable 2 - PCT	1.55	0.24	0.56	**0.75**
Variable 3 - PQT	1.23	0.55	2.87	**1.37**
Variable 4 - PCY	1.45	0.20	1.22	**1.11**
Variable 5 - PBD	1.99	0.17	0.22	**2.14**
Variable 6 -	**2.19**	**0.12**	**0.13**	**0.43**

3.5 Dynamic Pricing

Utilizing the identified customer segments, the dynamic price range for each segment is established. Dynamic Pricing employs a combination of statistical and machine learning techniques to pinpoint the suitable price range for each segment. Supervised learning proves to be more effective, leveraging past data to achieve greater accuracy. Assigning distinct price ranges to different segments proves beneficial, allowing for a more targeted approach tailored to the unique characteristics of each segment. The regression equation formulated for the cluster is expressed as follows.

$\beta = PORi+ PCTi+PQTi+PCYi+PBDi+PCNi\ Di + \beta 6PCNi$

Where Pi is the price of the ith cluster, and P’s are the coefficients of the slope and independent variables for every For each cluster, the price range is illustrated by the customer's purchasing power, resulting in distinct price ranges for each cluster. When a customer makes a repeat purchase from the store, their purchasing power is assessed using historical datasets. Depending on their spending and purchasing patterns, they are then categorized into a specific cluster. Predictions for their price range are made based on the cluster, and an offer value is determined for the customer. The regression results for the four clusters, based on purchasing power variables, are presented in Table 2. The overall variation within the clusters is significant enough to validate the obtained price range. Using these models, the price range for individual customers is deduced.

Table 2 Regression results for price prediction for individual clusters

Constant	0.04233*	0.050*	0.0325*	0.0251*
Variable 1 - POR	0.0676*	0.020*	0.04375	0.04265*
Variable 2 - PCT	0.423798*	0.250*	0.26886*	0.16325*
Variable 3 - PQT	0.202211	0.240*	0.2575*	0.3457*
Variable 4 - PCY	0.439663*	0.150	0.28225*	0.42875*
Variable 5 - PBD	0.315865*	0.100*	0.2125	0.2755*
Variable 6 - PCN	3.137064*	0.890*	1.21375	1.43745
R-Square	0.73	0.83	0.81	0.89
Price Range	$400-$400	$1000-$1500	$2000-$4000	$20000-$25000

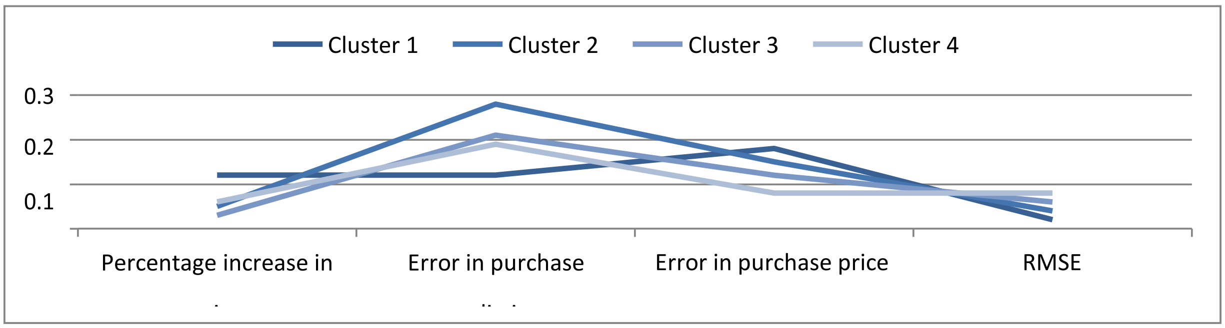
Significant at 0.05 level ** Significant at 0.01 level

3.6 Predictive Modeling

In this phase, Logistic Regression is employed to forecast whether, within a suitable customer group and a designated price range determined by dynamic pricing methodology, a customer is inclined to make a purchase or not. Opting for a binary predictor aligns with the outlined framework, aiding in discerning the ultimate purchase behavior of the customer. The outcomes of the logistic regression, considering purchasing power and price prediction from multiple regression, were computed using the dataset. The entire dataset was split into a training set and a test set in a 4:1 ratio. The area under the curve is illustrated in Figure 3.

4. Result and Discussion

The framework crafted for price prediction undergoes scrutiny for purchase predictions and the potential revenue benefits it can yield. When compared to a scenario where the same product is offered at a fixed price for a specific customer group, our proposed model demonstrates a more effective revenue generation system with fewer errors in predicting customer purchases. The outcomes are depicted in Figure 4. This framework is adept at accurately forecasting customer purchase behavior. Over time, as more data is accumulated, supervised learning will enhance its accuracy, further aiding in precise predictions of purchase behavior.



The presented study introduces a comprehensive framework for predicting online customer purchases through dynamic pricing, employing a combination of statistical and machine learning methodologies. The focus on optimizing pricing strategies on e-commerce platforms, with an emphasis on selecting the most suitable purchase price, underscores the importance of personalized and adaptive pricing. The integration of K-means clustering facilitates customer segmentation, identifying unique customer groups with distinct purchasing patterns. The dynamic pricing model, supported by regression equations for each customer cluster, successfully establishes tailored price ranges. The utilization of diverse data sources, including visit attributes, purchase history, and contextual insights, forms a robust foundation for this framework. The incorporation of machine learning algorithms enhances the accuracy of predicting purchase decisions based on adaptive pricing strategies.

4.1 Customer Segmentation:

The application of the K-means clustering algorithm results in meaningful customer segmentation, yielding distinct clusters with specific purchasing behaviors. The clusters exhibit significant variability, as indicated by the overall coefficient of variation of 83%. This robust segmentation allows for a more targeted approach in tailoring pricing strategies to the unique characteristics of each customer group.

4.2 Regression Results

The regression results for each cluster, considering purchasing power variables, are noteworthy. The coefficients and R-square values demonstrate the efficacy of the model in capturing the variation in purchasing power based on the selected variables. The derived price ranges for each cluster provide valuable insights into the relationship between customer characteristics and their potential spending capacity.

4.3 Logistic Regression for Purchase Prediction

The subsequent application of Logistic Regression for purchase prediction within designated price ranges enhances the framework's predictive capabilities. The binary predictor aligns seamlessly with the outlined framework, aiding in discerning the ultimate purchase behavior of customers. The Area Under the Curve (AUC) analysis illustrates the model's predictive accuracy, further validating the effectiveness of the proposed approach.

4.4 Comparison with Fixed Pricing

Comparative analysis with a scenario involving fixed pricing for specific customer groups reveals the superior revenue generation system and reduced errors in predicting customer purchases offered by the proposed dynamic pricing model. The outcomes, as depicted in Figure 4, underscore the potential economic benefits and improved customer targeting achieved through the dynamic pricing framework combining all of this.

5. Conclusion and Future Work

The devised framework utilizes potent methodologies such as Machine Learning, Data Mining, and Statistical Methods to forecast the buying patterns of online customers. This involves determining a suitable price range for customers through Dynamic Pricing. In conclusion, this study presents a holistic framework for predicting online customer purchases through dynamic pricing, leveraging a combination of statistical and machine learning methodologies. The emphasis on optimizing pricing strategies on e-commerce platforms, with a focus on selecting the most suitable purchase price rather than simply the cheapest, underscores the significance of personalized and adaptive pricing. The integration of K-means clustering aids in customer segmentation, identifying unique customer groups with distinct purchasing patterns. Supported by regression equations for each cluster, the dynamic pricing model establishes tailored price ranges, allowing for more precise targeting. Logistic regression further enhances the framework by predicting customer purchases within these customized price ranges, contributing to a nuanced understanding of customer behavior.

Looking ahead, there are promising avenues for future research in the dynamic pricing domain. An advanced exploration into personalized adaptive pricing, considering individual customer preferences, can refine the model further. Investigating real-time dynamic pricing strategies, particularly in rapidly changing market conditions, holds potential for enhancing the efficacy of the framework. Expanding the scope of data sources beyond current variables could provide a more comprehensive understanding of customer behavior. Assessing the applicability of the proposed framework across diverse industries and sectors will contribute to its versatility. Lastly, ethical considerations, including fairness, transparency, and customer trust, warrant continued exploration as dynamic pricing evolves in response to shifting consumer landscapes. In essence, this proposed framework lays a solid foundation for future research endeavors, anticipating the development of more sophisticated models and strategies aligned with the dynamic nature of e-commerce and online consumer behavior.

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References

[1] Al-Imran, M., Chowdhury, M. S., Ayanle, A. D., & Masum, A. A. (2022). Assessment of Micro Insurance as an Emerging Microfinance for the Poor: A Study on Somalia. *American International Journal of Business and Management Studies.* 4(1), 12-21. [Available from: https://doi.org/10.46545/aijbms.v4i1.280].

[2] Ayanle, A. D., Chowdhury, M. S., Al-Imran, M., & Rahman, S. (2022). The Role of Microcredit and Micro Savings for Raising Microfinance Sustainability in Somali. *Bangladesh Journal of Multidisciplinary Scientific Research.* 6(1), 30-39. [Available from: https://doi.org/10.46281/bjmsr.v6i1.1925].

[3] Abu Md S, Tayaba, M., Islam, M. T., Md Eyasin Ul I P, Md Tuhin M, Eftekhar H A, Nur N, & Bishnu P G. (2023). Parkinson's Disease Detection through Vocal Biomarkers and Advanced Machine Learning Algorithms. *Journal of Computer Science and Technology Studies*, *5*(4), 142–149. https://doi.org/10.32996/jcsts.2023.5.4.14

[4] Ahmed, A. H., Ahmad, S., Sayed, M. A., Ayon, E. H., Mia, T., & Koli, A. (2023). Predicting the Possibility of Student Admission into Graduate Admission by Regression Model: A Statistical Analysis. *Journal of Mathematics and Statistics Studies*, *4*(4), 97-105.

[5] Chowdhury, M. S., Al-Imran, M., Faisal-E-Alam, M., Hoque, M. E. U. & Parvin, T. (2022). Investigating the Financial Strength in the Energy Sector: A Study on TGTDCL. *American International Journal of Humanities, Arts and Social Sciences.* 4(1), 15-24. [Available from: https://doi.org/10.46545/aijhass.v4i1.285].

[6] Gupta, R., & Pathak, C. (2014). A machine learning framework for predicting purchase by online customers based on dynamic pricing. *Procedia Computer Science*, *36*, 599-605.

[7] Haque, M. S., Amin, M. S., Miah, J., Cao, D. M., Sayed, M. A., & Ahmed, S. (2023). Retail Demand Forecasting: A Comparative Study for Multivariate Time Series. *Journal of Mathematics and Statistics Studies*, *4*(4), 40-46.

[8] Ho, W. K., Tang, B. S., & Wong, S. W. (2021). Predicting property prices with machine learning algorithms. *Journal of Property Research*, *38*(1), 48-70.

[9] Khan R. H., Miah J., Rahman M. M. and Tayaba M (2023) A Comparative Study of Machine Learning Algorithms for Detecting Breast Cancer, 2023 IEEE 13th Annual Computing and Communication Workshop and Conference (CCWC), Las Vegas, NV, USA, 2023, pp. 647-652, doi: 10.1109/CCWC57344.2023.10099106.

[10] Khan, R. H., Miah, J., Arafat, S. M., Syeed, M. M., & Ca, D. M. (2023). Improving Traffic Density Forecasting in Intelligent Transportation Systems Using Gated Graph Neural Networks. *arXiv preprint arXiv:2310.17729*.

[11] Khan R. H. and Miah J., (2022) Performance Evaluation of a new one-time password (OTP) scheme using stochastic petri net (SPN), 2022 IEEE World AI IoT Congress (AIIoT), Seattle, WA, USA, 2022, pp. 407-412, doi: 10.1109/AIIoT54504.2022.9817203.

[12] Li, X., Xu, M., & Yang, D. (2021). Cause-related product pricing with regular product reference. *Asia-Pacific Journal of Operational Research*, *38*(04), 2150002.

[13] Mridha, M. M., Hossain, M. S., Chowdhury, M. S., Al-Imran, M. & Debnath, D. (2023). Factors influencing consumers' attitude towards online shopping in Rangpur City. *International Multidisciplinary Research Journal.* 13, 16-26. [Available from: https://doi.org/10.25081/imrj.2023.v13.8324].

[14] Miah, J., & Khan, R. H. (2019, November). Service Development of Smart Home Automation System: A Formal Method Approach. In *Proceedings of the 2019 2nd International Conference on Computational Intelligence and Intelligent Systems* (161-167).

[15] Miah, J., Ca, D. M., Sayed, M. A., Lipu, E. R., Mahmud, F., & Arafat, S. M. Y. (2023). Improving Cardiovascular Disease Prediction Through Comparative Analysis of Machine Learning Models: A Case Study on Myocardial Infarction. arXiv preprint, 2311.00517.

[16] Miah, J., Cao, D. M., Sayed, M. A., & Haque, M. S. (2023). Generative AI Model for Artistic Style Transfer Using Convolutional Neural Networks. *arXiv preprint arXiv:2310.18237*.

[17] Miah J, Khan R. H., Ahmed S. and Mahmud M. I., (2023) A comparative study of Detecting Covid 19 by Using Chest X-ray Images– A Deep Learning Approach, 2023 IEEE World AI IoT Congress (AIIoT), Seattle, WA, USA, 2023, 0311-0316, doi: 10.1109/AIIoT58121.2023.10174382.

[18] Namburu A, Selvaraj V M. (2022) Product pricing solutions using hybrid machine learning algorithm. Innov Syst Softw Eng. 2022 Jul 25:1-12. Doi: 10.1007/s11334-022-00465-3. Epub ahead of print. PMID: 35910813; PMCID: PMC9309595.

[19] Peiseler, F., Rasch, A., & Shekhar, S. (2022). Imperfect information, algorithmic price discrimination, and collusion. *The Scandinavian Journal of Economics*, *124*(2), 516-549.

[20] Syeed, M. M., Khan, R. H., & Miah, J. (n.d) Agile Fitness of Software Companies in Bangladesh: An Empirical Investigation.

[21] Sayed, M. A., Ahamed, S., Cao, D. M., Pavel, M. E. U. I., Sarkar, M., & Mia, M. T. (2023). Parkinson's Disease Detection through Vocal Biomarkers and Advanced Machine Learning Algorithms: A Comprehensive Study. *arXiv preprint arXiv:2311.05435*.