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Transforming E-Commerce: Unleashing The Potential Of Dynamic Pricing Optimization Through Artificial Intelligence For Strategic Management

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Abstract

Online pricing is quite straightforward and might be the main factor in an online purchase. Even while price volatility is not new and is frequently used to boost sales and profitability, online businesses really benefit from it. The suggested study is the outcome of an ongoing project that intends to improve customers' ability to acquire the proper price on an e-commerce platform by employing reliable machine learning algorithms to produce a broad structure and relevant methodologies. Although the focus of this study is mostly on inventory-led e-commerce businesses, online marketplaces without stocks can also adopt this paradigm. With the use of statistical and machine learning methods, the study aims to forecast consumer choices based on dynamic or adaptive product pricing.

Keyword: *Artificial Intelligence, E-Commerce, Dynamic Pricing, Strategic Management.*

Introduction

Dynamic pricing, which adjusts rates based on inventory levels and demand, has gained popularity since the airline sector was deregulated in the 1970s. [1] and [2] provided an overview of studies on perishable-asset revenue optimization, which includes managing yield, overbooking, and pricing. During recent corporate development, numerous sectors have been more active in managing revenue. Uber surge pricing method has been shown to significantly increase driving motivation [[1]3]. Zara has introduced a dynamic discount pricing strategy [4]. Kroger is testing electronic price tags at one shop in Kentucky. Because of the increased complexity of their operations, online merchants have a greater urge for dynamic pricing techniques. For example, Amazon.com offers 356 million goods (562 million today). In 2017, Walmart.com sold an estimated 4.2 million goods (2). Taobao.com is China's largest e-commerce marketplace, now selling billions of items. Implementing dynamic cross-selling on the Internet presents various obstacles. The programme should determine which goods to cross-sell based on inventory and client preferences, rather than relying on sales associates to inquire further. Dynamic cross-selling involves responding to each customer's purchase attempt, rather than using static criteria. Implementing dynamic cross-selling can be challenging as it generally involves offering discounted bundles,

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resulting in reduced profit margins. If a product in a package has little inventory, it may be more advantageous for a corporation to sell it individually. This is because the product is likely to sell at full price later.2 To make effective cross-selling selections, consider current inventory levels.

Setting optimum pricing for items is crucial in the ever-changing retail market [5]. Dynamic pricing is a complex strategy that adjusts rates in real time based on many parameters, replacing traditional pricing systems that used preset, seldom updated tags. Dynamic pricing is gaining popularity due to AI, which allows companies to make data-driven pricing choices quickly. This article examines the relationship between AI-driven price changes and Electronic Shelf Labels (ESLs) and their significant influence on retail. Dynamic pricing is a popular approach for maximising income, adapting to market trends, and meeting customer wants. AI-powered algorithms are at the heart of this price revolution, allowing merchants to respond quickly and precisely to a constantly shifting marketplace. Electronic shelf labels are a key component of this progression [6]. Digital price tags enable merchants to rapidly change pricing, promotions, and product information, improving the consumer experience and reducing internal processes. AI-driven dynamic pricing and ESLs provide significant benefits to merchants who use them. This article is organised into parts, each of which focuses on a distinct facet of the revolutionary retail approach. We will begin by presenting a summary of dynamic pricing, including its historical context and rising relevance in the retail industry [7].

Next, we'll discuss how Electronic Shelf Labels may help unlock the benefits of dynamic pricing. ESLs use cutting-edge technology to improve price uniformity, efficiency, and connection with customers. We will analyse how they affect shop environments and consumer perceptions. We will give case studies of shops who have successfully implemented AI-driven price adjustment with ESLs to demonstrate its practical advantages. These examples demonstrate how dynamic pricing may adjust according to supply and demand swings, follow rival price tactics, and adapt to changing customer behaviour. The presentation will cover ethical issues and potential difficulties about AI-driven dynamic pricing and ESL adoption. Retailers must prioritise openness, fairness, and consumer trust while implementing creative techniques.

Using these technologies can help shops compete in an increasingly competitive marketplace while also improving customer experience and assuring long-term success in data-driven retail. The effect on the mobile communication industry [8] can be ascribed to lower call prices, more competition, and enhanced network infrastructure. The car sector benefits from improved coordination between manufacturing processes and inventory choices, resulting in a direct-to-consumer business model [9]. Dynamic pricing has becoming increasingly popular due to improved network connectivity [10]. This has benefited both customers and vendors by reducing menu costs and providing a comprehensive database of customer information [11]. The internet has enabled self-service for buyers and customers, saving them time. Dynamic pricing, combining online connectivity and automation, benefits suppliers in several ways. The vendor's physical presence is eliminated [12], input costs are reduced, client information is integrated into a single database, and fresh catalogues are printed at a cheaper cost [13]. Additionally, it provides a venue for customers and sellers to debate and share reviews, resulting in improved services.

Dynamic pricing involves re-pricing items based on competitive prices. Prices are reduced during shortages and increased during high demand circumstances. This approach improves profitability for sellers by establishing appropriate pricing [14]. Dynamic pricing can also be implemented using short-term cycles, such as temporary and permanent markdowns. Temporary markdown refers to a deal that provides a defined reduction for a set period before reverting to the original price. Permanent markdown, often known as clearance, is when a product's upcoming price is lower than its present price.

Dynamic pricing is widely used in numerous sectors to improve purchasing and selling processes. Dynamic pricing has proven effective in several industries, including airlines, hotels, electric utilities, retail, online shopping, mobile communication systems, automobile, sporting events, vehicle rental, and insurance. Flexible pricing in the aviation business is often referred to as yield or revenue control [15]. The approach entails categorising passengers into three categories: business travellers, casual travellers, and hybrid travellers. In the automobile industry [16], dynamic pricing combines production plans with inventory choices to optimise supply chain management and profitability. Dynamic pricing improves customer demand presentation and equipment manufacturer status, providing additional benefits.

Literature Review

In today's environment, dynamic pricing is determined using various models. Many are used to set pricing for a wide range of items, while others are tailored to specific costs. There are several approaches for determining prices [17].

Agent-based modeling uses factors, agents, and rules to analyse individual or group pricing using computational techniques and actions. Inventory Based Model focuses on the amount of inventory and customer service. It may be further subdivided into three categories: replenishment and non-replenishment inventory, which comprises the pricing choice based on fixed inventory at a certain time the gradual replenishing of inventory in response to demand and supply. The second sub-division is reliant on and autonomous from demand over time, which refers to changing client expectations. With a data-driven model, prices are set using information gathered about consumer preferences and purchasing habits. When there are more sellers than customers, the Game Theory Model is used, considering more economic concepts. The Machine Learning Model integrates the utilisation of e-markets to comprehend consumer preferences and trends, as well as the use of algorithms to optimise profits. Any paradigm of decision-making may be applied to a simulation model. Furthermore, any of the other models listed may be utilised as a simulation model.

Six essential elements are needed for the Auction Based Model's dynamic pricing to be successful. There are several key components to an auction: a resource that needs to be auctioned off, a market structure that buyers and sellers have defined, a choice structure that involve product preferences provided by the agents, a bid structure that defines the versatility of the resource demand, market clearing that includes matching supply and demand, and information feedback that signals price to a bidder so they can adjust their bid in accordance with the winning bid. Combining the impacts of many models, which may have solved the Purchase Behaviour problem through adaptive pricing in a far more thorough manner, was not practical with the different models that were currently in use. Considering this, the present study suggests creating a framework that would maintain changing prices as the primary issue that needs to be resolved and identify the relevant client category in addition to projecting his most probable buy range. It is believed that the framework would provide effective outcomes.

Methodology

The agent regularly modifies the product pricing because of monitoring the situation of the environment. After that, the reward and the altered condition of the environment may both be witnessed. If an item is out of stock, then each price episode comes to an end. Prior to being utilised for offline evaluation, the model has been trained using previous sales data and pricing decisions made by prior specialists.

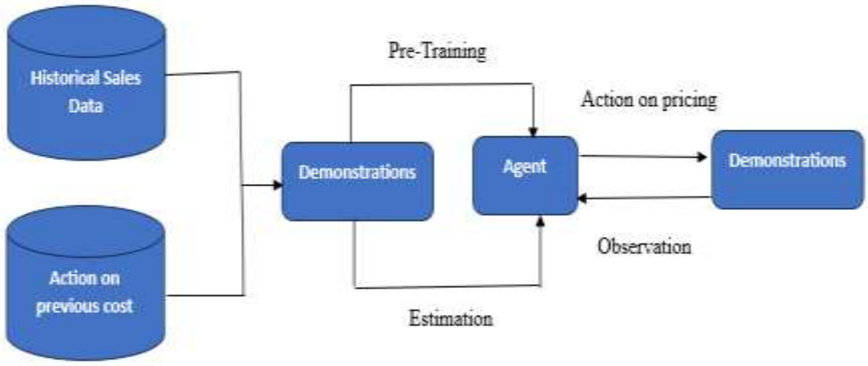

Fig. 1. Dynamic cost methodology with illustration on e-commerce platform

We examine a scenario where a collection of m items is sold via an online retailer. It is presumed that every product within the group caters to comparable market categories or is complimentary, hence offering the possibility of cross-selling (see to the introduction for examples). We also suppose that the scheduling horizon is divided into N decision epochs and is finite, meaning it represents the interval of time that separates two inventory replenishments [26]. The business looks at each product's inventory at the start of each decision era and decides on cross-selling (packaging and price). Making decisions about packing and price may happen as often as needed in an online setting, allowing for shorter decision epochs than a normal customer's wait time. As a result, we presume that there is just one consumer arriving for each period.

We represent the $\mu_j, j = 1, \ldots\ldots, n$, the possibility that during any time interval class j customer comes and request every unit of the j^{th} item. Subsequently, describe the possibility that customer arrival does not buy the item, but the issues can be re-calculated easily to focus on the customers who are able to purchase. The following succinctly describes the significant contribution of AI-driven dynamic pricing using Electronic Shelf Labels (ESLs): Enhancing Pricing Methods: Retailers may instantly optimise their price strategy using AI-driven dynamic pricing [18]. Retailers may increase profits and better adapt to market changes by utilising AI, which analyses a massive quantity of data, including rival pricing, market circumstances, past sales history, and consumer behaviour. Enhanced Revenue: By guaranteeing that items are priced to best meet the greatest demand at any given moment, AI-driven dynamic pricing might result in heightened revenue. With the ability to rapidly modify pricing in reaction to variations in demand, this technology can assist maximise profits during periods of high sales and reduce losses during periods of low sales.

Improved Customer Experience: Real-time pricing adjustments and information display are made possible by Electrical Shelf Labels (ESLs) [19,27]. Customers may have a more consistent and pleasurable shopping experience because of being able to rapidly learn about specials and product details, as well as having confidence that the prices shown on ESLs are correct. Operational Efficiency: ESLs eliminate the need for labour-intensive and prone to mistake manual price tag changes. Both labour expenses and operational efficiency are increased as a result. Additionally, retailers can alter prices for a whole product category or store at once. Inventory management: Retailers may more efficiently manage their inventory by utilising AI-assisted dynamic pricing. Retailers may minimise the expenses related to keeping surplus inventory and decrease overstock by modifying pricing based on inventory levels.

Personalisation: AI-powered dynamic pricing allows for the customisation of rates for certain clientele groups. This customisation may consider past purchases, browsing habits, consumer loyalty, and other factors. It enables merchants to provide specials and discounts that are targeted to clientele groups [20]. Adapting to Market Fluctuations: Seasonality, shifts in the economy, and world events are just a few of the unpredictability's that affect the retail market. Retailers can quickly adjust to these variations and continue to be profitable thanks to AI-driven dynamic pricing. Retailers need to be aware of the ethical ramifications of AI-driven price changes, including the need to refrain from exploitative or discriminatory pricing. Retaining client trust requires fairness and transparency [21].

The future of retail is a dynamic and revolutionary landscape with various important consequences, marked by the integration of Artificial Intelligence (AI) in pricing optimisation and Electronic Shelf Labels (ESLs). Improved Customer Experience: By giving customers access to real-time pricing changes and product details, ESLs enable merchants to improve the whole shopping experience. Customers may simply access product details, specials, and reviews, and they can rely on the accuracy of the pricing they see. AI-driven personalisation makes the buying experience more engaging and customer-focused by adapting to individual preferences. Dynamic Pricing Accuracy: Retailers may achieve remarkably accurate pricing optimisation because to AI's data analysis capabilities. Retailers can instantly modify their rates in response to a variety of circumstances, including demand, rival pricing, and even the actions of specific customers [22].

Data Collection

This is the most important and initial stage in the framework process. It entails gathering information from several data sources and organising it into an integrated database. We utilised a portion of an online marketplace's data for the study. The dataset schema is illustrated in table 1.

Table.1. Schema of Transaction Database

Customer ID	Store section	Company of item	Item brand	Date of purchase	Size of item	Measurement of item	Quantity of item	Amount of purchase
Offer name	Section of category	Price of offer	Item brand					

Since the variables such as consumer, chain, department, category, business, brand, size, and measure represented several IDs, most of the variables in the transaction database included categorical data. It was discovered that the purchase quantity and amount were continuous variables. Like this, the offers database only included continuous fields for offer price and product quantities; all other fields were categorical. In the database of about 2.4 million distinct clients, there were 350 million transactions altogether [24]. We only considered the clients who accepted the offers that were made to them for the transactions. In this method, we were able to compile a database of all the clients who bought items from different companies, brands, and categories within a range of prices.

Data Pre-processing

In this stage, all the data that has been gathered is processed based on how relevant it is to the price projection. To generate information sheets for the instruments needed for analysis, preprocessing is also necessary. Excel, SAS, and R were the instruments utilised in this investigation. Since the information was not continuous, additional variables had to be developed to produce data that was more useful. Buying by offer (POR), buy by category (PCT), buy by quantity (PQT), buy by company (PCY), buy by brand (PBD), and buy by channel (PCN) are the derived variables. These were determined by adding up each client's total purchases, calculating the overall amount of offers, and considering the firm, brand, channel, category, and quantity for each consumer [25]. After removing the data's outliers, the data was cleaned up for the several analytical tests. To carry out client segmentation, this phase entails choosing the qualities. To discover a specific instance for this project, only repeat consumers were taken into consideration in the current research. For a new client, visit characteristic, socioeconomic context, history of purchases, and purchase intents should be used as various characteristics from the selected data.

Selected characteristics are used to conduct customer grouping. The K-means clustering technique is employed to determine user similarities. A significant amount of the data set is covered by the overall coefficient of variance, which is determined to be 83%.

Parameters	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Frequency	4587	123207	76355	18321
RMS-SD	1.32	0.58	0.55	0.82
Parameter-POR	1.24	0.12	0.25	0.72
Parameter-PQT	1.67	0.12	2.67	1.21
Parameter-PCY	1.77	0.32	0.24	1.02
Parameter-PBD	1.84	0.16	0.23	1.14
Parameter-PCN	1.19	0.10	0.09	0.32

Active Pricing

The dynamic pricing range is established for every segment based on the different client segments that have been identified. Statistical and machine learning methods are used in dynamic pricing to determine the right price range for every section. Because supervised learning may reach greater accuracy based on historical data, it is more productive [28]. It will be helpful to allocate a separate price range to each section in order to focus attention on a specific group due to its unique features. The following is the regression equation that was created for the cluster:

$$l_i = \mu_o + \mu_1 POR + \mu_2 PQT + \mu_3 PCY + \mu_4 PBD + \mu_5 PCN \quad (1)$$

Since the customer's purchasing power is the cost range for every group, each cluster will have a distinct price range. Every time a consumer makes a repeat purchase, the purchasing power is identified using past data, and the customer is categorised into a particular cluster according to his buying and purchasing habits. The price range is estimated depending on the cluster, and the consumer is shown receiving an offer value.

Algorithm 1: Estimation of policy and illustration

Input: R> 0: total demonstration tuples for estimation. π: the estimation of policy

Output: t_π: average prize from policy α;

begin

T←0, M← 0;

for phase r϶ {1, 2…..R} do

repeat

tuple phase $<f_t, b_t, t_r, f_{r+1}>$;

S← $S + t_r, M \leftarrow M + 1$;

if M>0 then

S_π=S/M

else

$S_\pi = 0$

Result and Discussion

In the retail industry, the use of Electronic Shelf Labels (ESL) in conjunction with AI-Driven Dynamic Pricing has produced impressive results. Retailers can now fine-tune their pricing strategy in real time, increasing sales, improving margins, and boosting total profitability thanks to this state-of-the-art technology. AI-driven pricing algorithms help businesses establish the best rates for their items by considering a number of variables, including past sales data, rival pricing, and variations in demand. ESLs also guarantee pricing uniformity and accuracy across the business, which lowers pricing mistakes and improves client shopping.

Retailers have therefore seen notable increases in revenue, improved operational effectiveness, and more flexible reactions to shifts in the market. Furthermore, a higher degree of openness about prices and consumer confidence is fostered by the synergy among AI-driven pricing algorithms and ESLs. With access to real-time price information, shoppers can make better-informed judgements about what to buy, and shops may foster customer loyalty by using fair and transparent pricing strategies. In summary, the amalgamation of artificial intelligence with extended shelf life technology not only provides merchants with enhanced pricing tactics but also fortifies consumer bonds, hence propelling long-term prosperity in the ever-changing and fiercely competitive retail sector.

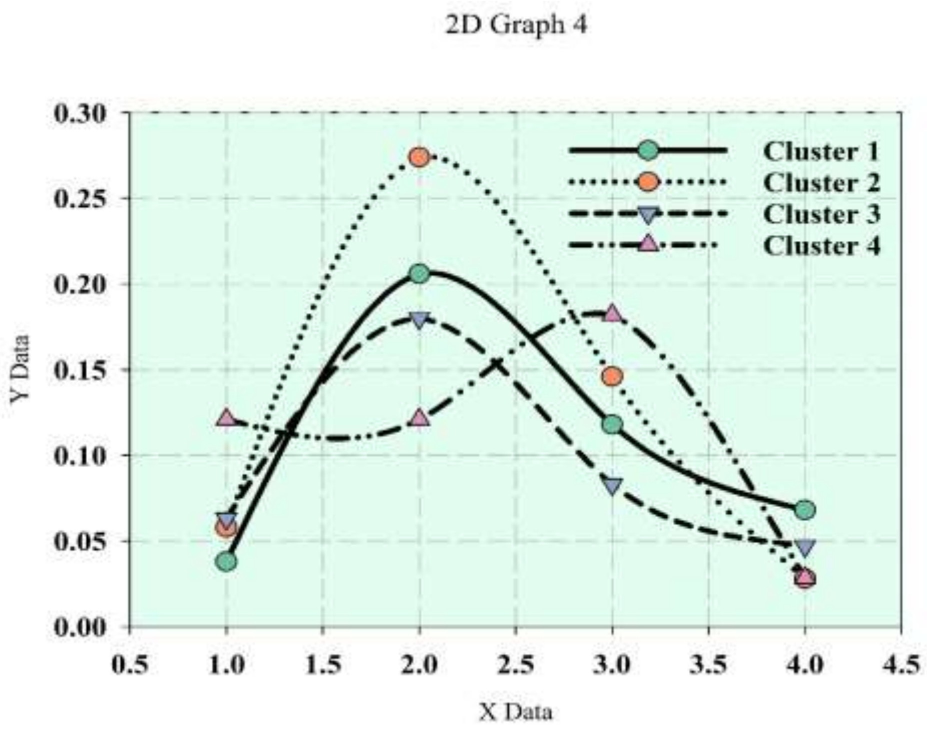

Fig.2. Illustration of outcome obtained from the analysis

The quantity of revenue advantages and purchase forecasts that can be generated by the price prediction framework are examined. Our suggested model observed a superior revenue generating system with less mistakes in forecasting client purchase for the same item given at a constant price for a specific set of consumers. Figure 2 presents the findings.

The customer's purchasing behaviour may be appropriately predicted by the framework mentioned above. Supervised learning will yield more accurate findings and be useful in deciding correct outcomes for buying behaviour as time goes on and more data is gathered.

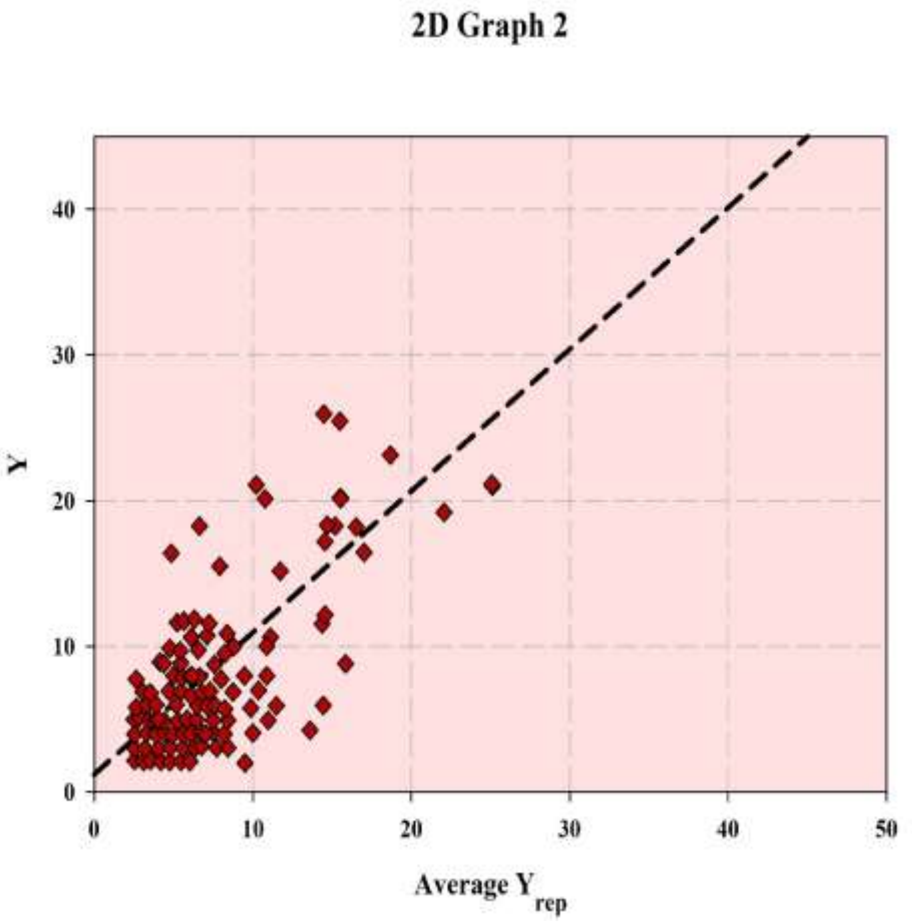

Fig.3. Average customer opinion for the item purchased on E-Commerce platform

The E-commerce platform sells different item irrespective of the categories, figure 3 depicts the average customer opinion for items that are purchased the most frequently in the E-commerce platform for a particular period. We saw many daily management operations during this portion of the trial (with some vouchers given out). Just under ten percent of overall revenue was impacted by these activities. Since the previously discussed link between simi-products could still be seen which is illustrated in figure 4.

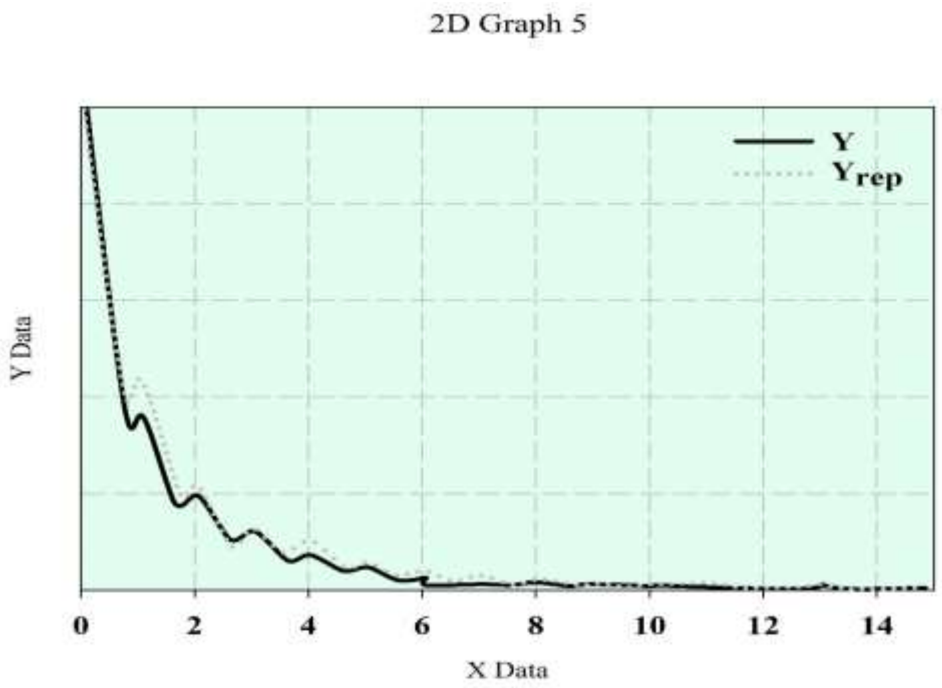

Fig.4. Average customer opinion for the item purchased on E-Commerce platform and offline

The E-commerce platform sells different item irrespective of the categories, figure 4 depicts the average customer opinion for items that are purchased the most frequently in the E-commerce platform and offline for a particular period.

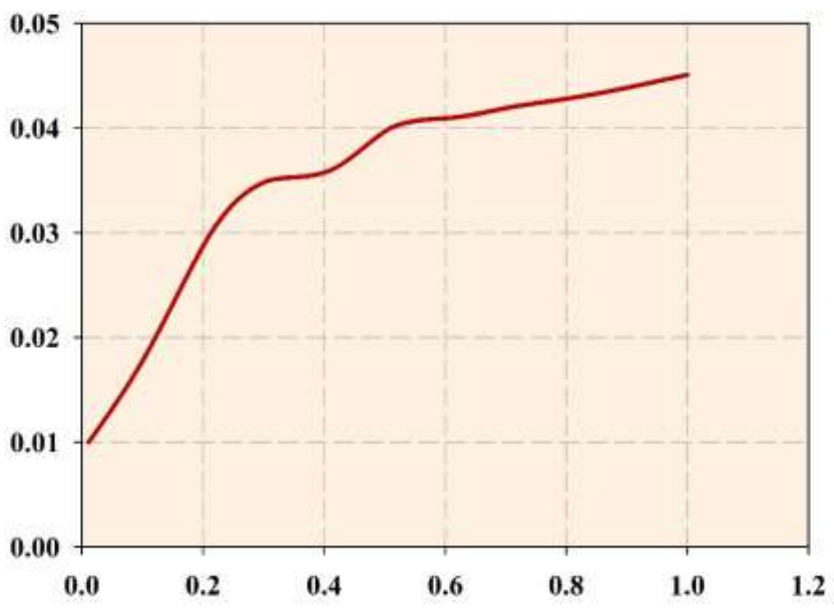

Fig.5. ROC arch for logistic regression

With the aforesaid framework, a binary classifier is a suitable option that aids in determining the customer's ultimate buying behaviour. The data set was used to determine the results of a logistic regression analysis based on buying power and cost prediction using multiple regression. The train set and testing set were created by splitting the whole data into a 4:1 ratio. Figure 5 shows the area below the curve.

Conclusion

The suggested framework has been created utilising the potent methods of data mining, machine learning, and mathematical techniques to forecast an online customer's purchasing behaviour by choosing a suitable price range for them based on price dynamics. The results of this framework's testing on an extensive data set for an online retailer are positive enough to warrant the framework's full implementation. Error rates are lowered and a far better pricing range that benefits the organisation and the client is established. The main architecture may be customised for applications and used in a variety of online sectors. The expansion of this study is anticipated to include a discussion of the work-in-progress outcomes. We saw many daily management operations during this portion of the trial (with some vouchers given out). Just under ten percent of overall revenue was impacted by these activities.

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