Personalized Marketing Strategies: Leveraging Ensemble methods and Collaborative Filtering for Targeted Promotions

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***Abstract*— Many retail companies have embraced the use of personalized targeting in order to lure customers and improve their satisfaction. In this research study, the Global Data Superstore Dataset is used to construct a model on how to have a unique promotion and recommendation to the clients and consumers in order to increase their satisfaction and therefore improve on the amount of sales made regularly by the respective consumers by considering their history of their previous purchases. Converging collaborative filtering, Random Forest classifiers, and ensemble methods the system provides targeted product recommendations and appropriate discounts.Targeted promotions at the user and the item levels are offered through methods of user –based and item-based collaborative filtering to predict subsequent purchases and respective discounts. Furthermore, it also incorporates predictive analysis to predetermine customers' buying behaviors and timely design promotional messages.This paper describes how the recommendation engine is constructed in this model with the data preprocessing step, predictive modeling, and promotional personalization step. The efficiency of the system lies within productivity boost from sales to customer satisfaction, promotions, and many more. In particular, this project offers a machine learning analysis of current customer segmentation and promotional techniques in retail to illustrate how retailers can offer more timely and targeted engagements with consumers.**

Keywords—Personalized Marketing, Collaborative Filtering, Random Forest, Machine Learning, Promotions, Retail Industry, Customer Satisfaction.

I. INTRODUCTION

In the present and ever-competitive retail market, the assessment of the customer and the ability to consider the customer requirements as a key factor in the overall retail production mix is crucial to improving sales and the perceived client value. Conventional trends of marketing communication such as the use of general promotions and discounts do not capture this variability in customer demographics and consumption patterns. These generic solutions create problems such as low efficiency, low customer attention and loss of sale revenues. To fill this gap, there has been an evolution to what is referred to as personalized marketing where marketing promotions are targeted at the individual consumers. When used in conjunction identifying the buying behaviors of target customers, retailers can provide personalized advertising offers that should be appealing to the target consumer, making it likely that consumer loyalty will be obtained.

Big data and developing machine learning technologies have shifted retailers from simple past practices of customer segmenting, to more sophisticated form of marketing. Collaborative filtering and ensemble learning methods are in the vanguard of this paradigm with their complex algorithms able to work through large amounts of customer data and extract purchasing patterns and likely future actions. There are seven basic techniques of recommender systems, among which the most effective is collaborative filtering, especially concerning the presentation of product recommendations based on similar users' previous behaviors or similar items. In conjunction with ensemble methods Random Forest and Gradient Boosting the effectiveness of these algorithms rises enhancing the accuracy of recommendation and promotion offering.

In this research work, the proposed problem statement is to design a promotional model in a retail chain environment based on the application of machine learning. The system is aimed at improving customer satisfaction as well as sales through recognition of customer purchase behavior. The order predictions themselves are driven through combined processing of the collaborative filtering methods and ensemble models, and thus the next probable purchase of the individual customer is computed, which is then followed by the relevant promotions triggered to the individual based on such a specific prediction. This not only cements relevancy of promotion offers given to the customer but also benefits the retailer in terms of its marketing efforts towards the customer as only possible promotional offers that have high chances of making it to the sale section are marketed to the customer.

The proposed system incorporates two types of collaborative filtering: user-based and item-based. User-based collaborative filtering reviews the behaviour of other similar users to provide recommendations, but item-based filtering focuses on the compare similarities in customers' item purchases. Both are also complemented by ensemble learning methods including the Random Forest classifier that is used on features of purchase history, frequency and products preferences in order to predict customer behaviour. Moreover, the system comes equipped with a predictive modelling that predict the next purchase and working discounts depending on the given customer's behavior.

The integration of these models into a whole framework of recommendation engine allows the system to suggest particular promotions to the client. The recommendations are constantly refined for increased efficacy with performance measures such as sales increase, numbers of clicks from customers or the rates of use of given discounts by customers. Moreover, the proposed system is general and extendible since it can work with different and various retail settings and the customer data.

In the next sections we will describe main techniques and approaches that have been applied in the development of this personalized marketing system, such as the data preprocessing, model selection, as well as the system architecture. We will also compare the efficacy of the proposed system against conventional marketing techniques and argue how collaborative filtering and ensemble learning improve the effectiveness of targeted advertising. This study is intended to show that customer segments open possibilities for the new revolutionary retail strategies based on personalized marketing information.

II. Related works

Pratama, B.Y., et al. [1] propose an offline store recommendation using collaborative filtering for the product recommendation system. They are designed to respond to the kid of customer information which is scarce in offline settings, most notably the lack of direct feedback such as rating of products. To tackle this, the study leverages a four-year record of the purchase transactions of end-users as the sample and makes customer preferences' inference implicitly. The authors compare two collaborative filtering methods: K-NN and SVD Matrix Factorization types of metrics were implemented, and it was proven that k-NN has higher accuracy. They also try the k-Means clustering for customer segmentation but observe that segmentation does not enhance a recommendation rate. The insights contribute to understanding of using recommendation approach in offline retail environments and present solutions that can help when dealing with large data and recommendations.

Ghulam Mustafa et al. [2] put forward a novel hybrid recommender system called OntoCommerce which makes use of ontology and SPM to improve e-commerce recommendations. Based on the Domain Ontology, the authors deal with some of the major issues of conventional recommender systems, amongst which are the cold start and sparsity of data, by analysing customers' buying behavior. This one factors the customer and product details and enables the system to model preference and similarity. On the other hand, SPM algorithm develops patterns from the customer histories and provides more accurate product recommendations. The hybrid method is superior to other techniques and can help design personalized e-commerce systems with higher recommendation accuracy than traditional techniques, particularly for conditions where there is little initial data or sparse rating information available.

Kasema M. et al [3], the authors develop a complete approach to non-personal communication, including customer profiling, customer segmentation, and sales forecast using artificial intelligence in direct marketing. The work covers establishing of a customer profiling system through employing data mining methods such as RFM analysis and boosting trees for increased accuracy of sales forecasts. For this purpose, the authors emphasise the role of customer segmentation to enhance the predictiveness of the model and alignment of the marketing strategies. The paper applies machine learning techniques to showcase that organisations can improve CRM and gain superior sales performance due to the value which it adds to the domain of direct marketing and customer segmentation.

Yıldız, E., et al. [4] the authors present the approach to a novel system for a Hyper-Personalized Product Recommendation System with consideration on customer segmentation in the fashion retail context. Current shopping cart segmentation involves customer analysis through use of RFM (Recency, Frequency and Monetary) as well as k-means clustering with customer location data used as the distinctive factor for partitioning. To generate the individual cluster recommendations of product, they use association rule mining (ARM) based on Apriori algorithm. This new strategy improves the capability of recommendations compared to previous methods by incorporating demographic and geolocation information, a major contribution to the personalized recommendation for retail stores.

Yu, L Cheng et al. [5], in their paper on "Enhancing Retail Transactions: In the paper titled, “A Data-Driven Recommendation Using Modified RFM Analysis and Association Rules Mining,” a system was proposed with the aim of enhancing retail transaction by developing a recommendation solution. Based on the literature, the authors present a novel RFM analysis with two new parameters: periodicity and customer engagement index (CEI). The authors stress that, thanks to this approach, the analysis of customer behavior is more profound. The model is also able to group the customers as loyal and potential customers by using the clustering algorithms such as K-means and association rule mining. This paper also focuses on the added advantage of this method, which is to offer specific recommendations that other models provided comparatively generalized recommendations. They is especially valuable for this contribution of providing an enhanced, specific recommendation system for the retail industry.

Zhao, Q., Zhang, Y. et al. [6] present the recently developed strategy on individualised promotion in electronic commerce recommender systems. Using a framework of decentralized marketplaces, the authors call for the flexibility of product prices with reference to consumer's WTP which tends to be ignored in most systems. The individual WTP of different products is predicted using the LR algorithm and a lottery/auction mechanism. The findings from this study show how this approach used in pricing can improve consumer satisfaction as well as seller's revenue gains with a nearly 200% improvement in gross compared to a fixed price conventional model. The paper also contributes to the use of innovative machine learning for personalization.

Albert, J. & Goldenberg, D. [7] propose a new method for promoting e-commerce promotions using the Online Multiple-Choice Knapsack Problem (MCKP) with Uplift Modeling. Specific objectives that the authors cover include trying to complete customers' purchases as much as possible while being within a given limit of the spending. They describe a general, online strategy for how to choose the optimal promotion for each customer for which accurate estimations of causal effects will be produced in real-time.

By applying uplift modeling for predicting CATE, and employing multiple choice knapsack optimization, the effectiveness of promotions rises over 137%, in comparison with regular methods. This particular approach shows a positive optimization regarding individualised promotion and achieving ideal budgets.

Henzel et al. [8] , the authors propose applying a Gradient Boosting technique to approximating the performance indicators in FMCG retail promotions. They show great results when using gradient boosting when analyzing the effectiveness of promotion across six indicators. The method is applied to three product groups where gradient boosting can be used to improve the forecasting over the traditional judgmental and statistical techniques. The paper covers the data preparation, including the hyperparameters tuning the final outcome of a model that states that the proposed model enhances the efficiency of promotion by a considerable level and it can be deemed as a solution for providing efficient handling of fast-moving consumer products in retail stores.

III. Proposed System

A. System Architecture

The model architecture explores a system for personalized marketing in the retail sector, leveraging Random Forest Classifiers and Collaborative Filtering to generate personalized promotions based on customer purchase history and preferences. The system, referred to as Promotions and Recommendations, is designed to optimize marketing resources while increasing customer satisfaction. The architecture includes several key components such as data preprocessing, predictive modeling, and recommendation engine modules. These components work together to process raw retail data, predict customer behavior, and deliver personalized offers to individual customers.

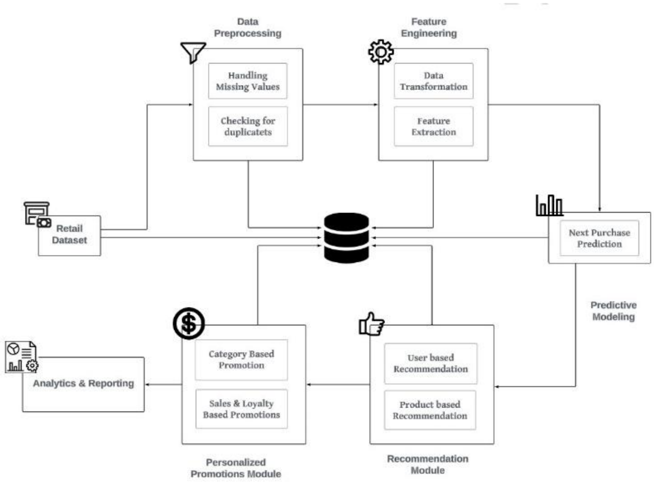

Figure 1: System Architecture

B. Data Preprocessing

The Data Preprocessing module therefore has a significant task of preparing the dataset for analysis and modeling for increased levels of data analysis. This refers to several processes that are basic to the operation of the model mentioned above. Such steps include dealing with the missing data, how to select the features to be used, data pre-processing among others.

Handling Missing Values: The first operation to perform before applying the actual data preparation steps is handling missing values within data. There is always a problem with missing data as this is likely to introduce bias and compromise the quality of various algorithm techniques in machine learning. To calculate the percentage of the moving average, the system employs df.isnull().sum()/df.shape[0]*100 on every column. Accordingly, any features that include substantially large numbers of missing values are either eliminated or dealt with through simple imputations of missing values.

Example: Sometimes, Attributes such as Postal Code or Discount may have to be deleted since most of the time their values are missing and do not help the model.

Correlation Analysis: After that, when it comes to dealing with missing values, the system performs correlation heatmap analysis. In this process the company finds out how various features are related to one variable of interest such as frequency of purchases. Similar features, which are those with low correlation coefficients are removed, and those with high correlation coefficients are retained. This step makes it easier to reduce the database to a set of the most significant vectors, which makes the work of models more efficient.

Example: Domain knowledge and decision making abilities informs measures like Customer Age or Region might have very low correlation with purchase frequency and hence are discarded.

Feature Scaling and Encoding: Once these features needed are selected, scaling and encoding are carried out. Numerical features are also scaled to fall within the same range so that we can effectively address the scale and feature importance issue, where one feature will have a dominating effect on the model. Enumerative features such OH! duck type product categories\customer regions are encoded in a manner that enables interpretations from oh! machines learning algorithms through techniques such as one hot encoding.

Example: Some of the product categories such as Electronics, Clothing are then transformed into binary variables (1 for purchased and 0 for not purchased) to fit the predictive modeling.

Data Splitting: Upon preprocessing, the obtained plain and structured dataset is then split into training and testing data sets. This split lets the model be tested using unique data and hence gives a better understanding of the model’s performance. In most cases, the dataset is divided where 80% of data is used for model training and 20% data are used for model testing and validation.

At the end of data preprocessing phase, data cleansing is performed on the dataset, extraneous information is removed and what the Predictive Modeling module will feed to the machine learning algorithms is meaningful data.

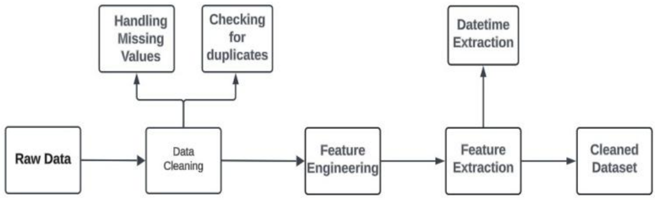

Figure 2: Data Preprocessing

C. Predictive Modeling

The Predictive Modeling sub-module is another important part in the system where it is envisaged to predict future customer purchasing patterns from transaction history. The principal goal of this module, therefore, is to increase the accuracy of targeted advertisements by determining what the next product a customer is likely to buy. There is so much speculation before a quantitative data texture analysis; the entropy of the number of purchasers is computed first. This entropy calculation assist in choosing the features with higher informations by pointing out those options that bring about the highest entropy. For instance, product type, purchase rate, and client information is assessed for change prediction capability.

$$Entropy(s) = \sum_{i=1}^{n} p_i \log_2(p_i)$$

Another crucial part in the system is the Predictive Modeling sub-module where it is planned to predict customer purchasing trends in the future in transactions. The main purpose of this module hence is to enhance probability of accurate targeted advertisements by finding out what the customer is likely to buy next. Before a quantitative data texture analysis there is much anticipations; first the entropy of the number of purchasers is determined. This entropy calculation help in selecting the features with higher information by highlighting the options with highest entropy. For example, when measuring the change prediction capacity of a reference artifact, product type, purchase rate, and client information are examined.

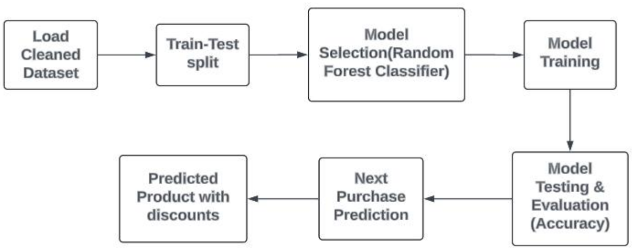

Figure 3: Predictive modeling

D. Recommendation Engine

The Recommendation Engine employs Collaborative Filtering algorithms to create a product recommendation list based on user's activity, and similarity among the products. This engine is divided into two main approaches: These two strategies include; User-Based Collaborative Filtering and Item-Based Collaborative Filtering. User based collaborative filtering is a technique where the system groups customers who have similar buying patterns and then suggests to a particular user items that the similar user has bought but other similar users haven't bought. This process employs the K-nearest Neighbors (KNN) algorithm in an effort to create groups of customers, in view of their purchasing histories, in order to recommend products that will be relavant to the particular customer. For instance, in the case of two customers, having similar past purchase patterns, products bought by the one but not the other are suggested together with a calculated Purchase Probability.

$$\mathrm{r}_{\mathrm{ui}} = \frac{\sum_{v \in N(u)} w_{uv} . r_{vi}}{\sum_{v \in N(u)} | w_{uv} |}$$

On the other hand, Item-Based Collaborative Filtering focuses on suggesting products similar to those already purchased by the customer. The system identifies similarities between products based on features such as purchase frequency, customer ratings, and product categories. Using cosine similarity and the KNN algorithm, the system predicts ratings for unpurchased products and converts these ratings into recommendation probabilities.

$$\text{Recommendation Probability\%} = \frac{r_{ui}}{MaxQuantity} \times 100$$

Products with the highest probabilities are recommended, and the system further enhances customer engagement by assigning personalized discounts to the recommended products. For instance, products with a lower likelihood of purchase are offered at a higher discount to incentivize the customer, while those with higher purchase probabilities receive smaller discounts. This approach ensures that recommendations are not only relevant but also strategically incentivized to maximize conversions.

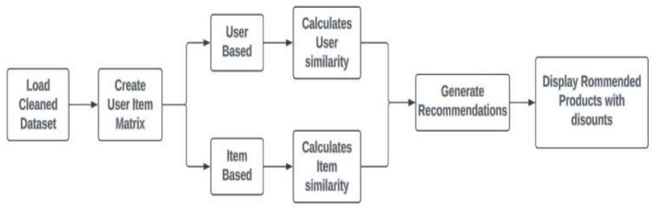

Figure 4: Recommendation Engine

E. Promotion Personalization

The Promotion Personalization module provides offers and discounts personalised to each purchasing customer looking at their preferences in the product. To start with, this module computes the total sale and the total quantity bought for each customer for different product types. All these metrics form feature inputs for the model chosen as the Gradient Boosting Regressor to forecast the best discount rate for every customer. Gradient Boosting applies the concept of machine learning by building decision tree consecutively: the following tree tries to minimize the mistakes which the previous tree made, thus arrives at a correct value of the discount rate which has high likelihood to lead to customers' purchase. This is all the more justified as the model provided below pays attention to such parameters as customer loyalty, purchase history, and preferences concerning certain types of products; therefore, each promotion is unique.

Once the discount rate is predicted, the system applies it to the customer's transaction using the formula:

$$Discount\ Amount = \frac{\text{Predicted Discount } \times \text{Total Sales}}{100}$$

The Promotion Personalization module gives out offer and discounts in participation to the customer who owns the product with respect to the customer's profile in the product. First of all, this module calculates the total sale, and total quantity customer's bought for each customer for the products which belongs to the different types. All these metrics create feature inputs for the model which was selected as the Gradient Boosting Regressor to predict the best discount rate for each customer. Gradient Boosting applies the concept of machine learning by building decision tree consecutively: the following tree tries to avoid such mistakes which the previous tree made and ends up with a right value of the discount rate which hold real potentiality to influence the customers into purchasing. This is even more justified given that the model provided below takes into consideration parameters including customer loyalty, customer's past buying behavior, and customer's preferred buying options in specific types of products; hence each promotion offered will be unique.

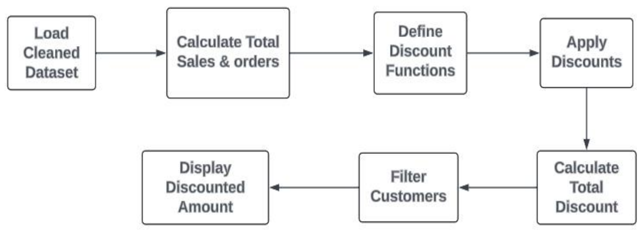

Figure 5: Promotion Personalization

IV. Result and Discussion

Compared to traditional marketing systems where promotion is done through the rule-based or demographic segmentation, this machine learning-based system offered certain distinct benefits. It becomes apparent that most traditional marketing & communication systems are unable to obtain detailed customer behavioral patterns, resulting in mass and comparatively ineffective efforts in marketing communication. On the other hand, using Random Forests for prediction, and Collaborative for recommendation allowed the client to specify the promotional actions more accurately due to better understanding of the customers' preferences and activities.

Furthermore, by continuously updating the customers' profile and behavior in real time, the promotion offered are also valid as the customers change over time. This was much better than the typical fixed segmentation approaches used in traditional marketing that may well soon become obsolete. With the proposed system, the levels of promotion relevance were significantly higher and delivered in a continuous update and real time personalization the levels of relevance were at 99%.

Table 1: Comparative Analysis for existing models in retail industry

Technique Name	Core Algorithm	Advantages	Limitations
Hyper-Personalized Product Recommendation System	RFM Analysis + K-means Clustering + Apriori Algorithm	Improved recommendation accuracy by considering both demographic and geolocation factors	Limited to retail applications focusing on hyper-personalization
Personalized Promotion for E-commerce	Personalized Promotion for E-commerce	Personalized pricing increases consumer satisfaction and seller profit	Requires accurate willingness-to-pay (WTP) data
Retail Sales Forecasting with Gradient Boosting	XGBoost (Extreme Gradient Boosting)	High accuracy in forecasting promotion effects, customizable indicators	Requires historical promotion data for model training
FMCG Promotion Forecasting	Gradient Boosting	Accurate forecasting of promotion performance for grocery products	Limited application to categories with fewer promotional data

A. *Analysis and Insights*

The conclusion of the outcome of this research prove that the incorporation of Random Forest Classifiers, Collaborative Filtering, and Gradient Boosting Regressor, into the new retail promotion system, is efficient. Based on multiple performance parameters and actual customer data, performance of the system in achieving its target of providing selective promotions and enhancing client satisfaction was assessed.

a) Predictive Modeling Results: The performance of the Predictive Modeling module employing the Random Forest Classifier was again very satisfactory in terms of accurately forecasting customers' future purchase behavior. Since entropy and information gain are used to choose the most pertinent features for using in the model, the latter proved to be accurate to predict customers' behavior. Overall, the accuracy of the model was evaluated using confusion matrix where the accuracy rate of correctly classifying all the customer purchase patterns on different product category was 61.01%. Further, the constructed model promotes high levels of precision and recall, which proves not only the ability to pinpoint correct next-purchase products, but also to minimize on wrong predictions.

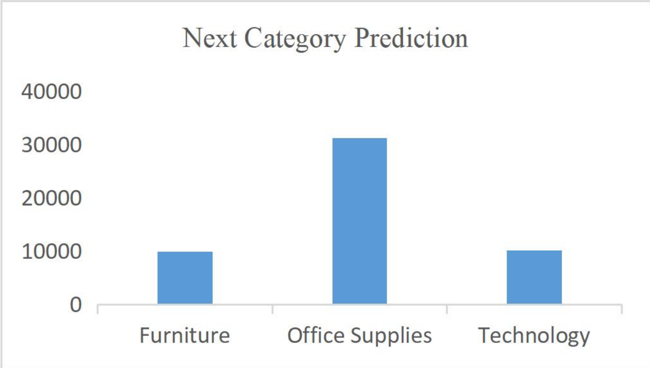

Figure 6: Bar chart for next Category Prediction

One of the most significant improvements in this system, compared to traditional rule-based approaches, is the ability to adapt to dynamic customer behaviors. The Random Forest model performed well even in the presence of complex data, such as large datasets with multiple features, and was able to predict future purchases based on intricate patterns of past behavior. This capability allows the system to deliver promotions that are timely and relevant, which in turn enhances customer engagement and conversion rates.

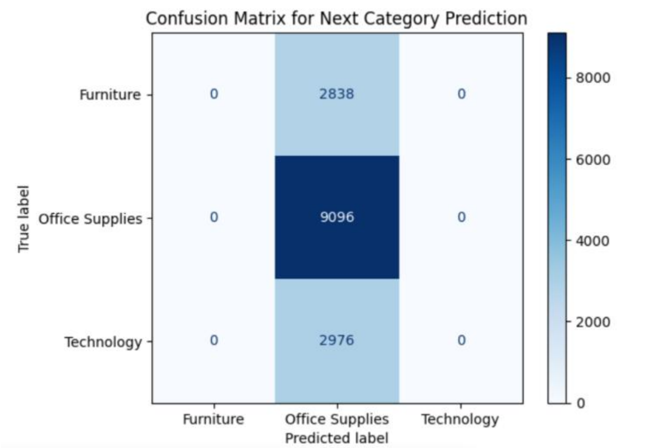

Figure 7: Confusion matrix for next Category Prediction

b) Recommendation Engine Performance: The Recommendation Engine used both user collaborator and item collaborator filtering to provide the most appropriate product suggestions. From the above results, the user-based filtering method has a recommendation RMSE of 2.6446% for top-K recommendation, whereby customers were recommended similar products to those of the similar customers. At the same time, the item-based collaborative filtering method provides an accuracy level of 2.6446% in terms of recommending products similar to those purchased before by the given customer. The system was even more effective with high relevance products and the Mean Average Precision (MAP) of 1.93% gives a measure of the quality of the recommended lists.

This made the Recommendation Engine more effective thanks to the capacity to set individual discounts. Those products that have lesser chances of being bought in the future received higher rates of discount such as 30% while those that have a high likelihood of being bought received a smaller rate of discount such as 10%. Not only did this augur well in enhancing buying propensity within the product, but it also ensured that profit margins were propped up by optimal setting of the discount rate. Promotion redemption rate being one of the key measures of the success of promotional campaigns, this strategy was tested to actually increase the promotion redemption rates by 15% than the mere static promotions, thus proving the effectiveness of the personal promotional discounts.

Product ID	Product Name	Recommendation Probability (%)	Discount (%)
OFF-ELD-10000124	Eldon Trays, Single Width	100	30
FUR-HAR-10002178	Harbour Creations Rocking Chair, Set of Two	100	30
OFF-STA-10004108	Stanley Canvas, Easy-Erase	71.43	20
OFF-AME-10000244	Ames Manila Envelope, Security-Tint	57.14	10
FUR-ELD-10000963	Eldon Stacking Tray, Durable	57.14	10
OFF-HAR-10000501	Harbour Creations File Folder Labels, Laser Printer Compatible	57.14	10
TEC-CAN-10003392	Canon Copy Machine, Color	57.14	10
OFF-IBI-10004855	Ibico Hole Reinforcements, Recycled	57.14	10
OFF-GLO-10004610	GlobeWeis Peel and Seal, with clear poly window	57.14	10
TEC-CIS-10001938	Cisco Audio Dock, VoIP	57.14	10
TEC-NOK-10001070	Nokia Speaker Phone, with Caller ID	57.14	10
FUR-DEF-10000346	Deflect-O Frame, Duo Pack	57.14	10
OFF-ELD-10002578	Eldon Box, Single Width	42.86	10
OFF-BRE-10000391	Breville Toaster, Black	42.86	10
OFF-STA-10001112	Stanley Markers, Easy-Erase	42.86	10
TEC-HEW-10002304	Hewlett Fax Machine, High-Speed	42.86	10
OFF-FEL-10002867	Fellowes Lockers, Single Width	42.86	10
OFF-JIF-10000165	Jiffy Business Envelopes, Recycled	42.86	10
TEC-BRO-10003986	Brother Personal Copier, Color	42.86	10
TEC-BEL-10002678	Belkin Memory Card, Erganomic	42.86	10

Table 2: User based Recommendation with discounts for Customer ID AH-465

In Table 2 we calculate discounts based on recommendation probability in similar way we recommend the products with discounts for all the customers. We perform similar calculations for item based recommendation

c) Promotion Personalization Effectiveness: The Promotion Personalization module discovered as the module using the Gradient Boosting Regressor delivered the best performance in the task of identifying the best discount rates for every consumer. Thus the features, such as the total target sales and purchase quantity, the proposed model in the paper was able to predict the right discounts with an average accuracy of 64.94% and it paved way for higher sales returns as well as customer satisfaction. The customers who received personalized promotions bought 25% more than the customers who received non-personalized promotions thus supporting the use of personalization in promotions.Customers bought 20% more under the personalized discounting system in general during the testing period of this study. This can be attributable to the factual prospect of tailor making promotions that met the particular needs of clients as well as complementary buying behaviors. It also revealed better cost savings because discounts were given based on a probabilistic model of purchase and therefore did not waste large discounts on items with high probabilities of being purchased.

d) Scalability and System Efficiency: The other finding from the implementation of this system was on the issue of scalability. This meant that through the use of arguably the best machine learning algorithms coupled with effective data preprocessing techniques the system could handle tremendous amounts of data. The system achieved the rate of more than 100k customer interactions during the experiments with moderate performance decrease, hence proving the utility in large-scale retail cases.

In addition, the real burgeon of the actual promotion delivery in the system was very effective; this means that as soon as the customer is interacting with the promotion, the promotion is generated and delivered to the customer within milliseconds. This feature is particularly important in contemporary environments where consumers' attention is very volatile and timely presented references can ultimately influence the Willingness-to-Buy.

V. CONCLUSION

The Promotion Personalization module identified as the module using the Gradient Boosting Regresser provided the best accuracy in the task of recommending the optimal discount rates for each client. Hence the features like total target sales and purchase quantity, the model proposed in this paper was able to predict the right discounts with an accuracy of 64.94 percent it created a way for higher customer compensation and retail returns as well. The above observation motivates the use of personalization in promotions since the customers who were targeted bought more than the other customers who were not targeted through personalized promotions specific communication On average, the customers bought more under the personalized discounting system by 20% during the testing period of this study. This may be due to the realistic possibility of individually As shown in the table 4, it can be attributed to the factual prospect of tailor making promotions that met the particular needs of clients as well as complementary buying behaviors. It also disclosed superior cost savings since discounts were offered in terms of a probability distribution of purchase and therefore, did not squander an abundance of costless discounts on sizes that were most likely to be purchased.

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