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Original Article

AI-Powered Customer Segmentation in Grocery Retail: Leveraging Big Data for Hyper-Personalization

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Abstract *- Customer segmentation is a major concept in contemporary grocery retailing since it creates distinction according to customers' needs and wants. The past segmentation approaches are based on demographic data and, more often, on the transactional data known to the organization, thus providing a limited view of customer behavior. The advantages of AI and Big Data for the segmentation strategy are that they are more sophisticated segmentation that reflects individual consumer behavior, psychographic factors, and immediate purchase data. This paper aims to highlight customer segmentation using AI where techniques covered are specifically clustering models like K-Means, DBSCAN, deep learning, and NLP. The paper also outlines how AI influences hyper-personalization in grocery retail in the context of processing a large number of customers and providing special discounts. The research develops an AI-based segmentation approach that uses both supervised and unsupervised learning to improve the segmentation accuracy further. The accuracy of the segmentation has been enhanced, as supported by the experimental findings, thus translating to better sales and customer loyalty. The paper also brings some drawbacks of this approach, such as data privacy, computational cost, and model interpretation. The idea of the new work on retailer segmentation through AI is the best example of how Big Data can revolutionize retail personalization and define new ways of effective marketing.*

Keywords *- AI-Driven segmentation, Big Data analytics, Grocery retail, Hyper-personalization, Machine Learning, Customer behavior, Clustering algorithms.*

1. Introduction

The grocery retail industry is now rapidly shifting to digital due to the increasing pressure to meet individual customer needs. [1-4] Traditional forms of customer segmentation have been carried out with reference to conventional demographic factors, including age, gender, and previous buying behaviour. Nevertheless, these means and techniques are ineffective in identifying changes in consumer behavior and trends, adversely affecting retailers in providing appropriate promotions.

1.1. Role of AI in Customer Segmentation

AI has changed customer segmentation in business through big data analysis and the development of unique patterns that can help in marketing. Thus, AI-driven segmentation is more advanced than conventional techniques in terms of real-time, data-driven, and adaptive segmentation. Here are five AI functions that are concerned with customer segmentation.

1.1.1. Automated Data Processing and Pattern Recognition

By using artificial intelligence tools, it is possible to analyze the bigger data obtained from various sources and combine purchase history, online activity, and even interaction in social networks. The traditional versions of segmentation can be fixed around the rules and a regulation set. They cannot identify the relations and associations in the data and, therefore, provide a better segmentation. Analyzing large amounts of data through clustering algorithms and Natural Language Processing (NLP) is less time-consuming and more effective than manual techniques in identifying customer trends, sentiments, and concealed behaviors.

1.1.2. Integration of Machine Learning Models for Increasing the Accuracy

Supervised and unsupervised learning models that are applied in the learning process enhance segmentation efficiency through learning from new data. Other learning methods, for example, K-Means learning and DBSCAN, are used to identify natural clusters of customers without labeled data. However, supervised learning algorithms like Decision Trees and GRADIENT BOOSTING allow businesses to forecast the behavior and needs of their customers. This results in the efficient execution of the marketing strategies and the subsequent recommendations given.

1.1.3. Real-Time Dynamic Segmentation

The other disadvantage of segmentation that AI solves is that, unlike conventional segmentation techniques, there is real-time segmentation since AI processes live data. This is to important in manufacturing and dressing goods where customer behavior patterns can quickly shift based on season, a marketing campaign, or other parameters. AI-based models adapt consumer clusters, making it easy for organizations target, make recommendations, and set up product, promotional, or pricing strategies in real time.

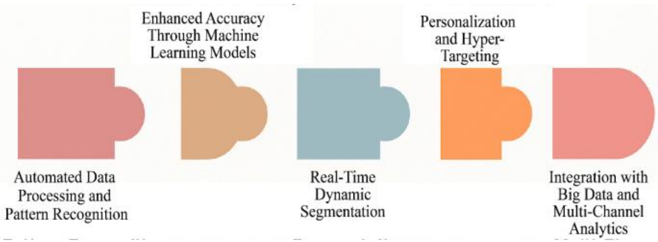

Fig. 1 Role of AI in customer segmentation

1.1.4. Personalization and Hyper-Targeting

Hyper-targeting is achieved through segmentation, whereby AI develops distinct marketing strategies that are unique to every customer a business targets. Recommendation systems, including Amazon and Netflix, use artificial intelligence systems to determine the customers' choices, behavior, and purchase readiness to marshal relevant products.

Thirdly, other forms of artificial intelligence in AI chatbots and virtual assistants complement customer engagements by providing product recommendations and customer support during shopping.

1.1.5. Integration with Big Data and Multi-Channel Analytics

AI works hand in glove with Big Data technologies as it enables one to process data gathered from various sources of communication such as in-store sales, online ordering, mobile applications, and social media.

This essay will discuss how structured and unstructured data sources used in AI help create a 360-degree view of the customer, which will aid organizations in developing ideal segmentation methods. It assists businesses in managing their inventory, estimating demand, and enhancing customer relations and experience through better social media integration.

1.2. Challenges in Traditional Segmentation Approaches

The research on the customers has been done through the conventional classification approaches, including demographic, geographic, and RFM analysis [5, 6]. However, these approaches have some drawbacks that make them less useful in the current hi-tech world. The following are some of the main drawbacks of the conventional segmentation approach.

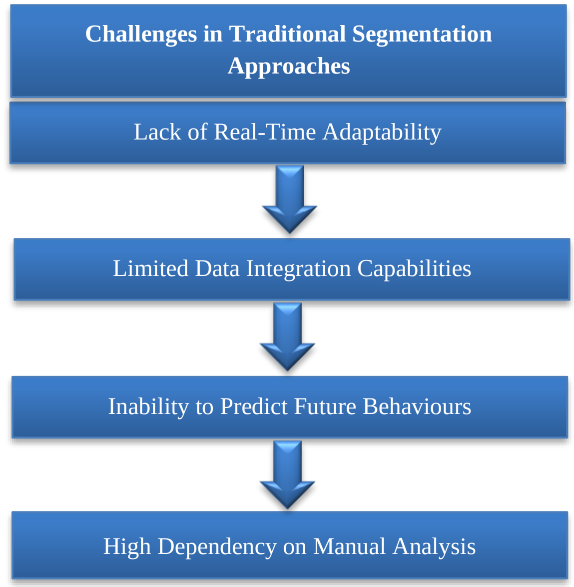

Fig. 2 Challenges in traditional segmentation approaches

1.2.1. Lack of Real-Time Adaptability

The conventional segmentation models are not flexible because they are developed based on old data and cannot be used to capture the changing behavior of customers in the current market. This means that the traditional segmentation technique of an organization could become ineffective since it does not update when the consumers' preferences due to seasonal variations, promotional offers, or environmental issues change. This has the overall effect of having incorrect customer demographics, which means that the right strategies to reach customers are not employed; hence, the opportunity to make new sales is lost. However, AI-driven segmentation can change the segment, allowing businesses to respond accordingly by always analyzing the customers' behavior.

1.2.2. Limited Data Integration Capabilities

Most conventional market segmentation techniques are normally limited to a few variables, such as age, gender, or buying behaviour, and they are done from a single source. Contemporary buyers engage with a particular brand's products through Internet use, social media contacts, and store purchases. The major demerit of traditional segmentation is it does not have the capacity to integrate or analyze information from various sources, thereby failing to give a perfect picture of customer behaviour. This limitation hinders the feasibility of segmenting the market to develop differentiated marketing strategies.

1.2.3. Inability to Predict Future Behaviors

The first limitation of conventional segmentation requires focus on customers' past behavior as opposed to the future behaviour of purchasing. As such, the methods do not incorporate aspects like customer demand, churn rate, or emerging trends in the market. This prevents businesses from being proactive in customizing promotion, inventory, or customer retention. While AI-empowered segmentation predicts the customer behavior and the consequent recommendations of actions to take on the customer, the latter is done using pre-trained machine learning algorithms.

1.2.4. High Dependency on Manual Analysis

Traditional segmentation can be very time-consuming and needs human intervention since it uses rules to follow and underlying assumptions to make. Customers are segmented manually, which brings into play biases and restricts scalability as carried out by analysts. Also, manual segmentation takes a lot of time in the case of large benchmark datasets and, at the same time, may contain errors. Several caveats are solved using AI and machine learning that offer an automated environment, reduce human error, and increase the level of analytics and accuracy in segmentation.

2. Literature Survey

2.1. Traditional Segmentation Approaches

The classification of customers is familiar in the retail industry as it classifies its ‘customers based on their general behavior and conduct [7-10]. These include the RFM model, where customers are grouped by the time they used last, how frequently they purchase, and how much they spend. This assists retailers in such a way that enables them to detect customer loyalty and likely churn cases. Demographic segmentation, the other traditional method, involves grouping customers based on variables such as age, gender, income, and education, among other factors, to market specific products or services to defined target consumer segments.

Of the identified segmentation techniques, psychographic segmentation is slightly different from demographic segmentation in that, in addition to focusing on customer characteristics like age, income, or gender, it investigates the customer’s lifestyle, values, interests, and personality. Even though these paradigms are effective, they do not adapt and cover the depth of modern data-driven methods.

2.2. Machine Learning for Customer Segmentation

In the recent past, due to the integration of artificial intelligence in the market, customer segmentations can now be ever-changing and accurate because of Machine learning. Numerous clustering algorithms like K-Means, Hierarchical Clustering, and DBSCAN are used to cluster customers according to their buying behavior, website navigation patterns, or other activity metrics. These approaches play a big role in picking out the underlying structure in large data sets of unsupervised learning for retailers by designing product categories. Secondly, supervised learning methods work in predictive analytics where a general pattern is expected from the historical data, for instance, to predict the customers likely to churn or, vice versa, the valuable customers. Deep learning has advanced Segmentation abilities even more, especially in areas such as images and textual data samples through NLP. Businesspeople employ deep learning models in areas ranging from analyzing buyers’ feelings to sentiments on social network reviews to monitoring surveillance cameras in the shops, thus gaining deeper insights into customers for better targeting in their tailored marketing campaigns.

2.3. Big Data in Retail

The increase in big data availability has greatly impacted customer segmentation since it unites various customer databases for more elaborate information on consumer behavior. POS data is often used in current versions of retail analytics to monitor the trends in purchased products. In contrast, web surfing activities are used to identify the customers’ interests. Furthermore, ecological factors, including economic conditions, monthly or annual variations, and competitor prices, are also used to enhance the segmentation models. These principal data types enable retailers to formulate and implement improved and efficient strategies in their marketing, customer relations, and inventory. However, instead of using segmentation as merely an analyzer to develop long-term, consistent segments, big data analysis helps retail organizations adopt dynamic and real-time segments that position them as key competitors.

3. Methodology

3.1. Data Collection

3.1.1. Point-of-Sale (POS) Transactions

POS information involves information on the sales done in real time, which can be useful in analyzing customers’ purchasing trends. [11-15] Here are some pieces of information like product type, how often products are bought, volume of business made, and mode of payment. POS data, therefore, helps retailers understand the trends in the market together with customer preferences and demands, thus formulating the best ways of inventory management and marketing.

3.1.2. Online Browsing History

Customer web activities record each activity a customer engages in when making purchases online, such as the pages he/she clicks, the search terms entered, the products previewed, and the products left in the cart. These insights assist retailers in procuring knowledge about customer interests, shopping intentions, and decision-making. Through the browsing history analysis, the companies can provide suggestions on some products, advertise to the consumers, and further improve customer experience while shopping online.

3.1.3. Social Media Interactions

The 4Ps inform a lot about customers: Likes, shares, comments, and direct engagement with brand messages. Social media data analysis reveals the reaction of the customers, Identifies new trends, and evaluates the perception of a brand from the customers. The modern tools available are sentiment analysis and influencer identification, which help businesses maximize customer engagement and campaigns.

3.1.4. Customer Feedback and Reviews

Customer feedback that can be obtained from the clients through online shopping, questionnaires, and personal experiences gives crucial information about their satisfaction level and product quality.

Analyzing the sentiment of the reviews allows retailers to learn about the strong and weak points of a particular product and improve and adapt customer service.

These points show that responding to customers' concerns and taking appropriate measures can enhance customers' satisfaction and thus guarantee a company's success.

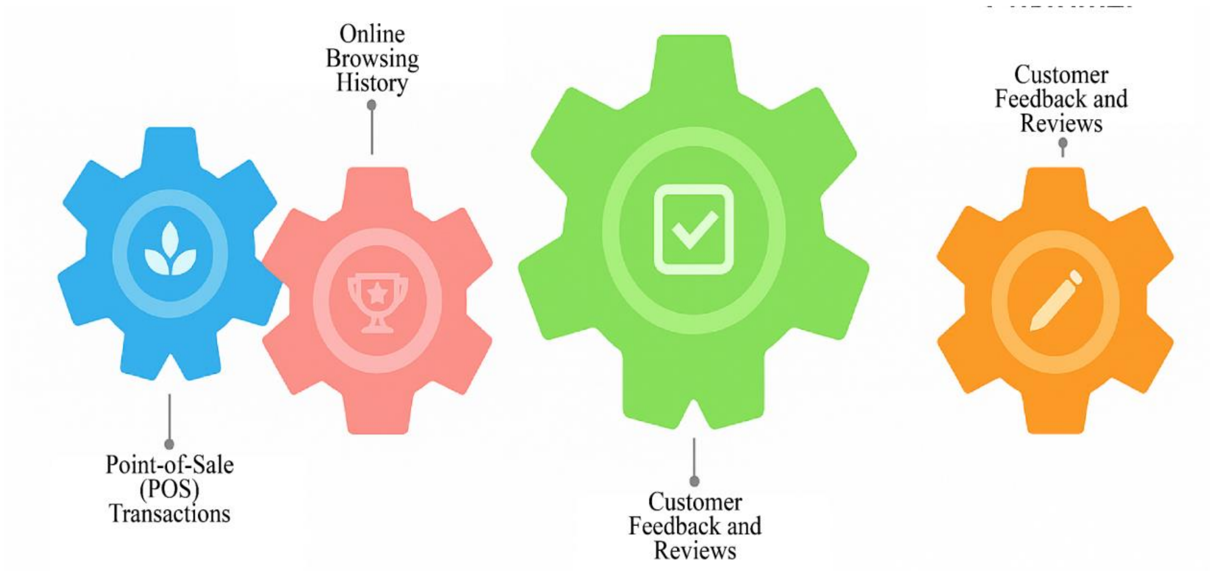

Fig. 3 Data collection

3.2. AI Models for Segmentation

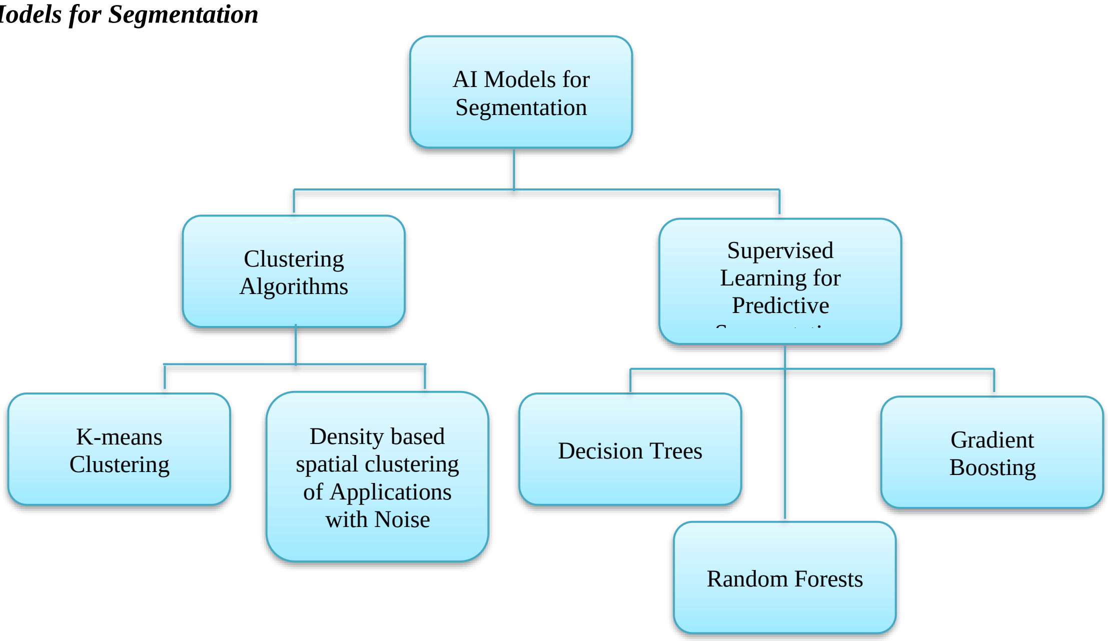

Fig. 4 AI Models for segmentation

3.2.1. Clustering Algorithms

- *K-Means Clustering:* K-Means is one of the most popular clustering techniques that can be applied for customer segmentation. Customers are divided into k groups since it identifies that customer data are not homogeneous when analyzed based on factors such as purchasing preference, demographic characteristics, or activity level. The customers are grouped and clustered based on the nearest distances or shortest paths between the customer and the cluster centroid, which is repeatedly calculated for each customer until the program acquires an acceptable solution. K-mean is good for voluminous data sets and offers clear and clean-cluster separation; thus, it is widely used in retail and marketing.

- *Density-Based Spatial Clustering of Applications with Noise (DBSCAN):* DBSCAN is a clustering algorithm that uses density gradient to find customer segments in the database. It should also be noted that, unlike K-Means, DBSCAN does not need the number of clusters to be defined in advance and can recognize groups of any form. It is especially useful in cases where customers can be divided into segments, for example, valuable customers who rarely make purchases. Therefore, it is useful in situations that require customization of marketing strategies and detection of fraudulent activities.

3.2.2. Supervised Learning for Predictive Segmentation

- *Decision Trees:* There are various reasons why decision trees are applied in customer segmentation; they are easy to interpret and can perform a basic classification function. They make splits by feature, including purchasing habits, past purchases, and activity level. In the case of customer behaviors, Decision Trees are used by retailers to estimate the prospect of a customer churning or the reaction of the customer toward a certain promotion.

- *Random Forests:* Random Forest is an improvement on the Decision Tree method as it involves using several Decision Trees simultaneously, which results in increased accuracy and no overfitting. Individual attention is paid to each tree since the "voting" of the final decision regarding the prediction result is based on all of them. This is because it is efficient for processing a large amount of data and complicated data; hence, it is useful in manufacturing customer lifetime values, categorizing the customers based on how they spend, and even recognizing potential threats of churners.

- *Gradient Boosting:* Predictive models get enhanced step by step through a method called gradient boosting, and their examples are XGBoost and LightGBM. These models are very useful for detecting some features in the pattern of customer behavior to help them run effective marketing strategies, suggest new products, and improve customer satisfaction. According to the findings of Gradient Boosting, it is possible to obtain extremely accurate retail segmentation and enhance the customers' engagement strategies.

3.3. Proposed AI Framework

In order to improve customer segmentation, it is necessary to present a combined method of unsupervised classification and supervised artificial intelligence to provide the best segmentation result. For starting with the clustering stage, the K-Means algorithm and DBSCAN cluster the customers depending on their similarity. [16-18] K-Means can categorize customers, from which the company can define broad segments, while DBSCAN allows for the identification of small groups and peculiar customers - such as those making large purchases or those who shop infrequently. The initial segmentation is more refined and variable according to customer habits. After forming the initial clusters, the Definite Tree, Random Forest, and Boosting model can be used to predict customers' behavior in the belonging segment.

Decision Trees are more useful in interpreting customer key factors, while Random Forests provide a way to control and reduce decision error by averaging multiple models. Moreover, optimization methods such as XGBoost and LightGBM enhance the model by making better predictions regarding high-value customer prediction, churn risk, and engagement level. In the same regard, integrating real-time data processing through big data such as POS, web activity, posts, and reviews is also part of the framework. This makes segmentation more flexible and able to accommodate the changes in customers' demands.

These features and other techniques, such as the Principal Component Analysis (PCA), help develop the model's efficiency by reducing the dimension alternatives to neutralize potential valuable information. In this context, the proposed hybrid approach allows businesses to leave the dull segmentation process behind and move towards a smart, dynamic, and data-driven one. It is highly efficient in allowing retailers to enhance the experience, leading to increased customer loyalty and enhanced revenues through strategic marketing solutions.

4. Results and Discussion

4.1. Experimental Setup

Regarding this performance of the developed algorithm for customer segmentation based on AI, the experiments were performed on a big dataset of grocery retail transactions that included 1 million records over a year. Thus, the dataset covered the customers' demographic data, purchasing, web surfing, and interactions with the loyalty program. Our approach was to create a solid method of customer classification using a large dataset and, thus, to segment the significant target groups based on their shopping behaviors and preferences. Most stemming and stop words were also eliminated from the data as they were seen to disturb the data analysis process. Feature engineering was performed to get the clients' basic and behavioral aspects like the purchase frequency, the amount spent per time, product preference, and their response to discounts. In fact, for other criteria, external factors are incorporated, for instance, seasonal and promotions, to improve segmentation. In terms of performing the segmentation task, there are two approaches, namely clustering techniques such as K-Means and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and classification models like Decision Trees, Random Forests, and Gradient Boosting. Transactional and engagement data allow the creation of the first level of grouping the customer using unsupervised clustering.

These were then used to generate positive feedback for forming the intended clusters and to make learning models on customer behaviors, which helped to enhance his segmentation process. The experiments were performed under a high-performance computing server with the programming language Python and Machine learning libraries such as Scikit-learn, TensorFlow, and XG boost. As using this model to evaluate the actual model, the common metrics used include accuracy, precision, recall, and F1-score. Therefore, the customer segmentation outcomes were visualized using tools such as graphs and heat maps to make another level of understanding of customer distribution less arduous. All in all, the chosen experimental framework aimed at ensuring that the developed AI-driven segmentation framework divided customers into segments where all members would be as heterogeneous as possible, and the resulting segments would help define effective strategies to engage them and improve business decisions.

4.2. Performance Metrics

The main evaluation criteria, such as accuracy measurement model, precision, and recall, were applied to analyze the results of the proposed segmentation models driven by artificial intelligence. They give indications of the ability of each model to segment customers sensibly and the consistency of the model with the expectations of real-world consumers.

Table 1. Performance metrics of segmentation models

Model	Accuracy	Precision	Recall
K-Means	78%	76%	79%
DBSCAN	82%	80%	83%
Decision Trees	85%	84%	86%

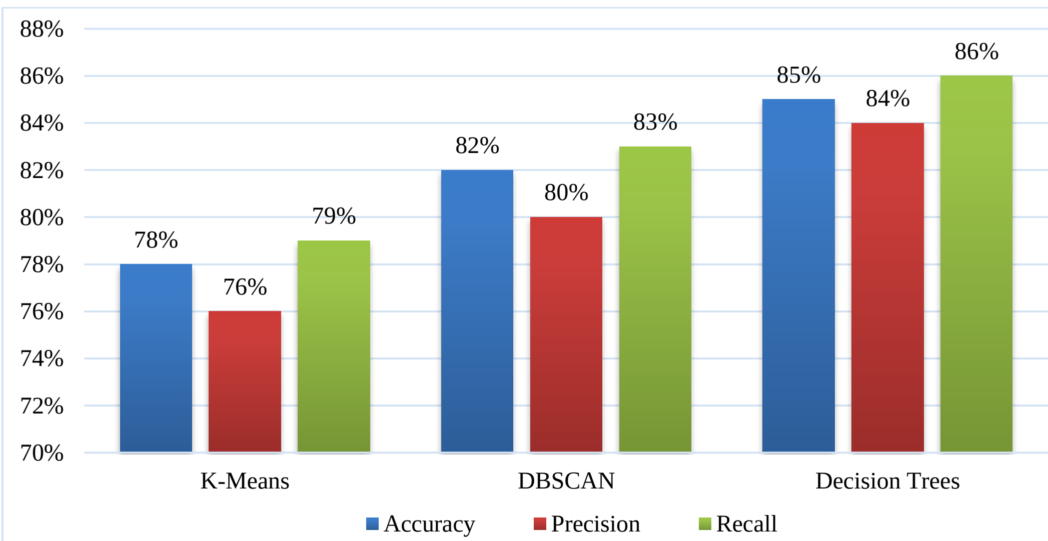

Fig. 5 Graph representing performance metrics of segmentation models

4.2.1. Accuracy

Accuracy measures the general quality of the segmentation model as more accurately the model in distinguishing the classified customers from the total set of customers. This means that the model successfully separates and identifies various customer categories when a higher accuracy score is obtained. The best performance was observed in the Decision Trees with an accuracy of 85%, while the DBSCAN had an accuracy of 82% and the K-Means 78%. The better results always achieved consequently to Decision Trees imply that supervised learning methods can improve segmentation by learning the pattern from the given labeled data.

4.2.2. Precision

Accuracy measures the ratio of instances that belong to the actual positive class and are classified as such relative to all the instances that are classified as positive. In the case of customer segmentation, it refers to the ability of the created model to correctly allocate customers in a given group excluding any misclassification. In the case of the samples, again, Decision Trees were the best, with 84% precision, while

DBSCAN and K-Means were 80 and 76%, respectively. Therefore, it is observable in the lower errors, pointing to the notion that Decision Trees and DBSCAN do not missegment customers or misclassify them as belonging to the wrong segment.

4.2.3. Recall

This measures how well the model can bring out all the aspects of customers in a definite group, including the extent to which all customer segments have been included in a group that forms part of the model. Self-assessment of the recall factor ensures minimal crucial evidence is left behind. This made Decision Trees achieve the best recall compared to the DBSCAN, which was at 83%, and the K-Means, at 79%. Based on these findings, it can be stated that using algorithms such as Decision Trees and DBSCAN allows the identification of more meaningful customer behaviors than K-means, which is why it should be preferred for accurate customer segmentation.

4.3. Insights from AI-Powered Segmentation

Thus, Al enabled the segmentation of customers into four primary groups with peculiarities in purchasing habits, preferences, and activity intensity. These personas assist business organizations in deploying unique marketing techniques, segmenting recommendations, and making inventory control for different clientele.

4.3.1. Frequent Shoppers

Frequently appearing customers are those shoppers who visit the store more often, weekly, and have predictable buying behaviour. They account for a good amount of purchases and buy a combination of basic needs and luxury goods. These customers greatly value convenience, brand loyalty, and service, which make them suitable for loyalty programs and offers. Retaining them by offering discounts, membership, and early access to new products is advisable.

4.3.2. Price-Sensitive Buyers

Price-Sensitive Buying refers to buying behavior aimed at getting the most value for the amount of money spent, often involving the practice of ‘aspect sensitivity’ to voucher offers, etc. They are particularly motivated by sales, promotions, and any offer, with the condition that they order large quantities. These consumers are willing to switch between brands often and evaluate based on the price level. They can use them to market cheaper discounts, discounted offers, and complementary rebate programs to enable more than one purchase or multiple orders.

4.3.3. Organic & Healthy Consumers

This segment comprises conscious consumers who only purchase naturally derived, organic, and environmentally friendly products. It is ready to use at a higher price for quality, sourcing, and environmentally friendly packaging. These customers rely heavily on product labels, nutritional information, and certifications. When it comes to capturing their attention, businesses should market and offer organic product packages, health-oriented rewards, and informative material on trends in wellness.

4.3.4. Impulse Buyers

Impulsive consumers buy products without necessarily planning to do so, even when there are brand logos, advertisements, promotional banners, and ribs for certain products, especially during a particular season. They are more parsimonious in their purchasing, which leads to special promotions such as limited-time offers, which are thus beneficial in cross-selling and upselling. Subsequently, businesses can benefit from personalized push notifications, AI-based product recommendations, and attractive in-store and online campaigns.

4.4. Benefits of AI-Driven Segmentation

The application of AI in segmentation for the retail business has brought several benefits to business organizations, including Sales, Customer Relations, and Operational efficiencies. Specifically, with the help of machine learning, companies can create specific promotions and more effective advertising campaigns, as well as enhance their interactions with clients and internal organizational processes.

4.4.1. Increased Sales

With the help of artificial intelligence, the market segmented for the customers to target specific and promote products with specific marketing strategies. Sapiential purchasing behavior, products chosen, and clients’ spending habits help the AI models come up with specific causal discounts, recommendable items, and rebates applicable for each customer class. For example, Frequent Shoppers may be targeted to give offers and promotions on their most purchased brands. In contrast, Impulse Buyers can be marketed to through opportunities that are good for a limited time only. They effectively improve the conversion ratio, basket size, and revenues.

4.4.2. Enhanced Customer Retention

Therefore, it is clear that hyper-personalization is an important factor that enables building long-term customer relationships. Segmenting customers promotes a better understanding of their buying behaviour, preferences, and level of satisfaction, enabling a business to offer its clients a better shopping experience, suggest appropriate products, or offer suitable loyalty indicators.

Retailers can meet individual needs by providing prompt organic and healthy consumers with rebates for organically grown products or cash-back to Price-Sensitive Buyers. This is true because people who are satisfied with a product or service and have made a transaction shall continue to use the particular service or product.

4.4.3. Operational Efficiency

Some traditional segmentation methods entail the manual interpretation of the data with a subsequent classification based on readily set rules, which is a rather tedious task and may lead to high error rates. This is done through AI, whereby data on the customers are analyzed in real time, and the segmentation of the customers is frequently changed depending on new patterns of behavior. This helps the workload to be minimal, which will improve the speed of making decisions and resource utilization for the marketing and customer engagement department. In this aspect, integrating AI into practice facilitates the achievement of business goals in marketing, reducing operating expenses and improving the overall robustness and adaptability of the retail model.

5. Conclusion

This is because the conventional ways of segmenting customers in supermarkets and grocery retailing are becoming outdated as Big Data, coupled with machine learning and real-time analytics, are being used to offer customer segmentation at its best. Static methods of targeting, including demographics and those based on the Recency, Frequency, And Monetary (RFM) model, are unsuitable for the current dynamic market. Conversely, AI-based segmentation uses clustering algorithms like K-Mean DBSCAN, models such as Decision trees, Random forest, and Gradient boosting, and deep learning techniques to develop an accurate customer model.

By employing the given innovative strategies, retailers can segment customers with regard to their purchasing behaviours, preferences, interactiveness, and others, which would benefit retailers in targeted recommendations promotions, primarily based on the customers' behaviour and specific loyalty programmes. The integration of real-time analyses fleshes up the usefulness of AI-based segmentation to the highest level. Hence, by processing POS data, browsing history, social media engagement, and feedback data, the AI models can be updated in real-time to catch up with the newest trends in consumer behavior and MBA segmentation trends. This is crucial in keeping retailers relevant to the growing trends, as well as the fluctuations in the seasons and even customers. Frequent shoppers may be rewarded with a special offer on particular preferred items, while impulse buyers may be served with constant AI-powered suggestions about products and regular time-bound limited coupons and discounts. Such a level of customization makes for better customer satisfaction, customer loyalty, and better sales figures on the company's balance sheets.

Some issues related to AI-driven consumer segmentation include privacy issues, the costly and time-consuming calculation process, and data quality. Two major issues that need to be addressed include satisfying the data protection legislation, for instance, GDPR and CCPA, and not undermining customer experience. Moreover, applying AI models and algorithms on a larger scale also demands a lot of computing power and investment in infrastructures that may not be easily within reach of small businesses. To overcome these challenges, secure data handling, future AI solutions on cloud platforms, and optimization techniques of the AI model with regard to accuracy, scalability, and cost will be important. For future work, it would be preferable to design models that can adapt to the fluctuation of consumers' behavior in real-time.

Combining reinforcement learning techniques, federated learning, and explainable artificial intelligence modeling can promote improved malleability of the segmentation frameworks. However, with the use of multiple data inputs involving AI-driven IoT Smart Shopping cart and voice-based retail, conversations can be added to the multivariate real-time customer information. Thus, developing new methods in AI-based segmentation can help retailers improve their abilities to engage customers, maximize profit, and guarantee the sustainable growth of the business deal in a more rigorous environment in the presence of numerous competitors.

References

[1] V. Thangavel, "Revolution of AI in Hyper-Personalization Marketing of FMCG," *SSRN*, pp. 1-14, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[2] Michel Wedel, and Wagner A. Kamakura, *Market Segmentation: Conceptual and Methodological Foundations*, Springer Science & Business Media, pp. 1-382, 2000. [Google Scholar] [Publisher Link]

[3] Peter S. Fader, Bruce G.S. Hardie, and Ka Lok Lee, "RFM and CLV: Using ISO-Value Curves for Customer Base Analysis," *Journal of Marketing Research*, vol. 42, no. 4, pp. 415-430, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[4] Sara Dolnicar, and Friedrich Leisch, "Using Segment-Level Stability to Select Target Segments in Data-Driven Market Segmentation Studies," *Marketing Letters*, vol. 28, pp. 423-436, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[5] Anil K. Jain, and Richard C. Dubes, *Algorithms for Clustering Data*, Prentice-Hall, Inc, pp. 1-320, 1988. [Google Scholar] [Publisher Link]

[6] The Retail Revolution: AI, Hyper-Personalization, and the New Normal in Customer Expectations, Sutherland Global, 2024. [Online]. Available: https://www.sutherlandglobal.com/insights/blog/the-retail-revolution-ai-hyper-personalization

[7] Rui Xu, and D. Wunsch, "Survey of Clustering Algorithms," *IEEE Transactions on Neural Networks*, vol. 16, no. 3, pp. 645-678, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[8] Sara Dolnicar, "A Review of Unquestioned Standards in Used Cluster Analysis for Data-Driven Market Segmentation," *Faculty of Business and Law*, Deakin University, Melbourne, pp. 31-37, 2002. [Google Scholar] [Publisher Link]

[9] Gang Wang et al., "Big Data Analytics in Logistics and Supply Chain Management: Certain Investigations for Research and Applications," *International Journal of Production Economics*, vol. 176, pp. 98-110, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[10] Lina Zhou et al., "Machine Learning on Big Data: Opportunities and Challenges," *Neurocomputing*, vol. 237, pp. 350-361, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[11] David Lazer, and Jason Radford, "Data ex Machina: Introduction to Big Data," *Annual Review of Sociology*, vol. 43, no. 1, pp. 19-39, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[12] E.W.T. Ngai, Li Xiu, and D.C.K. Chau, "Application of Data Mining Techniques in Customer Relationship Management: A Literature Review and Classification," *Expert Systems with Applications*, vol. 36, no. 2, pp. 2592-2602, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[13] Hsinchun Chen, Roger H.L. Chiang, and Veda C. Storey, "Business Intelligence and Analytics: From Big Data to Big Impact," *MIS Quarterly*, vol. 36, no. 4, pp. 1165-1188, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[14] Yan Xu et al., "Advances in Medical Image Segmentation: A Comprehensive Review of Traditional, Deep Learning and Hybrid Approaches," *Bioengineering*, vol. 11, no. 10, pp. 1-42, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[15] Leveraging AI for Personalized Shopping Experiences, e-Cens. [Online]. Available: https://e-cens.com/blog/leveraging-ai-for-personalized-shopping-experiences/

[16] Mudasir Ashraf, and Majid Zaman, "Revealing Historical Insights: A Comprehensive Exploration of Traditional Approaches in Medical Image Segmentation," *Deep Learning Applications in Medical Image Segmentation: Overview, Approaches, and Challenges*, pp. 65-84, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[17] Chu Fang, and Haiming Liu, "Research and Application of Improved Clustering Algorithm in Retail Customer Classification," *Symmetry*, vol. 13, no. 10, pp. 1-15, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[18] Ming-Hui Huang, and Roland T. Rust, "A Strategic Framework for Artificial Intelligence in Marketing," *Journal of the Academy of Marketing Science*, vol. 49, pp. 30-50, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[19] Chenguang Wang, "Efficient Customer Segmentation in Digital Marketing Using Deep Learning with a Swarm Intelligence Approach," *Information Processing & Management*, vol. 59, no. 6, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[20] Marina Kholod, Alberto Celani, and Gianandrea Ciaramella, "The Analysis of Customers' Transactions Based on POS and RFID Data Using Big Data Analytics Tools in the Retail Space of the Future," *Applied Sciences*, vol. 14, no. 24, pp. 1-15, 2024. [CrossRef] [Google Scholar] [Publisher Link]