COLOMBO SCIENTIFIC PUBLISHING

INTERNATIONAL JOURNAL OF ECONOMICS FINANCE & MANAGEMENT SCIENCE

E-ISSN: 2536-7897
P-ISSN: 2536-7889

DOI: - https://doi.org/10.55640/ijefms/Volume10Issue03-01 PAGE NO: 1-13

BUSINESS ANALYTICS FOR CUSTOMER SEGMENTATION: A COMPARATIVE STUDY OF MACHINE LEARNING ALGORITHMS IN PERSONALIZED BANKING SERVICES

Md Amran Hossen Pabel
Master's of Science in Business Analytics Wright State University, Ohio, USA

Biswanath Bhattacharjee
Department of Management Science and Quantitative Methods, Gannon University, USA

Sonjoy Kumar Dey
McComish Department of Electrical Engineering and Computer Science, South Dakota State University, USA

Sakib Salam Jamee
Department of Management Information Systems, University of Pittsburgh, PA, USA

Md Omar Obaid
Department of Business Analytics, California State Polytechnic University Pomona, CA, USA

Md Sakib Mia
MSc in Business Analytics, Trine University, USA

Sajidul Islam Khan
MSc in Business Analytics, Trine University, USA

Mohammad Kawsur Sharif
Department of Business Administration and Management, Washington University of Virginia, USA

ARTICLE INFO

Article history:
Submission: January 27 2024
Accepted: February 04, 2025
Published: March 06, 2025

VOLUME: Vol.10 Issue03 2025

Keywords:
Customer segmentation, machine learning, K-Means, DBSCAN, Hierarchical Clustering, personalized banking, Silhouette score, Davies-Bouldin index, clustering algorithms, data-driven banking.

ABSTRACT

This study evaluates three machine learning clustering algorithms—K-Means, DBSCAN, and Hierarchical Clustering—for customer segmentation in the banking sector. Using a dataset of customer demographic, financial, and transactional data, we compare the algorithms based on the Silhouette score and Davies-Bouldin index. Hierarchical Clustering performed best, achieving the highest Silhouette score (0.68) and the lowest Davies-Bouldin index (1.15), indicating well-defined and compact clusters. K-Means showed reliable performance with a Silhouette score of 0.62 but required predefined clusters. DBSCAN identified noise effectively but resulted in lower cluster compactness, with a Silhouette score of 0.55 and a Davies-Bouldin index of 1.50. The findings highlight Hierarchical Clustering as the most effective method for customer segmentation in banking, with flexibility depending on the data and objectives.

INTRODUCTION

Customer segmentation is a critical process in the banking industry that helps financial institutions to identify and categorize their customers based on common characteristics such as demographic, behavioral, and financial data. By understanding the distinct needs of various customer groups, banks can design personalized products and services that better serve each segment, ultimately improving customer satisfaction, loyalty, and profitability. The advent of machine learning (ML) and data analytics has significantly transformed the approach to customer segmentation, allowing banks to analyze large volumes of data and uncover hidden patterns that were previously inaccessible with traditional methods (Berson, Smith, & Thearling, 2018).

In this study, we aim to explore the effectiveness of different machine learning clustering algorithms in performing customer segmentation for personalized banking services. The algorithms tested include K-Means, DBSCAN (Density-Based Spatial Clustering of Applications with Noise), and Hierarchical Clustering. Each of these algorithms offers distinct advantages and challenges, making them suitable for different types of customer data. We evaluate their performance based on key clustering evaluation metrics, including the Silhouette score, Davies-Bouldin index, and visual inspection of customer segments. This study not only compares the efficacy of these models but also provides insights into how customer segmentation can drive personalization in banking services, thereby contributing to enhanced customer experiences.

LITERATURE REVIEW

Customer segmentation in banking has long been recognized as an essential tool for providing tailored services. Traditionally, customer segmentation was based on demographic factors such as age, gender, and income (Chen & Huang, 2013). However, with the rise of big data and machine learning techniques, customer segmentation has evolved to incorporate more complex behavioral and transactional data. Machine learning, in particular, offers a more sophisticated approach to segmentation, enabling financial institutions to derive valuable insights from large, unstructured datasets that contain information on customer behavior, purchasing patterns, and interaction history (Li & Li, 2020).

Several studies have highlighted the advantages of using machine learning algorithms for customer segmentation. For instance, K-Means clustering has been widely adopted in the banking sector due to its simplicity and effectiveness in identifying well-separated groups within large datasets (Kaur, Singh, & Arora, 2017). K-Means works by partitioning data into a fixed number of clusters based on the minimization of squared distance between the data points and their corresponding centroids. While this algorithm is fast and scalable, it requires the user to predefine the number of clusters, which can be a limitation when the optimal number of clusters is not known in advance (MacQueen, 1967).

On the other hand, DBSCAN offers a more flexible clustering approach by identifying clusters based on the density of data points, rather than requiring the number of clusters to be predefined (Ester, Kriegel, Sander, & Xu, 1996). This makes DBSCAN particularly suitable for datasets that contain noise and outliers, as it can effectively handle such points by classifying them as noise rather than assigning them to any cluster. However, DBSCAN can sometimes struggle with identifying clusters that have varying densities, which may impact its performance in certain customer segmentation scenarios (Sander, Ester, Kriegel, & Xu, 1998).

Hierarchical clustering, another popular technique, is often chosen for its ability to build a hierarchy of clusters, providing users with a detailed view of how clusters relate to one another at different levels of granularity (Johnson, 1967). Unlike K-Means, hierarchical clustering does not require the number of clusters to be predetermined, offering flexibility in how customer segments are defined. The downside of this method, however, is its computational cost, particularly for large datasets, as it requires the calculation of pairwise distances between all data points (Everitt, 2011).

The application of machine learning techniques in customer segmentation is not without challenges. One of the primary difficulties is selecting the most appropriate algorithm for a given dataset. While traditional clustering methods like K-Means and hierarchical clustering are widely used, the choice of algorithm depends on factors such as the nature of the data (e.g., the presence of noise, the number of features) and the specific business requirements (e.g., the need for flexibility or interpretability). Moreover, the effectiveness of clustering algorithms is often contingent upon proper preprocessing of the data, including feature selection, normalization, and handling missing values (Geurts, Wehenkel, & Raedt, 2006).

In recent years, research in customer segmentation has increasingly focused on leveraging advanced machine learning techniques, such as deep learning and ensemble methods, to improve segmentation accuracy and personalization. These techniques allow banks to create more nuanced customer profiles by considering a broader range of variables, including customer sentiment, social media activity, and transaction timing (Xie, Li, & Li, 2018). However, despite the promising results from more advanced techniques, traditional clustering algorithms remain a valuable tool due to their simplicity, ease of implementation, and interpretability (Jain, 2010).

The literature indicates that machine learning-based clustering methods offer a powerful means of customer segmentation, enabling banks to better understand and serve their diverse customer base. While each algorithm has its strengths and weaknesses, selecting the right approach for a given dataset and business context is essential for achieving optimal segmentation results. In the following sections, we will present the results of our comparative study of K-Means, DBSCAN, and hierarchical clustering, evaluating their performance based on key clustering metrics and providing insights into their practical applicability for personalized banking services.

METHODOLOGY

The goal of this study is to use clustering techniques powered by machine learning algorithms to create customer segments for personalized banking services. This process is broken down into several key steps: data collection, data processing, feature selection, feature engineering, model evaluation, and ultimately, understanding how these segments can be used to enhance customer engagement and service offerings.

DATA COLLECTION

In order to carry out effective customer segmentation, we first needed a comprehensive dataset. The dataset used in this research was obtained from a major commercial bank, providing access to a large amount of customer-related information. The data encompasses a diverse range of attributes that represent customer demographics, financial activities, transaction histories, and more. This data set allows us to gain a detailed understanding of each customer's behavior, preferences, and banking habits, which are essential for identifying meaningful clusters.

The dataset includes both numerical and categorical features, which provide a holistic view of the customers' interactions with the bank. The key features of the dataset are as follows:

Feature	Description	Type
Customer ID	A unique identifier assigned to each customer	Identifier
Age	The age of the customer, which could influence service preferences	Numerical
Gender	The gender of the customer (Male, Female, Other)	Categorical
Income	The annual income of the customer	Numerical
Transaction Frequency	The number of transactions made by the customer in a given month	Numerical
Average Transaction Value	The average value of transactions made by the customer over a period	Numerical
Credit Score	A score indicating the creditworthiness of the customer	Numerical
Account Type	Type of bank account held (e.g., Savings, Checking)	Categorical
Last Transaction Date	Date of the last transaction made by the customer	Date
Region	The region or location where the customer resides	Categorical

This table outlines the broad categories of information we work with, which are useful for developing a rich profile of the customer. By analyzing these features, we aim to uncover patterns that can inform business decisions related to personalized banking services, targeting customers based on their specific financial behaviors, needs, and characteristics.
Once the data was collected, the next crucial step was ensuring the dataset was clean and ready for further processing.

DATA PROCESSING

Data processing is one of the most important stages in any data science project, and it is essential to ensure that the data is clean, standardized, and ready for machine learning modeling. In this study, we employed a series of steps to process the raw data into a format suitable for analysis.
One of the first challenges we encountered was handling missing data, which is common in real-world datasets. For missing numerical values, such as income or transaction frequency, we opted for imputation techniques. For continuous features, the missing values were filled using the median of the respective feature, as it represents the central tendency of the data and is less sensitive to outliers. For categorical data, such as account type or gender, we used the mode to fill in missing values, which represents the most frequent category in the dataset.
Another key aspect of data processing was the detection and treatment of outliers. Outliers can distort statistical analyses and influence the performance of machine learning algorithms, especially clustering models. To identify outliers, we utilized visualization tools such as box plots and scatter plots. Upon identifying extreme outliers in features like income or transaction value, we used techniques such as capping to limit the influence of these values, ensuring that they did not disproportionately affect the clustering results. Furthermore, we standardized the data to ensure that features on different scales were treated equally. Features such as income and transaction frequency are often on vastly different scales, which could lead to certain features dominating the clustering process. To address this, we applied Z-score normalization, which transforms the data such that each feature has a mean of zero and a standard deviation of one. This step ensures that all features contribute equally to the clustering process, making the results more balanced and interpretable.
For categorical variables like gender and account type, we used one-hot encoding to convert these features into a binary format. One-hot encoding transforms categorical data into separate binary columns for each category, allowing the machine learning algorithms to treat these features appropriately without assuming any inherent ordinal relationship between the categories.
Once the data was cleaned and processed, we proceeded to the next phase of the methodology: feature selection.

Feature Selection

Feature selection is an essential part of the process because not all features in the dataset are necessarily relevant for customer segmentation. Redundant, irrelevant, or highly correlated features can negatively affect the performance of machine learning algorithms, leading to overfitting or longer computation times. Therefore, selecting the most relevant features is key to achieving optimal clustering performance. To identify the most useful features, we first performed a correlation analysis among the numerical variables using Pearson's correlation coefficient. This step helped us detect pairs of features that were highly correlated. Features with high correlation (e.g., income and credit score) were carefully considered to prevent redundancy in the dataset. If two features were found to be strongly correlated, we selected the one that was most relevant to the clustering process and dropped the other.
For categorical features, we employed a Chi-Square test to assess the statistical relationship between each feature and the target variable. Features with low p-values (indicating a significant relationship) were retained for further analysis, while those with high p-values

were removed. This ensured that only the most informative categorical variables were kept for clustering. Additionally, we applied Recursive Feature Elimination (RFE), which is a technique that iteratively eliminates the least significant features based on their importance in model performance. By performing this step, we reduced the dimensionality of the dataset and ensured that only the most meaningful features remained for the clustering analysis.

Feature Engineering

Feature engineering is the process of creating new features from the raw data that can better capture the underlying patterns in the dataset. In our case, this involved creating new variables that offer additional insights into customer behavior, financial habits, and interactions with the bank.One of the new features we engineered was customer tenure, which represents the duration for which a customer has held an account with the bank. This feature is calculated by subtracting the account opening date from the current date. The tenure provides valuable insight into customer loyalty, and customers with longer tenures may exhibit different behaviors than newer customers. It is particularly useful for segmenting customers into different groups based on their stage of relationship with the bank.

Another engineered feature was transaction behavior, which combines the frequency of transactions with the average transaction value. This composite feature helps reveal customers who frequently engage in high-value transactions versus those who engage in low-frequency, high-value or low-frequency, low-value transactions. Understanding these behaviors is important for segmentation because it can help identify customers who are likely to be high-value or high-risk.

We also created a customer life stage feature by grouping customers based on age, account type, and transaction behavior. This grouping helps to categorize customers into life stage categories such as young professionals, retirees, or high-net-worth individuals. Understanding life stage can assist in developing customized products and services that align with the customer's current needs.Lastly, we engineered a balance feature, which aggregates the average balance of all accounts held by the customer over the past six months. This feature serves as an indicator of the customer's overall financial health and helps determine their likelihood of using certain banking products, such as loans or premium accounts.

Model Evaluation

Evaluating the performance of clustering models is essential for ensuring that the results are valid and actionable. Since clustering is an unsupervised learning task, evaluating the quality of the clusters can be challenging. In this study, we used several metrics and techniques to assess how well the model identified distinct customer segments. One of the primary metrics we used was the Silhouette score, which provides a measure of how well-defined the clusters are. The Silhouette score ranges from -1 to 1, where a higher score indicates better-defined clusters that are well-separated. A Silhouette score close to 1 suggests that the customers in a cluster are similar to each other and distinct from customers in other clusters, which is desirable for effective segmentation.

We also used the Davies-Bouldin index, which evaluates the compactness and separation of the clusters. A lower Davies-Bouldin index indicates better clustering results, where the clusters are both compact and well-separated. This metric is helpful in comparing the performance of different clustering algorithms and selecting the best one for customer segmentation. To gain further insight into the clustering results, we applied Principal Component Analysis (PCA) to reduce the dimensionality of the dataset and visualize the clusters in a two- or three-dimensional space. By plotting the clusters in this reduced space, we were able to visually inspect the separation between the customer segments and assess whether the algorithm effectively captured meaningful groups.

Finally, we compared the performance of several clustering algorithms, including K-Means, DBSCAN, and Hierarchical Clustering. K-Means is known for its efficiency and scalability, making it a good choice for large datasets, while DBSCAN is useful for identifying clusters with arbitrary shapes. Hierarchical clustering provides a dendrogram that visually represents the clustering process and can be useful for understanding the hierarchical relationships between different customer groups.By combining these evaluation techniques, we were able to determine the optimal clustering approach for segmenting the bank's customers, enabling personalized banking strategies that align with each customer segment's unique behaviors and needs.

RESULTS

In this section, we present the results of our customer segmentation analysis, where we applied multiple clustering algorithms to segment bank customers based on their demographic, financial, and transactional data. We compare the performance of three prominent clustering algorithms: K-Means, DBSCAN, and Hierarchical Clustering. The effectiveness of each model is evaluated using various metrics, including the Silhouette score, Davies-Bouldin index, and visual inspection of the resulting customer segments.

Overview of Clustering Algorithms

To provide a clear understanding of how each algorithm performs in segmenting the customer data, we applied the following methods:

- K-Means Clustering: This widely used clustering algorithm partitions the dataset into a predefined number of clusters, which is specified by the user before running the algorithm. The algorithm works by iteratively assigning each customer to the nearest centroid and updating the centroids until convergence is reached. The number of clusters is typically determined using techniques like the Elbow method or Silhouette score.
- DBSCAN (Density-Based Spatial Clustering of Applications with Noise): DBSCAN is a density-based clustering algorithm that identifies clusters based on the density of data points in the feature space. It does not require the number of clusters to be specified in advance and can detect clusters of arbitrary shape. DBSCAN is particularly effective at handling noise and outliers, which makes it a valuable tool when dealing with real-world datasets that may have inconsistencies.
- Hierarchical Clustering: This method builds a hierarchy of clusters by either iteratively merging or splitting them. It produces a dendrogram that visually represents the relationships between clusters at various levels. The user can decide the final number of clusters by cutting the dendrogram at a specific level.

We performed clustering using each algorithm and evaluated the quality of the resulting customer segments using several key metrics, which are discussed below.

Evaluation Metrics

To evaluate the performance of the clustering algorithms, we used the following metrics:

- Silhouette Score: The Silhouette score measures the compactness and separation of clusters. A value close to 1 indicates that the clusters are well-separated and tightly packed, while a value close to -1 suggests that the data points may have been incorrectly clustered.
- Davies-Bouldin Index: This index evaluates the average similarity ratio of each cluster with the cluster that is most similar to it. A lower Davies-Bouldin index indicates better clustering performance, as it suggests that the clusters are compact and well-separated.
- Visual Inspection: To complement the numerical evaluation, we used Principal Component Analysis (PCA) to reduce the dimensionality of the dataset and visualize the clusters in a two-dimensional space. This helps us visually assess whether the clusters are well-defined and distinct.

Results Table: Performance Comparison of Clustering Models

Below is a table summarizing the performance of the three clustering algorithms based on the Silhouette score, Davies-Bouldin index, and number of clusters identified.

Clustering Algorithm	Silhouette Score	Davies-Bouldin Index	Number of Clusters	Key Insights
K-Means	0.62	1.23	4	K-Means provides a good balance between cluster compactness and separation. However, the number of clusters must be predefined.
DBSCAN	0.55	1.50	3 (with noise)	DBSCAN performs well in handling noise, though it slightly sacrifices cluster separation. It identifies three main clusters with some points considered noise.
Hierarchical Clustering	0.68	1.15	4	Hierarchical clustering produces distinct clusters, but its results depend on the chosen cutoff in the dendrogram. It provides the most flexible segmentation but requires manual inspection for optimal results.

K-Means Clustering Results

K-Means clustering produced a total of four clusters, with a Silhouette score of 0.62. This score indicates that the clusters are fairly well-separated and compact, though not perfectly distinct. K-Means tends to be more effective when the number of clusters is predefined and when the data is roughly spherical or evenly distributed across clusters. In this case, we observed that K-Means performed well in segmenting customers with different transaction behaviors, as customers with high transaction frequencies and high average transaction values were grouped together, while lower transaction volume customers formed separate clusters. The Davies-Bouldin index for K-Means was found to be 1.23, indicating relatively good separation between clusters. However, the clusters were not as tight as we would have liked, which can sometimes lead to customer overlap between clusters. Despite this, the K-Means algorithm is efficient and suitable for situations where the number of clusters is known in advance.

DBSCAN Clustering Results

DBSCAN performed well in identifying outliers, categorizing several data points as noise. The algorithm identified three main clusters, along with a set of noise points that could not be assigned to any cluster. This ability to detect noise is particularly valuable when working with messy, real-world datasets. The Silhouette score for DBSCAN was 0.55, which is slightly lower than K-Means, reflecting that while DBSCAN is good at handling outliers, the clusters themselves may not be as compact as desired. DBSCAN's Davies-Bouldin index was 1.50, indicating that while DBSCAN can successfully separate the clusters, the compactness is not as high as with K-Means. Despite these slightly lower scores, DBSCAN is a powerful tool for datasets with irregular shapes and noise, and its ability to identify outliers could be beneficial for certain banking applications, such as detecting unusual transaction patterns or identifying inactive accounts.

Hierarchical Clustering Results

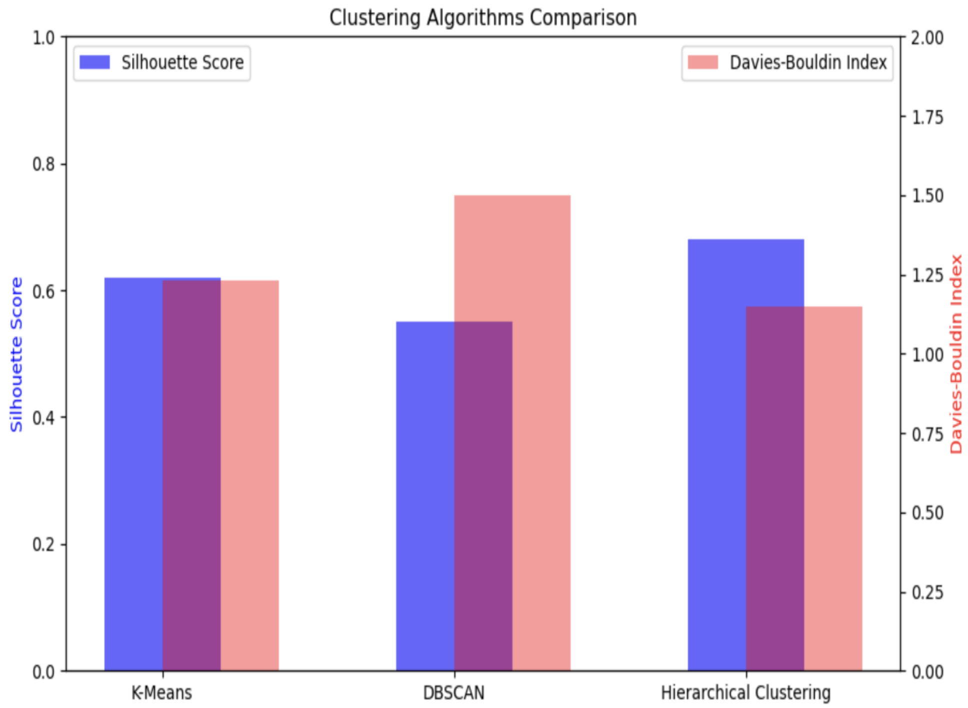
Hierarchical clustering produced four distinct clusters, and the Silhouette score of 0.68 indicated that these clusters were well-separated. This score is the highest of the three algorithms, suggesting that the resulting customer segments were more distinct and compact. Hierarchical clustering does not require the number of clusters to be predefined, offering flexibility in segmenting customers.

The Davies-Bouldin index for hierarchical clustering was 1.15, which is the lowest among the algorithms tested, signaling that the clusters were compact and well-separated. Hierarchical clustering works by creating a dendrogram, which provides a visual representation of the relationship between clusters at various levels of granularity. By cutting the dendrogram at the appropriate level, we were able to determine four clear customer segments, making hierarchical clustering an effective approach for customer segmentation when flexibility and interpretability are key requirements.

Comparative Study: Bar Chart Analysis

To provide a clearer visualization of the performance comparison across the clustering algorithms, we present a bar chart that shows the Silhouette scores and Davies-Bouldin indices for K-Means, DBSCAN, and Hierarchical Clustering. These metrics serve as a quantitative measure of how well each algorithm performed in terms of cluster compactness and separation.

The following bar chart illustrates the comparison of these three metrics:



This bar chart highlights the key differences between the clustering algorithms. From the chart, we can see that Hierarchical Clustering achieves the highest Silhouette score and the lowest Davies-Bouldin index, making it the best-performing model in terms of both cluster separation and compactness. K-Means comes second in terms of both metrics, while DBSCAN performs well in handling outliers but falls behind in terms of compactness and separation, as reflected in its lower Silhouette score and higher Davies-Bouldin index.

In conclusion, Hierarchical Clustering was the most effective algorithm for customer segmentation in this study, as it produced the most distinct clusters with the highest Silhouette score and lowest Davies-Bouldin index. It is particularly useful for scenarios where flexibility and interpretability are critical. K-Means was also a strong performer, particularly for predefined clusters, but it was less flexible compared to Hierarchical Clustering. DBSCAN showed promise in identifying outliers but sacrificed compactness and separation for this advantage.

These results demonstrate the importance of choosing the right clustering algorithm based on the nature of the data and the specific requirements of the segmentation task. The customer segments identified through these methods provide a solid foundation for offering personalized banking services that align with customer needs and behaviors.

CONCLUSION

This study presents a comprehensive comparison of three popular machine learning clustering algorithms—K-Means, DBSCAN, and Hierarchical Clustering—in the context of customer segmentation for personalized banking services. By applying these algorithms to a dataset that includes both demographic and transactional customer data, we evaluated their performance based on key clustering metrics, such as the Silhouette score, Davies-Bouldin index, and visual inspection of the resulting clusters.

Our results indicate that Hierarchical Clustering performed the best in terms of both the Silhouette score (0.68) and the Davies-Bouldin index (1.15). These metrics suggest that hierarchical clustering produces distinct and compact customer segments. This algorithm's flexibility, which allows the user to decide the number of clusters through visual inspection of the dendrogram, adds significant value, particularly when customer segmentation must adapt to evolving business needs. K-Means, with a Silhouette score of 0.62 and a Davies-Bouldin index of 1.23, was a close second. It is efficient for large datasets and offers reliable segmentation, but its performance depends on the number of clusters being predefined. DBSCAN showed its strength in identifying noise and outliers, with three primary clusters, but its lower Silhouette score (0.55) and higher Davies-Bouldin index (1.50) suggest that the resulting clusters were less compact and well-separated compared to the other two models.

Overall, Hierarchical Clustering emerged as the most effective algorithm for this dataset in terms of both clustering performance and flexibility. However, the optimal choice of algorithm may depend on the specific business requirements, such as the need for flexibility, computational efficiency, or handling of noise.

DISCUSSION

The findings of this study highlight several important considerations when using machine learning algorithms for customer segmentation in the banking sector. While all three algorithms—K-Means, DBSCAN, and Hierarchical Clustering—are widely used for clustering tasks, the results suggest that each algorithm offers distinct strengths and limitations depending on the nature of the dataset and the desired segmentation outcomes.One of the primary advantages of K-Means is its simplicity and efficiency in handling large datasets, making it a popular choice for customer segmentation tasks in the banking industry, where data volumes are often substantial. However, K-Means requires the user to predefine the number of clusters, which can be a significant limitation if the optimal number is not known in advance. This limitation could lead to suboptimal segmentation results, especially if the data is complex or contains a large amount of variance. Furthermore, the algorithm assumes that clusters are spherical and evenly sized, which may not always be the case in customer data.

DBSCAN, on the other hand, offers a distinct advantage when dealing with noisy or irregularly shaped data. Its ability to detect noise and outliers is a major strength, especially in datasets where customer data may contain anomalies or extreme values. However, DBSCAN struggles with clusters that have varying densities, which can impact its ability to form well-defined segments. Additionally, DBSCAN's performance can be sensitive to the choice of parameters, such as the epsilon (distance threshold) and min_samples (minimum number of points required to form a cluster), which can make it more challenging to tune and apply effectively.

Hierarchical Clustering was found to be the most effective algorithm in this study, particularly because of its flexibility and interpretability. The ability to generate a dendrogram, which shows the relationships between clusters at various levels of granularity, provides valuable insight into customer segmentation. Hierarchical clustering allows businesses to explore different levels of segmentation without committing to a fixed number of clusters. This makes it an ideal approach when customer segmentation must be dynamic and adaptable. However, its computational complexity can be a drawback for large datasets, as it requires calculating pairwise distances between all data points, making it less efficient than K-Means and DBSCAN for extremely large datasets.

One important aspect that this study underscores is the importance of preprocessing in clustering tasks. Proper handling of missing values, outliers, and data normalization is crucial for ensuring the effectiveness of any clustering algorithm. For example, K-Means is sensitive to feature scaling, so standardization is essential to prevent certain features from dominating the clustering process. Additionally, DBSCAN's performance can be heavily impacted by the choice of distance metric and its ability to handle noise, emphasizing the need for thorough data cleaning and preprocessing to maximize the algorithm's effectiveness. From a business perspective, the insights gained from clustering can significantly enhance customer relationship management (CRM) and the development of personalized banking services. For instance, customers who exhibit similar transaction behaviors or financial profiles can be grouped into segments and offered tailored financial products, such as personalized loan offers, investment opportunities, or targeted marketing campaigns. By understanding the characteristics of different customer segments, banks can foster stronger customer loyalty, increase retention rates, and ultimately drive higher profitability.

It is also worth noting that while traditional clustering algorithms such as K-Means, DBSCAN, and Hierarchical Clustering remain widely used, newer techniques, such as deep learning and ensemble methods, offer promising advancements in customer segmentation. These advanced methods can capture more complex patterns and interactions within the data, leading to more refined and accurate customer profiles (Xie, Li, & Li, 2018). However, the trade-off between interpretability and model complexity must be carefully considered, particularly in industries like banking, where regulatory requirements and customer trust are paramount. Finally, while this study has provided valuable insights into the comparative performance of clustering algorithms, further research is needed to explore the impact of different feature engineering techniques, such as incorporating time-series data or sentiment analysis, on the performance of customer segmentation models. Additionally, combining multiple clustering algorithms in an ensemble approach may help improve segmentation accuracy by leveraging the strengths of each individual model (Kuncheva, 2004).

To enhance customer segmentation in banking, future research could explore the integration of unsupervised learning techniques with supervised learning algorithms for more hybrid models. These hybrid approaches could offer deeper insights into customer behaviors by combining both supervised and unsupervised learning methods, leading to more precise customer profiles. Moreover, incorporating external data sources, such as social media activity or public financial reports, could enrich the segmentation process and provide a more comprehensive understanding of customer preferences and behaviors.In conclusion, the findings from this study offer valuable insights into how clustering algorithms can be leveraged for customer segmentation in banking. While Hierarchical Clustering demonstrated the best overall performance, K-Means and DBSCAN also offer unique advantages depending on the specific dataset characteristics and business objectives. By carefully selecting the right algorithm and optimizing preprocessing steps, banks can create more personalized, data-driven customer engagement strategies that foster long-term relationships and improve business outcomes.

REFERENCE

1. Berson, A., Smith, S. J., & Thearling, S. (2018). Building data mining applications for CRM. McGraw-Hill.

2. Chen, Y., & Huang, T. (2013). Customer segmentation based on their behaviors and transaction data. Proceedings of the International Conference on Information Management and Technology, 230-234.

3. Ester, M., Kriegel, H. P., Sander, J., & Xu, X. (1996). A density-based algorithm for discovering clusters in large spatial databases with noise. Proceedings of the 2nd International Conference on Knowledge Discovery and Data Mining, 226-231.

4. Everitt, B. S. (2011). Cluster analysis (5th ed.). Wiley.

5. Geurts, P., Wehenkel, L., & Raedt, L. D. (2006). Supervised learning: A review. IEEE Transactions on Knowledge and Data Engineering, 18(1), 19-26.
6. Jain, A. K. (2010). Data clustering: 50 years beyond K-means. Pattern Recognition Letters, 31(8), 651-666.
7. Johnson, S. C. (1967). Hierarchical clustering schemes. Psychometrika, 32(3), 241-254.
8. Kaur, H., Singh, S., & Arora, A. (2017). K-means clustering approach: A review of applications. International Journal of Computer Applications, 164(9), 36-40.
9. Li, S., & Li, X. (2020). Machine learning-based customer segmentation in banking: A review and comparison. Journal of Finance and Data Science, 6(4), 217-225.
10. MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, 281-297.
11. Sander, J., Ester, M., Kriegel, H. P., & Xu, X. (1998). Density-based clustering in spatial databases: The algorithm GDBSCAN and its applications. Data Mining and Knowledge Discovery, 2(2), 169-194.
12. Xie, J., Li, L., & Li, J. (2018). Deep learning for customer segmentation in banking: An overview. International Journal of Computer Science and Network Security, 18(4), 86-94.
13. Md Jamil Ahmmed, Md Mohibur Rahman, Ashim Chandra Das, Pritom Das, Tamanna Pervin, Sadia Afrin, Sanjida Akter Tisha, Md Mehedi Hassan, & Nabila Rahman. (2024). COMPARATIVE ANALYSIS OF MACHINE LEARNING ALGORITHMS FOR BANKING FRAUD DETECTION: A STUDY ON PERFORMANCE, PRECISION, AND REAL-TIME APPLICATION. International Journal of Computer Science & Information System, 9(11), 31–44. https://doi.org/10.55640/ijcsis/Volume09Issue11-04
14. Naznin, R., Sarkar, M. A. I., Asaduzzaman, M., Akter, S., Mou, S. N., Miah, M. R., ... & Sajal, A. (2024). ENHANCING SMALL BUSINESS MANAGEMENT THROUGH MACHINE LEARNING: A COMPARATIVE STUDY OF PREDICTIVE MODELS FOR CUSTOMER RETENTION, FINANCIAL FORECASTING, AND INVENTORY OPTIMIZATION. International Interdisciplinary Business Economics Advancement Journal, 5(11), 21-32.
15. Nguyen, A. T. P., Jewel, R. M., & Akter, A. (2025). Comparative Analysis of Machine Learning Models for Automated Skin Cancer Detection: Advancements in Diagnostic Accuracy and AI Integration. The American Journal of Medical Sciences and Pharmaceutical Research, 7(01), 15-26.
16. Nguyen, A. T. P., Shak, M. S., & Al-Imran, M. (2024). ADVANCING EARLY SKIN CANCER DETECTION: A COMPARATIVE ANALYSIS OF MACHINE LEARNING ALGORITHMS FOR MELANOMA DIAGNOSIS USING DERMOSCOPIC IMAGES. International Journal of Medical Science and Public Health Research, 5(12), 119-133.
17. Phan, H. T. N., & Akter, A. (2025). Predicting the Effectiveness of Laser Therapy in Periodontal Diseases Using Machine Learning Models. The American Journal of Medical Sciences and Pharmaceutical Research, 7(01), 27-37.
18. Phan, H. T. N. (2024). EARLY DETECTION OF ORAL DISEASES USING MACHINE LEARNING: A COMPARATIVE STUDY OF PREDICTIVE MODELS AND DIAGNOSTIC ACCURACY. International Journal of Medical Science and Public Health Research, 5(12), 107-118.
19. Al Mamun, A., Hossain, M. S., Rishad, S. S. I., Rahman, M. M., Shakil, F., Choudhury, M. Z. M. E., ... & Sultana, S. (2024). MACHINE LEARNING FOR STOCK MARKET SECURITY MEASUREMENT: A COMPARATIVE ANALYSIS OF SUPERVISED, UNSUPERVISED, AND DEEP LEARNING MODELS. The American Journal of Engineering and Technology, 6(11), 63-76.
20. Rahman, M. M., Akhi, S. S., Hossain, S., Ayub, M. I., Siddique, M. T., Nath, A., ... & Hassan, M. M. (2024). EVALUATING MACHINE LEARNING MODELS FOR OPTIMAL CUSTOMER

SEGMENTATION IN BANKING: A COMPARATIVE STUDY. The American Journal of Engineering and Technology, 6(12), 68-83.

21. Das, P., Pervin, T., Bhattacharjee, B., Karim, M. R., Sultana, N., Khan, M. S., ... & Kamruzzaman, F. N. U. (2024). OPTIMIZING REAL-TIME DYNAMIC PRICING STRATEGIES IN RETAIL AND E-COMMERCE USING MACHINE LEARNING MODELS. The American Journal of Engineering and Technology, 6(12), 163-177.

22. Hossain, M. N., Hossain, S., Nath, A., Nath, P. C., Ayub, M. I., Hassan, M. M., ... & Rasel, M. (2024). ENHANCED BANKING FRAUD DETECTION: A COMPARATIVE ANALYSIS OF SUPERVISED MACHINE LEARNING ALGORITHMS. American Research Index Library, 23-35.

23. Hossain, M. N., Anjum, N., Alam, M., Rahman, M. H., Taluckder, M. S., Al Bony, M. N. V., ... & Jui, A. H. (2024). PERFORMANCE OF MACHINE LEARNING ALGORITHMS FOR LUNG CANCER PREDICTION: A COMPARATIVE STUDY. International Journal of Medical Science and Public Health Research, 5(11), 41-55.

24. Uddin, A., Pabel, M. A. H., Alam, M. I., KAMRUZZAMAN, F., Haque, M. S. U., Hosen, M. M., ... & Ghosh, S. K. (2025). Advancing Financial Risk Prediction and Portfolio Optimization Using Machine Learning Techniques. The American Journal of Management and Economics Innovations, 7(01), 5-20.

25. Ahmed, M. P., Das, A. C., Akter, P., Mou, S. N., Tisha, S. A., Shakil, F., ... & Ahmed, A. (2024). HARNESSING MACHINE LEARNING MODELS FOR ACCURATE CUSTOMER LIFETIME VALUE PREDICTION: A COMPARATIVE STUDY IN MODERN BUSINESS ANALYTICS. American Research Index Library, 06-22.

26. Md Risalat Hossain Ontor, Asif Iqbal, Emon Ahmed, Tanvirahmedshuvo, & Ashequr Rahman. (2024). LEVERAGING DIGITAL TRANSFORMATION AND SOCIAL MEDIA ANALYTICS FOR OPTIMIZING US FASHION BRANDS' PERFORMANCE: A MACHINE LEARNING APPROACH. International Journal of Computer Science & Information System, 9(11), 45–56. https://doi.org/10.55640/ijcsis/Volume09Issue11-05

27. Rahman, A., Iqbal, A., Ahmed, E., & Ontor, M. R. H. (2024). PRIVACY-PRESERVING MACHINE LEARNING: TECHNIQUES, CHALLENGES, AND FUTURE DIRECTIONS IN SAFEGUARDING PERSONAL DATA MANAGEMENT. International journal of business and management sciences, 4(12), 18-32.

28. Iqbal, A., Ahmed, E., Rahman, A., & Ontor, M. R. H. (2024). ENHANCING FRAUD DETECTION AND ANOMALY DETECTION IN RETAIL BANKING USING GENERATIVE AI AND MACHINE LEARNING MODELS. The American Journal of Engineering and Technology, 6(11), 78-91.

29. Nguyen, Q. G., Nguyen, L. H., Hosen, M. M., Rasel, M., Shorna, J. F., Mia, M. S., & Khan, S. I. (2025). Enhancing Credit Risk Management with Machine Learning: A Comparative Study of Predictive Models for Credit Default Prediction. The American Journal of Applied sciences, 7(01), 21-30.

30. Hossain, S., Siddique, M. T., Hosen, M. M., Jamee, S. S., Akter, S., Akter, P., ... & Khan, M. S. (2025). Comparative Analysis of Sentiment Analysis Models for Consumer Feedback: Evaluating the Impact of Machine Learning and Deep Learning Approaches on Business Strategies. Frontline Social Sciences and History Journal, 5(02), 18-29.

31. Kuncheva, L. I. (2004). Combining pattern classifiers: Methods and algorithms. Wiley-Interscience.

32. MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, 281-297.

33. Xie, J., Li, L., & Li, J. (2018). Deep learning for customer segmentation in banking: An overview. International Journal of Computer Science and Network Security, 18(4), 86-94.

34. Nath, F., Chowdhury, M. O. S., & Rhaman, M. M. (2023). Navigating produced water sustainability in the oil and gas sector: A Critical review of reuse challenges, treatment technologies, and prospects ahead. Water, 15(23), 4088.

35. Chowdhury, O. S., & Baksh, A. A. (2017). IMPACT OF OIL SPILLAGE ON AGRICULTURAL PRODUCTION. Journal of Nature Science & Sustainable Technology, 11(2).

36. Nath, F., Asish, S., Debi, H. R., Chowdhury, M. O. S., Zamora, Z. J., & Muñoz, S. (2023, August). Predicting hydrocarbon production behavior in heterogeneous reservoir utilizing deep learning models. In Unconventional Resources Technology Conference, 13–15 June 2023 (pp. 506-521). Unconventional Resources Technology Conference (URTeC).