International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 08 | Aug - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Customer Segmentation Using K-Means Clustering

Anusha k [1] Dr.Shankaragowda B B [2]

[1] Student,4th Semester MCA, Department of MCA, BIET, Davanagere

[2]Associate Professor & HOD, Department of MCA, BIET, Davanagere

Abstract

Demonstrates a thorough method of client segmentation using K-Means clustering on a dataset of mall patrons, utilizing behavioral and demographic characteristics like age, yearly income, and spending score. To find underlying patterns and relationships, the technique starts with data exploration and visualization. A noticeable inflection point in the inertia plot indicates that the Elbow Method is used to estimate the ideal number of clusters, which directs the choice of a suitable cluster count for significant segmentation. Customers are then divided into discrete segments using the K-Means technique, and characteristic profiles are revealed by interpreting each cluster centroid. Additionally, the solution is implemented as a web application built with Flask, which allows users to interactively examine their segmentation findings and administrators to control user activities. The results show that by providing data-driven, customized marketing and consumer engagement tactics, unsupervised machine learning approaches combined with intuitive online interfaces can greatly enhance decision-making in retail settings.

Keywords: customer Segmentation, K-Means, Clustering.

I.INTRODUCTION

Understanding consumer behavior and preferences has become essential to organizational success in today's fiercely competitive corporate environment. Businesses need to use data-driven strategies to stay ahead of the competition as marketplaces get more crowded and customer expectations change. client segmentation is one such tactic, which entails breaking up a large client base into discrete groups based on shared traits. Businesses may improve resource allocation, customize product offers, and customize marketing efforts by utilizing customer segmentation, which will ultimately increase consumer satisfaction and loyalty.

The way organizations engage with their customers has changed as a result of the exponential increase of data and the spread of digital technology. Today, retailers in particular may gather a great deal of information about the demographics, buying behaviors, and engagement patterns of their customers. However, it is extremely difficult to get useful insights from this data due to its enormous amount and complexity. The varied demands and interests of contemporary consumers cannot be adequately met by traditional marketing techniques, which frequently rely on broad, undifferentiated concepts. Adopting cutting-edge analytical methods that can reveal hidden patterns in customer data and enable better informed decision-making is imperative in light of this paradigm change.

Clustering techniques in particular, which are part of unsupervised machine learning, have become effective tools for client segmentation. Unsupervised learning algorithms are capable of detecting innate structures in datasets without prior knowledge of the results, in contrast to supervised learning, which necessitates labeled data. By minimizing the variance within each cluster, K-Means clustering, one of the most popular unsupervised learning methods, divides data into a predetermined number of clusters. Applications where the objective is to categorize clients according to several characteristics, such age, income, and spending habits, are especially well-suited for this approach.

The application of K-Means clustering to client segmentation in a retail mall setting is the main topic of this research. Age, yearly income, spending score, gender, and other demographic and behavioral data for a sample of mall patrons are included in the dataset used in this study. Finding unique consumer segments with comparable characteristics and behaviors is the main goal in order to develop more focused and successful marketing campaigns. The dataset is explored first, followed by data cleansing, visualization, and the discovery of important patterns and connections. Understanding the data's structure and providing guidance for the ensuing clustering process depend heavily on this exploratory stage.

Finding the ideal number of clusters, represented by the letter K, is a major problem in clustering analysis. By oversimplifying the customer base or by forming excessively granular groups that are not useful, choosing an incorrect value for K can result in suboptimal segmentation. To address this challenge, the Elbow Method is employed to evaluate the inertia, or within-cluster sum of squared distances, for different values of K. By identifying the point at which the reduction in inertia begins to plateau, the Elbow Method provides a systematic approach for selecting the most appropriate number of clusters for the dataset.

The K-Means algorithm is used to divide the clients into discrete groups after the ideal number of clusters has been determined. The centroid of each cluster, which stands for the average values of the attributes in that group, is what defines it. By examining these centroids, one can gain important knowledge about the traits that distinguish each consumer group. Groups of youthful, well-off consumers with high spending scores or elderly, somewhat well-off customers with lesser spending might be identified by the study, for instance. Because they allow companies to customize their tactics to the particular requirements and preferences of each sector, these insights are crucial in directing marketing and commercial development initiatives.

This article includes an analytical component as well as the creation of an intuitive web application that makes use of the Flask framework. Within the framework of customer segmentation, the application is made to enable smooth communication between administrators and users. While users can register, log in, and explore their designated consumer segments, administrators can manage user accounts, answer questions, and supervise the segmentation process. In addition to improving the segmentation results' accessibility, this interactive platform encourages efficient stakeholder involvement and communication.

The practical implementation of data-driven solutions in corporate settings has advanced significantly with the incorporation of machine learning techniques with web-based applications. The suggested solution enables dynamic user interactions and real-time access to segmentation insights, empowering firms to make better decisions and adapt to shifting market conditions. Additionally, the application's modular design makes it simple to adapt and extend to other industries, like banking and e-commerce, where client segmentation is just as important.

The use of K-Means clustering for consumer segmentation in a retail setting is demonstrated in this study, along with a strong web-based interface for handling and examining the findings. The method offers a complete solution for companies looking to use consumer data for strategic benefit by fusing thorough data analysis with realistic deployment concerns. This work adds to the expanding corpus of research and practice in data-driven customer relationship management by carefully choosing clustering criteria, developing an interactive platform, and thoroughly examining the dataset. The results demonstrate the potential for combining analytical models with user-centric apps to spur corporate innovation and expansion, as well as the usefulness of unsupervised machine learning in gleaning relevant insights from complicated datasets.

II.RELATED WORK

1. The aim of this paper is to develop and validate a comprehensive machine learning-based methodology for customer segmentation in utility distribution grids, specifically targeting unobservable customers who lack advanced metering infrastructure and only provide monthly billing data1. By introducing the coincident monthly peak contribution (CMPC) metric and leveraging clustering, classification, and regression techniques, the paper seeks to accurately estimate the impact of these customers on system peak demand. This approach enables utilities to design more effective, data-driven segmentation strategies that enhance operational efficiency and planning, even in the absence of granular consumption data.[1]
2. This paper addresses the growing significance of customer-oriented marketing, particularly as personalized, one-customer strategies increasingly replace traditional mass marketing approaches in the e-commerce sector. Recognizing the necessity of understanding individual customer interests and motivations, the paper aims to provide a structured overview of segmentation methods and their evolution. Through an extensive literature review covering 105 publications from 2000 to 2022, the study presents a comprehensive analysis of the segmentation techniques employed in customer behavior analysis. The review identifies a four-phase process common to segmentation studies: data collection, customer representation, customer analysis via segmentation, and customer targeting. Special attention is given to

the methods used for customer representation—primarily manual feature selection and RFM (Recency, Frequency, Monetary) analysis—and for segmentation, where k-means clustering emerges as the most prevalent technique across use cases and data sizes. The paper also explores temporal trends and the suitability of various methods for different dataset dimensionalities, concluding that k-means remains the dominant approach in recent years, reflecting its adaptability and effectiveness in customer segmentation tasks.[2]

3. The findings of a joint project with the Belgian National Grid Operator ELIA are reported in this paper. The research focused on the segmentation and analysis of energy consumption data from 245 HV-LV substations, each of which was represented by time series measurements spanning four years. For precise short-term forecasting and substation load simulation, the study uses Periodic Time Series modeling. The authors determine distinct daily customer profiles for every substation by utilizing the stationarity characteristics of these models. The substations are divided into several classes by grouping these daily profiles, which allows for a better comprehension of consumer behavior trends throughout the grid. As a result, the suggested technique provides a cohesive strategy that tackles forecasting and clustering issues, enabling better operational and planning choices for grid management.[3]

4. This article aims to investigate and illustrate the wide range of potential that customer segmentation offers as a strategic tool for businesses looking to improve product development and marketing efficacy. Through an analysis of Migros Turk's creative segmentation tactics, the study shows how businesses may develop both a-priori and specific post-hoc segmentation strategies to generate substantial value. The study also offers a thorough analysis of general segmentation approaches, with a focus on sophisticated statistical and analytical models like logistic regression, different types of cluster analysis (including both descriptive and predictive methods), and latent class models that can handle complicated, mixed-type data. The purpose of the research is to demonstrate the adaptability and strength of contemporary segmentation strategies in practical business settings by applying these models to a sizable dataset from a global specialty-goods store.[4]

5. The purpose of this article is to describe the creation and deployment of an automated, intelligent system that will assist major sales and marketing companies, like Intel's Sales and Marketing Group, in effectively locating and comprehending new markets, clients, and partners worldwide. The system offers fine-grained classification of businesses by industry segment and functional role by utilizing sophisticated semi-supervised multi-label, multilingual deep learning models, external data enrichment, and extensive web mining. The study shows how this method makes it possible to create a dynamic, real-time knowledge graph that greatly improves the identification of business prospects and facilitates data-driven decision-making in intricate corporate settings.[5]

6. The purpose of this article is to describe the creation and deployment of an automated, intelligent system that will assist major sales and marketing companies, like Intel's Sales and Marketing Group, in effectively locating and comprehending new markets, clients, and partners worldwide. The system offers fine-grained classification of businesses by industry segment and functional role by utilizing sophisticated semi-supervised multi-label, multilingual deep learning models, external data enrichment, and extensive web mining. The study shows how this method makes it possible to create a dynamic, real-time knowledge graph that greatly improves the identification of business prospects and facilitates data-driven decision-making in intricate corporate settings.[6]

7. In light of the growing complexity and dynamic nature of consumer preferences in contemporary marketplaces, the purpose of this research is to present a thorough evaluation of customer segmentation strategies utilizing data mining tools. The study emphasizes the value of segmentation in developing more robust customer connections and focused marketing strategies by examining how businesses might convert heterogeneous consumer data into homogeneous categories. The paper thoroughly looks at a variety of data mining approaches, such as supervised, unsupervised, and other cutting-edge methods, that are used to find hidden patterns and maximize marketing campaigns according to consumer preferences. The study provides insightful information about the state of data mining-driven client segmentation in modern marketing through this analysis.[7]

8. The purpose of this study is to augment the conventional LRF framework with a new "Staying Rate" component in order to create and assess an advanced customer segmentation model, LRFS, especially tailored for the e-commerce industry. The LRFS model improves the accuracy and granularity of consumer segmentation using Google Analytics data by incorporating this additional indicator. The study compares the performance of LRFS to previous models using dimensionality reduction methods including PCA, t-SNE, and Autoencoder in conjunction with the clustering algorithms K-Means and K-Medoids. Empirical findings show that LRFS provides better segmentation accuracy and more profound insights into consumer behavior, especially when paired with K-Medoids and t-SNE. The study goes on to provide real-world examples of how the LRFS model may assist companies in improving their marketing tactics and comprehending their online clientele, making it a more sophisticated and useful tool for customer relationship management and e-commerce marketing.[8]

9. This study uses extensive digital journey data from an e-scooter provider in a large German city to examine and segment consumer behaviors in the developing free-floating e-scooter sharing industry. The study uses customer clustering approaches to discover four unique consumer categories by utilizing large-scale datasets that capture every step of the customer experience, from registration to ride completion. In order to improve scooter usage

and profitability, e-scooter providers may better understand customer needs, customize their services, and modify their business models thanks to the actionable data this segmentation offers for business development. The results provide helpful advice for maximizing the match between the problem and the solution in the quickly changing e-scooter sharing market.[9]

10. By using consumer segmentation and personalization strategies to improve marketing efficacy and customer pleasure, this article seeks to address the issue of information overload in e-commerce. In order to enable firms to customize their services and marketing strategies to particular consumer demands and preferences, the study highlights the significance of customer segmentation based on demographic and psychographic data. The study determines discrete consumer segments and assesses the best grouping method using K-means clustering. The segmented data is then classified using Support Vector Regression (SVR), which yields useful information for focused marketing. By providing more individualized and pertinent experiences, the results show how these data-driven strategies may assist e-commerce companies in gaining new clients, avoiding ineffective targeting, and eventually boosting sales.[10]

III. METHODOLOGY

This project's K-Means clustering client segmentation process is organized into multiple methodical stages that guarantee both analytical precision and real-world relevance. The steps listed below describe the complete procedure for a web application, from data collecting to deployment:

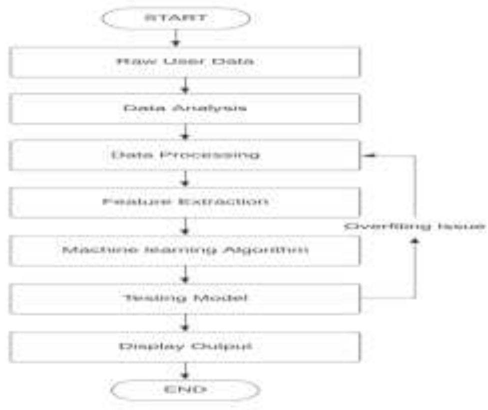

Fig.3.1. Proposed Methodology

1. **Data Collection and Understanding:** The collecting and understanding of a mall customer dataset is the basis of this research. Typically, this dataset contains each customer's age, gender, annual income, and spending score, among other crucial demographic and behavioral characteristics. It is essential to comprehend the dataset's structure and content as these factors influence the choice of pertinent features and the layout of the analysis that follows. A thorough review of the data format, attribute definitions, and the data collection context guarantees that the analysis is both significant and in line with practical business goals.

2. **Data Preprocessing:** The raw data needs to be well cleansed and prepped before any modeling can begin. This include eliminating duplicate entries, resolving missing numbers, and spotting outliers that can distort the findings. To concentrate on the most pertinent factors—age, yearly income, and spending score—that best reflect consumer behavior in a retail setting, feature selection is carried out. To find early patterns, trends, and relationships in the data, exploratory data analysis (EDA) is carried out

utilizing statistical summaries and visualizations including boxplots, scatter plots, and histograms. In order to prevent variables with greater scales from controlling the analysis, normalization or standardization procedures are also used to guarantee that every feature contributes equally to the clustering process.

3. **Determining the Optimal Number of Clusters (K):** A crucial stage in the K-Means clustering procedure is choosing the right number of clusters. By executing the K-Means algorithm for a variety of cluster numbers and charting the resulting inertia (the sum of squared distances from each point to its assigned cluster centroid), the Elbow Method is used to find the ideal value of K. The ideal number of clusters for the data is indicated by the "elbow" point on the diagram, where the rate of inertia decrease abruptly slows. To make sure that the selected K value results in significant and actionable customer groups, further validation methods, like silhouette analysis, may occasionally be employed to further evaluate the quality and coherence of the clusters.

4. **K-Means Clustering Algorithm Implementation :** The K-Means clustering algorithm is used to divide the client base after the ideal number of clusters has been determined. Each data point is iteratively assigned to the closest centroid based on Euclidean distance after the method initializes K random centroids. The centroids are recalculated as the mean of the points in each cluster once all the points have been allocated. Until a predetermined number of iterations is reached or the assignments no longer vary appreciably, this process is repeated. The result is a collection of unique clusters, each of which represents a collection of clients with comparable traits. A cluster identification is assigned to each client in the dataset to aid in additional analysis and interpretation.

5. **Cluster Analysis and Interpretation:** Following the formation of the clusters, a thorough investigation is carried out to interpret the traits of each segment. To determine the characteristics that distinguish each segment, the centroids of the clusters—which stand for the average age, income, and spending score for each group—are analyzed. The distribution of clusters is shown via visualizations like scatter plots, which also offer a clear understanding of the segmentation outcomes. Meaningful client profiles, such as young, low-spending customers or high-income, high-spending customers, can be found thanks to this analysis. Following that, these insights are converted into workable business plans, such focused advertising campaigns or tailored product suggestions.

6. **Deployment as a Flask-Based Web Application:** The project involves creating a web application with the Flask framework to make the segmentation findings accessible and useful. This application has separate user and administrator interfaces. In order to maintain seamless platform operation, administrators can examine and remove registered users, manage user accounts, and reply to user inquiries. In order to obtain individualized insights about their purchasing habits, users can register, log in, and explore the client segments they have been assigned. In order to bridge the gap between data science and end-user interaction, the application

additionally facilitates interactive examination and display of the segmentation results.

7. **Evaluation and Business Application:** Assessing the customer segmentation's efficacy and turning the results into commercial value constitute the last stage. Both quantitative measurements and qualitative business interpretation are used to evaluate the detected clusters' coherence and usefulness. A variety of business methods, such as targeted marketing, client retention programs, and the creation of individualized service offers, are informed by the resulting customer segments. The research illustrates the usefulness of K-Means clustering in promoting data-driven decision-making and improving customer engagement in retail and similar industries by coordinating the segmentation results with organizational goals.

IV. TECHNOLOGIES USED

The K-Means clustering consumer segmentation project makes use of a variety of contemporary tools and technologies from web construction to data processing, machine learning, and visualization. The main technologies and their functions within the project are listed below:

1. Python Programming Language:

Python's ease of use, readability, and adaptability make it the foundation of this consumer segmentation project. Because of its simple syntax, code for data analysis and machine learning tasks may be written and maintained effectively by both novice and seasoned engineers. Python is a great option for creating scalable analytics solutions because of its broad use in the data science community, which guarantees a wealth of documentation and support.

2. Pandas:

Pandas Pandas is a robust Python package for analyzing and manipulating data. It offers adaptable data structures, like as DataFrames, that facilitate data cleaning, filtering, sorting, and grouping. To ensure the data is well-structured for the following machine learning phases, Pandas is used in this project to preprocess the customer dataset, manage missing values, and do exploratory data analysis.

3. NumPy:

For effective numerical calculations in Python, NumPy is necessary. It provides a set of mathematical functions that simplify operations on big datasets, along with a sturdy N-dimensional array object. Many of the computations needed for data normalization, distance calculation, and matrix operations—all essential to clustering algorithms like K-Means—are supported by NumPy in the context of customer segmentation.

4. Scikit-learn (sklearn):

A complete Python machine learning framework, scikit-learn offers user-friendly tools for data preprocessing, model selection, and assessment. It is used in this project to scale features, apply the K-Means clustering technique, and use the Elbow Method to find the ideal number of clusters. It is essential for creating reliable machine learning pipelines because of its uniform API and compatibility with other Python modules.

5. Matplotlib and Seaborn:

Visualization tools like Matplotlib and Seaborn are essential for interpreting and presenting data analysis results. While Seaborn expands on Matplotlib to produce more visually appealing and educational statistical visualizations, Matplotlib provides a wide range of features for producing static plots of publishing grade. Plotting feature distributions, visualizing clusters, and illuminating trends in customer data are all made possible by these tools, which facilitate insight analysis and dissemination.

6. Flask

The consumer segmentation model will be implemented as an interactive web application using Flask, a lightweight and adaptable Python web framework. Both administrators and users may engage with the clustering results, manage queries, and study customer segments in real time because to its ability to create user-friendly interfaces. Because of its modular architecture, Flask is simple to extend and integrate with other databases and tools.

7. Jupyter Notebook:

Workflows for data analysis can be developed, documented, and shared in an interactive environment with Jupyter Notebook. It is especially helpful for machine learning model creation, exploratory data analysis, and presenting findings using narrative prose, embedded code, and visuals. Prior to deployment, this project's early stages involve testing data preparation, grouping, and visualization strategies using a Jupyter Notebook.

8. Database (e.g., SQLite or MySQL):

An SQLite or MySQL relational database is suggested for the long-term storing of user data, queries, and segmentation results. These databases guarantee safe and effective data management for the web application by integrating easily with Flask and Python. They contribute to a strong backend architecture by supporting crucial functions including data retrieval, query tracking, and user authentication.

9. HTML, CSS, and JavaScript:

The web application's front end is constructed with JavaScript for interactivity, CSS for styling, and HTML for structure. These technologies improve the entire user experience for administrators and customers by making ensuring the user interface is responsive, aesthetically pleasing, and simple to use.

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V. TEST CASE

VI. RESULTS AND ANALYSIS

Module	Input	Expected Result	Status
Admin	Login with valid credentials	Admin logs in successfully	Tested OK
Admin	View and delete a registered user	Admin sees user list and can delete a user	Tested OK
Admin	View and reply to user queries	Admin views queries and replies successfully	Tested OK
User	Register with valid details	User registration successful	Tested OK
User	Login with valid credentials	User logs in successfully	Tested OK
User	View customer clustering	Customer clustering data displayed correctly	Tested OK
User	Ask query and view admin reply	User query submitted and admin reply visible	Tested OK

The application of the KMeans clustering algorithm to the customer data resulted in the identification of five distinct clusters, as determined by the Elbow Method. The optimal number of clusters was found by analyzing the Within-Cluster Sum of Squares (WCSS) across a range of cluster values from 1 to 10. The WCSS plot

appropriate balance between complexity and interpretability.

Each cluster represents a unique segment of customers based on their annual income and spending score. Upon examining the cluster centroids and their distribution, the following patterns emerged: Cluster 1 includes high-income customers who have low spending scores, suggesting a group of conservative or value-focused consumers. Cluster 2 represents customers with average income and moderate spending behavior, possibly reflecting the typical mall customer. Cluster 3 includes customers with both high income and high spending scores, making this segment the most valuable or "target group" for premium products, marketing campaigns, and loyalty programs. Cluster 4 consists of low-income customers with high spending scores, indicating potentially impulsive buyers or highly engaged consumers despite limited income. Cluster 5 comprises customers with low income and low spending scores, likely representing budget-conscious individuals who are less responsive to premium marketing efforts.

While clustering is an unsupervised learning method and does not yield an accuracy score like supervised models, its effectiveness can be assessed through visual separation of clusters and the interpretability of the centroid data. The clusters show meaningful distinctions in both income and spending behavior, validating the suitability of KMeans for this segmentation task. These insights allow businesses to tailor their strategies for each group, maximizing customer engagement and optimizing marketing resource allocation. Thus, this segmentation approach provides a practical framework for enhancing customer targeting and improving overall business performance.

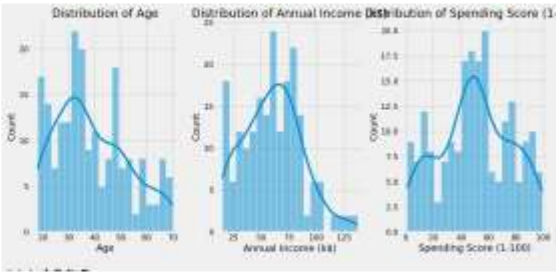

Fig.6.1. Distribution Chart

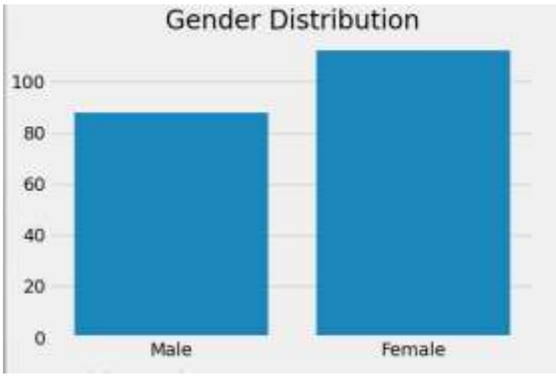

Fig.6.2. Gender Distribution

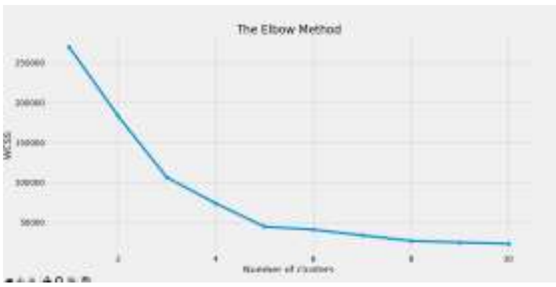

Fig.6.3. Elbow Method

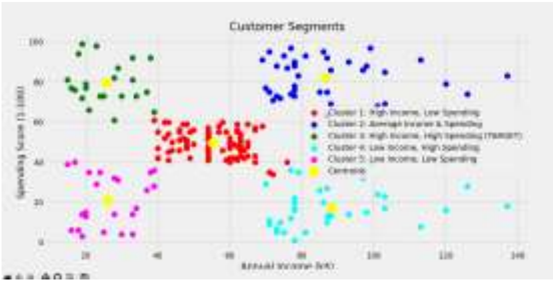

Fig.6.4. Customer Segments

VII. CONCLUSION

To sum up, using K-Means clustering for customer segmentation gives organizations a strong, data-driven strategy to comprehend and interact with their customers more effectively. This approach identifies discrete client groups by examining important characteristics including age, yearly income, and spending score. This allows for more focused marketing, individualized service offerings, and better use of available resources. Both technical and non-technical stakeholders can access, understand, and act upon segmentation insights thanks to the combination of powerful data science tools and an intuitive Flask web application. In the end, this strategy not only increases client loyalty and satisfaction but also propels strategic company expansion in cutthroat markets.

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