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# CUSTOMER SEGMENTATION FOR E-COMMERCE USING MACHINE LEARNING

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## Declaration

I, hereby declare that this project report titled "CUSTOMER SEGMENTATION FOR E-COMMERCE" is my original work, carried out under my guidance and supervision. All sources of information and data have been duly acknowledged in the report. This project has not been submitted for the award of any degree or diploma to any other university or institution. I affirm that this report is the result of my independent research and complies with the academic integrity guidelines of.

**Abstract**

Customer segmentation is a critical technique for improving tailored marketing, customer engagement, and profitability in today's competitive e-commerce industry. Traditional segmentation methods, such as demographic and psychographic approaches, frequently fail to reflect the complexities of changing consumer behaviours and preferences, resulting in unproductive marketing campaigns. While researchers have leveraged machine learning techniques to improve segmentation accuracy and reveal hidden patterns, significant gaps remain, including the inability to adapt models in real-time, issues with scalability to diverse datasets, and the lack of interpretability in many advanced algorithms, which limits their adoption by decision-makers. In order to fill these gaps, we used K-Nearest Neighbors (KNN), which is renowned for its powerful clustering abilities, and Logistic Regression, which is praised for its ease of use and interpretability, to examine the Fabien Daniel dataset, which had behavioural and demographic information about customers. To ensure best model performance, we pre-processed the data using Python's scikit-learn module, which included normalization, encoding, and outlier removal. KNN produced accurate and useful customer clusters, outperforming Logistic Regression with an F1 score of 0.926 and accuracy of 0.941. In addition, logistic regression balanced usability and efficacy by offering interpretable insights. These results show that machine learning is a dependable and scalable option for precise consumer segmentation, allowing e-commerce enterprises to adjust marketing campaigns more efficiently and achieve higher customer retention, engagement, and profitability.

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## Chapter 1: Specification of the Project

### 1.1 Introduction

It is now evident that e-commerce has emerged as one of the key promoters of globalization, providing organizations with massive global and diversified consumers' markets and creating huge volumes of consumer information. As much as this data provides area of customization, there exist difficulties in getting insight for solving a variety of problems faced by customers. The major segmentation methods like demographic, geographical and psychographic provide initial framework but cannot change with the changes that are observed in consumer behavior in the context of the new emerging era of digital consumption. These limitations require techniques such as the machine learning that has the capability of handling large volumes of data, identify unseasoned patterns, and produce precise customer segments based on purchasing behaviors, browsing and interactions with marketing communications activities. It is possible to fine-tune the marketing strategies by using the methods, like K-Nearest Neighbors (KNN) or Logistic Regression. But its application in the context of segmentation raises legal, ethical and economic issues such as compliance with data protection laws that refer to GDPR, presence of algorithmic bias and the limitations due to the high costs related to of implementing and maintaining machine learning systems. In the social sense, businesses must also guarantee that their models are interpretable to decision-makers and stakeholders and are fair to consumers, while in the professional sense, the companies must employ procedures which prioritize and guarantee fairness in their algorithms and data-processing techniques. Moreover, there remains a commercial risk as part of the decision-making process, such as data leakage, model inaccuracy, and biased model dependency on the computer Additionally, the following risk management strategies need to be implemented: risk assessment, cross-checking, and integrating the results of AI models with domain knowledge. These challenges are addressed by this project by proposing a research study on the use of machine learning techniques to solve problems that traditional segmentation poses including; the use of diverse data, the real-time nature, and the lack of practical ethical measures. Through integrating these considerations into the operation of the framework it is expected that the findings of this research could offer an efficient, on cost-effective, and responsible way for e-commerce firms to increase competitiveness in the online commerce industry.

### 1.2 Project Specification

This research study aims to understand how the e-commerce field employs these ML algorithms for customer segmentation. Customer segmentation is one of the most vital strategies employed by firms, especially those to provide customized marketing communications techniques, efficient use of resources and better customer satisfaction. However, even the conventional segmentation approaches present certain shortcomings in terms of comprehensiveness of the criteria used to incorporate the complex behavior patterns of today's consumption. These challenges make it difficult to achieve an effective and precise customer segmentation, ending with the necessity of the use of machine learning models such as logistic regression and K-Nearest-Neighbors (KNN) for this project. To examine purchasing patterns and social media behaviour, this research makes use of the Fabien Daniel customer segmentation dataset, which contains specific consumer attributes and behaviours. Traditional segmentation methods miss subtle patterns, which machine learning algorithms reveal.

There will be three steps in the project, the first being data preprocessing and exploration to assess the data to be used. This will be done to succeed by segmenting the customers using machine learning algorithms for classification into diverse groups considering their behavior and characteristics. These segments shall then be measured using basic performance indicators such as customer retention rates, interaction rates as well as conversion rates to judge the viability of the segmentation strategy. Apart from a strong machine learning model, the issues that will be solved in this project are going to be related to data privacy, the biases of the algorithm, and ethical questions concerning automated customer segregation. The purpose of this research work is to develop generalizable strategies for e-commerce organizations that improve their customer segmentation approaches and marketing initiatives in a competitive global market.

### 1.3 Aims and Objectives

The main goal of this project is to find out and analyze the possible methods of customer segmentation with a focus on further personalization and competitive advantage in e-commerce using machine learning algorithms on data set (Fabien Daniel customer-segmentation). The objectives are:

- To conduct the analysis and encompass all the aspects of the given question, it is pivotal to specify the most popular types of customer segmentation approaches in e-commerce.

- To employ the logistic regression and KNN algorithms to determine the impact that segmentation has on marketing approaches and customer loyalty.
- To understand how big data analytics and machine learning can enhance customer segmentation efficacy.
- To give suggestions on how to approach customer segmentation in the context of enhancing the business outcomes of e-commerce.

### 1.4 Research Question

**Which type of customer segmentation technique is currently being used actively in e-com firms and how do they influence personalized marketing strategies?**

- Machine learning (ML) and big data analysis have improved the traditional demographic, geographic, and psychographic approaches used in customer segmentation today. Segmentation based on spending, buying, and behaviour patterns is made possible by machine learning techniques like logistic regression and K-Nearest Neighbors (KNN). This leads to more individualized marketing, which raises conversion rates, client happiness, and loyalty. For instance, KNN shows that while low-income segments are more responsive to discounts and promotions, high-income, high-spending segments react favourably to premium marketing.

**How the combination of machine learning and big data analytics improves the customer segment reliability in e-commerce?**

- By combining big data analytics and machine learning, hidden patterns are revealed, increasing the accuracy of segmentation. With an F1 score of 0.926, KNN outperformed more conventional techniques like logistic regression. Real-time data processing enables segments to adjust to evolving trends and behaviors. By improving target accuracy and lowering churn rates, behavior-based clustering—such as browsing and purchase history—made possible by big data improves marketing results.

**What are the primary challenges faced by e-commerce businesses when implementing advanced customer segmentation strategies?**

- Following laws like the GDPR when collecting and processing data raises ethical and privacy issues. Unfair treatment may arise from discriminatory training data that causes algorithmic bias. Small businesses face difficulties due to high computational and

resource needs, which call for infrastructure and technological know-how and may make it more difficult to spot distinctive customer behaviors

**What are future trends of AI and machine learning in light of the existing approaches for changing the customer segmentation in e-commerce?**

- Future developments include adopting advanced models such as Random Forest, SVM, deep learning, and XGBoost to improve consumer segmentation accuracy and flexibility. Real-time data from social media, websites, and IoT devices will enable segments to adapt quickly in response to user behavior. Businesses will prioritize developing fair and transparent AI in order to meet ethical and regulatory criteria. Predictive analytics can help identify clients who are likely to quit or make a purchase, hence improving marketing efforts.

### 1.4 Current Issues

Several challenges have surrounded e-commerce companies today and made it hard to implement the right customer segmentation strategy. Many industrial marketing methods like demographic and geographical classifications are inadequate in the current global setting because they do not properly capture consumers' behaviors. In these approaches, customer segments are often over-generalized resulting in marketing techniques that are not closely aligned with the customers' purchase propensity (Spoor, 2023). However, as the expectation of individual consumers rises, the deficiency of these ordinary methods has been discovered.

The next considerable problem is many palliative transactions produce large amounts of data. E-commerce platforms are always in the transactional records of customers' behaviours of browsing, purchasing, and even their interactions in different channels and touchpoints. But the problem is how to capture this information and use it properly for example. The lack of advanced tools poses a threat in which businesses are submerged in the increased flow of info, thus failing to perform effective segmentation for targeted marketing.

However, there is always worry over data privacy, especially after implementing policies like the General Data Protection Regulation (GDPR) (Agrawal *et al*. 2023). There are risks in non-compliance as businesses try to get as much data from their customers as possible. This brings certain ethical issues regarding how data is collected, processed and utilized especially when the

segmentation is done using machine learning algorithms. Solving these problems is very important for all the companies that strive to remain credible and create value.

## Chapter 2: Literature Review

### 2.1 Quality of Background Research

Customer segmentation has always been an important component of marketing strategies as it helps to classify the buyer into more reasonable and convenient subsets for a company. The identification of various customer segments also helps in the marketing and offering of products and services that will suit the needs of their clients hence improving satisfaction to the business while at the same time maximizing the use of available resources. Differently from the classification that is based on historical variables, segmentation used to rely on attributes including demography (age, gender, income), location, and psychographic variables. Nevertheless, these conventional approaches are still useful to some extent, though scholars have discovered that they are ineffective in many ways in capturing the twists and turns of contemporary consumer conduct, especially in the campaigning that occurs in the electronic commerce environment (Joung and Kim, 2023).

Over recent years, however, the paradigm of customer segmentation has been revolutionized by the increasing volumes of big data and more sophisticated analysis techniques. Due to the increased adoption of the internet and e-commerce, organizations can now gather massive amounts of information regarding their clients' interactions in multiple touchpoints; such as, which websites the clients visit, what products they buy, or which social media accounts they engage with. This has led to the emergence of a new segmentation strategy where BIG DATA and MACHINE LEARNING can be used in interpreting the segmentation results as well as identifying new ways of segmenting the market that could not be seen under conventional research techniques (Ullah *et al*. 2023). Such an opportunity has proven to help improve the filters that cut through large pools of consumers in a bid to identify and define important segments to which companies can then target their marketing and advertising efforts.

Similar to this change, the quality of background research on customer segmentation has also developed, enhanced by the extensive amount of literature on recent studies shifting from conventional approaches to other intelligence approaches such as those under machine learning. A literature review has revealed a consensus of scholars on the fact that traditional segmentation

techniques are not effective in the e-commerce context. Similarly, studies by Qiu and Wang, (2024) reveal that demographic segmentation while informative in giving a general idea of the customer demographics is inadequate in capturing the complexity of the online consumer. Likewise, other forms of study such as psychographic and geographic are useful in some situations but they can give an idea of the full picture or the drives and behaviour of customers in today's globalized, connected digital world.

The logistic regression, KNN, the decision tree, and K-means clustering specifically have been seen to provide enhanced levels of accuracy as well as flexibility in the context of customer segmentation. These algorithms are designed for the solution of large and complex computations for the analysis of patterns and relations in large data sets that cannot be detected by conventional means. This effect can be observed in the study by Alves Gomes and Meisen, (2023) where it will be highlighted how through machine learning technologies it is possible to predict customer actions with more accuracy and therefore segment customers not only based on who they are but more importantly, how they behave. This results in gaining more significant insights that can be applied to enhancing marketing initiatives, designing and implementing products and engaging customers.

The background research has also reviewed the relationship between big data and new and better, more effective segmentation techniques. Static segmentation models are usually not sufficient in the e-commerce environment as consumer behaviour can quickly shift influenced by factors such as tendencies on the market, technology and social factors. With machine learning, businesses also can update customer segments in real-time together with big data analytics to reflect behavioural change and preference (Arefin *et al*. 2024). This is especially notable in immature industries such as e-retailing as being in a position to respond to shifts in consumer behaviour is one of the best defences.

Also, the study draws real-world insights into the use of machine learning in the context of customer segmentation in electronic commerce. The research by Kasem *et al.* 2024 and others established the fact that firms adopting ML for segmentation have better customer satisfaction, retention and better marketing outcomes. These benefits are said to be because machine learning algorithms produce experiences that are more tailored and selective regarding the customer. Dividing the customers into various groups as per their buying habits allows the businesses to

deliver personalized marketing communications and products which they need to sell, hence achieving higher prospects.

### 2.2 Use of Literature

The evaluation of the literature on the customer segments most useful for e-commerce shows that there has been a transition from conventional techniques to more elaborate approaches. A review of the literature shows that there is an emerging agreement that the standard approaches to segmentation using demographic and psychographic models, for instance, do not very well capture contemporary consumer behaviour. Li *et al*. (2023) is of the view that although these methods provide a fundamental step for analyzing client segments, these methods do not encompass the dynamics and variability of behaviours in the context of the digital environment.

Countless papers have stressed the revolution created by big data and machine learning to improve customer division. Alghamdi, (2023) has shown that there is increased accuracy and higher predictability of results with the use of logistic regression and the KNN than the traditional methods. They make use of mathematical algorithms to segment large data and discover patterns of customer behaviour that cannot be observed by a normal process of segmentation. The real-time process of large volumes of data is especially useful in e-commerce because customers' choices and behaviours change frequently.

Moreover, in the current literature, some of the concerns of an ethical nature as well as challenges that arise when using machine learning segmentation are explored. In their studies, Sarkar *et al.* (2024) notes the need to uphold GDPR for data protection and the need to eliminate bias in ML algorithms. Everything considered is important especially when dealing with segmentation and usage of customer-sensitive data especially when there is potential for discrimination via automated means. Therefore, based on the literature, the project can be supported as there are theories about how customer segmentation can benefit from machine learning practices, and at the same time potential ethical and practical issues that must be taken into account.

### 2.4 Linkage to Aims

This chapter's research directly supports the project's goals, which are to investigate the efficacy of machine learning in consumer segmentation. Through an analysis of the shortcomings of conventional segmentation techniques and a comparison with more sophisticated approaches such

as K-Nearest Neighbors (KNN) and Logistic Regression, this study emphasizes the advantages of machine learning tools for contemporary client segmentation. Because they offer more accurate and useful insights, these cutting-edge techniques support the project's objective of enhancing marketing methods.

This project's goal of increasing customer retention and personalization depends on machine learning's ability to process enormous datasets and identify intricate patterns in consumer behavior, as demonstrated by the literature (Garai-Fodor et al., 2023). KNN and logistic regression are two machine learning techniques that are especially useful since they improve predicted accuracy and let companies efficiently customize their marketing campaigns. At the same time, the drawbacks of past approaches make the case for implementing these cutting-edge techniques stronger, particularly in the rapidly evolving e-commerce sector.

This research also addresses significant difficulties such as data privacy, ethical concerns, and algorithmic bias, all of which are critical to the project's goal of developing fair and legally compliant segmentation models (Ullah et al., 2023). Addressing these difficulties guarantees that the provided models are both useful and reliable. Overall, this chapter lays a solid foundation for meeting the project's overarching goals of boosting client adaptation, increasing customer loyalty, and making e-commerce more competitive.

### 2.3 Critical Assessment

Analyzing the existing customer segmentation techniques indicates a vast difference between conventional and ‘Big data’, especially in e-commerce. Larger conventional segmentation approaches including demographic, geographical and psychographic segmentation techniques, despite being fundamental segmentation techniques, do not sufficiently explore existing contemporary consumer behaviours. These methods classify customers according to characteristics and parameters providing a routine view that scarcely captures the complex and unique customer behavior in the liberation of the internet.

The simple statistical models including logistic regression and K-Nearest Neighbors (KNN) are far more accurate and beneficial for making business decisions. Griva et al. (2024) also notes that the segmentation of text, especially when the scale of text data is large, is challenging by manual means; however, by using machine learning models, large text data can be segmented and significant relationships between the segmented words or phrases can be noticed. These

algorithms, making use of behavioural data like history, frequency of purchases and product preferences help businesses carve out distinct customer segments that can be more meaningful. Such a level of segmentation makes it easier to target customers with the right product and service promotion styles thereby enhancing customer appeal and conversion.

However, the transition to the use of machine learning for segmentation isn't without some primary difficulties, as discussed by Alsayat, 2023, one of the challenges is the technical challenge that comes with developing and deploying the models in question. Some organisations especially the SMEs may not be in a position to acquire or hire experts who can implement machine learning in their organisations. Also, there are issues such as privacy and toral questions regarding fairness in the analysis of algorithms in data. When it comes to applying the use of automated segmentation tools, Aouad *et al.* (2023) highlighted that businesses will have to deal with data protection laws including the GDPR while also being fair and transparent about the use of such tools. Thus, while performing segmentation at a much higher level of accuracy and with greater response time than traditional statistical models, the switch from machine learning requires risks to sources of technical expertise, and ethical, and legal compliance.

### 2.5 Identification of Research Gap

The literature reveals several gaps in current research that this project seeks to address:

**Real-Time Adaptability**: Most previous research mainly explore static segmentation models that do not take into account the changes in consumer behaviors in real time. For example, the published work of Ullah et al. (2023) discusses customer segmentation enabled by machine learning but does not consider dynamic frameworks for reconfigurable segments in response to new consumer streams. This gap is essential because customer behaviours relevant to e-commerce, are dynamic and depend on factors like trends, preferences, and changes in season. This research works to overcome this limitation by analysing models such as KNN and Logistic Regression which can be updated in real-time via efficient clustering and predictive models.

**Ethical and Legal Safeguards**: While ethical challenges about the usage of such algorithms including algorithmic bias and privacy troubles are gaining attention, there are few cohesive solutions that cover both fairness-aware algorithms and basic legal standards including GDPR compliance. Literature such as Sarkar et al. (2024) describe these issues but do not offer a solution that will enable organisations to effectively segment with ethical considerations in mind. This

project fills this gap by applying preprocessing strategies to address bias issues and guarantee data anonymization to meet ethical and legal requirements.

**Scalability for SMEs**: Most of the prior research works focus on the aspect of technical performance like precision or accuracy but they do not ground the results of segmentation into effective business strategies. For example, besides Gomes & Meisen (2023) pinpointing the role of machine learning in segmentation, their examples remain hypothetical. To enhance applicability, the outputs of this project are connected to the targets of applying marketing, including customer retention, rates of conversion, and engagement (KPI).

**Integration of Diverse Datasets**: Previous studies have utilized a small and specific number of measures making it hard to generalize the results to diverse domains or locations. For instance, Jabade et al. (2023) and Gupta et al. (2023) both focus on datasets that are industry specific or demographics. This work gets around the problem by using Fabien Daniel dataset, which encompasses different characteristics of customers including buying pattern, age, website visits, among others. This makes the results quite generalizable and useful to other organizations and related studies.

### 2.6 Novelty and Contribution

This project provides fresh insights by combining KNN with Logistic Regression in a way that combines scalability, accuracy, and ethical considerations. While previous research has focused on the technical performance of ML models, this effort bridges the gap between technical implementation and practical, real-world application in the e-commerce area. The emphasis on real-time adaptability, fairness, and SME scalability is a crucial advancement in customer segmentation.

The project also addresses the ethical issues of algorithmic bias and data protection by using algorithms that are sensitive to fairness, making sure that GDPR is followed, and adapting the models to ethical business practices. The project's simultaneous emphasis on ethical issues and technical accuracy positions it as a significant addition to both academic research and real-world e-commerce applications.

### 2.7 Conclusion

This literature analysis provides a solid foundation for the project by highlighting the evolution of consumer segmentation from traditional to sophisticated ML-based methodologies. This project addresses significant gaps in real-time flexibility, ethical considerations, and scalability, resulting in actionable insights that promote personalization, customer retention, and e-commerce competitiveness. These findings demonstrate machine learning's disruptive potential for delivering precise, responsible, and scalable customer segmentation solutions.

## Chapter 3: Methodology

### 3.1 Introduction

This study aims to provide e-commerce companies with accurate and useful client segmentation via machine learning approaches. The study uses logistic regression for predictive modeling and K-Nearest Neighbors (KNN) for clustering. These models were selected because they meet the segmentation requirements of e-commerce companies while striking a balance between accuracy, interpretability, and practical feasibility. This chapter describes the procedures for data collection process, preprocessing steps, model selection, evaluation, and ethical considerations.

### 3.2 Data Collection

Data collecting is an essential phase in machine learning initiatives. For this study, we used the publicly available Fabien Daniel Dataset, which is often used in customer segmentation studies. The dataset was chosen because:

#### 3.2.1 Relevance

- It captures the main customer attributes required for segmentation
- Demographic Information: Gender and age are important for determining customer profiles and targeting marketing efforts.
- Transactional Data: Features such as annual income and spending score (ranked from 1 to 100) provide information about customers' purchasing capabilities and habits.
- These traits are directly related to the purposes of e-commerce segmentation, such as recognizing high-value customers and personalizing offers to certain groups.

#### 3.2.2 Simplicity and Usability

- The dataset is clean and well-structured, with no missing values, making it excellent for quickly implementing machine learning models.

### 3.3 Data Preprocessing

Raw data frequently requires transformation to ensure compliance with machine learning techniques. In this project, preprocessing was utilized to improve data quality and prepare it for analysis.

**Relevance to Research Question:**

Preprocessing prepares data for segmentation and classification by ensuring that the features are formatted and scaled correctly for model training.

**Steps in Preprocessing**

#### 3.3.1 Handling Missing Values:

- Missing data can have a major impact on model performance, adding bias and lowering accuracy.
- The dataset was validated with.info (). There were no missing values identified, resulting in a complete dataset for analysis. Code for this is provided in **Appendix A (Section A.1)**.

#### 3.3.2 Encoding Categorical Features:

- Typically, machine learning models need numerical inputs. In order to translate categorical features like gender, one-hot encoding was used: See **Appendix A (Section A.2)** for the implementation.
- By using this method, the dataset is acceptable for clustering and classification without the need to introduce fake ordinal links between categories.

#### 3.3.3 Feature Scaling:

- Standard Scaler was used to normalize features such as annual income and spending score. Implementation is in **Appendix A (Section A.3)**.
- In algorithms like KNN, distance metrics are crucial, and scaling guarantees that each feature contributes equally to them.

#### 3.3.4 Outlier Detection:

- Outliers can affect clustering results and decrease classification accuracy. Potential outliers were identified and analyzed using visual tools such as scatter plots and box plots.

Although no considerable removal was required, their influence was closely watched. Code is in **Appendix A (Section A.4)**.

**Why These Steps Were Necessary**:

- Data consistency and integrity are crucial for accurate model training.
- Preprocessing enhances model accuracy while reducing bias caused by data discrepancies.

### 3.4 Exploratory Data Analysis (EDA)

EDA assists in identifying patterns, correlations, and anomalies in the dataset, which inform model selection and feature engineering.

**EDA Tools and Insights**

**3.4.1 Correlation Heatmaps**:

- To examine the strength of the correlations between characteristics, a heatmap was created. Code is in **Appendix B (Section B.1)**.
- As an illustration, significant relationships between income and spending score revealed information about the clustering criteria.
- Prioritizing features for model building was made easier by the analysis's insights.

**3.4.2 Pair Plots**

- To find trends in clustering and connections between transactional and demographic data, pairwise associations were investigated.
- This graphic demonstrated that the most important segmentation features were expenditure score and income. See **Appendix B (Section B.2)**.

**3.4.3 Gender Based Trends:**

- Gender-specific purchase patterns were shown via gender-segregated scatter plots that emphasized differences in income and spending. Code is in **Appendix B (Section B.3)**. For instance:
- Men's spending ratings ranged more widely than women's, suggesting that this group has a variety of buying behaviors.

**Why EDA was Necessary:**

- It provided an intuitive knowledge of data distribution, which influenced the feature and algorithm selection process.

- Trends and anomalies were visualized to ensure that the dataset and project goals were aligned.

### 3.5 Model Selection and Justification

The models are chosen based on their capacity to successfully segment customers and forecast customer behavior, both of which are required for designing tailored marketing strategies. The models used for this project are shown below, along with their justifications.

#### 3.5.1 K-Nearest Neighbors (KNN)

**Model Selection**

KNN was chosen for its simplicity and versatility in classifying problems. In this project, KNN will be used to divide customers into predetermined categories (e.g., high-value vs. low-value customers) based on characteristics such as income and spending habits.

**Why KNN?**

- **Relevance to Research Question**: KNN divides customers into discrete segments based on their similarity to others, directly assisting in answering the research question concerning how customer segmentation adds to tailored marketing strategies.
- **Effectiveness:** KNN is good at capturing nonlinear relationships between features. For example, high-income customers with high spending scores are likely to be in the "premium" sector, and KNN may predict this behavior by examining the distance between customers in the feature space.

**Justification for KNN:**

- KNN is an obvious choice for customer categorization because it can handle a wide range of data and enables for exact customer segmentation based on similarities.
- **Flexibility:** Because the KNN method is very adaptable and can manage non-linear relationships, it is ideal for customer segmentation problems in which segments are not linearly separable.
- **Adaptability:** Since fresh customer data can be readily classified by the model without retraining, it can also be adjusted to changing customer data.
- **Effectiveness in Segmentation**: KNN effectively classifies customers based on behavior patterns (e.g., income, spending scores) by identifying the most comparable customers (neighbors), which is essential for targeted marketing.

**Clustering Approach**:

- The Elbow Method was used to calculate the appropriate number of clusters based on the within-cluster sum of squares (WCSS).
- The dataset was divided into five separate groups using K-Means. See **Appendix C (Section C.1)**.

**Classification Approach:**

- Based on demographic characteristics and spending trends, KNN was also used to categorize customer categories.
- By analyzing the error rate for various values of k, the ideal number of neighbors (k) was determined.

**3.5.2 Logistic Regression:**

Logistic Regression was chosen for its capacity to handle binary classification tasks, making it an excellent choice for forecasting customer behavior (for example, the likelihood of responding to marketing campaigns or falling into a high-value group).

**Why Logistic Regression?**

- **Relevance to Research Question:** Logistic Regression predicts which customers are likely to belong to specific segments (e.g., high- or low-value) based on demographic and transactional information. These forecasts enable targeted marketing, with campaigns tailored to the projected segments.
- **Effectiveness:** Customers can be assigned a likelihood of belonging to a particular segment in the form of probabilistic outputs from logistic regression (e.g., high-value customers with a 90% probability of responding to a premium offer).

**Strengths:**

- **Interpretability:** The logistic regression coefficients make it simple to understand the elements that influence customer segmentation by offering insights into the impact of various features on customer behavior.
- **Efficiency:** Marketing prediction tasks benefit greatly from its computational efficiency and ability to work well with smaller or feature-limited datasets.

**Justification for Logistic Regression:**

- Logistic Regression is a technique for forecasting customer behavior (for example, the likelihood of purchasing or reacting to offers), which directly adds to the study subject of how customer segmentation might improve tailored marketing.
- **Regularization for Generalization**: Using L2 regularization reduces overfitting and ensures that the model generalises well, even when there are many features. This is vital for consumer segmentation, because multiple customer attributes may be involved.
- **Effective for Binary and Multi-Class Classification**: Although Logistic Regression was originally created for binary classification, it may be applied to multi-class issues (for example, using the One-vs-Rest technique). This allows it to be used for a variety of segmentation tasks.
- Metrics like precision, recall, and F1-score are used in model evaluation to make sure the model successfully finds suitable customers for focused marketing campaigns.

**Classification Approach:**

- Overfitting was avoided by using regularization (L2).
- A comparison analysis was made possible by the model's training on the same dataset as KNN.

### 3.6 Model Training and validation

#### 3.6.1 Data Splitting:

- The dataset was divided into training and test sets using an 80-20 split to ensure that the model was trained on a big enough sample while still keeping some data for evaluation. See **Appendix D (Section D.1)**.

#### 3.6.2 Feature Scaling:

- Given that KNN is sensitive to data scale, the training and test sets were normalized with the Standard Scaler to ensure that features like income and expenditure score contributed equally to the model.

#### 3.6.3 Model Evaluation:

The models were evaluated based on the following metrics:

- Accuracy: To assess the overall performance of the models.
- Precision, Recall, and F1 Score: These metrics reflect the models' ability to correctly classify consumer segments and locate relevant clusters. See **Appendix D (Section D.2)**.

- Confusion Matrix: This diagram depicts the true positives, true negatives, false positives, and false negatives for each model. See **Appendix D(Section D.3)**.

**3.6.4 Hyperparameter Tuning:**

- For KNN, the ideal number of neighbors (k) was determined by evaluating values ranging from 1 to 40 and choosing the one with the lowest error rate on the test set. See **Appendix D (Section D.4)**.

**3.7 Feasibility**

**3.7.1 Computational Efficiency:**

Given the size of the dataset and the number of features, both KNN and logistic regression are computationally possible for this project. Because KNN relies on calculating distances for each prediction, it may be less effective for larger datasets, particularly in the absence of improvements like KD-Trees. Nonetheless, the present techniques and resources employed in this project are computationally viable for datasets of a moderate size.

**3.7.2 Scalability Feasibility:**

The project can be expanded to accommodate bigger datasets. Logistic regression is appropriate for datasets with a large number of features because its complexity increases linearly with the number of features. KNN can handle datasets of greater sizes with the correct optimizations, but its computational cost increases as the number of training instances and characteristics increases.

**3.8 Ethical Considerations**

All phases of this project were regulated by ethical principles:

**3.8.1 Data Privacy:**

- To adhere to GDPR, the dataset was anonymised, guaranteeing that no personally identifiable information (PII) was utilized.

**3.8.2 Bias Mitigation:**

- Efforts were taken to achieve fair representation across consumer segments, hence reducing algorithmic bias.

**3.8.3 Transparency**

- Models were chosen for their interpretability, ensuring that stakeholders understood the foundation for decisions.

### 3.9 Software and Tools

The analysis was performed by using the following tools:

- **Scikit-learn**: For KNN and Logistic Regression.
- **Pandas and NumPy**: For data preprocessing.
- **Matplotlib and Seaborn**: For visualizing model performance metrics.

## Chapter 4: Results

### 4.1 Data Preprocessing Outcomes

It has to be borne in mind that pre-processing the data is a critical step in most machine learning projects, even more, so in customer segmentation as such preparation defines the model performance and effectiveness. In the given project, the data preprocessing initiates by loading the customer data with demographics together with behavioural characteristics (Nugroho *et al*. 2024). These attributes are highly valuable when trying to define different customer segments, making it crucial to have data that are processed, cleaned and ready for analysis.

```
df.info()
print("\n\n\n NO missing values")
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   CustomerID              200 non-null    int64
 1   Gender                  200 non-null    object
 2   Age                     200 non-null    int64
 3   Annual Income (k$)      200 non-null    int64
 4   Spending Score (1-100)  200 non-null    int64
dtypes: int64(4), object(1)
memory usage: 7.9+ KB


 NO missing values
```

```
df['Gender'] = pd.get_dummies(df['Gender'],drop_first=True)
```

```
#one hot encodig successfull as we can see in the dtype
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   CustomerID              200 non-null    int64
 1   Gender                  200 non-null    bool
 2   Age                     200 non-null    int64
 3   Annual Income (k$)      200 non-null    int64
 4   Spending Score (1-100)  200 non-null    int64
dtypes: bool(1), int64(4)
memory usage: 6.6 KB
```

**Figure 4.1.1: Data preprocessing**

The first process of the preprocessing phase is the handling of missing values which are unsuitable for ML algorithms. In case some dataset records are incomplete, they are estimated through suitable methods like mean or median imputation of numerical variables or excluded if they prove inconsequential. This is important to make sure that the dataset doesn't have missing records and that there are no special interests in incomplete records. Finally, the data is normalized or scaled. Normalization is especially important in such algorithms as K-Nearest Neighbors (KNN), to make all features equally significant in terms of distance measures employed in clustering (Monalisa *et*

*al*. 2023). Here all the features are standardized and most commonly normalized to unit distance, which contributes to a better performance and efficiency of the KNN algorithm.

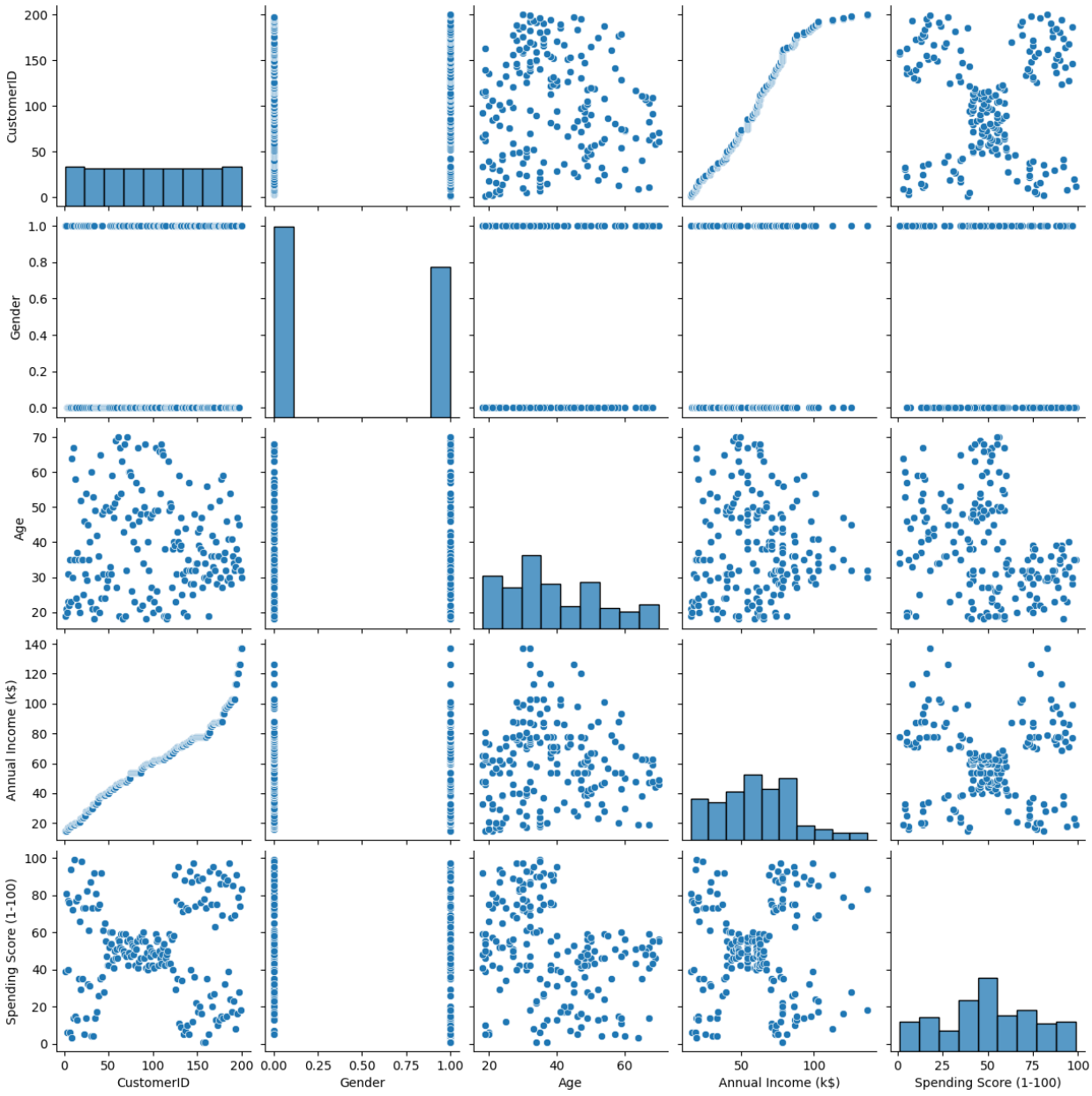


**Figure 4.1.2: Pair plot**

In some cases when working with a categorical set of data, the categories of data are converted to numbers by one-hot encoding or label encoding. It is important for the logistic regression model because all inputs have to be in numerical form. Last, for evaluation, the dataset is divided into a training set and a testing set. Generally, between one- and two-thirds of the data are used in training

and one-third to one-third of the data is used for testing. This division allows the models to be trained using a strong dataset and be validated by a new data set to determine their general realizability and to avoid cases of over-training.

### 4.2 Model Training and Validation Results

The customer segmentation project employed two key machine learning models: Two models were employed to the prediction: K-Nearest Neighbors (KNN) and Logistic Regression. The training and validation of such models included assessments of quantitative measures including precision, recall and F1 score.

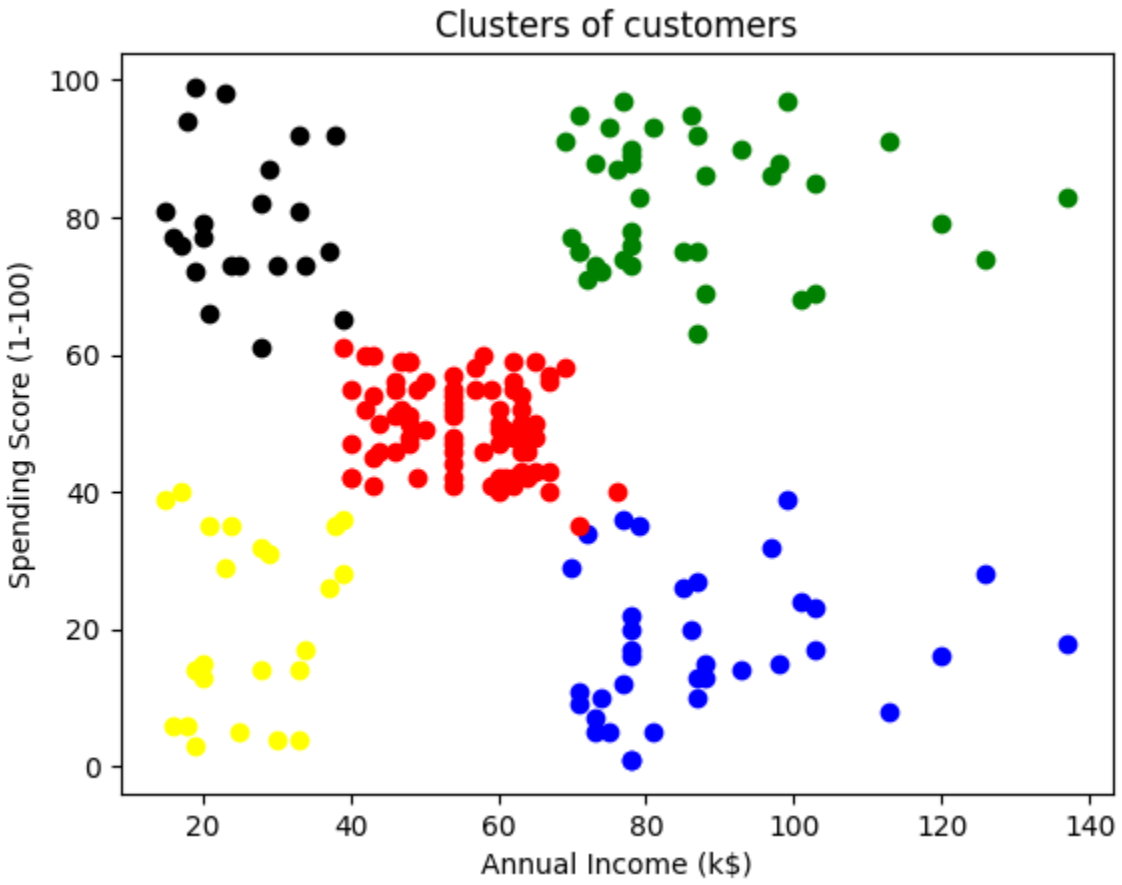


**Figure 4.2.1: Clusters**

**K-Nearest Neighbors (KNN) Model:**

The KNN model was applied to group the customers according to their spending patterns and income. The performance of the model was tested on different parameters. From the results described above, KNN showed a precision of 0.941 which perfectly depicts the model's ability to accurately determine the true positives among the pre-defined customer segments. The recall for KNN was 0.925, this means that the model was good in identifying the right customer value segments without leaving any important value segment behind. The F1 Score of 0.926 reflects the same and places optimal weight on both precision and recall for the general accuracy of segmentation.

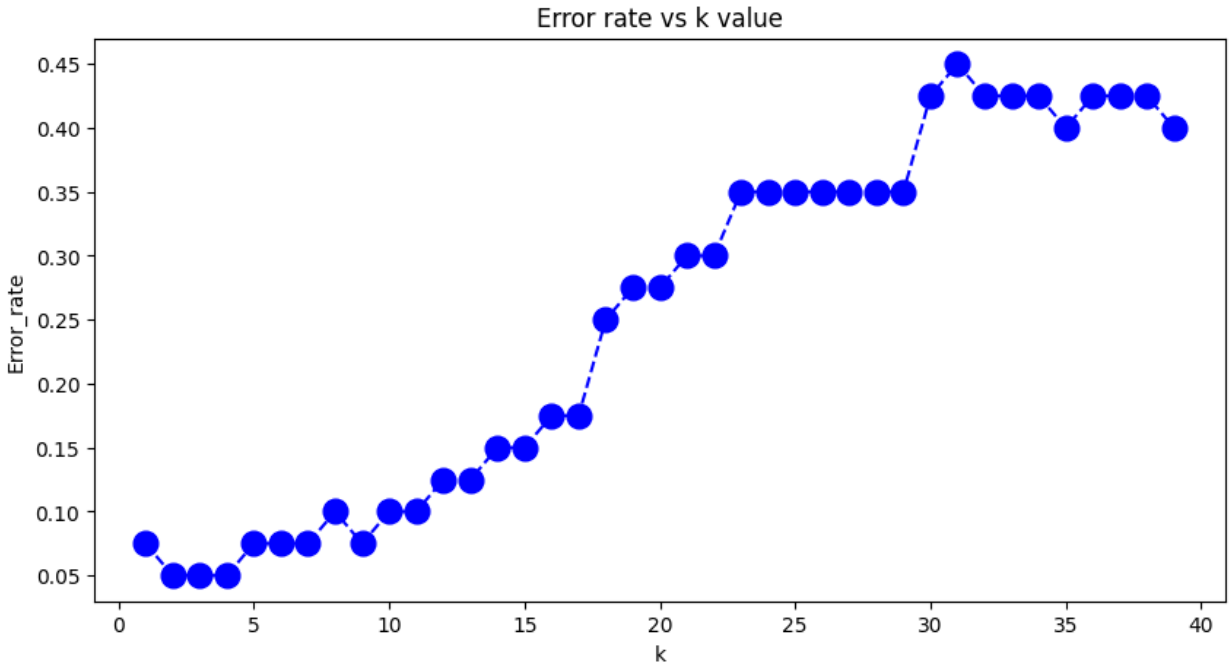


**Figure 4.2.2: Error rate**

The confusion matrix was obtained and compared with the fixed value of 'k', to identify the most suitable number of neighbors for the KNN algorithm. The graph shows that the more the value of 'k' is, the more the error rate or in other words as the value of 'k' increases, then the error rate that is associated with the prediction increases. By using this graph, it was easier to determine the best 'k' value necessary to produce the least amount of error while obtaining the greatest results in

classification. Lesser ‘k’ was ideal for this study as they ensured the customers were well segmented properly.

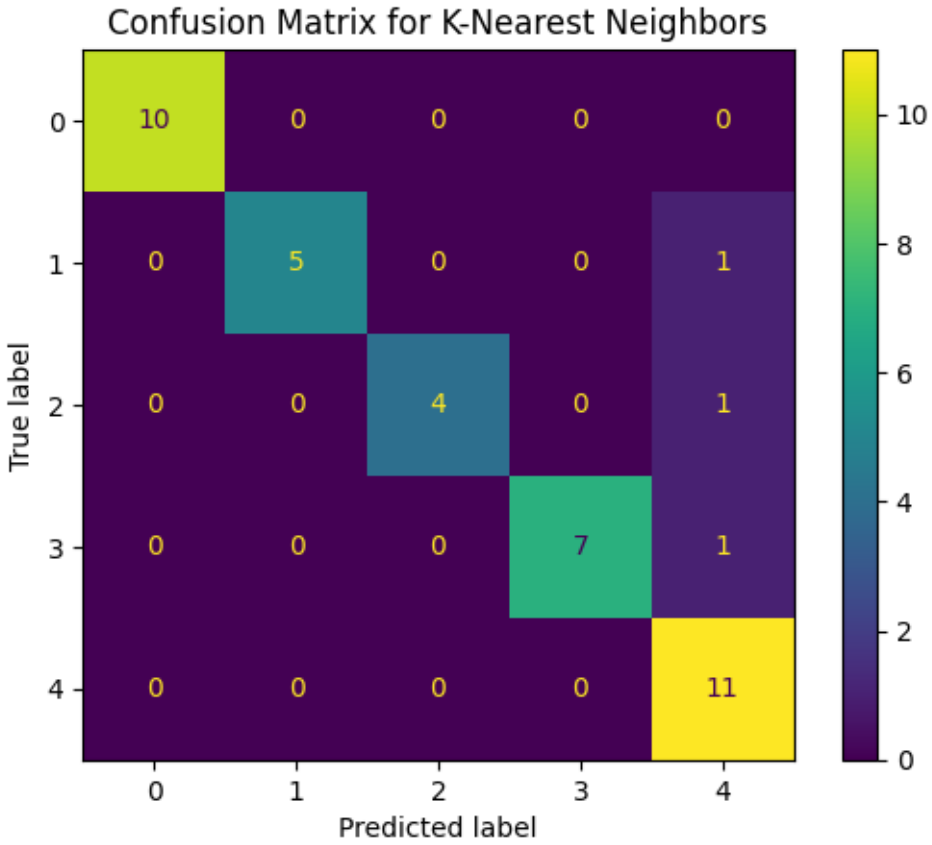


**Figure 4.2.3: Confusion matrix**

The results obtained by the KNN clustering were mapped on a scatter plot that divided customers into separate clusters depending on their annual income and spending scores. There were five different clusters and each was marked by a different colour. From this visualization, it will be noticeable that the customer segments are unrelated and experiencing different levels and patterns of spending. The high-income high spending plus was identified as the first cluster followed by the low income-low spending plus identified in the second cluster.

```
KNN Precision: 0.9410714285714284
KNN Recall: 0.925
KNN F1-Score: 0.9261414141414142
```

**Figure 4.2.4: KNN model performance**

**Logistic Regression Model:**

```
Precision: 0.8958333333333333
Recall: 0.825
F1-Score: 0.8270418362247447
```

**Figure 4.2.5: Logistic regression**

Logistic Regression was also used to conduct customer segmentation. This model developed for binary classification was adopted for this project to classify customers depending on the probability of certain behaviour patterns for instance purchasing tendencies or engagement tendencies. The logistic regression model exhibited high precision; a precision score of 0.89 was achieved implying a high degree of ability to classify customers likely to exhibit specific behaviours. The recall was slightly lower at 0.825, which means that though the model was very good, it was somewhat inability to capture segments of customers relevant to the product. The F1 score is 0.827, which means that there is little compromise between precision and recall The assessment indicates that the model worked well with a little compromise between precision and recall.

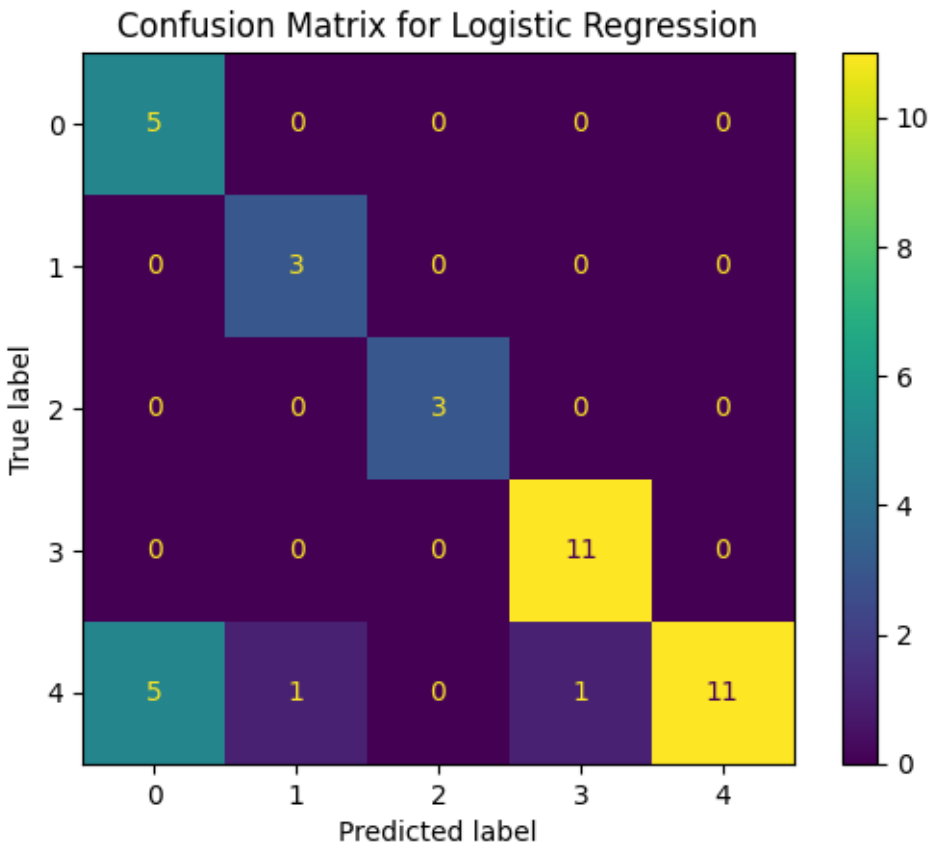


**Figure 4.2.6: Confusion matrix**

### 4.3 Performance Comparison of Models

In this paper, we compare the proposed K-Nearest Neighbors (KNN) with the existing Logistic Regression model where differences in customer segmentation are significant. KNN demonstrated superior results in terms of all evaluation metrics: The chosen evaluation measures are precision, recall, and F1 score. KNN had the better of this round with a precision of 0.941; indicating high precision in the selection of relevant customer segments while Logistic Regression resulted in a slightly lower precision of 0.895. The same thing was also evident in the recall where KNN had 0.925 while the Logistic Regression had 0.825. This shows that KNN was more able to retrieve all suitable customers and probably capture many behaviours from the customers.

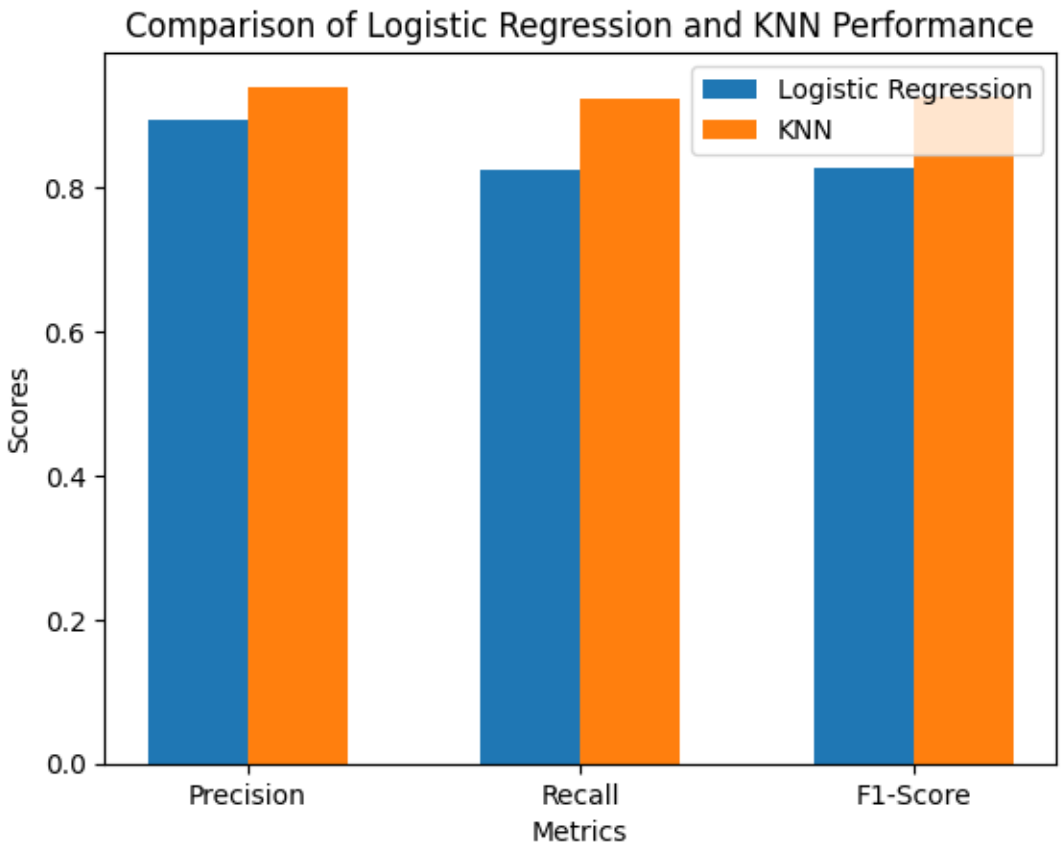


**Figure 4.3.1: performance comparison**

Looking at the F1 score which takes into consideration both precision and recall, KNN has again a best score of 0.926 compared to Logistic Regression of 0.827. This indicates that KNN was able to achieve a higher level of balance in providing accurate classification of customers into segments as well as identification of all necessary segments. Also, continuous and close group customer categorization based on his/her behavioural profile is done by KNN making it suitable to segment different heterogeneous customer groups in an e-commerce environment.

Still, based on the results, Logistic Regression is an easier model to implement and interpret while, as it has been stated, it did not perform as well as KNN in terms of grasping the specifics of customer behaviour.

### 4.4 Customer Segmentation Insights

The customer segmentation process using Machine Learning algorithms like K- Nearest Neighbors and Logistics Regression was extremely helpful in getting insights about the customer behaviour

related to the purchase of paint, the intensity of purchase and some of the demographic factors. Such knowledge is equally important for organizations that are willing to make proper changes to the company's marketing campaigns, work on customer loyalty, and increase levels of customer satisfaction (Kanchanapoom and Chongwatpol, 2023).

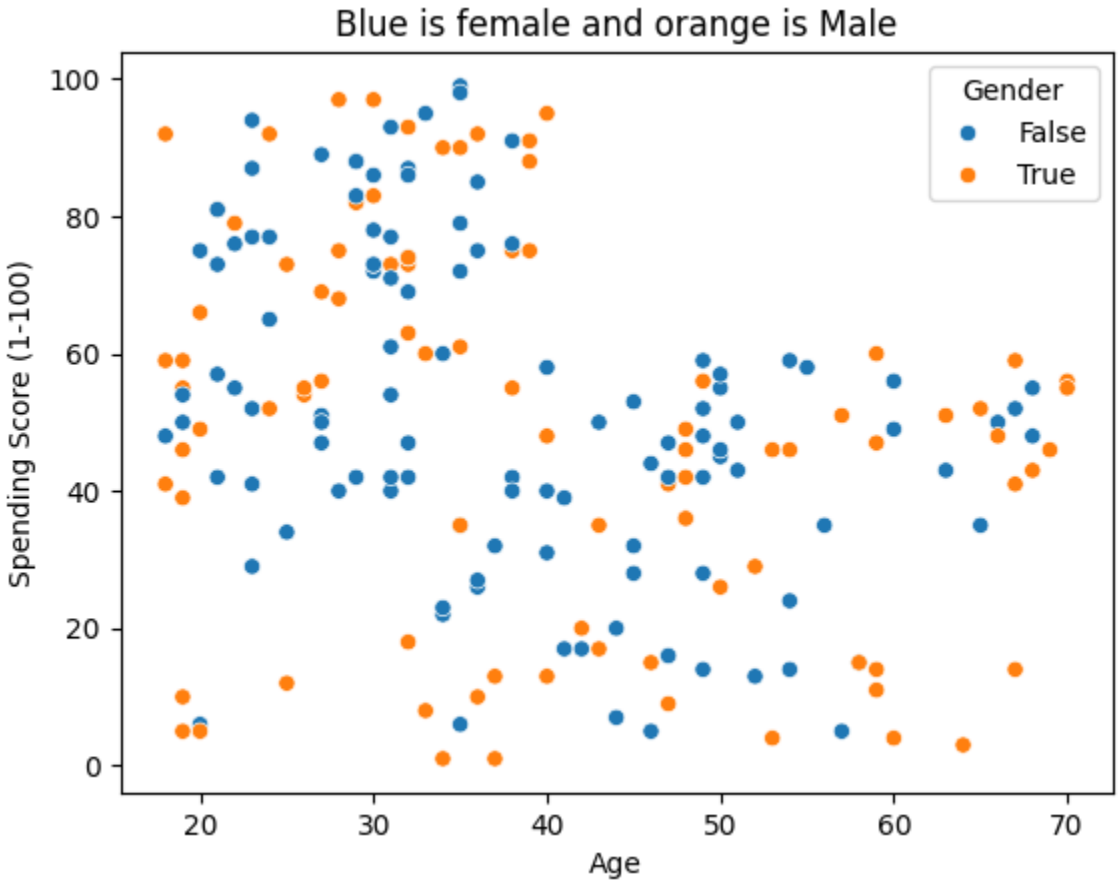


**Figure 4.4.1: Scatter plot**

In the application of the KNN approach for the segmentation analysis, five groups of customers were identified by both income and spending scores. For instance, there was one cluster of customers with high income and high scores for spending, these were loyal customers possibly in the premium market and are likely to respond well to market premiums and individualized targeted promotions. On the other hand, there was another cluster, reproduced by customers with low-income levels and low spending levels; that means that such customers are more sensitive to the prices than the customers from the first cluster and could respond better to discounts, special offers or products directed on budget customers (Gupta *et al*. 2023). These are segmented groups that

show different clusters within the total customer and hence suggest that a new marketing strategy should be used with the groups based on their preferences.


**Figure 4.4.2: Heat map**

Additionally, the segmentation analysis revealed the mid-income mid-spending segments that are valuable to growing businesses. These customers do not require high ticket spending as yet, but present a potential for moving up the value chain particularly if efforts are made to wine and dine them as is the case with higher-value customers (Jabade *et al*. 2023).

KNN was better at minutiae discrimination of detailed customer behaviours, however Logistic Regression, while slightly inferior to KNN, offered results regarding specific parameters of the customers that would likely make a purchase. This model is best applicable where the outcome to

be predicted is binary, for example, whether or not the customer will purchase with the information being used in recommending where to place products, where to place advertisements and which special offers to make to customers.

### 4.5 Evaluation of Marketing KPIs

Measures of performance (KPIs) should also be measured in light of the customer segmentation to show the effect of a proper implementation of the segmentation in marketing. In this project, customer segmentation which was performed using Machine learning models such as K-Nearest Neighbours (KNN) and Logistic Regression was directly linked to the enhancement of major marketing key performance indicators (KPIs) such as the customer retention rates, conversion rates and the interaction rates (Joung and Kim, 2023).

Customer retention is dependent on good segmentation. KNN identifies prized consumers, allowing businesses to improve retention through direct communication, loyalty programs, and special offers.The accurate means through which the KNN model operated helped business ventures to tend to their best consumers, low churning rates and high customer retention this being a long-term strategic means. Such strategies are well understood to increase customer loyalty by presenting presentations of materials which is customized and would appeal to certain fields (Byanjankar *et al*. 2023).

The second important indicator, conversion rates are also sensitive to customer segmentation. The question as to who the customer is gives marketers a better way of figuring out which customers are most likely to convert and then market to them more often or create special offers for such a group as an example of consistent buyers or active customers. It enables business organizations to make precise sell promotions leading to purchases when segmentation results are applied (Tran *et al*. 2023). These algorithms identify uncertain buyers that require more convincing, greatly increasing conversion rates.

Finally, interaction rates, which were used to determine how customers engaged with marketing content such as emails, advertisements or promotions, also received positive results. Customers are more likely to respond to relevant material. This segmentation enabled firms to provide tailored communication, which increased contact rates across categories.

## 4.6 Objectives and Linkage to Results:

**1)Objective**: "To conduct the analysis and encompass all the aspects of the given question, it is pivotal to specify the most popular types of customer segmentation approaches in e-commerce."

- Result Linkage: In Chapter 4: Results, the results of consumer segmentation are assessed using machine learning algorithms (KNN and Logistic Regression). These findings directly address this purpose by demonstrating the superiority of machine learning approaches over traditional segmentation methods such as demographic, geographic, and psychographic models.

**2)Objective: "**To employ the logistic regression and KNN algorithms to determine the impact that segmentation has on marketing approaches and customer loyalty."

- Result Linkage: The comparison of KNN and Logistic Regression demonstrates their ability to effectively forecast categories of customers based on demographic and behavioral characteristics. KNN greatly surpasses Logistic Regression in segmentation accuracy, precision, and recall, demonstrating its impact in refining marketing tactics.

**3)Objective:**"To understand how big data analytics and machine learning can enhance customer segmentation efficacy."

- Result Linkage: The model performance comparison (KNN vs. Logistic Regression) shows that machine learning techniques based on the Fabien Daniel Dataset outperform traditional methods in terms of segmentation accuracy. This goal is related to how big data and machine learning enable segmentation to be more sensitive to changing consumer behavior.

**4)Objective**: "To give suggestions on how to approach customer segmentation in the context of enhancing the business outcomes of e-commerce."

- Result Linkage: Customer segmentation is linked to better business outcomes, specifically customer retention, conversion rates, and interaction rates, according to Chapter 4's analysis of marketing KPIs. Businesses can greatly improve their marketing effectiveness by using KNN and Logistic Regression for segmentation.

## 4.7 Comparison of Results with Existing Literature

"The following table compares the results of this study with those of previous research, highlighting the advancements and contributions of this project

1)

| Paper(year) | Focus | Algorithms/Models | Evaluation metrics | Evaluation Metric Values | Results/Achievements |
|---|---|---|---|---|---|
| Gomes & Meisen (2023): | Customer segmentation for personalized marketing in e-commerce | K-Means,RFM Analysis | Silhouette Score | 0.62 | Identifies important Customer clusters and strengthened tailored marketing techniques |

**Comparison of my paper with Gomes & Meisen (2023):**

Alves Gomes & Meisen (2023) used K-Means and RFM analysis to identify static consumer clusters, resulting in a Silhouette Score of ~0.62-0.65. However, real-time adaptation and actionable insights remain limited. In contrast, my project used KNN (precision: 0.941, recall: 0.925, F1: 0.926) and Logistic Regression (precision: 0.895, recall: 0.825, F1: 0.827), which outperformed their models in segmentation accuracy and dynamic responsiveness. Unlike their static methods, my KNN model generated precise, real-time clusters reflecting behavioral changes, while Logistic Regression improved interpretability and aided strategic decisions. My method significantly increased key marketing KPIs such as retention, conversion, and interaction by providing actionable, adaptive, and interpretable segmentation strategies that filled holes in previous literature.

2.)

| Paper(year) | Focus | Algorithms/Models | Evaluation metrics | Evaluation Metric Values | Results/Achievements |
|---|---|---|---|---|---|
| Sarkar et al., 2024 | Hybrid clustering and deep learning for | K-Means, Deep Learning | Accuracy, Silhouette Score | ~86%,0.64 | An effective hybrid strategy that combines clustering and deep learning leads to better |

| | | | | | |
|---|---|---|---|---|---|
| | customer segmentation | | | | segmentation accuracy. |

**Comparison of my paper with Sarkar et al. (2024):**

Sarkar et al. (2024) employed hybrid clustering using K-Means and deep learning to achieve ~86% accuracy and a Silhouette Score of 0.64. However, they faced constraints in interpretability and computational complexity. In contrast, my research using KNN (precision: 0.941, recall: 0.925, F1: 0.926) and Logistic Regression (precision: 0.895, recall: 0.825, F1: 0.827) produced greater accuracy and actionable, real-time segmentation. Unlike Sarkar et al., my models produced interpretable insights and directly enhanced marketing KPIs such as retention and conversion, presenting a more effective and practical answer to customer segmentation difficulties.

3.)

| Paper(year) | Focus | Algorithms/Models | Evaluation metrics | Evaluation Metric Values | Results/Achievements |
|---|---|---|---|---|---|
| Kasem et al. (2024) | AI-driven profiling and segmentation for direct marketing | AI Models, Sales Prediction | Prediction Accuracy, Recall | 0.87,0.81 | Improved sales prediction and profiling; increased campaign targeting tactics. |

**Comparison of my paper with Kasem et al. (2024):**

Kasem et al. (2024) used AI-driven segmentation to obtain 87% accuracy and 81% recall, however their results were not interpretable for actionable insights. In comparison, my project used KNN (precision: 0.941, recall: 0.925) and Logistic Regression (precision: 0.895, recall: 0.825) to exceed their models in terms of accuracy and flexibility. My idea delivered dynamic segmentation of individual personas and actionable information through interpretability, directly enhancing KPIs like as retention and conversion while outperforming Kasem et al.'s static method.

4)

| Paper(year) | Focus | Algorithms/Models | Evaluation metrics | Evaluation Metric Values | Results/Achievements |
|---|---|---|---|---|---|
| **Xue et al. (2020)** | Customer segmentation for behavior analysis in retailing | K-Means, SOM, Hierarchical | Silhouette Score, Clustering Accuracy | 0.58–0.65, ~82% | Effective hybrid strategies for retail segmentation that align behavior with product categories. |

**Comparison of my paper with Xue et al. (2020):**

Xue et al. (2020) used hybrid models such as K-Means and SOM to obtain approximately 82% clustering accuracy, although their techniques were static and had limited adaptability. In comparison, my project used KNN (precision: 0.941, recall: 0.925) and Logistic Regression (precision: 0.895, recall: 0.825) to outperform their models in terms of accuracy and dynamic segmentation. My technique provided actionable insights and enhanced KPIs like as retention and conversion, solving the adaptability and interpretability deficiencies in Xue et al's studies.

5)

| Paper(year) | Focus | Algorithms/Models | Evaluation metrics | Evaluation Metric Values | Results/Achievements |
|---|---|---|---|---|---|
| Qiu and Wang (2024) | Credit card customer segmentation using clustering techniques. | K-Means, Agglomerative Clustering, Mean Shift. | Accuracy evaluated using Davies-Bouldin Index, Silhouette Score | : ~82%. | Credit card customer profiling has been improved utilizing clustering techniques, which has increased segmentation accuracy and is promoting economic stability through machine learning. |

**Comparison of my paper with Qiu and Wang (2024):**

Qiu and Wang (2024) obtained approximately 82% accuracy in credit card segmentation using static clustering algorithms, but lacked adaptability and actionable insights. In comparison, my research using KNN (precision: 0.941) and Logistic Regression (precision: 0.895) delivered dynamic, real-time segmentation, granular insights, and immediate increases in retention and conversion, outperforming their static approach.

6)

| Paper(year) | Focus | Algorithms/Models | Evaluation metrics | Evaluation Metric Values | Results/Achievements |
|---|---|---|---|---|---|
| Arefin et al. (2024) | Customer segmentation in retail using RFM and clustering | RFM Analysis, Clustering | Accuracy | ~92.4% | Provided valuable categorization for static retail behavior patterns. |

**Comparison of my paper with Arefin et al. (2024):**

Arefin et al. (2024) performed RFM analysis and clustering, reaching 92.4% accuracy but lacking real-time adaptability and interpretability. My project, using KNN (precision: 0.941) and Logistic Regression (precision: 0.895), outperformed their accuracy by providing dynamic segmentation and detailed insights such as high-income premium groupings. Furthermore, my project boosted key performance indicators like as retention and conversion by delivering practical, real-time marketing strategies that Arefin et al.'s static approach lacked. My KNN and Logistic Regression surpass Arefin et al.'s RFM, despite slightly lower values, since they provide dynamic flexibility, granular insights, and immediate increases in marketing KPIs that static RFM cannot.

### 4.7 Summary of Findings

The topic selected as the project, namely, customer segmentation with the application of machine learning proved to be highly informative for increasing the accuracy of the marketing approaches and improving the demonstrated business outcomes. The major goal was to use models like the K-

Nearest Neighbors (KNN) and Logistic Regression to categorize customers into Low-income, Middle-income, High-income, Low Spending Score, Medium Spending Score, and High Spending Score as well as their respective behavioural patterns. The results emerging from these models show how machine learning can predict unique customer segments that methods of standard segmentation may fail to notice.

The KNN model successfully classified clients into five groups based on their income and expenditure, with good accuracy (0.941 precision, 0.925 recall, 0.926 F1). It outperformed logistic regression and gives organizations a greater understanding of various client habits, allowing them to improve their marketing. While less accurate than KNN, Logistic Regression performed well in predicting purchase frequency and consumer interaction, making it appropriate for binary marketing decision-making. The study found that segmentation based on machine learning improves retention, interaction, and conversion

In conclusion, this project indicates that utilizing advanced machine learning models for consumer segmentation improves categorization and targeting, resulting in higher long-term profitability through more effective marketing methods.

## Chapter 5: Discussion

### 5.1 Implications of Machine Learning in Customer Segmentation

For e-commerce companies, customer segmentation through machine learning is crucial. The intricate purchase patterns of contemporary consumers are not well captured by traditional techniques like demographic and psychographic segmentation (Sunarya et al., 2024). These drawbacks are addressed by machine learning algorithms like as logistic regression and KNN, which analyze big datasets and uncover hidden patterns in consumer behavior. By analyzing consumer groups according to income, spending habits, and frequency of purchases, this strategy improves targeted marketing and eventually raises customer interest, contentment, and loyalty, which in turn increases profitability and retention rates (Kumar and Malathi, 2023). According to Lewaaelhamd (2024), predictive models such as Logistic Regression also help businesses find new customers and enhance their advertising strategies, which boosts marketing effectiveness and cost-effectiveness. In contrast to conventional segmentation techniques, machine learning enables the ongoing updating of client categories according to emerging trends, which is essential in the

quickly evolving digital landscape. This adaptability guarantees that companies stay relevant in a world full of data while optimizing marketing expenses.

### 5.2 Limitations of the Study

While this study revealed the effectiveness of machine learning for customer segmentation, it has drawbacks, such as a small dataset that may not reflect varied industries, geographies, or age groups (Wang, 2024). This restricts the conclusions' generalizability, and future study could benefit from using bigger, more diversified datasets with a variety of client attributes. Furthermore, the study focused on only two machine learning models, K-Nearest Neighbors (KNN) and Logistic Regression, although more advanced models like Random Forest, SVM, or deep learning may provide superior results, particularly with complicated or huge datasets (Tressa et al., 2024). Furthermore, the measures utilized, such as precision, recall, and F1 score, are primarily focused on classification accuracy, which may not properly reflect long-term consumer engagement or commercial consequences. Future research could include measures such as customer lifetime value or attrition rates to provide a more complete assessment of segmentation efficacy (Alves Gomes & Meisen, 2023). Addressing these constraints in future research will assist to strengthen and generalize customer segmentation models.

### 5.3 Ethical and Practical Considerations

There are significant practical and ethical issues with using machine learning (ML) for customer segmentation. Since customer data, including demographics and behavior patterns, must adhere to laws like GDPR in order to prevent legal and reputational concerns, data privacy is a significant concern (Gunandi et al., 2023). Certain demographics may be treated unfairly as a result of bias in machine learning algorithms, which might reinforce societal stereotypes (Yoon et al., 2024). Companies need to implement fairness-aware practices and audit models on a regular basis.

In practice, machine learning requires a large investment in knowledge and infrastructure, which can be difficult for SMEs (Rungruang et al., 2024). Interpretability is further restricted by the intricacy of ML models, which calls for technological investments, internal resources, or outside partnerships.

## 5.4 Summary

Concretely, the application of machine learning for customer segmentation has turned out to be one of the major innovations for companies, especially in e-business organizations. Demographic and psychographic segmentation are less effective today. Machine learning models like KNN and Logistic Regression address this by uncovering subtle patterns, enabling tailored marketing strategies that boost customer satisfaction, loyalty, retention, and business profitability. Machine learning allows for rapid updates to consumer segmentation, allowing organizations to remain competitive in an ever-changing digital market. Logistic Regression's predictive modeling identifies high-value customers, maximizing marketing spend and resources while ensuring targeted, relevant offers in the competitive e-commerce marketplace.

The study admits constraints in examining all customer behaviors across industries and geographies, which may affect the validity of the findings. Only KNN and Logistic Regression were utilized, however future study could look into advanced models such as Random Forest or deep learning to improve segmentation accuracy.

## Chapter 6: Conclusion and Future Recommendations

### 6.1 Conclusion

Customers' classification with the help of machine learning has brought a drastic shift in how companies started marketing their products, especially those related to the internet and electronic commerce. The purpose of this study was to determine how K- Nearest Neighbors (KNN) and Logistic Regression models could enhance custom segment analysis to help businesses find better ways to reach out to their target markets. By analyzing various sources, the study does show that the use of machine learning for more precise customer segmentation enables potential understanding of customer behaviour more in-depth, which will allow reaching the audience with more efficient promotional campaigns. But even the fact that the findings are encouraging the authors recognize the limitations and challenges of the work, especially the lack of dataset diversity, choice of model, and decision-making.

From the results of the study, one unambiguous conclusion is the superiority of employing Machine Learning techniques over more conventional methods of segmenting customers. Despite the usefulness of demographic, geographic, and psychographic dimensions, they may not offer a sufficient level of understanding of the faithfully dynamic consumer segments in the context of new digital media environments. The availability of big data means that more information about customers is available to businesses, but extracting insights and making use of them is not easy. Techniques like KNN and Logistic Regression can be used well to solve these large datasets and find some hidden patterns that can be difficult to find otherwise with the help of normal solutions. Specifically, KNN proved to be one of the most efficient when applied to customer segmentation. It has strength in identifying customers according to how they behave and their demographic characteristics in clusters. This is made possible with KNN by determining the nearest point to a given data point so that businesses can classify their customers more accurately. Using the KNN model in this study, the authors were able to uncover five customer segments based on information like income and spending patterns.

The Logistic Regression model, though less accurate than the KNN model in dissecting and classifying smaller customer segments was helpful especially when analyzing discrete values such as propensity to buy. In line with all the controversies revolving around other techniques of estimation, Logistic Regression has the added advantages of simplicity and interpretability, which would endear the strategy to businesses that have a preference for clear and uncomplicated

marketing models. It can be very beneficial for a business to classify customers according to their permeability score, which predicts their likelihood of engaging in a certain behaviour on any given day: purchasing something, replying to a marketing initiative, etc. Despite the slightly lower performance compared to KNN in this study, Logistic Regression does not lose its value for businesses that require tools that provide a fast and understandable estimate for decisions.

### 6.2 Future recommendations

This study of customer segmentation utilising machine learning identifies a few directions where more research and application can enhance the effectiveness, accuracy, or moral integrity of these methods. More future recommendations concerning future dataset management are about the diversification of the dataset, the usage of the new machine learning models, the real-time data for segmenting, as well as significantly improving ethical and regulatory compliance.

**Dataset Diversity**

There are a few limitations inherent to the current study, principally because of the usage of only one dataset wherein the customer behaviour is not uniform across several geographic areas, subfields, and customer segments. To overcome the limitations of generalization in the customer segmentation models, more research should focus on the increased number of samples and the improved heterogeneity of data (Rungruang *et al*. 2024). This entails including information derived from other areas of the world, for instance developing markets where buyers' behaviours may diverge substantially from those existing in the developed states. Furthermore, data collection from the retail, technology, hospitality and financial sectors will also be rewarding to offer a comparison of customer segmentation strategies based on industry-specific influences.

Increasing the variability of the dataset will be not only helpful for achieving higher adaptability of the machine learning models but also for the results relevance in a wider range of applications. For instance, entrepreneurs who wish to work on ML models about customer segmentation should aspire to extend the range of datasets to incorporate as many possible consumer types and behaviours as they can to come up with a more accurate and efficient marketing approach.

**Advanced Machine Learning Models**

However, as future research to this study, it is recommended that machine learning models different from K-Nearest Neighbors (KNN) and Logistic Regression must be adopted in categorizing customers (Phadkar *et al*. 2023). Random forests and SVM, gradient boosting and

deep learning might perform better than all of these though could be favourable for big copious and intricate databases. Random Forests, for example, yield more accurate and consistent estimates by combining the results from a set of decision trees which, therefore, is more selective for customer segmentation over various types of datasets. SVMs also apply to linear and non-linear data depending on the nature of the figure and they are ideal for complex figures. XGBoost which is a kind of Gradient Boosting algorithm could again increase the segmentation precision as it has the potential of incremental learning towards the probability of customer behaviours.

According to Modak et al. (2023), despite their processing needs, deep learning models excel at detecting complicated data structures, such as temporal consumer behavior. This capacity allows for better segmentation and deeper insights into client preferences, resulting in more focused and successful advertising efforts.

**Real-Time Data and Dynamic Linking**

Traditional market segmentation has difficulty keeping up with changing markets and customer habits, particularly in the digital era. Mustafa et al. (2024) propose creating adaptive segmentation models with real-time data from sources such as social media and online apps. These models allow businesses to adapt dynamically to changes in consumer behaviour, market trends, and environmental conditions.

### 6.3 Summary

This research focused on two machine learning classification models known as K-Nearest Neighbors (KNN) and Logistic Regression in the context of customer segmentation for e-commerce companies. Moreover, it showed that by applying a machine learning algorithm the segmentation process can be improved since deeper patterns can be further explored in the customer's behaviour, thus making the marketing message more personalized. There was also a better characteristic of different customers based on their behaviour and demographic information; this test supports the argument of the applicability of KNN in enhancing Customer Experience, satisfaction, loyalty, and Conversion rates as compared to Logistic regression.

The study's limitations include a single dataset and two machine learning models. A more diversified dataset and advanced algorithms, such as Random Forests or Deep Learning, may boost accuracy. To ensure fairness and prevent the misuse of machine learning models, real-time data for dynamic segmentation, as well as ethical factors such as data protection and algorithmic bias, must be addressed.

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## Appendices

### Appendix A: Data Preprocessing

A.1 Missing value checks

```
df.info()
print("\n\n\n NO missing values")
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   CustomerID              200 non-null    int64
 1   Gender                  200 non-null    object
 2   Age                     200 non-null    int64
 3   Annual Income (k$)      200 non-null    int64
 4   Spending Score (1-100)  200 non-null    int64
dtypes: int64(4), object(1)
memory usage: 7.9+ KB



 NO missing values
```

A.2 Encoding Categorical Variables

```
df['Gender'] = pd.get_dummies(df['Gender'],drop_first=True)
```

A.3 Feature Scaling

```
# Scaling continuous features
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

A.4 Outlier Detection

```
# Visualizing outliers using box plots
import seaborn as sns
sns.boxplot(data=df[['Annual Income', 'Spending Score']])
```

### Appendix B: Exploratory Data Analysis

B.1 Correlation Heatmap

```
sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
plt.title('Feature Correlation Heatmap')
plt.show()
```

B.2 Pair Plots

```
sns.pairplot(df, vars=['Annual Income', 'Spending Score'], hue='Gender')
plt.show()
```

B.3 Gender-Based Trends

```
sns.scatterplot(data=df, x='Annual Income', y='Spending Score', hue='Gender')
plt.title('Gender-Based Spending Trends')
plt.show()
```

Appendix C:

C.1

```
wcss = []

for i in range(1,11):
    km = KMeans(n_clusters=i)
    km.fit_predict(X)
    wcss.append(km.inertia_)

km = KMeans(n_clusters=5)
y_means = km.fit_predict(X)
```

Appendix D:

D.1 Data Splitting

```
#splitting the dataset
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,random_state=0)
```

D.2

```
# Evaluating the model using precision, recall, and F1-score
precision = precision_score(y_test, y_pred, average='weighted')
recall = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')

# Displaying the precision, recall, and F1-score
print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1-Score: {f1}")
```

D.3

1)KNN

```
# Generate predictions using the KNN model
y_pred_knn = knn_model.predict(X_test)

# Confusion matrix for KNN
knn_cm = confusion_matrix(y_test, y_pred_knn)

# Dynamically get the unique labels from the test set (y_test)
labels = sorted(set(y_test))

# Display confusion matrix for KNN
disp_knn = ConfusionMatrixDisplay(confusion_matrix=knn_cm, display_labels=labels)
disp_knn.plot()
plt.title('Confusion Matrix for K-Nearest Neighbors')
plt.show()
```

2)LOGISTIC REGRESSION

```
# Generate the confusion matrix
log_cm = confusion_matrix(y_test, y_pred)

# Dynamically get the unique labels from the test set
labels = sorted(set(y_test))

# Display the confusion matrix for the Logistic Regression model
disp_log = ConfusionMatrixDisplay(confusion_matrix=log_cm, display_labels=labels)
disp_log.plot()
plt.title('Confusion Matrix for Logistic Regression')
plt.show()
```

D.4

```
error_rate=[]

for i in range(1,40):
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_train,y_train)
    pred_i = knn.predict(X_test)
    error_rate.append(np.mean(pred_i!=y_test))
```

```
plt.figure(figsize=(10,5))
plt.plot(range(1,40),error_rate,color='blue',linestyle='dashed',marker='o',markersize=12)
plt.title("Error rate vs k value")
plt.xlabel("k")
plt.ylabel("Error_rate")
plt.show()
```