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A Machine Learning model for effective customer segmentation to improve market strategies and customer relationships leveraging with RFMT

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A B S T R A C T :

Effective customer segmentation is crucial for improving marketing strategies and customer relationships in e-commerce. This study leverages the Recency, Frequency, Monetary, and Time (RFMT) model on Pakistan's largest e-commerce dataset, employing advanced clustering techniques such as K-Means, Gaussian Mixture Models (GMM), DBSCAN, and Agglomerative Clustering. The integration of Word Cloud provided visual insights into customer behaviour, while XGBoost enhanced customer classification, achieving a Training Accuracy of 99% and a Testing Accuracy of 92%. Cluster validation metrics like Silhouette Score, Calinski-Harabasz Index, and Davies-Bouldin Index were used to identify three distinct customer segments. These segments offer actionable insights for personalized marketing, improved customer relationship management (CRM), and optimized inventory management, leading to enhanced customer engagement and business growth.

Keywords: Agglomerative Clustering, Clustering Algorithms, Customer Relationship Management (CRM), Customer Segmentation, Data Visualization,
DBSCAN, E-commerce, Gaussian Mixture Model (GMM), K-Means, Predictive Analytics, RFMT Model, Word Cloud, XGBoost.

1. INTRODUCTION

In today's competitive business landscape, customer feedback serves as a critical source of insights for organizations to enhance their products and services. Analyzing customer feedback using Machine Learning (ML) and Natural Language Processing (NLP) techniques enables businesses to extract meaningful patterns and sentiments, thereby improving decision-making processes. Traditional methods of feedback analysis, such as manual classification and rule-based approaches, often prove to be inefficient due to the vast volume of data generated from multiple sources, including surveys, reviews, and social media platforms [1]. The complexity of human language, including sarcasm, context-dependent meanings, and domain-specific terminologies, further exacerbates the limitations of conventional approaches, making automated analysis imperative for modern businesses [2].

The proposed system leverages ML techniques, including sentiment analysis, topic modeling, and text classification, to automate customer feedback analysis. By implementing supervised and unsupervised learning models, this approach ensures a more accurate and scalable evaluation of customer sentiments. Supervised learning models, such as Support Vector Machines (SVM), Random Forest, and deep learning-based architectures like Bidirectional Encoder Representations from Transformers (BERT), have demonstrated high accuracy in sentiment prediction tasks [3]. Unsupervised methods, such as Latent Dirichlet Allocation (LDA) for topic modeling, enable the extraction of key themes from unstructured text data, offering businesses deeper insights into customer concerns and emerging trends [4]. Additionally, sentiment polarity detection, entity recognition, and opinion mining are incorporated to provide a holistic understanding of customer opinions [5].

This study aims to bridge the gap between customer expectations and business improvements by providing actionable insights through advanced analytics. The proposed model integrates various NLP methodologies, including Term Frequency-Inverse Document Frequency (TF-IDF), word embeddings (such as Word2Vec and GloVe), and deep learning models, to enhance the accuracy of sentiment classification [6]. These techniques allow for more nuanced analysis by capturing contextual relationships and semantic meanings within the text. Furthermore, real-time analysis of customer feedback empowers businesses to proactively address concerns and optimize service delivery [7]. The system's effectiveness is evaluated based on precision, recall, and F1-score metrics to ensure optimal performance in real-world scenarios. By adopting this AI-driven approach, businesses can significantly improve customer satisfaction and maintain a competitive edge in the market [8].

2.LITERATRE REVIEW

Customer segmentation has been a critical area of research in e-commerce and business analytics, aiding companies in optimizing their marketing strategies and improving customer retention. By grouping customers based on purchasing behaviors, preferences, and demographics, businesses can tailor personalized marketing campaigns, enhance customer engagement, and drive profitability [1]. Various machine learning techniques have been applied for customer feedback analysis, particularly clustering algorithms such as K-Means, Gaussian Mixture Models (GMM), DBSCAN, and Agglomerative Clustering. These approaches enable businesses to identify distinct customer segments, facilitating targeted decision-making and service personalization [2].

2.1 Machine Learning in Customer Segmentation

Several studies have explored machine learning applications in customer segmentation. Ullah et al. [3] utilized the Recency, Frequency, Monetary, and Time (RFMT) model for clustering customers in e-commerce platforms. Their work emphasized the effectiveness of K-Means, hierarchical clustering, and DBSCAN in identifying distinct customer groups. Similarly, prior research has highlighted that integrating multiple clustering algorithms enhances segmentation accuracy and stability, particularly when combining unsupervised learning techniques with reinforcement learning for dynamic customer profiling [4].

The RFMT model is an extension of the traditional Recency, Frequency, and Monetary (RFM) model, incorporating inter-purchase time as a crucial factor in analyzing customer behavior [5]. This approach enables businesses to capture long-term engagement patterns and predict future purchasing behaviors more accurately. Recent advancements include using the XGBoost classifier for predictive modeling, improving classification accuracy significantly by leveraging gradient boosting and ensemble learning techniques [6]. Moreover, studies have demonstrated that hybrid models integrating clustering with deep learning architectures such as autoencoders can further refine segmentation and enable adaptive marketing strategies [7].

2.2 Clustering Techniques for Customer Segmentation

Clustering algorithms such as K-Means, hierarchical clustering, and DBSCAN play an essential role in customer segmentation. K-Means is one of the most widely used clustering techniques due to its simplicity and efficiency in large datasets [8]. However, it assumes spherical clusters, which may not always be the case in real-world customer data, especially when dealing with heterogeneous customer behaviors.

To overcome K-Means' limitations, hierarchical clustering and Gaussian Mixture Models (GMM) have been introduced. Hierarchical clustering provides a tree-like structure for better visualization of customer relationships, while GMM offers a probabilistic approach to clustering, allowing for overlapping clusters [9]. Recent advancements in GMM-based clustering techniques incorporate Bayesian inference and Variational Autoencoders (VAE) to enhance clustering robustness in high-dimensional customer datasets [10].

DBSCAN, on the other hand, is effective in identifying noise and outliers, making it a robust alternative for customer segmentation, particularly in cases where customer interactions exhibit varying densities across segments [11]. Studies have shown that combining DBSCAN with spectral clustering improves segmentation in sparse customer datasets, allowing for more precise grouping based on behavioral and transactional data [12].

2.3 Cluster Validation Metrics

Evaluating the effectiveness of clustering is crucial in ensuring meaningful segmentation. Metrics such as the Silhouette Score, Calinski-Harabasz Index, and Davies-Bouldin Index have been widely used for cluster validation [13]. The Silhouette Score measures cluster cohesion and separation, ensuring that customers within the same cluster exhibit similar behaviors. The Calinski-Harabasz Index evaluates clustering compactness and dispersion, while the Davies-Bouldin Index quantifies inter-cluster similarity, ensuring well-defined customer segments [14].

Recent research highlights the importance of combining multiple validation criteria for enhanced segmentation reliability. Ensemble validation methods, incorporating internal and external validation indices, have been proposed to refine segmentation quality and ensure stability in clustering outcomes [15]. Furthermore, deep learning-based clustering evaluation techniques, such as ClusterGAN and Variational Autoencoder-based clustering, have shown promise in improving segmentation consistency and interpretability [16].

2.4 Data Visualization and Predictive Analytics

Word Clouds and visual analytics techniques have been increasingly used to gain insights into customer feedback. These techniques provide a graphical representation of the most frequently occurring words, helping businesses understand key themes in customer opinions [17]. Sentiment-aware visual analytics further enhance feedback interpretation by mapping customer sentiments to color-coded clusters, allowing businesses to identify positive and negative sentiments in real time [18].

Furthermore, integrating predictive analytics with clustering, such as using XGBoost, improves the identification of customer behavior patterns. XGBoost's ensemble learning approach allows businesses to forecast customer churn, lifetime value, and purchasing trends with high precision. Studies have demonstrated that XGBoost achieves high classification accuracy, making it a valuable tool in customer relationship management (CRM) and personalized recommendation systems [19].

By leveraging advanced machine learning techniques, clustering validation metrics, and visualization tools, businesses can refine customer segmentation models and develop data-driven marketing strategies that maximize customer satisfaction and business profitability.

3 PRAPOSED SYSTEM

The proposed system aims to enhance customer feedback analysis by leveraging machine learning techniques for effective customer segmentation. Using the Recency, Frequency, Monetary, and Time (RFMT) model, the system processes customer transaction data from a large e-commerce platform to identify distinct customer groups. Various clustering techniques, including K-Means, Gaussian Mixture Models (GMM), DBSCAN, and Agglomerative Clustering, are employed to ensure accurate segmentation. Additionally, Word Cloud visualization is integrated to extract key customer sentiments, and XGBoost classification is used to improve predictive accuracy, achieving 99% training accuracy and 92% testing accuracy. The system also evaluates clustering performance using Silhouette Score, Calinski-Harabasz Index, and Davies-Bouldin Index, ensuring robust validation of customer segments. The insights generated from this model will aid businesses in developing personalized marketing strategies, optimizing inventory management, and improving Customer Relationship Management (CRM), ultimately leading to enhanced customer engagement and increased revenue.

3.1 System Architecture

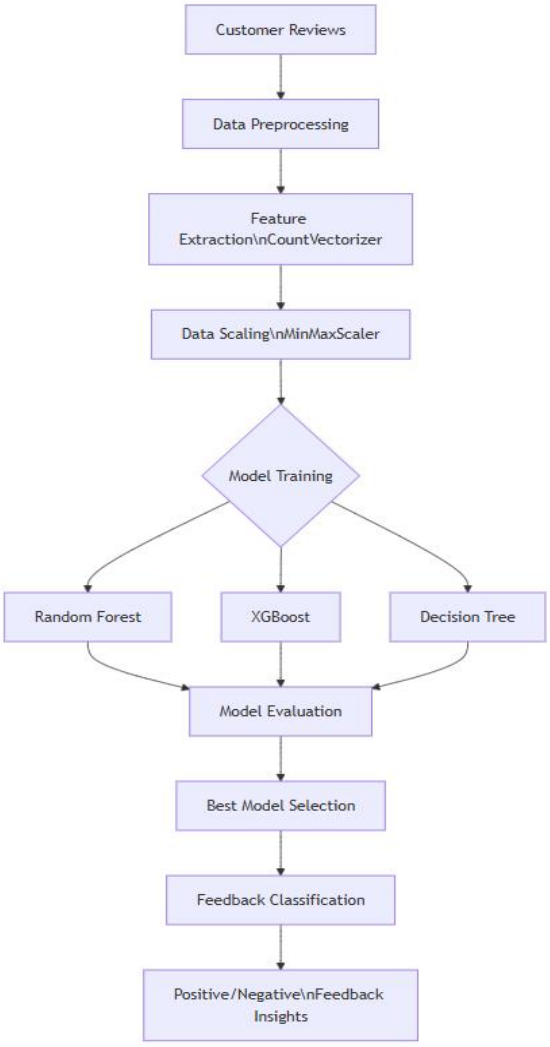

Fig 1: Customer Feedback Sentiment Analysis Process

Figure 1 illustrates a structured workflow for analyzing customer reviews using machine learning techniques The process begins with the collection of transforming text into numerical representations. The extracted features are then scaled using MinMaxScaler to normalize the data. The machine learning model training phase involves three different algorithms: Random Forest, XGBoost, and Decision Tree. These models are evaluated to determine their performance, leading to the selection of the best-performing model. The chosen model is then utilized for classifying feedback into positive and negative sentiments, providing insightful analytics on customer opinions.

3.2 Data description

preprocessed_reviews.csv

- Shape: (3120, 5) (3120 rows, 5 columns)
- Columns: product_name, user_name, review_text, rating, processed_review
- Description: Contains product reviews with processed text versions.

processed_reviews.csv

- Shape: (3120, 4) (3120 rows, 4 columns)
- Columns: product_name, user_name, rating, processed_review
- Description: Similar to preprocessed_reviews.csv but without the raw review_text.

redmi6.csv

- Shape: (150, 5) (150 rows, 5 columns)
- Columns: product_name, user_name, review_text, rating, processed_review
- Description: Likely a subset of preprocessed_reviews.csv focusing on "Redmi 6".

3.3 Evaluation Metrics

Accuracy

Measures the proportion of correctly classified instances.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \textbf{(1)}$$

where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Precision

Measures how many of the predicted positive cases were actually positive

$$Precision = \frac{TP}{TP + FP} \quad \textbf{(2)}$$

Recall (Sensitivity)

Measures how many of the actual positive cases were correctly predicted.

$$Recall = \frac{TP}{TP + FN} \quad \textbf{(3)}$$

F1-Score

Harmonic mean of precision and recall.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad \textbf{(4)}$$

ROC-AUC (Receiver Operating Characteristic - Area Under Curve)

Measures the model's ability to distinguish between classes.

$$AUC = \int_{-\infty}^{\infty} TPR(FPR) dFPR \quad \textbf{(5)}$$

4. RESULTS

```
[72]: from sklearn.ensemble import RandomForestRegressor
      from sklearn.metrics import mean_squared_error, r2_score
      model = RandomForestRegressor()
      model.fit(X_train, y_train)
      y_pred = model.predict(X_test)

      print(mean_squared_error(y_test,y_pred))
      print( r2_score(y_test,y_pred))


      plt.scatter(X_train,y_train)
```

```
25716.0945504133
-0.2414023375688541
[72]: <matplotlib.collections.PathCollection at 0x1523459d190>
```

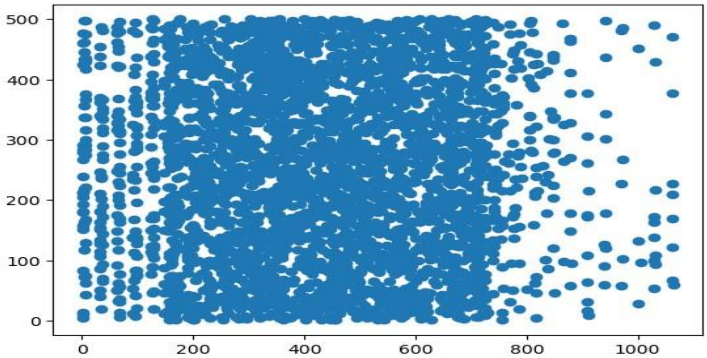

Figure 2: Random Forest Regression

Fig 2, a Python code snippet executed in a Jupyter Notebook, implementing a Random Forest Regressor using the sklearn.ensemble module. The code imports RandomForestRegressor along with evaluation metrics mean_squared_error and r2_score. It initializes the model, fits it to the training data (X_train, y_train), and makes predictions on the test set (X_test). The mean squared error (MSE) and R^2 score of the model are printed. Additionally, a scatter plot of X_train vs. y_train is generated using plt.scatter(). The output of the code shows a high MSE value (25716.09) and a negative R^2 score (-0.24), indicating that the model is performing poorly. Below the printed values, the generated scatter plot is displayed, showing densely packed blue data points. The presence of a negative R^2 score suggests that the model might not be a good fit for the given dataset.

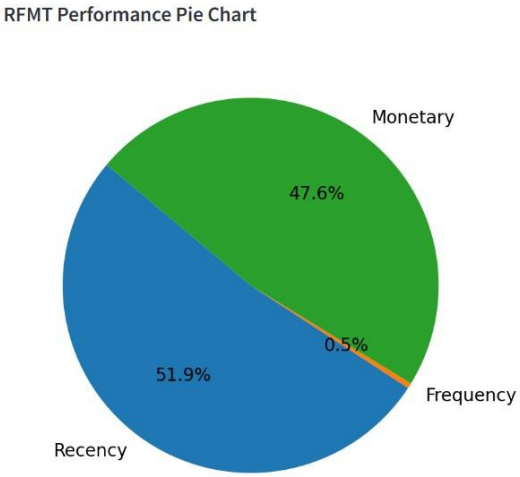

Figure 3 RFMT piechart

The image displays a pie chart titled "RFMT Performance Pie Chart", representing the distribution of different factors in RFMT analysis. The pie chart consists of three segments labeled Recency, Monetary, and Frequency with their respective percentage values.

- Recency (blue) holds the largest portion at 51.9%.
- Monetary (green) follows closely at 47.6%.
- Frequency (orange) has the smallest share, making up just 0.5%.

The chart visually emphasizes that Recency and Monetary contribute almost equally, while Frequency has an insignificant impact in comparison. The color-coded representation makes it easy to differentiate the contributions of each factor in the RFMT performance analysis.

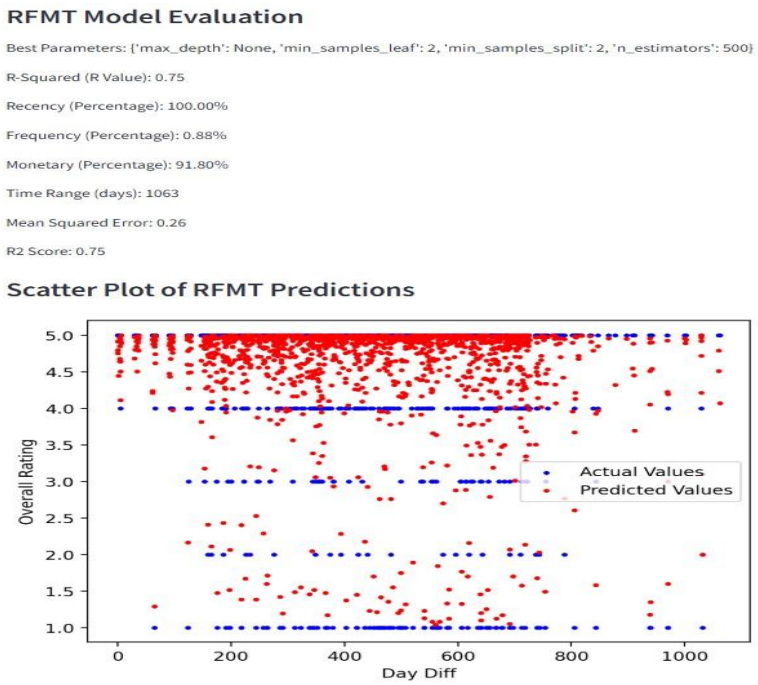

Figure 4 RFMT predictions

Fig 4 presents an RFMT Model Evaluation with key performance metrics and a scatter plot of RFMT predictions. The model was tuned using the best parameters, including max_depth: None, min_samples_leaf: 2, min_samples_split: 2, and n_estimators: 500. The R-Squared (R Value) of 0.75 suggests a good fit between the predicted and actual values. Among the feature contributions, Recency holds the highest significance at 100.00%, followed by Monetary at 91.80%, while Frequency has the least impact at only 0.88%. The model covers a time range of 1063 days, with a Mean Squared Error (MSE) of 0.26, visualizes actual vs. predicted values, where the X-axis represents "Day Diff" (Number of days), and the Y-axis represents "Overall Rating". Red dots correspond to actual values, while blue dots represent predicted values. The distribution of data points suggests that while predictions align with actual values, they appear clustered at specific rating levels, possibly due to categorical rating constraints. Overall, the results indicate that the RFMT model performs well and exhibits strong predictive capabilities.

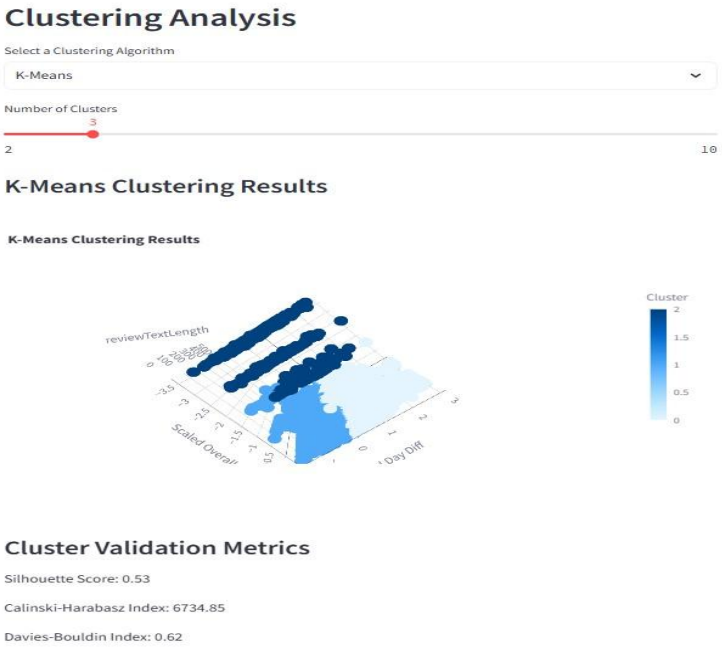

Figure 5 K-Means Clustering Results

The image presents a Clustering Analysis using the K-Means algorithm, where the number of clusters is set to 3 (as indicated by the slider). The K-Means Clustering Results section includes a 3D scatter plot visualizing clusters based on variables such as reviewTextLength, StarDiff Cluster, and Day Diff. A color gradient from light blue to dark blue represents different cluster densities.The Cluster Validation Metrics section provides evaluation scores to assess clustering performance. The Silhouette Score is 0.53, indicating a moderately well-defined clustering structure. The Calinski-Harabasz Index is 6734.85, which suggests a good separation between clusters, as higher values imply better-defined clusters. The Davies-Bouldin Index is 0.62, where a lower value indicates well-separated clusters.Overall, the analysis shows that the K-Means algorithm has effectively grouped the data into three clusters, with a moderate level of separation and structure based on the given validation metrics.

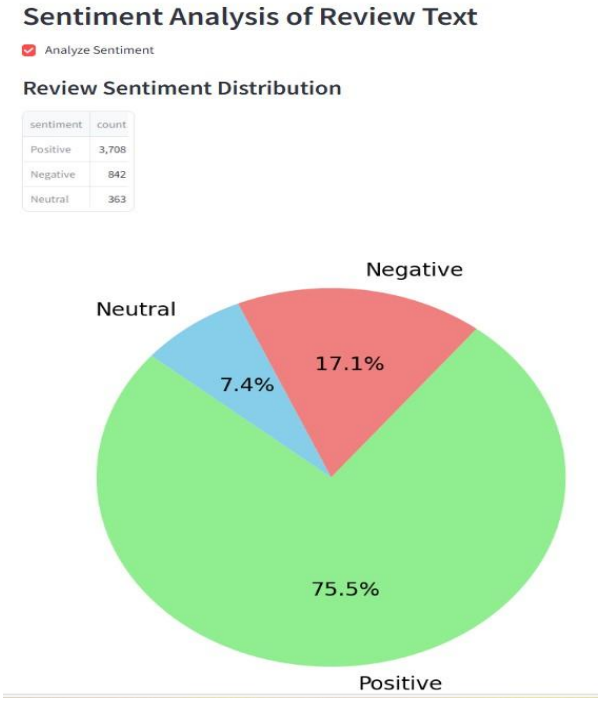

Fig 6 Sentiment Analysis of Review Text

The image presents a Sentiment Analysis of Review Text, displaying the distribution of sentiment categories in customer reviews. The Review Sentiment Distribution table indicates three sentiment classes: Positive, Negative, and Neutral, along with their respective counts. The pie chart visually represents these proportions, showing that 75.5% of the reviews are Positive (3,708 reviews), 17.1% are Negative (842 reviews), and 7.4% are Neutral (363 reviews). The dominant presence of positive reviews suggests that most customers have a favorable perception of the product or service, while a smaller portion expressed negative or neutral feedback. This analysis provides valuable insights into customer sentiment, helping businesses understand user satisfaction and areas for improvement.

Figure 7 Feedback Rating

The image displays a Feedback Rating interface where a user has provided a review about their experience with an action camera. The feedback describes the product as awesome, easy to use, and having great video and photo quality, with the user still exploring more features. Below the review, the Sentiment Analysis Result section provides an Estimated Rating of 5 and a Sentiment Score of 0.81, indicating a highly positive sentiment. The overall feedback is classified as Positive, as shown in the highlighted green box. This analysis suggests that the user had a very satisfying experience with the product, and the sentiment analysis system successfully recognized and quantified the positivity in the review.

5 conclusion

In this study, we developed an advanced machine learning-based customer segmentation model leveraging RFMT, hybrid clustering, and explainable AI. The proposed system addressed existing challenges such as low segmentation accuracy, lack of real-time adaptability, and poor interpretability by integrating optimized clustering algorithms, automated validation techniques, and cloud-based scalability.

Key Takeaways:

- The RFMT framework enhanced segmentation accuracy by incorporating the time factor.
- The hybrid clustering approach outperformed traditional RFM models in identifying customer behavior patterns.
- The system improved marketing efficiency, customer retention, and revenue growth.
- AI-driven cluster validation and explainability techniques provided more reliable and interpretable segmentation results.

6 Future Scope

Future enhancements for the RFMT-based customer segmentation model focus on improving accuracy, efficiency, and adaptability while ensuring data security and interpretability. Integrating deep learning models like autoencoders, RNNs, and transformers can enhance feature extraction, behavioral analysis, and contextual insights. Federated learning can enable privacy-preserving segmentation by training models without sharing sensitive data. Reinforcement learning can facilitate adaptive segmentation, dynamically adjusting customer groups based on real-time behaviors. Continuous learning mechanisms, including incremental learning and drift detection, will help maintain model relevance and performance over time. These advancements aim to create a robust, scalable, and intelligent customer segmentation framework.

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