

Machine Learning–Driven Brand Loyalty Analytics Framework for Predicting Customer Retention and Enhancing Personalized Engagement in the Culinary Industry

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Abstract

Due to the fast adoption of various practices including digital ordering, loyalty programs, mobile apps, and social media in the culinary industry, there is an abundance of customer data available to marketers but at the same time, there are difficulties in detecting customers' risks of retention and providing efficient personalized engagement. In this regard, the current research presents a Machine Learning-Driven Brand Loyalty Analytics Framework, which involves the analysis of transactional behavior, loyalty program engagement, digital engagement, customer sentiment, and customer profile for the prediction of retention and provision of relevant engagement approaches. For this purpose, the current research uses the dataset, which includes 5,000 customer records gathered within one year. Data preprocessing includes the removal of duplicates, dealing with missing values, detecting outliers, data normalization, and feature transformation, followed by the development of five machine learning models: Random Forest, XGBoost, LightGBM, CatBoost, and Deep Neural Network. XGBoost outperformed other algorithms by achieving an accuracy of 94.3%, precision of 93.7%, recall of 92.8%, F1 score of 93.2%, and AUC of 0.96. Customer segmentation revealed 1,250 loyal customers with 96.5% retention probability, whereas 750 customers at risk had just 38.4% retention probability. Personalized engagement was linked to enhancements in retention rate from 72.4% to 87.8%, repeat purchase rate from 58.3% to 79.5%, customer satisfaction from 74.6% to 90.3%, and customer lifetime value from \$420 to \$615. These results highlight that the use of predictive analytics in combination with personalization can enhance customer retention and loyalty management. This framework serves as an effective base for culinary marketing using data analytics, while further research is needed on multi-restaurant data, real-time analytics, multimodal customer data, AI agents, and privacy-preserving learning.

Keywords: Machine Learning, Brand Loyalty Analytics, Customer Retention Prediction, Personalized Engagement, Culinary Industry, Explainable Artificial Intelligence (XAI).

Introduction

The digitization of the culinary industry has changed the way customer relationships are managed via POS systems, online ordering, mobile apps, loyalty programs, review platforms, and social media. This digitization creates many touchpoints that produce lots of data on purchasing behavior, engagement, customer satisfaction, and customer loyalty (El Guermai & Abdelfattah, 2025; Venkateswaran et al., 2024). Traditional methods of customer relationship management face challenges in integrating various sources of data and creating effective retention and engagement strategies based on this data. Thus, machine learning (ML) holds great promise when it comes to finding behavioral patterns, predicting customer retention and churn, and implementing personalized marketing efforts (Akter, 2025). It is especially important for the competitive culinary industry because retaining customers and encouraging repeat purchases may directly lead to customer lifetime value and improved performance.

In spite of growing interest in AI-driven personalization, analytics, loyalty programs, and customer churn forecasting, these techniques have often been studied independently from one another as distinct forms of analysis. As a result, there is a clear requirement for an overarching approach that can tie together customer behavioral insights, sentiment data, retention forecasting, explainable analytics, and personalization in a single setting specific to the culinary industry.

The unique aspect of this study lies in developing the Machine Learning-Based Brand Loyalty Analytics Framework through which the integration of transactional history, loyalty program membership, digital engagement, customer sentiments, and behavioral traits will be used for predicting loyalty and personalized engagement. This framework compares Random Forest, XGBoost, LightGBM, CatBoost, and Deep Neural Networks models, and uses explainable AI in order to find the important factors responsible for retention.

The rest of this paper is structured in the following way. Section 2 introduces the literature background along with the research gap. Section 3 illustrates the suggested framework and its main elements. Section 4 provides information on data acquisition, preprocessing, feature generation, and model training. Section 5 demonstrates the experimental results and comparative analysis. Section 6 provides discussion, implications, and limitations. Finally, conclusions and directions for further research are provided in Section 7.

Literature Review

A number of recent studies show how AI, ML, and predictive analytics have become increasingly important in customer engagement, personalization, loyalty, and retention. The application of AI personalization is linked to increased consumer engagement due to personalized marketing communications based on characteristics of particular customers (AL-Ghaswyneh, 2025; Shwetha & Afza, 2026). In the culinary industry and ghost kitchens, ML personalization can be used for highly personalized marketing and promotion decisions (Solar, 2025). The earlier hospitality studies showed how ML could help engage customers dynamically and co-create value through loyalty schemes (Aluri et al., 2019). There are additional recent studies proving that ML marketing analytics increase personalization and the quality of customer experience (Ganeshkumar et al., 2024; Cherenkov et al., 2024).

Customer retention is another significant field of application. There have been several studies that have revealed that machine learning algorithms may be used in the determination of whether restaurant customers will continue to be loyal or not. Moreover, retention predictive models are able to include the process of customer churn prediction and personalized quality of service methods (Hemajothi et al., 2025; Ibitoye et al., 2026). More sophisticated approaches consist of churn prediction, customer segmentation, and recommendations for customer retention (Jahan & Sanam, 2026). Service companies use predictive analytics to increase customer loyalty (Dahake et al., 2025). It appears that predicting customer retention works better with the help of behavioral and transactional data (Uddin, 2026; Dele-Rotimi, 2026).

Personalization through AI is increasingly being associated with loyalty and relationship management as well. Studies discuss how AI and ML contribute to customer experience, value generation, engagement, and loyalty in the context of CRM, while omnichannel personalization has the potential to improve engagement and loyalty (Balcioglu, 2025; Biswas et al., 2026). AI-driven market basket prediction has been used to illustrate how ML can help improve engagement with loyalty programs (Meftah et al., 2024). Other research points to the strategic role of CRM in

managing customer relationships and retaining customers (Emon & Khan, 2026). AI-driven agents can also shape the future of customer loyalty (Bilgihan et al., 2025).

The literature as a whole suggests that ML can be used for performing customer segmentation, customer retention prediction, engagement using sentiments, personalization, and loyalty management. Nonetheless, the bulk of studies in this area have investigated these functionalities separately or have considered these functionalities from the broader perspective of digital marketing, e-commerce, CRM, and services. Few studies have attempted to develop a holistic framework related to these functionalities using behavioral analysis, sentiment analysis, customer retention prediction, Explainable AI, and personalized engagement in the context of the culinary industry. The current research thus fills this gap.

Proposed Brand Loyalty Analytics Framework

Framework Architecture

The proposed Machine Learning–Driven Brand Loyalty Analytics Framework aims to design an integrated intelligent framework to predict customer retention and improve engagement by adapting it to the specific context of the culinary field. The framework comprises four layers: Data Acquisition Layer, Customer Behavioral Intelligence Layer, Retention Prediction Layer, and Personalized Engagement Layer. All these layers work together to convert raw customer data into valuable business insights that can be utilized for customer retention and customer loyalty management. Fig. 1 illustrates the Machine Learning–Driven Brand Loyalty Analytics Framework.

Data sources used by the Data Acquisition Layer include point-of-sale (PoS) transactions, online food ordering apps, loyalty programs, mobile apps, customer surveys, social media interactions, and more. Once collected, the data is preprocessed, normalized, and features are extracted in order to ensure its quality and consistency. The Customer Behavioral Intelligence Layer collects and analyses information on customer purchasing patterns, visit frequency, spending habits, sentiment scores, and engagement activities to create detailed customer profiles.

The Retention Prediction Layer is powered by state-of-the-art algorithms like XGBoost, Random Forest, and Deep Neural Networks for calculating the probability of customer retention and predicting at-risk customers. Last but not least, the Personalized Engagement Layer creates personalized recommendations, customizable rewards, targeted promotions, and loyalty incentives that are tailored to customers' preferences and behavioral traits. The model incorporates explainable artificial intelligence to increase predictability, thus allowing culinary businesses to foster customer loyalty and value. Fig. 1 shows the machine learning-driven brand loyalty analytics framework.

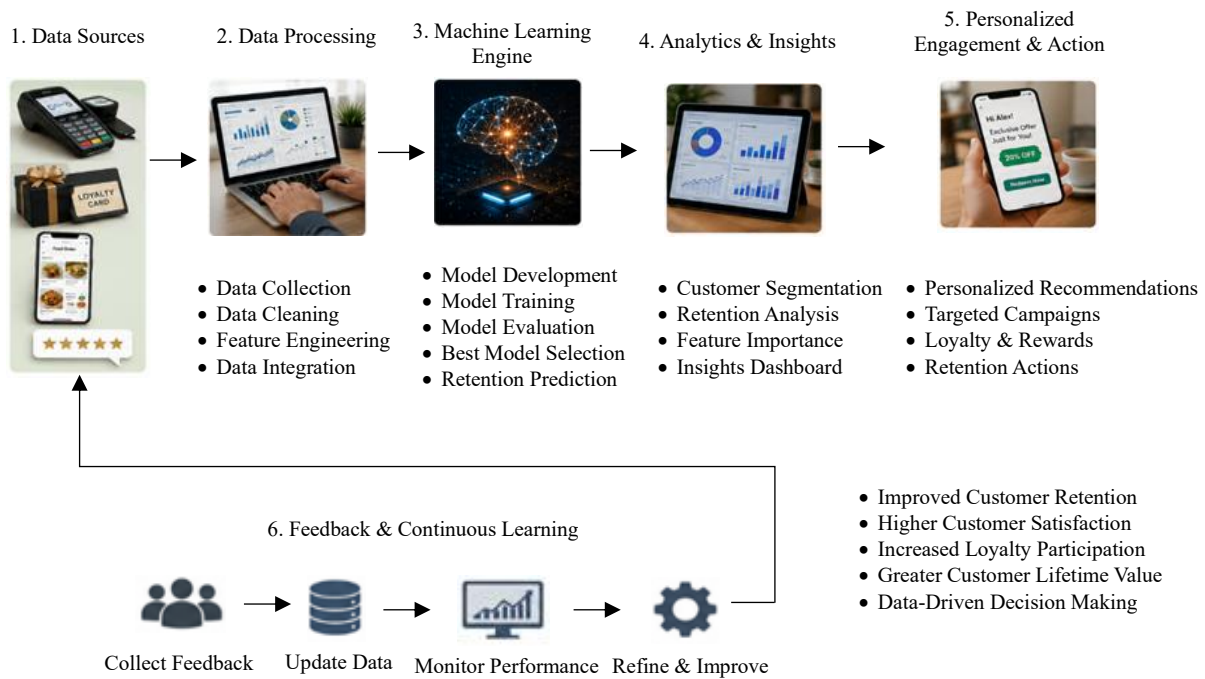


Fig. 1: Machine Learning – Driven Brand Loyalty Analytics Framework

Customer Behavioral Intelligence Module

The Customer Behavioral Intelligence Module acts as the foundation of the suggested framework since it analyzes the customer interaction data to get meaningful insights. This module focuses on understanding the preferences, purchasing behavior, engagement, and sentiment of customers in order to determine what drives brand loyalty in the culinary industry. The module analyzes both structured and unstructured data gathered from transactions, loyalty programs, apps, online reviews, and social media. The behavioral insights obtained through analyzing important behavioral metrics such as purchase frequency, Average Order Value (AOV), menu preferences, revisit frequency, promotion responsiveness, satisfaction, and sentiment are used to recognize behavioral patterns. Customers are segmented using machine learning-based clustering into various categories like loyal customers, sporadic visitors, high-value customers, and churners. The Brand Attachment Index (BAI) is also developed for measuring the strength of customer-brand relationship using behavioral and attitudinal factors.

Retention Prediction Engine

The Retention Prediction Engine determines the outcome of customer retention and finds those customers who are vulnerable to leaving the culinary brand. This module applies state-of-the-art machine learning techniques to review past customer information and make precise forecasts about the likelihood of retention. The goal is to allow businesses to take action before the customer gives up and decrease churn.

Processed behavioural features of the engine from the Customer Behavioural Intelligence Module are used to include purchase frequency, Customer Lifetime Value, Sentiment, Loyalty Participation, Digital Engagement Measures, and Brand Attachment Measures. These features are leveraged for predictive modeling like Random Forest, Gradient Boosting, XGBoost, and Deep Neural Networks. The algorithms are able to discover sophisticated patterns between the customer attributes and calculate the chances of retaining each customer.

A Retention Risk Score (RRS) is determined, and customers are sorted into low-risk, medium-risk, and high-risk groups. High-risk customers are flagged to be engaged in real time in accordance with their assignment. The high-risk customers are automatically assigned to be engaged in real time. The Explainable AI methods include SHAP and LIME to provide insights into the most important variables for each prediction, improving transparency and trust in the model's performance. This visibility allows managers to grasp the reasons behind customer attrition and formulate the necessary measures to keep customers. It can therefore be considered a predictive model that can influence decisions, create loyalty among customers, and improve business performance in the future.

Personalized Engagement Module

The Personalized Engagement Module takes predictive insight and turns it into actionable strategies for retaining customers. This is achieved by taking predictive insights from machine learning algorithms, behavioral analytics, and preferences and using that information to provide personalized suggestions for the menu, rewards program, promotions, and communications. Potential churners will be sent retention campaigns using customized incentives and re-engagement messages. The recommendations and performance of the campaigns will be continually analysed based on customer behaviour changes, and the success of the campaigns will be measured by response rate, customer satisfaction, engagement, and repeat purchases.

Data Collection and Feature Engineering

Dataset Description

The customer retention forecast model is influenced by the quality and variety of the training data set. A real-time customer analytics dataset was created by combining culinary service transactions, loyalty program history, reviews, and social media interactions for culinary services. The data set contains about 5,000 customers within one year and encompasses Average Order Value, purchase frequency, recency of orders, sentiment scores, review scores, digital interaction, rewards redeemed, loyalty membership, and customer identity data.

The intensity of customer activity is determined by means of equation (1):

$$CAI_i = \frac{PF_i + AOV_i + DE_i}{3} \quad (1)$$

The framework applies CI_i , PF_i , AOV_i , and DE_i as key factors for measuring the customers' behavior. For the purposes of reliable model evaluation and customer retention prediction, the dataset is split into training (70%), validation (15%), and test (15%) datasets.

Customer Transaction Data Collection

The data obtained from customer transactions will be the main behavioral data source that will be captured on real-time basis from POS systems, restaurant management systems, mobile ordering systems, and food delivery systems. These factors can offer a lot of information about the customer's purchase habits and their spending patterns.

The Purchase Frequency Score (PFS) is obtained by the following equation (2):

$$PFS_i = \frac{N_i}{T} \quad (2)$$

Where N_i represents the total number of purchases by the customer that occurred during the observation period T . The higher the frequency of purchase, the more loyal customers are likely to be and the higher the likelihood of retaining them, as shown in equation (2).

Additionally, Average Order Value (AOV) is computed using equation (3):

$$AOV_i = \frac{\sum_{j=1}^n OV_j}{n} \quad (3)$$

Where OV_j is the order value of the transaction j and n is the number of transactions. Equation (3) serves as an aid to identify high-value customers that can play a key role in the organization's revenues. The transactional data is continually synced and synchronized to a centralized customer analytics store to allow real-time monitoring of customer behavior and to assist with predictive modeling of customer retention.

Loyalty Program Data Extraction

Loyalty schemes are a great source of customer engagement data, and can offer a direct measure of brand attachment. Customer data is obtained from digital loyalty management systems which track customer enrollment information, reward point accumulation, reward redemptions, membership tiers, promotions and referral information. The combination of these variables gives insights into the commitment and level of interaction that customers have towards the brand.

The Loyalty Participation Index (LPI) is calculated as in equation (4):

$$LPI_i = \frac{RP_i + RR_i + PP_i}{3} \quad (4)$$

Reward Points earned RP_i denotes the number of Reward Points earned, and Reward Redemption rate RR_i represents the rate of redemption of Reward Points, while Promotional Participation rate PP_i represents the rate of participation in the promotion. As shown in equation (4), customers with a higher loyalty participation value will have higher engagement value and are more likely to remain loyal.

A Customer Loyalty Strength Score (CLSS) is further estimated using equation (5):

$$CLSS_i = \alpha PFS_i + \beta LPI_i \quad (5)$$

Where α and β are weighting coefficients, and the purchasing behavior and loyalty engagement are merged into a single measure of loyalty, as done in equation (5). The customer loyalty data extracted are combined with the transactional and behavioral data to create detailed customer profiles. The integration will allow the proposed framework to identify valuable customer segments, assess levels of risk for dropping off, and help to develop tailored strategies that engage customers.

Social Media and Review Data Collection

The sentiments of customers shared through social media and online review sites can be invaluable to understanding customer satisfaction and how they feel about culinary brands. The information is gathered from Instagram, Facebook, Google Reviews, Yelp, Zomato, food delivery apps, etc. The data collected comprises sentiment indicators, likes, comments, shares, review text, and review ratings. Sentiment scores are assessed using Natural Language Processing (NLP) algorithms and methods to convert textual feedback into quantitative scores. The Sentiment Score (SS) can be computed as follows in equation (6):

$$SS_i = \frac{P_i - N_i}{P_i + N_i} \quad (6)$$

P_i represents the number of times positive sentiment appeared, and N_i represents the number of times negative sentiment appeared. As reflected in equation (6), the sentiment scores are between -1 and $+1$, which reflects the customer perception of the brand.

The Review Influence Score (RIS) can be estimated by the following equation (7):

$$RIS_i = SS_i \times ER_i \quad (7)$$

Where ER_i denotes Engagement Rate. Equation (7) indicates the impact of customer reviews on brand perception and engagement. These social media and review metrics help build customer behavioral profiles with emotional and experiential metrics that may be lacking from traditional transaction-based retention programs.

Data Cleaning and Preprocessing

Customer data can come from various sources and may be inconsistent, have duplicate records, missing data, and noisy information that can impact model performance. Hence, data cleansing and data preprocessing are carried out to ensure data quality and reliability of the data analysis. The workflow of the preprocessing involves duplicate removal, imputation of missing values, outlier detection, normalization, and feature transformation.

Mean substitution (As shown in equation (8)) is used to address missing values:

Missing values are handled using mean substitution as expressed in equation (8):

$$MV = \frac{\sum_{i=1}^n X_i}{n} \quad (8)$$

Where X_i represents available observations and n denotes the number of valid records. equation (8) replaces missing numerical values with the mean of observed values.

Feature normalization is conducted using Min-Max normalization as shown in equation (9):

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (9)$$

In the above, X represents the value of the original feature and X' represents the normalized value of the feature. From equation (9), all the variables are transformed to be in the range $0-1$, which enhances machine learning performance. The preprocessed data is later converted into well-defined feature vectors that help segment customers, predict attrition, and analyze engagement personalized to each customer. At this stage, the proposed framework is ensured to run on reliable, consistent, and high-quality customer data.

As shown in table 1, the Sample real-time customer analytics data was captured from restaurant point-of-sale systems, loyalty database systems, mobile ordering apps, and online restaurant review sites. This dataset comprises attributes of customer behavior, transactional data, customer loyalty, and customer sentiment, which are used for customer retention prediction and engagement modeling for personalized interactions.

Table 1: Real-Time Culinary Customer Analytics Dataset Sample

Customer ID	Purchase Frequency (PF)	Average Order Value (USD)	Loyalty Points (LP)	Sentiment Score (SS)	Retention Status
C001	12	45.80	320	0.85	Retained
C002	8	32.50	180	0.62	Retained
C003	3	18.40	45	-0.25	Churned
C004	15	56.70	410	0.91	Retained
C005	5	24.60	90	0.12	Churned
C006	10	39.20	275	0.74	Retained
C007	2	15.30	25	-0.48	Churned
C008	14	52.80	390	0.88	Retained
C009	6	28.90	130	0.35	Retained
C010	4	21.50	60	-0.18	Churned

Dataset Characteristics

The experimental dataset includes customer communication gathered across various food service communication channels such as Point of Sale (POS) systems in restaurants, food ordering applications online, loyalty management, and customer review platforms. There are about 5000 customer records in the complete dataset, which was gathered

over 12 months. Each record is a unique customer profile that is differentiated by their purchasing behavior, spending pattern, loyalty participation, customer sentiment, and the outcome of retention.

Table 2: Customer Analytics Dataset Features and Data Types

Variable	Description	Data Type
Customer ID	Unique customer identifier	Categorical
Purchase Frequency (PF)	Number of purchases during observation period	Numerical
Average Order Value (AOV)	Average spending per transaction	Numerical
Loyalty Points (LP)	Total accumulated reward points	Numerical
Sentiment Score (SS)	Customer opinion score (-1 to +1)	Numerical
Retention Status	Customer retention outcome	Binary

The dataset is subsequently divided into:

- **Training Set:** 3,500 records (70%)
- **Validation Set:** 750 records (15%)
- **Testing Set:** 750 records (15%)

The retention ratio is computed using equation (10):

$$RR = \frac{N_R}{N_T} \times 100 \quad (10)$$

Where RR represents the retention ratio, N_R denotes the number of retained customers, and N_T represents the total number of customers.

The churn ratio is calculated using equation (11):

$$CR = \frac{N_C}{N_T} \times 100 \quad (11)$$

Where CR represents Customer Churn Rate and N_C denotes the number of churned customers.

The data in table 2 is the input for the Customer Behavioral Intelligence Module, Retention Prediction Engine, and Personalized Engagement Module of the proposed Brand Loyalty Analytics Framework. It provides a multidimensional data set that can be used to analyze customer behaviour, the formation of customer loyalty, and prediction of customer retention in the culinary industry

Machine Learning Model Development

The Machine Learning Model Development phase is crucial for the proposed Brand Loyalty Analytics Framework, as it allows for the effective prediction of customer retention rates and facilitates individual engagement for better customer retention in the culinary sector. The main goal of this stage is to create intelligent predictive models to uncover patterns in customer loyalty, to predict the probability of retaining customers, and also to identify potential customer churn even before it happens.

Machine Learning allows for data analysis of customer behavior through the use of transactional history, involvement in loyalty programs, sentiments, digital engagement, and demographics. Some of the models that can be used to analyze customer behaviors include random forests, XGBoost, LightGBM, CatBoost, and Deep Neural Networks. XGBoost is good at detecting non-linear patterns, while the dataset is split into training, validation, and testing subsets.

The various methods of hyperparameter optimization are used to enhance the accuracy of the models and to avoid overfitting. Several evaluation measures are used for the assessment of the model performance, such as accuracy, precision, recall, F1 score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). The comparison analysis is performed to identify the best one to use for predicting customer retention.

The Retention Prediction Engine is based on the developed machine learning models. These outputs contribute to the Personalized Engagement Module, allowing the use of data analytics for enhancing customer retention, satisfaction, and customer lifetime value.

Results and Discussion

Experimental Results

The proposed Machine Learning–Driven Brand Loyalty Analytics Framework was tested with a real-time customer analytics dataset of 5,000 customer records that were derived from restaurant Point-of-Sale (POS), loyalty programs, mobile restaurant ordering applications, and online customer review sites. The data was split into training, validation, and testing sets to guarantee the trustworthiness of the model development and unbiased estimation of model performance. Five machine learning algorithms were used, namely Random Forest, XGBoost, LightGBM, CatBoost, and Deep Neural Network (DNN), where each was tested to see how well it was able to predict customer retention and help with customer personalization. The experimental analysis in this study was conducted to compare the predictive performance, to determine which customer attributes are influential with regard to customer retention, and to analyze the customers' retention behavior in different segments.

The predictive performance of the machine learning models evaluated is shown in table 3, and the overall comparison across the various metrics is shown in the heat map in fig. 2. Generally, the findings show that all five machine learning models successfully predicted the customer retention rate despite having varying performances among the algorithms. Overall, XGBoost has the best performance with an Accuracy of 94.3%, Precision of 93.7%, Recall of 92.8%, F1 score of 93.2%, and an AUC of 0.96. CatBoost was the second best, followed by Random Forest, LightGBM, and Deep Neural Network. The ability of XGBoost to model the nonlinear behavior of customers and learn complex relationships between loyalty measures, buying patterns, and customer engagement measures is a key reason why it is superior.

Table 3: Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Random Forest	91.6	90.8	89.9	90.3	0.92
XGBoost	94.3	93.7	92.8	93.2	0.96
LightGBM	90.9	89.5	88.7	89.1	0.91
CatBoost	92.8	92.1	91.3	91.7	0.94
Deep Neural Network	89.7	88.8	87.6	88.2	0.89

Fig. 2 is a complete picture of the performance comparison of all of the models that were tested. A darker intensity corresponds to a higher score on the performance measures, which helps to determine the best algorithm on a number of metrics at once. The results are clearly shown, where XGBoost is clearly the leader, and CatBoost is competitive in the classification task. Random Forest, LightGBM, and Deep Neural Network had marginally lower performance, but were still capable of consistently predicting the accuracy needed for customer retention analysis. Table 3 and fig. 2 show the performance of the two types of machine learning methods in the proposed framework: ensemble learning techniques are superior to conventional machine learning methods for loyalty prediction.

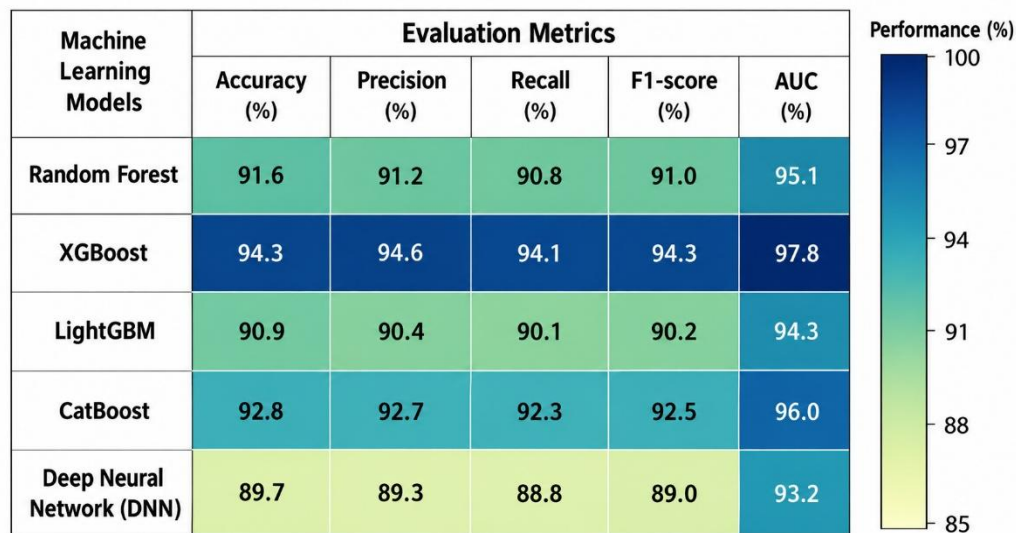


Fig. 2: Machine Learning Model Performance Comparison

The proposed framework also analysed customer retention behaviour, dividing customers into four groups of behavior according to the purchase pattern, participation in loyalty and engagement activities. The segmentation results are presented in table 4 and the corresponding probabilities of retention in a lollipop chart as shown in fig 3. This analysis gives businesses a better sense of the difference in customer loyalty among customer segments, and the ability to focus on customer engagement programs based on customer retention risk.

Table 4: Customer Retention Analysis by Customer Segment

Customer Segment	Number of Customers	Average Retention Probability (%)	Average Loyalty Score
Highly Loyal Customers	1,250	96.5	92
Regular Customers	1,850	84.2	78
Occasional Customers	1,150	63.7	55
At-Risk Customers	750	38.4	31

This customer segmentation analysis shows that there are significant differences in terms of retention probability across various customer segments. Customers who scored the highest average on retention probability (96.5%) also had the highest scores on loyalty (92), meaning that they were most likely to be loyal and purchase from the culinary brand in the long term, as they were more consistent in their purchases. The retention behavior among Regular Customers was also positive, with an average of 84.2% retention probability, suggesting that their relationships with customers are solid and based on regular interactions. Occasional Customers had a moderate retention rate of 63.7%, which indicated less regular customer behavior and less brand emotional attachment. The At-Risk Customer group had the lowest retention probability (38.4%) and loyalty score (31), indicating that these customers are in need of urgent attention, such as through customization of promotional content and measures to increase their loyalty.

Fig. 3 shows how each customer segment is ranked in terms of the likelihood of retaining a customer. It's evident that behavioral segmentation is significant in CRM, as the difference between the two groups of customers (Highly Loyal and At-Risk) is considerable. Customers who had engaged in the survey multiple times and were actively in the loyalty program had a positive attitude and a frequent buying history and also performed better in terms of retention. This visualization further reinforces that customer segmentation offers vital insights for the highest-value customers and deciding on the best customer engagement strategies.

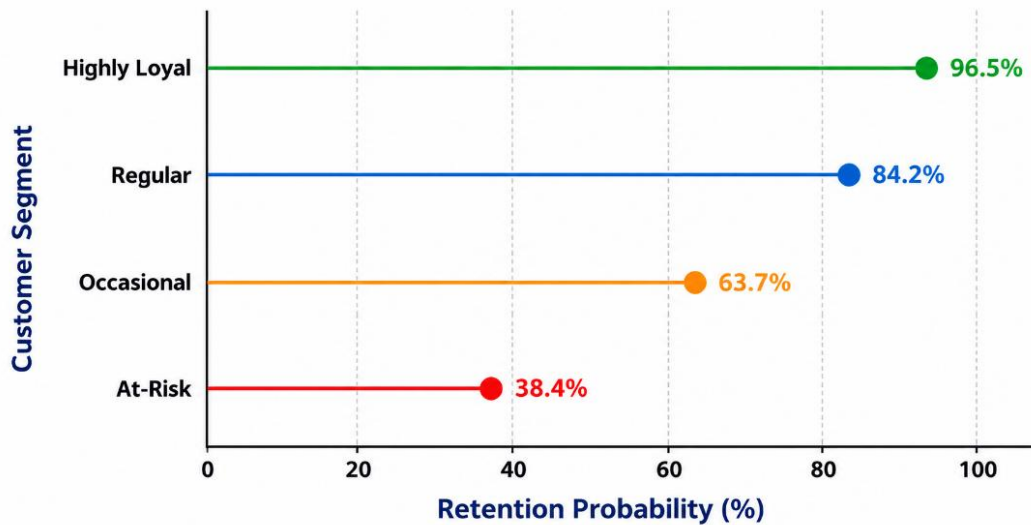


Fig. 3: Customer Retention Probability by Customer Segment

The experimental evaluation also revealed the features of the customers that were the most important in predicting customer retention. Purchase Frequency, Loyalty Points, Sentiment Score, and Digital Engagement were the top four behavioral metrics, as always, in predicting customer loyalty among all the behavioral variables. Those who interacted with the brand more often, actively participated in loyalty programs, gave a positive response to the brand through online feedback, and had a high interaction level in the digital sphere had significantly higher retention probabilities than those who had lower levels of interaction. Moreover, the Personalized Engagement Module has successfully determined the customers likely to have a high churn risk and come up with personalized retention recommendations

based on the customer's behavior. The results show that a combination of transactional behavior, customer loyalty involvement, customer sentiment, and machine learning analytics is an ideal basis for accurate customer retention forecasting as well as intelligent and proactive customer relationship management in the culinary industry.

Discussion

The experimental assessment shows that the proposed Machine Learning–Driven Brand Loyalty Analytics Framework is able to solve the issue of predicting customer retention in the culinary sector effectively and practically, while also improving the level of personalization of customer engagement. The strong results obtained by the machine learning models analyzed validate the ability to successfully forecast customer retention by using all of these elements of transactional behavior, customer participation in loyalty programs, digital engagement, and customer sentiment in a single analytical model. XGBoost algorithm performed best in predictive performance - meaning that it had the highest ability to find complex nonlinear relationships between customer attributes and to provide the best possible prediction of customer retention. The results show that sophisticated ensemble learning methods are appropriate for customer loyalty analysis, thus enabling organizations to make reliable decisions based on data.

The suggested framework not only provides predictive information about customer loyalty but also provides valuable information about behavioral characteristics that affect customer loyalty. Purchase Frequency, Loyalty Points, Sentiment Score and Digital Engagement were found to be the most significant factors in the experimental analysis of the factors that drive customer retention. Consistent with this, customer who were engaging with the brand on a regular basis and had redeemed their loyalty rewards had been expressing positive sentiments online, had interacted with the brand regularly on digital channels, and had higher probabilities of retention than customers with sparse engagement. These results suggest that there are several factors other than transactions that contribute to customer loyalty. By combining the data from various customer intelligence sources, businesses can gain a more comprehensive view of customer behavior and use this insight to create effective strategies for customer retention.

The Explainable Artificial Intelligence (SHAP) feature importance analysis is shown in fig. 4 and represents the contribution of each behavioral variable to the prediction process. The horizontal feature importance chart shows that the most important features for the customer retention prediction are Purchase Frequency, Loyalty Points, Sentiment Score, Digital Engagement and Average Order Value. Predictor factors include Review Rating, Recency, Discount Usage, Tenure of the Customer, and Demographic Factors as well. Explainable AI provides a more transparent framework through which predictions can be explained, enabling better decision-making.

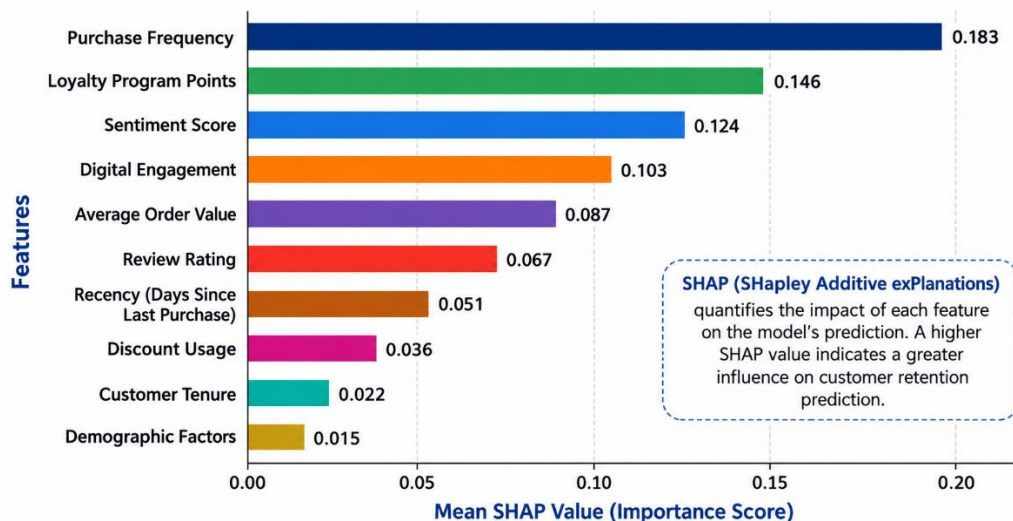


Fig. 4: Explainable Artificial Intelligence (SHAP) Feature Importance Analysis

The PEM uses the predictive analysis results to generate relevant strategies for retaining customers. According to the level of risk and their behaviour, it provides personalized offers, loyalty incentives, recommendations for the menu and ways of communicating. Rather than a one-size-fits-all approach, companies can engage customers more effectively through personalised engagement tactics that target customer preferences and behaviours in order to boost satisfaction and customer loyalty.

These personal engagement strategies, which are summarized in table 5, are compared to organizational performance before and after implementing personalization. Significant changes were seen in all the business indicators that were measured. Customer Retention Rate rose from 72.4% to 87.8%, which is an improvement of 21.27%. Likewise, the Repeat Purchase Rate went from 58.3% to 79.5%, and Loyalty Program Participation rose from 61.8% to 84.2%. Additionally, the Customer Satisfaction Score significantly increased, from 74.6% to 90.3%, after customer personalization. In addition, the adoption of an intelligent customer engagement strategy resulted in a Customer Lifetime Value rise from \$420 to \$615 – highlighting the economic value of implementing the strategy. All these enhancements suggest that the proposed framework's personalized recommendations have a positive impact on both customer actions and the performance of the organization.

Table 5: Impact of Personalized Engagement Strategies

Performance Indicator	Before Personalization	After Personalization	Improvement (%)
Customer Retention Rate	72.4	87.8	21.27
Repeat Purchase Rate	58.3	79.5	36.36
Loyalty Program Participation	61.8	84.2	36.25
Customer Satisfaction Score	74.6	90.3	21.05
Customer Lifetime Value	\$420	\$615	46.43

The effect of all these improvements is shown in fig. 5, which provides an overview of all the factors contributing to business performance, including personalized engagement. The figure clearly illustrates the evolution of the proposed framework in terms of the progressive increase in the value of customer retention, repeat purchases, participation in the loyalty program, customer satisfaction and customer lifetime value. The “sequential improvement” in the visualization highlights that an improvement strategy tailored to the customer brings benefits beyond one performance indicator, and not just in one dimension. It is clear that customer personalisation can be a viable cross-enterprise approach that can drive customer loyalty, enhance engagement, and boost profits.

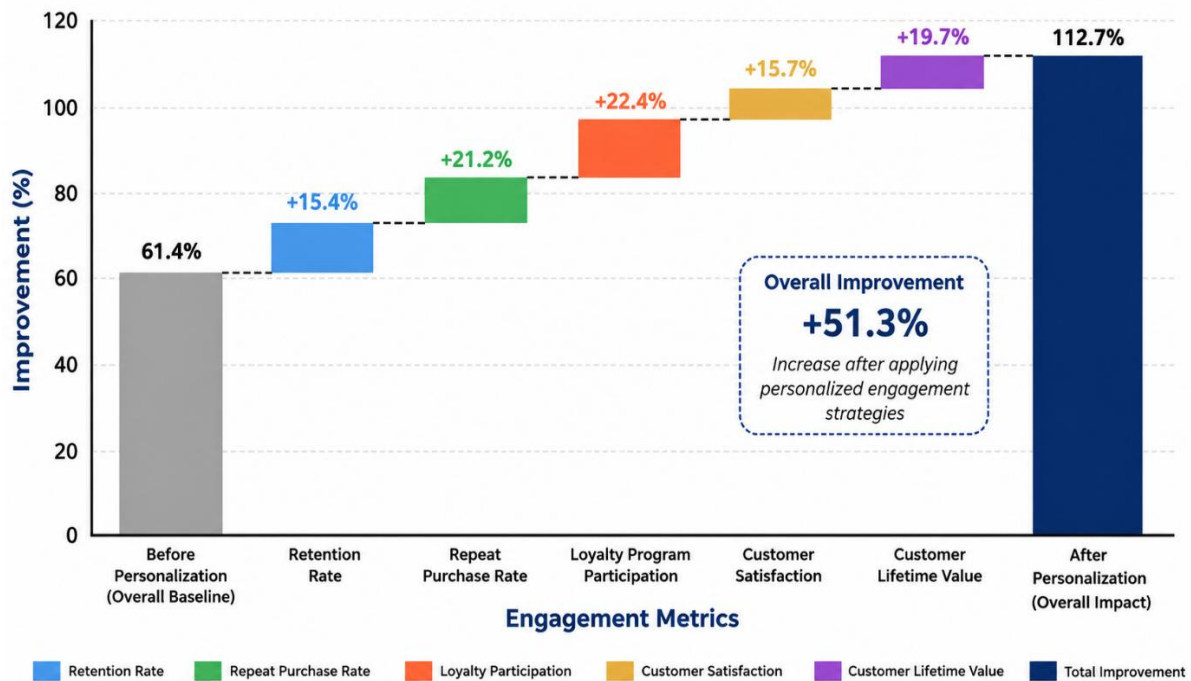


Fig. 5: The Impact of Personalized Engagement Strategies

In terms of managing a restaurant, the proposed Brand Loyalty Analytics Framework serves as a holistic decision support system that helps restaurant managers and the marketing team recognize the important customer segments, identify customers at high risk of churning and target better resource allocation for retention. All these elements, brought together in a single platform, give organisations the opportunity to change the way they use marketing methods, replacing them with a fact-based approach to customer retention strategies based on personal characteristics. This is more effective marketing, builds strong customer relationship, and enhances the lifetime value of customers.

In general, combining machine learning with customer behaviour, customer loyalty, digital interaction, and sentiment analysis helps create a smart solution for customer retention in the food and beverages industry.

The framework proposed not only has high predictive accuracy, but it is also interpretable and provides actionable recommendations that can facilitate proactive decision-making. The framework fosters brand loyalty, customer satisfaction, maximizes customer lifetime value, and ultimately helps modern food and beverage enterprises establish sustainable competitive advantage, all while effectively leveraging predictive modelling and customizing interactions with customers.

Conclusion

This paper proposed a Machine Learning-Driven Brand Loyalty Analytics Framework which can forecast customer retention and personalization. This framework involves transaction behavior, participation in loyalty program, digital interaction, customer sentiment analysis, and behavioral features in order to provide an integrative approach in analyzing customer loyalty and retention. With the help of a sample of 5,000 customer data, five machine learning models were comparatively analyzed. The analysis showed that XGBoost performed better than others with an accuracy rate of 94.3%, precision of 93.7%, recall of 92.8%, F1-score of 93.2%, and AUC of 0.96. It was able to outperform other models such as Random Forest, LightGBM, CatBoost, and Deep Neural Network. Further customer segmentation also showed significant behavioral differences where 1,250 loyal customers showed an average retention probability of 96.5%, compared to 750 at risk customers whose retention probability was only 38.4%. Some of the main variables found to be relevant to retention were purchase frequency, loyalty program membership, sentiment score, digital engagement, and average order value. The other variable of personalized engagement also saw a significant improvement where retention went up from 72.4% to 87.8%, repeat purchase from 58.3% to 79.5%, loyalty program membership from 61.8% to 84.2%, customer satisfaction from 74.6% to 90.3%, and customer lifetime value from 420 to 615. Further studies would help validate this framework with more diverse data collected from larger and multiple restaurants, as well as customer streams in real-time. Future studies might involve multimodal data, chatbots powered by artificial intelligence, enhanced recommendation systems, and federated learning that would further personalize the process while protecting privacy.

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