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BASED ON XGBOOST AND LIGHTGBM MODELS, THE REASONS BEHIND BANK CUSTOMER ATTRITION: EVIDENCE FROM THE KAGGLE DATASET JIAYI CAI

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Abstract:
The development of Internet finance presents additional difficulties for the traditional banking sector as the digital economy grows. Banks face a number of challenges, including fintech competition, dwindling consumer loyalty, and digital transformation. Bank managers can better understand the reasons behind bank customer churn, identify issues, quickly identify potential churn customers, and create effective retention strategies based on customer traits and preferences by analyzing the potential factors of churn from a variety of angles and building models for predicting churn. In this work, we analyzed the parameters used to forecast bank customer turnover from several viewpoints, including feature selection, using a mix of visualization, data mining, and machine learning techniques.
(PCA) for feature extraction, visualization, and Random Forest Feature Importance Ranking, among others. Additionally, we built two churn prediction models—XGBoost and LightGBM—based on gradient boosting tree techniques. We also compared the evaluation measures before and after feature selection, as well as before and after tweaking parameters, and we used SHAP methods to understand the model. Following the publication, the following deductions were made: (1) The analysis and prediction of customer churn relies heavily on Total Trans Amt, Total Trans Ct, and Total Revolving Bal; (2) The SHAP Summary Plot can respond to the visual analysis of customer churn predictors to a certain extent; (3) The impact of feature selection on the evaluation of the results is occasionally negligible; (4) Adjusting parameter settings can improve model performance to some degree, However, the best settings might change depending on the preprocessing technique used. These findings will help banks build a higher performance churn prediction model, carry out a thorough result synthesis analysis, and gain a deeper understanding of customer churn drivers.

Keywords:
customer churn; predictors of churn; churn prediction models; machine learning

1. Introduction

The business models and service approaches used by the financial industry have been drastically altered by the growth of the fintech sector and the digital economy, posing serious challenges to the established banking sector. An increasing number of FinTech and BigTech companies are emerging as providers of digital financial services [1], building FinTech platforms and providing clients with a wide array of services like trading and capital markets, insurance, digital banking, personal financial management, lending, crowdfunding, enterprise financial management, and payment and remittance [2]. This pattern has strengthened financial services while hastening disruptions in the financial industry and democratizing financial services.the strong interaction between financial service providers and clients, as well as the reduction of switching costs for customers seeking to change service providers [3]. Many customers think that conventional banking intermediaries are outmoded, with FinTech "disintermediating" retail money and finance [4]. Digital finance can influence competitiveness in the banking industry via three intermediate mechanisms: the deposit effect, the loan effect, and the collaboration impact. For example, the growth of digital finance has impacted commercial banks' savings deposit and household lending operations [5]. Although some research have demonstrated that fintech credit and banking may be complimentary [6], and that fintech credit adds to bank stability [7], Banks may lose their competitive advantage in the processing of soft credit information and relationship lending when compared against innovative technology businesses. Tech businesses might use their information advantage to tailor the distribution of debt products and gain market share, hurting the profitability of traditional banks [6]. Furthermore, blockchain applications have promise that goes beyond financial institutions and payment networks. Blockchain technology is also gaining popularity, particularly among millennials [8].

Specifically, demonstrating a high interest in fintech goods and services [9]. Notably, the COVID-19 worldwide pandemic has accelerated the digital transformation of financial services, making people's lives increasingly virtual. Technology businesses are exploring ways to integrate digital items into people's daily life [9]. A research found that during the COVID-19 worldwide pandemic, firms like Amazon and Tescent that used fintech advances proved

Strong resilience resulted in considerable revenue increase [2]. Furthermore, as a result of the global economic crisis and financial storm, traditional banks' services are no longer enough to satisfy the expectations of their consumers [10]. Simultaneously, digital transformation and technology improvements have enabled many technological enterprises to satisfy their customers' demands at a low cost [9]. As a consequence, clients' switching motive will be strengthened, and they will be more aggressive in searching out profitable financial institutions.promise or provide more cost-effective services [10]. Unprecedented disintermediation has increased competition in the financial industry and jeopardised the business model of established banks [3]. According to one poll, 66.8% of existing bank customers have used or expect to utilize bank accounts from rising fintech businesses in the next three years [11]. Furthermore, the CustomerGauge 2018 NPS and CX Benchmarking Report [12] reveals a concerning reality for the banking industry: the industry performs poorly in terms of Average Net Promoter Score (NPS), which is near the bottom of the cross-industry scale, while also facing challenges such as a relatively low Average Retention Rate and Average Return on Retention. Customer loss may negatively impact banks' profitability, cost structure, brand reputation, and risk management. Customers are the most essential source of profit for banks [13], and losing customers implies that banks may lose their source of revenue, which diminishes profitability. Meanwhile, client retention improves financial performance and contributes to the bank's sustainability [14]. It is well known that the cost of recruiting new consumers outweighs the cost of maintaining current ones [15]. This is due to the need for banks to devote more resources to attracting new clients to replace those who have left, as well as spend more time developing strong relationships with new customers. Furthermore, research has demonstrated that brand reputation correlates with consumer inertia and retention [10]. Customer turnover may harm a bank's brand perception, thereby impacting Customer retention and new customer trust. Customer turnover may also result in a reduction in loan quality, increasing the bank's credit risk. As a result, in the information-intensive financial services sector, it is not enough to focus on client acquisition; banks must also thoroughly study the elements that lead to customer attrition.

Identify churn tendencies promptly. Understanding customer churn tendencies in advance and conducting a churn analysis will help banks allocate resources more efficiently to retain their customers, ensure sustainable profit [15], and achieve long-term sustainability, particularly in situations where customers can independently terminate their use of banking services at any time and freely choose services from different financial institutions.

The financial industry, which is heavily reliant on relationships, is in desperate need of increasing customer brand experience (BE) and promoting customer engagement (CE) [16] in order to enhance consumer inertia and loyalty, and so achieve long-term client retention. However, standard retail banks' methods have not proven effective in encouraging clients and retaining long-term customer loyalty [17]. At this point, efficient technologies like as visualization, data mining, and machine learning are critical. Using these tools, bank management may understand the reasons of

client turnover and discover the difficulties in customer management and business areas that existed prior to the current scenario so that they may be optimized and improved. Furthermore, unlike a comprehensive marketing strategy, bank managers can categorize customers, identify individuals with favorable credit situations or future growth potential, and implement customer retention programs that are tailored to their characteristics and preferences [10]. This contributes to meeting the demands of various consumer groups and improving the customer brand experience (BE), resulting in increased customer satisfaction and loyalty [16]. Additionally, effective churn A prediction model may accurately forecast customer attrition, allowing bank marketers to take proactive efforts to improve customer engagement (CE) and give a better customer experience [16]. The goal of this paper is to conduct a comprehensive analysis and exploration of the factors used to predict customer churn in banks from multiple perspectives using visualization, data mining, and machine learning methods, as well as to develop two churn prediction models using the Gradient Boosting Tree algorithm, XGBoost, and LightGBM, and then make targeted recommendations based on comparative evaluation. This will allow banks to better grasp the variables of consumer turnover, create higher performance churn prediction models, and be able to conduct a complete analysis of the outcomes in order to maximize resource use and avoid substantial losses due to customer churn. This would enhance banks' competitiveness and promote long-term development despite strong competition.

This paper's uniqueness is the use of a complete strategy to investigate and analyze from many angles. Next, the paper is arranged as follows: Section 2 will provide a literature assessment of approaches for forecasting client attrition. Section 3 will describe the study technique and evaluate and preprocess the dataset. Section 4 will offer a detailed study of the components utilized for customer churn prediction, such as conducting feature selection (random forest feature significance). rating, feature extraction (PCA), and visual analysis. Section 5 will compare several approaches for forecasting client attrition. Finally, Section 6 will summarize the findings and provide applicable suggestions.

2. Literature review of Customers Churn Prediction Methods

Customer churn prediction is an intricate task that requires processing large amounts of data and exploring multiple methods to find the best solution. Existing research on customer churn prediction methods focuses on statistical analysis methods, time series analysis, machine learning, cluster analysis, ensemble learning, and hybrid methods. The purpose of this chapter is to provide the reader with the chance to make a more informed choice of methods for real-world applications by reviewing the research and applications of different churn prediction methods.Statistical modeling approaches were first used in the marketing and financial industry to solve churn analysis and prediction tasks [18]. For example, survival analysis that models the occurrence and timing of events. Analysis of Variance (ANOVA) is used to reveal customer behavior. T-tests and chi-square statistics were used to predict customer behavior and perceptions. Khodadadi et al. [19] presented ChOracle, an oracle that forecasts user churn by modeling user return times to a service utilizing a blend of Temporal Point Processes and Recurrent Neural Networks. And they showcase ChOracle’s outstanding performance across various real datasets. On the other hand, Oskarsdóttir et al. [20] utilized a time-series approach to forecast customer churn in the telecommunications industry, utilizing a time- series that represents the dynamics of customer behavior. This approach of exploiting dynamic behavior makes sense instead of exploring previous static classification applications.

However, as data availability increases and problem complexity increases, there is a growing tendency to adopt machine-learning methods that can handle large-scale data and complex features. In machine learning, numerous algorithms exist to facilitate various tasks.

Some of the traditional single machine learning algorithms include Logistic Regression (LR), Decision Trees, Random Forest, Support Vector Machines (SVM), and K-Nearest Neighbors (K-NN). However, all these methods have some limitations. For example, when using Logistic Regression, the unbalanced data impacts the accuracy and precision of estimated parameters, leading to the model’s poor predictive ability [21]. It has also been shown that the performance of models such as Decision Trees [22] can be affected by imbalanced datasets. In addition, machine learning algorithms, such as deep neural networks [23, 24] and cluster analysis, are usually unsuitable for directly dealing with imbalanced datasets. However, an approach has been proposed by researchers such as Carl Yang [25], who developed a coherent and robust framework, called ClusChurn, for interpretable new user clustering and churn prediction. This framework is capable of delivering real-time data analytics and prediction results, thus benefiting multiple aspects. However, some machine learning algorithms and methods for unbalanced data also exist, such as ensemble learning, algorithm optimization, hyperparameter tuning, and hybrid methods.

Geiler et al. [18] recommend ensemble approaches, such as AdaBoost, Gradient Boosting, or XGBoost, for predicting churn. In particular, XGBoost has demonstrated superiority in handling imbalanced datasets [26]. However, some studies suggest that XGBoost can be used in combination with other ensemble methods for achieving state-of-the-art performance [27]. In addition, Khoh et al. [28] have proposed an optimized weighted soft voting ensemble learning model, shown through empirical results to have higher prediction accuracy than machine learning and deep learning models, among others, for customer churn prediction systems. Algorithmic optimization methods were also utilized by Vani Haridasan et al. [29], who employed an arithmetic optimization algorithm (AOA) in conjunction with a stacked bidirectional long short-term memory (SBLSTM) model, demonstrating potential in performance compared to recent approaches. Thakkar et al. [30] proposed a novel class-dependent cost- sensitive boosting algorithm called AdaboostWithCost that reduces errors and misclassification costs, thereby reducing the cost of churn. Arshad et al. [31] on the other hand, proposed a hybrid model called “A Hybrid System for Customer Churn Prediction and Retention Analysis via Supervised Learning (HCPRs)” which used Synthetic Minority Over-Sampling Technique (SMOTE) and Particle Swarm Optimization (PSO) to solve the problem of imbalance class data and feature selection. Extensive experiments are conducted to assess the model’s performance across Random Forest (RF), Linear Regression (LR), Naïve Bayes (NB), and XGBoost. The results indicate that the proposed model has a higher accuracy under the curve (AUC) of 98% when used with the XGBoost classifier compared to other methods.

Nowadays, propelled by the advancements in machine learning, the exploration and application of customer churn prediction methods have become more and more popular. The models used to predict customer churn are becoming increasingly sophisticated, but the predicted results are becoming more accurate and reliable. However, the generalization ability of many models has yet to be verified. While the choice of machine learning models is contingent on dataset characteristics, a limited number of studies have conducted experiments across diverse churn datasets from various domains to establish the models’ validity and assess their performance [15]. Therefore, in the future, there is still a need to focus on this aspect of generalization ability, to construct more advanced hybrid models with better generalization ability and novel feature engineering methods, among others.

3. Research Methodology and Data Preprocessing

The crucial steps in Customer Churn Prediction (CCP) encompass data analysis, feature extraction, identification of pivotal features influencing retention, and the reasonable selection of a classification model. Understanding the data is paramount before applying machine learning algorithms involving data cleaning and feature selection. [32]. Therefore, this study plans to use visualization, data mining, and machine learning methods to preprocess the dataset and then explore and analyze the dataset from multiple perspectives. And visualize and analyze the dataset after extracting the key predictor features of customer churn. In addition, this study plans to construct two churn prediction models based on Gradient Boosting Tree algorithms, XGBoost and LightGBM, for comparative evaluation and targeted comments.

This section will be divided into four parts: sample selection, outlier handling, descriptive statistics, and unbalanced data processing using SMOTE.

3.1 Sample Selection

The study is based on a set of data from Kaggle called Credit Card Customers. This dataset contains 10127 credit card customers, each with 23 features. Out of the 23 features, there are seven types of float-type features, ten types of int-type features, and six types of object-type features. These features can be roughly customized into two categories: the basic characteristics of the customer and the characteristics and usage of the customer’s credit card. In the basic characteristics of the customer, in addition to the CLIENTNUM (Customer Number), Attrition Flag, Age, Gender, Education Level, Marital Status, and Income Category, there is a Dependent count (The number of dependents of the customer).

The characteristics and usage of the customer’s credit card include: Card Category, Months on book (Length of time the customer has held the credit card), Total Relationship Count (Total number of products held by the customers), Months Inactive 12 mon (The number of months inactive in the last 12 months), Contacts Count 12 mon (The total number of interactions or contacts made between the customer and the bank within the past 12 months), Credit Limit (The maximum amount of credit that the bank extends to a customer), Total Revolving Bal (The unpaid amount that carries off on the next credit card’s cycle), Avg Open To Buy (The average amount of credit available for a customer to use or spend), Total Trans Amt (The total amount of transactions made by a customer in the last 12 months), Total Trans Ct (The total count or number of transactions made by a customer in the last 12 months), Avg Utilization Ratio (The average percentage of available credit that a customer has utilized or borrowed), Total Amt Chng Q4 Q1 (The net change in the total transaction amount during a specific period, typically comparing the fourth quarter (Q4) to the first quarter (Q1) of the same year) and Total Ct Chng Q4 Q1 (The net change in the total transaction count during a specific period, typically comparing the fourth quarter (Q4) to the first quarter (Q1) of the same year) , etc.

3.2 Outlier Handling

The Education Level, Marital Status, and Income Category features contain unknown labels. First, replace them with nulls, as they do not provide any information. Then, they were calculated based on the K-Nearest Neighbors (K-NN) values to remove all nulls. However, the analysis revealed that all three variables had very little effect on the dependent variable and could be used individually or eliminated. Exclusion was chosen in this study. In addition, this study also chose to exclude CLIENTNUM and the last two complex features, as none of these features affect customer churn.

3.3 Data Transformation

This study transforms six types of object-type features into data to facilitate subsequent machine learning. The two features, Attrition Flag and Gender, are distinguished by 0 and 1, respectively. The remaining four features, Education Level, Marital Status, Card Category, and Income Category, are all ranked from 1. The transformations are presented in Table 1.

Table 1. Data Transformation

Attrition Flag	Existing Customer=1 Attrited Customer=0
Gender	M=1 F=0
Education Level	Uneducated=1 High School=2 College=3 Graduate=4 Post-Graduate=5 Doctorate=6
Marital Status	Single=1 Married=2 Divorced=3
Income Category	Less than $40K=1 $40K - $60K=2 $60K - $80K=3 $80K - $120K=4 $120K +=5
Card Category	Blue=1 Silver=2 Gold=3 Platinum=4

3.4 Descriptive Statistics

Descriptive statistics were applied to the dataset, and the outcomes are displayed in Table 2.

Table 2. Descriptive Statistics

	Count	Mean	Std	min	50%	max
Attrition Flag	7081.0	0.842819	0.363997	0.0	1.000	1.000
Age	7081.0	46.347691	8.041225	26.0	46.000	73.000
Gender	7081.0	0.523372	0.499489	0.0	1.000	1.000

Dependent count	7081.0	2.337805	1.291649	0.0	2.000	5.000
Education Level	7081.0	3.065810	1.404962	1.0	3.000	6.000
Marital Status	7081.0	1.664031	0.619564	1.0	2.000	3.000
Income Category	7081.0	2.343313	1.355904	1.0	2.000	5.000
Card Category	7081.0	1.082757	0.328819	1.0	1.000	4.000
Months on book	7081.0	35 981359	8.002609	13.0	36.000	56.000
Credit Limit	7081.0	8492.773831	9126.072520	1438.3	4287.000	34516.000
Total Relationship Count	7081.0	3.819376	1.544444	1.0	4.000	6.000
Months Inactive 12 mon	7081.0	2.342607	0.995104	0.0	2.000	6.000
Contacts Count 12 mon	7081.0	2454456	1.104917	0.0	2.000	6.000
Total Revolving Bal	7081.0	1167.501624	812.315606	0.0	1282.000	2517.000
Avg Open To Buy	7081.0	7325.272207	9131.217585	3.0	3250.000	34516.000
Total Amt Chng Q4 Q1	7081.0	0.760584	0.223139	0.0	0.735	3.397
Total Trans Amt	7081.0	4394.299816	3468.461606	510.0	3831.000	17995.000
Total Trans Ct	7081.0	64 503319	23 809330	10.0	67.000	134.000
Total Ct Chng Q4 Q1	7081.0	0.711508	0238693	0.0	0.700	3.714
Avg Utilization Ratio	7081.0	0.282313	0.278731	0.0	0.186	0.999

3.5 Unbalanced data processing using SMOTE

When it comes to classification problems, class imbalance often occurs, which significantly impacts the model [33]. Therefore, churn datasets with class imbalance problems (CIP) must be treated appropriately before being used as input to machine learning algorithms [15]. Typically, diverse sampling methods are employed to alter the class distribution [18]. This enhances the accuracy of models and imparts greater stability to them [33]. Sampling methods can be broadly categorized into three types: oversampling (e.g. SMOTE, ADASYN), undersampling (e.g. Tomek Links, ENN), and hybrid sampling. Although it has been shown that undersampling tends to overtake oversampling [18], Tékouabou et al.

[33] do not recommend an undersampling approach as it can lead to the loss of information that could have otherwise contributed to the model, and instead propose a succinct and detailed process of machine learning model construction including combining SMOTE to balance the data and employing ensemble methods, complemented by cross-validation.

3.5.1 Churn rate analysis

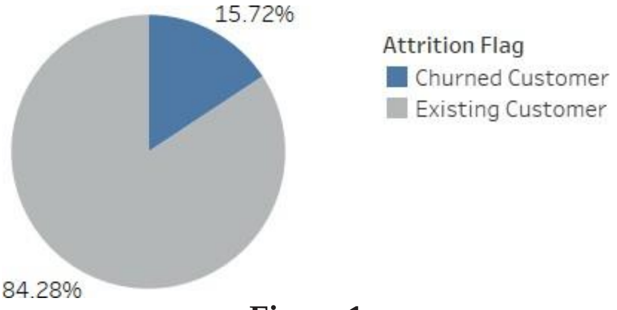


Figure 1

As shown in Figure 1, only 15.72% percent of the customers are churned, which indicates an imbalance between churned customers and existing customers. A single traditional machine learning algorithm model is unsuitable for predicting customer churn in this dataset, as it cannot precisely and comprehensively identify customers with a propensity for churn due to its limitations. Therefore, before constructing a churn prediction model, this study will balance the dataset by cross-validating combinations of SMOTE, supplemented with heat maps for visualization and analysis.

3.5.2 Correlation Heat map after SMOTE

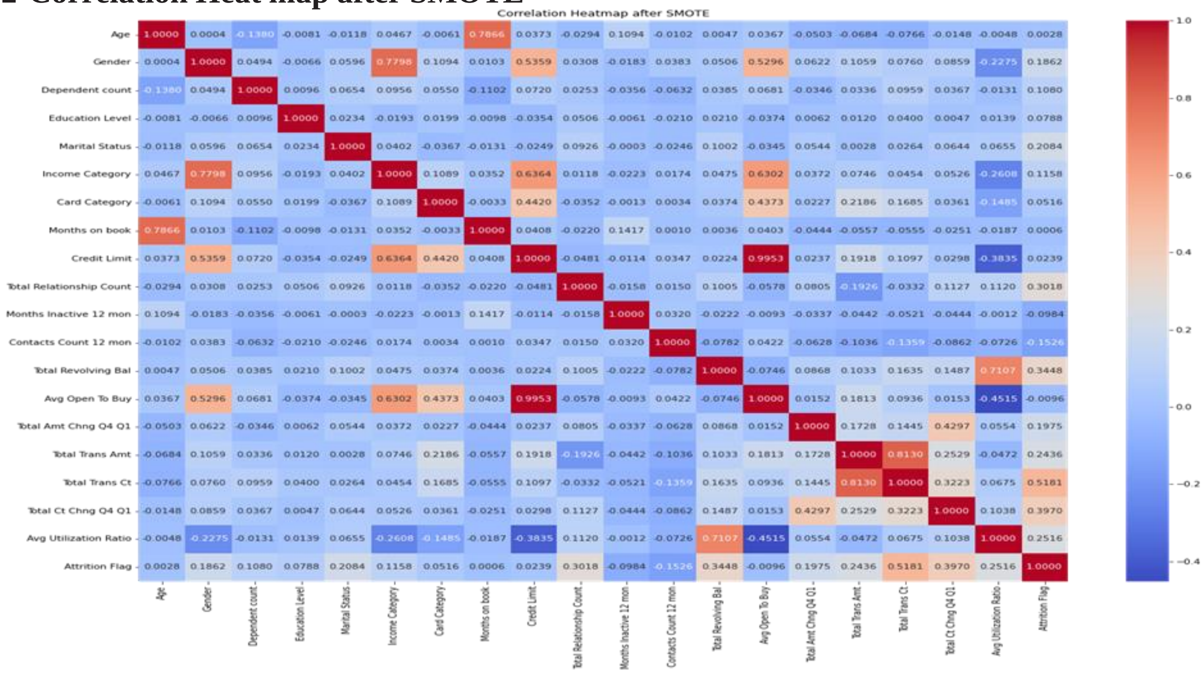


Figure 2

Figure 2 is a visual heat map after balancing the classes using SMOTE. In Figure 2, by using colors, we can easily determine which features are positively correlated with each other and which are negatively correlated. Red means it is positively correlated; conversely, blue means it is negatively correlated. In addition, we can quickly know the degree of correlation between individual features. The redder the color, the more positively correlated; conversely, the bluer the color, the more negatively correlated. Attrition flags are positively correlated with Total Trans Ct, Total Ct Chng Q4 Q1, Total Revolving Bal, and Total Relationship Count, and negatively correlated with Contacts Count 12 mon and Months Inactive 12 mon.

Analysis of factors predicting customer churn

In churn datasets, many features are usually involved, and dealing with such a large number of features leads to high computational costs and storage space [34]. Therefore, dimensionality reduction methods must be used to reduce overfitting, thereby enhancing the data's performance and the generalization of prediction models [18]. Feature selection and feature extraction, as two different feature engineering methods, are critical steps in the machine learning process as they enhance the machine learning model performance, reduce dimensionality, reduce computational cost, and improve the interpretability of models. Combining feature selection and feature extraction into one analysis helps better understand the data. In this study, we chose to apply the methods of feature selection and feature extraction separately to the balanced dataset and visualize and analyze them after extracting the key predictor features of churn.

4.1 Random Forest Feature Importance Ranking

The Random Forest Feature Importance Ranking is a feature selection method that utilizes the Random Forest model to assess the importance of data features. This technique allows us to understand the relative importance of each feature and thus determine which features are critical to model performance. By performing the Random Forest feature importance ranking multiple times, we can derive the seven most important factors used to predict customer churn, consistent with those shown in Figure 3: Total Trans Amt, Total Trans Ct, Total Revolving Bal, Total Ct Chng Q4 Q1, Avg Utilization Ratio, Total Relationship Count and Total Amt Chng Q4 Q1.

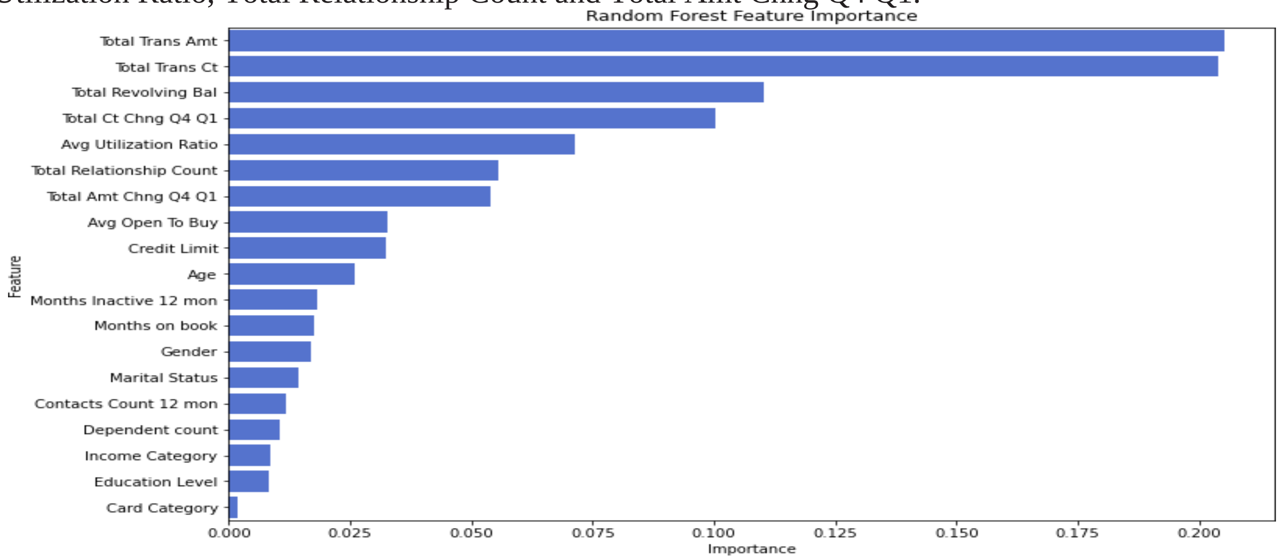
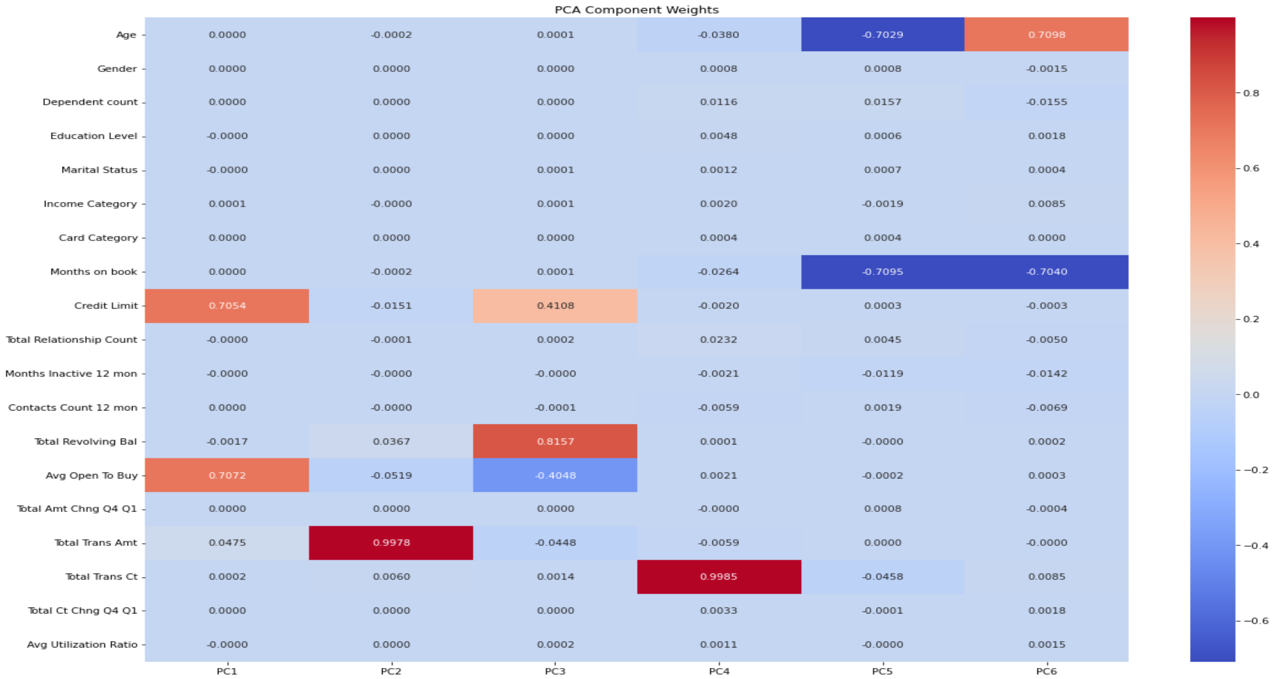


Figure 3

4.2 Visualization of principal component weights

Principal Component Analysis (PCA) is a feature extraction method and product of linear algebra mathematics [35]. PCA transforms the original data into a new set of axes by linear transformation, i.e., principal components are obtained by linear combination. Thus, PCA can transform multi-dimensional data into low- dimensional data, which assists in feature selection [32]. In the PCA technique, we can utilize eigenvalues to select key features. Higher feature values imply more significant features and higher principal component scores, which indicate that they contribute more to the data and can be used for prediction. Additionally, we can visualize the principal component weights, which helps analyze how much each raw feature contributes to the principal components, identify which raw features significantly impact the principal components, and understand the data more deeply.



	PC1	PC2	PC3	PC4	PC5	PC6
Age	0.0000	-0.0002	0.0001	-0.0380	-0.7029	0.7098
Gender	0.0000	0.0000	0.0000	0.0008	0.0008	-0.0015
Dependent count	0.0000	0.0000	0.0000	0.0116	0.0157	-0.0155
Education Level	-0.0000	0.0000	0.0000	0.0048	0.0006	0.0018
Marital Status	-0.0000	0.0000	0.0001	0.0012	0.0007	0.0004
Income Category	0.0001	-0.0000	0.0001	0.0020	-0.0019	0.0085
Card Category	0.0000	0.0000	0.0000	0.0004	0.0004	0.0000
Months on book	0.0000	-0.0002	0.0001	-0.0264	-0.7095	-0.7040
Credit Limit	0.7054	-0.0151	0.4108	-0.0020	0.0003	-0.0003
Total Relationship Count	-0.0000	-0.0001	0.0002	0.0232	0.0045	-0.0050
Months Inactive 12 mon	-0.0000	-0.0000	-0.0000	-0.0021	-0.0119	-0.0142
Contacts Count 12 mon	0.0000	-0.0000	-0.0001	-0.0059	0.0019	-0.0069
Total Revolving Bal	-0.0017	0.0367	0.8157	0.0001	-0.0000	0.0002
Avg Open To Buy	0.7072	-0.0519	-0.4048	0.0021	-0.0002	0.0003
Total Amt Chng Q4 Q1	0.0000	0.0000	0.0000	-0.0000	0.0008	-0.0004
Total Trans Amt	0.0475	0.9978	-0.0448	-0.0059	0.0000	-0.0000
Total Trans Ct	0.0002	0.0060	0.0014	0.9985	-0.0458	0.0085
Total Ct Chng Q4 Q1	0.0000	0.0000	0.0000	0.0033	-0.0001	0.0018
Avg Utilization Ratio	-0.0000	0.0000	0.0002	0.0011	-0.0000	0.0015

Figure 4

Figure 4 shows the visualization of principal component weights after extracting six principal components by principal component analysis. In Figure 4, we can easily see that the seven original features of Age, Months on the book, Credit Limit, Total Revolving Bal, Avg Open To Buy, Total Trans Amt, and Total Trans Ct have contributed more to the six extracted principal components, especially Total Trans Amt and Total Trans Ct, the degree of contribution to PC2 and PC4, respectively, has reached

0.99. In addition, the positive and negative correlations and the magnitude of the weights can be judged by the color and shade.

Feature selection and feature extraction, as two different feature engineering methods, have different purposes and methods for extracting features. As a result, the features they extract also tend to be different. Therefore, the seven most important predictors of customer churn in the balanced credit card customer dataset extracted by the feature selection (Random Forest Feature Importance Ranking) method are Total Trans Amt, Total Trans Ct, Total Revolving Bal, Total Ct Chng Q4 Q1, Avg Utilization Ratio, Total Relationship Count, and Total Amt Chng Q4 Q1, while the seven predictors of customer churn extracted using feature extraction (PCA) method are Age, Months on book, Credit Limit, Total Revolving Bal, Avg Open To Buy, Total Trans Amt, and Total Trans Ct. Most of the extracted features are different under both methods, but there are the same three features: Total Trans Amt, Total Trans Ct, and Total Revolving Bal. These three features are both the top three in the random forest feature importance ranking and the top three with the highest principal component weights. However, the choice as to whether to go for feature selection or feature extraction depends both on the specific task and requirements and on the subsequent machine learning algorithm used. If one wants to preserve the interpretability and meaning of the original features, feature selection may be more appropriate. Feature extraction may be more appropriate if one wishes to reduce data dimensionality and eliminate redundancy. Furthermore, the feature selection (K-Best) method demonstrated superiority over the feature extraction (PCA) method when paired with four different classification algorithms (XGBoost, Random Forest Classifier, Logistic Regression, and Support vector classifier) in a particular scenario [32].

4.3 Visualization Analysis

The three features, Total Trans Amt, Total Trans Ct, and Total Revolving Bal, are both the top three in theimportance ranking of Random Forest features and the top three with the highest principal component weights. Therefore, they are important in the study of customer churn.

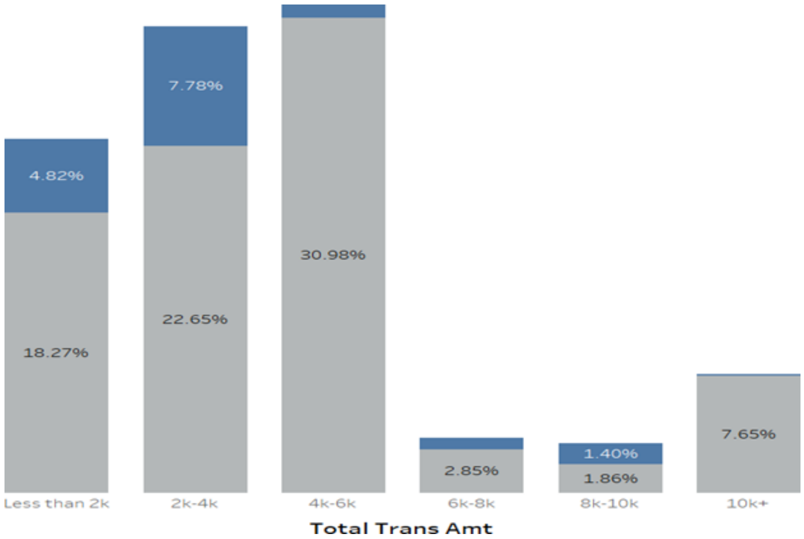


Figure 5

Figure 5 shows the cumulative number of transactions carried out by a customer within the past 12 months. In the dataset, Total Trans Amt has a minimum of 510 and a maximum 17,995. Because of the large span, it is divided into six categories: less than $2k, $2k-4k, $4k-6k, $6k-8k, $8k-10k, and $10k and above. Figure 5 shows that $2k-4k churned customers are the highest, followed by less than 2k. Therefore, customers with fewer total transactions may be more prone to churn. However, churned customers of $8k-10k account for a higher percentage of existing customers of $8k-10k, and hence, omers of $8k-10k also need to be noticed.

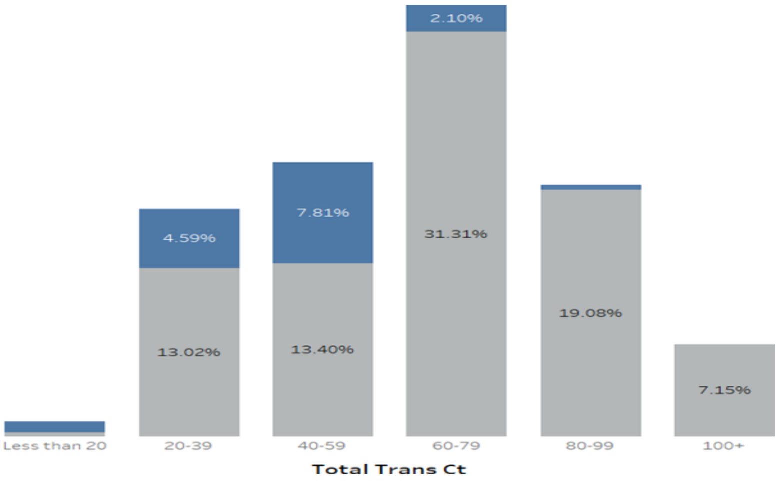


Figure 6

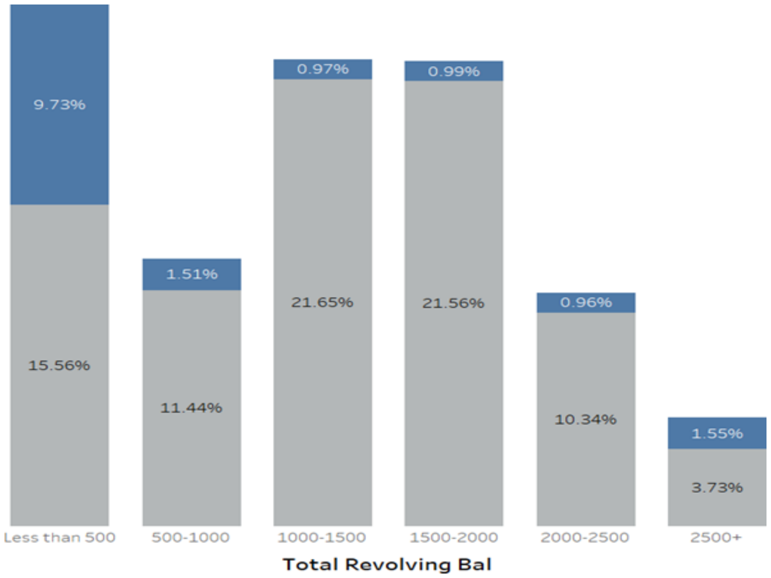


Figure 7

Figure 6 shows the total count of transactions conducted by a customer in the last 12 months. The dataset's minimum number of total transactions is 10, and the maximum is 134. For ease of analysis, it is also divided into six categories,: less than 20, 20-39, 40-59, 60-79, 80-99 and 100 and above. Clearly, the most churned customers are those with 40-59 transactions and customers with fewer transactions are also more likely to churn. When the number of transactions reaches 80 or higher, the churn rate among customers is very low. Figure 7 shows the outstanding amount that will carry over to the next credit card cycle. The minimum amount outstanding is 132, and the maximum is 2,517, and again can be categorized into six categories: less than $500, $500-1,000, $1,000-1,500, $1,500-2,000, $2,000-2,500,

and $2,500 and above. Customers with a total revolving amount of less than $500 are the ones who churn the most. According to Figure 5, Figure 6, and Figure 7, customers with low total transaction amounts, low numbers of transactions, and low unpaid amounts are relatively more prone to churn. This phenomenon may be related to Customer Engagement (CE), as customers with lower characteristics may be less dependent on banking services, which means they may also be less loyal to the bank [16]. In addition, this also sidesteps the fact that customers with strong ties to financial institutions, owning a substantial number of goods and services and borrowing extensively from banks, are less inclined to close their accounts [11]. Therefore, banks should regularly identify and observe general service-delivery trends to detect customers at risk of churning. In addition, banks should also enhance the ability to predict customer churn and provide preventative structural measures in weak areas [36].

5. Comparative analysis and evaluation of customer churn prediction models

5.1 XGBoost and LightGBM

Both XGBoost and LightGBM are gradient-boosting- based decision tree integration algorithms commonly employed to address classification and regression issues [31]. However, they differ in their splitting strategy. Specifically, LightGBM distinguishes itself from XGBoost by implementing one-sided sampling to filter out data splits. It means that it does not need to sort out the feature values, improvings training speed and efficiency [35]. Despite their different approaches, they both employ a gradient-boosting framework, which can promote weak and strong learners and provide robust performance and accurate predictions [31]. In solving the Class Imbalance Problem (CIP), Boo and Choi [37] compared different ensemble techniques,including Random Forest (RF), Extra-Trees, and XGBoost, as well as various oversampling and undersampling methods. The study findings indicated that the XGBoost model best predicted after SMOTE oversampling. In addition, Mirabdolbaghi and Amiri [35] pointed out that feature reductions can effectively improve speed. Among the feature reduction algorithms, Xgboost performs well. However, in terms of imbalanced metrics and accuracy, LightGBM is more outstanding, especially in evaluating imbalanced related metrics; the Bayesian-based LightGBM algorithm performs excellently. In addition, they also emphasized that boosting algorithms as robust classifiers requires tuning of several hyperparameters, such as learning rate and depth, as optimization of the parameters can enhance the model's performance and accuracy. Therefore, this study used two algorithms, XGBoost and LightGBM, to construct the customer churn prediction model, respectively. After 5-fold cross-validation, the evaluation measures before and after feature selection and before and after adjusting parameters were compared and analyzed.

5.2 Evaluation measures

The evaluation measures are crucial in determining the most effective model for churn prediction methods [35]. These evaluation measures help evaluate the model performance and directly affect the business decisions and outcomes. When evaluating a prediction model [18], different metrics can be relied upon, such as Accuracy, ROC curves and AUC values, F1 scores, and Mathews Correlation Coefficient (MCC). This study used Accuracy, AUC, and f1-Score as evaluation measures.Accuracy is the proportion of correctly predicted samples out of the total number of samples [38], which can help us understand the correct classification ratio of the model in the overall sample. Typically, accuracy takes precedence as a primary criterion for evaluating the performance of churn prediction models [35]. In general, higher accuracy means that the model categorizes the data more accurately, so high accuracy is usually the goal of the model. However, in the case of class imbalance, the accuracy may be affected by the uneven distribution of categories. The F1 score, denoting the harmonic mean of precision and recall [39], is a comprehensive evaluation metric, especially well-suited for dealing with unbalanced datasets. A superior F1 score generally suggests that the model maintains a more effective equilibrium between recall and precision [35]. A perfect model has an F1 score of 1 [39]. The ROC curve is a visual representation illustrating the balance between the True Positive Rate and False Positive Rate for a binary classification model at different thresholds. On the other hand, the AUC, or Area Under the Curve, is a comprehensive metric employed to evaluate a model's classification ability [35]. Often, comparing ROC curves of different models can be challenging; therefore, opting for AUC is preferable [40]. A greater AUC value indicates superior model performance [39].

5.3 Feature Selection Methods Evaluation

In section 4.1, this study identifies the top 7 predictors of customer churn using feature selection (Random Forest Feature Importance Ranking) and feature extraction (PCA) methods, respectively. Therefore, this part chose to combine these factors for analysis. At this point, there are eleven features in total, which are Total Trans Amt, Total Trans Ct, Total Revolving Bal, Total Ct Chng Q4 Q1, Avg Utilization Ratio, Total Relationship Count, Total Amt Chng Q4 Q1, Age, Months on book, Credit Limit and Avg Open To Buy.

The dataset used in this section is the SMOTE-balanced dataset. In addition, the customer churn prediction model's target variable is Attrition Flag.

First, the eleven features selected in the dataset for predicting customer churn are brought into the parameter- free XGBoost model for splitting. Then, it is cross- validated with five folds. Finally, the evaluation measures before and after feature selection are derived. Same for the LightGBM model. The results of the evaluation are presented in Table 3.

Table 3. Evaluation results before and after feature selection

	Accuracy	AUC F1-Score	
Parameter-free XGBoost before feature selection	0.897033	0.961250	0.851721
Parameter-free XGBoost after feature selection	0.894938	0.947880	0.849457

Parameter-free LightGBM before feature selection	0.893515	0.917931 0.847805	
Parameter-free LightGBM after feature selection	0.893598	0.892431 0.847765	

Table 3 reveals that the XGBoost model, following SMOTE oversampling, exhibits a slight performance advantage over the LightGBM model in all evaluation measures. As mentioned earlier, the XGBoost model after SMOTE oversampling performs well in prediction, especially in the AUC evaluation metrics [35]. This also indicates that the SMOTE oversampled XGBoost model is superior in classification ability, i.e., it can effectively differentiate between positive and negative categories relative to the SMOTE oversampled LightGBM model. However, the effect of feature selection on the evaluation results is not significant for either the XGBoost model or the LightGBM model. The following reasons may cause this: 1. The dimensionality of the dataset is already relatively low, and feature selection is no longer necessary. Feature selection may be more suitable for datasets with fewer samples and more features than the present dataset;

2. Combining feature selection and feature extraction adds complexity and uncertainty. If one of the methods already provides sufficient performance for the model, then further methods may introduce unnecessary complexity.Therefore, careful trade-offs and separate experiments are needed; 3. Evaluation metrics are less sensitive to feature selection, e.g., accuracy is usually less affected by feature selection; 4. Distributional characteristics of the data may affect the effectiveness of feature selection.

5.4 Hyperparameter Tuning Implementation

Fine-tuning the parameters not only enhances the model's overall performance but also mitigates the risk of overfitting, thereby improving the model's generalization capability. Li et al. [41] have proposed parameter settings for XGBoost and LightGBM models for the original dataset. However, this study proposes an alternative parameter setting for XGBoost and LightGBM models due to different data preprocessing methods. Given that the combined feature selection and feature extraction exert minimal influence on the evaluation outcomes, the features used in this section are all the features in the dataset after SMOTE balanced except the target variable (Attrition Flag). Table 4 displays specific parameter configurations.

Table 4. Parameterization of XGBoost and LightGBM models

The parameters set by Li [41] et al.	XGBoost	n_estimators	300
		max_depth	4
		learning_rate	0.2
		booster	"gbtree"
	LightGBM	num_boost_round	162
		learning rate	0.1
		max_depth	7
		num_leaves	65
		feature_fraction	0.8
		bagging_fraction	0.6
Parameters improved under this method	XGBoost	learning_rate	0.4
		max_depth	5
		n_estimators	500
	LightGBM	learning_rate	0.4
		max_depth	5
		n_estimators	300

After adjusting the parameters, the evaluation outcomes are presented in Table 5.

Table 5. Evaluation results before and after adjustment of parameters

	Accuracy	AUC F1-Score	
Parameter-free XGBoost before feature selection	0.897033	0.961250	0.851721
XGBoost with the parameters set by Li [41] et al.	0.896530	0.954835 0.852231	
XGBoost with improved parameters	0.902060	0.972499 0.863830	
Parameter-free LightGBM before feature selection	0.893515	0.917931 0.847805	
LightGBM under the parameters set by Li [41] et al.	0.896949	0.944565 0.852412	
LightGBM with improved parameters	0.902060	0.969959 0.860289	

The scores of XGBoost and LightGBM are roughly similar, but there is a slightly larger difference in AUC. Compared to the parameter settings proposed by Li et al. [41], the parameters proposed in this study were slightly better in terms of evaluation results under the data preprocessing method of this study. After adjusting the parameters, the scores of both the XGBoost and LightGBM models improved, although the overall change was small. The small change may be due to the following reasons: 1. the models may already have relatively good performance, and thus by adjusting the parameters, it may not be possible to significantly enhance the models' performance; 2. the number of parameters adjusted and the range of parameter choices are somewhat limited, which may cause the models to miss out on better parameter combinations due to the failure to adequately cover a wide range of the parameter search space; 3. the data itself may limit the models.

5.5 Interpretability of the model

Given the importance of churn prediction, a deep understanding of the model is crucial [35]. The SHAP method is part of the feature interpretation, quantifying the extent to which each feature contributes to the predictions made by the model and provides a more comprehensive analysis of feature importance. This aids in comprehending the model's predictions and their impact on the final predictions.

There are many ways to apply SHAP, such as SHAP Feature Importance, SHAP Summary Plot, SHAP Interaction Values, KernelSHAP, and TreeSHAP. Given that the visualization methods are more intuitive and the XGBoost model with improved parameters in the previous paper is slightly better regarding evaluation results. Therefore, this study will be based on the improved parameterized XGBoost algorithm, using the SHAP Feature Importance and SHAP Summary Plot methods to visualize and analyze the influence degree of features as a whole.

5.5.1 SHAP Feature Importance

The SHAP Feature Importance is determined by calculating the mean of the absolute values representing the extent to which a feature influences the target variable, which indicates that feature's importance. The Feature importance shows the extent to which each feature contributes to the predictive power, and the larger the SHAP value, the more influential the feature is. While SHAP Feature Importance, Feature Selection, and Feature Extraction all involve the analysis and processing of features, Feature Selection and Feature Extraction are typically used for data preprocessing to reduce the dimensionality of the dataset, and SHAP value is used to understand the model predictions. As a result, a different ordering of importance is derived. The results of the SHAP Feature Importance are shown in Figure 8.

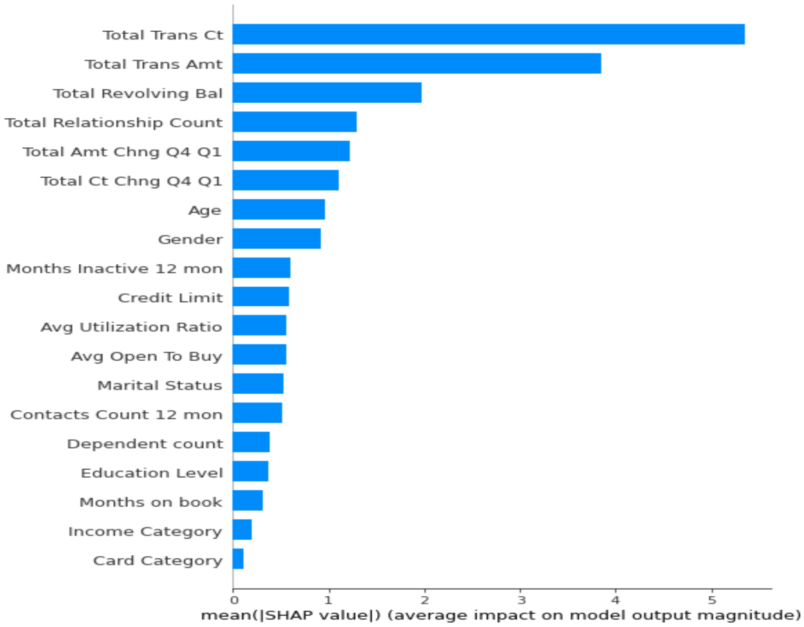


Figure 8

As can be seen from Figure 8, Total Trans Ct is the most important feature, changing the predicted churn probability by more than five percentage points on average (more than five on the x-axis). In addition, Total Trans Amt and Total Revolving Bal ranked second and third in importance, respectively. This is consistent with the first three features extracted earlier through feature selection and feature extraction.

5.5.2 SHAP Summary Plot

The SHAP Summary Plot combines the significance of features with their impact, providing a comprehensive representation of both positive and negative relationships between predictors and target variables. This helps to understand the overall pattern and detect predictive outliers in time. In the SHAP Summary Plot, the horizontal coordinate is the SHAP value, the magnitude of which indicates the extent to which the feature contributes to predicting customer churn. A positive SHAP value indicates that a feature positively contributes to increasing the probability of the model's predicted outcome; conversely, a negative SHAP value suggests a negative influence on the predicted outcome's probability. In addition, each row in the plot corresponds to a feature, and each point represents a sample. The color gradient reflects the feature values, with redder shades indicating higher values and bluer shades indicating lower values. The overlapping points along the y-axis provide insights into each feature's distribution of SHAP values. The SHAP Summary Plot is typically organized by the magnitude of SHAP values, representing their respective importance.

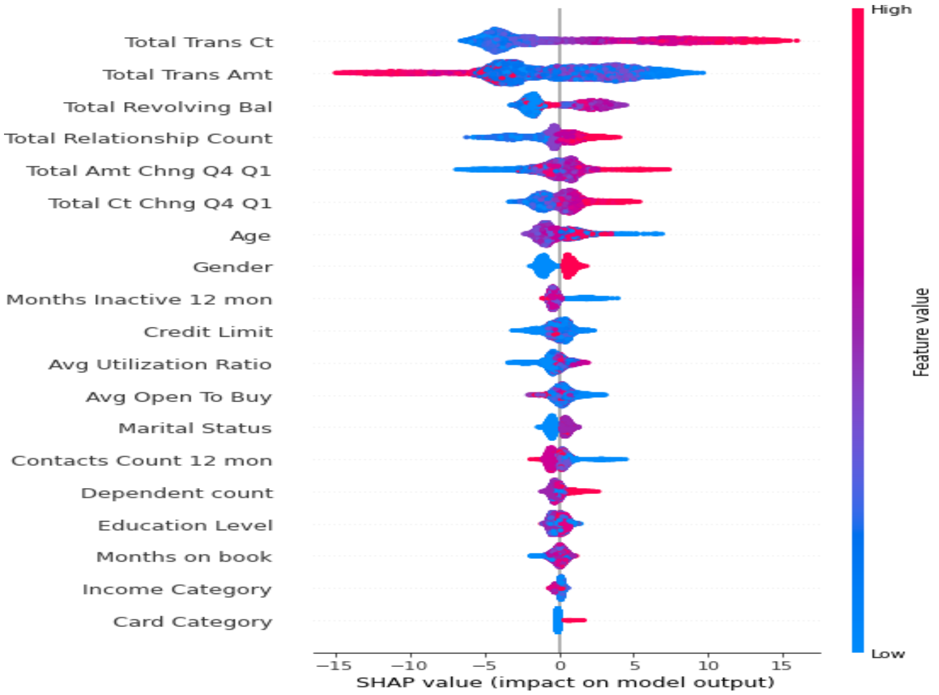


Figure 9

With Figure 9, it is intuitive to see that the dots on the far right of the Total Trans Ct row are essentially red,indicating that the larger the feature, the more positively it affects customer retention. Similarly, the total revolving

balance is positively correlated with the target variable. However, the larger the Total Trans Amt is, the more negatively it affects customer retention, as the leftmost point on the Total Trans Amt row is essentially red. And while this is, as mentioned earlier, customers with fewer Total Trans Amt may be more prone to churn, customers in the $8k-$10k range need to be looked at as well, since $8k-$10k churned customers make up a higher percentage of existing customers in the $8k-$10k range. It is important to note that all of the impacts in this section only describe the model’s behavior and do not equate to a causal relationship that necessarily exists in the real world.

The SHAP methodology and related visualization tools better enhance the analysis and interpretation of machine learning models’ predicted results, which helps focus on the customer and understand the root causes of churn, leading to improved models, increased efficiency, and better management decisions [35].

6. Conclusions and Recommendations

This article investigates the reasons and strategies for forecasting bank client attrition. Using Kaggle's "Credit Card Customer" dataset and a combination of visualization, data mining, and machine learning algorithms, this article investigates and evaluates the important characteristics that predict customer turnover in banks from several angles. In addition, two churn prediction models using the Gradient Boosting Tree technique, XGBoost and LightGBM, are developed. The study reached various results, which are as follows. First, Total Trans Amt, Total Trans Ct, and Total Revolving Bal are crucial for monitoring and forecasting client turnover. They are not only the top three most significant common features recovered by the Feature Selection (Random Forest Feature Importance Ranking) and Feature Extraction (PCA) methods, but their significance has also been proved by the SHAP Feature Importance technique. Second, the SHAP Summary Plot can provide some insight into the elements that predict customer attrition. Third, the impact of feature selection. The effect on the evaluation outcomes is often negligible, as in this dataset after the study's data pretreatment procedures. Fourth, the tuning parameter will improve the model's performance to some extent, but the best parameter choices will vary based on the preprocessing approach. Based on the facts presented above, this study offers the following recommendations: First, banks must frequently analyze trends in client transaction behavior because. Customers with low overall transaction amounts, transaction counts, and outstanding balances are more likely to churn. This indicates that banks must deliver timely interactions and improve customer engagement (CE) rather than focusing simply on the practical aspects of the service [16]. Furthermore, banks must improve the brand experience (BE), such as by delivering personalized goods or services that improve the customer's consumer experience. This also helps to keep customers loyal. Second, banks may improve the usage of machine learning and mixed visualization technologies.

Visualization tools provide bank managers with intuitive insights, such as improved visualization of customer usage, needs, and preferences, understanding market data, and monitoring transaction trends, which can aid in better understanding the current state of affairs and, as a result, developing relevant policies and strategies. Machine learning, on the other hand, assists bank managers in analyzing massive volumes of financial data to detect possible dangers such as fraud and credit risk. Furthermore, machine learning enables banks to study client behavior and improve their capacity to forecast customer attrition, as well as future market trends and investment risks, in order to offer early warning and implement targeted preventative actions at probable weak places [36]. The combination of visualization and machine learning methods will enable bank managers to gain a comprehensive and in-depth understanding of various aspects such as business dynamics, customer needs, and potential risks, allowing them to better use data to make decisions, improve business efficiency, and maintain a competitive edge in the highly competitive financial market. Third, the data preparation procedure. Has a significant influence on feature selection and model performance. As a result, banks should carefully pick and optimize data preparation methods to ensure that the model makes the most use of available data and improves prediction accuracy. Fourth, altering model parameters can increase performance, although the values vary based on the data preparation approach. Banks should devote time and money in tuning model parameters to get the highest model performance possible. To summarize, the aforementioned guidelines can

help banks better understand the factors that contribute to customer churn, improve their products and services, improve their customer relationship management, and develop more effective policies and strategies to increase customer inertia, which can result in cost savings, lower churn, and improved performance. Furthermore, banks must pay special attention to client use and implement relevant measures in actual business choices.

This work uses visualization, data mining, and machine learning to Investigate and evaluate the elements that influence bank customer turnover from various angles. In addition, two churn prediction models, XGBoost and LightGBM, were developed, compared, and examined in terms of feature selection and model tuning. This research also uses SHAP approaches to thoroughly explain the model findings. This study gives valuable insights for future research into related methodologies. As machine learning advances, algorithms for forecasting client attrition have developed

Although increasingly sophisticated, their expected results have gotten more accurate and trustworthy. However, limited research has been conducted on integrated techniques that combine visualization with machine learning, as well as multi-perspective analysis and validation. As a result, future research should highlight the integration of approaches in order to conduct a more thorough and effective examination. Furthermore, generalization ability remains a significant barrier, and future research might investigate the development of hybrid models suited to domains with superior generalization ability or unique feature engineering approaches. Furthermore, future study should examine widening the parameter search and attempting alternative models. Architectures with trade-offs and experiments tailored to unique challenges and data characteristics. Furthermore, the model's performance must be monitored and refined on a regular basis in order to improve its performance and applicability. However, this study has drawbacks. The combination of feature selection and extraction methods adds complexity and unpredictability, posing issues for machine learning applications. Second, model tweaking was undertaken, although only a few Parameters were modified within a specific range. As a result, the influence of tuning on evaluation outcomes requires further verification. Finally, the research in this study is based solely on the dataset of "credit card customers," needing additional verification to validate the model's generalization capabilities.

In conclusion, to improve the credibility of this work, further validation on various other datasets should be explored, and To discover the best model configuration, consider exploring novel assessment metrics and tweaking processes.

Furthermore, customer segmentation approaches that may be evaluated from several viewpoints, such as employing the k-means algorithm for finer customer segmentation, can be investigated in order to obtain more accurate customer turnover prediction and management. Unbalanced datasets may be used to build more reliable and efficient customer churn models, and optimization strategies aren't restricted to parameter adjustment. Most significantly, a mix of techniques can be Considered for comprehensive examination.

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