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Machine Learning-Based Analysis: Retired Customer Attrition and Its Societal Implications

Roza Süleymanoğlu¹   & Hakan Kaya¹ ¹ Doğu University, Vocational School of Social Services Programme Chair, İstanbul, Türkiye² Bursa Kestel Municipality, Bursa, Türkiye

Abstract

Retired customers constitute a stable and valuable customer base for banks. Adapting to the evolving needs of this group to reduce customer attrition (churn) is essential for banks' sustainability. This study aims to analyse the attrition rates of retired customers to understand the reasons why customers discontinue banking services and assess the potential societal implications of retired customer attrition. Decision tree and random forest machine learning models were trained to identify the key factors influencing customer attrition. The main intention of the research methodology followed in the article is to determine the best possible approach that would aid in effectively predicting customer churn. Within the methodological framework, exploratory data analysis (EDA), performance metrics, data cleaning, feature engineering, confusion matrix, and ROC-AUC analyses were applied. The results indicate that factors such as estimated salary, age, and tenure significantly influence customer attrition. In addition to that, the generalisation abilities of both models proved strong. But the random forest model performed well in terms of accuracy. These results allow banks to target vulnerable clients more effectively, make their customer retention processes more efficient, and improve bank customer retention in general. Furthermore, the exclusion of retirees from the world of financial services increases the vulnerability of the concerned society to financial exclusion, economic insecurity, social isolation, lack of social trust, lack of access to online banking services, and digital inequality. As a result, the detailed research analysis of customer loss of retiree clients has strategic significance in the context of customer management as well as in reducing social inequalities.

Keywords

Retired Customer Churn Prediction • Decision Tree • Machine Learning • Societal Implications • Social Inequality



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✉ Corresponding author: Roza Süleymanoğlu r.suleymanoglu@gmail.com



Machine Learning-Based Analysis: Retired Customer Attrition and Its Societal Implications

Despite the best efforts of banks to obtain and maintain the account of retired clients, banks remain faced with the problem of customer churn due to factors such as increasing levels of competition in the industry, the growing list of services offered by banks, and the ease of switching banks. The significance of the retired customer group to banks goes beyond steady salary deposits since there exist prospects for long-term relationships and risk-free financial practices (Amuda & Adeyemo, 2019).

Customer churn results in costs to the bank in terms of lost incomes, inhibited growth prospects, and deteriorating customer satisfaction in the banking industry (Ahmed et al., 2024). Given the negative effects of customer churn in the industry, risk management plans adopted by banks ought to target segments of the clients that have steady financial backgrounds, for instance, retired individuals who have more of the required time.

Within this context, machine learning algorithms appear to also offer a promising approach to the design of strategies for the prediction and prevention of customer churn. Machine learning algorithms form the backbone of customer churn prediction modeling. They have the capability to detect unseen patterns in customer behavior in a dataset. According to Kaynar et al. (2017), customer churn prediction modeling accessed by the application of data mining and artificial intelligence techniques has become a significant approach in studies in the banking and telecommunication industry. The lack of studies specifically focusing on the retired/elderly customer group, in contrast to more general consumer profiles (Shirazi & Mohammadi, 2019), however, seems to point to the need to specifically tackle the challenges of the particular customer type.

In addition to their crucial role in providing financial services, the banking industry also has a social responsibility. To this effect, the turnover of retired customers in the banking industry/sector can be considered more than a challenge facing the industry; instead, it is a complex phenomenon that also has social implications. According to Sun & Marcelin (2021), the exit of the retiree customer group from the financial industry contributes to the vulnerability of the economy in terms of the risk of financial exclusion for the retiree customer group receiving fixed incomes. Additionally, the lack of preparedness to cope with the digital services of the banks contributes to the enhancement of the problem of digital inequality (Lyu, 2025) and may also lead to social isolation of the customer group to bank. A weakened connection to the financial industry may also affect overall consumption. Thus, there is critical strategic importance in the correct analysis of the retiree customer turnover.

To overcome the research gaps in the existing body of knowledge, the research will utilize the concepts of the Decision Tree model and the Random Forest model to analyze the churn rates amongst the retired clientele in the banking industry. Through the application of the mentioned models, the research aims to analyze the occurrence of customer attrition amongst the retired clientele to comprehend the reasons behind their discontinuation of service utilization and the larger social implications. In light of the research objectives, the dissertation aims to seek the answer to three major research questions: (1) How do the Decision Tree model and the Random Forest model aid in the analysis of customer churn rates in the banking industry? (2) Which factors influence the churn rates of the retired clientele in the banking industry? (3) In what manner can the machine learning algorithms aid in the prevention of customer churn?

The article takes up a total of five parts. Section 2 contains the literature review. Section 3 discusses the materials and methods of the research. Section 4 presents the findings of the research. Section 5 provides the conclusions and recommendations.

Literature Review on Customer Attrition and Its Societal Implications

Customer attrition takes place through the switching of customers to their competition in the industry due to advantage in product/service quality (such as the availability of new technology provided by the competitor) to the current service providers, together with the particular attention offered to the customer by the customer-focused personnel (Parasuraman et al., 1988). Other factors include the pricing advantage of reduced transaction costs for switching to the competitor (Keaveney, 1995; Jones et al., 2000). With regards to banks specifically, customer attrition is also affected by the location advantage of the bank to the customer and the attraction caused by the competitor's advertising (Keaveney, 1995).

Customer churn analysis can be denoted as a vital process in which the business employs customer churn information to determine the type of clients leaving the business, motives for customer attrition, clients at high risk of imminent customer churn, in addition to strategies to lessen customer churn (Mouli et al., 2024). The customer churn analysis process has become a central component in designing strategies for risk consideration, given the pivotal cost benefit of keeping present clients compared to attracting new ones. Efforts to avert customer churn should thus be conceptualized in the context of customer lifetime value maximization instead of emphasizing present costs of business transactions (Reicheld & Sasser, 1990).

Effective customer churn analysis enables the adoption of proactive strategies to promote customer loyalty for the identified churners by permitting the detection to occur ahead of the churn in a timely manner (Kaynar, Tuna, Görmaz & Deveci, 2017). Proactive strategies may involve the allocation of a customer service ambassador for the purposes of exhibiting greater empathy skills in service delivery to comply with customer expectations of service. Personalized strategies in the context of customer service may therefore promote the long-term bank-customer association by demonstrating consideration for the needs of the customer in their service delivery (Berry & Parasuraman, 2004).

The problem of churn prediction has also been explored extensively in the existing literature. For instance, Amuda & Adeyemo (2019) supported the claim in the Harvard Business Review article that a mere 5% decrease in churn can boost business profits by 25%-85%, but even more at 140% according to Business Week.

With the insights derived from the proposed framework in the context of the prediction problem identified in the research question, the application of big data analytics techniques based on the processing of complex big data sets has become more prevalent in existing studies. A pertinent example of the application in the article of the big data analysis techniques related to the prediction problem identified in the research question includes the framework for churn prediction presented in Shirazi & Mohammadi (2019) that incorporated the Hadoop ecosystem into a business intelligence system utilizing a CRT decision tree. Other relevant contributions in the existing literature to date have been the XGBoost Model presented in Jain & Nayyar (2018) for the prediction of worker churn in a business organization. Mundada (2019) further affirmed the improved accuracy of a deep feed-forward network in the churn prediction of clients in the banking industry. Sjarif (2019) presented a test accuracy of approximately 97.78% utilizing the Pearson Correlation & K-Nearest Neighbors in the context of churn prediction. Azzopardi (2021) identified the gradients of boosting to have improved accuracy for churn prediction in the application of the techniques of Data Mining. Chakraborty et al. (2021) developed a new algorithm for the analysis of the sentiment of posts in social networks to determine the accuracy of the sentiment in social networks. Singh et al. (2022) applied Machine

Learning to churn analysis to effectively determine the causes of churn in business. Maharana (2022) also identified the accuracy of the model mentioned in the research question of 87% for the prediction of worker churn in the context of the IBM Watson Data Set. Abualkashik et al. (2023) integrated the optimization technique into a BI model utilizing the deep learning technique for improved accuracy. Chong et al. (2023) compared the accuracy of the selected classification techniques of K-Nearest Neighbors, Random Forest, AdaBoosting, Logistic Regression, XG-Boosting & Support Vector Machine for the telecommunication churn prediction problem to determine the accuracy of the XG-Boosting technique of approximately 79.67% over the other classification techniques. Another relevant application in the article of the big data analysis technique utilized in the prediction problem identified in the research framework includes the application of the multilayer perceptron & the neural network technique to offer approximately 94% accuracy in the telecommunication industry presented in the article of Utku & Akcayol (2024). The cost-effectiveness of customer retention in the telecommunication industry was supported in the article of Wu et al. (2021). Mardi and Ghorbani (2024) emphasized that the LightGBM and Random Forest algorithms showed superior performance in detecting customer churn.

Despite the mentioned improvements in methodology and industry specifics, there exist relatively few studies on the problem of machine learning application in the attrition of the retired clientele—a very important audience in the banking industry. There exist very few studies directly on the profiles of the elderly or retirement account clients compared to the general attrition of bank clients (Shirazi & Mohammadi, 2019). One of the latest studies on the problem states that the churn rates of the older clients are 23% higher compared to the younger clients and the churn rates of the male clients are 36% lower compared to the churn rates of the female clients (Gaojiong Wu, 2025).

On the banking side, churn analysis research based on the application of logistic regression has been documented (Mutanen, 2006). A holistic approach to data mining was also applied in the context of credit card churn (Naveen et al., 2009). Researches concerned with churn in online banking services—covering internet banking, telebanking, mobile banking, and ATM networks—applied decision trees to determine the effects of customer dissatisfactions, service utilization, and demographic factors (age, gender, employment, education) together with customer loyalty period and the number of customer complaints (Keramati et al., 2016).

Different parameters regarding customer churn in the banking sector are also taken into account. For example, Bilal Zoric (2016) investigated gender, age, average monthly income, consumer status (such as student, retired, unemployed, employed), and whether the customer used two or more bank products as control variables in a Neural Network model. The probability of customer churn decreased as the use of banking products increased.

In the study by Guliyev and Yerdelen Tatoğlu (2021) where customer churn risk was analyzed using explainable machine learning models, it was determined that certain demographic and behavioral variables were significant on churn risk; for example, age and the customer relationship (such as interaction intensity, transaction volume, number of products) were found to affect the risk of customer churn.

Studies that directly measure retired customer loss and its associated societal consequences in banks are limited. Most research focuses on more general topics such as aging populations, financial inclusion, digital banking, and financial exclusion (Doerr et al., 2022; Alonso et al., 2023; Usta, 2023).

The aging population affects the business model and credit-deposit balances in the banking sector; as the population ages, credit demand falls, and the propensity for deposits and risk-taking decreases. The decision of the aging population to stop being bank customers affects banks' credit portfolios, financial intermediation capacity, and consequently, social financial stability (Imam & Schmieder, 2024). The implica-

tions of the financial intermediation process may include a possible contraction in the number of resources allocated to investments, home loans, and business loans, thereby affecting social welfare.

The lack of access to financial services may result in the social isolation of retired individuals. This may affect their sense of savings and security, therefore creating psychosocial risks for their self-esteem (Servon, 2002).

Methodology

This research investigates retirement-era customer churn in Turkish banking, using a dataset with 9,406 records drawn from the retirement portfolios of three big banks, two private and one public. The data covers customers in "retired" status between 2020 and 2024, while the whole research process was carried out using Python.

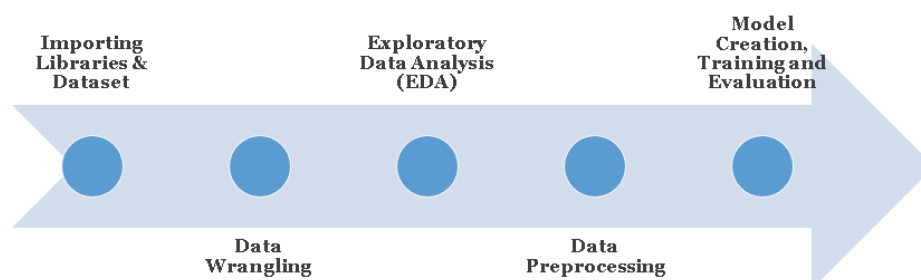
Preprocessing comprised of handling missing values (<0.1% of records), encoding the target variable (Exited) into labels, and performing one-hot encoding of categorical features (Geography, Gender, Type). A check for skewness was carried out for numerical features (Table 2); only Age showed somewhat of a left-skew of (-0.281) and had a log transformation done for it to be more normal (Kim, 2013). The data was divided into 80% training (n=7,524) and 20% testing (n=1,882) while maintaining the class balance. The issue of class imbalance (79.7% retained against 20.3% churned) was solved by SMOTE (Synthetic Minority Oversampling Technique; Chawla et al., 2002) which was only applied to the training set in order to avoid data leakage. Hyperparameter tuning utilized a 5-fold cross-validation method with GridSearchCV to achieve the best generalization performance while at the same time reducing the risk of overfitting.

First, the researchers rated twelve features in order of their importance and then used Decision Tree and Random Forest models to predict whether customers would churn or stay. Key performance metrics were calculated for both models in terms of Accuracy, Recall (Sensitivity), Precision, and F1-Score to understand their performance in prediction.

Data were obtained from the CRM systems of banks by random sampling, including only observations from those customers who had consented to data processing. The data for this study were anonymized to maintain the privacy of customers and also to satisfy regulatory needs: it contains only socio-demographic and transaction-based features required for the analysis, after removal of identifiers such as customer identity, account number, branch code, and addresses. Note that consent-based limitations could make the dataset not representative for all retired customers.

Before modeling, the data underwent feature extraction and format conversion in preparation for training and prediction. Care has been taken to ensure that data usage in banking does not violate ethical and legal norms.

Figure 1
Steps of the Machine Learning Model Development



The development of the ML model thus followed a well-structured path: data collection, preprocessing, feature selection, algorithm choice, training, and then evaluation; next came hyperparameter tuning, deployment, and ongoing maintenance for various applications.

Algorithms Used

Decision Tree

A Decision Tree is a hierarchical model where features are stored in nodes, decision rules in the branches, and the outcome in leaves. While recent applications in banking contexts have been documented (Kaya, 2024a), the theoretical foundations of decision tree induction trace back to Quinlan's ID3 (Quinlan, 1986) and its successor C4.5 (Quinlan, 2014), which introduced handling of continuous attributes and pruning mechanisms to enhance generalization. In this study, the CART (Classification and Regression Trees) variant was employed (Breiman et al., 2017), which utilizes Gini impurity as the splitting criterion and supports binary splits for both categorical and continuous features. Hyperparameter tuning by Grid Search was performed to avoid overfitting, setting max depth to 10 and minimum leaf size to 5.

Random Forest

The random forest is an ensemble of several decision trees; it hence offers high accuracy and robustness in classification and regression. Each tree is trained on different samples and randomly chooses features to help avoid overfitting and improve generalization (Kaya, 2024b).

Gini impurity was used as the splitting criterion at each constituent tree of the Random Forest ensemble. It is defined as:

$$G = 1 - \sum_{i=1}^c p \binom{2}{i} \quad (1)$$

where $p(i)$ is the proportion of class i in a node and c is the number of classes (Breiman, 2001). In binary classification problems, it was found that Gini impurity has a considerably lower computational cost than entropy and the change in classifier performance is insignificant. Therefore, Gini impurity was chosen as a split criterion.

Performance Metrics Used

Accuracy

Accuracy is calculated as the ratio of the correct predictions produced by the system to the total number of predictions (Naseer, 2022).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

where TP, TN, FP, and FN refer to True Positives, True Negatives, False Positives, and False Negatives.

Precision

Precision is a measure of how many predicted positives are actually positive (Sokolova, 2006).

$$\text{Precision} = \frac{TP}{TP + FP} \quad (3)$$

Recall

Recall measures how many actual positives were correctly identified (Muneer and Fati, 2020).

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

F1-Score

The F1-Score is the harmonic mean of precision and recall, useful when class balance is uneven.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

Core Features of the Data

Table 1 presents the summary of major features used for the prediction of churn.

Table 1

Summary of the Key Features

Key Feature	Information
RowNumber	Row Number that uniquely identifies each record; does not directly contribute to the analysis.
CustomerId	Used to track and distinguish individual customers.
Geography	Helps in understanding churn behavior based on geography/region.
Gender	Allows for the examination of churn tendencies based on gender.
Age	Important for analyzing churn patterns related to age.
Tenure	Indicates customer loyalty and length of service (tenure); affects the likelihood of churn.
Type	Illustrates the retirement-package products that banks offer to retired customers with the purpose of securing their income. Classifications include 4A: Basic Retirement Salary Account, 4B: Savings-Supported Retirement Product, and 4C: Premium Retirement Account. Such categorization will help demarcate different income and product relationships.
NumOfProducts	Reflects the diversity of services used; affects customer loyalty.
HasCrCard	A binary variable indicating credit card ownership; may affect churn behavior.
IsActiveMember	Indicates the active membership status; affects the tendency to churn.
EstimatedSalary	Estimates the customer's income level; important in churn analysis.
Exited	Target Variable: 1 = Churned (Left the bank), 0 = Retained (Stayed with the bank).

The dataset contains 9,406 records and 12 columns, out of which 8 represent numerical and 4 categorical features. These core features are key to understanding customer behavior and thus giving accurate churn forecasting for allowing differential targeted strategies to curb attrition.

Geographical labels (CityN, CityO, CityY) have been anonymized in accordance with confidentiality agreements. Nevertheless, CityN is a metropolitan area with a large population and well-developed banking penetration. CityO is a medium-sized city with a cool economy, whereas CityY is a region experiencing a lot of young people moving out and having a larger percentage of elderly residents. These demographic settings are useful for understanding the patterns of customer attrition that have been observed.

Data Wrangling

Data Wrangling is a critical step since data wrangling, or data munging, cleaned, reshaped, and prepared the raw data to be analyzed. This consisted of handling missing values, resolving inconsistencies, and structuring such data for analysis (Jiang and Kahn, 2020).

The RowNumber and CustomerId columns are unique identifiers for the customers and do not seem useful for predicting churn. In order to perform a better analysis, all the irrelevant features have been

removed, the target variable was renamed as 'Churned', and its values were changed from '0' to 'No' and '1' to 'Yes'. This conversion allows for a more efficient EDA and derivation of valuable insights from the dataset.

Evaluation of Research Findings

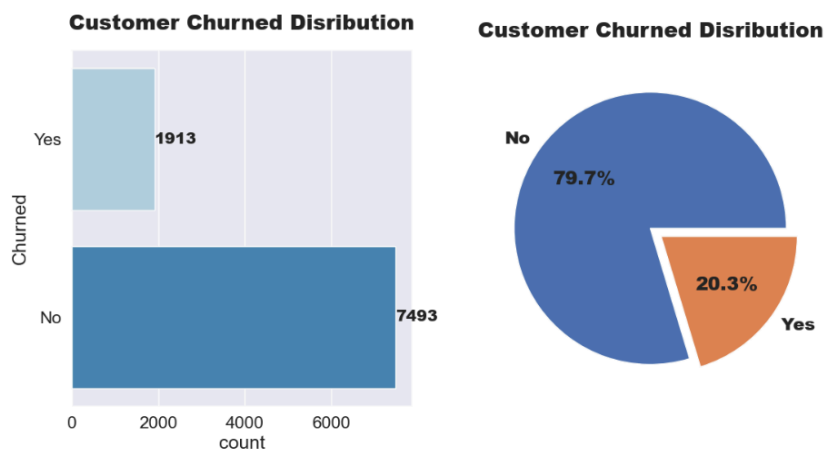
This section summarizes how different machine learning models do in terms of retiree churn prediction, focusing on every step from data preparation to modeling and comparing the results.

Exploratory Data Analysis (EDA)

EDA helps to understand the structure of the dataset and to discover patterns and relationships. Visualizing dependent as well as independent variables is crucial; charts are built for inspecting distributions and ties between variables.

Figure 2

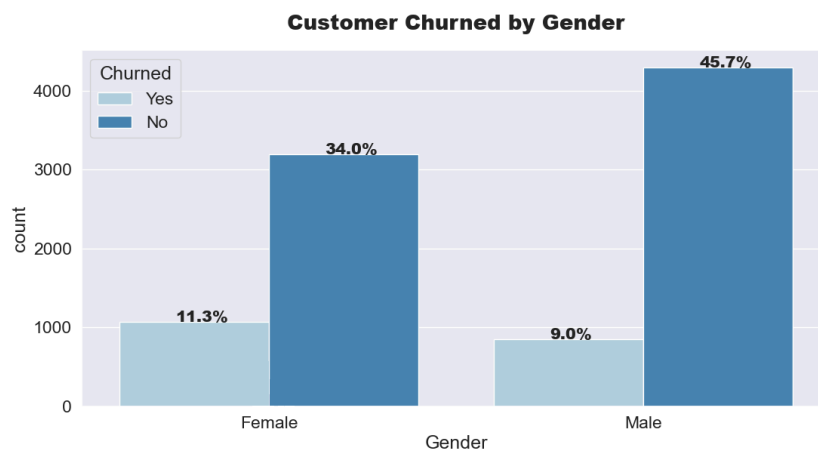
Customer Churned Distribution



EDA was performed to comprehend and reduce churn. The knowledge gained here guides feature selection and therefore helps boost model performance.

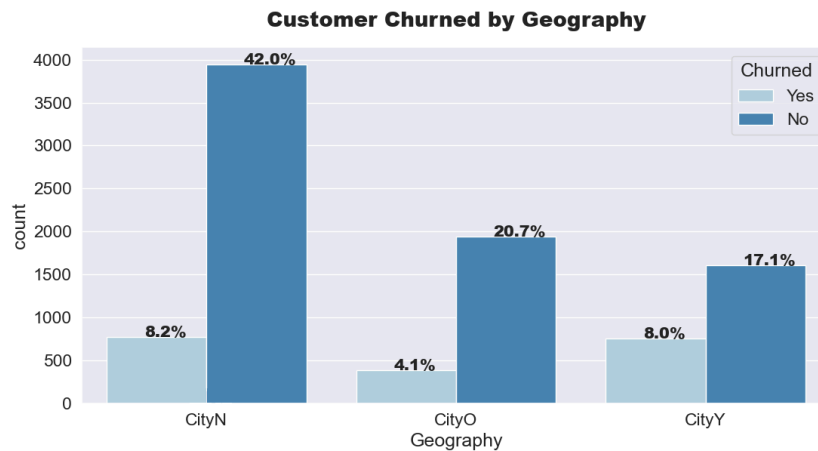
Figure 3

Customer Churned by Gender



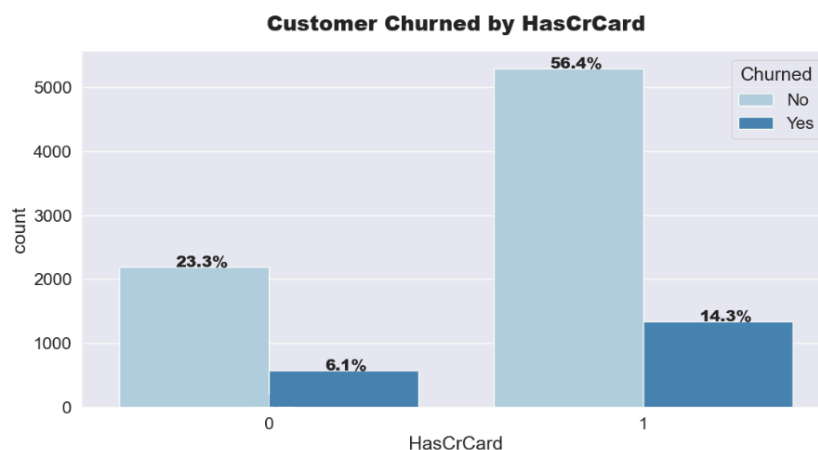
The probability of churning is higher for females compared to males, indicating that female customers are more likely to stop using the banking service. Targeting specific campaigns and enhancing the customer experience is suggested for better retention in this group.

Figure 4
Customer Churned by Region



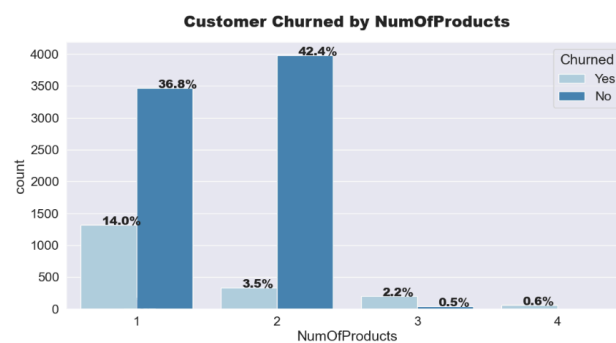
Roughly half of the customers come from CityN, followed by CityO and then CityY. Even though CityN and CityY have very different totals, the respective churn rates are identical. CityO and CityY have roughly similar counts, but the churn rate for CityY is nearly twice that of CityO. It would be beneficial to research CityN's customer behavior and implement similar strategies for CityY.

Figure 5
Customer Churn by HasCrCard



According to the data, over 70% of customers hold a credit card, and cardholder to non-cardholder churn ratios are about 1:4, suggesting that ownership is not a strong determinant of churn.

Figure 6
Customer Churned by NumOfProducts



Most customers have one or two banking products. Those holding two products churn less; one product or more than two products see higher churn. Incentives could be focused on holding at least two products.

Figure 7

Customer Churned by IsActiveMember

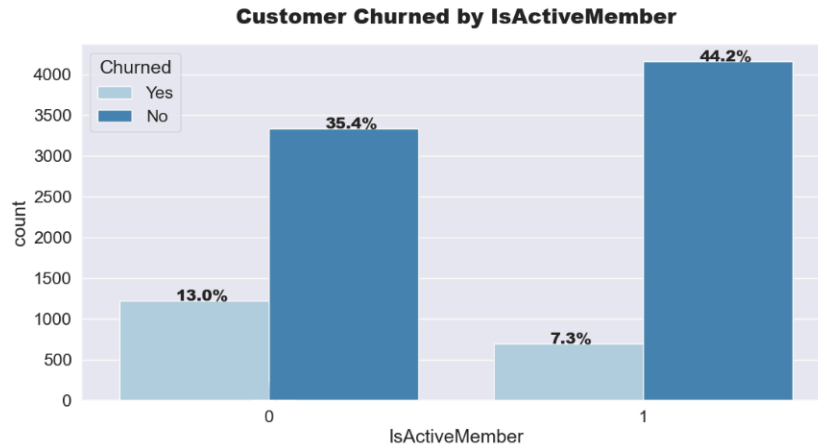


Figure 8

Customer Churned by Tenure

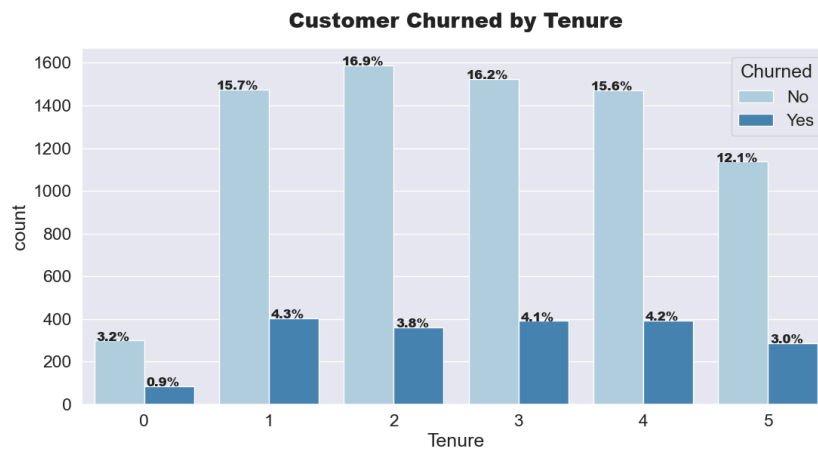


Figure 9

Customer Churned by Type

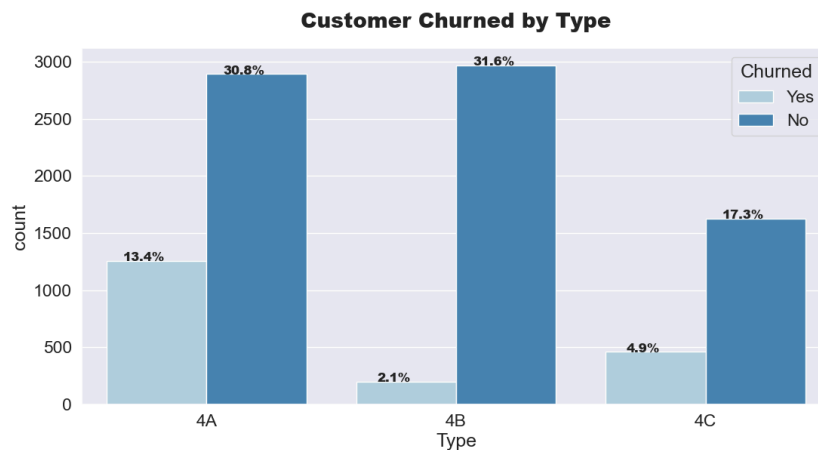


Figure 10
Customer Churned by Age

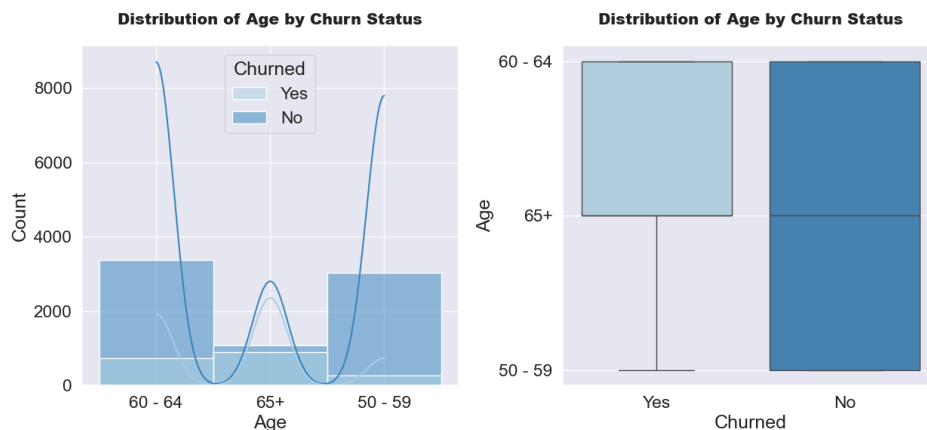
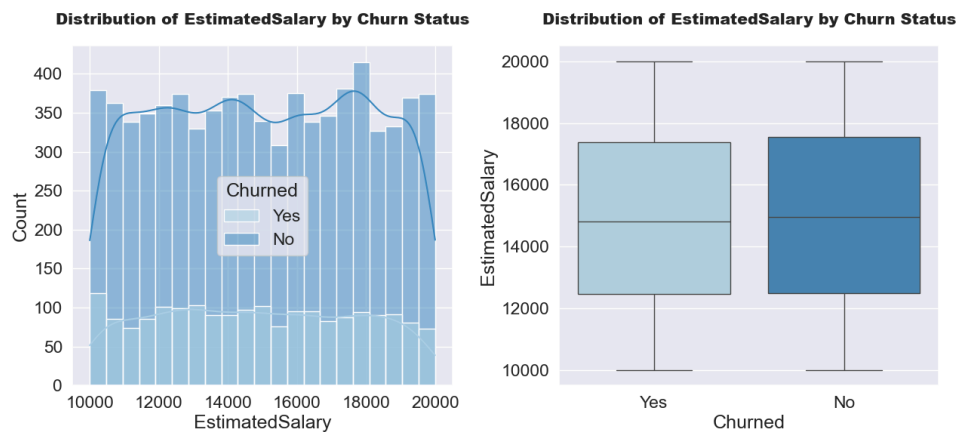


Figure 11
Customer Churned by EstimatedSalary



The median value of the estimated salary shows very little difference between the churned and non-churned groups, indicating that there is no significant relationship between this variable and the churn status.

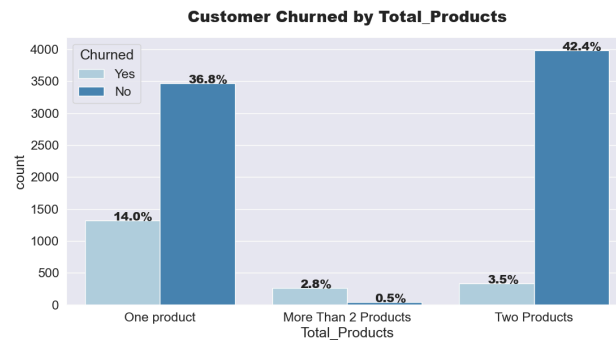
Feature Engineering

Deriving meaningful features from existing data can improve the process of churn prediction a great deal (Fati, 2024).

A new introduced another categorical feature named Total_Products based on NumOfProducts, categorized as One Product, Two Products, and More Than Two Products, whose churn rate is visualized by Figure 12.

Customers in the One Product group show relatively higher churn compared with others. Recommend loyalty programs, wider product choices, and feedback-oriented marketing strategies that could help improve customer experience.

Figure 12
Customer Churned by Total Products



Data Preprocessing

Data preprocessing aims to transform raw data into clean, analysis-ready data. Have counted unique values in the categorical columns: Region, Gender, and Total_Products and applied One Hot Encoding. Next, encode the target variable, check feature skewness, and perform a log transformation for Age. Splitting the dataset, it results in 80% for training (7,524 samples) and 20% for testing (1,882 samples).

Because the classes were imbalanced (79.7% retained and 20.3% churned), during preprocessing, used SMOTE oversampling to balance the training set. This helps metrics like AUC and accuracy be more reliable on imbalanced data.

Table 2

Table of Feature Skewness

	Feature Skewness
Age	-0.280784
EstimatedSalary	0.002651

The feature Age is -0.281-skewed, which indicates a slight left-skew. EstimatedSalary: skewness value is 0.003, near-zero, indicating near-symmetry.

Calculation of Model Accuracy

The Decision Tree and Random Forest were trained on the same train/test split. In order to avoid overfitting in the Decision Tree, 5-fold hyperparameter tuning (GridSearchCV) for max_depth, min_samples_split, and min_samples_leaf. For Random Forest, tuning was performed for n_estimators (100–500), max_depth (5–15), and max_features ("sqrt", "log2"). This improved generalization and reduced the risks of overfitting. Given the intrinsic limits of a single decision tree, its generalization is weaker than that of Random Forest; thus, the final choice favored Random Forest. The accuracy results for both models are given in Table 3:

Table 3

Computing Model Accuracy

	Decision Tree	Random Forest
Accuracy Score of Model on Training Data	99.99 %	88.24 %
Accuracy Score of Model on Testing Data	76.62 %	84.43 %

The Decision Tree reached a near-perfect 99.99% on training data but dropped to 76.62% on test data, signaling overfitting. The Random Forest turned in strong accuracy for both training and test sets, which is indicative of better generalization.

Model Evaluation with Different Metrics

Table 4
Results of Different Metrics

	Decision Tree	Random Forest
F1 Score of the Model	0.766	0.844
Recall Score of the Model	0.766	0.844
Precision Score of the Model	0.766	0.844

All metrics (F1-Score, Recall, Precision) of the Decision Tree model are approximately 0.76, which indicates that the model's classification performance is quite good. The Random Forest model exhibited a strong performance with a metric value of approximately 0.844.

These values appear to be the same in Table 4 due to circular rounding. The F1-score is the harmonic mean of precision and recall, and here it is approximately in the middle of these two values. This indicates that the model identifies the positive class in a balanced manner.

The reason why Precision, Recall, and F1 values are the same in the Random Forest model is the symmetric distribution of predictions belonging to the positive class and the equality of both the true positive and false negative rates in this model. This result stems from the calculation of metrics using the "macro average" method. Small differences were observed when calculated with the "weighted average" (Precision = 0.846, Recall = 0.842, F1 = 0.844).

Feature Importance

In the Decision Tree and Random Forest algorithms, the variables that contributed most to the model's decision-making processes were determined:

Most Influential Variables: EstimatedSalary, Age, and Tenure stood out as important factors affecting customer churn. However, during the Exploratory Data Analysis (Figure 11), no significant difference was observed in the median value of EstimatedSalary between the two groups (churned/retained). This apparent contradiction can be explained by the fact that the EstimatedSalary variable does not have a linear relationship on its own but contributes to the prediction power by interacting with other features (such as 'Age' or 'NumOfProducts') in complex models like Random Forest. The model shows that salary can really stand out, but only when you look at it in conjunction with context-such as how old the customer is or how many products they own. So, its top spot in the feature importance list isn't because salary in and of itself drives things; rather, it is because of its interaction effect with other variables. The Random Forest can pick up those interactions, and that's why salary's overall contribution looks strong even if its individual impact is modest.

The least influential variables were Gender_Female, One_Product, and CityN, which contributed very minimally to the decision process.

This underlines that for banks, loyalty efforts and promo strategies need to be tailored, considering factors such as age, income, and how long a customer has been with the bank.

Figure 13
Feature Importance of in Decision Tree Prediction

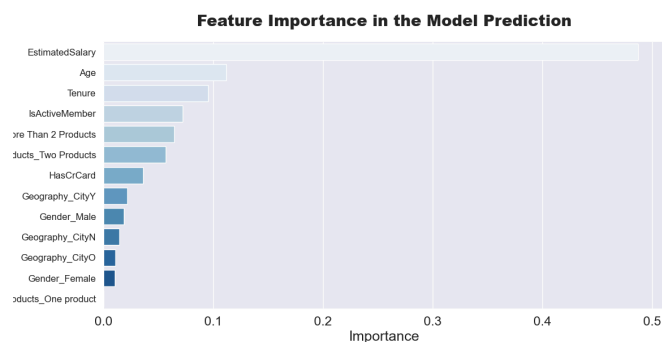
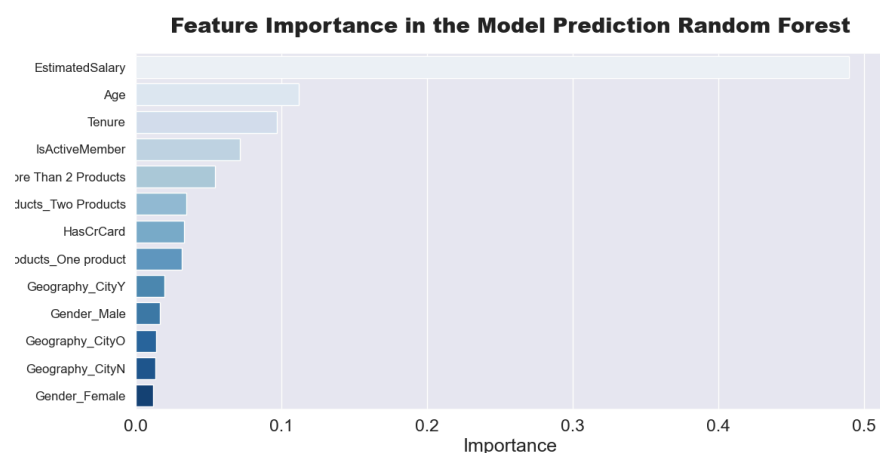


Figure 14
Feature Importance of in Random Forest Prediction



Model Evaluation with the Confusion Matrix

The confusion matrix is helpful in visualizing the performance of a classification model. As Vujović (2021) pointed out, there are four core elements of the confusion matrix: TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative).

The Decision Tree showed a high True Positive rate, but a rather high False Negative rate.

The Random Forest provided a better balance between the numbers of True Positives and False Negatives, thereby increasing overall classification success.

Figure 15
Model Evaluation Using Confusion Matrix for Decision Tree

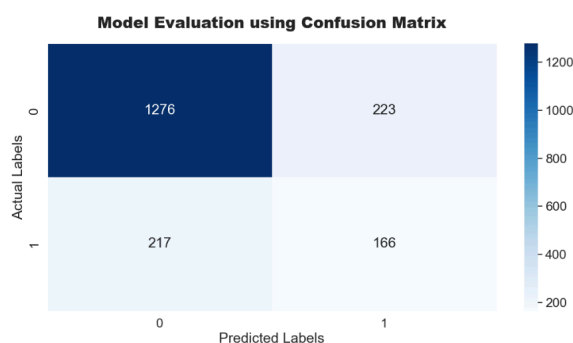
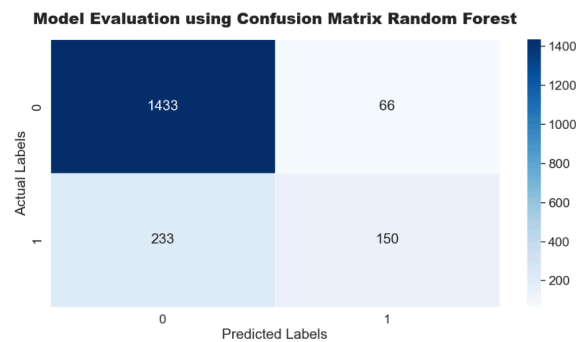


Figure 16
Model Evaluation Using Confusion Matrix for Random Forest



In other words, the Decision Tree had an excellent True Positive rate, but the number of False Negatives was very noticeable. Random Forest gave a more balanced and trustworthy matrix.

ROC Curve and AUC Value

The ROC curve plots True Positive Rate against False Positive Rate across thresholds. AUC measures how well the model can discriminate between classes (Janssens and Martens, 2020).

Figure 17

ROC Curve for Decision Tree

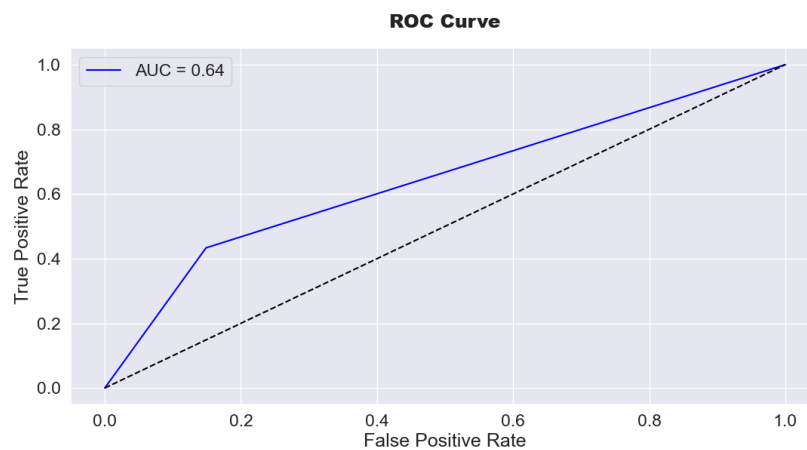
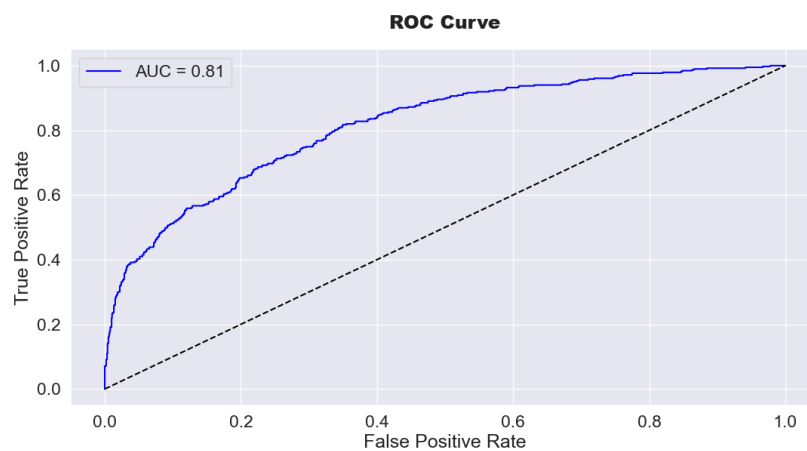


Figure 18

ROC Curve for Random Forest



The Random Forest yielded an AUC of 0.81, making a much better separation between positives and negatives compared to the Decision Tree. This means that Random Forest would best fit the prediction of customer churn in banking contexts.

Conclusion and Recommendations

The present research contributes to the data-driven churn-prediction discussion for the retired customer segment, not deeply explored in previous literature, and indicates how commonly used machine learning tools in other industries can be applied to banking data. An in-depth analysis using Decision Tree and Random Forest to understand and predict why retired customers churn in banking. Machine learning models allow banks to identify at-risk customers early, prevent attrition, and optimize resource utilization.

The important predictors of estimated salary, age, and tenure in explaining why customers may exit banking services are not purely linear in their influence but rather interact with other variables. The Decision Tree performed with almost perfect accuracy on the training data but scored about 77% on test data, indicating overfitting. The Random Forest generalized much better, with roughly 90% training accuracy and 85% testing accuracy. Moreover, due to a balanced weighting strategy that takes care of class imbalance, the Random Forest also returned reliable positive predictions with a minimum number of false positives; Precision, Recall, and F1-Score around 0.84.

The results generally indicate that banks can improve loyalty among their retired customers by implementing the following:

Develop Effective Communication Channels: Establish personalized and multi-channel communication strategies (mobile, branch, call center, e-mail, etc.) with retired customers.

Loyalty and Reward Programs: Offer special campaigns, interest advantages, or fee reductions that reward long-term customers.

Feedback-Driven Service Improvements: Continuously improve product and service quality by systematically collecting customer feedback.

Strengthen the Digital Experience: Provide user-friendly digital banking interfaces, easy access, and rapid support mechanisms for retired customers.

Data Ethics and Security: Reinforce customer trust by adopting transparent policies regarding the security and ethical use of personal data.

Long-Term Financial Planning and Consultancy: Develop financial consultancy and investment solutions appropriate for the fixed income structure of retired customers.

Societal and Social Approaches: Strengthen customer relationships through social responsibility projects, community events, and health support programs.

These strategies will contribute to banks achieving a sustainable competitive advantage by increasing Customer Lifetime Value (CLV), in addition to reducing customer churn.

It is clearly seen that machine learning models have become a fundamental component of customer churn prevention strategies in the banking sector. In particular, the fact that the Random Forest algorithm yielded high accuracy results in the retired customer segment demonstrates that this method can be used effectively in future customer behavior modeling.

Based on these findings, the following can be suggested for future research:

1. Emotional analysis (sentiment analysis) or text mining methods can be added to the model scope to extract the emotional tone from customer communications.

2. Deep Learning based networks (e.g., LSTM or Transformer models) can be used for dynamic customer behavior prediction that also takes the time dimension into account.
3. Clustering can be performed on the retired segment based on different income levels, lifestyles, or regional distributions.
4. Generalizability can be tested through comparative analyses between different banks (public/private, local/international) or between countries.
5. More advanced sampling techniques than SMOTE can be tested to address the class imbalance problem, and the effect of these techniques on model performance can be compared.



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Author Details

Roza Süleymanoğlu (Asistant Professor)

¹ Doğuş University, Vocational School of Social Services Programme Chair, İstanbul, Türkiye

 0000-0003-2649-7572  r.suleymanoglu@gmail.com

Hakan Kaya

¹ Doğuş University, Vocational School of Social Services Programme Chair, İstanbul, Türkiye

 0000-0002-0812-4839 

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