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Predicting of Credit Card Customer Churn Using Machine Learning Methods

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Keywords: Credit Card, Customer Churn, Card Cancellation, Machine Learning, Prediction

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ABSTRACT

Today, customers can give up using credit cards for various reasons, and this situation has negative consequences for banks. Therefore, it is necessary to predict potential customers who will cancel their credit cards in advance and to turn these cancellations in favor of the bank and thus to regain the customers. This situation is also very important in terms of monitoring customer churn and preventing such churn. In this context, a model is proposed using machine learning methods to detect the card cancellation status of customers using credit cards and thus predict customer churn. A dataset obtained from the Kaggle platform was utilized to create the model. This dataset contains credit card data belonging to a total of 10127 customers. Although there were 23 features in the dataset, 2 features were deleted without being included in the model because they did not affect the results. As a result, a total of 21 different variables were used, 20 inputs and 1 output. The models were created using Artificial Neural Networks, Logistic Regression, Support Vector Machines, K-Nearest Neighbor, Decision Tree, Random Forest, Ada Boost, and Gradient Boosting machine learning algorithms. As a result, it was seen that the model with the highest performance was Gradient Boosting with a rate of 98.70%, and the model with the lowest performance was Support Vector Machines with a rate of 67.9%. All these results clearly show that Credit Card Customer Churn can be effectively predicted by machine learning methods.

Kredi Kartı Müşteri Kaybının Makine Öğrenmesi Yöntemleri Kullanılarak Tahmin Edilmesi

ÖZ

Günümüzde müşteriler muhtelif sebeplerle kredi kart kullanımlarından vazgeçebilmekte ve bu durum bankalar açısından olumsuz sonuçlar doğurmaktadır. Dolayısıyla, kredi kartı iptali yapacak muhtemel müşteriler önceden tahmin edilerek sözkonusu iptallerin banka lehine çevrilmesi ve böylece müşterilerin geri kazanılması gerekmektedir. Bu durum, müşteri kaybının takibi ve sözkonusu kaybın önlenmesi açısından da oldukça önem arzetmektedir. Bu bağlamda, çalışmada kredi kartı kullanan müşterilerin kart iptal durumlarını tespit etmek ve dolayısıyla müşteri kaybını tahmin etmek için makine öğrenmesi yöntemleri kullanılarak bir model önerilmiştir. Modelin oluşturulması için Kaggle platformundan elde edilen bir verisetinden yararlanılmıştır. Bu veri setinde toplam 10127 müşteriye ait kredi kart verisi bulunmaktadır. Veri setinde 23 özellik olmasına rağmen 2 özelliğin sonuçlara etkisi olmadığından modele dahil edilmeden silinmiştir. Sonuç olarak 20 girdi, 1 çıktı olmak üzere toplamda 21 farklı değişken kullanılmıştır. Modeller; Yapay Sinir Ağları, Lojistik Regresyon, Destek Vektör Makineleri, K-En Yakın Komşu, Karar Ağacı, Rastgele Orman, Ada Boost ve Gradient Boosting makine öğrenmesi algoritmaları kullanılarak oluşturulmuştur. Sonuç olarak, en yüksek performansı gösteren modelin %98.70'lik bir oranla Gradient Boosting, en düşük performansın ise %67.9'luk bir oranla Destek Vektör Makineleri modeli olduğu görülmüştür. Elde edilen tüm bu sonuçlar, Kredi Kartı Müşteri Kaybının makine öğrenmesi yöntemleriyle etkili bir şekilde tahmin edilebileceğini açıkça göstermektedir.

Anahtar Kelimeler: Kredi Kartı, Müşteri Kaybı, Kart İptali, Makine Öğrenmesi, Tahmin

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1. Introduction

A highly dynamic and competitive market has emerged with the existence of a large number of service providers such as banks worldwide [1]. These banks have become reliable places for the storage of money and similar valuable metals. With the increase in competition, the most important thing for banks is the customer. Because customers are very important for banks to survive in difficult market conditions. What is important here is customer loyalty. Because banks make high profits by keeping customers in their organization for a long time, therefore, banks should keep customer churn to a minimum [2]. Harvard Business Review stated that companies can make a profit between 25% and 85% with 5% deviation in the number of customers [3]. In this context, customer churn basically means customers giving up on preferring the company due to competition [4].

Customer churn can be defined as a customer giving up or not preferring a bank. The increase in customer churn rates is inversely proportional to the rate of campaigns and satisfactory services that banks carry out compared to each other. In other words, the more customer satisfaction there is, the less churn there is. In this process, access to technological facilities, low transaction fees, staff quality and competence, advertisements, proximity in terms of location and similar services are also very effective [5,6]. Churn is the transfer of a customer to another bank or the complete abandonment of the bank, thus decreasing the bank's profit. It is very important for banks to predict this situation before a customer switches to another bank [7].

In today's competitive environment, banks should know their customers well and be honest with them in order to provide faster and more effective service to their customers, to reach all of their customers, and therefore not to lose customers. With the development of technology, banks record and use the data they obtain. It is important to analyze this data, which develops and grows every day. Banks use many technologies for data analysis. Thanks to these technologies, they can analyze the data in question effectively, quickly, and statistically reliably [3]. With the analysis of data, banks can take some campaigns or actions by predicting many problems in advance. These analyses prevent possible customer churn or regain customers who have left the bank [8].

This entire process is only possible with current and new technologies such as machine learning. Machine learning is a subset of artificial intelligence and is a mathematical model established to help the computer learn the model or subject without direct guidance. A high-performance machine learning model can provide effective resource management or savings. Machine learning models are trained based on given examples and automate the task given to them by detecting certain patterns. Unlike traditional methods, it produces results by giving input and output in the process of solving any problem [9,10].

Machine learning actually works with trial-and-error logic and allows programs to make predictions. Machine learning algorithms can be used in almost every field from health to tourism, from sports to education. There are different types such as supervised, unsupervised, and reinforced [11]. When the literature is scanned, it is seen that different methods are used to predict the losses that will occur in bank customers. In the literature, machine learning algorithms such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), Logistic Regression (LR), Decision Trees (DT), and Random Forest (RF) are mostly used for this prediction [12-16].

Therefore, in this context, the aim of the study is to predict customer churn (credit card cancellation cases) with an up-to-date and effective approach such as machine learning methods, thus offering a new approach to the problem of customers quitting credit card use and providing a proactive perspective for the future. The second part of the study includes all the details of the material and method. The third part includes experimental findings and discussion, and the fourth part includes information on the results and recommendations obtained from the study.

2. Material and Methods

This section includes all the details of the study, including the dataset, dataset preprocessing, model selection, model creation, and findings from model performance. In the study, the card cancellation status of credit card customers and thus customer churn were estimated using machine learning methods. For this purpose, a total of 8 different methods were used, including Ada Boost, RF, ANN, KNN, LR, DT, SVM, and Gradient Boosting (GBoosting). Before moving on to the models, information about the dataset was provided.

2.1. Dataset

The data set was obtained from the address 'Credit Card Customer Dataset' [17] and contains 10127 data and consists of 23 attributes. Two attributes that were not seen to directly affect the results were deleted and reduced to 21 (20 Inputs, 1 Output). Info Gain, Gain Ratio, Gini, ANOVA, Chi2, ReliefF, and FCBF (Fast Correlation Based Filter) were used to determine the extracted attributes (Figure 1).

			#	Info. gain	Gain ratio	Gini	ANOVA	χ^2	ReliefF	FCBF
1	N	Total_Trans_Ct		0.117	0.059	0.040	NA	1165.960	0.090	0.097
2	N	Total_Revolving_Bal		0.081	0.041	0.033	NA	544.972	0.078	0.066
3	N	Total_Trans_Amt		0.077	0.038	0.023	NA	335.959	0.071	0.000
4	N	Total_Ct_Chng_Q4_Q1		0.075	0.038	0.032	NA	688.376	0.009	0.060
5	N	Avg_Utilization_Ratio		0.066	0.033	0.028	NA	541.112	0.045	0.000
6	N	Months_Inactive_12_mon		0.027	0.015	0.009	NA	190.317	0.021	0.022
7	N	Contacts_Count_12_mon		0.026	0.013	0.009	NA	219.283	0.019	0.020
8	N	Total_Relationship_Count		0.019	0.010	0.007	NA	195.035	0.039	0.000
9	N	Total_Amt_Chng_Q4_Q1		0.013	0.007	0.005	NA	57.527	0.008	0.000
10	N	Avg_Open_To_Buy		0.013	0.006	0.005	NA	11.070	0.010	0.000
11	N	Credit_Limit		0.003	0.002	0.001	NA	20.585	0.011	0.000
12	N	CLIENTNUM		0.003	0.001	0.001	NA	30.128	0.004	0.002
13	C	Gender	2	0.001	0.001	0.000	NA	7.443	0.012	0.000
14	C	Income_Category	6	0.001	0.000	0.000	NA	9.431	0.056	0.000
15	C	Education_Level	7	0.001	0.000	0.000	NA	0.339	0.096	0.000
16	N	Customer_Age		0.001	0.000	0.000	NA	3.202	0.016	0.000
17	N	Dependent_count		0.001	0.000	0.000	NA	3.851	0.012	0.000
18	C	Marital_Status	4	0.000	0.000	0.000	NA	1.303	0.054	0.000
19	N	Months_on_book		0.000	0.000	0.000	NA	1.479	0.003	0.000
20	C	Card_Category	4	0.000	0.000	0.000	NA	0.986	0.002	0.000

Figure 1. Scores of input and output variables

The attributes in the dataset are as follows: Client_Num (Client Number), Customer_Age (Customer's Age in Years), Gender (Demographic variable - M=Male, F=Female), Dependent_Count (Number of Dependents), Education_Level (Educational Qualification of the account holder), Marital_Status (Married, Single, Divorced, Unknown), Income_Category (Annual Income Category of the account holder), Card_Category (Type of Card), Months_on_Book (Period of relationship with bank), Total_Relationship_Count (Total no. of products held by the customer), Months_Inactive_12_mon (No. of months inactive in the last 12 months), Contacts_Count_12_mon (No. of Contacts in the last 12 months), Credit_Limit (Credit Limit on the Credit Card), Total_Revolving_Bal (Total Revolving Balance on the Credit Card), Avg_Open_To_Buy (Open to Buy Credit Line (Average of last 12 months)), Total_Amt_Chng_Q4_Q1 (Change in Transaction Amount (Q4 over Q1)), Total_Trans_Amt (Total Transaction Amount (Last 12 months)), Total_Trans_Ct (Total Transaction Count (Last 12 months)), Total_Ct_Chng_Q4_Q1 (Change in Transaction Count (Q4 over Q1)), Avg_Utilization_Ratio (Average Card Utilization Ratio), and Attrition_Flag (Internal event (customer activity) variable - if the account is closed then 1 else 0). The features, types, and value ranges found in the dataset are given in Table 1.

Table 1. Dataset features

INPUT			
Number Value	**Feature**	**Type**	**Range**
1	Client_num	Numerical	No Limit
2	Customer_Age	Numeric	0-150
3	Gender	Categorical	Female, Male
4	Dependent_count	Numeric	0-50
5	Education_Level	Categorical	College, Doctorate, Graduate, High School, Post-Graduate, Uneducated, Unknown
6	Marital_Status	Categorical	Divorced, Married, Single, Unknown
7	Income_Category	Categorical	$40k-$60k, $60k-$80k, $80k-$120k, $120k+, Less than $40k, Unknown
8	Card_Category	Categorical	Blue, Gold, Platinum, Silver
9	Months_on_book	Numeric	No range
10	Total_Relationship_Count	Numeric	No limit
11	Months_Inactive_12_mon	Numeric	No limit
12	Contacts_Count_12_mon	Numeric	No limit
13	Credit_Limit	Numeric	No limit
14	Total_Revolving_Bal	Numeric	No limit
15	Avg_Open_To_Buy	Numeric	No limit
16	Total_Amt_Chng_Q4_Q1	Numeric	No limit
17	Total_Trans_Amt	Numeric	No limit
18	Total_Trans_Ct	Numeric	No limit
19	Total_Ct_Chng_Q4_Q1	Numeric	No limit
20	Avg_Utilization_Ratio	Numeric	No Limit
OUTPUT (Target)			
Number Value	**Feature**	**Type**	**Range**
1	Attrition_Flag (Customer Activity)	Categorical	Customer Churn Existing Customer

2.2. Data preprocessing

During the preprocessing phase of the data set, two different columns indicating the change in the number of transactions and the type of change in the number of transactions were ignored and not included in the model. Repeating rows or inconsistent data in the data were revised. The first column contains classification data for customer activity (customer churn). The other columns contain the number of customers, customer age, gender, number of dependents, education level, marital status, income category, card category, months (duration of relationship with the bank), credit limit, total number of relationships, number of inactive months in the last 12 months, number of people in the last 12 months, revolving balance on the credit card, credit limit open for purchase (average of the last 12 months), total transaction amount (12 months), total number of transactions (12 months) and average card usage rate. Therefore, "Customer Churn" was estimated using the data in all these columns in the study. A sample section from the data set after preprocessing is given in Table 2.

Table 2. A Sample section from the dataset

CN	CA	G	DC	EL	MS	IC	CC	MB	TRC	MI_12_mon	CC_12_mon	CL	TRB	AOB	TAC_Q4_Q1	TTA	TTC	TCC_Q4_Q1	AUR	AF
709188108	45	M	2	Graduate	Single	$60K - $80K	Silver	33	4	2	2	34516	1529	32987	0.609	13940	105	0.81	0.044	Existing Customer
719106783	52	M	1	High School	Single	$80K - $120K	Blue	41	4	1	4	4103	1972	2131	0.665	16344	118	0.788	0.481	Existing Customer
713437008	40	F	3	Graduate	Married	Unknown	Blue	25	1	2	3	6888	1878	5010	1059	9038	64	0.829	0.273	Customer Churn
719574033	38	M	1	High School	Single	$60K - $80K	Blue	28	2	2	2	21906	0	21906	0.696	15349	119	0.7	0	Existing Customer
710005683	56	M	2	College	Single	$80K - $120K	Blue	46	3	3	5	12540	1696	10844	0.799	16518	115	0.716	0.135	Existing Customer
801036033	31	M	0	High School	Single	$40K - $60K	Blue	25	3	2	3	4493	1388	3105	0.795	17744	104	0.763	0.309	Existing Customer
716644008	55	M	3	Graduate	Single	$120K +	Silver	36	4	3	4	34516	0	34516	1007	9931	70	0.75	0	Customer Churn
718372458	42	M	2	Graduate	Unknown	$40K - $60K	Blue	30	3	2	5	3735	1723	2012	0.595	14501	92	0.84	0.461	Existing Customer
720608658	33	F	1	Uneducated	Single	Less than $40K	Blue	36	5	3	3	8398	1875	6523	0.727	16706	123	0.757	0.223	Existing Customer
717185658	51	M	1	High School	Married	$80K - $120K	Blue	36	4	3	4	22754	0	22754	0.799	8531	77	0.791	0	Customer Churn
715474083	51	M	3	Graduate	Single	$60K - $80K	Silver	36	3	2	2	29663	1743	27920	0.667	14638	93	0.722	0.059	Existing Customer
709646433	59	F	1	High School	Married	Less than $40K	Blue	50	1	4	3	5043	743	4300	0.805	10170	66	0.784	0.147	Customer Churn
717494358	58	F	0	Graduate	Single	Less than $40K	Blue	48	2	2	5	4299	1334	2965	0.66	15068	123	0.685	0.31	Existing Customer
713924283	61	M	0	Graduate	Single	$60K - $80K	Blue	54	2	1	4	11859	1644	10215	0.866	8930	79	0.837	0.139	Customer Churn
714471183	47	M	4	Graduate	Divorced	$80K - $120K	Blue	39	4	3	4	17504	476	17028	0.892	10468	66	0.737	0.027	Customer Churn
780613758	47	M	5	High School	Single	Less than $40K	Blue	35	4	3	5	4165	0	4165	0.813	17093	111	0.82	0	Existing Customer
718225683	56	M	1	Graduate	Single	$80K - $120K	Silver	49	5	2	2	34516	1091	33425	0.64	15274	108	0.714	0.032	Existing Customer
710734308	49	M	1	Graduate	Single	$60K - $80K	Blue	40	6	3	3	6481	1569	4912	0.692	15937	119	0.803	0.242	Existing Customer
708564858	33	M	2	College	Married	$120K +	Gold	20	2	1	4	34516	0	34516	1004	9338	73	0.622	0	Customer Churn
713733633	27	M	0	High School	Divorced	$60K - $80K	Blue	36	2	3	2	13303	2517	10786	0.929	10219	85	0.809	0.189	Customer Churn
712210458	38	M	1	Uneducated	Single	$40K - $60K	Blue	36	2	3	2	5639	1558	4081	0.614	16628	109	0.946	0.276	Existing Customer
714109308	46	M	5	College	Single	$80K - $120K	Blue	36	1	2	3	13187	2241	10946	0.689	15354	112	0.931	0.17	Existing Customer
712503408	57	M	2	Graduate	Married	$80K - $120K	Blue	40	6	3	4	17925	1909	16016	0.712	17498	111	0.82	0.106	Existing Customer
716893683	55	F	3	Uneducated	Single	Unknown	Blue	47	4	3	3	14657	2517	12140	0.166	6009	53	0.514	0.172	Customer Churn
710841183	54	M	1	High School	Single	$60K - $80K	Blue	34	5	2	0	13940	2109	11831	0.66	15577	114	0.754	0.151	Existing Customer
713899383	56	F	1	Graduate	Single	Less than $40K	Blue	50	4	1	4	3688	606	3082	0.57	14596	120	0.791	0.164	Existing Customer

CN: Client_Num, **CA:** Customer_Age, **G:** Gender, **DC:** Dependent_Count, **EL:** Education_Level, **MS:** Marital_Status, **IC:** Income_Category, **CC:** Card_Category, **MB:**Months_on_Book, **TRC:** Total_Relationship_Count, **MI_12_mon:** Months_Inactive_12_mon, **CC_12_mon:** Contacts_Count_12_mon, **CL:** Credit_Limit, **TRB:**Total_Revolving_Bal, **AOB:** Avg_Open_To_Buy, **TAC_Q4_Q1:** Total_Amt_Chng_Q4_Q1, **TTA:**Total_Trans_Amt, **TTC:** Total_Trans_Ct, **TCC_Q4_Q1:** Total_Ct_Chng_Q4_Q1, **AUR:** Avg_Utilization_Ratio, **AF:** Attrition_Flag

As seen in Table 2, the first column is determined as the output (target). The remaining 20 columns constitute the study's inputs.

2.3. Model infrastructure

The models used in the study to classify credit card customer churn are Logistic Regression, Artificial Neural Network, K-Nearest Neighbor (one neighbor), K-Nearest Neighbor 2 (tree neighbors), K-Nearest Neighbor 3 (five neighbors), Decision Tree, Random Forest, Support Vector Machines, Ada Boost, and Gradient Boosting. Brief explanations of these models are given in this section.

2.3.1. Random forest (RF)

RF is an algorithm that uses randomization to create many decision trees. This algorithm aims to obtain more accurate and reliable results by training multiple decision trees and combining their predictions. Each tree is trained on a randomly selected subset of features, and then the predictions of these trees are combined. The output of these trees is collected into a single output using averaging for classification or regression problems [18,19].

2.3.2. Support vector machine (SVM)

SVM is a powerful supervised learning algorithm used for classification and regression analysis. It is effective in high-dimensional spaces and is versatile due to the variety of kernel functions that can be used. SVM is known for its ability to handle outliers and is suitable for scenarios with a large number of features compared to the number of samples [20,21].

2.3.3. Decision tree (DT)

DT is a method of analyzing a dataset using a tree structure that represents a series of decisions in the dataset. A decision tree consists of many nodes and the edges connecting these nodes. Each node corresponds to a feature or decision. Starting from the first node, it branches according to the value of a feature in the dataset. Decision trees stand out with their understandability and interpretability. In addition, thanks to their ability to handle complexity in the dataset, they can be used in various tasks such as classification and regression [22,23].

2.3.4. Adaptive Boosting (AdaBoost)

AdaBoost is a machine learning algorithm that combines strong learners to form an ensemble. This algorithm uses an adaptive method to improve the performance of weak learners. The basic principles of AdaBoost are Weak Learners, Weights and Error Focus, Ensemble Building, and Boosting [24,25].

2.3.5. Gradient boosting (GBoost)

GBoost is an ensemble method that combines weak learners to form a strong model. This method uses gradient descent to eliminate the weaknesses of the model. The basic principles of GBoost are Weak Learners, Error Focus, Gradient Descent, and Boosting. GBoost is often used effectively in regression and classification problems. This method is known for its ability to create complex and high-performance models [26].

2.3.6. Logistic regression (LR)

LR is a parametric model used for binary classification. It estimates the probability that a given input belongs to a given category. It is relatively fast and efficient, which makes it a good starting point for classification tasks. However, it may not perform well in complex relationships in the data [27].

2.3.7. Artificial neural network (ANN)

An ANN is a model inspired by biological neural networks and is known for its ability to learn complex relationships. ANNs have a structure consisting of layers of interconnected neurons. Each neuron receives input values, multiplies them with weights, subjects them to an activation function, and transmits the output to other neurons. In this way, the network gains the ability to learn complex relationships in the dataset [28-30].

2.3.8. K-nearest neighbor (KNN)

It is one of the machine learning methods and is a supervised learning algorithm with effective, parameter-free learning. This algorithm is used in classification and regression problems. Its basic logic is to determine the class of a data point by considering its KNNs. The KNN model works according to the proximity principle by considering the nearest neighbors in the feature space of the data to be classified [31]. The Euclidean distance between the training samples and the test sample is used to predict the label of the test sample [32].

2.4. Creating models

First, the inputs and outputs of the study were determined to create the models. Then, the steps of loading the dataset, preprocessing steps, creating the models, performance evaluation, and visualization of the results were carried out respectively. First, the machine learning methods to be used and the basic features to be used for each were determined. After the dataset was loaded into the system, the data were examined and possible data-cleaning processes were carried out at this stage. Finally, the models were created and the results and the graphs of the created models were obtained. In the preprocessing process of the data, two variables were deleted without being included in the model since it was seen that they did not affect the results much. Then, the data were checked again. While evaluating the model results, the data were normalized to obtain more reliable data, and the general results were answered.

2.4.1. Inputs and outputs

Inputs; number of customers, customer activity (current customer-lost customer), customer age, gender, number of dependents, education level, marital status, income category, card category, months (duration of relationship with the bank), credit limit, total number of relationships, number of inactive months in the last 12 months, number of people in the last 12 months, revolving balance on the credit card, credit limit open for purchase (average of the last 12 months), total transaction amount (12 months), total number of transactions (12 months), change in transaction amount (from 4th quarter to 1st quarter), change in number of transactions (from 4th quarter to 1st quarter) and average card usage rate.

The output is Customer Churn and Existing Customer, which are in two categories.

2.4.2. General structure of the study

In the process of creating the models, first of all, the available data was divided into two parts 80% training and 20% test. Then, training and test performances were measured for each model and the most appropriate model was decided. The general structure of the study including all models is given in Figure 2.

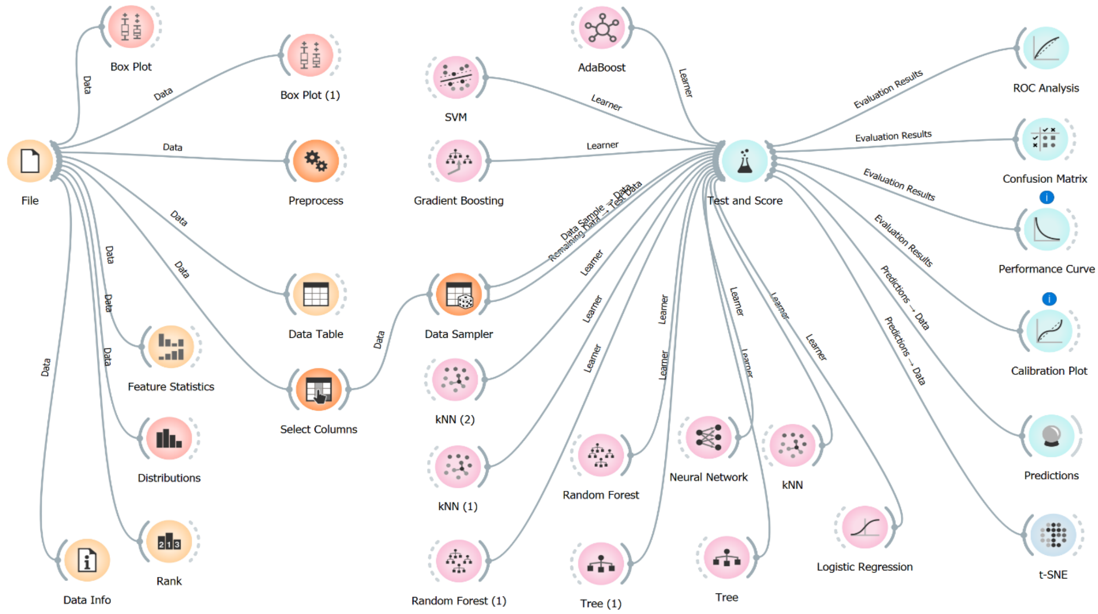


Figure 2. The general structure of the study

When Figure 2 is examined, in the first section, the file named File containing the dataset was obtained and then it was subjected to a preprocessing process to create the models. After the dataset was prepared, exploratory data analysis was performed using tools such as tables, graphics, feature statistics, and distribution.

In the second section, the dataset was integrated into the models (AdaBoost, GBoost, SVM, RF, LR, DT (1 and 2 leaves), ANN and KNN (1, 2 and 3 neighbors) in light of the previously determined features. Then, using the Test and Score tool, the test results/outputs of the models were obtained under six headings in total, namely ROC analysis, Confusion Matrix, Performance Curve, Relationship Graph, t-SNE and Prediction.

3. Experimental Findings and Discussion

This section includes the evaluation of the performance of the created models and a detailed analysis of the results obtained.

3.1. Performance of models

ROC Analysis, Confusion Matrix, Scatter Plots, Accuracy Value (AUC), Sensitivity, Specificity, and F1 score values to evaluate the performance in the study were taken into consideration. In this context, visualization tools such as ROC analysis, confusion matrix, recall-precision, and scatter plots were used. ROC analysis is used to evaluate the sensitivity and specificity of classification models. The larger the area under the ROC curve (AUC), the higher the performance of the model. AUC Value, the size of the area under the ROC curve, is a measure of the classification performance of the model. If the AUC value takes a value between 0-1 and approaches 0.5, the classification performance of the model is no different from random selection. An AUC value approaching 1 indicates that the model has high sensitivity and low false positive rates and that the classification performance increases. Sensitivity and Specificity, ROC curve shows the balance between sensitivity and specificity. Ideally, the closer the curve is to the upper left corner, the better the model performs. The ROC curve also shows the relationship between sensitivity and specificity values in the test. A steep curve indicates a model that provides high sensitivity and specificity [33,34]. The confusion matrix is a matrix that shows the classification performance of the model in more detail. The confusion matrix shows how the model predicts positive (separated) and negative (non-separated) classes. High TP and TN values indicate the overall correct classification ability of the model. FP and FN values represent incorrect classifications [35,36]. The scatter plot provides the opportunity to visually examine the distribution of data points belonging to different classes. Recall expresses the ratio of correctly predicted positive values to all true positive class values. Precision is the ratio of correctly predicted positive class values to all positively predicted class values [37].

First of all, the general performances of the models used in the study were evaluated. Here, the type of kernel function used for SVM was determined as RBF. The numbers 1, 2 and 3 specified for KNN indicate the number of neighbors used. Regularization type Ridge (L2) and C value were determined as 1 for LR. For ANN, the number of neurons in the hidden layer was determined as 100, the activation function was determined as Adam, the ReLu learning optimization algorithm, and the maximum iteration number as 200. The number of trees was determined as 10 for RF. For DT, the number of leaves was taken as 2 and the maximum tree depth was taken as 1000, and it was decided to stop when majority reached 95. For AdaBoost, the number of predictors was taken as 50, the classification algorithm was SAMME.R, the Regression loss function was taken as Linear, and the learning rate was taken as 1. Finally, for the GBoost model, the number of trees was determined as 100, the learning rate was 0.1, and the individual tree depth limit was determined as 3.

When the overall accuracy performances of the models created using these features are examined, it is seen that the values of 86.8% for the LR model, 94.2% for ANN, 70.5% for SVM, 95.6% for RF, 96.0% for GBoost, 93.2% for AdaBoost, 87.2% for KNN (1), 88.4% for KNN (3), 88.7% for KNN (5) and 92.5% for DT are obtained. In light of this information, the AUC values of the models in the study were between 67.9% and 98.7%. When the findings obtained from the models are examined in general, it can be said that the models exhibit a classification performance that can be considered good to a large extent.

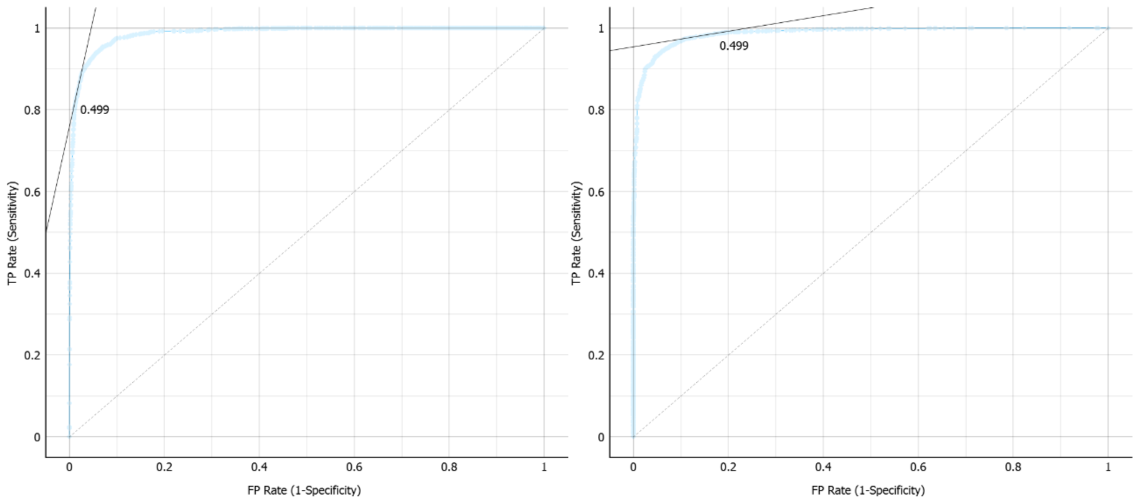
3.1.1. Gradient boosting model

As seen in the Confusion Matrix created for GBoost (Figure 3), 91.7% (1078) of those who are actually Customers were predicted correctly, while 3.2% (224) were predicted incorrectly. In addition, 96.8% (6703) of those who are actually Existing Customers were predicted correctly, while 8,3% (97) were predicted incorrectly.

Actual \ Predicted	Customer Churn	Existing Customer	∑
Customer Churn	91.7 %	3.2 %	1302
Existing Customer	8.3 %	96.8 %	6800
∑	1175	6927	8102

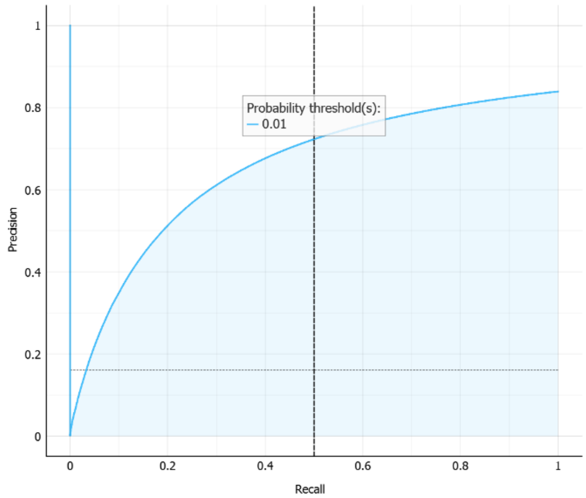
Figure 3. Confusion Matrix - GBoost

When we look at the ROC curves for Customer Churn and Existing Customer in Figure 4, we observe high sensitivity and specificity in terms of classification success with the size of the area under the curves. In addition, in Figure 5, the recall and precision graphs also reveal the high success of the model. While the area under the curve for the Customer Churn is 0.652, it is obtained as 0.997 for the Existing Customer.

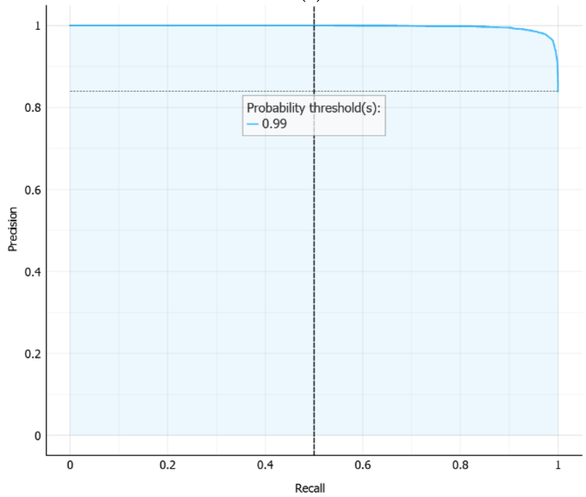


(a) (b)

Figure 4. ROC analysis- GBoost a) Customer churn, b) Existing customer



(a)



(b)

Figure 5. Performance curve (precision-recall) – Gboost a) Customer churn, b) Existing customer

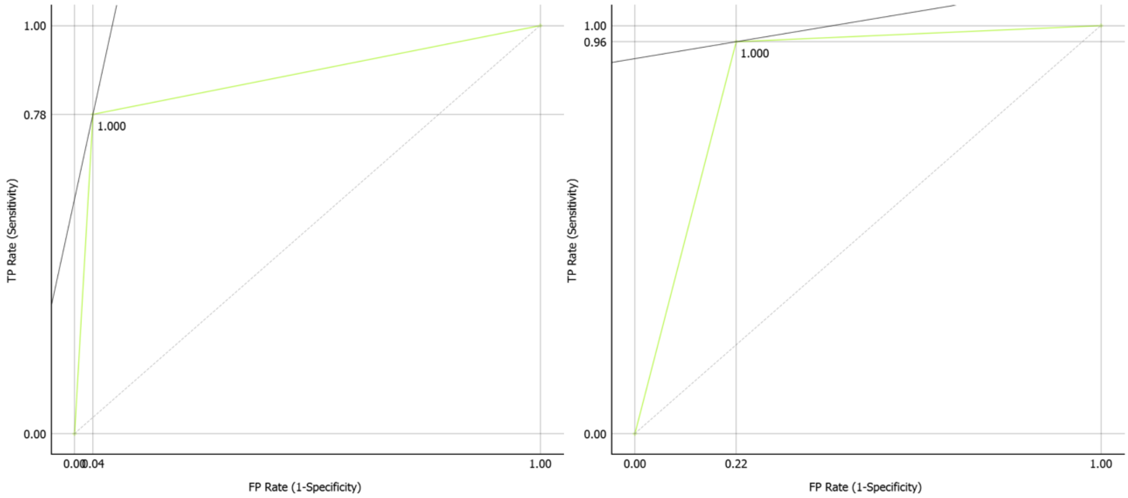
3.1.2. AdaBoost model

As seen in the Confusion Matrix created for the AdaBoost algorithm (Figure 6), 79.8% (1021) of those who are actually Customer Churns were predicted correctly, while 4.1% (283-1) were predicted incorrectly. In addition, 95.9% (6541) of those who are actually Existing Customers were predicted correctly, while 20.2% (259) were predicted incorrectly.

Actual \ Predicted	Customer Churn	Existing Customer	Σ
Customer Churn	79.8 %	4.1 %	1302
Existing Customer	20.2 %	95.9 %	6800
Σ	1280	6822	8102

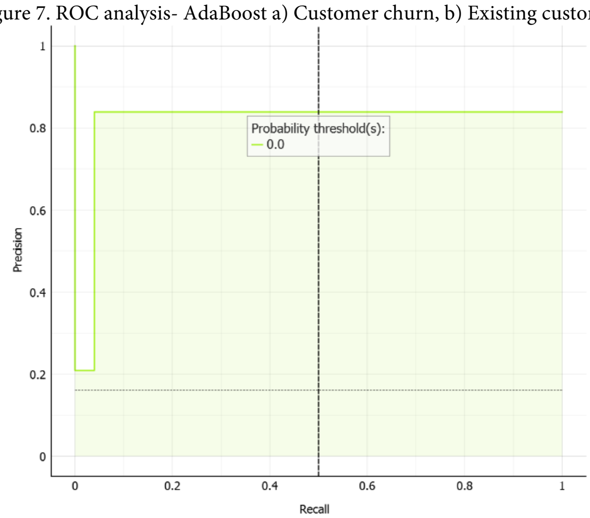
Figure 6. Confusion matrix – AdaBoost

When we look at the ROC curves for Customer Churn and Existing Customer in Figure 7, it cannot be said that the size of the area under the curves shows a good success in terms of classification success. In addition, in Figure 8, the recall and precision graphs also reveal the success of the model. While the area under the curve for the Customer Churn is 0.24, it is obtained as 0.998 for the Existing Customer.

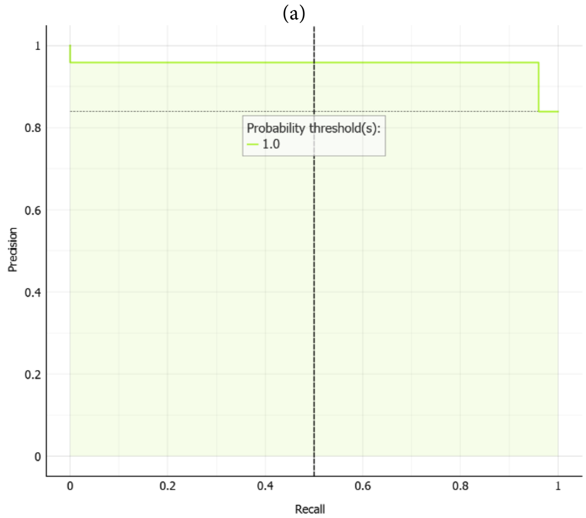


(a) (b)

Figure 7. ROC analysis- AdaBoost a) Customer churn, b) Existing customer



(a)



(b)

Figure 8. Performance curve (Precision-Recall) – AdaBoost a) Customer churn, b) Existing customer

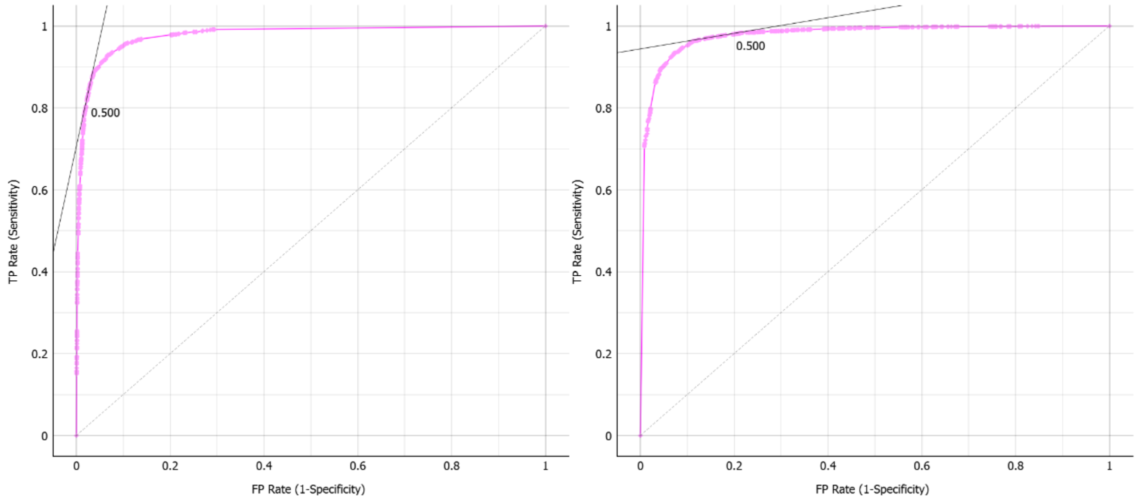
3.1.3. Random forest

As seen in the Confusion Matrix created for the RF algorithm (Figure 9), 89.6% (1065) of those who are actually Customer Churns were predicted correctly and 3.4% (237) were predicted incorrectly. In addition, 96.6% (6676) of those who are actually Existing Customers were predicted correctly and 10.4% (124) were predicted incorrectly.

		Predicted		
		Customer Churn	**Existing Customer**	**∑**
Actual	**Customer Churn**	89.6 %	3.4 %	**1302**
	Existing Customer	10.4 %	96.6 %	**6800**
	∑	**1189**	**6913**	**8102**

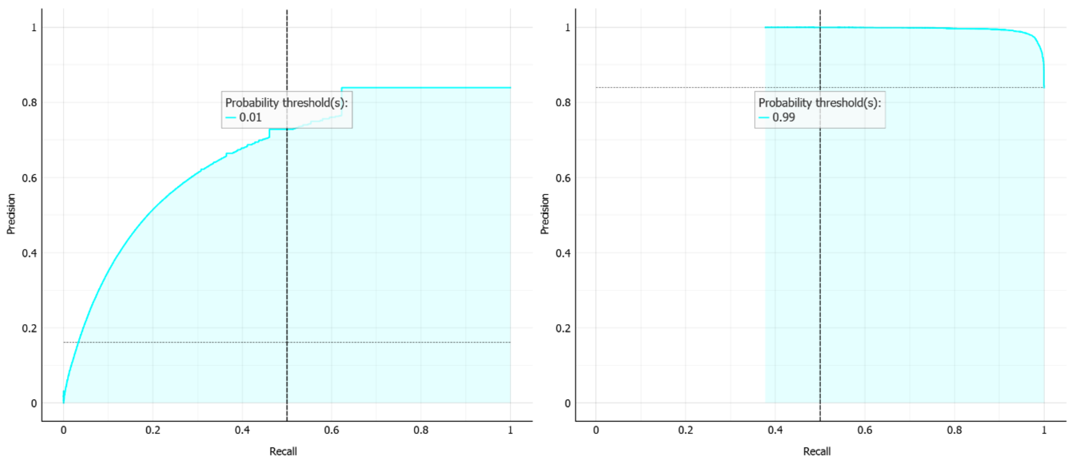
Figure 9. Confusion matrix – Random forest

When we look at the ROC curves for Customer Churn and Existing Customer in Figure 10, the size of the area under the curves shows high sensitivity and specificity in terms of classification success. In addition, in Figure 11, the recall and precision graphs also reveal the success of the model. While the area under the curve for Customer Churn is 0.636, it is obtained as 0.626 for Existing Customer.



(a) (b)

Figure 10. ROC analysis- Random forest a) Customer churn, b) Existing customer



(a) (b)

Figure 11. Performance curve (Precision-Recall) – Random forest a) Customer churn, b) Existing customer

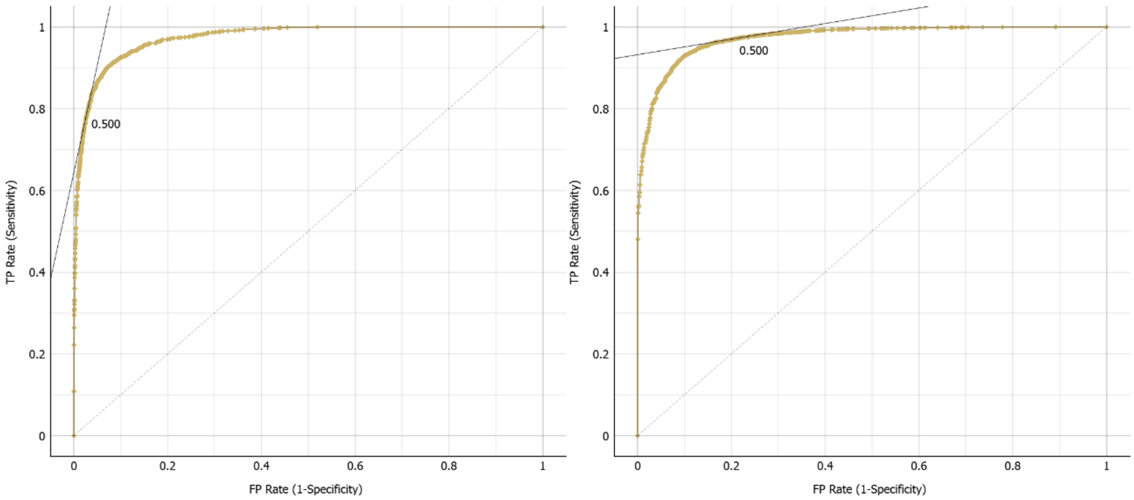
3.1.4. Artificial neural network model

As seen in the Confusion Matrix created for the ANN algorithm (Figure 12), 82.3% (984) of those who are actually Customer Churns were correctly predicted, while 4.6% (318) were incorrectly predicted. In addition, 95.4% (6588) of those who are actually Existing Customers were correctly predicted, while 17.7% (212) were incorrectly predicted.

		Predicted		
		Customer Churn	Existing Customer	Σ
Actual	Customer Churn	82.3 %	4.6 %	1302
	Existing Customer	17.7 %	95.4 %	6800
	Σ	1196	6906	8102

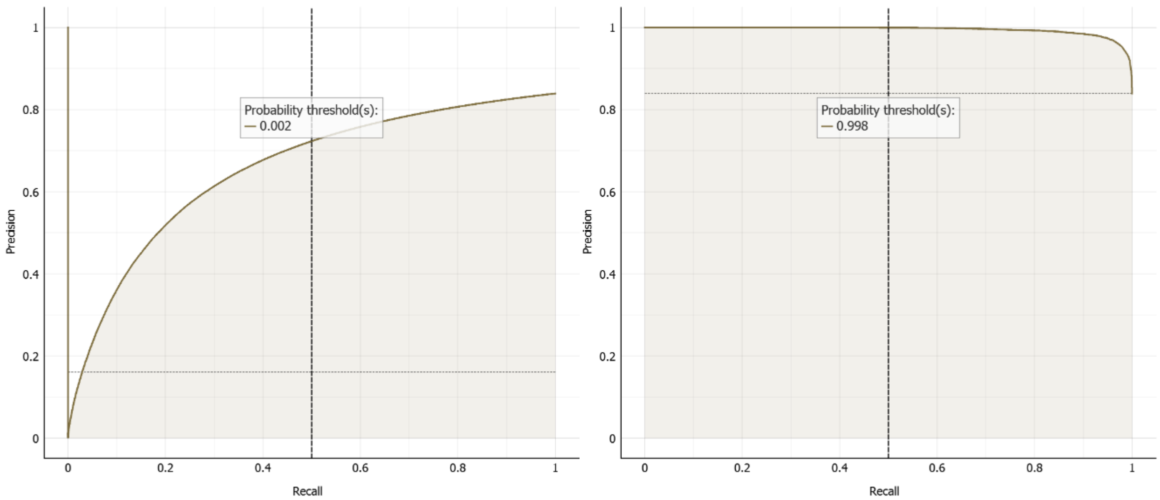
Figure 12. Confusion matrix – Neural network

When we look at the ROC curves for Customer Churn and Existing Customer in Figure 13, the size of the area under the curves shows high sensitivity and specificity in terms of classification success. In addition, in Figure 14, the recall and precision graphs also reveal the high success of the model. While the area under the curve for Customer Churn is 0.654, it is obtained as 0.995 for Existing Customer.



(a) (b)

Figure 13. ROC analysis- Neural network a) Customer churn, b) Existing customer



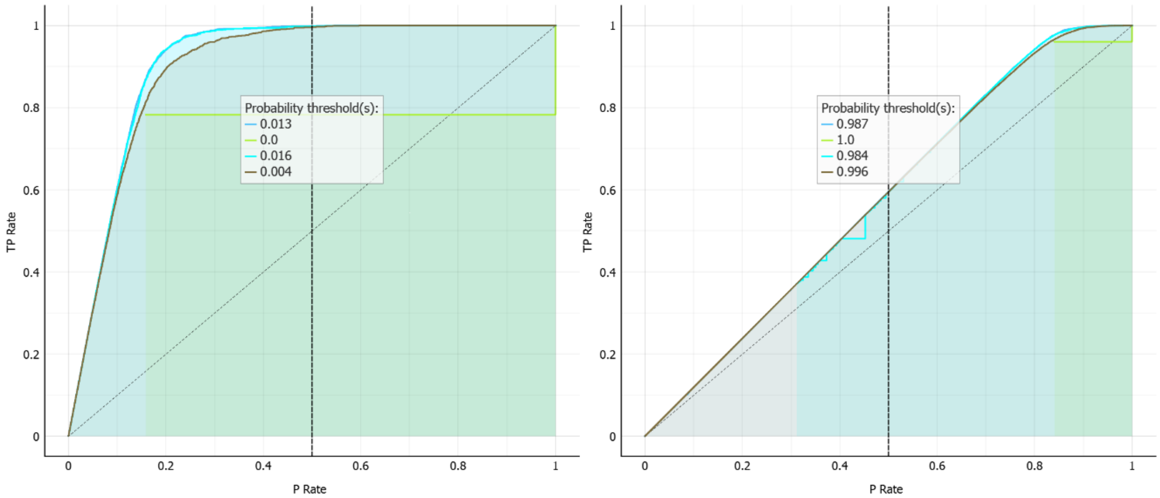
(a) (b)

Figure 14. Performance curve (Precision-Recall) – Neural network a) Customer churn, b) Existing customer

This section includes a comparison of the general performance curves of the four models. In these graphs, the ratio of true positive data samples was analyzed according to the threshold of the classifier or the number of samples classified as positive. Although the results were close to each other, the best result was obtained from the Gradient Boosting and AdaBoost models.

3.2. Cumulative gains curve and t-SNE

In the study, the Cumulative Gains Curve and t-SNE distribution graph were also examined. The Cumulative Gains Curve shows the support, which is the ratio of true positive samples to current customers and the fraction of positively predicted samples to customer churn, assuming that the samples are sequential. According to the probability of the model being positive for Customer Churn, the larger the area between the curve and the baseline (dashed diagonal line), the better the model is. It can be said that the model created in the study is meaningful. Here, since the model is looked at for lost customers, we see that it remains below the line in the Performance Curve analysis. This table can be looked at again by multiplying the data in the data collection for customer churn.



(a) (b)

Figure 15. Cumulative gains curve a) Customer churn, b) Existing customer

Finally, a visualization is created using t-distributed stochastic neighbor embedding with t-SNE. The aim here is to reduce one dimension by mapping points into two-dimensional space according to their probability distributions. It accepts a data table or distance matrix as input.

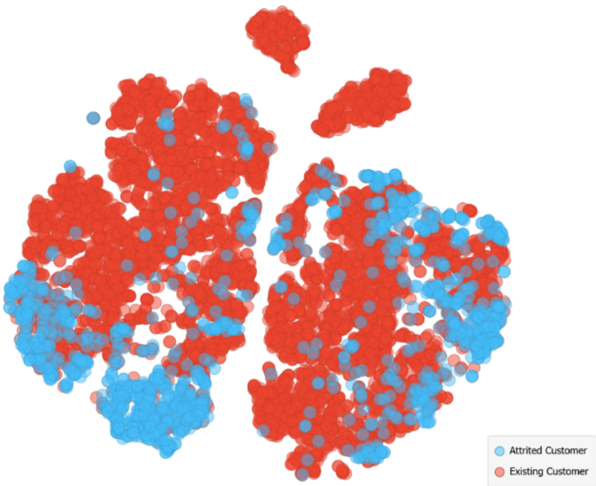


Figure 16. T- distributed stochastic neighbor embedding (t-SNE)

As seen in Figure 16, the distribution of the number of Customer Churns and Existing Customers generated by considering the distances between data points is shown. The graph clearly shows the distribution pattern of the two customer categories. There are clusters with a higher density of existing customers (red) in some regions and a higher density of customers who left (blue) in other regions. There are also areas where the two categories overlap significantly. The graph shows the regions where customers are more likely to be Churned or Existing. Identifying these regions can help understand the characteristics or behaviors that cause customer churn or customer retention. This shows that although there is some overlap, there are clear areas that can be targeted with specific strategies to reduce churn or increase retention.

As a result, the prediction performance results of the ANN, RF, SVM, KNN, DT, AdaBoost, LR, and GBoost models are given in Table 3 for comparison.

Table 3. Findings from all models

Model	AUC	CA	F1	Precision	Recall	MCC
GB	98,7	96,1	96	96	96,1	94,9
RF (1)	98,5	95,6	95,6	95,5	95,6	83,4
RF	97,7	95,1	95	95	95,1	81,3
ANN	97,3	94,3	94,2	94,2	94,3	78,3
LR	88,7	88,2	86,8	87,1	88,2	49,4
KNN (5)	88,3	89,1	88,7	88,5	89,1	57,1
AdaBoost	87,2	93,2	95,4	97,3	92,7	74,6
KNN (3)	85,5	88,8	88,4	88,2	88,8	56
DT	81,3	92,8	92,5	92,5	92,8	71,9
KNN (1)	75,7	87,3	87,2	87,1	87,3	52,3
SVM	67,9	66,3	70,5	79,1	66,3	19,5

When Table 3 is examined, it is clearly seen that the highest performance is GBoost; the lowest performance is obtained with the SVM model, and the other models produce results with similar and different values. At this stage, the results obtained from the models were compared with the experimental results in the literature. In Table 4, some of the studies in the literature related to customer churn prediction and summary information about the proposed study are given in the last line of the table. Models have been developed using various data mining and machine learning methods in these studies. Some of these and their details are summarized below:

The studies given in Table 4 show that various machine learning and data mining techniques have been successfully applied for customer churn prediction in different sectors. In particular, the highest success rate (99.67%) was obtained in study number 3, and in the table in general, it is seen that a success rate of over 95% was obtained in studies number 3 and 10. At this point, very little data was used in study number 3, which showed the highest performance. This situation also brings to mind that the model memorizes. In addition, studies number 14 and 15 also have high rates (around 95%).

The most striking study in the table is study number 2 with a very low success rate (68%). The reason for the low success in this study may be the use of the Naïve Bayes algorithm, which is not fully suitable for the study. In addition, the fact that the data number was too large (50000) and could not be included in the preprocessing/cleaning process can also be shown as a reason. As a result, a high success rate of 98.70% was obtained in the proposed study. Although this rate is not the highest, there is approximately 1 point difference between it and 99.67% (study number 3).

Table 4. Comparison of the models created in the study with the literatüre

No	Author(s)	Industry	Methods Used	Number of Data	Dataset Properties	Results	Performance
1	Keramati et al. (2014) [38]	Telecommunications	Decision Tree, Artificial Neural Networks, K-Nearest Neighbor, Support Vector Machines	3150	Data from a telecommunications company in Iran	Mixed methodology achieved high accuracy. Additionally, a new methodology for extracting influential features in the dataset was introduced and tested.	95%
2	Nath (2014) [39]	Telecommunications	Naive Bayes	50000	Geographic and demographic data, call details, service quality, package features	Customer churn analysis was conducted using the Naive Bayes method. A framework was developed to help customers analyze their own business.	68%
3	Dahiya and Bhatia (2015) [40]	Telecommunications	Logistic Regression, Decision Trees	50, 100, 608	50, 100, and 608 features	Decision Tree model showed the best performance.	99.67%
4	Kaynar et al. (2017) [41]	Telecommunications	Support Vector Machines, Artificial Neural Networks, Naive Bayes	4667	4667 customers, 21 features	Artificial Neural Networks provided more successful results than other methods.	91.35%
5	Rautio (2019) [42]	Software	Artificial Neural Network, Support Vector Machines, Random Forest	Unspecified	Business metrics, feature usage, platform usage metrics, service quality metrics, event metrics	Support Vector Machines showed the best performance.	85%
6	Ullah et al. (2019) [43]	Telecommunications	Random Forest, J48, Naive Bayes, Logistic Regression, IBK, and LWL	64,107 and 3,333	Data from 64,107 and 3,333 customers	Random Forest model achieved the highest accuracy.	88.63%
7	Özbaş (2020) [44]	Telecommunications	OptiScorer, Python, Knime	7043	21 columns (variables) and 7043 rows (customers)	Customer churn prediction was performed using the OptiScorer engine.	82%
8	Deng et al. (2021) [45]	Banking	Catboost, LightGBM, Random Forest	10000	Banking customer data	Random Forest model achieved the best results with 91% accuracy.	91%
9	Haddadi et al. (2022) [46]	Banking	Bi-LSTM, Decision Tree, Naive Bayes, Logistic Regression	50000	Customer data from a bank in Iran	Bi-LSTM model outperformed other models.	84%
10	Peng, K., Peng, Y., and Li, W. (2023) [47]	Banking	Seven classifier models including decision trees and neural networks	10000	Bank customer data with demographic and transaction features	Achieved high prediction accuracy; emphasized the importance of model interpretability in understanding churn factors. SMOTEENN proved more effective than SMOTE and ADASYN in handling unstable banking data.	96.08%
11	Özcan, B., Kayapınar, K., and Adem, K. (2023) [48]	Banking	Random Forest, Decision Tree, Gaussian, K-Nearest Neighbor, Adaboost, Logistic Regression	10000	Composed of 12 features	Random Forest algorithm yielded the highest accuracy rate. Other algorithms' success followed in the order of K-Nearest Neighbor, Decision Tree, Adaboost, Gaussian, and Logistic Regression.	84%
12	Khattak et al. (2023) [49]	General	Composite deep learning models	7033	Large-scale customer datasets with behavioral features, 20 different features	Deep learning techniques provided superior performance in churn prediction compared to traditional machine learning models.	81%
13	Mouli et al. (2024) [50]	General	Various classification models including logistic regression and support vector machines	7043	Customer data across multiple industries	Identified the most effective classification models for churn prediction, providing insights for businesses to select appropriate techniques.	85%
14	Vu, V. H. (2024, July) [51]	Banking	Combined feature selection methods with machine learning classifiers	Unspecified	Banking customer data with various attributes	The integrated approach improved prediction accuracy, aiding in early detection of potential churners in the banking sector.	95.13%

Table 4. Comparison of the models created in the study with the literatüre (Contuniue)

No	Author(s)	Industry	Methods Used	Number of Data	Dataset Properties	Results	Performance
15	He, C., and Ding, C. H. (2024) [52]	General	Ensemble-Fusion model combining multiple machine learning algorithms	8500	Diverse customer data with feature selection	The proposed model outperformed traditional methods in predicting churn, demonstrating higher accuracy and robustness.	95.35%
16	Calp (2025)	Banking	RF, DT, Gradient Boosting, LR, ANN, KNN, SVM, and AdaBoost	10127	21 different variables in the dataset	The highest performance was achieved with Gradient Boosting (98.70%), while the lowest performance was with Support Vector Machines (67.9%).	98.70%

4. Conclusion and Recommendations

In this study, the churn of bank customers, their departure from the bank, or card cancellations were predicted using various machine learning algorithms. The fact that machine learning is a powerful tool in every field, has started to be used, and can find solutions to important problems has been effective in its use in this study. The algorithms used include RF, DT, GBoost, LR, ANN, KNN, SVM, and AdaBoost. All machine learning methods used were compared and evaluated. According to the results obtained from the models, GBoost showed the highest level of performance with a high accuracy rate, and a good result was obtained in predicting customer churn with this algorithm. The model created with SVM ranked last in terms of performance and remained below the performance expected from the algorithm. Despite all this, it has also been observed that the models have significant accuracy rates regarding credit card customer churn. At this point, much higher performances will be achieved by reaching more customers, obtaining more data, and recording this data. At this point, both increasing customer registration and using hybrid models will positively increase the success of the model. As a result, this study clearly showed that Credit Card Customer Churn can be effectively predicted with machine learning methods. Finally, the use of powerful algorithms such as deep learning or hybrid approaches is considered in the future planning of the study. In addition, it is planned to develop an online system where business managers can make effective decisions. The system in question can be developed within the scope of an expert system or decision support system, which will have some important features such as identifying customer situations, strengthening customer satisfaction, increasing customer loyalty, and being able to track customer movements instantly.

Conflict of Interest Statement

The author declare that there is no conflict of interest.

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