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Evaluating the Performance of Machine Learning Algorithms in Predicting the Best Bank Customers

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Abstract. The best customer refers to the potential interaction of customers with the company during certain time periods. When companies understand the best customer and realize that the best customer can provide customized services for different customers, then they will achieve effective customer relationship management. This research is focused on the banking industry and systematically integrates data mining techniques and management topics to analyze the best customers. This study first uses the fuzzy hierarchical analysis method to weight the existing variables and then examines the DFMT model as an input to the k-means technique for clustering customers based on the desired criteria in the DFMT model. By using the proposed scoring model, it starts forming a customer value pyramid and categorizes customers into 4 value spectrums. Finally, in order to analyze the classes obtained from the customer value pyramid and implement the learning process from the available data, it uses the tenor classification techniques of decision tree, support vector machines and random forest along with the six characteristics and among They introduce the most appropriate model-characteristic based on available criteria.

2020 *Mathematics Subject Classification.* Primary 60J05; Secondary 60J20.
Key words and phrases. customer relationship management; customer value pyramid; K-means; decision tree theory; support vector machines; Artificial Intelligence (AI); banking industry.

1. Introduction

Financial institutions and banks are one of the organizations that need risk management processes due to the nature of their work (Boobier, 2020)[6]. Meanwhile, the credit risk related to customers is of particular importance, and managers must provide a suitable solution for evaluating and identifying the customers' risk (Sheth et al., 2022)[30], so that the efficient allocation of credit facilities is possible (Mehrara, 2011)[21]. In the discussion of credit risk management, it is particularly important to identify customers and separate them into good and bad groups and estimate the risk associated with each one (Hamta et al., 2018)[14]. Considering the huge volume of customer data, data mining can be used to classify and predict customer behavior(Deepthi et al., 2022)[8]. In fact, today, data mining is one of the most important tools available to these organizations for evaluating and identifying diverse risks (Dekamini and Ehsanifar, 2021)[10].

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Today, financial institutions play a key role in the economic development and progress of any country (Rahman et al., 2021)[28], and banks, as the main provider of financial resources, are considered one of the most important pillars of the country's economic system. Banks, like any institution involved in financial and economic processes, are exposed to various types of risks (Omoge et al., 2022)[25], which in a general category include interest rate, market, operational and credit risks (Deepthi et al., 2022)[8]. Considering that the capital of banks is low compared to the value of their total assets, even if a small percentage of loans lose their ability to collect, the bank faces the risk of bankruptcy (Kaur et al., 2020)[16]. The most significant existing risk that the bank faces due to its central and core activity is the default risk of the recipients of the facilities, or in other words, the credit risk of the customers of the loans and facilities of the banks (Donepudi, 2017)[11]. Evaluating the credit status of customers, before granting loans, can play a very effective role in reducing the risk of customer default and significantly reduce the probability of expected bankruptcy (Xue et al., 2020)[35]. Therefore, the investigation and research about the credit risk assessment models and their suitability with regard to the internal structures of banks is very necessary and important in the field of economic research. Finding a suitable internal model to assess the risk of a bank can help bank managers and decision makers on macro-credit decisions (Najmi et al., 2018)[24].

In other words, credit rating is a set of decision-making models and related methods that help lenders in granting credit to customers, such as Artifical Intelligence (AI) and Machine Learning (ML). From a broader perspective, the global application of AI in banking has been dramatically escalating (Taghipour et al., 2022)[32]. Allied Market Research indicates that AI in the banking market was valued at $3.88 billion in 2020 and is expected to reach a staggering $64.03 billion by 2030. Some other anticipations offer a much higher number. For instance, Statista suggests that by 2030 the business value from AI in banking will reach $99 billion in the Asia Pacific region alone (Figure 1). Regardless of any prediction, one thing is clear: AI in banking will be further applied and it will bring massive changes in credit systems. To have a better grasp on how the technology is integrated into banking, and credit risk management in particular, one should explore several key areas of adoption.

According to the studies conducted and the results obtained in the field of credit rating of customers (Boobier, 2020)[6], it can be said that currently statistical methods based on numerical calculations, due to the volume of high and complex mathematical calculations, low prediction accuracy and also being time-consuming, they are rarely used (Deepthi et al., 2022)[8]. This is despite the fact that the methods based on AI and data mining knowledge, including neural network, clustering and support vector machine, etc., cover well the mentioned weaknesses and have a very high flexibility in dealing with the problem ahead (Donepudi, 2017)[12]. Setting the accuracy and being unlimited in the amount of problem inputs is one of the advantages of their superiority over other methods (Caron, 2019)[7]. Therefore, the goals of the current research are to evaluate the performance of machine learning algorithms in predicting the best bank customers, determine the performance of machine learning algorithms and determine a model for predicting the best bank customers with machine learning algorithms. According to the mentioned cases, the main question in this research is, how is the performance of machine learning algorithms in predicting the best bank

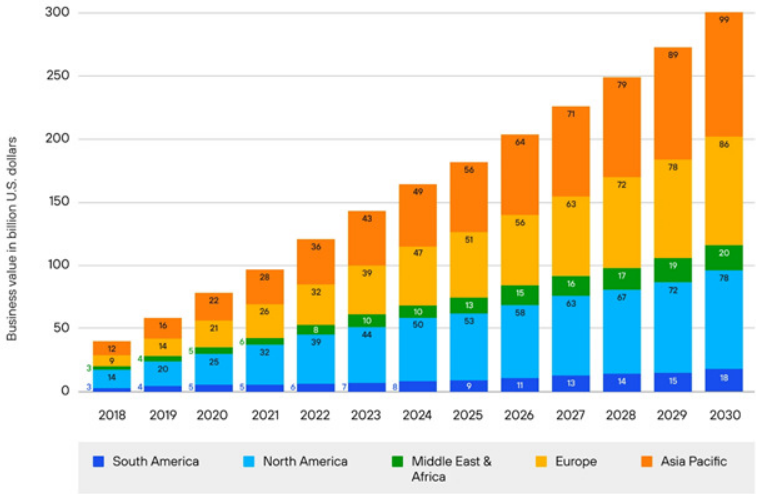

FIGURE 1. The business value derived from AI in the banking industry worldwide.

customers? What is the performance of machine learning algorithms and what is the model for predicting the best bank customers with machine learning algorithms?

2. Theoretical foundations and research background

All people who refer to banks, whether private or non-private, for banking activities are called bank customers (Lee et al., 2009)[19]. The relationship between an organization and its customers is a continuous, two-way, interactive and very valuable and beneficial relationship (Alsajjan& Dennis, 2010)[2]. This relationship can be short or long term, continuous or discrete (Khazaei et al., 2021)[18], repeated or one time. Even if the customers have a positive opinion about the organization and its products, still their behavior regarding buying from the organization is unpredictable and depends a lot on the conditions and situation (Dehghan Nayeri et al., 2020)[9]. Customers in all banks are divided into two general categories: real and legal, in legal terms, a real person is any human being. This word is placed in front of the word legal entity which may be a legal entity of public law such as the government or a legal entity of private law such as a commercial company with a non-commercial entity. In general, banks and financial institutions have two tasks: first, they provide means of payment between individuals and the economy (Khazaei et al., 2021)[17], and enable the transfer of funds from the lender to the borrower, that is, households, institutions, and the government (Ramezani et al., 2021)[29]. The second task is financial intermediation, which helps to bridge the gap between lenders and borrowers by creating a financial market. Considering that after granting facilities to customers, this facility is a demand for the bank from the borrower, in some correspondences and bank definitions, it is also referred to those demands. The scientific study of algorithms and statistical models used by computer systems that use patterns and inference to perform tasks rather than using clear instructions. Machine learning is the science that

No.	Researcher(s)	Purpose(s)
1.	(Bai et al ,2016)	They demonstrate that cryopreservation of Human precision-cut lung slices (hPCLSs) facilitates banking of live human lung tissue for routine use.
2.	(Mrass et al ,2018)	This paper investigate three seminal projects that Deutsche Bank completed with the crowdworking platform Jovoto and that aimed at exploring AI trends and developing concepts for the future of banking.
3.	(Agarwal ,2019)	This paper will highlight the applications of AI and evaluate its utility in different functional areas of financial industry focusing primarily on automation of banking operations and customer engagement.
4.	(Leo et al ,2019)	This paper seeks to analyse and evaluate machine-learning techniques that have been researched in the context of banking risk management, and to identify areas or problems in risk management that have been inadequately explored and are potential areas for further research.
5.	(Beutel et al ,2019)	This paper compared the out-of-sample predictive performance of different early warning models for systemic banking crises using a sample of advanced economies covering the past 45 years.
6.	(Suresh & Rani ,2020)	The study has highlighted the basic modernism through the AI technology in the banking sector which helps the customers and the banking industry.
7.	(Thisarani& Fernando ,2021)	They reviewed the conceptualizations of privacy concerns and the antecedents and consequences of using AI-power in the banking sector.
8.	(Ashta& Herrmann ,2021)	They showed that AI innovations analyze big data to help cut costs, reduce risk, and increase customization, leading to economic growth through an increase in aggregate demand and investments.
9.	(Payne et al ,2021)	They investigated the relationships that influence the value co-creation process and lead to consumer comfort by the means of AI and mobile banking (AIMB) service platforms.
10.	(Jawant ,2022)	They trained learning agents to present investment advices that is aligned with prototype financial personality traits which are combined to make ultimate recommendations.
11.	This Research	This research is focused on the banking industry and systematically integrates data mining techniques and management topics to analyze the best customers.

Table 1. Literature review and purpose of the present paper.

makes computers learn about a particular subject without the need for an explicit program. As a subset of artificial intelligence, machine learning algorithms create a mathematical model based on sample data or "training data" in order to make predictions or make decisions without overt programming (Piryonesi et al., 2020)[27]. As a matter of fact, it is called the algorithms that predict bank customers. In what follows, we will delve into the most outstanding research papers conducted in the mentioned contexts to clarify the research backgrounds.

The research papers reviewed in the literature that we have studied in a deeper way show that so far no research has dealt in depth with the problem of evaluating the performance of machine learning algorithms to find the best customer. Therefore, this research can compensate for the aforementioned gap.

3. Research method

The current research method is a survey type and in terms of its nature is applied and with data mining method. The information obtained from the information database is the transaction data of customers in the years 2020-2022. The banking information of the customers has been collected from 3 branches of Tejarat Bank in one of the biggest provinces in Iran, and for each branch, the data of about 100 account holders have been evaluated, and a total of 285 customers of the bank branches are available for the research. It is placed according to the selected community, 15 samples of questionnaires have been distributed in the target community and were given to managers, specialists and bank experts, of which 10 questionnaires were accepted.

By examining the available cases to select a suitable case study among organizations, the banking industry was selected for this research using the guidelines provided. In this way, to obtain the data of the bank's customers, the study and risk control department of Tejarat Bank in Tehran province was referred. After visiting in person and reviewing the request letter, the draft letter related to this research was requested for further review in this office.

After preparing the draft of the relevant letter, the draft of the letter was submitted to the secretariat of this department for review and approval in the specialized committee of the Department of Studies, Risk and Strategic Planning of Tejarat Bank. Also, a list of considered variables from customer data was compiled and sent to the attachment. After the investigations carried out in the mentioned department, the final letter was given to the management of the branches of one of the biggest provinces in Iran, which indicated the approval and approval of the implementation of this research and the availability of the customers' bank data.

Clustering is generally used for market segmentation. The purpose of clustering is to divide the existing data into several groups in such a way that the data of different groups have maximum differences with each other and the data in one group are very similar. One of the main segmentation methods used in data mining is the K-means technique. To achieve the goals mentioned in this research, before the clustering operation, the data are placed in the container that is based on the variables in this research, and are clustered by the developed RFM model. Then, using the proposed scoring model, K-means data mining technique will be scored separately for clusters and customers in each department, and the customer value pyramid will be formed (Figure 2).

After forming the customer value pyramid, the results obtained from the customer value pyramid were analyzed using data mining techniques of decision tree, support vector machine and random forest. Moreover, the softwares used in this research include Excel, Rminer, Weka, which is used for data analysis.

4. Findings

The variables based on which the transactional data of customers were extracted are classified into two main parts: customer demographic characteristics and financial

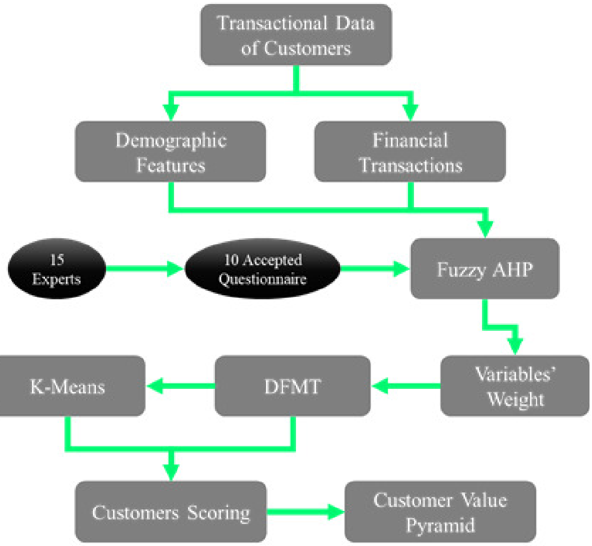

FIGURE 2. Operational stages of research.

Indicator	Financial transaction (FMT)	Demographics (D)	Normalized weight	Weight is not normalized
Financial transaction (FMT)	(1،1،1)	(1،5/7،8)	0/72	**1**
Demographics (D)	(1، 0/253، 0/14)	(1،1،1)	0/28	**0/39**

TABLE 2. The result of the comparison of the decision-making committee for the main indicators and weights obtained for each of the main criteria.

Demographics (D)	Age (D1)	Level of education (D2)	Type of activity (D2)	Weight is not normalized	Normalized weight
Age (D1)	(1،1،1)	(7 ،1/61 ،0/11)	(7 ،1/31 ،0/11)	0/91	0/32
Level of education (D2)	(9 ،4/63 ،0/14)	(1،1،1)	(9 ،1/11 ،0/11)	0/95	0/33
Type of activity (D2)	(9 ،6/03 ،0/14)	(9 ،6/11 ،0/11)	(1،1،1)	1	0/35

TABLE 3. The result of the comparison of the decision-making committee for demographic sub-criteria.

transactions. In order to estimate the weight of each variable, a questionnaire based on the fuzzy hierarchical analysis method was prepared and distributed among banking experts and completed by them. In this questionnaire, the variables were compared in pairs. The results of the comparisons after the DFMT steps in the fuzzy hierarchical analysis method model with triangular fuzzy numbers are as follows:

A.: Pairwise comparison of DFMT indices

B.: Pairwise comparison matrix under demographic criteria (D)

Financial transactions (FMT)	Average balance of account (M1)	Balance at the end of the period (M2)	Debt turnover sum (F1)	Sum of credit turnover (F1)	Bounced check (T)	Normalized weight	Weight is not normalized
Average balance of account (M1)	1-1-1	0/11-6/16-9	5-7/8-9	0/11-6/91-9	0/11-2/2-9	0/217	**0/99**
Balance at the end of the period (M2)	0/11-2-9	1-1-1	0/33-6/27-9	0/11-4/87-9	0/11-1/52-9	0/208	**0/95**
Debt turnover sum (F1)	0/11-0/13-0/2	0/11-0/72-3	1-1-1	0/11-0/67-3	0/11-0/22-1	0/147	**0/67**
Sum of credit turnover (F1)	0/11-1/02-9	0/11-2/68-9	0/33-5/73-9	1-1-1	0/11-1/11-9	0/206	**0/94**
Bounced check (T)	0/11-5/3/-9	0/11-5/83-9	1-7/2-9	0/11-6/3-9	1-1-1	0/219	**1**

Table 4. The result of the comparison of the decision-making committee for the financial transaction sub-criteria.

Confision matrix SVM(D-F1-F2-T)		PREDICTED CLASS				
		Class=Gol	Class=Lea	Class=Pla	Class=Sil	Class.error
ACTUAL CLASS	Class=Gol	57	9	1	19	0/3372
	Class=Lea	4	53	0	11	0/2205
	Class=Pla	4	0	10	2	0/375
	Class=Sil	7	9	0	99	0/139
Measure		Accuracy	Precision	Precision	F-Meausre	
Result		0/7684	0/8006	0/7319	0/7647	

Table 5. Perturbation matrix D1-F2-F1-T SVM.

C.: Pairwise comparison matrix under financial transaction criteria (FMT)

5. Support vector machine analysis by 6 characteristics

In this section, the analysis of the support vector machine resulting from the application of the 6 desired characteristics has been discussed, and the results are presented as follows:

The support vector machine obtained by applying the characteristic D1-F1-F2-T of the resulting disturbance matrix is shown in Table 5. The support vector machine resulting from the application of D1-F1-M1-T characteristics of the resulting disturbance matrix is shown in Table 6.

The support vector machine resulting from using the characteristic D1-F2-M1-T of the resulting disturbance matrix is shown in Table 7: The support vector machine resulting from applying the D1-F2-M1-T characteristic of the resulting disturbance matrix is shown in Table 8: The support vector machine obtained by applying the D1-F2-M2-T characteristic of the resulting disturbance matrix is shown in Table 9: The support vector machine resulting from the application of D1-M2-M1-T characteristics of the resulting disturbance matrix is shown in Table 10: Comparison of the results of

Confision matrix SVM(D-F1-M1-T)		PREDICTED CLASS				
		Class=Gol	Class=Lea	Class=Pla	Class=Sil	Class.error
ACTUAL CLASS	Class=Gol	57	10	1	18	0/3372
	Class=Lea	4	53	0	11	0/3305
	Class=Pla	4	0	10	2	0/375
	Class=Sil	7	9	0	99	0/1319
Measure	Accuracy	Precision	Precision	F-Meausre		
Result	0/7684	0/7995	0/7319	0/7642		

Table 6. Perturbation matrix D1-F1-M1-T SVM.

Confision matrix SVM(D-F1-M2-T)		PREDICTED CLASS				
		Class=Gol	Class=Lea	Class=Pla	Class=Sil	Class.error
ACTUAL CLASS	Class=Gol	58	10	1	17	0/3255
	Class=Lea	3	54	0	11	0/2058
	Class=Pla	3	0	11	2	0/3125
	Class=Sil	3	6	0	106	0/783
Measure	Accuracy	Precision	Precision	F-Meausre		
Result	0/8035	0/8332	0/7694	0/8000		

Table 7. Perturbation matrix D1-F2-M1-T SVM.

Confision matrix SAM (D-F2-M1-T)		PREDICTED CLASS				
		Class=Gol	Class=Lea	Class=Pla	Class=Sil	Class.error
ACTUAL CLASS	Class=Gol	56	9	1	20	0/3488
	Class=Lea	5	53	0	10	0/2205
	Class=Pla	4	0	10	2	0/375
	Class=Sil	5	9	0	101	0/1217
Measure	Accuracy	Precision	Precision	F-Meausre		
Result	7719	8036	7334	8077		

Table 8. Perturbation matrix D1-F2-M1-T SVM.

Confision matrix SVM(D-F2-M2-T)		PREDICTED CLASS				
		Class=Gol	Class=Lea	Class=Pla	Class=Sil	Class.error
ACTUAL CLASS	Class=Gol	61	8	1	16	0/2906
	Class=Lea	4	53	0	11	0/2205
	Class=Pla	3	0	11	2	0/3125
	Class=Sil	2	6	0	107	0/0695
Measure	Accuracy	Precision	Precision	F-Meausre		
Result	0/8140	0/8414	0/7766	0/8077		

Table 9. Perturbation matrix D1-F2-M2-T SVM.

support vector machine perturbation matrices –characteristic: In Figure 3, the state of the 4 meatures for all the 18 states of the characteristic model is shown.

Confision matrix SVM(D-M1-M2-T)		PREDICTED CLASS				
		Class=Gol	Class=Lea	Class=Pla	Class=Sil	Class.error
ACTUAL CLASS	Class=Gol	58	10	1	17	0/3255
	Class=Lea	4	53	0	11	0/2205
	Class=Pla	3	0	11	2	0/3125
	Class=Sil	2	6	0	107	0/0695
Measure	Accuracy	Precision	Precision	F-Meausre		
Result	0/8035	0/8328	0/7679	0/7990		

TABLE 10. Perturbation matrix D1-M2-M1-T SVM.

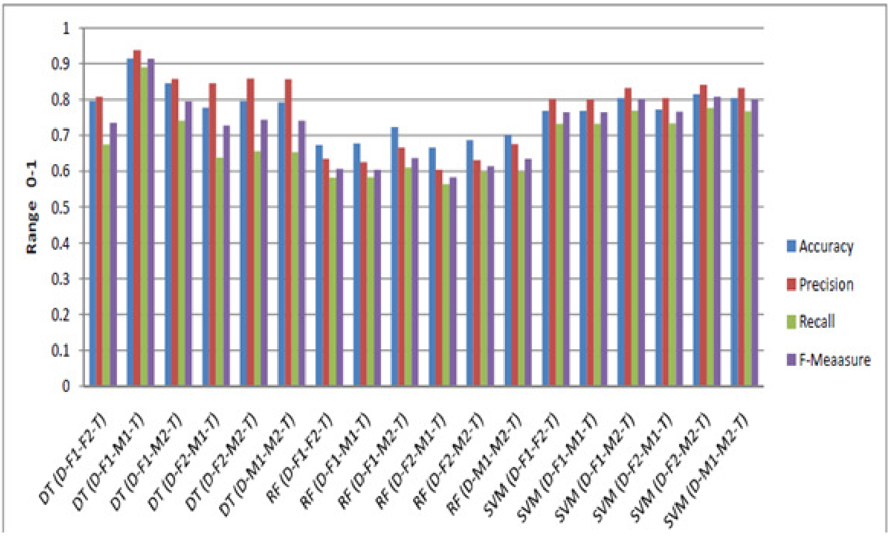

FIGURE 3. The business value derived from AI in the banking industry worldwide.

6. Conclusions

Since the awareness of customer value provides objective information for the performance of banks in the existing competitive environment, the implementation of customer relationship management strategy in banks and financial institutions helps to identify and segment customers; Therefore, understanding and measuring it by banks will be a vital factor for their success in the long term. On the other hand, information technology and customer valuation, which is an approach of customer relationship management, can be used as an important stimulus in increasing the profitability of banks, minimizing customer support costs, and using integrated information to provide superior services. and consistent interactions with envisioned customers. Customer valuing includes actions related to identifying the most valuable and loyal customers and then changing services according to different levels of

Spectrum	Average value	The number of customers in the range
platinum	0/214254125	16
golden	0107755406	86
silver	0/057720653	115
lead	0/027064636	68

Table 11. The 4 spectrums of customer value.

customer value, which banks and financial institutions should consider appropriate measures in the implementation of this important.

This research was done with the aim of determining a mechanism for valuing customers in Tejarat Bank branches. The innovation of this research is to focus on the high number of variables in the process of customer valuation, which due to the existing strictures regarding the acquisition of customer transaction data, these variables have rarely been studied and analyzed in research. It is also possible to point out the use of a scoring mechanism that shows the impact of all the criteria involved in the customer's valuation proportionally next to each other.

Based on the DFMT process, regarding the results of the research, it is possible to refer to the evaluation of the impact of the criteria of the fuzzy hierarchical analysis model and the separation and segmentation of customers for each of the criteria of the model under the title of customer cluster value. The calculation process of each step of the three DFMTs of customer valuation has been evaluated for all 285 people of the statistical population of Bank Tejarat branches in one of the biggest provinces in Iran, and finally the value of each customer has been calculated, which is included in 10 value classes of the value pyramid of customers. were classified into 4 golden, silver, lead and iron ranges, each of which represents the importance of customers for the bank, and the results are shown in 1.

By using the results obtained from the customer value pyramid and applying decision tree classification techniques, support vector machine and random forest and 6 characteristics obtained from the combination of the sub-criteria proposed, Precision, Accuracy in the research, the model - characteristics that are in The parameters of the best results compared to other states of the model - class error and F-Measure, recall have been shown, it was introduced as a learning characteristic model, the corresponding results are in Table 11.

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