Research Article

Data-driven Decision Making for Direct marketing of Banking Products with the use of Deep Learning and Random Forests

Doi: 10.30508/KDIP.2023.379306.1056

Hematyar, Amirhosein[1]

Received: 10/12/1401
Accepted: 05/02/1402
Page 00-00

Abstract

Nowadays due to the more customer-oriented era and increasing competition and advancing technologies, direct marketing becoming one of the most commonly-used marketing approaches worldwide. Many businesses, such as banks, apply direct marketing methods to reach more positive responses from their customers to minimize the campaigning cost and maximize the return on investment. To achieve this goal, banking and finance have to determine the target customer group to promote the bank product and services for them. It means that they need to know their customer attitude and characteristic individually to predict their needs and their reactions to product promotion. A huge amount of customer data has been stored in bank databases. This data as a rich resource can be analyzed to determine the most appropriate product to offer to each customer through the most effective channel. Since manually analyzing this data is not effortlessly feasible, this task should be executed automatically.

In this work, a predictive model which is appropriate for bank product offerings was designed and built, which firstly classifies the customers to decide if they are interested in the product offering, and then clusters them for product and channel suggestions.

This article combines data mining models with practical problems of the banking industry, and establishes a bank predictive response model and customer targeting, through Random Forest, Naive Bayes, and Neural network machine learning algorithms to classify customers and proposes corresponding suggestions for bank marketing based on the best classification in terms of accuracy and sensitivity of the result. The extracted classification rules and patterns can effectively help banks to divide customer groups with K-means clustering and take targeted measures to improve marketing efficiency.

Keywords: Customer Behavior, Data-driven Decision Making, Direct Marketing, Machine learning, Deep learning

1- Engineering department/Farabi college/Tehran university/Tehran/Iran

1- Introduction

Launching a successful marketing campaign in a very competitive market segment, such as retail banking, is undoubtedly a challenging issue. Customers› attention to the movements in such market conditions is less and less effective, as customers are constantly exposed to different kinds of advertisements, and learned to ignore them. One of the solutions, that is increasingly becoming popular in recent years, is personalized, direct marketing (Gordan,Sabbagh-Yazdi, Ismail, Ghaedi, Carroll, McCrum, & Samali, 2022). This kind of marketing allows customizing the product to align with customer needs and wants, consequently, it leads to increasing campaign efficiency and reducing costs (Iosifidis, Papadopoulos, Rosenhahn, & Ntoutsi, 2023). many businesses such as banks apply direct marketing methods to implement acquisition, retention, and expansion. By these, customer response might be the purchase of banking products or acquisition of customer information and it means the client is a customer and eventually becomes a promoter of the bank and a loyal customer (Duman, 2023). The bank's obtain in direct marketing is usually related to worldwide reach, reduced cost, and better customer relationship management (CRM) (Kolarovszki, Tengler, & Majerčáková, 2016., Bahari, & Elayidom, 2015). Furthermore, in the competitive environment, Banks are faced with the challenge of continually rising their direct marketing campaign cost and high investment cost on new products and services with decreasing response rates from customers (Miguéis, Camanho, & Borges, 2017).

To the aim of reducing the campaigning cost and maximizing the return rate in direct marketing, we need to target beneficial customers who are more likely respondents to our products with a high probability of purchasing our product and services in the future. Based on historical data, Customer› past purchasing behavior show their loyalty. customers are loyal, if they purchase more in their lifetime, buy products recently, and spend more money during their lifetime.

Understanding the interests of each customer and making the relationship between the customer and the companies easier is one of the most essential issues in marketing strategies. Due to the competitive market environment, advancement in technology, and changing behavior of customers, recognizing consumers who are more probable to respond to product offers will be a difficult task, while the appropriate product should be offered for each customer with the most effective channel. Therefore, to achieve this goal, firms need to understand the buying behavior of each customer in the field of individual customized products and channels.

Due to extracting these patterns and knowledge, a huge amount of customer data should be analyzed through the knowledge discovery in the database process. Consequently, by using data mining techniques for customer segmentation and building a predictive model we can recommend the right products to the right customers and provide individual marketing decisions for each customer (Almana, Aksoy, & Alzahrani, 2014). Therefore, customers receive products according to their requirements via more appropriate channels. Consequently, they will be satisfied and purchase more on time and finally, they will be loyal customers. On the other hand, firms spend the low cost for customer acquisition and retention and reach profitability. Machine learning algorithms used in direct marketing can be applied for recognizing our profitable clients (Khalili-Damghani, Abdi, & Abolmakarem, 2018). Various data mining techniques can be applied for effective customer segmentation and target selection marketing (Sing›oei, & Wang, 2013). In this work, the problem can be described as follows: As direct marketing activities are costly and customers› positive response rate is decreasing these days, we should be able to predict our customer response behavior and send our promotions to our selected and valuable customers with a high probability of product purchasing. Since accurate measurement or prediction of targeted and valuable customers is crucial for successful customer selection, Therefore, the segmentation of customers based on their customer lifetime value (CLV) empowered the firms to combat numerous problems such as decisions associated with identifying, maintaining, and acquiring customers. By implementing an appropriate CLV model which uses accessible historical data the companies will be empowered to estimate valuable customers. An appropriate CLV predictive performance is defined as a quality prediction result that is stable although it should be achieved among all applied datasets with high accuracy. The RFM model is the most common segmentation method that involves three measures (recency, frequency, and monetary). RFM is defined as customer segmentation based on customer analysis (Khajvand, Zolfaghar, Ashoori, & Alizadeh, 2011). It not only provides information on customer's purchasing patterns but also current buying and the profit achieved. A combination of the RFM analysis method and data machine learning techniques provides useful information, knowledge, and purchase behavior patterns for existing and new customers. By applying the extracted knowledge, it will be expected that the right product will be offered through an appropriate channel based on the customer's characteristics.

The main purpose of this study is to design and build appropriate data-driven decision-making for banking products and channels to predict our customer response behavior based on their previous purchase history and use the extracted information in the next marketing campaign to lunch a more efficient and effective marketing campaign.

This paper is designed as follows. Section 2 summarizes the related work of our research. Section 3 describes the methods that are proposed to solve our problem. Section 4 presents the results of the experiments. In the end, section 5 includes the conclusion.

2- Literature review

Clustering and classification methods of machine learning are widely used in different industrial areas. Prediction of power performance in power plants, forecasts of wind conditions to get optimal performance from wind power, and retaining existing customers in a telecom company are some of the examples in different areas that researchers work on to predict unknowns using machine learning techniques (Almana, etal, 2014., Nachev, & Hogan, 2014., Özkan, 2014). Especially, in customer relationship management (CRM), clustering and classifying datasets using customer characteristics with respect to the related campaign is used to increase profit and enhance return of investment (ROI) (Ngai, Xiu, & Chau, 2009). Delivering "the right product to the right customer at the right time" with multiple product campaigns, multiple communication channels and multiple time periods is one of the biggest issues in bank direct marketing (Cohen, 2004). The solution of Cohen in his paper is based on satisfying global maximization while increasing return rate of proposed campaign. The first enhancement accomplished with this study is twice as much profit than previous solutions. Second improvement is that extracted information from campaigns can be applied for the future ones to increase ROI. This work of Cohen does not include data mining; however, it proposes new opinions about the subject (Cohen, 2004., Chiu, 2002), identify the model for predicting the clients' shopping behavior and also, describes Genetic algorithm, based on the approach of the increased adjustment process. The following sections present the comparison of the two models, where GA-CBR shows better performance compared to the regression model.

Research is data mining implementation in order to discover laws and making of management decisions in a big data stream. The first part of this paper presents short view of the decision tree, neural networks, and the support vector machine. The following sections present the DPP (data pre-processing) analysis in order to identify its importance for the accuracy of the projection. In the end, the influence of various DPP techniques is considered as regards the performance of the decision tree, as well as of neural networks and of the support vector machines (Crone, S. F., Lessmann, S., & Stahlbock, 2006). Research proposes the application of the method of calibration, which is here called likelihood-mapping approach. Algorithms used in the research are scaling algorithm and likelihood-mapping algorithm. Two types of mapping are identified: linear and nonlinear likelihood. After completion of the study the likelihood-mapping approach was defined as being among the best algorithms and its use is recommended in everyday business operations (Coussement, K., & Buckinx, 2011). The aim of the (Chun, 2012) research is to provide clients› response in the direct marketing campaign.

Different methods are considered for assessing clients' response and necessary requirements for the existence of responses are discussed. The method of maximum likelihood is applied, as well as Chi-square method and method of nonlinear regression The efficiency of the three methods in the Monte-Carlo simulation is assessed. Finally, the results obtained show that the most precise method for assessment of a client's response is the method of maximum likelihood. (Duman, 2023) recommends an innovative, time series-based method of conducting personalized credit product marketing campaigns designed for each of customer. The encouraging results lead to extracting important patterns from customers› historical transaction data and predicting credit product buying likelihood.

(Aeron, Kumar, & Janakiraman, 2010) discover applications of data mining techniques for predicting CLV and its factors are studied. Some data mining techniques such as logistic regression, decision trees, artificial neural networks, genetic algorithms, fuzzy logic, and support vector machines are analyzed. finally, a case study is considered to predict a few CLV parameters for a direct marketing campaign.

3- Method

The main focus of this work is based on gathering secondary data. Internal secondary data were gathered from Saman Bank›s database. Essentially, customer data were gathered from Saman Bank›s databases for building a predictive model. Saman Bank has about 3,000,000 customers in total and their information is stored in the bank database. 6807 instance was randomly selected through the IT section. Each entry in the dataset shows a customer with several characteristics and attribute descriptions.

Customer historical purchase data and customer transaction data include such information as a unique ID for each customer, type of accounts (Long termed investment deposit accounts, Short termed investment deposit account, saving account, Current account) that the customer has in the bank, number of accounts, the date that customer opens an account, the date that customer close an account, type of services that the customer takes (SMS, EMS, ISS, Telephone- Bank), number of services and start date of service. the number of transactions for each account, date of each transaction for each account, type of transaction (Debit or Credit) and amount of money that the customer put in the bank, amount of money that the customer draws from the bank, type of communication channels that customer is used (call center, SMS).

Proposed model

Models are established in order to forecast the business path so that the managers can make more savvy determinations. Stability is one of the most factors that must be considered when a model is developed. A stable model can predict even the data which is not yet available. The first phases for developing models for prediction are the same and it does not depend on the data mining method. The data entered into the model must be classified into three sets of training, test, and assessment data. Since each set of data is used for a specific goal, they must not have any common data records.

The available data of the business are formulated into the model and the model uses it to forecast the future of that business. This is the way the model is trained. In model training, the patterns are identified in order to estimate the future. Then the test set of data improves the model by restricting the model to remember the training set of data so that the model can be generally used for any type of data in the future. These two sets of data must be distinct with no common records. The assessment set of data analyzes whether the model is still accurate if used for the external data which is not in the model data set. This set of data which is also known as the score set is not categorized and is separate from the data sets used in the model. You cannot predict the results of applying the model to the assessment data set. When the model is

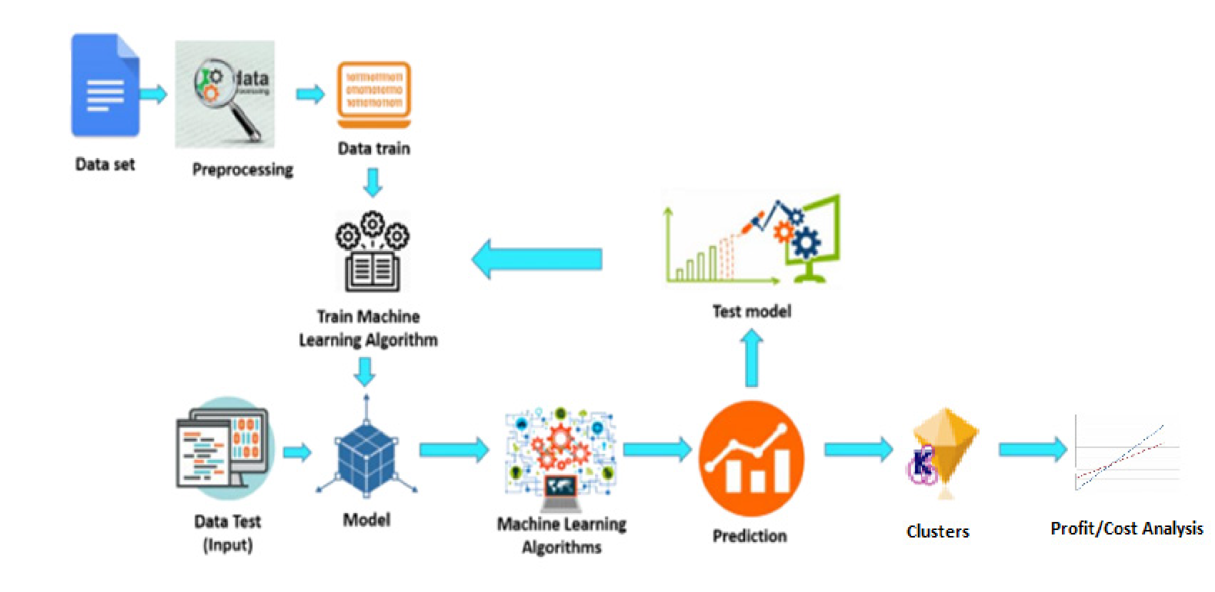

Figure (1): Prediction Model Process

developed, it is used for a set of assessment data and the re-
.sults are used to predict the future and make better decisions

This hybrid proposed model (Figure 1) consists of three phases, which are classified as the first phase and clustering as the second phase, and finally profit/cost analysis as the third phase. In the classification phase, different classification models such as Random Forest (Gupta, A., & Gupta, G. 2019), Naive Bayes (Karim, & Rahman, 2013), and Neural network (Kaefer, Heilman, & Ramenofsky, 2005) were applied to predict whether a customer will buy a product or not. Then different classification models evaluate in terms of accuracy and sensitivity.

In the prediction phase, if the response of the new customer was predicted to be no, it was decided that the customer didn't buy any product. Therefore, who was not offered any product. However, if the response of a new customer was predicted to be yes, it would be decided that the product would be bought. In the second phase, prediction continues with which product should be offered through which kind of channel. To this aim, the K-means clustering technique (Anitha, & Patil, 2022) was conducted only on "yes" response instances. In order to make it possible to evaluate the models by using the partitioning method 70% of the data was randomly selected as a training set and the remaining 30% was considered as the test set. A training set was used to build the model and then the test set was used to evaluate the accuracy of the models. Moreover, All the modeling and analysis were done using IBM SPSS Modeler Program.

In the continuation of this process, different clusters' accuracy is measured by silhouette values, and finally in the third phase by using profit/cost analysis calculates and compares the amount of cost and profits of each cluster.

Banking product and channel predicting

Here we suggest a combined algorithm consisting of two steps of classification and clustering (Zaharia, 2016). Using various methods of classification such as Random Forest, Naïve Bayes, and Neural Network, the model predicts if a customer will buy a product or service in the future. Then, the product or service will not be presented to the customer if the model predicts that the customer will not buy it. On the other hand, if it is predicted that the customer will buy the product or service, it is predicted through the K-means method of clustering which product is suitable to be offered to the customer and how it can be sold.

Banking product and channel profit/cost analysis

Profit/cost analysis is a way to find out how changes in variable and fixed costs affect a firm's profit. Banks can use profit/cost analysis to see how units with different costs can be more profitable. In other words, which unit with a lower cost can cause more profit. Also, Profit/cost analysis can be conducted in order to measure the effect of applying an appropriate response model on total marketing cost decreasing.

profit/cost ratio is a critical factor for bank product marketing. Finding customers that will accept the promotion is not the only important factor, but maximizing profit and minimizing the cost of promotion is also significant for banks. Therefore, we perform analysis on profit and cost constraints on our model-based method with Neural Network prediction and K-means clustering.

4- Experimental results

According to table 4.4, the result of the confusion matrix for each of Random Forest, Naïve Bayes, and Neural Network has been calculated. Based on the result obtained, the Neural Network algorithm has the best performance in terms of accuracy in the test data set among the results of the other models Random Forest model had the best function in second place with a slight difference after the Neural Network model. Furthermore, although the performance of the Neural Network is slightly weaker than the Random Forest model in terms of sensitivity rate, but overall other indicators have better results.

Consequently, Neural Network has been chosen as the best model in these various prediction models. In Other words, Table 1 shows that Neural Network has better average results than other model predictions such as Random Forest and Naïve Bayes models. Further, based on the evaluation of prediction models, this model had the best average result.

The second phase of the bank product and channel predictive model has been defined as a clustering task. In this stage, the predictive model continues by predicting the most appropriate product and channel for offering to each of customer based on their attitude and RFM features.

To this aim according to the three types of products and channels that have been considered in this work, all of the instances in the "Yes" class are classified into nine categories of data based on the product and channel.

In the following, the data in each of the nine categories are classified by using the silhouette

Table (1): Results of Different Predictive Model Evaluation

Model	Data Set	Precision	Negative Predictive Value	Specificity	Sensitivity	Accuracy
Random Forest	Train Data	0.44	0.49	0.55	0.7	0.69
	Test Data	0.49	0.45	0.43	0.75	0.70
Naïve Bayes	Train Data	0.64	0.67	0.52	0.71	0.65
	Test Data	0.72	0.44	0.48	0.73	0.69
Neural Network	Train Data	0.68	0.71	0.6	0.72	0.72
	Test Data	0.80	0.75	0.57	0.67	0.8

The coefficient in the auto-clustering function works based on the K-means algorithm.
The result of applying the Random Forest model for identifying the most optimal K-means clustering model which consists of the best number of the cluster for each of the models based on the silhouette coefficients and the most important variable in terms of predictability for nine categories of product-channel were gathered in Table 2.
The result of applying the Naïve Bayes model for identifying the most optimal K-means clustering model based on the silhouette coefficients and the most important variable in terms of predictability for nine categories of product-channel were gathered in Table 3.
Finally, The result of applying the Neural Network model for identifying the number of the cluster for each of the models based on the silhouette coefficients for nine categories of product-channel was gathered in Table 4.
According to Table 2 – Table 4, several classification methods are applied to the data set and then clustering methods with a different number of clusters are applied. Best results are obtained with Neural Network, Naïve Bayes, and Random Forest, respectively. Neural Network results are better than Naïve Bayes. Compared to the K-means clustering method, the average of the silhouette coefficient increases as well as the

Table (2): Results of applying Random Forest for checking product-channel

Product category	Channel category	Average of silhouette coefficient	Number of Clusters
Current Account	Branch	0.45	5
	Call center	0.38	8
	Mobile App	0.31	4
Deposit Account	Branch	0.55	10
	Call center	0.51	10
	Mobile App	0.39	10
POS Loan	Branch	0.45	9
	Call center	0.52	3
	Mobile App	0.36	10

Table (3): Results of applying Naıve Bayes for checking product-channel			
Product category	Channel category	Average of silhouette coefficient	Number of Clusters
Current Account	Branch	0.65	5
	Call center	0.44	7
	Mobile App	0.37	10
Deposit Account	Branch	0.45	1
	Call center	0.71	8
	Mobile App	0.62	8
POS Loan	Branch	0.65	9
	Call center	0.7	8
	Mobile App	0.47	10

accuracy with the Neural Network prediction model. Also, we experiment with a different number of the best cluster count for each prediction model to find the best product channel. Based on results, clustering with Neural Network prediction results shows that with 0.88 silhouette coefficient and 10 clusters, the best result of product-channel is achieved.

Profit/cost analysis is a way to find out how changes in variable and fixed costs affect a firm's profit. Banks can use profit/cost analysis to see how units with different costs can be more profitable. In other words, which unit with a

Table (4): Results of applying Neural Network for checking product-channel			
Product category	Channel category	Average of silhouette coefficient	Number of Clusters
Current Account	Branch	0.66	8
	Call center	0.45	3
	Mobile App	0.50	5
Deposit Account	Branch	0.78	10
	Call center	0.75	8
	Mobile App	0.58	5
POS Loan	Branch	0.88	10
	Call center	0.64	5
	Mobile App	0.51	8

ower cost can cause more profit. Also, Profit/cost analysis can be conducted in order to measure the effect of applying an appropriate response model on total marketing cost decreasing.

profit/cost ratio is a critical factor for bank product marketing. Finding customers that will accept the promotion is not the only important factor, but maximizing profit and minimizing cost of promotion are also significant for banks. Therefore, we perform analysis on profit and cost constraints on our model-based method with Neural Network prediction and K-means clustering.

The profit of each product and the cost of each channel is shown in Table 5.

The highest silhouette coefficient which provides the highest profit values is obtained in Table 5. Therefore, the highest profit/cost rate is with 10 clusters. Note that Table 5. shows the results of profit/cost analysis for the best product (POS Loan) and channel (Branch) extracted from Neural Network prediction that is shown in Table 4. However, we get a 4.3 profit/cost rate with 840516 Rials profit of POS Loan product and 195520 Rials of Branch channel.

5- Conclusion

According to the main purpose of this research by applying this predictive model most proper products with suitable channels should be offered to each customer in the next direct marketing campaign. To this aim, for each new customer, based on the superior Neural Network model, it is decided whether to buy the offered product or not. In the next step, based only on the positive response the customer with a "yes" response will experiment in each of the nine k-means models to find the best cluster with the least distance from the center of the cluster. Trough recognizing the appropriate cluster related to each product-channel category.

Table (5): Results of applying profit/cost analysis for best channel product results

Number of Clutsters	silhouette coefficient	Profit (Rial)	Cost (Rial)	Profit/cost
1	0.66	805325	220365	3.65
2	0.45	752776	202584	3.71
3	0.50	780550	208856	3.73
4	0.64	798633	219504	3.63
5	0.81	832265	194218	4.28
6	0.73	815598	195887	4.16
7	0.45	740550	200740	3.68
8	0.64	812364	219550	3.70
9	0.51	775412	210607	3.68
10	0.88	840516	195520	4.30

As a result, the best product offered via the most effective channel with the highest probability of a positive response will be conducted.
Moreover, for a “No” response it is assumed that no product purchase will be made in the future, so a product offer will not be made.
Consequently, by using this model we are expected to achieve a higher response rate by optimizing products and channels for each customer. It means we will have a more effective direct marketing campaign and eventually, marketing costs will be reduced. Total the return on investment of the company will be increased.
Now, discuss future research guidelines for investigating the direct marketing process and data analysis.
Investigators are encouraged to further test and validate our findings in different cultural and industrial contexts (e.g., finance, property, music, and sport).
Future research could be investigating other aspects of consumer purchase behavior, refining this measure, and investigating the intermediate stages of the direct marketing response, such as the opening and keeping rates of direct marketing tools.
Studies that focus on how to apply data mining techniques for direct marketing purposes for acquiring new customers would complement our study.
This model may be enhanced in the future by adding new attributes related to the customer’s behavior to interpret the customer’s behavior more deeply.
Further studies can apply the proposed LRFMP model as an extended model to the RFM concept.
This study focused on Random Forest, Naïve Bayes, and Neural Network techniques for building predictive models. Applying other classification algorithms and comparing their performances are suggested for future studies.
The model can be tested on some datasets for a longer period and various campaigns to explore the effect of data in different seasons. examining the possibilities of the different methods as a kind of recommendation method would be interesting when predicting customer behavior.

References

54-Gordan, M., Sabbagh-Yazdi, S. R., Ismail, Z., Ghaedi, K., Carroll, P., McCrum, D., & Samali, B. (2022). State-of-the-art review on advancements of data mining in structural health monitoring. *Measurement*, *193*, 110939.

55-Iosifidis, V., Papadopoulos, S., Rosenhahn, B., & Ntoutsi, E. (2023). AdaCC: cumulative cost-sensitive boosting for imbalanced classification. *Knowledge and Information Systems*, *65*(2), 789-826.

56-Duman, E. (2023). Social media analytical CRM: a case study in a bank. *Journal of Intelligent & Fuzzy Systems*, (Preprint), 1-12.

57-Kolarovszki, P., Tengler, J., & Majeráková, M. (2016). The new model of customer segmentation in postal enterprises. *Procedia-Social and Behavioral Sciences*, *230*, 121-127.

58-Bahari, T. F., & Elayidom, M. S. (2015). An efficient CRM-data mining framework for the prediction of customer behaviour. *Procedia computer science*, *46*, 725-731.

59-Miguéis, V. L., Camanho, A. S., & Borges, J. (2017). Predicting direct marketing response in banking: comparison of class imbalance methods. *Service Business*, *11*, 831-849.

60-Almana, A. M., Aksoy, M. S., & Alzahrani, R. (2014). A survey on data mining techniques in customer churn analysis for telecom industry. *International Journal of Engineering Research and Applications*, *4*(5), 165-171.

61-Khalili-Damghani, K., Abdi, F., & Abolmakarem, S. (2018). Hybrid soft computing approach based on clustering, rule mining, and decision tree analysis for customer segmentation problem: Real case of customer-centric industries. *Applied Soft Computing*, *73*, 816-828.

62-Sing'oei, L., & Wang, J. (2013). Data mining framework for direct marketing: A case study of bank marketing. *International Journal of Computer Science Issues (IJCSI)*, *10*(2 Part 2), 198.

63-Khajvand, M., Zolfaghar, K., Ashoori, S., & Alizadeh, S. (2011). Estimating customer lifetime value based on RFM analysis of customer purchase behavior: Case study. *Procedia computer science*, *3*, 57-63.

64-Özkan, M. B. (2014). *Data mining-based power generation forecast at wind power plants* (Master's thesis, Middle East Technical University).

65-Heinermann, J. P. (2016). *Wind power prediction with machine learning ensembles* (Doctoral dissertation, Universität Oldenburg).

66-Nachev, A., & Hogan, M. (2014). Application of multilayer perceptrons for response modeling. In *Proceedings on the International Conference on Artificial Intelligence (ICAI)* (p. 1). The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp).

67-Ngai, E. W., Xiu, L., & Chau, D. C. (2009). Application of data mining techniques in customer relationship management: A literature review and classification. *Expert systems with applications*, *36*(2),

2592-2602.
68-Cohen, M. D. (2004). Exploiting response models—optimizing cross-sell and up-sell opportunities in banking. *Information Systems*, *29*(4), 327-341.
69-Chiu, C. (2002). A case-based customer classification approach for direct marketing. *Expert systems with Applications*, *22*(2), 163-168.
70-Crone, S. F., Lessmann, S., & Stahlbock, R. (2006). The impact of preprocessing on data mining: An evaluation of classifier sensitivity in direct marketing. *European Journal of Operational Research*, *173*(3), 781-800.
71-Coussement, K., & Buckinx, W. (2011). A probability-mapping algorithm for calibrating the posterior probabilities: A direct marketing application. *European Journal of Operational Research*, *214*(3), 732-738.
72-Chun, Y. H. (2012). Monte Carlo analysis of estimation methods for the prediction of customer response patterns in direct marketing. *European Journal of Operational Research*, *217*(3), 673-678.
73-Aeron, H., Kumar, A., & Janakiraman, M. (2010). Application of data mining techniques for customer lifetime value parameters: a review. *International Journal of Business Information Systems*, *6*(4), 514-529.
74-Gupta, A., & Gupta, G. (2019). Comparative study of random forest and neural network for prediction in direct marketing. In *Applications of Artificial Intelligence Techniques in Engineering: SIGMA 2018, Volume 2* (pp. 401-410). Springer Singapore.
75-Karim, M., & Rahman, R. M. (2013). Decision tree and naive bayes algorithm for classification and generation of actionable knowledge for direct marketing.
76-Kaefer, F., Heilman, C. M., & Ramenofsky, S. D. (2005). A neural network application to consumer classification to improve the timing of direct marketing activities. *Computers & Operations Research*, *32*(10), 2595-2615.
77-Anitha, P., & Patil, M. M. (2022). RFM model for customer purchase behavior using K-Means algorithm. *Journal of King Saud University-Computer and Information Sciences*, *34*(5), 1785-1792.
78-Zaharia, M. (2016). *An architecture for fast and general data processing on large clusters*. Morgan & Claypool