Designing a forecasting model to identify cross-selling opportunities using data mining techniques in insurance companies

Abstract

The Iranian insurance industry is one of the economic leverage of the government, which, along with the Central Bank, plays an essential role in economic development. One of the major concerns of the insurance industry is the development of sales in companies, and one of the most effective ways to develop sales in a business organization is cross-selling. This increases the customer more tied with the organization, and it will cost much less than acquiring new customers for the business, so the profitability of the organization will also increase. The main purpose of this research is to design a forecasting model using data mining techniques, with the help of which we can first identify potential customers of our target product and then offer them a marketing proposal to buy our product.

The insurance product that we focused on was life insurance because its sales are lower than other insurance products and it has a good profit for insurance organizations. Therefore, in this study, first important indicators for identifying a life insurance customer were identified through a literature review and then interviews with insurance industry experts, and then using the XGBoost classification algorithm, the forecasting model was designed, trained, and evaluated through which we can identify potential life insurance customers among the property insurance clients of the insurance company (Vehicle Insurance) and offer them to buy life insurance.

Keywords: *cross-selling, data mining, life insurance.*

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Introduction

There are two ways to develop organizational sales in an industry. The first way is to develop sales by acquiring new customers and the second way is to develop sales by focusing on existing customers.

Since the cost of customer acquisition is increasing day by day and customer acquisition is becoming more expensive for businesses, it makes more sense for companies to focus on their existing customers and expand their sales plans by increasing Customer Lifetime Value (CLV). Customer lifetime value is the amount of net profit that a business can earn from a customer during the customer's relationship with the company. Data from various businesses show that the second way, focusing on existing customers, is a much more effective strategy for achieving sustainable and predictable revenue. Studies show that 44% of companies spend more time and money on acquisitioning new customers, while only 16% of businesses focus on their existing customers. So businesses are oblivious to their current customers. Marketing literature also mentions that customer acquisition for businesses costs 5 times as much as retaining existing customers.

In this regard, there are two ways to increase the Customer lifetime value. The first is by increasing the sales volume to a customer of one product (Upselling) and the second is by selling several different products to a customer or the same cross-selling.

Therefore, it can be said that cross-selling includes the sale of products other than products that the customer has already purchased from the company.(Kamakura, W.A.2008) These two tactics, which are the most basic parts of customer development in customer relationship management, (Kamakura, W.A.2008) and (Xiu and Chau, 2009) are considered win-win methods because, in addition to creating satisfaction and a sense of loyalty in the customer, they also bring maximum revenue to the company. Studies show that cross-selling response rates are 2 to 5 times higher than other marketing methods. (Andrews. 2017). Therefore, these two methods can help the organization to increase the customer lifetime cycle, improve the organization's relationship with the customer and also reduce the customer loss rate. (Kamkura, 2008; Prinzie and Van den Poel, 2006).

In this study, we intend to identify potential customers of life insurance using data mining techniques among the car insurance customers of the insurance company and offer a marketing offer to buy life insurance to this group of current customers of the company to increase the retention rate of the company's customers and reduce marketing costs due to the selection of target customers with high potential to buy the product.

The importance of the subject

Over the past few decades, businesses have been developing approaches to customer relationship management to develop cross-selling of their products.

In the insurance industry, due to the low penetration rate and increasing competitiveness, and the growth in the number of insurance companies, increasing sales by customer acquisition will lead to more costs day by day. Insurance companies have to focus their sales development policy more on increasing the lifetime value of their current customers through bulk sales or cross-selling. (McKinsey and Company, 2013).

In the insurance industry, increasing sales volume occurs by adding insurance coverage as a type of insurance policy for the current customer. In cross-selling with the sale of a new policy and in addition to the customer's previous insurance, sales development will occur significantly. Therefore, a slight increase in cross-selling to customers can create a significant increase in the total revenue of a business. (McKinsey and Company, 2013).

In Iran, due to the mandatory nature of car insurance, insurance companies have easy access to a large potential target market for cross-selling other insurance products, and due to the disadvantageous of the car insurance industry, to increase The value of the customer's longevity, the need to sell profitable products such as life insurance along with car insurance is essential. The following table shows a comparison between third-party insurance and life insurance. (Insurance Industry Statistical Yearbook. 2018).

Table1-Comparison between the third party and life insurance in the Iran insurance industry (2018)

Scale	Third-party insurance	life insurance
Market volume (million Rial)	205,344.3	86,330.2
Market share	40%	29.7%
Loss Ratio	107%	48.9%
Number of the Insurance policy issued	22,925,317	2,071,781

As can be seen in the table above, in the third party field, the market share is 40%, which can be said that about half of the country's insurance market belongs to this insurance field, and also the loss ratio in this field is 107%, which indicates a high amount of losses Paid compare to the premium in the field of third party insurance. Therefore, this field of insurance, with a very large market volume and very high losses, as well as being mandatory, is a product that insurance companies are forced to export despite being unprofitable. Therefore, insurance companies must proceed from the sale of other insurance products, such as life, which have a low loss ratio (48.9%) to earn profits and compensation for losses from third parties. Meanwhile, the field of life insurance, although it has a very good potential for profitability for insurance companies, has a relatively small market share (2 million life insurance policies vs. 22 million third-party insurance policies), and insurance companies focusing on this field can increase profits and their market share. Also, the cross-selling rate at best in insurance companies is less than 10% (between the third party field and the car insurance).

To develop sales in the insurance industry, there is no place in the marketing and insurance literature for examining the acceptance of life insurance offered by a property insurance customer in an insurance company. Therefore, in the present study, we tried to fill this gap and use the data mining methods to create a forecasting model to help identify insurance company customers who are prone to buy life insurance before marketing campaigns and Investing in a specific target community.

Literature Review

In this study we provide the whole literature review in table 2 which includes different variables for each research. All these researches used cross-selling and data-mining technique.

Table 2- A review of articles in similar research fields

Extracted index	Year of publication	authors	Article name	No
• Insured age • Insured gender • Number of loans requested by the insured • Whether or not the insured has already repurchased an insurance policy • Number of insurance products purchased by an insured • The duration of the customer relationship with the organization • Number of complaints filed by an insured	2018	Mau, S., Pletikosa, I., & Wagner, J	Forecasting the next likely purchase events of insurance customers	1

• Insured age • Province of the insured place of residence • The number of insurance premiums paid • Number of insurance products purchased by an insured • Type of customer communication channel with the organization	2018	Staudt, Y., and Wagner, J	What policyholder and contract features determine the evolution of non-life insurance customer relationships?–A case study analysis.	2
• Insured age, gender, marital status, occupation • Province of the insured place of residence • Pay insurance premiums on time • premiums monthly installments • How long it takes the insurer to settle its premium • Compensation paid on condition of death of the insured	2017	Rahman, M. S., Arefin, K. Z., Masud, S., Sultana, S., and Rahman, R. M	Analyzing Life Insurance Data with Different Classification Techniques for Customers' Behavior Analysis	3
• Age of the insured, gender, job, income • Height and weight insured • Insured province of residence	2017	Kaewkiriya, T	Framework for prediction of life insurance customers based on multi-algorithms	4
• Insured age, income, social class • Distance of the insured place of residence with the branches or representative of the insurance company • Duration of customer relationship with the organization • The amount of insured travel to the insurance company	2016	Krishna, G. J., and Ravi, V	Evolutionary computing applied to customer relationship management: A survey	5
• Age of the insured • Insured gender • Insured annual income • The number of insurance premiums paid	2017	Estrella-Ramón, A	behavior	6
• Age of the insurer • Insured gender • Insured annual income • The insurance policy issued is individual or group	2018	Chiang, W. Y.	Identifying high-value airlines customers for strategies of online marketing systems	7
• Number of insured children • Insured job • Insured annual income	2016	Chen, Z. Y., Fan, Z. P., and Sun, M	A multi-kernel support tensor machine for classification with multitype multiway data and an application to cross-selling recommendations.	8

• Payment of insurance premiums is made in a lump sum or monthly installments • Life insurance policies that have more than one beneficiary	2017	Quijano-Sanchez, L., and Liberatore, F	The BIG CHASE: A decision support system for client acquisition applied to financial networks	9

Research Methods

The purpose of this study is to investigate the application of data mining techniques in sales development in the insurance company to improve the performance of this organization, so it can be said that the present study is considered practical in terms of purpose; Because in this study, a set of valid (reliable) and systematic rules and tools will be used to investigate the events, discover the unknowns, and also to find solutions to problems. From the perspective of the research environment, it is descriptive; because the researcher cannot manipulate the data, he only works with it as an observer. Because this study explores different patterns, it is in the realm of predictive and causal research, and in the sense that this study uses field tools to collect data, it is survey research.

The research process is shown in figure 1:

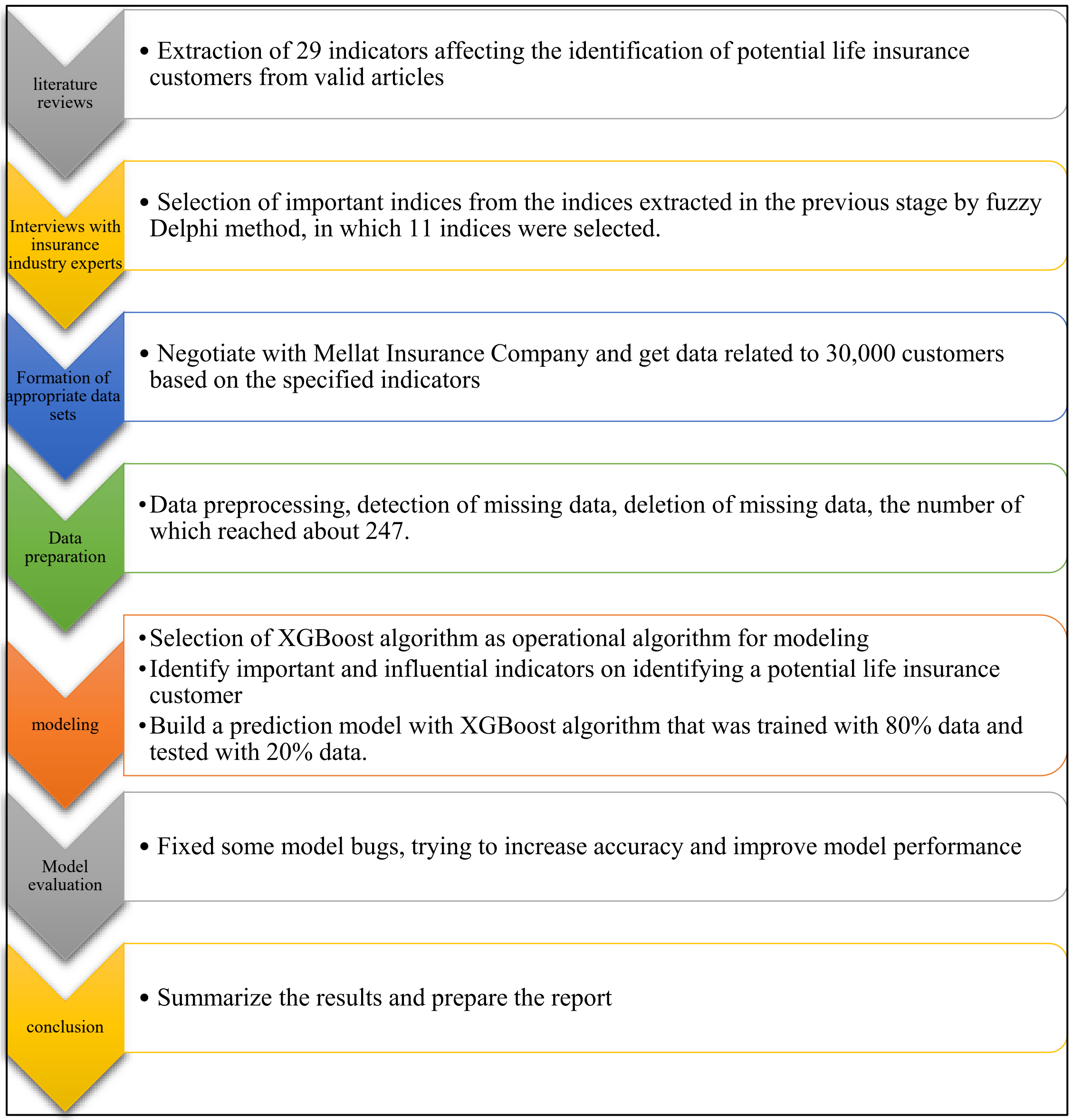

Figure 1 General research process

Data Mining (Crisp Methodology)

Implementing a data mining project involves the following steps:

1. Analysis: The most important activity in this phase is a deep understanding of the problem.
2. Design: The most important activity of this phase is to formulate the problem using key concepts.
3. Implement or maintain and improve.

There are several ways to implement data mining projects. One of the most powerful methods is the crisp method that is based on the experiences of those who do data mining projects in the real world.

Data mining operations

Operations in data mining can be classified into two main groups forecasting and descriptive methods. The present study is among the forecasting methods which use the values of some attributes to predict the value of a particular attribute. Methods of classification, regression, and detection of deviation are three methods of learning the model in data mining with predictive nature. Classification is a process in which by finding common features between a set of objects in the database, it divides them into different categories based on classification models (Saniei Abadeh and Mahmoudi, 2015). Types of classification methods include decision tree-based methods, neural networks, support vector machines, aggregation methods, and so on. In the following, we will explain Ensemble methods.

Ensemble Method

Some algorithms take a set of weak categories and combine their output to create the final category in a way that is more efficient than the individual categories used in the algorithm. Finally, it determines the category of unseen records (evaluation records) in the evaluation stage by combining the output of each of the small categories used. The following figure shows the general idea of these algorithms. If it is the original data set.

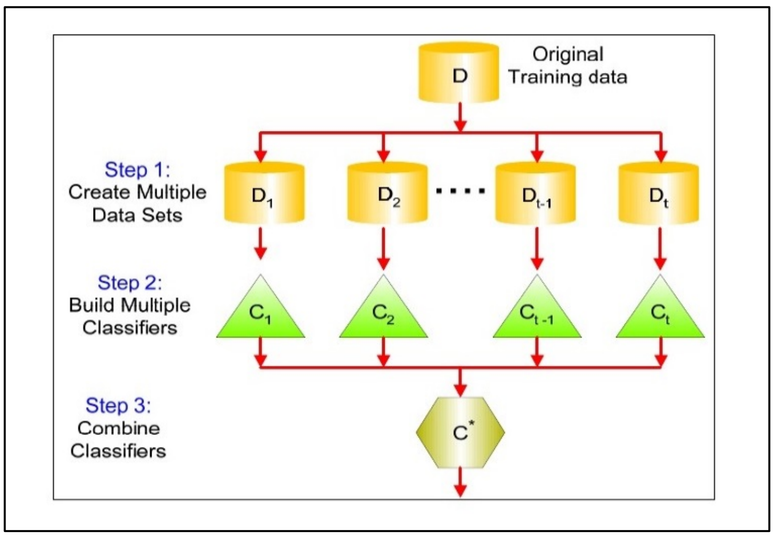

Figure 2 How Ensemble categories work

The use of the Ensemble Method reduces errors. When the output of several categories is combined to achieve the final output, the Classifier will overlap.

In an Ensemble Method, there are two ideas for combining categories, which are: Bagging and boosting.

Boosting algorithms come in a variety of forms, one of which is the XGBoost model.

XGBoost algorithm

(Chen and Gusterin, 2016) proposed the XGBoost algorithm as an alternative method for predicting response variables concerning other specified variables. The main idea of this algorithm is that XGBoost tries to create a certain number of Classification and regression trees one by one. Therefore, each of the subset decision trees is trained based on the remainder of the previous three. In other words, the new model first corrects the mistakes made by the previously trained tree, then predicts the result to correct its model each time and provide a more accurate result. (Pesantez-Narvaez, J., Guillen, M., and Alcañiz, M. 2019)

Data analysis and algorithm implementation

At first, by reviewing the literature, a total of 29 indicators were extracted from different articles, and after sorting in the form of a Delphi questionnaire, 5 experts from the Iranian insurance industry, all of whom were senior managers of different insurance companies, were presented with their opinions. Regarding the importance of indicators, it was obtained through a questionnaire. The result of the questionnaire can be seen in the table below.

Table 3 results of the fuzzy Delphi questionnaire related to the selection of important indicators

		Final non-fuzzy result	Middle limit of fuzzy Delphi	The lower limit of fuzzy Delphi	The upper limit of fuzzy number	Experts Questionnaire Code					Indices	
		SA=(UA+4*MA+LA)/6	MA	LA	UA	5	4	3	2	1	Index description	
	4.448345	4.448344573	4.42251686	4	5	4	5	4	4	5	Insured age	1
	3.767361	3.767360555	3.65104083	3	5	3	4	3	3	5	Gender of the insured	2
	1.654096	1.654096276	1.23114441	1	4	1	4	1	1	1	Gender of the beneficiary	3
	3.736395	3.736395141	3.85459271	2	5	4	4	2	4	5	Marital status of the insured	4
	3.51208	3.512080219	3.51812033	2	5	3	2	2	5	5	Number of children of the insured	5
	3.720708	3.720708002	3.831062	3	4	4	4	3	4	4	The job of an insured	6
	3.755939	3.755939413	3.63390912	3	5	5	3	4	4	3	The annual income of the insured	7
	2.886896	2.88689612	2.83034418	2	4	3	4	3	2	3	Level of education	8
	2.621481	2.621480545	2.43222082	1	5	5	3	1	3	2	The social class of the insured	9

	3.087268	3.087268111	3.13090217	1	5	2	4	1	4	5	Height and weight of the insured (conditions of the insurer in terms of health criteria)	10
	1.320763	1.320762942	1.23114441	1	2	2	2	1	1	1	Distance between the place of residence of the insured and the branches or agencies of the insurance company	11
	3.25486	3.254860487	3.13229073	3	4	4	3	3	3	3	Province of residence of the insured	12
	0.833333	2.110354001	1.915531	1	4	3	2	4	2	1	Number of loans requested by the insured	13
	3.664561	3.664560635	3.49684095	3	5	3	5	5	3	3	Payment on time	14
	3.25486	3.254860487	3.13229073	3	4	4	3	3	3	3	Premiums are paid in one lump sum or monthly installments	15
	3.687238	3.687238321	3.53085748	3	5	5	4	4	3	3	The number of insurance premiums paid	16
	4.415632	4.415632197	4.3734483	4	5	4	5	4	5	4	Type of life insurance	17
	3.651806	3.651805953	3.72770893	2	5	5	4	2	4	4	Additional coverage on the insurance policy	18
	1.954529	1.954528554	1.68179283	1	4	2	4	4	1	1	How long does take for the insurer to settle its premium	19

	1.166667	1.166666667	0	3	4	3	4	4	4		Compensation paid on condition of death of the insured	20
	0.833333	0.833333333	0	2	3	2	3	3	3		Whether or not the insured has repurchased the policy	21
	2.518372	2.518372207	2.52755831	1	4	3	4	1	4	2	Life insurance policies that have more than one benefit	22
	4.064203	4.064202699	4.09630405	3	5	3	5	5	4	4	Number of insurance products purchased by an insured	23
	4.077077	4.077077119	4.11561568	3	5	4	5	4	3	5	Whether the insurance policy is issued individually or in a group	24
	4.514875	4.514874506	4.52231176	4	5	4	5	5	5	4	Duration of customer relationship with the organization	25
	4.157156	4.15715605	4.23573407	3	5	4	5	3	4	5	Type of customer communication channel with the organization	26
	3.541209	3.541209066	3.5618136	2	5	5	4	3	2	5	Number of complaints filed with an insured	27
	3.203827	3.203827435	3.05574115	2	5	3	5	4	2	3	How did the insured, buy the insurance policy?	28
	1.814587	1.814586983	1.72188047	1	3	3	1	2	3	1	The amount of Commuting of the insured to the insurance company	29

The above table shows the analysis of the result of distributing the questionnaire to 5 industry experts using the fuzzy Delphi method. The steps for completing the questionnaire are as follows:

Step 1: Review the theoretical literature related to the topic.

Step 2: Selection of experts for the initial design of the questionnaire.

Step 3: Design a questionnaire with a Likert scale.

Step 4: Select experts between 10 and 50 people to complete the questionnaire.

Step 5: Completion of the questionnaire by selected experts.
Step 6: Perform calculations.
Step 7: Presenting selected indicators and analyze them.
The description of how the fuzzy Delphi questionnaire works is that after designing a questionnaire by several experts with different opinions, the questionnaire is distributed among the selected experts. In this study, there were 5 experts and specialists in the country's insurance industry. Consensus continues, and eventually, the most important indicators are selected.
Then, according to the scores given by the experts to the indicators, the indicators were accepted in terms of the importance of ranking and a total of 19 indicators, as a result of scaling by the fuzzy Delphi method, and our final data set was formed by table 3. These selected indicators are highlighted in green. After obtaining 19 main indicators, it entered into negotiations with one of the major companies in the Iranian insurance industry, and according to the restrictions related to the database of the mentioned insurance company, there was a database of customers with 10 indicators out of 19 indicators given to them. In addition, two other indicators, namely the sum insured of insurance policy and also the current status of the insurer (is the current customer of the insurance company or not) were added to the total indicators , and finally, a database with 13 indicators was formed.
The final dataset includes the following indicators:
1. Current status of the insured (whether the company is a current customer or not)
2. Insured job
3. Insured age
4. Insured gender
5. Insured education
6. Insured marriage status
7. Insured province of residence
8. Additional covers purchased such as sickness coverage, hospitalization coverage, and disability coverage
9. The number of years that a person has been a customer of the company
10. Premium payment method (lump sum, monthly, annual, etc.)
11. Sum Insured
12. Premium
13. Insured income

Therefore, the data used in this study is provided by a commercial insurance company in Iran and related to 2019. The database includes 30,000 customers in total who have purchased a car body insurance product from this insurance company during the last 10 years (2009 to 2019). Some of these customers, who number about 3,000 people, have bought a life insurance product from this insurance company at the same time and have two insurance products from this company at the same time.
Since there was a missing value in the database, we must pre-process the data before analyzing the data. Because the number of missing data in the database was small, we deleted them directly to keep the database tidy and clean. In the next step, to use the data mining algorithm, we have to convert the qualitative data into quantitative, so we encoded each of the qualitative sub-indices.
For example, the data related to 10 customers after coding the indicators are given in the table below.

Table 4. Sample data of 11 customers after coding the indicators

Customer ID	Status	Job	Age	Genre	Education	Married	Region	Extra coveraage1	Extra coverage2	Extra coverage3	Year	Payment method	Capital	Premium 1	Premium 2	Income
1	1	33	4	1	2	0	13	0	0	0	98	1	50000000	59892000	0	9
2	0	10	4	1	3	1	24	1	0	0	88	4	50000000	20284000	325000	6
3	0	37	5	0	1	1	18	0	0	0	93	1	60000000	23153000	389000	8

12	3	13	1	1	3	13	7
24396000	0	0	0	90580000	0	0	8928000
214000	64416000	8400000	49400000	25200000	15500000	6000000	19416000
50000000	3E+08	1E+08	3E+08	1.2E+08	2.5E+08	1.5E+08	50000000
4	5	2	1	2	2	4	4
98	93	98	89	89	92	93	98
1	1	0	0	1	0	1	1
0	0	0	1	0	0	1	0
1	0	1	1	0	1	0	0
14	23	20	1	12	17	1	0
0	1	1	1	0	0	0	1
1	1	2	4	2	3	4	3
1	1	1	1	1	0	0	1
1	5	4	4	1	5	3	3
7	21	11	10	2	29	34	9
1	1	1	0	1	0	1	1
4	5	6	7	8	9	10	11

Finally, 29,972 customers and 13 related indicators formed our final database.

Implementation

The XGBoost algorithm can tell us which independent variables are more important in determining whether a customer will accept our marketing offer.

5 variables that are most important to us are education level, age, income, number of years that the insurer has been in contact with the organization, and also the province of residence. The variable of education is the most important because the level of insurance awareness and its importance is higher among people with higher education. Therefore, insurance companies should conduct a study on their various customers according to their level of education, and this research can be a good source for customer relationship management (CRM) units as well as technical units of insurance companies.

In this study, we used 80% of the data set to teach the model and 20% of the data set to test the model. The result of training and evaluation of the model and consequently the accuracy of the model made using the XGBoost algorithm can be seen in the table below.

Table 4. The result of the performance of the designed model

```
[[6886    0]
 [ 222  385]]
              precision    recall  f1-score   support

           0       0.97      1.00      0.98      6886
           1       1.00      0.63      0.78       607

    accuracy                           0.97      7493
   macro avg       0.98      0.82      0.88      7493
weighted avg       0.97      0.97      0.97      7493

0.9703723475243561
```

Result and Discussion

The prediction model used in this study shows that the most important variables that can be used to identify potential life insurance customers are education level, age, income, number of years that the insured has been associated with the organization, and also Province of the customer's residence. Therefore, it can be concluded that these 5 are the most important factors through which we can identify potential life insurance customers from among car body insurance customers.

Therefore, by identifying potential life insurance customers with the help of the forecasting model presented in the present study, customers who had previously purchased only one insurance policy from the company were more likely to leave and go to another insurance company, Now, with the marketing offer to buy life insurance, they own two insurance policies and their relationship with the company has increased compared to the past, Their dependence on the company has increased more than before, and since life insurance is a long-term insurance policy, the possibility of the customer leaving the insurance company will have both financial and emotional costs for him, because after a few years of contact with a company is harder for a customer to leave.

Conclusion

In the present study, we went to the car body insurance customers of an insurance company and tried to identify potential life insurance customers among them. To do this, we studied the literature and extracted 29 indicators that were crucial for a life insurance customer. Then, using the Delphi questionnaire, we interviewed insurance industry experts and as a result of these interviews, we selected 11 basic indicators. We put 30,000 car body insurance customers, including nearly 2,900 people with life insurance, in a data set, for each of which these 11 indicators were assigned. On the advice of industry experts, we added two other indicators to our data set, which were insurance capital and customer status. So we got 13 indicators for 30,000 customers.

We then pre-processed the data, of which 246 were deleted and 29,754 remained. Then they were coded and we categorized them using the XGBoost algorithm. We identified important indicators and prepared a high-precision forecast model that can determine whether a person will accept life insurance offers from us by entering customer data. This avoids the waste of marketing costs and we know exactly which group of our current customers to offer to buy life insurance.

Our prediction model in this research was made using the XGBoost algorithm and we presented the results shown in the table below by presenting the experimental section. Here again, the accuracy of the prediction model used in the research is 97%, which is a very good accuracy among studies in this field.

Limitations

- A lot of data is needed to get accurate results. Although there is no defined rule for determining the number of data required for different problems, the number of data required depends on the training algorithm, the complexity of the problem, and the disturbances in the data. And due to the lack of access to more data, this issue is considered one of the limitations of the research.
- Due to the lack of access to other effective data such as compensation in the background of each customer, etc., it has not been possible to use them as an independent variable.
- To use algorithms such as XGBoost, since they are formed through training and learning from previous data, in practical work, it is necessary to constantly retrain and update the forecasting model to include new changes and more accurate results.

Policy implications

- Companies, especially insurance companies, should strive to enrich their database as much as possible and receive more information from their customers so that they can carry out more and more complete projects in the field of data mining, marketing, and customer relationship management.
- The forms provided to customers to complete as insurance policy forms should be reviewed and the information that is necessary to study the customers

and will be useful in projects such as the present study should be included in the forms in the form of questions to help enrich the insurance company's database.

- Insurance companies hold life insurance sales festivals for the body insurance customers of the company and allocate prizes for the representatives who cross-sell these two insurance products so that the cross-selling can be done purposefully in the insurance company.

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