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Predicting the Level of Salesperson's Performance in Encouraging Customers to Use Appropriate Shopping Strategies in Sports Clubs

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ABSTRACT

The customers of a sports club are among the important pillars of its survival. In this paper, with the help of data mining and machine learning methods, a framework is presented to predict the level of effectiveness of salespersons' performance to encourage customers of clubs to choose an appropriate shopping strategy. This framework uses a set of data on the topics of idealized influence behavior, inspirational motivation behavior, intellectual stimulation behavior, individualized consideration behavior, and smart selling behavior, as its inputs. In the proposed framework, first, the data is refined using the Pearson criterion, and invaluable questions/features are removed from the data set. There are five levels of effectiveness in our questionnaire, and each of them has a different number of records in the data set. So, in the second step, the data set is balanced using repetition, SMOTE, and Int-SMOTE methods. The Int-SMOTE balancing method is introduced in this paper for the first time. It is a SMOTE method with integer outputs. Finally, using different classifiers, we predict the level of effectiveness of salesperson's behaviors in encouraging customers. Evaluating the models indicates that the different models have been able to correctly identify the level of effectiveness of salesperson's behaviors between 76.16% to 96.82%. Also, we confirm our findings about the effects of different salesperson's behavior to encourage customers using several other published papers.

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Introduction

Today, environmental changes are happening rapidly in all areas. In these extensive developments, organizations have not been without changes. In this regard, changes in behavior, technology, and management technologies have greatly complicated sales environments (Sheth and Sharma, 2008). One of the most important goals of organizations has always been to make a profit by improving sales performance, which is not possible without considering the needs and expectations of customers and close communication with them. In other words, identifying the factors affecting sales is very important. These factors include salespersons and their performance in organizations and stores. Therefore, identifying and improving the situation of factors affecting the sales performance of sellers is one of the main concerns facing companies (Krishnan et al, 2002). Due to the complexity of the sales process, the seller must have specific knowledge, skills, motivation, and competencies. Sales are the result of a special interaction between the seller and the potential customer and face-to-face contact with him. The outcome of these interactions and behaviors depends on how the two parties see each other and react to each other. Successful salespersons are those who adapt their communication styles to better engage with customers. Therefore, to communicate more effectively, salespersons need to understand the motivation and attitude of the customers who receive their messages (Dyreen, 2008). Therefore, it is the sellers who influence the customer and their followers, with their sales performance.

Effective sales behaviors include customer acceptance, the ability to influence them, the use of influence techniques, and the control of sales interactions (Richard and Reid, 1994). On the other hand, due to the importance of salesperson performance in attracting customers and establishing long-term relationships with customers, as well as affecting the growth, survival, effectiveness, and success of the company, the effect of behaviors on salesperson performance, has been paid more attention by businesses and academia (Verbeke et al., 2011). Interactive sales behavior can be in the form of idealized influence behavior, inspirational motivation behavior, intellectual stimulation behavior, individualized consideration behavior, and smart selling behavior (Dyreen, 2008):

- **Idealized influence behavior** includes charismatic behavioral characteristics of the seller such as a high level of trust, presentation, great talent, freedom from internal contradictions, and firm belief in goals.
- **Inspirational motivation behavior** refers to the seller's behaviors and appropriate choices that inspire the customer and make the customer committed and loyal.
- **Intellectual stimulation behavior** is behavior that gives rise to ideas and values. In this type of behavior, sellers help to develop solutions, to solve the challenges ahead. The proper delivery of the message by the seller, understanding of the seller's speech, and attention to the needs of customers are among these behaviors.
- **Individualized consideration behavior** describes the role and support of the seller. The salesperson, like a trainer and mentor, helps them to gain weight by all means. Understands customers' concerns and communicates with them.
- **Smart selling behavior** is appropriate behavior that the seller shows when adapting to the customer and the existing conditions. Not insisting on buying a product, adapting to the customer, paying attention to the customer, and being patient with him are among these behaviors.

On the other hand, sales performance means the result of customer interaction and the impact on the seller, which results in the sales process (Jazayeri, 2014). Sale is a two-way road between the customer and the seller. So, it is more effective than one-way channels such as advertising. Product sales methods are a kind of relationship with the customer, and this concept in the new millennium is a long-term and lasting relationship with the customer, most of which is the responsibility of the salesperson (Park and Deitz, 2006).

Developing the capabilities of vendors can lead to the growth and profitability of companies. That is why it was stated that it is very important and necessary to identify and improve the status of the agents influencing the sales performance of the debtors. Major research in the field of sales performance has focused on the individual-level patterns of the salesperson such as personality traits, attitudes, cognitive capabilities, and customer-oriented approach. (Dwayne et al., 2013) shows increasing attention to categories such as the emotional and perceptual competence of customers by salespersons can play an effective role in improving sales performance and increasing customer satisfaction and loyalty. In this regard, (Bayaa et al., 2009) show salespersons' personality traits such as demographic information, psychological characteristics, backgrounds, and technical-specialized capabilities have a great impact on sales performance. It suggests to strengthen sales and improve them, we need training courses for sellers. (Fletcher et al, 2007) states there is a negative and positive relationship between the competitive atmosphere and sense of competence with sales performance, respectively. Findings in the research of (Singh et al, 2021) show customer orientation of salespersons strongly affects customer relationship building and also improves customer performance. In the study of (Terho et al., 2015), customer-oriented behaviors and value-based behaviors are found to be effective in improving and increasing sales behaviors and strengthening sales performance. (Lussier and Hartmann, 2017) found psychological stimuli have a positive effect on customer-oriented behaviors and customer-oriented behavior plays a mediating role in the relationship between psychological stimuli and salesperson performance. (Rosendo-Ríos and Martín-Dávila, 2015) found that vendor-customer orientation has a positive and significant effect on salesperson performance. Miao & Wang (2016) shows operational interactions between seller and buyer in a customer-oriented environment affect the creative performance of the seller. (Kim et al., 2017) found emotional work affects employee sales performance.

On the other hand, Nowadays, most countries are on the path of industrialization and this path is developing every day, so organizations should look for the most up-to-date strategies such as sales strategies and optimal use of salespersons to increase sales performance, which in itself leads to the development of organizations. Although (Akbari and Moradipour, 2021) and (Akbari et al., 2017) focus on the role of characteristics and promotion efforts of salespersons, we cannot find a study working on the prediction of the level of this performance. In this regard, the purpose of this study is to predict the level of salesperson's performance to encourage customers to use appropriate shopping strategies in sports clubs, using data mining methods. In other words, our goal in this paper is to determine how much salespersons can help them choose the right purchase strategies from a customer's point of view. The importance of this research is that proper and informed purchase leads to an increase in the customer's willingness to continue buying from the organization. Therefore, by early discovering possible gaps in the interactive behaviors of the salespersons, organizations can take steps to cover them.

Data mining is the art of extracting new information from existing information. Modeling, discovering relationships, justifying phenomena, and predicting future outcomes are the most important parts of data mining. Although the beginning of data mining backs to 3 decades ago, the history of data mining in sports is a little over a decade. In 2010, the book (Schumacher et al., 2010) highlighted the use of data mining in various sports. In 2019, Springer published a new book, (Brefeld, 2019), on the use of machine learning techniques and data mining in sports analysis. Also, over the past years, various articles on the use of data mining in cases such as trade-in sports (Liao et al. 2009), win analysis in sports competitions (Pelechrinis and Evangelos, 2018), rapid analysis of inertial measurement units (Rojas-Valverde et al., 2019), analysis of performance parameters in sports Rock climbing (Huynh et al., 2018), prediction of sports injuries (Liu et al., 2018) and improving the quality of badminton training (Yang, 2018) have been published.

In this paper, we focus on presenting a framework for predicting the effectiveness of a salesperson's performance, using data mining techniques.

2. Methodology

The present applied and descriptive/correlational research was done using the technique of Data mining. To achieve the purpose of the research, first, we prepared a data set containing the answers of several customers of sports clubs in Arak City, Markazi province, Iran. Then, with the help of feature selection methods, we determine the most important questions that have a strong impact on determining the level of effectiveness of salespersons encouraging behaviors. We removed the other questions from the data set. There are five different levels of effectiveness in the questionnaire. Because of is a different number of records in each level in our study, in the intermediate stage, we balance the number of records. In this step, we propose Int-SMOTE, a new version of the SMOTE algorithm with modified output. Finally, using 12 different classifiers, we try to predict the level of effectiveness in a group of test records. To evaluate the accuracy of the classifiers, IBM SPSS Modeler 18 and MATLAB R2013 software have been used.

2.1 Sampling and Research Tools

first, all the clubs were divided into 5 geographical regions (north, south, east, west, and center of the city), and then, from each region, several clubs were randomly selected and a sample was selected from each club (convenience sampling method). At this stage, 300 questionnaires were distributed; 274 questionnaires were returned and 266 questionnaires were analyzed. Data were collected using a two-part questionnaire including the first part, including demographic characteristics such as gender, age, occupation, education, club type (public or private), club usage history (by year), club usage hours per week, shared customer percentage, and relationship life cycle. In the second part, the main questionnaire included 5 questions on idealized influence behaviors, 4 questions on inspirational motivation behaviors, 4 questions on intellectual stimulation behaviors, 5 questions on individualized consideration behaviors, and 5 questions on club smart selling behaviors. The second part is similar to the questionnaire by (Nemin et al., 2019). The last question, as a class label, is the question asked about the club's sales performance in encouraging customers to use appropriate shopping strategies. All 24 final questions have five possible answers: very low, low, medium, high, and very high. Later, we changed these answers to values 1 to 5 for ease of working with the tools. Also, answering all questions was mandatory. In this way, the data set has no null values, nor outlier data. The answer to the last question is also considered as determining the class of records. So there are a total of five different classes of opinions available. The information in this collection includes the answers of 266 people who referred to sports clubs in Arak. The content validity of the questionnaire was confirmed using the qualitative method by a group of experts (15 university faculty members and sports marketing researchers) to examine the wording and proper meaning of the items and check for any grammatical errors, and the quantitative method included convergent and divergent validity. For evaluating the reliability of the research questionnaire, Cronbach's alpha (All dimensions above 0.7) was used.

2.2 The Proposed Framework for Constructing Forecasting Models

In this section, we provide the details of the proposed framework to determine the performance of salespersons to encourage customers. Figure 1 shows the implementation diagram of the proposed framework. As shown in this figure, in short, the proposed model consists of four steps. Details of these steps are discussed as follows.

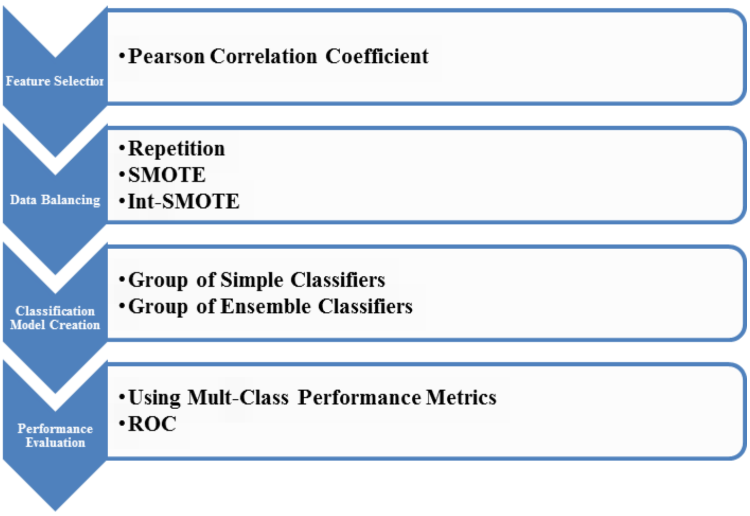

Figure 1. The proposed framework

2.2.1 Feature Selection

Feature selection is a function to select the best subset of features related to the class labels. This subset has the most positive effect on determining the class of a record. Feature selection reduces the running time of the algorithms. Also, in some cases, removing irrelevant features will improve the accuracy of the classifiers. So, we chose feature selection as the first step of the framework.

All the statistical population questions mentioned above, except the last one, are considered features of the data set used in this paper. The last question is about the class label.

To select the most important features of a collection, various solutions have been proposed in several papers. The used solution in this paper is using the Pearson criterion to determine the correlation of variables. This criterion is defined by Equation 1:

$$Corr\left(X,Y\right)=\frac{Cov\left(X,Y\right)}{\sigma_X\sigma_Y} \tag{1}$$

where *Cov* is the symbol of covariance of the values *X* and *Y*, and σ is the symbol of standard deviation. The value of the correlation coefficient indicates the intensity and weakness of the dependence of the two variables on each other and has a value range of -1 to +1. A positive correlation value means that as the value of one variable increases (decreases), the value of the other variable will also increase (decrease). On the other hand, the value of negative correlation means that as the value of one variable increases (decreases), the value of the second variable will decrease (increase). Also, the value of zero means that there is no relationship between the two variables. To select the top attributes, using the Pearson correlation criterion, we rank all attributes. Then we only select those attributes that have ranks above the α threshold and remove the rest.

2.2.2 Balancing

Balancing is one of the most important preprocessing steps in data sets where the number of records in different classes is not equal. The issue of imbalance in classes is raised in cases of cost-sensitive learning. In this case, the cost of not discovering minority class records can have adverse negative effects, the first effect of which is a noticeable decrease in class accuracy. To prevent this problem, four general approaches are considered: high sampling, low sampling, change of threshold code, and integrated methods (Han et al., 2011).

In the first approach, an attempt is made to increase the number of minority class records by duplicating records or constructing artificial records close to real ones. In the second approach, the procedure is reversed and an attempt is made to reduce the number of samples in the majority class, to provide a basis for equalizing the number of samples in different classes. It should be noted that this method, due to the reduction in the number of records, reduces the accuracy of classification learning and therefore is not used on small data sets. In the threshold change approach, instead of manipulating the data set, the threshold decision limits of the classifiers are considered. In other words, in this method, the modification of existing classifications is considered to comply with the conditions of unbalanced classes. This approach is also not very successful due to avoiding working with common classifiers. This is highlighted when we know that the performance of different classifiers in the face of different data sets varies. In other words, the superiority of a classifier when working with one data set is not a reason for its superiority over other data sets. In the last approach, a combination of data set manipulation and classification modification is considered.

Because of the negative effects of imbalanced data sets, we chose to balance as the second step of the framework. Since during data collection, the interviewers were selected randomly, the collected data was unbalanced. In this paper, we use the first approach to balance records. For this purpose, first, we calculate the total number of records of different classes, and then based on the number of records of the majority class, we determine an increased coefficient for the number of records of other classes. In this way, the number of records in different classes is relatively equal. Because the requested value is declared as a fractional coefficient, it cannot be expected that the number of records in the different classes will be exactly equal.

For balance, we use three methods in this paper. The first method used to balance the data is to replicate minority class records to a specified value. This method is one of the most basic methods of sampling style balancing. The second method we considered in this paper for over-sampling and creating artificial records of minority classes is SMOTE (Drost, 2002). In this method, with the help of records of a class, new artificial records with values close to reality are created and added to the data set. The SMOTE method is one of the most popular and widely used methods of balancing unbalanced data sets and has been used in several papers, e.g. (Torres et al., 2019), (Guo et al., 2019), (Fernández et al., 2018) and (Douzas et al., 2018). The important point in this method is that because the values are artificial and based on the values of the nearest neighbor records, the values of their fields will inevitably be decimal. Since the outputs of the questionnaire used in this paper are in integer form, in the third method, called Int-SMOTE, we modify the outputs of the SMOTE. For this purpose, inaccurate data are rounded to the nearest integer using the following function:

$$Int-SMOTE(x)=\begin{cases}\lceil x\rceil & if \quad x\geq\lceil x\rceil-0.5\\ \lfloor x\rfloor & else\end{cases} \tag{2}$$

2.2.3 Classification

Classification is the third step of the proposed framework. With the help of classifiers, efficient models can be created to predict the values of class labels in records. To perform classification, the data set must first be divided into two parts: the training set and the test set. There are several solutions to this, one of the most common of which is to allocate two-thirds of the existing data set to the training set and to assign other records to the test set. Here, we use this strategy. After separating the training and test sets, the classifier goes through the learning process with the help of the training set. After training, the accuracy of the trained classifier is evaluated using the test data set. Given that today different individual or ensemble classifiers are available, and on the other hand, each of these classifiers just works well in some data sets, in this paper, we use a set of different methods and their results have been compared with each other.

3. Research Findings

In this part, we present the results of the performance evaluation of the proposed framework. To do this, firstly we have a look at the performance criteria, that have been used in the evaluations. Then the results are reported. Finally, we review and confirm the interesting findings of the framework.

3.1 Evaluate the Performance of the Proposed Framework

Criteria and Tools for Evaluating the Efficiency of Multi-Class Predictor Models are presented as follows.

One of the common problems in existing data mining tools is their inability to extract performance information of models created for data sets with more than two classes. The problem presented here is a multi-class one. So, we need to use extended criteria for evaluating the performance of the proposed framework. To do this, it is first necessary to provide the following four basic definitions (Han et al., 2011):

- **True Positive (TP):** The number of positive records that have been correctly accepted by the positive class label classifier.
- **True Negative (TN):** The number of negative records that have been correctly accepted by the negative class tag classifier.
- **False Positive (FP):** The number of negative records that have been incorrectly accepted by the positive class tag class.
- **False Negative (FN):** The number of positive records that have been incorrectly accepted by the negative class tag class.

Based on these definitions, the following parameters are used as common parameters to evaluate the results of different classification methods (Han et al., 2011):

- **Classification accuracy**: The percentage of records that are properly classified in their class.
- **Error Rate:** The percentage of records that are incorrectly classified in a class other than their own.
- **Precision:** The percentage of records declared for a class that correctly belongs to that class.
- **Recall:** The percentage of all records in a class that is correctly classified in that class.
- **F-Measure:** The weighted harmonic average of two criteria of precision and recall.

Among the above parameters, classification accuracy and error rate indicate performance accuracy and classification error and are inversely related (increasing one is accompanied by decreasing the other). It is important to note that in unbalanced data sets, accuracy numbers and error rates may not necessarily indicate the positive or negative performance of a classifier. For example, in a medical data set that contains information about whether a person is sick or not, given that under normal circumstances the number of non-sick people is far greater than the number of sick people, then without the use of classification, we can introduce all people as non-sick people with high accuracy. In this case, however, finding sick people is especially important to us. To solve this problem, it is necessary to calculate the three parameters of precision, recall, and F-measure for data sets to determine the actual performance of the classifier. The precision parameter indicates what proportion of the elements declared as members of a class were members of that class. On the other hand, the recall parameter indicates what proportion of the elements that should be introduced as members of a class are introduced as members of that class. The F-measure is also a kind of indicator of the used class accuracy. The low value of this parameter indicates the high variance of the values of the data set properties concerning the class labels.

Since the models used in this paper are multi-class, it is not possible to use the common two-class evaluation equations for them. Therefore, we use evaluation equations presented in (Sokolova and Lapalme, 2009) to evaluate the results of the multi-class models. In multi-class models, two microscopic and macroscopic procedures are defined for this purpose. The difference between the two procedures is that in the microscopic model, the average of all sample values in different classes is used. However in the macroscopic model, the average values obtained for the classes are used. The source (Sokolova and Lapalme, 2009) formulates the above evaluation parameters as follows for a data set with L classes:

$$Average \quad Accuracy = \frac{\sum_{i=1}^{L} \frac{TP_i + TN_i}{TP_i + TN_i + FP_i + FN_i}}{L} \tag{3}$$

$$Error \quad Rate = \frac{\sum_{i=1}^{L} \frac{FP_i + FN_i}{TP_i + TN_i + FP_i + FN_i}}{L} \tag{4}$$

$$\Pr ecision_{\mu} = \frac{\sum_{i=1}^{L} TP_i}{\sum_{i=1}^{L} (TP_i + FP_i)} \tag{5}$$

$$\operatorname{Re} call_{\mu} = \frac{\sum_{i=1}^{L} TP_i}{\sum_{i=1}^{L} (TP_i + FN_i)} \tag{6}$$

$$FMeasure_{\mu} = \frac{(\beta^2 + 1) \times \Pr esicion_{\mu} \times \operatorname{Re} call_{\mu}}{\beta^2 \times \Pr esicion_{\mu} + \operatorname{Re} call_{\mu}} \tag{7}$$

$$\Pr ecision_{M} = \frac{\sum_{i=1}^{L} \frac{TP_i}{(TP_i + FP_i)}}{L} \tag{8}$$

$$\operatorname{Re} call_{M} = \frac{\sum_{i=1}^{L} \frac{TP_i}{(TP_i + FN_i)}}{L} \tag{9}$$

$$FMeasure_{M} = \frac{(\beta^2 + 1) \times \Pr esicion_{M} \times \operatorname{Re} call_{M}}{\beta^2 \times \Pr esicion_{M} + \operatorname{Re} call_{M}} \tag{10}$$

In the above equations, equations 5 to 7 are related to the macroscopic model, and equations 8 to 10 are related to the macroscopic model. Also, for calculating the F-measure, a value of one is usually considered for β, which is also called the F1-Measure. It should be noted that in the above equations, for each class, the correctness or incorrectness of a record belonging to that class must be calculated separately from other classes.

Given that the data used in this paper is unbalanced, the use of the Receiver Operating Characteristic Curve (ROC) is a useful option for demonstrating the performance of predictive models. This diagram shows the relationship between correctly recognizing class member records versus incorrectly recognizing records as members of other classes in a predictive model. Faster growth of the ROC chart means better and higher model performance. In this paper, we draw separate ROC diagrams for the data balancing and classification models.

Also, we have used IBM SPSS Modeler 18 and MATLAB R2013 to implement and evaluate the performance of the proposed framework.

3.2 Applying Feature Selection and Balancing Methods

By applying the attribute selection process with a value of α equal to 0.95, except for one case, all behavioral questions found the highest degrees of priority and remained in the final set. But out of the first 10 questions, only two questions, the customer share, and the relationship life cycle remained and the rest were removed.

Due to the imbalance of the data in the initial data set, we balanced this data according to the proposed framework, using duplicate records, SMOTE and Int-SMOTE. As shown in Figure 2, most of the primary data are in Class 4. We use tools within SPSS Modeler to balance records by repeating records. After balancing, the number of records in other classes has reached a number with a maximum difference of 5% from the number of Class 4 records, which is acceptable for balanced data sets. Due to the absence of SMOTE and Int-SMOTE algorithms in SPSS Modeler, we implemented them in MATLAB software and the results of its implementation were applied to the data set. In this case, due to the better controllability in MATLAB, the number of records of all classes is selected exactly equal to the number of Class 4 records.

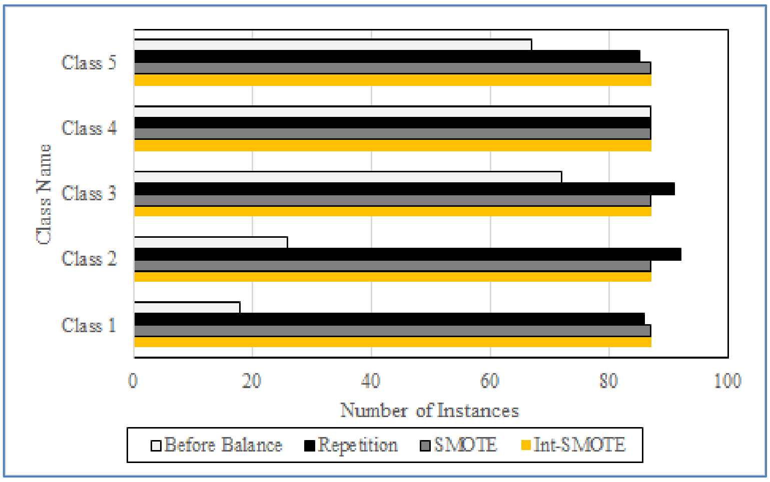

Figure 2. Number of records related to each class, before and after balancing

3.3 Evaluating the Performance of the Classifiers

To evaluate the performance of the prediction, we use 12 types of classifiers introduced in SPSS Modeler software. In addition to the Random Forest model (a well-known ensemble classifier), we used a specific Ensemble model of SPSS Modeler too. In this model, for the final inference, first, a poll is conducted from several classification clauses and then, based on the collective wisdom and the opinion of these classifications, the final opinion is announced. Ensemble models provide the best possible results in most cases due to the combination of different ideas. In the Ensemble model presented here, first, we applied 11 classifiers to the data set, and then the 5 classifier models with the highest accuracy on the data were selected for the final phase. The final result of the classification was selected and announced based on the majority vote of these 5 models.

Table 1 shows the different values of the performance evaluation parameters defined for the models created by the different classifiers by balancing with the repetition of records. As can be seen in this table, the best performance among the various classes is related to the Ensemble classification. The weakest performance among the various classifiers belongs to the Tree-AS classification. Although the CHAID algorithm is at the heart of this algorithm, because this algorithm is primarily designed for distributed environments, we see that it is significantly less efficient than the CHAID.

Table 2 shows the results obtained from different classifiers at the time of data balancing using the SMOTE algorithm. As mentioned earlier, this algorithm creates artificial record samples for balancing, and as a result, the type of their values is Real. The primary type of data in the data set is Integer. So, we changed it into Real to adapt to the new ones. Although working with artificial values seems to reduce the accuracy of classifiers in most cases, it should be noted that the results presented by balancing with the help of repetition (see Table 1) are not so fair, because a record may be seen in both the training set and the test set.

As can be seen in Table 2, the random trees classifier provided the best accuracy and error rates. This forest is an ensemble classification algorithm that obtains its final result based on averaging the results of several different random trees created on the data set. The construction of this classifier makes it suitable for over-fitting data in training sets and data sets with artificial values. Among other options, the LSVM and the Bayes network classifiers provide better precision, recall, and F1-measure values, due to the nature of working with real numbers in them. However, in both macroscopic recall and F1-measure, the best performance again belongs to the random trees classifier, which can be justified by the definition of these two parameters and the superiority of the average accuracy of this classifier for specific classes.

Table 3 shows the results obtained from different classifiers at the time of data balancing using the Int-SMOTE algorithm. Here, the SVM method has the highest accuracy and the lowest error, but in other parameters, the LSVM, the Bayes network, and random trees methods have a clear advantage over the other methods. These results are similar to the results in Table 2. Also, according to Table 3, in the Tree-AS and the Quest methods, the amount of precision measurement could not be calculated by the macro method. Therefore, the value of macro F1 measurement has not been calculated for them.

Table 1. Accuracy of different classifiers using repetition

Row #	Classifier	Average Accuracy	Error Rate	Micro			Marco		
				Precision	Recall	F1-Measure	Precision	Recall	F1-Measure
1	CHAID	0.9033	0.0967	0.7582	0.7582	0.7582	0.7565	0.7547	0.7556
2	C5.0	0.9190	0.0810	0.7974	0.7974	0.7974	0.7950	0.7721	0.7834
3	Random Trees	0.9477	0.0523	0.8693	0.8693	0.8693	0.8409	0.8396	0.8402
4	Tree-AS	0.7830	0.2170	0.4575	0.4575	0.4575	0.4575	0.4584	0.4580
5	C&R Tree	0.8543	0.1457	0.6358	0.6358	0.6358	0.6603	0.6299	0.6448
6	Neural Network	0.8824	0.1176	0.7059	0.7059	0.7059	0.7161	0.7131	0.7146
7	SVM	0.9582	0.0418	0.8954	0.8954	0.8954	0.8974	0.8932	0.8953
8	LSVM	0.9603	0.0397	0.9007	0.9007	0.9007	0.9094	0.8996	0.9044
9	Bayes Network	0.9320	0.0680	0.8686	0.7778	0.8207	0.8651	0.7768	0.8186
10	KNN	0.9060	0.0940	0.7651	0.7651	0.7651	0.7750	0.7645	0.7697
11	Quest	0.8107	0.1893	0.5267	0.5267	0.5267	0.4973	0.5182	0.5076
12	Ensemble	**0.9682**	**0.0318**	**0.9205**	**0.9205**	**0.9205**	**0.9197**	**0.9184**	**0.9190**
	Average	0.9021	0.0979	0.7584	0.7508	0.7544	0.7575	0.7449	0.7509

Table 2. Accuracy of different classifiers using SMOTE

Row #	Classifier	Average Accuracy	Error Rate	Micro			Macro		
				Precision	Recall	F1-Measure	Precision	Recall	F1-Measure
1	CHAID	0.8199	0.1801	0.5497	0.5497	0.5497	0.5951	0.5562	0.5750
2	C5.0	0.8543	0.1457	0.6358	0.6358	0.6358	0.7267	0.6182	0.6681
3	Random Trees	**0.9073**	**0.0927**	0.7682	0.7682	0.7682	0.7645	**0.7709**	**0.7677**
4	Tree-AS	0.7748	0.2252	0.4371	0.4371	0.4371	0.4371	0.4394	0.4382
5	C&R Tree	0.8066	0.1934	0.5166	0.5166	0.5166	0.5670	0.5365	0.5513
6	Neural Network	0.8437	0.1563	0.6571	0.4570	0.5391	0.6772	0.4500	0.5407
7	SVM	0.8914	0.1086	0.7285	0.7285	0.7285	0.8390	0.7166	0.7730
8	LSVM	0.8967	0.1033	0.7417	**0.7417**	**0.7417**	0.7840	0.7336	0.7579
9	Bayes Network	0.8901	0.1099	**0.8617**	0.5364	0.6612	**0.8926**	0.5226	0.6593
10	KNN	0.8755	0.1245	0.7714	0.5364	0.6328	0.7860	0.5184	0.6247
11	Quest	0.7695	0.2305	0.4238	0.4238	0.4238	0.4083	0.4387	0.4229
12	Ensemble	0.8834	0.1166	0.7086	0.7086	0.7086	0.8308	0.6951	0.7569
	Average	0.8455	0.1545	0.6406	0.5676	0.5970	0.6763	0.5616	0.6088

Table 3. Accuracy of different classifiers using Int-SMOTE

Row #	Classifier	Average Accuracy	Error Rate	Micro			Macro		
				Precision	Recall	F1-Measure	Precision	Recall	F1-Measure
1	CHAID	0.8755	0.1245	0.6887	0.6887	0.6887	0.6902	0.6983	0.6942
2	C5.0	0.9311	0.0689	0.8278	0.8278	0.8278	0.8264	0.8442	0.8352
3	Random Trees	0.9576	0.0424	0.8940	0.8940	0.8940	0.8944	**0.8994**	**0.8969**
4	Tree-AS	0.7616	0.2384	0.4040	0.4040	0.4040	0.0000	0.4270	0.0000
5	C&R Tree	0.8225	0.1775	0.5563	0.5563	0.5563	0.5671	0.5817	0.5743
6	Neural Network	0.8861	0.1139	0.7152	0.7152	0.7152	0.7312	0.7230	0.7271
7	SVM	**0.9709**	**0.0291**	0.9272	0.9272	0.9272	0.9357	0.9301	0.9329
8	LSVM	0.9470	0.0530	0.8675	**0.8675**	**0.8675**	0.8639	0.8712	0.8676
9	Bayes Network	0.9589	0.0411	**0.9167**	0.8742	0.8949	**0.9206**	0.8742	0.8968
10	KNN	0.9232	0.0768	0.8079	0.8079	0.8079	0.8049	0.8088	0.8068
11	Quest	0.7642	0.2358	0.4106	0.4106	0.4106	0.0000	0.4249	0.0000
12	Ensemble	0.9603	0.0397	0.9007	0.9007	0.9007	0.8976	0.9050	0.9013
	Average	0.8966	0.1034	0.7431	0.7359	0.7412	0.6777	0.7490	0.6778

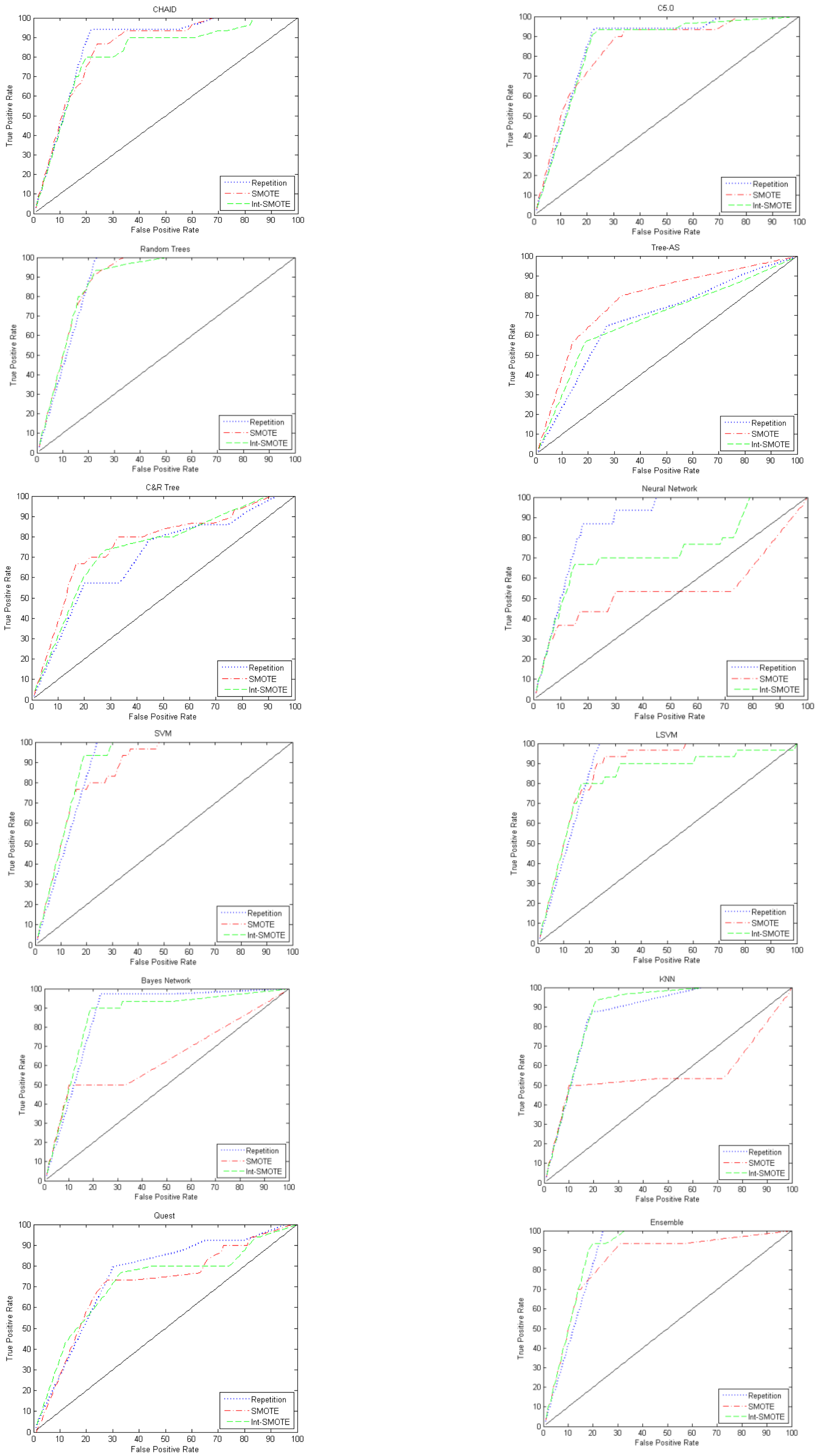

Figure 3. ROC diagrams of different classifiers using different balancing methods

Figure 3 shows the ROC diagram for each of the 12 classifiers. As can be seen in these images, the performance of the Int-SMOTE method is often competitive with the performance of the record repetition method. However, it does not the problem of justice in repeating records. On the other hand, the SMOTE method has better performance than the other two methods only with the help of the Tree-AS classifier. In contrast, this method, along with the neural networks, the KNN, and the Bayes network classifiers, has very poor performance compared to the rest. This performance weakness seems to be directly related to the decimal outputs on SMOTE, which has led to deviations from the predictions of different models.

3.4 Discussion

The results of this paper reveal interesting findings as follows.

3.4.1 Technical Implementation Findings

Upon the results, we find several interesting findings from a technical implementation point of view. The first one is that, during the feature selection step, eight of the ten first questions in the questionnaire were removed. The removed questions are the questionnaire number, gender, age, occupation, education, club type (public or private), club usage history (by year), and club usage hours per week. By looking at these items, we can see that special characteristics of customers, e.g. gender, age, occupation, and education, and clubs, e.g. club type, usage history, and usage hours, have no strong and decisive effects on salespersons' performance in sports clubs. However, conditions may change in other organizations.

On the other hand, the feature selection strategy selects the whole interactive questions. This finding shows that organizations should continuously work on training and increasing the communication and interaction capabilities of their employees, especially salespersons.

The third finding is that during data preprocessing, the balancing method has a significant effect on the final results. So, working in this area and using/applying different balancing methods may increase the performance of the predictors. Especially, the final evaluation results show that the ensemble classifiers stand among the best. However, the results of the SVM show that this data set has enough capabilities to be divided with high precision. This means that applying data balancing methods that work on boundaries possibly could have positive effects.

The last finding is related to the microscopic and macroscopic results. As can be seen in Tables 1-3, when we used repetition and Int-SMOTE, the average of the microscopic results was higher than the average of macroscopic results. This relation is vice-versus when using SMOTE. Although the differences between these values are small, this comparison shows that in this data set, by focusing on evaluating all sample values, instead of class values, we can obtain better results.

3.4.2 Model Confirmation

The accuracy of the classifiers is very important in discovering the effectiveness of the seller's behavior to encourage customers to choose an appropriate shopping strategy. We chose the methods with the highest accuracy for each balancing method in tables 1-3 and tried to analyze the most important parameters in the behavior of the seller that have the highest impact on the accuracy of the models. In balance with the help of repeating records, the best accuracy is related to the Ensemble model. In balance with the help of SMOTE, the best accuracy is related to the Random Trees model. In balance with the help of Int-SMOTE, the best accuracy is related to the SVM model. However, because this model does not provide specific information about the influencing parameters in the process of building the model, instead of this model, we chose the Ensemble and Random Trees models, which are standing in the second and third positions of the best accuracies. Table 4 shows the number of selected questions of different behavioral categories, during the feature selection process in different models.

As shown in Table 4, in the models with the highest detection accuracy with the help of different balancing methods, the individualized consideration behaviors have the most impact on the accuracy of the model. This point of view confirms that a salesperson is more successful in sales when he can quickly align himself with the customer's conditions, empathize, and speak the same language. In this way, by creating a mental connection with peace of mind with the customer, he assures the customer that he has well understood the customer's conditions from different points of view. After that, idealized influencing behaviors and smart selling have the highest number of effective questions in the models. After these three categories, the questions related to inspirational motivation behaviors are placed in fourth place with a little distance in terms of repetition in the decision-making process of the models. This is while, on the opposite point, questions related to intellectual stimulation behaviors have been far less welcomed and used in decision-making models with a significant distance. This finding shows that customers of sports clubs have the least desire for long explanations from salespeople to create a sense of satisfaction and persuasion in purchasing products and services.

Table 4. Number of selected behavioral questions using different balancing methods

Behavioral category	Balancing with repetition	Balancing with SMOTE	Balancing with Int-SMOTE (Ensemble)	Balancing with Int-SMOTE (Random Trees)	Total
Idealized Influence	1	2	3	6	12
Inspirational Motivation	2	1	2	6	11
Intellectual Stimulation	2	4	2	0	8
Individualized Considerations	2	7	2	3	14
Smart Selling	2	6	1	3	12
Total	9	20	10	18	

In terms of comparing these findings, by examining the opinions raised by the authors of the article (Nemin et al., 2019), the following points can be presented. After evaluating the interactive behaviors of salespeople with customers in the field of audio and video equipment, the authors (Nemin et al., 2019) examine the effects of each of the five behavioral areas on the final decision of customers. They respectively select idealized influence behaviors, smart selling, individualized considerations, and inspirational motivation as Influential factors. Also, the various evaluations show that the hypothesis of the influence of intellectual stimulation behaviors on the salesperson's performance is not acceptable. By comparing our results with the results of the article (Nemin et al., 2019), it can be seen that in the field of ranking the influence of idealized influence behaviors, smart selling, and inspirational motivation, both studies have a similar point of view. Also, the results of both studies confirm the fact that intellectual stimulation behaviors do not have a high position in affecting the final performance of the salesperson.

The only obvious difference in the results of these two articles refers to the issue of the place of individualized consideration behaviors. While the authors of (Nemin et al., 2019) put this in the third position, in this paper, the individual consideration behaviors are in the first place in the field of sports clubs. The most important reasons for this difference in these two areas are, respectively, the high speed of technological changes in the field of audio and video equipment compared to the field of sports and the creation of a long-term relationship between customers and sports clubs in comparison to short-term relationships in the sale of audio and video equipment.

Also, the research results are consistent with the findings of (Akbari and Moradipour, 2021) and (Terho et al., 2015) in the dimension of idealized influence behaviors (paying attention to the values and beliefs of the leader). Our findings are in line with those (Miao & Wang, 2016) in terms of interactive and customer-oriented salesperson behaviors. From another point of view, it can be said that the results of the research are consistent with the research of (Bayaa et al., 2009) in the field of individualized and specialized sales characteristics. In confirmation of the same results, (Singh et al, 2021) states customer communication skills affect sales performance. In other dimensions of seller's behaviors, (Lussier & Hartmann, 2017) state psychological stimuli have an effect on the customer-oriented behaviors of the seller, which is again somehow confirmed by the results of this research.

4. Conclusion

Modeling, evaluating, and understanding the behaviors of sports club customers is very important in the process of spending money and buying them from clubs. This article provides a general framework for processing and understanding the level of effectiveness of salespersons' encouraging behaviors for their customers, focusing on the club choosing the right sales strategies. For this purpose, in the first step, we use the Pearson criterion to reveal relevant questions and remove the rest from the process. Following the proposed framework, the data are balanced to match the number of records in different classes. This reduces the negative effects of the majority or minority classes on the accuracy and the final results of the classes. Finally, with the help of modified data and different classification methods, different predictors have been developed and their results have been evaluated. The evaluations indicate that among different classifiers, the performance of ensemble classifiers has been relatively better than the rest. Also, reviewing the structures of the top classifiers shows that individualized consideration behaviors, idealized influencing behaviors, and smart selling behaviors are the most effective behaviors in the accuracy of the classifiers and the performance of the salespersons. Increasing the domain of prediction models into fuzzy and deep learning models stands as our future work.

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