Optimal Approach for Predicting the Success Rate of Customer's Subscription in Telemarketing Dataset

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ABSTRACT

Direct marketing permits banks and diverse financial institutions concentrate on those customers who present the prospect of signing up to their products or services, marketing managers need to increase marketing stream in campaigning strategies, whereas organizations evade both expenses and business expansion. In determining the most significant factor and financial attribute that contributes to the customer's retention is critical to telemarketing strategies. We designed our experiments to improve the classification accuracy of the success rate of a customer's subscription in telemarketing dataset using Two Way T-Test feature selection and Adaboost classifier. The system incorporated modelling and development phases to validate the integrity and efficiency of the developed modelled and system. The data mining task deployed followed a procedural approach. The steps involve data collection of telemarketing data from UC Irvine (UCI) repository. We relate UCI machine learning repository to direct marketing activities (phone calls) of a Portuguese banking institution. The study result shows data filtering and the normalization which helps to remove outliers and inconsistent data. Our results also showed Adaboost classifier added to the success rate with a very high percentage classification accuracy of 98.7%, fast computation time and very low error rate 0.0132743.

Keywords— Telemarketing, Data mining, Data Classification

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1. INTRODUCTION

The high account of development in the banking sector is result of the basic but crucial service for an economy to enable significant support in the opportunity for providing research resources. Overtime, cutting edge products such as the credit card and services such as automatic teller machines and, began to spread globally in the nineteen sixties while the electronic secured transactions also gained pace in the eighties. Direct telemarketing is a satisfactory approach for banks in the face of global competition and the financial crisis but exhibit poor performance. Direct marketing enables banks and other financial establishments to concentrate on those clients who present the possibility of signing up to their products or services, and related activities [2]. Usually, establishing these groups of customers presents a problem to financial institutions. In line with the aforementioned, there are drawbacks to direct campaigns, especially to improve the damaging attributes that customers credited to banks. To overcome such problems, attractive long-term deposit campaigns should be planned and managed effectively.

Effective approaches to enhance business include marketing selling campaigns, and direct marketing by contacting potential customers from the contact centre of the organisation, i.e. telemarketing. Prior screening of targeted customers for telemarketing with the more likely of subscribing to products will reduce the cost of marketing. Using available information and customer metrics, it is possible to build and establish automated protocols for selecting customers in advance. Such a protocol allows one to reduce the time and costs of campaigns and performing fewer and more effective phone calls will diminish client stress and intrusiveness [17]. Statistical predictive modelling could be a useful tool to support the decision-making process.

2. RELATED LITERATURE

2.1 Bank Telemarketing

The bank marketing campaigns depend on customers´ data. The size of these data is so huge that is impossible for Data Analyst to extract good information that could help in the decision-making process. Machine Learning models are completely helping in the performance of these campaigns. Telemarketing is a form of direct marketing in which salesperson approaches the customer either face to face or phone call to persuade them to buy the product [3]. Telemarketing attains most popularity in the 20th century and still gaining ground. Nowadays, telephone (fixed-line or mobile) are widely in use. It is cost effective and keeps the customers up to date [1]. In the banking sector, marketing is the backbone to sell its product or service. [14] in his thesis observed that contacting customers by a centre agent with a list of customers for marketing a product or service is direct marketing. It requires a directed communication channel for enabling contacts, as opposed to mass marketing, with advertising being broadcast through the social media. Usually, contacts are embodied within a campaign context, which encloses the global strategy for the product being offered, the designated customers, and selling approach [13]. The usage of the telephone for executing calls to clients in a Marketing operation is denominated telemarketing.

2.2 Data classification

Data classification is the use of Machine Learning techniques to assemble datasets into related subgroups, not previously specified in the dataset. This can uncover hidden characteristics within data and identify hidden categories that new data belongs. [8] opines that classification is the most popular data mining task, of which the objective is to discover a discrete labelled outcome according to the knowledge found from the features that characterize an item. Classification is learning a function mapping on data items into one of some predefined classes [21], the input of a classification includes a training dataset where each record contains attributes and a class label.

2.3 Business Intelligence and Data Mining

[19], defined Business Intelligence is an umbrella term that encompasses architectures, tools, databases, applications and techniques with the intention of managing data to support decisions of business managers. Data Mining is a Business Intelligence expertise that uses data-driven representations to extract useful knowledge (e.g. patterns) from complex and vast data [22]. [14] defined Data mining as a broad concept that involves methods and techniques associated with the extraction of valuable knowledge from raw data. Such knowledge can take the form of explanatory knowledge, by providing interesting insights for leveraging decision making, or predictive knowledge and applied directly to forecasting the result of future occurrences [22]. The use of the internet and modern information technology, which involves increased acceptance of big data greatly, indicating the capacity to extract and analyse such great amounts of data are fundamental in this information age [17]. In recent times researchers are paying more attention to data mining and its impact in different domains of study [5].

Data mining demands for a structured dataset of problem events characterized by a list of common features, there are other types of problems in which such structured dataset is not easily available, thus the raw data is displayed in an unstructured fashion, harshening the process of mining for knowledge. If the problem instances are characterized by an unstructured text, or if they consist in text documents, then text mining provides an interesting approach for extracting knowledge [14].

Establishing cost control and promoting efficiency is the primary procedures for a company to realize profit maximization and obtain the ideal economic benefit from market activity. Undoubtedly, a good strategy is the key to long-term economic operation. Nowadays, commercial banks implement telemarketing campaign to enhance the appropriation of resources, satisfy the needs of customers thus enhancing the productivity of companies [10]. Through a marketing campaign about contacting clients on telephone directly, the bank intends to select the best set of clients. It is beneficial for narrowing the range of possible customers, intensifying the rate of success and reducing the cost of the marketing process efficiently.

Most of the successful direct telemarketing usually focuses on the quality of prospect data, data mining technique are deployed to predict the expected outcome of the customer with a higher probability to be committed to using a service. It is important to understand the customer's behaviour, this can be done by following a predictive approach based on the data mining to anticipate the customer data for organizing the customers before providing specialized services. Prediction or classification is one of the most critical tasks in the data mining that is consistently applied to classify the group of data [20]. With respect to the marketing campaign, to improve the success of telemarketing, data mining helps to establish numerous models to solve the problems of direct marketing [10]. Studies have been conducted by different researchers using various data mining tools in predicting the success of bank telemarketing to determine customer retention. [16] proposed a data mining method to investigate the likelihood of success. For the sake of extracting the key information, feature selection was underlined by using Neural Network (NN).

[15] observed that, each campaign is managed in an organized fashion and the results for all calls and clients within the campaign are gathered collectively, in a flat file report regarding only the data used to do the phone call. The agents were all human, thus no automatic calls through Interactive Voice Response (IVR) or Voice Response Unit (VRU) were performed, and they had a campaign script that helps to manage the conversation with the client. They also noted that the early stage, there is a need to analyze the dataset supplied. First, the main goal is to know the outcome of a telemarketing campaign call to sell a deposit: the client subscribed it or not. Hence, at a first glance, the outcome to predict is a nominal value making it a classification problem. In determining the success rate of customer retention for a product or service using telemarketing dataset, reports resulting from applied telemarketing campaigns can recognise trends of the customer's behaviour. Administrators are shifting from conventional statistics analysis towards more advance data mining methods, to extract useful knowledge from raw data [15].

In a related study, [11] developed and evaluated several predictive models to forecast the progress of telemarketing calls for marketing bank long-term deposits using a publicly applicable dataset from a Portuguese retail bank collected from 2008 to 2013. This is well reported in [17], decision support system. [12] [12] establish an Intelligent Bank Market Management System (IBMMS) for bank administrators who want to achieve profitable marketing campaigns. IBMMS was the first system developed by merging the power of data mining with the proficiencies of expert systems in this area. IBMMS included relevant features that enable some level of intelligent and provides the manager with guidance on how the campaign will be conducted by considering the situations of the customers.

The manager can follow the customers as individuals or as a whole group on the decision tree and can make a campaign decision that leads to the desired response by the customers. By using Data Mining to analyse forms and trends, bank managers can more precisely foresee customer reactions to modifications of interest rates, such as which customers will likely commit to new product offers and which customers will have a higher risk of not paying a loan, thus making customer relationships more rewarding [12], [4] noted that banks can use Data Mining to determine their most lucrative credit card customers or high-risk loan applicants.

[18] observed further that most marketing managers in recent times invest in directed telemarketing campaigns with a firm selection of contacts. To achieve a better result in direct campaigns, there is a need to enhance and drive the concept using Business Intelligence and Data mining. The authors described an application of a data mining scheme based on the CRISP-DM approach. The data for the project was obtained from a Real-world collected from a Portuguese marketing campaign linked to bank deposit subscription.

[2] looked at the ordinary case of bank direct advertising campaign dataset with two main intentions. First, to forecast customer response to bank direct marketing by employing four classifiers namely, Multilayer Perceptron Neural Network (MLPNN), Decision Tree (C4.5), Logistic Regression (LR) and Random Forest (RF). Results from the study describe that Random Forest Classifier with an accuracy of 87% is the most prolific classifier in terms of predictive ability. [1] applied Data Classification to investigate a dataset related to direct marketing campaigns (phone calls) of a Portuguese banking institution. The purpose of the classification is to forecast if the client will subscribe to a Term Deposit. In a related study conducted by [6] with input from other researchers, the study predicted given relevant customer info and determine if a customer will subscribe to a term deposit product. More also, to ascertain the level of usefulness of such the prediction to the bank in question; In general, direct marketing campaigns require assigned in-house or out-sourced call centres. The cost of running such sales teams or call centre agents can put a significant burden on the expense ratio of the product. A selected approach in which the team is able to identify consumers more likely to subscribe is preferable and would allow greater focus on those customers most feasible to generate a sale.

[14] suggested approach ranges from finding new data for adding value to the database, computing values based on existing data and a divide-and-conquer strategy. [17] Conducted a study that focused on targeting through telemarketing phone calls to sell long-term deposits. Within a campaign, the human agents deal with phone calls to specific clients. to advertise the deposit (outbound) or, if the client calls the contact-centre for any alternative reason, clients are asked to subscribe the deposit (inbound). They used in 52, 944 phone contacts gathered from a Portuguese retail bank, beginning from May 2008 to June 2013. [17], investigated four binary classification Data Mining models, as carried out in the rminer package of the R tool [7] for logistic regression (LR), decision trees (DTs), neural network (NN) and support vector machine (SVM). Findings from the study prove that the results are plausible for the banking domain and maintain valuable knowledge for the telemarketing campaign manager. [21] demonstrate to reduce the feature of input data and readjust the training set for the predictive model to help the bank enhance the prediction rate.

Several methods and marketing strategies are employed to augment a new customer procurement including existing customer's retention. Marketing managers need to increase marketing stream in campaigning strategies, whereas organizations elude expenses and business expansion. In determining the most significant factor and financial attribute that contributes to a customer's retention is critical to telemarketing strategies. This paper aims to advance the classification accuracy of the marketing campaigns and help the financial institution determine factors that describe the dataset and recognizing the most significant features for predicting customer's subscription.

3. THE METHOD

The purpose of the design phase is a planned solution of problem specified by the proposed system. We designed the study to improve the classification accuracy of the success rate of a customer's subscription in telemarketing dataset using Two Way T-Test feature selection and Adaboost classifier. The system implements a modelling and a developing phase to validate the integrity and efficiency of the developed approach and system. The system follows a procedural approach to data mining task. The steps involve data collection of telemarketing dataset from https://archive.ics.uci.edu/ml/datasets/bank+marketing#. The UCI machine learning archive data is a leading marketing campaigns (phone calls) of a Portuguese banking institution. The classification objective is to forecast if the client will subscribe to a term deposit. We further carried out filtering of the data and the normalization which helps to remove outliers and inconsistent data. We all employed the conservative T-Test for feature selection and the Adaboost classifier for classification of the optimal data subset. System Experimental Setup.

The developed system examined and tested the effect T-Test Filter Selection and Adaboost machine learning method for the prediction of success rate in telemarketing dataset.

T-test: The T-test is a filter selection process that help sevaluate the substantial difference of the predicting variables and the class label. We selected 16 features and categorized as the most predominant factor.

Adaboost:Adaptive Boosting (Adaboost) enable strong classification from a set of weak classifications [28]. Given a weak classifier (1) from a set of weak classifier$(\alpha_1 f_1(x) + \alpha_2 f_2(x) + \ldots \alpha_M f_M(x))$. We derive the outcome from the set of outcomes with the weights popular vote.

$$F(x) = \text{sign}\left(\sum_{m=1}^{M} \alpha_m f_m(x)\right) \quad (1)$$

The f_m is $m = \{1,2,\ldots,M\}$ weak classifier and the coefficients α_m are corresponding weights from the boosting algorithm. Output for each $f_m(x)$ is compared for more accurate classifier. The effect is to produce greater influence to a better and more accurate classifier in the sequence. The $w_1, w_2, \ldots, w_N$ for the set of observations are also updated for each boosting step and misclassified observations weights. At the initial step $m = 1$, the weights are uniformly distributed (2). Once initialized, the weighted error ε in (3) and coefficient α_m in (4) are work out. This will be followed by weights w_i update (5) and finally the output $F(x)$ in (1).

$$w_i = \frac{1}{N} \quad (2)$$

$$\varepsilon = \frac{\sum_{i-1}^{N} w_i \mathcal{J}(y^{(i)} \neq f_m(x^{(i)}))}{\sum_{i=1}^{N} w_i} \quad (3)$$

$$\alpha_m = \log\left(\frac{1-\varepsilon_m}{\varepsilon_m}\right) \quad (4)$$

$$w_i \leftarrow w_i \exp[\alpha_m \mathcal{J}(y^{(i)} \neq f_m(x^{(i)}))] \quad (5)$$

We implemented the experiment with the Matlab programming (MATLAB 2016A) for various functions and linked to a graphic user interface (GUI) for user interactivity and response. The developed tool required components environments in Matlab toolbox for output results of the data mining tasks.

Matlab Command Window: The Matlab command window illustrate the results from the data mining task in a console screen for readability and clear expression of results.. It is a command prompt that allows the display of results obtained from the (GUI) for better readability and interpretation of solutions and outcomes.

Dataset Settings: The dataset collected is applied to direct marketing campaigns of a Portuguese banking institution. We based the marketing campaigns on phone calls. Usually, more than one contact to the same client was required, in order to access if the product (bank term deposit) would subscribe to the ('yes') or not ('no'). The table below gives the names of the predicting attributes.

3.1 Interactive Developmental Stage

We show the algorithm in Fig. 1 and overall developed system at runtime in Fig. 2. The combined model for the prediction of success rate in telemarketing dataset follows the experimental procedure below.

- Data Collection: Collects the marketing campaigns dataset for further preprocessing.
- Dataset Filtering: The process reduce noise or error from the collected data.
- Dataset Feature Selection:Selecting features that contribute more to the model performance.
- Dataset Partitioning: Splitting the data into meaning dimensions and each dimension is a subset of the data.
- Classification: The process of developing a class model from the class label from the class features after the training.
- Performance Evaluation: The process of predicting the test label from the test features using the model developed.

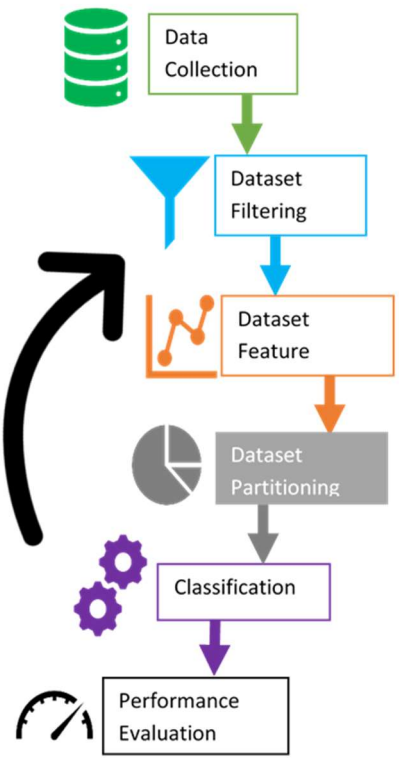

Fig. 1: Initial Start-up Flow

The layout of the initial startup the application at runtime gives a platform to automate all the working process of the developed platform.

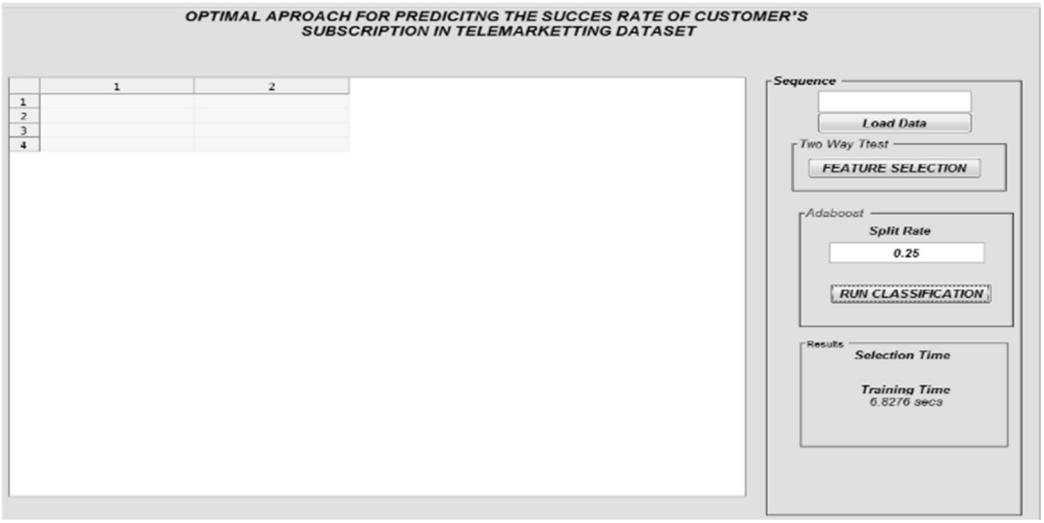

Fig. 2: Initial Start-up Screenshot

4. RESULT AND DISCUSSION

This section presents the stepwise results for the prediction of success rate in telemarketing dataset. Data Filtering The filtered data helps to present a well-formatted data for the system. The data was filtered by converting a string to numeric variable. A sample case study is shown in Fig. 3

7	35	5	3	3	1	23	2	141	2	2	747	1	176	3	1	1
8	36	7	2	3	2	14	5	341	1	4	307	1	330	2	1	1
9	39	10	2	2	2	6	5	151	2	3	147	1	-1	0	1	1
10	41	3	2	3	2	14	5	57	2	3	221	3	-1	0	1	1
11	43	8	2	1	2	17	4	313	1	2	-88	1	147	2	1	2
12	39	8	2	2	2	20	5	273	1	3	9374	3	-1	0	1	1
13	43	1	2	2	2	17	4	113	2	3	264	1	-1	0	1	1
14	36	10	2	3	1	13	8	328	2	3	1109	1	-1	0	1	1
15	20	9	3	2	1	30	4	261	1	3	502	1	-1	0	1	1
16	31	2	2	2	2	29	1	89	1	2	360	1	241	1	1	2
17	40	5	2	3	1	29	8	189	2	3	194	1	-1	0	1	2
18	56	10	2	2	1	27	8	239	5	3	4073	1	-1	0	1	1
19	37	1	3	3	2	20	4	114	1	2	2317	1	152	2	1	1
20	25	2	3	1	2	23	5	250	1	3	-221	3	-1	0	1	1
21	31	8	2	2	1	7	7	148	1	4	132	1	152	1	1	1
22	38	5	1	3	2	18	11	96	2	3	0	1	-1	0	1	1
23	42	5	1	3	1	19	11	140	3	3	16	1	-1	0	1	1
24	44	8	3	2	1	12	6	109	2	3	106	3	-1	0	1	1
25	44	3	2	2	1	7	7	125	2	3	93	1	-1	0	1	1
26	26	4	2	3	1	30	1	169	3	3	543	1	-1	0	1	1
27	41	5	2	3	1	20	11	182	2	3	5883	1	-1	0	1	1
28	55	2	2	1	2	5	5	247	1	3	627	3	-1	0	1	1
29	67	6	2	3	1	17	8	119	1	2	696	2	105	2	1	1
30	56	7	2	2	1	30	7	149	2	3	784	1	-1	0	1	2

Fig. 3: Dataset Normalization

4.1 Feature Selection

The two sample T-test was carried out to find the relationship between the predicting variables and the response variables, each of the predicting variables was compared to the response variable to check their level of significance, and the degree of significance was set at 0.05 (95%) for the confidence interval. Ten attributes were selected from the main 16 attributes which define the factors that are most significant to predicting the success rate of a customer's subscription. The selected features with their corresponding ranking ability of the two-way test value are shown in Table I.

Tanble 1: Selected attributes

The rank order of selected Attributes	Attributes	Probability value
1	Age	0
2	Job	0
3	Marital	0
4	Education	
7	Housing	0
10	Day	0
11	Month	0
12	Duration	0
13	Campaign	0
16	Poutcome	0
6	Balance	7.73E-298
9	Contact	4.26E-192
14	Previous	2.67E-136
15	P outcome	6.81E-112
5	Default	1.58E-52
8	Contact	1.87E-16

4.2 Training

We employed the Adaboost classifier at this stage to train the dataset after we passed the filtered dataset for processing. We partitioned the dataset into 75% training dataset. This was used to create an adaptable learning rate to build the knowledge base of the Adaboost classifier while the 25% was held to test the viability of the trained classifier. This method is symbolic to the held out technique used in partitioning dataset..

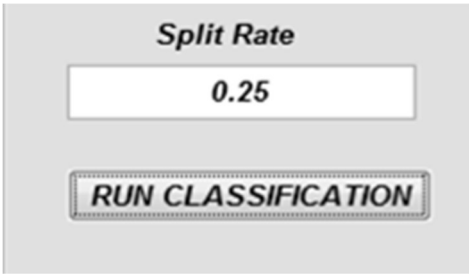

Fig. 4: Hold-Out technique, a sub section of the oveall GUI

4.3 Classification Results and System Evaluation

4.3.1 Statistical Evaluation

We show the statistical analytical results in Fig. 5 obtained for the dataset with the actual class label passed into the Adaboost Algorithm. The results show the weighted positive and negative rates, the confusion matrix, analysis per class and other statistical variation. Sensitivity (recall or true positive rate) measures the proportion of positives that are correctly identified; Specificity (true negative rate) measures the amount of negatives values correctly recognized. Precision is the positive predictive value (1 – specificity).

The F-Score F_1 is defined by (6). It is also called the F-Measure.

$$F_1 = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \qquad (6)$$

The F-score conveys the balance between the precision and the recall. The true positive rate shows the Positive and Negative class correctly identified as Positive and Negative class and the Positive and Negative class incorrectly identified Positive and Negative class.

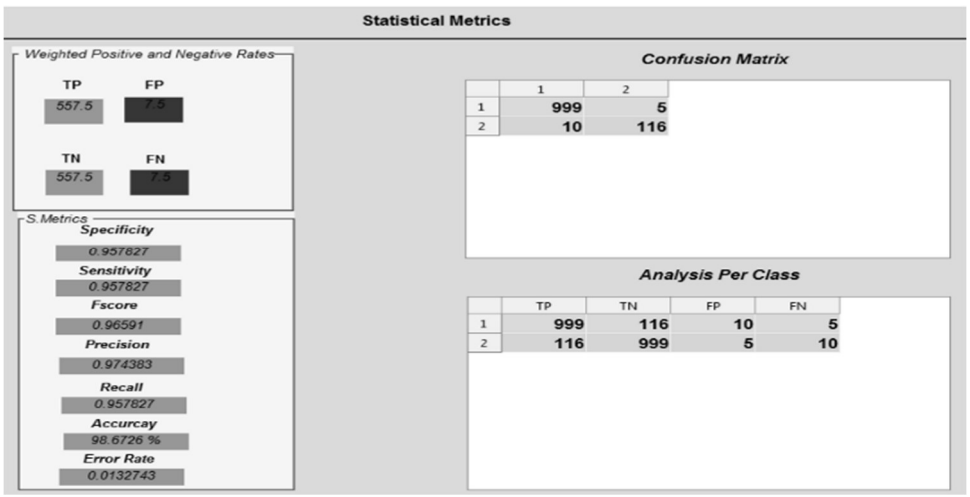

Fig. 5: Case A Statistical Evaluation.

4.3.2 Confusion Matrix

The confusion matrix is an indication of the correctly and incorrectly classified class. The class 1 represents the client subscribed a term deposit a total observation of 1004 observations for the validation set. A total of 999 were classified correctly and 5 were classified incorrectly, while the class 2 represents the client does not subscribe to a term deposit which shows a total of 126 observations for the validation set 116 were classified correctly and 10 as incorrect.

Table 2: Statistical Metrics

Classification Metrics	Results
Weighted True Positive Rate	557.5
Weighted False Positive Rate	7.5
Weighted True Negative Rate	557.5
Weighted False Negative Rate	7.5
SENSITIVITY = TP / (TP + FN)	0.957827
SPECIFICITY = TN / (TN + FP)	0.957827
ACCURACY = TP + TN / (FP + FN + TP +TN)	98.6726 %
ERROR RATE	0.0132743
FSCORE	0.96591
TRAINING TIME	6.8276secs

4.3.3 Classification Accuracy and Training Time

Figure 6 below shows the time taken for the Adaboost classifier to train and adapt to experimental data while the classification accuracy shows the predictive success rate and percentage of instances the algorithm was able to classify successfully.

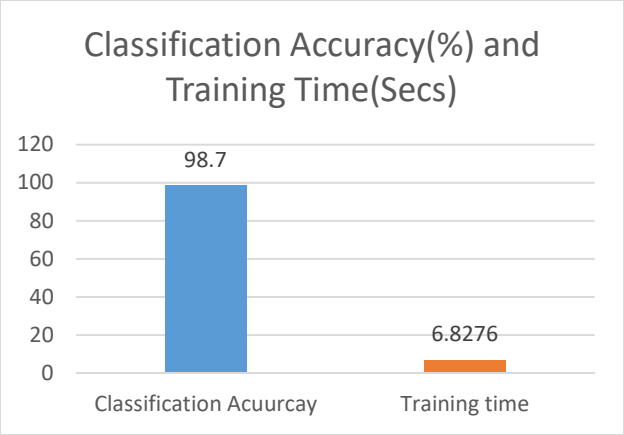

Fig. 6: Classification accuracy and training time

5. CONCLUSION

The impact of improving the success rate of telemarketing datasets in a financial institution and spotting on the most dominant factors for predicting customer's subscription optimizes the performance of business managers. It is evident from our results that Adaboost classifier added to the success rate with a very high percentage classification accuracy of 98.7%, fast computation time and very low error rate 0.0132743.

6. SUGGESTION FOR FURTHER RESEARCH

Further studies can be conducted in the area of data clustering to determine the risk level are at high, medium and low rates of retention in bank marketing for the existing subscriber and incoming subscribers.

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