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Customer Churn Prediction with Machine Learning Methods In Telecommunication Industry

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Abstract

With the emergence of new competitors and increasing investments in telecommunication services, change often occurs and hence importance of marketing strategies and customer behavior prediction have become an important demand for companies. New regulations and technologies increase competition among mobile operators. Since acquiring a new customer is more expensive than acquiring active customers, companies seek solutions to reduce the churn rate. Therefore, telecommunications companies want to analyze the concept of the customer's desire to change service provider and take necessary measures to protect their existing customers. In this study, usage information, usage trends, subscription commitment, subscription age, ARPU and billing information, competitor familiarity, outgoing call information, number porting experience, etc. Loss estimation modeling is taken into account. Dataset includes 593 columns and 1826588 lines. Corporate mobile customers are analyzed by dividing into three subgroups as Single Line Mobile Customers, 2-5 Line Mobile Customers, and 6-15 Line Mobile Customers. In order to estimate customer loss, four different ML methods are used while creating loss prediction models. The model is developed by using 600 different variables and loss estimation. ROC curves and lift chart results for different corporate mobile customer groups are compared, and the most suitable models are depicted.

Keywords: *Machine Learning; Telecommunication; Churn Prediction; Random Forests; Customers; Data Analysis; AI*

1. Introduction

Customer retention is one of the most important issues for companies in today's competitive business environment, especially in telecom industry. New regulations and technologies allow easy switching between mobile operators. The process of switching from one service provider to another compromises various parameters, such as good services or rates, or the competitor's providing various advantages to customers, arising an essential problem in a highly competitive and rapidly developing industry. Telecommunication sector has a very high customer loss rate [1-3]. In today's conditions, since acquiring a new customer is more expensive than keeping an existing customer, companies take every precaution to retain their customers. Therefore, identifying factors that cause customers to move away due to different reasons, such as withdrawal, running away... should be handled with priority in terms of competitiveness and sustainability.

Churn refers to the number of customers that the business has lost in a period. Churn Analysis, determining the situations that cause customer loss and estimating churn rate, has become crucial. According to research [3-7], acquiring a new customer costs 5 times more than retaining existing customers. In addition, it costs 10 times more to acquire an unsatisfied customer than to retain existing customers. Although operators in France making large customer acquisition expenditures [8], they lose about 30 percent or more of their subscribers annually. For this reason, companies develop new strategies by looking for different solutions to retain their existing customers. In [6, 9], customer churn management is defined as to predict customers that are about to lose by looking at customers' behavior and to find the right marketing strategy to retain these customers. [10] shows that even small increases in retention are important to a company's profitability. [11] argues that even a 1 percent increase in customer retention has a significant impact on results. Therefore, companies are conducting various studies to improve customer churn estimation.

Big data analytics and machine learning techniques are used to predict customer churns. With the increasing importance of marketing strategies and the conscious behavior of customers, the Customer Relationship Management (CRM) approach has become a priority for companies. As part of this, loss forecasting models are applied to identify potential customer losses. The most effective method of customer retention is accurate loss forecasting models and effective loss prevention strategies. The main purpose of this project is to find the best model in the scope of CRM with machine learning models to predict customer churn in the telecommunications industry. SAS Miner and SAS EG programs are used for statistical analysis. While applying loss estimation models, data mining and machine learning methods are used.

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The increase in customer churn rate from 20 percent to 40 percent is worrying for telecommunications companies. In the article, various methods are proposed to estimate customer losses, the results are compared and evaluated with statistical analysis. In this project, customer usage information, usage trends, subscription commitment, subscription age, contact/invoice information, competitor acquaintance, outbound call information, number porting experience, silent lines were taken as the main criteria. The main contribution of our work is to develop a churn prediction model which assists telecom operators to predict customers who are most likely subject to churn. The dataset contained all customers' information over 12 months, and is used to train, test, and evaluate the system at a big Telecommunication company in Turkiye. The model experimented four algorithms: Decision Tree, Random Forest, Gradient Boosted Machine Tree "GBM" and Extreme Gradient Boosting "XGBOOST" as depicted in **Fig. 1**.

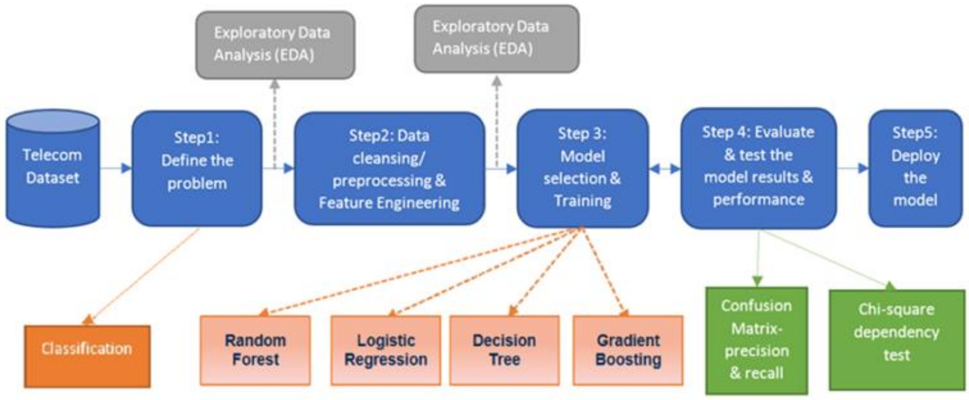

Figure 1. *Learning/Prediction steps for churn prediction process.*

2. Related Work

In the telecommunication domain, there are still various important open problems [3, 6, 7, 12], and among those churn prediction is one of the major and urgent problems. In [1], the researcher applies face-to-face surveys to many customers in order obtain their mobile phone usage perception. [13] analyzes churn detection problem with ML techniques and social media data is combined as a supporting information and they obtain the best results with Gradient Boosting. In other research [14], DCNN is used to predict churn and gives high results. However in their work they deal with only 18.000subscribers, which is relatively small data size in this domain. In [15] researchers combine game players communication in text and extract player comments from games, which is later used to predict tendency in their opinion for churn. In [16] a big amount of data, 127 million, is extracted to analyze user behavior by using various ML techniques and observe their performance. However they focus on three parameters only, that are time, frequency and money spend during a period. In their work [17], they focus on land-line customer churn prediction and evaluates 7 different ML techniques across various parameters. Other group [18] of researchers highlight three data challenges in churn prediction domain: 1) the customer churn data set is substantially imbalanced in reality, 2) the samples in feature space are relatively scattering, 3) the dimension of feature space is high. They use random forest for dimension reduction and apply decision tree for classification. This emphasizes the importance of our work well.

3. Churn Prediction Framework

The decision of the customer to terminate the relationship with the existing telecommunications firm is called churn. If a firm has a 70 percent loyalty rate then the churn rate is 30 percent. When working on the churn prediction, it is important to understand the business field and dataset in detail. In this study, datasets are prepared using SQL queries. Since binary variables are used in this project, the model is applied as Churn / Not Churn. The work done in this project is carried out in the SAS Miner program and integrated into the codes in SAS EG as Proc SQL.

3.1. Dataset and Evaluation

Data pre-processing, cleaning, transformation, and data selection are handled initially. Blank values and missing values are replaced with the mean or median of the column. Converting the continuous variable to a significant factor variable is used to improve model performance and help understand insights of the data. It is also necessary to check the format and adjust the parameters to the appropriate format. By drawing histograms and box plots, outliers in the data set can be understood. In addition to outliers, the data set contains duplicate values, and these duplicate values are removed from the data set for proper analysis.

Some parameters such as accuracy, sensitivity, recall or F1 score can be calculated to test whether the model works correctly. For evaluation, for example, 30% of the data set aside for testing and 70% is used in the training phase. The results are evaluated by looking at the relationship of the ROC curve with the cumulative gains and lift curve. Lift is a widely preferred evaluation matrix in marketing strategies [14,18, 22]. The Lift Chart measures the effectiveness of models by calculating the ratio between the result obtained with a model and the result obtained without a model. The Cumulative Lift Chart represents the lift factor which shows how many times it is better to use a model in contrast to not using a model. The probability of customer churn based on the customer's contract and operational data (P (Churn = 0/1)) is calculated. Based on this probability, a predicted class data line will be assigned (Churn) = 0/1. Remember that customers with churn = 0 are, hopefully, much more customers with churn = 1 than customers with Churn = 1.

In the ROC curve, the true positive rate (Sensitivity) is plotted in the function of the false positive rate (100-Specificity) for different breakpoints of a parameter. Each point on the ROC curve represents a sensitivity / specificity pair corresponding to a certain decision threshold. The area under the ROC curve (AUC) is a measure of how well a parameter can distinguish two groups. Specificity is true negatives divided by sum of true negatives and false positives. True negatives can be described as predicted customers who will not churn, actually non-churners. However, if model predicts customer will not churn, but in reality, it will churn, this is false positive. The main difference between specificity and sensitivity is specificity measures proportion of actual negative cases, that identified correctly whereas sensitivity measures proportion of actual positive cases, that identified correctly. Precision gives the proportion of shakers actually leaving the company. F1 Score value gives us the harmonic average of Precision and Recall values. The reason why it is a harmonic average instead of a simple average is that extreme cases cannot be ignored. If a simple mean calculation was used, the F1 Score of a model with a Precision value of 1 and a Recall value of 0 would be 0.5. This does not give an accurate result. The main reason for using the Score value instead of Accuracy is not to make an incorrect model selection in non-uniform data sets. In addition, F1 Score is very important in the evaluation of the model, as a measurement metric is needed that includes not only False Negative or False Positive, but also all error costs.

$$F_1\,Score = \frac{2 \times Pecision \times Recall}{(Pecision + Recall)} \tag{1}$$

Cost sensitive learning was applied by using weighted random forests, one of the machine learning methods. As we predict a stochastic gradient increasing learner, another method used is boosting. Many comparative studies such as logistic regression, decision tree, gradient boosting and random forest were made in the article. In this study, churn estimation of mobile customers of one of the largest telecommunications companies has been made. The data is real and big. Therefore, it differs significantly from the methods used in previous comparative studies. Classification is more difficult as it is studied on big data and real data.

3.2. Implementation Details

The data is taken from marketing intelligence department of a large telecom company, so Corporate Mobile Customer audience is selected and analyzes are carried out on soho and sme audiences. Loss estimation modeling is performed by analyzing the usage information of customers, usage trends, subscription commitment, subscription age, ARPU (average revenue per user) and billing information, competitor familiarity, outgoing call information, number porting experience, etc. Random Forest, Regression Analysis, Decision Tree and Gradient Boosting machine learning methods [19, 20, 21] are applied and the developed prediction methods are currently being used for monthly churn forecasts [22, 23]. SAS Enterprise Miner tool is used in the study and processes a validation dataset as a way of measuring model performance independently. Verification data set is formed by segmentation of raw analysis data. In the SAS Enterprise Miner program, a third part called test data set can also be created. The test data set provides unbiased estimates of model performance from a single selected model. Methods available in the tools [24-26] are Regression, High Performance Regression, Decision Trees, Random Forest, High Performance Tree, Variable Selection, Stat Explore, Variable Selection, LARS/LASSO, High Performance Variable Selection, Variable Clustering, Principal Components and Weight of Evidence. The data set includes 593 Columns and 1826588 lines.

4. Enterprise Mobile Customers Churn Prediction

The data set consists of postpaid mobile SME and SOHO customers as in **Fig. 2** with active voice usage, with a maximum subscription age of more than 2 months, 15 or less lines. (SME: Small and Medium-sized Enterprises, SOHO: Small Office/Home Office) A learning set covering different seasonal periods (over a year) is applied in order to reduce the seasonal effects on customer basis and to eliminate the incidental effects that may be seen in a certain period. In order to measure the consistency and reliability of the model, a test is conducted over 2 months proving the generalizable characteristics of the models. **Table 1** and **Table 2** give data distribution. The Churn risk model is divided into 3 main customer segments: Single-line, 2-5-Line, 6-15-

Line. Single Line Customers were grouped as "Uncommitment", "Commitment 0 - 90 Days" and "Commitment Over 90 Days", and a total of 5 different churn risk models were developed.

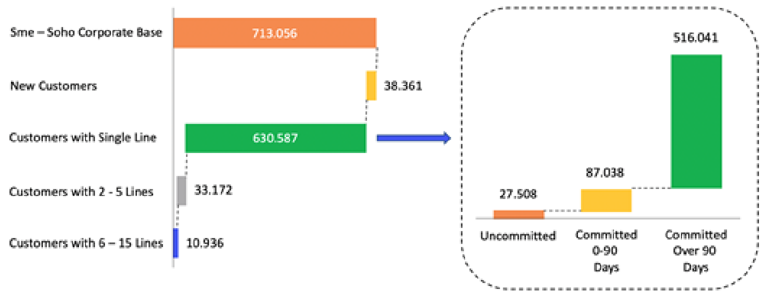

Figure 2. *Learning/ Sme-Soho corporate mobile customers distribution.*

Table 1. *Model Split of Sme-Soho corporate mobile customers.*

Type	# of Customers
Uncommitted	27.508
0-90 Days	87.038
Over 90 Days	516.041
Single Line Total	630.587
2-5 Lines Customers	33.172
2-5 Lines Subscribers	99.758
6-15 Lines Customers	10.936
6-15 Lines Subscribers	92.443

Table 2. *Data based on May 2022 and churn rates over July, August 2022.*

Model Split	*Total Customer Number*	*Total Churn Number*	*Churn Percent*
Single Line/Uncommitted	27,508	2,790	10,14 %
Single Line/Committed 0-90 Days	87,038	14,932	17,16 %
Single Line/Committed Over 90 Day:	516,041	10,443	2,02 %
2-5 Lines	33,171	1,705	5,14 %
6-15 Lines	10,936	807	7,38 %
Total	674,695	30,677	4,55%

Model Split	*Total Subscriber Number*	*Total Churn Number*	*Churn Percent*
Single Line/Uncommitted	27,508	2,790	10,14 %
Single Line/Committed 0-90 Days	87,038	14,932	17,16 %
Single Line/Committed Over 90 Day:	516,041	10,443	2,02 %
2-5 Lines	99,758	4,264	4,27 %
6-15 Lines	92,443	4,994	5,4 %
Total	822,788	37,423	4,55 %

a) Sme-Soho corporate mobile customer churn rates b) Sme-Soho corporate mobile subscriber churn rates

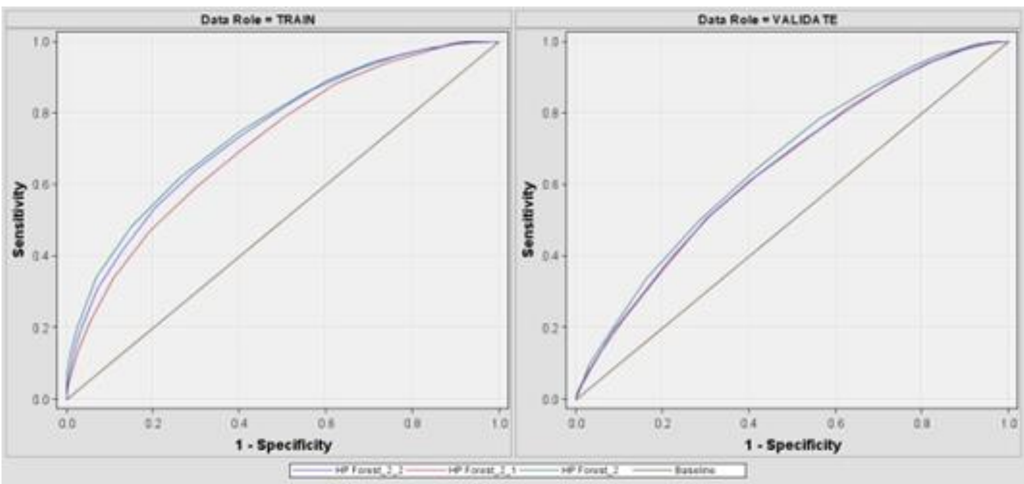

Figure 3. *Random Forest ROC Curves for Single Line Uncommitted Customers*

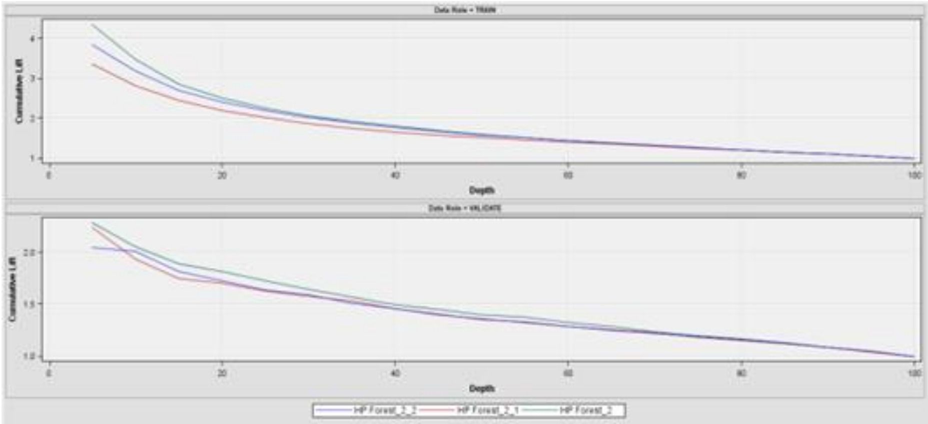

Figure 4. *Random Forest Cumulative Lift Curves for Single Line Uncommitted Customers*

5. Experimental Results

In this work, experimental results are presented by analyzing ROC curves, Cumulative Lift Curves, Churn graphics, and final Lift curves. Example results from the first split are given for each graphical analysis, whereas only ROC curves are given for the rest of the splits. This is the part of author's master thesis [27], in which details e.g. including codes, statistical analysis for all parameters, and detailed graphics can be found.

5.1. Prediction Model with Single Line / Uncommitted Customers

Fig.3, **Fig.4** and **Fig. 5** depict the experimental results. The train ROC Index value of the HP Forest model is 0.754, and the valid ROC Index value is 0.662. It is seen that it is higher than the other models applied. Therefore, Random Forest (HP Forest_2) method is chosen for churn estimation of Single Line Uncommitted customers. When the Decision Tree and Gradient Boosting model are compared, the highest ROC Index value is 0.721 which is below Random Forest.

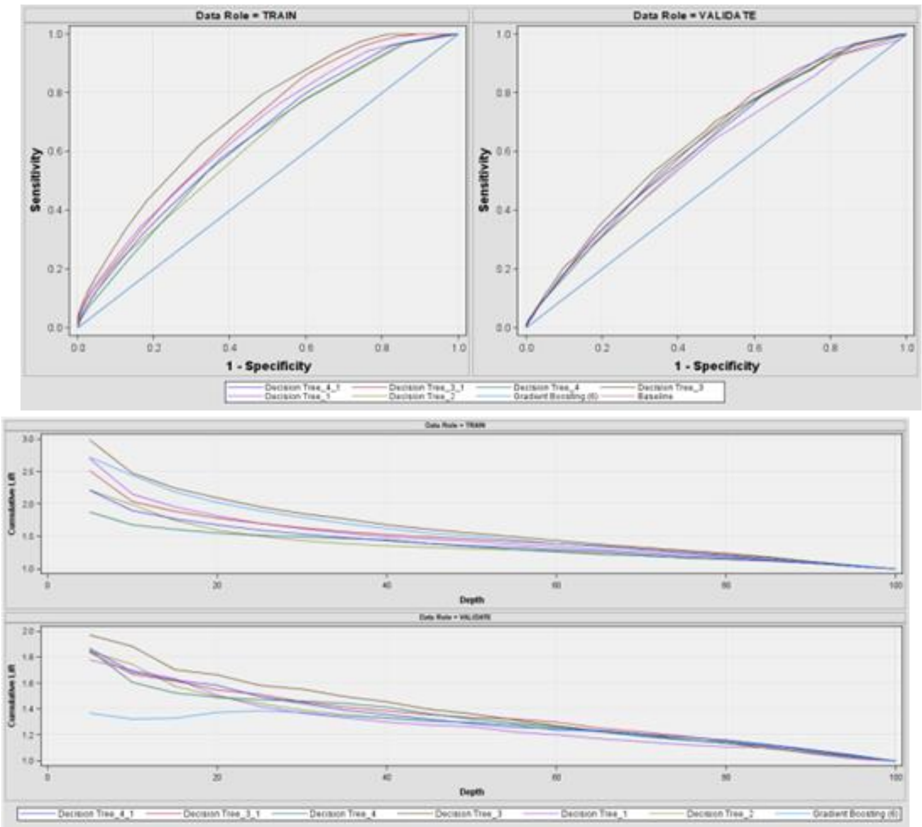

Figure 5. *Decision Tree and Gradient Boosting ROC and Lift Curves for Single Line Uncommitted*

Fig. 6 and **Fig. 7** present two important curves for this customer split, where the first one shows churn graphic in this split and the second one shows the Lift graphic. Therefore, these models are not used as churn forecasting models of single-line uncommitted customers. This split has a total of 27,508 subscribers and 2,790 churn. When the 5 percent slice is reached in line with the risk score, a total of 1,375 subscribers are reached. This corresponds to 9.8 % of the churn for the split. Lift is seen as approximately 2. The probability of catching churn is observed as 19.85.

Figure 6. *Churn Graphic for Single Line Uncommitted Customers (Final Random Forest)*

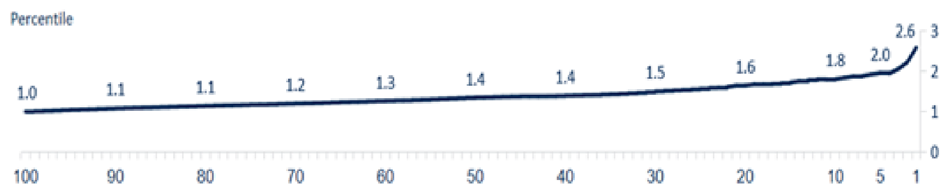

Figure 7. *Lift Curve for Single Line Uncommitted Customers (Final Random Forest)*

5.2. Prediction Model with Single Line / Committed 0 – 90 Days Variables

When the results of the applied machine learning models are compared, the highest Train:ROC Index value is Decision Tree_7 with a value of 0.686. The values of other machine learning models are below the Decision Tree_7 ROC Index. Train:Gini Coefficent value is 0.371, Train:Kolmogorov Smirnov Statistics value is 0.263, with the highest value compared to other models. Train:Cumulative Lift value is 2.216812. Therefore, Decision Tree_7 model was chosen for Single Line / Committed 0-90 Days customers. There are a total of 87,038 subscribers and 14,932 churn in this split. A total of 4,351 subscribers are reached when the 5 percent slice is reached in line with the risk score. This corresponds to 11.14 % of the churn for the split. Lift is seen as 2.22. The probability of catching churn is observed as 38.22.

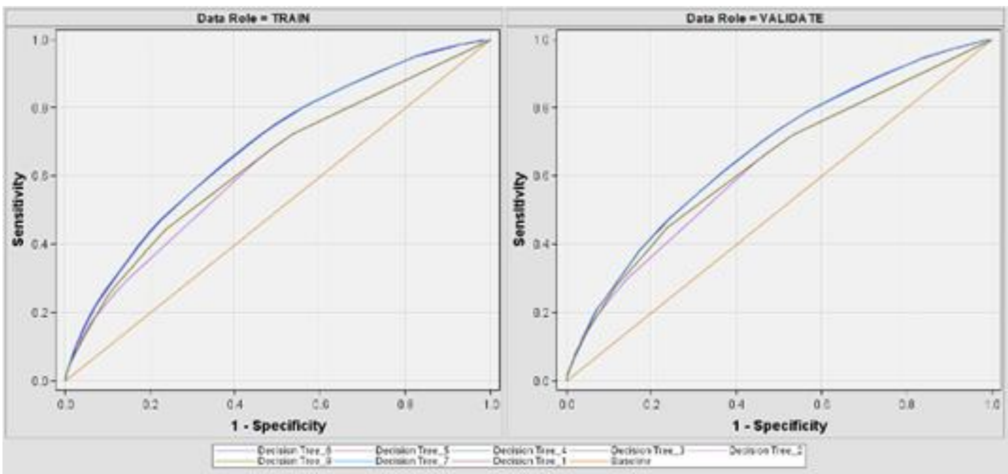

Figure 8. *ROC Curves for Single Line / Committed 0 – 90 Days Variables (Decision Tree)*

5.3. Prediction Model with single line/committed over 90 days customers

The highest ROC Index value is given for Regression (2) with a value of 0.749. Although the Regression (2) model gives better results than the other applied models, the lift of the Decision Tree_1 model is 3.9. The results of the Decision Tree _1 model give better results compared to other models. Therefore, Decision Tree_1 model is chosen for the churn estimation of Single Line / Committed Over 90 Days customers. This split has a total of 516,041 subscribers and 10,443 churn. When the 5 percent slice is reached in line with the risk score, a total of 25,802 subscribers are reached. This corresponds to about 20% of the churn. Lift is seen as 3.9. The probability of catching churn is observed to be 7.9.

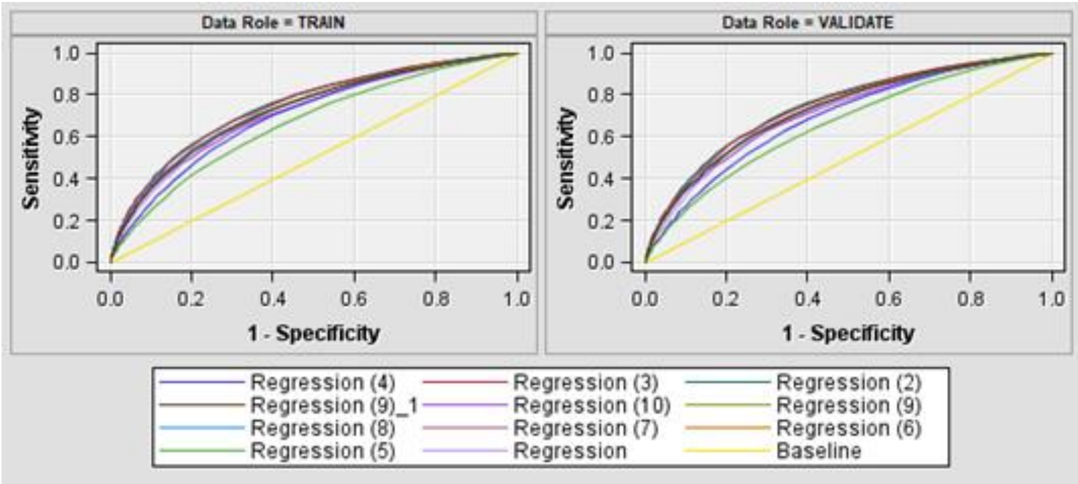

Figure 9. *ROC Curves for Single Line / Committed Over 90 Days Variables (Regression)*

5.4. Prediction Model with 2-5 Lines Customers Variables

When the results of the applied Gradient Boosting models are compared, the highest ROC Index value is 0.766. Therefore, Gradient Boosting is chosen for loss estimation of 2-5 Line customers. This split has a total of 33.172 customers and a total of 99.758 subscribers. 1.705 of these customers have churned and this corresponds to 4.264 cancellations on a subscriber basis. When the 5 percent slice is reached in line with the risk score, a total of 1,658 customers are reached, which corresponds to a total of 4,987 subscribers. For the 5 percent slice in this split, it corresponds to 24.44 % of churn on subscriber basis. The lift is seen as 4.9 on subscriber basis and the probability of catching churn is observed as 20.89.

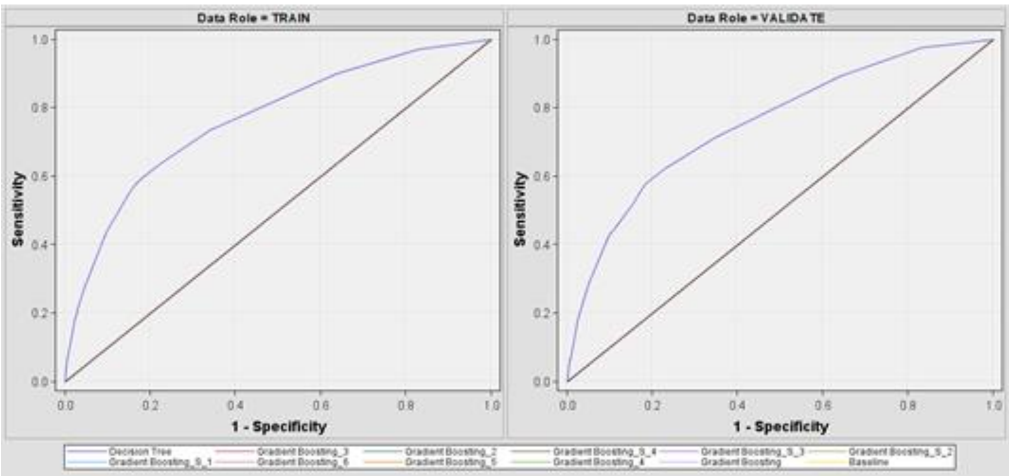

Figure 10. *ROC Curves for 2-5 Lines Customers Variables (Gradient Boosting)*

5.5. Prediction Model with 6-15 Lines Customers Variables

When the results of applied Regression & Gradient Boosting models are compared as in **Fig. 11**, Regression_5_1 Train: ROC Index value has the highest ROC index with 0.737, which is the highest values compared to other regression models. Therefore, Regression_5_1 model is chosen for loss estimation of Line 6-15 customers.

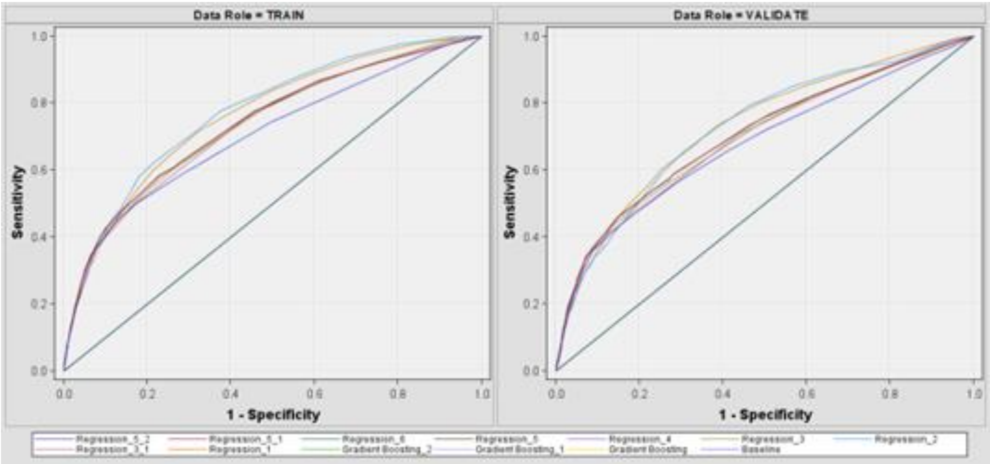

Figure 11. *ROC Curves for 6-15 Lines Customers Variables (Regression&Gradient Boosting)*

When the results of the applied Decision Tree models are compared as in **Fig. 12**, Decision Tree_3 Train:ROC Index value is 0.745 and although it has the highest ROC index, it is not chosen because its Cumulative rise is lower than the Regression_5_1 model. This split has a total of 10.936 customers and a total of 92.443 subscribers corresponding to this customer. 807 of these customers have churned and this corresponds to 4,994 cancellations per subscriber. When the 5 percent slice is reached in line with the risk score, a total of 546 customers are reached, which corresponds to a total of 4.622 subscribers. For the 5 percent slice in this split, it corresponds to 24.42 percent of churn on subscriber basis. On a subscriber basis, the lift is seen as 4.9 and the probability of catching a churn is observed as 26.40.

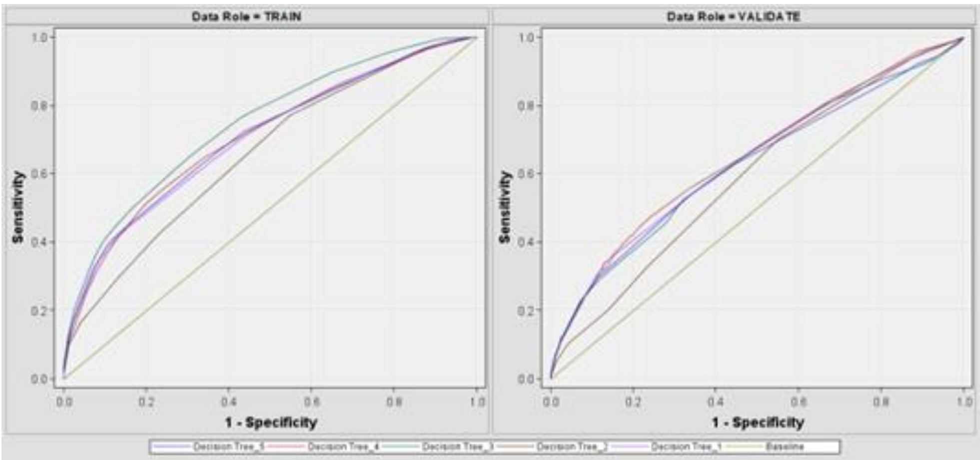

Figure 12. *ROC Curves for 6-15 Lines Customers Variables (Decision Tree)*

6. Discussion and Conclusions

The main purpose of this project is to find the best model to predict customer churn in the Telecommunications industry with machine learning models. Important variables are determined with descriptive data analysis and used in Single Line, 2-5 Line, and 6-15 Line customer models. The target variable is CHURN. For the single line uncommitted model, customers with lines 2-5 and 6-15 were eliminated from the data. The experiments show that HPDMForest method implemented in SaS gives the best results. For single line committed 0-90 Days customers data, decision tree is shown to be the most suitable model in line with the risk score, when the 5 percent slice is reached, a total of 4,351 subscribers are reached and this corresponds to 11.14 percent of the churn for the split. The lift is seen as 2.23, the probability of catching churn is observed as 38.22. Regression and decision tree machine learning methods are applied for Single Line Over 90 Days customers. Decision Tree gives the best results in line with the Single Line Over 90 Days risk score as the 5 percent slice is reached, a total of 25,802 subscribers are reached, and this corresponds to approximately 20 percent of the churn for the split. Lift is seen as 3.9, the probability of catching churn is observed as 7.9.

Gradient Boosting and Decision Tree machine learning algorithms have been applied for 2-5 Line Enterprise customers. In this split, for the 5 percent slice, it corresponds to 24.44 percent of the churn on a subscriber basis. On the basis of subscribers, the lift is seen as 4.9 and the probability of catching churn is observed as 20.89. The regression model is chosen as the most suitable model for customers with 6-15 lines by after evaluating regression, gradient boosting, decision tree methods. In this split, for the 5 percent slice, it corresponds to 24.42 percent of the churn on a subscriber basis. On the basis of subscribers, the lift is seen as 4.9 and the probability of catching churn is observed as 26.40. This work demonstrates the potential application of major ML methods for successful churn prediction. It shows that there is no single method for all customers. The best approach is smart categorization of customers depending on usage period and type.

To further expand the dataset, the dataset can be expanded by adding parameters from the call center. For example, the number of times the agent calls the customer and the difference between the last call and the cancellation date can be included in the data set. In addition to the estimation of customer churn, the effectiveness of the call center can also be measured. Other parameters can be included in the dataset, taking into account business requirements. Depending on the dataset, this model will be more department specific. For example, loss estimation is often considered a scope of marketing analytics but call centers that call collections can use these formulas. To some extent, after the recent coronavirus outbreak, customers are using online channels more often than before, and call centers are becoming more important than before. A data set can be created that includes whether the customer has paid and continued to use the existing service provider or has disabled the service.

Declaration of interest

The authors declare that there is no conflict of interest.

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