OVERVIEW OF CUSTOMER CHURN ANALYSIS IN TELECOM INDUSTRY

Radhika Patil[1], Dr. Roopa G M[2]
[1] Assistant Professor, Department of Computer Science and Engineering, BIET, Davanagere
[2] Associate Professor, Department of Computer Science and Engineering, BIET, Davanagere
Email: ps.radhika@gmail.com[1], roopa.rgm@gmail.com[2]

Abstract— Customer churn is the phenomenon where customers no longer want to continue interaction with business. Customer Churn rate is quantitative mathematical calculation of number of customers ceasing to use products/services of a business. CustomerChurn in Telecommunications Industry is a pressing issue that has to be dealt to retain customers and build a competitive advantage over the others in the market.Thispaperfocuses on surveying the factors affecting the customer churn, various evaluation metrics used, different churn prediction models used worldwide over a decade. It also discusses aboutvarious challenges faced.Customer churn is difficult to continuously predict and prevent when products, services and business models are constantly changing, as companies struggle to meet the rising demands of customers and stay ahead of the competition. After churn prediction, company has to take further action by providing various incentives to reduce and prevent the churn. Companies have to use such identified churns and put efforts to gain customer loyalty.

Keywords— Customer Churn, Prediction models, Customer retention, Customer loyalty

I. INTRODUCTION

In the last few years, revolutionary things have happened in the telecommunications industry, such as, new services, technologies and the liberalizations of the market opening up to competition in the market. Since the customer is the major source of profit, a method to properly manage customer churn gains vital significance for the survival and development of any telecommunication company. For many telecoms companies, figuring out how to deal with Churn is turning out to be the key for continued existence of their organizations [1, 2].

As markets become saturated and competition oriented, customers have more choices with the concern of their purchasing power [3]. Competitors in the telecommunication market is constantly tempting customers with more incentives to make churn over the service providers. This leads to churn management, the process of retaining customers, a major challenge for tele service providers to turn unreliable subscribers into customers. Customer churn also generates loss in brand value. To meet these challenges, communication companies are employing sophisticated customer relationship management (CRM) and churn management techniques [3].

Customer churn is to denote the customer switching from one service provider to another. There can be various reasons such asunhappy with the quality of service, high costs, unattractive plans, no understanding of the service plan, bad support, etc. Furthermore, the customer quits contract without the aim of switching to a competitor. This can be due to change in their situationthat makes impossible for the customer from further continuing the service, e.g., financial problems, unable to pay or change in geographical location of the customer to a place where the company does not provide service. Generally, there is no single reason, but a combination of factors that lead to customer dissatisfaction.

To expand their business, companies usually have a greater focus on customer acquisition than customer retention. However, it can cost five times more to attract a new customer than it does to retain an existing one. Increasing customer retention rates by 5% can increase profits by 25% to 95%, according to research done by Bain & Company. Customer churn metric helps companies to understand the reason behind churn, churn numbers and address those factors, with appropriate action plans.

Telecommunication Service Providers have implemented CRM (Customer Relationship Management) with intention to reduce the number of Customer churn. Yet the Telecom Industry is facing high churn rate.It is required to these signals and take necessary actions before customer churn.

Churn management is an essential concept in CRM; it manages the most fundamental aspects that may change the customers' behaviour such as price, service quality, company’s reputation and effective advertising competition. Offering retention incentives is the primary way to reduce customer churn [4]. The customer lifetime value is usually defined as the total net income from the customer over his lifetime [5]. The concept of customer retention, loyalty, and churn is gaining importance in many industries. This is important in the customer lifetime value context. A company can understand how much is really being lost because of the customer churn and the scale of the efforts required for customer retention. The mass marketing approach cannot succeed in the diversity of consumer business today.

Developing successful retention techniques is important for businesses in general, and for mobile operators in particular since they are losing 20% to 40% of their customers each year [6,7,8,9,10,11,12]. Attracting new customers costs a lot in advertising, educating, creating new accounts. Such costs do not exist in the case of retaining existing customers. As a result, keeping an existing customer is five times cheaper than one attracting a new one [13]. Improving customer retention contributes in reducing churn rate from 20% to 10% annually saved about £25 million to the mobile operator Orange [14].

By the end of 2020, the number of mobile phone users is expected to reach 6.918 billion, which is over 84% of the population globally [15]. However, the ICT market, particularly the telecom industry, has reached market saturation and the average annual churn rate reaches between 10 - 67% monthly due to the strong competition between service providers to attract new customers [16,17].

Commercial companies in general and telecom companies in particular are considered as one of the top sectors that suffer from customer churning [18]. This means a company could lose approximately half of its customers and could result in a drop in its profits. Furthermore, research works from different countries such as Nigeria [19], India [20], Kenya [21], Indonesia [22] and Ghana [23] acknowledged the existence of the problem of churn in telecom companies. Churn management is an essential concept in CRM

An effective deployment of quality systems in the telecom sector is vitally important to enable their companies attract, obtain and retain customers. It is certainly cost-effective to maintain existing customers than obtaining new ones [24]. Therefore, the companies save millions of dollars by investing in customer churn analysis and prediction [25]. The companies through CRM work by ranking the margin of the propensity of customers to defect and facilitate their marketing team to provide incentives to those highly ranked. This saves the companies from losing the reputation and image dents of their brands and services. The telecom services are now customer-oriented or customer-centric [25].

II. CHURN PREDICTION

Churn prediction is a binary classification task which differentiates churners and non-churners. Churn prediction methods gives the prediction about customers who likely to churn in the near future whereas churn management helps on the other side which aims to identify such churners and to carry out some positive actions to minimize the churn effect. Van den Poel et al., focused four sets of data variables for customer attrition, that is,

1. Customer behaviour,
2. Customer perceptions,
3. Customer demographics and
4. Macroenvironment.

Customer behaviour recognizes the exact components of the service are utilizing and how often are they employing them. In telecommunications, for example, the number and length of calls, period between calls, the usage of the network for data exchange, etc could be taken by the provider.

Customer perceptions are identified as the way a customer pick up or stop the service and can be calculated with customer surveys and include data link overall contentment, quality of service, problem experience, satisfaction with problem handling, interest given, location convenience, image or reputation of the company, customer perception of dependency to the vendor, etc

Customer demographic includes age, sex, education, social status, geographical data are also used for churn calculation.

Macro environment variable identifies the changes in the world and the different experience of customer which affect the way they use the service. For instance, in the telecommunication trade people who have survived a natural disaster and could rely on their mobile phones during it are more likely to continue using the service.

To reduce customer churn, company should be able to predict the behaviour of customer accurately and establish links between customer attrition and keep factors under their control. In the literature, many prediction algorithms have been applied to predict the customer churn. Identifying the churners can help companies retain their customers. It can be achieved by customer data. It can be a valuable source for meaningful insights and to train customer churn models. It helps in learning from the past, and gives strategic information at hand to improve future interaction with customers. Telecommunication industry has lot of information. It has large amount of customer data. The emergence of sophisticated artificial intelligence and data analytics techniques further help leverage this rich data to address churn in a much more effective manner.

According to Umayaparvathi &Ilyakutti (2012) [26], the customer churn prediction problem is normally characterized into three major stages, namely,

1. **Train:** the historical data such as call details and personal and/or business customers' data, is obtained and retained by the telecommunications service providers. Furthermore, in the training stage, the labels are structured in the list of churners' records.
2. **Test**: the trained model with the highest accuracy is tested to predict the churners' records from the actual dataset which does not contain any churn label.
3. **Prediction**: also known as the knowledge discovery process, the problem is classified as predictive modeling or predictive mining.

In the prediction stage, which is Customer churn prediction helps the Customer Relationship Management (CRM) to avoid customers who are expected to churn in future by proposing retention policies and offering better incentives or packages to attract the potential churners in order to retain them. Hence, the possible loss of the company's revenue can be prevented [26].

Several reasons are presented in the work of [27] for when customers decide to stop using the service and why. The authors classified the causes of churn into three groups: controllable churn, uncontrollable churn and non-pay/abuse. The controllable includes anything that is under the control of the company: Defecting to a competitor, response to poor service and the service price. Uncontrollable includes all the reasons that are outside the control of the company hands such as, death, illness and moving to a different country. The last group includes the causes that are related to non-payment, abuse, theft of service or other causes in which the company made the churn decision for the customer and it is unclear whether any of the non-pay/abuse is controllable or not. A wide variety of factors play a great effect on churn in the telecom industry such as; income level, educational background, marital status, age, gender, geographical location, the effect of family and friends, cultural habits, service quality and price. In [28], the authors decided to investigate account length, international plan, voice mail plan, number of voice mail messages, total day minutes, total evening minutes, total night minutes, total international minutes, and number of calls to customer service factors. Some other works use income level, educational background, marital status and friends' factors [29] and economic patterns: rate plans, tariffs and the promotion available from different service providers [30]. The author in [31] conducted research to analyse customer behavioural and demographic characteristics. The behavioural factors include rate plan (i.e., number of rate plan changes made with the carrier), handset changing frequency (i.e., number of handset changes made with the carrier), contract (Customer's service contract), rate plan suitability, customer tenure (i.e., number of months the customer stays with the service provider since service activation) and account status (still active or already churned at the end of the study period). The demographic factors include age, location (Western Canada or Eastern Canada) and language (English or French). There are other factors and their complex relationships affect customer churn such as service quality which is a combination of features such as network coverage, signal strength, voice quality, customer service is that provided by the service provider to the customer. This factor has a direct influence on encouraging customers to switch to another service provider as confirmed in the work of [32, 33].

The authors in [34] concluded that service quality has a positive relationship in controlling customer churn and also affect customer value positively. Service usage, switching cost, customer dissatisfaction and demographic factors play a very important role for a customer to switch to another service provider [35].

III. LITERATURE REVIEW

The data of customers are stored in such CRM systems which can then be transformed into valuable information with the help of ML techniques which aid telecom companies to formulate new polices, develop campaigns for existing clients and figure out the main reasons behind customer churn. In this way, companies can easily observe their customer's behaviour from time to time and manage them effectively. Therefore, ML approaches are needed in telecom sectors which remain the corner-stone of customer churn control and can play a fundamental role in decreasing the probability of churners. Due to the increased amount of data collection, organization and companies can store vast amount of data and information using several types of storage technologies at low cost. However, the challenge is to analyse, summarize and discover knowledge from these stored data. ML and statistics aiming at automatically discovering useful information and identifying hidden patterns in large data warehouses. ML involves few phases from raw data collection to some of the interesting patterns and this process includes data cleaning, transformation, selection and evaluation.

The prediction models have been applied in Telecom Industry to predict the dissatisfied customers who are likely to change the service provider. Due to immense financial cost of customer churn in telecom, the companies from all over the world have analysed various factors (such as call cost, call quality, customer service response time, etc.) using several machine learning techniques such as decision trees, support vector machines, neural networks, probabilistic models such as Bayes, etc.Machine Learning techniques that have been applied worldwide through the last decade as shown in Table1.

TABLE I
ML TECHNIQUES USED IN TELECOM INDUSTRY

Technical Paper	Used Techniques	Outcomes
(Idris et al., 2012, [36])	Adaboost style boosting – Artificial Neural Network (ANN) and Random Forest (RF)	GP- AdaBoost based model offers higher accuracy than ANN and RF. The GPAdaBoost achieved a prediction accuracy of 89% for Cell2Cell dataset and 63% for the other dataset.
(Miguéis et al., 2013,[37])	Logistic Regression (LR)) and Multivariate Adaptive Regression Splines (MARS)	MARS achieved better results when the whole set of variables are used. However, the LR outperforms MARS when variable selection procedures are applied.
(Brandusoiu &Toderean, 2013, [38])	Support Vector Machine (SVM) with four kernel functions:	SVM model using polynomial kernel (SVMPOLY) showed

	Radial Basis Function kernel (RBF), linear kernel (LIN), Polynomial kernel (POLY) and sigmoid kernel (SIG)	superiority over other SVM models.
(Lemmens& Gupta, 2013, [39])	gain/loss matrix and gradient boosting	The results indicated that improvements are achieved by using gain/loss matrix and gradient boosting approach for companies with no additional implementation cost.
(Keramati et al., 2014,[40])	Decision trees, ANN, KNearestNeighbors and SVM	ANN shown higher accuracy than Decision trees, K-Nearest Neighbors and SVM.
(Effendy et al., 2014, [41])	Weighted RF(WRF)	The combined sampling techniques able to help WRF algorithm to achieve better performance and predict the churn effectively
Chen et al., 2015, [42])	LR, Decision tree (C4.5), ANN (multilayer perceptron, (MLP)) and SVM	C 4.5 outperformed the other models and. the most significant variables for customer churn: Length, recency and monetary.
(Vafeiadis et al., 2015, [43])	SVM-poly, Decision tree, ANN, Naïve Bayes, Regression Analysis	SVM-poly using AdaBoost obtained 97% accuracy and F-measure over 84%.
(Zhang et al., 2015, [44])	DT and Regression	The relationship between profit and retention is good when prediction algorithm sufficiently good, when capability of retention is good enough, the relationship of profit and retention is convex and when both prediction algorithm and retention capability are not effective enough, the operators should not take any actions
(Hassouna et al, 2016, [45])	Decision tree (CART, C 5.0, CHAID) and LR	C 5.0model is better than the LR model
(Umayaparvathi&Iyakutti, 2016, [46])	Gradient Boosting (GB), DT, SVM, RF, KNearest Neighbour, Ridge Regression and LR	GB model has a higher performance than other techniques and six attributes: day minutes, voice, mail plan, night charge, international calls, evening calls, and day calls minutes have upmost importance towards churn prediction in the Cell2Cell dataset
(Brânduşoi	Neural	SVM achieved

u et al., 2016,[47])	networks, SVM and Bayesian networks.	better performance compared to other techniques
(ArtitWang perawong, Cyrille Brun, and RujikornPav asuthipaisit. 2016, et al, (2016), [48]	CNN, Autoencode rs	Deep convolutional neural networks and autoencoders outperforms other simpler models such as decision tree modeling
(Coussemen t et al, 2017,[49])	CART, Bayesian network, J4.8 decision tree, MLP, Naive Bayes, RF, SVM with RBF kernel function and Stochastic gradient boosting	Data preparation treatment (DPT) improves prediction performance. Logistic regression-DPT approach outperformed the empirical methods remarkably
(Prashanth et al, 2017,[50])	Linear: LR, non-linear: RF, Deep Learning: Deep Neural Network, Deep Belief Networks and Recurrent Neural Networks	Non-linear techniques performed better than the linear and both RF and deep learning gave comparable performance
(Amin et al, 2017, [51])	Rough Set Theory (RST), Exhaustive Algorithm (EA), Genetic Algorithm (GA), Covering Algorithm (CA) and LEM2	RST-GA based model showed satisfactory results for extracting implicit knowledge.

	algorithm (LA)	
(Azeem et al., 2017,[52])	Neural Network, Linear regression, C4.5, SVM, AdaBoost, Gradient Boosting, RF and Fuzzy classifiers: Fuzzy NN, VQNN, OWANN and Fuzzy Rough NN	Fuzzy classifiers shown superior performance compared to other used models
(Zhu et al., 2017,[53])	LR, Decision Tree (C4.5), SVM and RF	Sampling approaches power lies in the used evaluation metrics as well as the classifiers.
(A. Mishra and U. S. Reddy, 2017, [54])	CNN	It showed good performance in terms of accuracy with an accuracy of 86.85%, error rate of 13.15%, precision 91.08, recall 93.08%, F-score 92.06%
(Gui, C. et al., 2017, [55])	RF	SRC combined with SMOTE method achieved the best results
(De Caigny et al., 2018,[56])	Decision trees and LR	The hybrid model provided more accurate model than using its building blocks; decision trees and LR; as a standalone classification models
(Ullah et al.,	JPK, LR,	RF performed

2019, [57])	MLP, Naïve Bayes, AdaBoostM1, attribute selected classifier, decision stump, RF, J48, random tree and LWL	better in terms of prediction of churners
(JafariMarandi et al., 2020, [58])	ANN, Self-organizing map	The proposed profit driven models proved to be effective for telecom churn prediction

IV. EVALUATION METRICS

There are several standard performance metrics proposed in the literature to compare the effectiveness of the different classifiers for churn prediction. These metrics are suitable for analysing the performance of any model which is built using both balanced and unbalanced dataset. The metrics are stated below[Umayaparvathi, V., &Iyakutti, K. (2016, March) [46]:

1. **Confusion matrix:** It is a table with two rows and two columns that reports the number of false positives (FP), false negatives (FN), true positives (TP), and true negatives (TN). It provides the required information for analysing the churn prediction accuracy in terms of false.
2. **Accuracy:** Accuracy of the given prediction model is defined as below ACC = (TP + TN) / (TP + TN + FP + FN)
3. **Precision:** It is defined as below Precision = TP / (TP + FP)
4. **Recall** = TP / (TP + FN)
5. **F1-score:** It is defined as below F1 = 2 TP / (2TP + FP + FN)
6. **AUC curve:** In contrast with other metrics AUC is not influenced by any threshold value as it takes into account all possible thresholds on the predicted probabilities.

V. CHURN CLASSIFICATION AND ANALYSIS MODELS

The classifier must be able to recognize users who have a tendency to churn in the near future. Churn prediction can be dealt with by using different classification statistical and machine learning techniques.

1. **Linear Regression:** In linear regression, the relationships are modelled using linear predictor functions whose unknown model parameters are estimated from the data. Such models are called linear models.
2. **Logistic regression:**It is an algorithm used for binary classification problems. It predicts the likelihood of an event by measuring the relationship between a dependent variable and one or more independent variables (features). More specifically, logistic regression will predict the possibility of an instance (data point) belonging to the default category
3. **K-means**: k-means clustering is a method of vector quantization, originally from signal processing, popular for cluster analysis in data mining.
4. **Decision tree**: It is a type of supervised learning algorithm (with a predefined target variable).Mostly used in classification tasks, it can handle numeric data as well. This algorithm splits a data sample into two or more homogeneous sets based on the most significant differentiator in input variables to make a prediction.
5. **Neural Networks:** It is a technique that is based on the functioning of neurons in human brain.“The neural network simulates this behaviour in learning about collected data and then predicting outcomes,” (Mark Stadtmueller, VP,Lucd)
6. **K-Nearest Neighbours (KNN) algorithm**:It is a simple, easy-to-implement supervised machine learning algorithm that can be used to solve both classification and regression problems.
7. **Support Vector Machines (SVMs):** They are supervised learning methods used for classification and regression tasks that originated from statistical learning theory (V. Vapnik, Statistical learning theory. Wiley, New Tork (1998))
8. **Naïve Bayes Classifier**: It is a supervised learning algorithm, which is based on Bayes theorem and used for solving

classification problems. It is mainly used in text classification that includes a high-dimensional training dataset.

9. **CART (Classification and Regression Trees) analysis:**It predict or classify cases according to a response variable. CART uses a binary recursive partitioning method that produces a decision tree. The tree is structured as a sequence of simple (split) questions based on several predictor variables.
10. **Ensemble Classification [59]:**Ensemble model is a machine learning approach to combine multiple other models in the prediction process. Machine learning algorithms have their limitations and producing a model with high accuracy is challenging. If we build and combine multiple models, the overall accuracy could get boosted. They are also called as meta-algorithms.
    a. **Bagging:**Each model learns the error produced by the previous model using a slightly different subset of the training dataset.
        i. *Bootstrapping:*It creates multiple sets of the original training data with replacement.
        ii. *Random Forest:* Uses subset of training samples as well as subset of features to build multiple split trees. to fit each training set. The distribution of samples/features is typically implemented in a random mode.
        iii. *Extra-Trees Ensemble:*The predictions are combined from many decision trees. Similar to Random Forest, it combines a large number of decision trees. However, the Extra-trees use the whole sample while choosing the splits randomly.
    b. **Boosting:**creates a strong classifier from a number of weak classifiers.The most well-known boosting algorithm is AdaBoost
        i. *Adaptive Boosting (AdaBoost):*It build models on the top of several weak learners
        ii. *Gradient Boosting:*Great techniques that have high predictive performance. Xgboost, LightGBM, and CatBoost are popular boosting algorithms used for regression and classification problems.
    c. **Stacking:** It is a process of learning how to create a stronger model from all weak learners' predictions.

VI. CHALLENGES

There have been numerous researches carried out on churn prediction.Customer often compares their service provider with other competitors in the market and churn to whoever they feel provides better service. Researchers have found service quality [60,61,62] as the top factor for customer churn.

Poor customer care and slow response to their needs and complaints are another factor which can also play a vital role in increasing the probability of customers to change to another service provider [63]. Another factor that needs further attention is the customer's tenure (i.e., churn time) with the service provider and its relationship with the prediction of customer churn in the telecom sector as confirmed in the work of [64,65]. It has been confirmed that a high correlation exists between churn risk and customer dissatisfaction and the role of telecom companies to prevent dissatisfaction of customers from churning [66]. To tackle the problem of customer churn, telecom companies use different strategies for churn management. They include: identifying churners first by using a predictive model, followed by targeting those customers with retention incentives to encourage them to stay [67]. A recent approach is focused on choosing the target customers based on the profit potential of each, the likelihood of churning, the number of customers the company decides to target and the incentive cost to maximize the overall return from the retention campaign [68,69]. Despite intensive efforts, it is difficult to generalize best performance of the predictive techniques for customers churn prediction in the telecom sector. Therefore, a review and benchmarking experiment need to be done to allow comparing the performance of a variety of classification techniques. All kinds of data have different attributes that might pose problems for ML techniques to extract the most crucial patterns in datasets due to class imbalanced in datasets. The classes whose number of instances are below the average number of instances per calls are termed as minority classes, while the instances that are above the average number of instances per class are termed as majority classes. Many studies have carried out comparisons on sampling techniques for handling class imbalance problem in the pre-processing phase. However, none of the literature reached to a final conclusion about which sampling technique is suitable for customers churn problem in telecom sector. Feature selection main goal is to select the most important features without changing the original data representation, and therefore, selecting a subset of the features relevant for the task to achieve the highest classification accuracy. Searching for the optimal subsets of features is necessary pre-processing step in ML techniques. Variable or feature selection eliminates irrelevant features and obtains the best feature subsets that play a vital role in the models' accuracy and their final results. None of the previous works confirmed which ML techniques can perform the best for feature selection. To evaluate the performance of a classifier, it is essential to specify at the beginning which evaluation measures should be used to fix the optimization objective for the entire analysis. Churn prediction problem is considered as a binary classification task because the outcome has only two possible values (churner or non-churner). Accuracy, recall, and precision measures are often used to evaluate the classification quality of binary classifiers [70]. Recall measures the proportion of positive cases (churners) that are correctly classified. Precision measures the proportion of cases classified as churners that are correctly churners. In other works, the authors confirmed that the use of the confusion matrix represents the primary source for accurate estimation of churn prediction in the telecom sector [71]. Despite the intensive research efforts, there is still no consensus exists on the validation of results and far from agreeing on any standards. Therefore, it is important to verify how the model performs. In ML, validation strategies are used to validate a model's performance, and generalized their outcomes. One of the useful and popular mechanisms for validating a customer churn model performance and its accuracy is the cross-validation technique [72].

VII. CONCLUSIONS

Many ML techniques have been applied so far. There is no such algorithm that provides 100% accuracy. There will always be a trade-off between precision and recall. That's why it's important to test and understand the strengths and weaknesses of each classifier and get the best out of each.

This paper discusses on the process of churn prediction in Telecom industry. From the literature review conducted it is understood that churn prediction in communication is very important for customer retention for all kind of service industry. The purpose of this paper is not to propose a new algorithm, but focus on recognizing the implementation and the understanding of the existing predicting models. There are many different ways of churn prediction and new techniques continue to emerge not only in communication sector but also in other fields. Future research direction is planned in the direction of developing a new model for churn prediction. Good prediction models have to be constantly developed and a combination of the proposed techniques has to be used. They have to be properly customized by the companies for their existence.

From the literature review, we can appreciate the importance ofchurn prediction for customer retention in Telecom Industry. Customer retention is applicable for all kind of service industry. The purpose of this paper is not to propose a new algorithm, but focuses on knowing different implementation of churn prediction models used. There are many different ways of churn prediction and new techniques continue to emerge not only in communication sector but also in other fields. Future research direction is planned in the direction of developing a new model for churn prediction. Good prediction models have to be constantly developed and a combination of the proposed techniques has to be used. They have to be properly customized by the companies for their existence.

Creating and delivering superior customer value is considered one of the corner-stones in the telecom market. Knowing the reasons for churning and predicting which customers are about to churn can yield a significant return in the profitability of the telecom companies. This paper gives a survey on the importance of customer churn, reasons behind customers churn and the state-of- the- art of ML approaches applied in Telecom Industry and its challenges.It can be concluded that monitoring churn is the first step in understanding how good you are at retaining customers and identifying what actions might result in a higher retention rate.All industries suffer from churn. The survival of any business is based on its ability to retain customers. Churn always happens, eventually. But the efforts that is done to lower down the impact, will make all the difference

REFERENCES

[1] Y. Huang, B. Q. Huang, M. T. Kechadi, “A New Filter Feature Selection Approach for Customer Churn Prediction in Telecommunications”, Proceedings of the IEEM, IEEE (2010) 338-342

[2] Yongbin Zhang, Ronghua Liang, Yeli Li, Yanying Zheng, Michael Berry “Behavior-Based Telecommunication Churn Prediction with Neural Network Approach”, Proceedings of International Symposium on Computer Science and Society IEEE (2011), 307 – 310.

[3] Geppert, K. (2002), Customer churn management. KPMG International, A SWISS Association.

[4] Shaffer, Greg, and Z. John Zhang. "Competitive one-to-one promotions." Management Science 48, no. 9 (2002): 1143-1160.

[5] Hoekstra J., Huizingh E.: The Lifetime Value Concept in Customer-Based Marketing. Journal of Market Focused Management, 3, 257-274 (1999).

[6] Jonathan, L., Janghyuk, L., & Lawrence, F. (2001). The impact of switching costs on the customer satisfaction-loyalty link: Mobile phone service in France. Journal of Services Marketing, 15(1), 35-48. http://dx.doi.org/10.1108/08876040110381463

[7] Ahn, J. H., Han, S. P., & Lee, Y. S. (2006). Customer churn analysis: Churn determinants and mediation effects of partial defection in the Korean mobile telecommunications service industry. Telecommunications Policy, 30(10), 552-568. http://dx.doi.org/10.1016/j.telpol.2006.09.006

[8] Seo, D., Ranganathan, C., &Babad, Y. (2008). Two-level model of customer retention in the US mobile telecommunications service market. Telecommunications Policy, 32(3), 182-196. http://dx.doi.org/10.1016/j.telpol.2007.09.004

[9] Ordenes, F. V., Theodoulidis, B., Burton, J., Gruber, T., &Zaki, M. (2014). Analyzing customer experience feedback using text mining: A linguistics-based approach. Journal of Service Research, 10(1), 242-256. http://dx.doi.org/10.1177/1094670514524625

[10] Hu, C., Shu, H., &Qiao, X. (2014). Customer segmentation model research based on organizational customer life cycle in telecom operator. 2014 International Conference on Education Technology and Social Science, Atlantis Press. http://dx.doi.org/10.2991/icetss-14.2014.88

[11] Tarhini, A., Hassouna, M., Abbasi, M. S., & Orozco, J. (2015). Towards the acceptance of RSS to support learning: An empirical study to validate the technology acceptance model in Lebanon. Electronic Journal of e-Learning, 13(1), 30-41. Retrieved from http://www.ejel.org/volume13/issue1

[12] Orozco, J., Tarhini, A., Masa’deh, R., &Tarhini, T. (2015). A framework of IS/business alignment management practices to improve the design of IT Governance architectures. International Journal of Business and Management, 10(4), 1-12. http://dx.doi.org/10.5539/ijbm.v10n4p1

[13] McIlroy, A., & Barnett, S. (2000). Building customer relationships: Do discount cards work? Managing Service Quality, 10(6), 347-355. http://dx.doi.org/10.1108/09604520010351491.

[14] Aydin, S., &Özer, G. (2005). The analysis of antecedents of customer loyalty in the Turkish mobile telecommunication market. European Journal of Marketing, 39(7), 910-925. http://dx.doi.org/10.1108/03090560510601833

[15] The Radicati Group, INC, a technology market research firm, Mobile Statistics Report 2014-2018, available at: https://www.radicati.com/wp/wpcontent/uploads/2016/01/Mobile-Growth-Forecast-2016-2020-ExecutiveSummary.pdf, (Accessed 19, September 2020).

[16] Database Market institute (2017), Churn reduction in the telecom industry, available

at: http://www.dbmarketing.com/telecom/churnreduction.html (Accessed Accessed 2, October 2020).

[17] Database Marketing Institute. Churn reduction in the telecom industry a valuable at: http://www.dbmarketing.com/2010/03/churn-reduction-in-the-telecom-industry/, (Accessed 2, October 2020).

[18] AT&T inc financial review 2019, Available at: https://investors.att.com/~/media/Files/A/ATT-IR/financial-reports/annualreports/2019/complete-financial-review-2019.pdf, (Accessed 2, October 2020).

[19] Oghojafor, B., Mesike, G., Bakarea, R., Omoera, C., &Adeleke, I. (2012). Discriminant analysis of factors affecting telecoms customer churn. International Journal of Business Administration, 3(2), 59.

[20] Tenhunen, S. (2008). Mobile technology in the village: ICTs, culture, and social logistics in India.Journal of the Royal Anthropological Institute, 14(3), 515-534.

[21] Halim, J &Vucetic J (2015). Causes of Churn in the Wireless Telecommunication Industry in Kenya. DOI: 10.14355/ijmser.2016.0301.01

[22] Saefuddin, A., Setiabudi, N. A., &Achsani, N. A. (2011). The effect of overdispersion on regression-based decision with application to churn analysis on Indonesian mobile phone industry.

[23] Sey, A. (2009). Exploring mobile phone-sharing practices in Ghana. info, 11(2), 66-78

[24] Lemmens, A., & Gupta, S. (2013). Managing churn to maximize profits. Working Paper, http://www.hbs.edu/faculty/Publication%20 Files/14-020_3553a2f4-8c7b-44e6- 9711-f75dd56f624e.pdf

[25] Bit Refine group available at: https://bitrefine.group/aboutcompany/news/248-mobilenetwork-operators-combat-customer-churn-through-prediction-breakthrough, (Accessed 2, October 2020)

[26] V Umayaparvathi, K Iyakutti, International Journal of Computer Applications 42 (20), 5-9

[27] Braun, M., &Schweidel, D. A. (2011). Modeling customer lifetimes with multiple causes of churn.Marketing Science, 30(5), 881-902.

[28] Antipov, E., &Pokryshevskaya, E. (2010). Applying CHAID for logistic regression diagnostics and classification accuracy improvement.Journal of Targeting, Measurement and Analysis for Marketing, 18(2), 109-117

[29] Wong, K. K. K. (2011). Getting what you paid for: Fighting wireless customer churn with rate plan optimization.Journal of Database Marketing & Customer Strategy Management, 18(2), 73-82

[30] Ranaweera, C. (2007). Are satisfied long-term customers more profitable? Evidence from the telecommunication sector.Journal of Targeting, Measurement and Analysis for Marketing, 15(2), 113-120.

[31] Wong, K. K. K. (2011). Using Cox regression to model customer time to churn in the wireless telecommunications industry.Journal of Targeting, Measurement and Analysis for Marketing, 19(1), 37-43

[32] Lemmens, A., &Croux, C. (2006). Bagging and boosting classification trees to predict churn.Journal of Marketing Research, 43(2), 276-286.

[33] Foster P, and Fawcett T. (2013). Data Science for Business: What You Need to Know About Data Mining and Data Analytic Thinking, O'Reilly Media, 2013.

[34] Marwanto, S. T., &Komaladewi, R. (2017). How to restrain customer churn in telecommunication providers: study in west java Indonesia.Review of Integrative Business and Economics Research, 6, 51.

[35] Al-Mashraie, M., Chung, S. H., & Jeon, H. W. (2020). Customer switching behavior analysis in the telecommunication industry via push-pull-mooring framework: a machine learning approach.Computers& Industrial Engineering, 106476.

[36] Idris, A., Khan, A., & Lee, Y. S. (2012, October). Genetic programming and adaboosting based churn prediction for telecom. In Systems, Man, and Cybernetics (SMC), 2012 IEEE International Conference on (pp. 1328-1332).

[37] Miguéis, V. L., Camanho, A., & e Cunha, J. F. (2013). Customer attrition in retailing: an application of multivariate adaptive

regression splines. Expert Systems with Applications, 40(16), 6225-6232.

[38] Brandusoiu, I., &Toderean, G. (2013). Churn prediction in the telecommunications sector using support vector machines.Margin, 1, x1.

[39] Lemmens, A., & Gupta, S. (2013). Managing churn to maximize profits. Working Paper, http://www.hbs.edu/faculty/Publication%20 Files/14-020_3553a2f4-8c7b-44e6- 9711-f75dd56f624e.pdf

[40] Keramati, A., Jafari-Marandi, R., Aliannejadi, M., Ahmadian, I., Mozaffari, M., &Abbasi, U. (2014). Improved churn prediction in telecommunication industry using data mining techniques. Applied Soft Computing, 24, 994-1012.

[41] Effendy, V., &Baizal, Z. A. (2014, May). Handling imbalanced data in customer churn prediction using combined sampling and weighted random forest. In Information and Communication Technology (ICoICT), 2014 2nd International Conference on (pp. 325-330)..

[42] Chen, K., Hu, Y. H., & Hsieh, Y. C. (2015). Predicting customer churn from valuable B2B customers in the logistics industry: a case study. Information Systems and eBusiness Management, 13(3), 475-494.

[43] Vafeiadis, T., Diamantaras, K. I., Sarigiannidis, G., &Chatzisavvas, K. C. (2015). A comparison of machine learning techniques for customer churn prediction. Simulation Modelling Practice and Theory, 55, 1-9.

[44] Zhang, Z., Wang, R., Zheng, W., Lan, S., Liang, D., &Jin, H. (2015, November). Profit Maximization Analysis Based on Data Mining and the Exponential Retention Model Assumption with Respect to Customer Churn Problems. In Data Mining Workshop (ICDMW), 2015 IEEE International Conference on (pp. 1093-1097).

[45] Hassouna, M., Tarhini, A., Elyas, T., &AbouTrab, M. S. (2016). Customer Churn in Mobile Markets A Comparison of Techniques. arXiv preprint arXiv:1607.07792.

[46] Umayaparvathi, V., &Iyakutti, K. (2016, March). Attribute selection and Customer Churn Prediction in telecom industry. In Data Mining and Advanced Computing (SAPIENCE), International Conference on (pp. 84-90). IEEE.

[47] Brânduşoiu, I., Toderean, G., &Beleiu, H. (2016, June). Methods for churn prediction in the pre-paid mobile telecommunications industry.InCommunications (COMM), 2016 International Conference on (pp. 97-100).

[48] ArtitWangperawong, Cyrille Brun, and RujikornPavasuthipaisit. 2016. Churn Analysis Using Deep Convolutional Neural Networks and Autoencoders. arXiv preprint arXiv (2016), 1–6.

[49] Coussement, K., Lessmann, S., &Verstraeten, G. (2017). A comparative analysis of data preparation algorithms for customer churn prediction: A case study in the telecommunication industry. Decision Support Systems, 95, 27-36.

[50] Prashanth, R., Deepak, K., &Meher, A. K. (2017, July). High Accuracy Predictive Modelling for Customer Churn Prediction in Telecom Industry.In International Conference on Machine Learning and Data Mining in Pattern Recognition (pp. 391-402). Springer, Cham.

[51] Amin, A., Anwar, S., Adnan, A., Nawaz, M., Alawfi, K., Hussain, A., & Huang, K. (2017). Customer churn prediction in the telecommunication sector using a rough set approach.Neurocomputing, 237, 242-254.

[52] Azeem, M., Usman, M., & Fong, A. C. M. (2017). A churn prediction model for prepaid customers in telecom using fuzzy classifiers.Telecommunication Systems, 1-12

[53] Zhu, B., Baesens, B., &Backiel, A. (2017). Benchmarking sampling techniques for imbalance learning in churn prediction. Journal of the Operational Research Society.

[54] A. Mishra and U. S. Reddy, ‘‘A novel approach for churn prediction using deep learning,’’ in Proc. IEEE Int. Conf. Comput. Intell. Comput. Res. (ICCIC), Dec. 2017, pp. 1–4.[54]

[55] Gui, C. (2017). Analysis of imbalanced data set problem: The case of churn prediction for telecommunication. Artificial Intelligence Research, 6(2), 93.

[56] De Caigny, A., Coussement, K., & De Bock, K. W. (2018). A new hybrid classification algorithm for customer churn prediction based on logistic regression and decision

trees.European Journal of Operational Research, 269(2), 760-772.

[57] Ullah, I., Raza, B., Malik, A. K., Imran, M., Islam, S. U., & Kim, S. W. (2019). A churn prediction model using random forest: analysis of machine learning techniques for churn prediction and factor identification in telecom sector.IEEE Access, 7, 60134-60149.

[58] Jafari-Marandi, R., Denton, J., Idris, A., Smith, B. K., &Keramati, A. (2020). Optimum profit-driven churn decision making: innovative artificial neural networks in telecom industry.Neural Computing and Applications, 32(18), 14929-14962

[59] Mohammed Alhamaid, A guide to learning ensemble techniques in a simple walkthrough, https://towardsdatascience.com/ensemble-models-5a62d4f4cb0c.

[60] Lemmens, A., &Croux, C. (2006). Bagging and boosting classification trees to predict churn. Journal of Marketing Research, 43(2), 276-286.

[61] Foster P, and Fawcett T. (2013). Data Science for Business: What You Need to Know About Data Mining and Data Analytic Thinking, O'Reilly Media, 2013.

[62] Marwanto, S. T., &Komaladewi, R. (2017). How to restrain customer churn in telecommunication providers: study in west java Indonesia.Review of Integrative Business and Economics Research, 6, 51.

[63] Sathish, M., Kumar, K. S., Naveen, K. J., &Jeevanantham, V. (2011). A study on consumer switching behaviour in cellular service provider: A study with reference to Chennai. Far East Journal of Psychology and Business, 2(2), 71-81.

[64] Mahajan, V., Misra, R., & Mahajan, R. (2017). Review on factors affecting customer churn in telecom sector.International Journal of Data Analysis Techniques and Strategies, 9(2), 122-144.

[65] Gopal, R. K., &Meher, S. K. (2008, May). Customer churn time prediction in mobile telecommunication industry using ordinal regression. InPacific-Asia Conference on Knowledge Discovery and Data Mining (pp. 884-889). Springer, Berlin, Heidelberg.

[66] Radclifte, N. J., & Simpson, R. (2008). Identifying who can be saved and who will be driven away by retention activity. Journal of Telecommunications Management, 1(2).

[67] Coltman, T. (2007). Why build a customer relationship management capability? The Journal of Strategic Information Systems, 16(3), 301-320.

[68] Foster P, and Fawcett T. (2013). Data Science for Business: What You Need to Know About Data Mining and Data Analytic Thinking, O'Reilly Media, 2013.

[69] Marwanto, S. T., &Komaladewi, R. (2017). How to restrain customer churn in telecommunication providers: study in west java Indonesia.Review of Integrative Business and Economics Research, 6, 51.

[70] Burez, J., & Van den Poel, D. (2009). Handling class imbalance in customer churn prediction.Expert Systems with Applications, 36(3), 4626-4636

[71] Faris, H., Al-Shboul, B., &Ghatasheh, N. (2014, September). A genetic programming-based framework for churn prediction in telecommunication industry. In International Conference on Computational Collective Intelligence (pp. 353-362). Springer, Cham.

[72] Neslin, Scott A., Sunil Gupta, Wagner Kamakura, Junxiang Lu, and Charlotte Mason. "Defection detection: Measuring and understanding the predictive accuracy of customer churn models." Journal of marketing research 43, no. 2 (2006): 204-211.