ISSN: 0974-5823 Vol. 7 No. 2 February, 2022

International Journal of Mechanical Engineering

Churn Prediction Model using Hierarchical clustering and Customer Retention using Probability Model

[1]R.Sudharsan and [2]Dr. E.N.Ganesh

[1]R.Sudharsan, Research Scholar, Department of Computer Science and Engineering, Vels Institute of Science, Technology & Advanced Studies, Chennai

[2]School of Engineering, Vels Institute of Science, Technology & Advanced Studies,Chennai

Abstract

Database of telecom industries have unstructured data in today's world. Researches to identify Data analysis tool which can format all these business data, have been undergoing. Another challenge that Telecom industries has is the churn prediction and problems in retaining customers. Recommended approach can overcome problems of unstructured data as it converts them to structured format with the help of prediction model and classification of customers. This approach makes use of the data preprocessing technique which can minimize the high dimensional data with the help of feature selection. The customer classification is performed with the help of the k-nearest neighbor to churn customer and non-churn customer. CLV (customer life time value) is found by using the probability model which is the second proposed method. The higher CLV value refers to the longer time retention of customer.

Results: The proposed framework is implemented with MATLAB R 2014b software and its results are conferred.

Conclusion:

Considering current competitive telecom domain market, churn prediction becomes crucial issue in CRM. This actual issue in CRM is to sustain valuable customers in finding same set of customers and giving best services/offers which are competitive to associated groups. Hence, there are researches in progress to look for Churn's key parameters to preserve customer and provide resolution to CRM problems and making company decisions. Data analytics and data validation which is derived through standard evaluation metrics, are provided with a customer churn model in this study. The identified results states that our recommended churn model worked better with the help of techniques in machine learning. K-nearest neighbor 90% and RNN generated better F-measure result which is almost 95%.

We discovered primary factors of churn from dataset and made cluster profiling in accordance with its churning risk. At the end, guidelines were provided related to retaining customer's decision-makers in telecom domain. Future requirements may lead to further investigation on approaches of excited leaning and lazy learning in finding improved churn prediction. Artificial Intelligence techniques can be applied to this study to analyze changes in churn pattern behavior in predictions and analyzing trends

Index Terms - churn, customer, telecom, customer retention, customer life time value, KNN algorithm.

INTRODUCTION

Information and communication technology sector consists of all companies of telecommunications and internet service providers. The telecommunications industries in this sector plays the pivotal role in mobile communications evolution and society of information [1]. Since 90's, Telecommunication sector has been growing drastically in India. It also plays an important role in modern world. Every Indians daily life is mostly engaged with Telecommunication. On parallel growing phase of telecommunication sector, there are prominent growth in following factors. I) reduction in transaction costs, ii) Increase in speed of the internet, iii) enablement of free calls across India which has changed entire societies lifestyles and services also the brands. Also growth of the sector has now reached another milestone by enabling 4G technology in India [2]. Market structure has massively impacted by this change and lead to increased competition across telecom operators. In the world, Mobile market of India is rapidly-growing market. 5G technology seems to be reality in India by evolving existing 4G networks. 5G will become milestone in communications field in future as it brings instant high-power connectivity to all the devices. Digital transformation and Technological revolution are almost close to be achieved which will provide consumers a multiple services [3]. Demand on quality services becomes common Consumers mentality from service providers. Machine leaning and artificial intelligence can provide solution to these demand.

India's telecom sector's growth and development has become Indian economy's key contributor and up gradation of social status. Each departments and Telecom Sector's service provider is helping to provide best quality infrastructure in their operation area to provide services to their customers which in turn increases the country growth in global market. Across the world, customers view Mobile phone service as a commodity. As per current trend, providers of mobile phones have given more attentions on acquiring customer at the cost of quality of the service and their retention [4]. This has developed buyer's controlled market trend where best deals motivates the customers during the initial or sign-up phase of carrier relationship. Multiple factors like monthly fees reduction, increase in minutes and receipt of enhanced phones decide customers to change carriers of their own choice. Longer value of customer lifetime is impacted by retaining the Customer which gives more profit to the firms especially which emerges for sustainability and growth during shrinkage of market leading to contracting economy. Retaining of Customer is crucial when decrease in loyalty and cycles of sales are infuriating the business. During such times, loss of crucial customer to another competitor will apparently have impact on company's growth and profit. Existing customer retention is determined by satisfaction of the customers, a study says.

Additionally, quality of the network was considered to be a non-significant predictor in satisfaction of customer [5]. Also, the highest competition level within service providers to adopt new service techniques for customer in retaining their current customer and encouraging new customers also. In this paper aim to minimize churning and enhancing loyalty of the customers, telecommunication industries are using multiple strategies for customer retention.

Nowadays the telecommunication sectors are vastly investing in modern technologies to minimize the churn rates of them. Customer behavior can be predicted by insight tools and Customer analytics that helps service providers to find the best practices for enhancing retention rates. In order for telecommunication service providers to efficiently compete, they should concentrate on solutions for giving best customer experience to their customers and improve the loyalty so as to minimize churning. The proposed work able to identify the customer churn and to quantify the no. of unsubscribed customers or those who cancelled the contract, metric is used. Churn rate is used to identify if customers have better experience with services or they are not satisfied with it and about to leave the carrier. Next session discuss about the literature survey, the session 3 discuss about the proposed system. A session 4 algorithm for the churn prediction and customer retention in the telecom service. The session 5 discuss about the result and discussion and session 6 comprises of the conclusion for the work.

LITERATURE SURVEY

The neural network model and the decision tree model make use of the feature variables. Statistical methods are not applied in feature set selection. Gain of Information and attributes' Entropy are computed to show the efficiency to identify the churn. In general Data mining is to learn the knowledge [information]. As far as literature is concerned, data mining is the process of pattern extraction, pattern analysis and their associations and meaningful data from colossal databases. This kind of mining approach is also clled as Knowledge Discovery in databases (KDD) [6]. A developed technique to model applications on the basis of Data Mining approaches which denote a reasonable framework to develop application of Data Mining. Process of Data Mining modeling is recommended here and it is tested by multiple applications of data mining to predict churning of prepaid customers in the telecommunication industry [7]. The primary objective of this paper is to define an efficient model to predict possible prepaid churners, where the crucial part is to find the input variables set which are higher to build reliable and precise prediction model. Various models were developed and comparisons made based on various Data Mining approaches and algorithms (decision trees, neural networks and logistic regression). Churn of the Customers is a significant issue in service industries where higher competition exist. However, prediction of customers churn will denote source of theoretically huge additional revenue when it is performed during earlier stage. The prime motive of this work is to generate a predictive model which produces good outcomes and evaluates churn rate of the customer in telecommunication service providers.

The model created in this research makes use of techniques in machine learning on data of churn customer. Recommended method of peer grading regression approach which is helped in prediction of churning of the customers. Peer grading regression is scientific process in reviewing churn customer work and investigating and testing of model of prediction that encircling relationships within various constructs like critical churn oriented variables, reasons for switching, usage of service, behavior and costs [8]. The journalist [9] emphasized a met heuristic on the basis of churn prediction approach which works prediction of churn on high data of telecom. A mongrelized procedure of Firefly algorithm is utilized as the classifier.

Component that is needed to compute the Firefly algorithm is comparison block where every firefly is compared with other to find out the intensity. Simulated Annealing replaces this component and the process of classification is performed. Firefly algorithm, as it is met heuristic its type, could efficiently find optimal solutions while comparing to other algorithms which are statistics based. Fireflies intensity determines the Movement of the fireflies, given by the firefly intensity parameter. The application of only dependent parameter results in requirement of lesser memory; therefore, this algorithm can operate at huge data. The main disadvantage of this algorithm is that for each iteration, a firefly needs to be compared with each other firefly within the system, which increases the number of computations. Therefore computations level maximizes to its best extend due to increase in numbers of the fireflies in search space.

Finally, retention is the opposite of churn. The customer is said to be churned if they have finalized to stop transaction with the company [10]. In addition, churn is concluded by the end of transactions of customers with the firm. To summarize, retention is said to be in continued transactions and it is applicable to a most of the businesses, irrespective of availability of contract between customer-firm or transactions types. The problems occurred with our top customers due to segmentation and prediction of lifetime value; hard work should be done in order to retain the customers. Based on these activities, it is inferred that Rate of Retention is one of the most crucial metrics. Quality of the data is the one of the biggest problems in segmentation of customers. If data is inaccurate, final grouping will also be poor.

Accuracy of the resulting segments is inaccurate if these attributes are not properly maintained which will lead to not useful information. If the users are not comfortable with data quality, they are possibly not going to make use of the segments. Improper maintenance may also lead to issues in Data quality and continuous cleansing is required to assure the accuracy.

OBJECTIVE

The problems in the customer segmentation inaccurate data quality lead to the poor grouping. To overcome the problem proposed system uses the hierarchical clustering to improve the grouping based on the customer classification for K-Nearest Neighbor.

To compute lifetime value (LTV) for machine learning model training. The customers are considered to be highly valuable with respect to lifetime value however there are often few customers who reduce the profitability. The system wants to determine the pattern behaviors, performs customers segmentation and act in accordance to that.Telecommunication providers deal with a vast collection of data like user data, device data, location data, etc. from different sources. Since last decade, the telecommunications sector has emerged significantly. Only companies which are ready to adapt new practices can continue to lead the industry. Most of the telecommunication companies understand that they do have poor quality issue with data and finds no time to fix all these data manually. These industries seem to find this process quite time consuming and expensive; hence there is no system which can correct or organize these poor data. Other telecommunication companies understand the issues with data quality and take some steps to manage them but they are not given high priority [11]. Companies in Telecommunications sector are not able to afford to NOT efficiently make use of the data available with them. Most of the telecommunications companies have undergone mergers or some acquisitions with other different operators with data and data systems. Hence, it is unavoidable to contain a disorganized data set. This data set consists of multiple variables which explain the telecom industry attributes and numerous factors presumed to be crucial when it deals with telecom industry's customers. Here use this data set to forecast the customers who is likely to churn or who is not likely to churn based on multiple variables that are available.

The customer details like the customer identity number, income, adults, marital status, own rent, monthly revenue, monthly mean, monthly revenue, day mean and active customer per days. The customer records are arranged using the analysis of hierarchical clustering is an algorithm which combines alike objects into groups that are called clusters. The place where every cluster is unique from other cluster and object inside every clusters are roughly alike to each other, is called endpoint [12].

HIERARCHICAL CLUSTERING USING K-NEAREST NEIGHBOR

I. *Data Preprocessing:*

Converting raw data into understandable or readable format is called as the data preprocessing. It is one of the data mining techniques. In preprocessing, data is cleaned by various processes like missing value filling, smoothing data with noises or resolution of data inconsistencies. This method is better approach in resolving most of the problems [13].

II. *Feature Extraction Process:*

Feature Extraction is the process of reducing an attribute. Most significant attributes are selected and retained in feature selection process whereas Feature Extraction process indeed transforms the attributes. The attributes that are transformed or featured are linear combinations of the actual original attributes. Smaller and richer attribute sets are created as a result of Feature Extraction process. User can specify the maximum number of features or they can be identified by the algorithm. The algorithm determines them by default. When complex data set is reduced to either two or three dimensions, it can effectively be visualized [14].

III. *The feature extraction algorithm:*

Linear algebra and multivariate analysis techniques are used in Non-Negative Matrix Factorization (NMF). Matrix M is decomposed into matrices W and H which are lower ranked. The sub-matrix W consists of the basis of NMF; the sub-matrix H has the related coefficients (weights). The algorithm iteratively changes W and H values resulting to their product moving toward M. The technique retains same structure as its original data and assures that both values are (basis and weights) non-negative. When approximation error gets converged or defined no. of iterations are reached, the algorithm will be terminated [15].

In order to indicate iterations starting point, the NMF algorithm should be initialized along with a seed. The proper initialization is critical to get important results since processing space has the high dimensionality and non-availability of global minimization algorithm. Oracle Data Mining of Oracle utilizes a random seed which can initialize the W and H values on the basis of the uniform distribution [16]. This method performs well in many cases. The data like customer identity number, income, adults, marital status, own rent, revenue monthly, monthly mean, day mean and equivalent days.

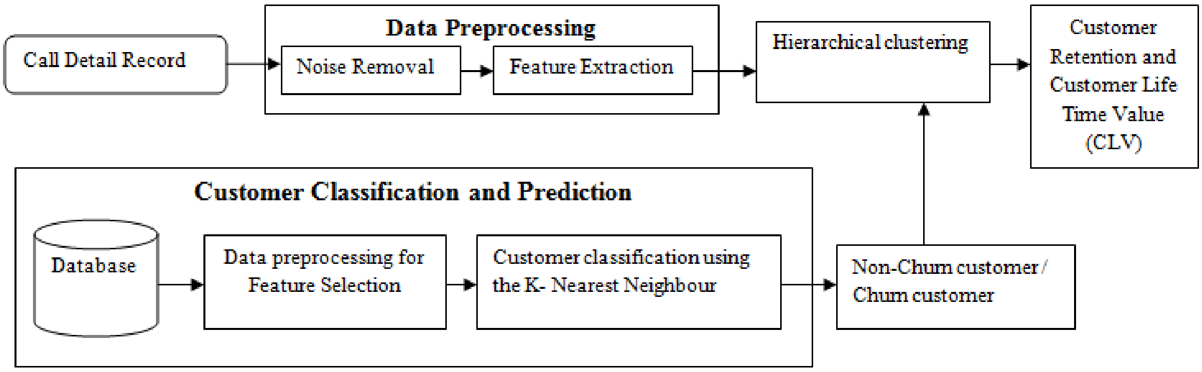

Figure 1: Hierarchical clustering for Customer retention and customer life time value (CLV).

The figure 1 shows the three stages of call detail records like data pre-processing, customer classification and churn prediction stage and customer retention with customer life tie value (CLV). The customer segmentation and poor grouping are reduced over the customer classification with k-nearest neighbor into two classes namely the non-churn and churn customer. These steps involve the high quality of hierarchical clustering group. It is easy to enable the customer life time value. The customer details take for the analysis in the customer classification and prediction with k- Nearest Neighbor [17].

Table 1: Filtered feature for Customer classification

Sl. No.	Customer Details	Parameter
1	customer identification	customer_ID
2	average revenue	avgrev
3	average monthly	avgmou
4	average quarterly	avgqty
5	average of 3 months detail	avg3mou
6	average of 3 quarterly detail	avg3qty
7	average of 3 month revenue	avg3rev
8	average of 6 months detail	avg6mou
9	average of 6 month quarterly detail	avg6qty
10	average of 6 month revenue	avg6rev

The customer details like the average revenue for the 3–6 month average values are taken for the analysis. The customer belongs to the average values of 3-6 month are classified using the k- Nearest neighbor Algorithm. The classification result able to understand the churn and non- churn classification algorithm [18] and [19]. The second method involves the classification of Recurrent Neural Network (RNN) algorithm. The customer life time value (CLV) using probability model involves the churn and non-churn customer with higher accuracy as given in figure 2.

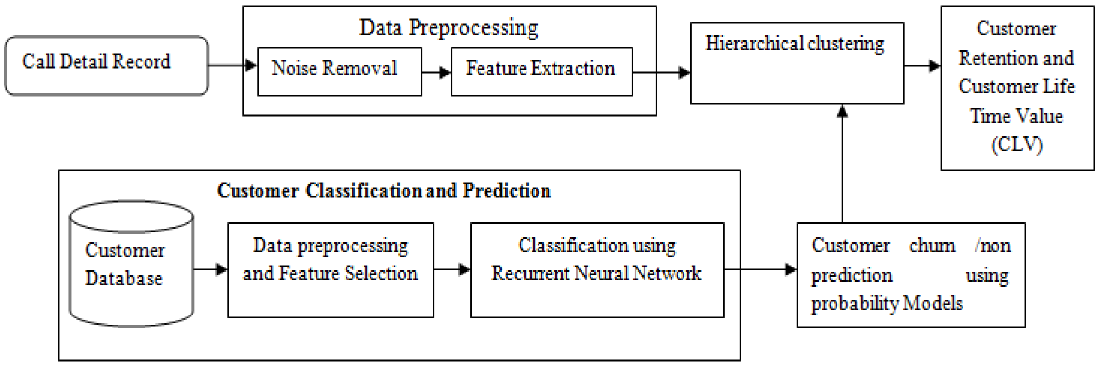

Figure 2: Customer Churn prediction and retention using the probability model.

The probability model is a random phenomenon which is mathematically represented. Sample space, events within it and probabilities which is related with every event define probability model. The sample space ’S’ indicates the probability model is set of all probable outcomes. The outcomes verify the all possible outcomes to take the churn and non-churn customer. A probability is a mathematical value which is associated to a specific event A. The probability of any event is specified P (A), and defines event’s long-run relative frequency. The 0 indicates the non-churn customer and 1 indicates the churn customer.

The initial two simple rubrics of probability are as follows:

#1: probability P(A) is a number between 0 and 1 ($0 < P(A) < 1$).

#2: The probability of the sample space S is equal to 1 ($P(S) = 1$).

If one of the marbles is selected, the probability of choice of the churn customer, $P(A) = 1/5$. Generally, the forthcoming formulation defines the calculation of equally likely outcomes of probabilities: If k is possible outcomes of a phenomenon and everyone is equally likely, then every individual outcome’s probability is 1/k. A is the churn customer event occurring indicates by the P(A).

Probability of any event A(churn customer) is (1)

If the 2 events do not hold any common outcomes, it will be called as disjoint. The churn customer and non-churn customer.

RESULT ANALYSIS

Data used for Telecom customer churn prediction can have multiple variables and can have millions of records. These variables provides important attributes about the industry and various vital features about the customers. The focused variable here is churn which provides information about the customer whether he leave the service provider or not. This dataset is used to predict the customers who is likely to leave or who won’t leave subject to the variables available. https://www.kaggle.com/abhinav89/telecom-customer/data#

I. *Calculate Customer Retention Rate and customer life time value:*

Customer retention rate is the percentage of existing customers to the number you had at the start of the period. New customers will be not calculated here. To calculate customer retention, below the there important numbers.

Total customer at the end of a duration (E)

Total new customers acquired during that duration (N)

Total customers at the starting of the duration (S)

Excluding the new customers, total existing customer at the end of given duration can be calculated by subtracting N from E.

Customer Retention Rate is calculated as ((E-N)/S)*100----- (2)

Calculating Lifetime Value is the easy part. First we need to select a time window. It can be anything like 3, 6, 12, 24 months. By the equation below, we can have Lifetime Value for each customer in that specific time window:

Life time Value: Total Gross Revenue - Total Cost ------ (3)

The customer life time and the customer retention of the system evaluated and the performance are shown using the confusion matrix.

II. *Performance Evaluation Metrics:*

Classification model performance is generally described in a table which is called as a confusion matrix. This is done with set test data set where we know true values. Left most parameters are used to calculate all the measures excluding AUC. Hence, let’s first discuss these four parameters [20].

	Predicted class		
Actual Class		Class = Yes	Class = No
	Class = Yes	True Positive	False Negative
	Class = No	False Positive	True Negative

Figure 3: Confusion matrix.

The figure 3 shows the correctly predicted class of true positive and true negative in the table and hence they are highlighted in green. Values in red highlight should be minimized where false positives and false negatives fall. Since these terminologies are ambiguous, they are explained in following section to understand thoroughly.

True Positives (TP) – It's an accurately predicted value with positive figure; It means both actual class value and predicted class value are yes. E.g. if value of actual class specifies that a customer is in service and the outcome of predicted class will also tell you same thing.

True Negatives (TN) – This value is an accurately predicted value with negative figure; it means that both actual class value and predicted class value are No. E.g. if value of actual class states that a customer is not in service and value of predicted class will also confers you same thing.

When value of actual class and value of predicted class contradicts, false positives and false negatives values will occur.

False Positives (FP) – This occurs when value of actual class says No, whereas value of predicted class states yes. E.g. if value of actual class refers that a customer is not in service but value of predicted class states you that customer is in service.
False Negatives (FN) – This case happens when value of actual class shows yes however value of predicted class is no. E.g. if actual class predicts the customer is in service whereas value of predicted class mentions you that the customer is not in service.

As we understand these key four parameters, we should be able to calculate other measures like precision, recall, F1 score and accuracy.

Accuracy – Most natural measure of performance is Accuracy and it is in general the ratio of accurately predicted observations to entire total observations. It may be presumed that if it has high accuracy, it would be the best model. Exactly, accuracy is one of the greatest measures; however, only if we have symmetric datasets in which false positive values and false negatives values are nearly same. Hence, it is required to know other parameters for evaluating our model performance. We have obtained accuracy of 0.799 for this model which indicates that this model is almost. 79% accurate.

Accuracy is calculated as TP+TN/TP+FP+FN+TN ----------- (4)

Precision – Correctly predicted positive values and total predicted positive values help in identifying Precision measure. It is the ratio of these two gives Precision of the model. The question here is that as per metric answer, all customers are labeled as in service, how many are in actual service. Low false positive rate refers to high precision. We have received 0.787 precision that is really good.

Precision is calculated as TP/TP+FP------------------- (5)

Recall (Sensitivity) – Recall is referred as the ratio of rightly predicted positive value to all actual class' observations in Yes in actual class. Recall actually answers how many were we labelling out of all customers who actually use service. Our recall value is 0.631 that is good as it's more than 0.5.

Recall is calculated as TP/TP+FN---------------------- (6)

F1 score – Weighted average of recall and precision is mentioned as F1 Score. All false positives and all false negatives will be considered for score computation. Best accuracy can be observed if false positives and false negatives have the same cost value. We have achieved a score of 0.70 for F1.

F1 Score is calculated as 2*(Recall * Precision) / (Recall + Precision) -------------------- (7)

Table 2: Performance evaluation result

Sl.No.	Existing Method	Incorrectly Classified Instance (%)	Correctly Classified Instances (%)	Time for Building Tree (sec)
1	Random Forest	11.37	88.6	108.48
2	Navie Bayes	52.37	47.63	0.48
3	Logistic Regression	29.02	70.98	1.87
4	**Proposed method-I**	**8.63**	**90.26**	**0.36**
5	Attribute Selected	11.66	88.34	4.08
6	Decision Stump	11.39	88.61	13.98
7	AdaBoost M1	16.05	83.95	9.24
8	**Proposed method-II**	**7.2**	**95.63**	**0.045**

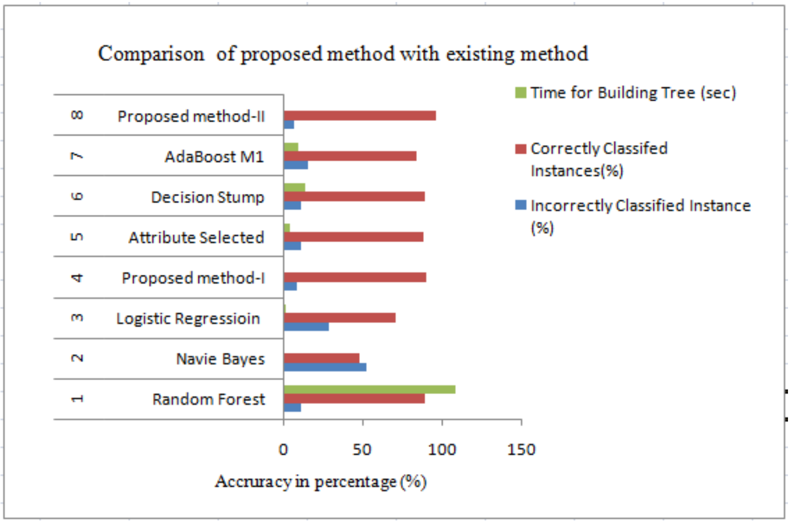

Figure 4: Comparison of existing method with proposed method.

The table 2 specifies the comparison of current method like Random Forest, Logistic Regression and Navie Bayes and the proposed method –I improves the correctly classified of 90.26 % with the incorrectly classified of 8.63 %. . The existing method Attribute Selected, Decision Stump and AdaBoost M1 compared with the proposed method-II improves the performance of 95.63% accuracy and the incorrectly measure of 7.2 %. Hence the proposed system improves in the accuracy results as shown in figure 4[20].

CONCLUSION

Considering current competitive telecom domain market, churn prediction becomes crucial issue in CRM. This actual issue in CRM is to sustain valuable customers in finding same set of customers and giving best services/offers which are competitive to associated groups. Hence, there are researches in progress to look for Churn's key parameters to preserve customer and provide resolution to CRM problems and making company decisions. Data analytics and data validation which is derived through standard evaluation metrics, are provided with a customer churn model in this study. The identified results states that our recommended churn model worked better with the help of techniques in machine learning. K-nearest neighbor 90% and RNN generated better F-measure result which is almost 95%.

We discovered primary factors of churn from dataset and made cluster profiling in accordance with its churning risk. At the end, guidelines were provided related to retaining customer's decision-makers in telecom domain. Future requirements may lead to further investigation on approaches of eager leaning and lazy learning in finding better churn prediction. Artificial Intelligence techniques can be applied to this study to analyze changes in churn pattern behavior in predictions and analyzing trends.

REFERENCES

[1]. K. Reddy Sai Sravanth, N. Sundaram, Desti Kannaiah. PEST Analysis of Present Indian Telecom Sector. International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-2, December 2019, DOI: 10.35940/ijitee.B6384.129219.

[2]. Nandini Borah. The Changing Indian Telecommunication Industry. Article in SSRN Electronic Journal. December 2014, DOI: 10.2139/ssrn.2539956.

[3]. Dr. Papori Baruah. Telecom Sector in India: Past, Present and Future. International Journal of Humanities & Social Science Studies (IJHSSS). Volume-I, Issue-III, November 2014, Page No. 147-156.

[4]. Amulya.M. Customer Retention Strategies In Telecom Service Providers In India. International Journal of Engineering and Management Sciences, I.J.E.M.S., VOL.4 (2) 2013: 132-143.

[5]. Md. Alamgir Hossain1+ Md. Rakeullah Chowdhury2 Nusrat Jahan3. Customer Retention And Telecommunications Services In Bangladesh. International Journal of Asian Social Science , Vol. 7, No. 11, 921-930 .

[6]. DR. M.BALASUBRAMANIAN *, M.SELVARANI. Churn prediction in mobile telecom system using Data mining techniques. International Journal of Scientific and Research Publications, Volume 4, Issue 4, April 2014, pp 1-5.

[7]. Goran Kraljević & Sven Gotovac. Modeling Data Mining Applications for Prediction of Prepaid Churn in Telecommunication Services. Journal for Control, Measurement, Electronics, Computing and Communications. ATKAFF 51(3), 275–283(2010).

[8]. M.HemaLatha, S.Mahalakshmi. Predicting Churn Customer in Telecom using Peergrading Regression Learning Technique. International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-6, April 2020,pp-1025-1037.

[9]. Ammar A. Q. Ahmed, Maheswari D. Churn prediction on huge telecom data using hybrid firefly based classification. Egyptian Informatics Journal, 18 (2017) 215–220.

[10]. Eva Ascarza1 & Scott A.Neslin2 & Oded Netzer1 & Zachery Anderson3 & Peter S. Fader4 & Sunil Gupta5 & Bruce G. S. Hardie6 & Aurélie Lemmens7 & Barak Libai8 & David Neal9 & Foster Provost10 & Rom Schrift4. In Pursuit of Enhanced Customer Retention Management: Review, Key Issues, and Future Directions. Cust. Need. and Solut. https://doi.org/10.1007/s40547-017-0080-0.

[11] J. Hadden, A. Tiwari, R. Roy, and D. Ruta, ``Computer assisted customer churn management: State-of-the-art and future trends," Comput. Oper. Res., vol. 34, no. 10, pp. 2902_2917, Oct. 2007.

[12] H.-S. Kim and C.-H. Yoon, ``Determinants of subscriber churn and customer loyalty in the Korean mobile telephony market," Telecommun. Policy, vol. 28, nos. 9_10, pp. 751_765, Nov. 2004.

[13] Y. Huang and T. Kechadi, ``An effective hybrid learning system for telecommunication churn prediction," Expert Syst. Appl., vol. 40, no. 14, pp. 5635_5647, Oct. 2013.

[14] A. Sharma and P. K. Kumar. (Sep. 2013). ``A neural network based approach for predicting customer churn in cellular network services." [Online]. Available: https://arxiv.org/abs/1309.3945

[15] Ö. G. Ali and U. Aritürk, ``Dynamic churn prediction framework with more effective use of rare event data: The case of private banking," Expert Syst. Appl., vol. 41, no. 17, pp. 7889_7903, Dec. 2014.

[16] A. Amin, F. Al-Obeidat, B. Shah, A. Adnan, J. Loo, and S. Anwar, ``Customer churn prediction in telecommunication industry using data certainty," J. Bus. Res., vol. 94, pp. 290_301, Jan. 2019.

[17] S. A. Qureshi, A. S. Rehman, A. M. Qamar, A. Kamal, and A. Rehman, ``Telecommunication subscribers' churn prediction model using machine learning," in Proc. 8th Int. Conf. Digit. Inf. Manage., Sep. 2013, pp. 131_136.

[18] V. Lazarov and M. Capota, ``Churn prediction," Bus. Anal. Course, TUM Comput. Sci, Technische Univ. München, Tech. Rep., 2007.

[Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/download? doi=10.1.1.462.7201&rep=rep1&type=pdf

[19] R. Vadakattu, B. Panda, S. Narayan, and H. Godhia, ``Enterprise subscription churn prediction," in Proc. IEEE Int. Conf. Big Data, Nov. 2015, pp. 1317_1321.

[20] V. Umayaparvathi and K. Iyakutti, ``Applications of data mining techniques in telecom churn prediction," Int. J. Comput. Appl., vol. 42, no. 20, pp. 5_9, Mar. 2012.