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Customer Chrun Prediction Using Ensemble Learning In Telecommunication Industry

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Abstract - *The importance of Customer Churn Prediction (CCP) has increased lately particularly in telecommunication industries. Different versions of Churn Prediction Models (CPMs) have been designed by different authors. Technologies like machine learning, data mining and other meta-heuristic algorithms have been used in these models. The significant churn prediction methods designed over the recent years have been discussed in this paper. The purpose of this study is to evaluate the customer survival and customer threat scenarios which result in understanding the cause of churns in telecommunication businesses. The clients who are about to turn into churns are also examined and the time they take to turn into churns is also calculated. The causes of customer churn and the behavior of churn are highlighted through this study. To have a better understanding of the churn prediction, this research summarizes the various churn prediction methods. In most of the models, instead of using individual algorithms, hybrid models are designed. Thus, the telecommunication businesses can improve their services towards the high-risk clients so that the decision of clients to opt for churn is avoided. The voting classifier and SVM classifier are implemented for the churn prediction. The performance of voting classifier and SVMclassifier is compared in terms of accuracy, precision and recall. It is analyzed that accuracy, precision and recall of voting classifier is high as compared to SVM classifier.*

***Key Words*: Churn Prediction, Data Mining, Telecommunication Industry**

1. INTRODUCTION

Machine learning is a branch of artificial intelligence that allows computer systems to learn directly from examples, data, and experience. Through enabling computers to perform specific tasks intelligently, machine learning systems can carry out complex processes by learning from data, rather than following pre-programmed rules. Recent years have seen exciting advances in machine learning, which have raised its capabilities across a suite of applications. Increasing data availability has allowed machine learning systems to be trained on a large pool of examples, while increasing computer processing power has supported the analytical capabilities of these systems. Within the field itself there have also been algorithmic advances, which have given machine learning greater power. As a result of these advances, systems which only a few years ago performed at noticeably below-human levels can now outperform humans at some specific tasks. Many people now interact with systems based on machine learning every day, for example in image recognition systems, such as those used on social media; voice recognition systems, used by virtual personal assistants; and recommender systems, such as those used by online retailers. As the field develops further, machine learning shows promise of supporting potentially transformative advances in a range of areas, and the social and economic opportunities which follow are significant. Machine learning algorithms are generally categorized into unsupervised, supervised, and semi-supervised learning. If instances are given with known labels (the corresponding correct outputs) then the learning is called supervised, in contrast to unsupervised learning, where instances are unlabelled. Semi-supervised learning combines both labeled and unlabeled examples to generate an appropriate function or classifier.

Today's customers have infinite numbers of data sources. Smartphone allows a quicker access to the product, brand and price-comparison data. Consequently, companies in several industries are taking striving to attract recollecting customers. Because of quick technological improvements and improved competition, customers have several options. The tasks have been developed from telecommunication operators. Companies are dropping many revenues because the clients switch their interests and choose other service providers. This procedure is known as "Churn".

Churn is one of the most significant administration features in telecommunication industry [1]. Churn can be defined as a broader term that might include several actions like the customer's service is done through customer themselves or by a service provider through discrete service agreements [2], [3]. But, the most important and the most common reason of churn is the non-satisfaction of customer towards any service accessed through a provider [4], [5]. Yet these do not simply cause. It is described that several issues have been arising due to the customer churn because of increase in competition, saturated markets, dynamic conditions, and beginning novel attractive customers. Frequently, client started churn is complicated and issues related to each churn might vary for every customer. Thus, this study emphasizes on studying the various types of churns and the different methods proposed as a solution to avoid their issues.

In telecommunication businesses, both, voice and information service customers choose service-provider by a huge range of businesses and have self-determination towards switching their privileges from one service provider to another which can lead to improvement. There is huge growth in such competition. The clients demand top level of products and services at significantly reduced prices [6]. Several telecommunication companies use retention approaches [7] towards coordinate services to save customers through extensive tenure. In such case, a key business has been developed with the aim of reducing churn. Reducing the churn is proposed for the provisional telecommunication corporations. To avoid huge losses for clients and to evaluate the time of churn in sequence of including their requirements, this step is important [8]. In common, several data mining methods [9], [10] are employed to forecast churns like there are approaches which are associated with sentiment analysis. Machine learning and meta-heuristic methods [11] are also importantly presented as churn prediction approaches.

Churn is an issue caused by the customers who are further exclusive in obtaining new clients. Client revocation should be specified while client has been clogged by their SIM card. When the word churn is mentioned, the one thing which comes in mind is that customer churn which is a major issue of the telecommunication market [12]. Churn intends those customers who want to leave in the nearby future. There is essential need to predict those customers on behalf of some parameter to initiate some suitable actions for minimizing their leaving. Most of the mobile phone companies invest under CRM (Customer Relationship Management) technology [13] [14].

2. Churn Prediction Techniques Methodology

The greatest churn prediction techniques are the meta-heuristic algorithms which are designed from greatly precise prediction. Following are the techniques, algorithms, and methodologies that are used by different researchers in their research.

2.1 Decision Tree (DT)

Decision Tree is maximum prominent predictive model that is used for the purpose of classification of upcoming trial [20], [21].It comprises two stages, tree pruning and tree building. In tree building training set data is recursively partitioned in accordance with the values of the attributes. This procedure serves on up to there is no one partition is left to have identical values. In this process some values may be removed from the data due to noisy data. Major evaluated error rate branches are selected and then unconcerned in pruning. Towards predict accuracy and reducing complexity of the decision tree is called tree pruning [16], [17].

2.2 Linear Regression Model (LRM)

To predict customer satisfaction, the regression analysis model is another popular technique that is based on supervised learning model. In this model a data set of past observations is used to see future values of explanatory and numerical targeted variables [17]. The formula of LRM is given [18].

$$Prob(y=1) = \frac{e^{\beta_0} + \sum_{k-1}^{k} \beta_k X_k}{1 - e^{\beta_0} - \sum_{k-1}^{k} \beta_k X_k}$$

y is a binary variable. This shows an event. If y = 1 the event occurs else not occur.

X_1, X_2, ……, X_K be the self-determining inputs.

B_0, B_1, …., B_K be the failure.

2.3 Naive Bayes Model (NBM)

In this model, the probabilities of specified input sample are calculated that goes towards a particular classy. The set of variable is given (X1---Xn).The given formula is used to calculate probabilities [19].

$$(y_j|X) = p(y_j|X)p(y_j) = p(x_1, x_2, \ldots x_n|y_j)p(y_j)$$

The y_j is the probability of the previous calculations. The probability of independent variable is independent.

2.4 Neural Networks Model (NNM):

The Neural Networks Model is used to elaborate functionality like non-linear. The model holds the capability to learn due to its comparable data processing structure. These techniques provide successful results after applying to many problems like classification, control, and prediction due to the biological brain [15]. The model is dissimilar to classification model as well as decision tree due to its likely hood prediction. The neural network has several techniques having merits and demerits. The researcher suggests neural network is well than decision tree and regression analysis model of churn prediction [16].

2.5 Support Vector Machine (SVM)

The Support Vector Machine classifier deals with a linear permutation of subset of the training set by finding a maximum edge over-energized plane. The SVM plots the data into high dimensional features space closing to infinite with the help of most important part if vectors are nonlinearly divisible input features [22] and then categorize information through maximum scope hyper-plane.

$$F(\bar{X}) = sgn\left(\sum_{i}^{M} y_i\, \alpha_i \Phi(\bar{X}, \bar{X}) + \delta\right)$$

Where,

M = No. of samples in to a training data set.

Xi= Vector support when ai>0

/ = Core function

X = Unidentified sample feature vector

d = Doorstep.

(ai)is a parameter that is the result of curved quadratic programming problems with respect to linear constraint[23].

2.6 Fuzzy Logic Algorithm:

A fuzzy logic technique is very simple to understand due to its very simple mathematical concepts and fuzzy reasons. Fuzzy logic has the property of flexibility, tolerant of indefinite data. The function of random data can be implemented in this model. In most of the cases, the fuzzy logic system spends the idea of the predictable managed techniques and streamlines the operations. In telecommunication industries no work has been achieved related to churn prediction with fuzzy logic techniques [24].

2.7 Evolutionary Learning Data Mining Techniques

Evolutionary learning data mining techniques are stochastic search algorithms which are inspired by the process of neo-Darwinian evolution. Data mining by evolutionary learning technique is inherited classification techniques. The motivation for applying evolutionary learning to data mining is that they are robust, adaptive search techniques that perform a global search in the solution space [45]. Such types of genetic algorithms have some set of rules. It creates a series of random rules to be checked against a training dataset. The rules which most closely fit the data are selected and are mutated. These techniques apply these rules on some given dataset that provide decision-making results [25].

2.8 K-means clustering

The most well-known and relevant technique of clustering is K-Means presented by Mc. Queen in 1967.The following are the main steps in K means clustering. In K mean cluster in approach, in the first step we select k objects that have their center (mean). In this method the remaining objects are not selected yet are assigned to cluster with respect to the similarity of the object with cluster. These similarities are measured on the behalf of the distance between cluster mean and object and after this calculation, the new center point is calculated on the behalf of above fact and we repeat these steps until the required function is achieved. In k mean clustering, the most important point is to find the numbers of clusters that are optimum as well as the distance between cluster mean and objects. The algorithm works until no new cluster element leave a cluster and enter into other cluster and no new center point is set for any cluster. When this target is achieved the algorithm is stopped [26].

2.9 Ant Colony Optimization (ACO)

Ant colony optimization met empirical motivated seeking performance of actual ant colonies [27].An algorithm is a practical behavior of actually living ant that is an insect having some rules used by them to find the food from his nest through shortest path first towards food source. 1st Ant colony algorithm was designed as ant system [28]. Ant colony optimization has workforce artificial ants works like biological ant to find the optimum solution. In Ant system in first step an ant selects a path to reach a point we set pheromone value but in case of problem, a heuristic value is set. The pheromone value shows the trail and heuristic value shows the problems. Ant colony optimization is applied to a large collection of problems [27], [30], like vehicle routing problem, scheduling [29] and routing in packet-switched networks [31, 32] in recent times. Ant colony optimization has applied under data mining field [33].

3. LITERATURE REVIEW

J. Bures et al, [33] investigated the ways through which the class imbalance of churn prediction could be handled more appropriately. Inspecting (random and progressive under-sampling), cost-sensitive learner (weighted random forests (WRF)) and boosting (gradient boosting machine (GBM)) are utilized by adjusting for calculating churn expectation precision. An improvement in the prediction accuracy was achieved by applying under-sampling.

Veronika Effendy et al, [34] anticipated proficient system through the imbalanced information taking care of issue of upgrading client churn expectation. Planned method integrates the examination by adjusting the dataset with the aim of upgrading churns forecast exactness. Examining procedure is itself blending of under-inspecting and SMOTE (Synthetic Minority Oversampling Technique). The core procedure includes examination by irregularity information issue when WRF groups data using specific churn prediction. Combined inspecting procedure expands F-measure & precision esteems demonstrating decrease of information records through exact forecast. Despite the fact that exhibition is entirely great it is not much beneficial to utilize common under-sampling plan.

Ning Lu et al, [35] proposed a method in which boosting was applied to improve a client churn prediction model. Depending upon the weight assigned by boosting algorithm, the clients were separated into two clusters. This results in identifying a higher risk client cluster. As a basic leaner, the logistic regression was applied in this research. On each cluster a churn prediction model was designed. Experiments were conducted and a comparative analysis of proposed and a single logistic regression model was presented. The outcomes showed that for churn prediction analysis, boosting provided highly efficient results. Xiaojun Wu et al, [36] suggested a prediction strategy dependent on enhanced SMOTE and AdaBoost by anticipating internet business client churn. In this methodology, at first better SMOTE is connected in order to process uneven datasets using blend of over-examining & under-sampling. At that point decent dataset is prepared into AdaBoost learning algorithm using weak classifier towards order clients & anticipate churn. G. Ganesh Sundarkumar et al, [37] planned one-class SVM built under-inspecting by improving churn & protection fraud discovery. At first, information is under sampled utilizing one-class SVM and after that; grouping is performed using machine learning algorithms. In view of outcomes it is inferred that decision tree performs superior towards further classification algorithms and alongside one-class SVM it reduces system complexity nature & increases forecast precision. Qiu Yihui et al, [38] recommended that current CCP techniques don't have many logical, system theory and strategy so it is unable to fulfill application requirements. Creators planned an element determination technique dependent on oriented ordering pruning method. This methodology provided the pruning question of classifier blend rather than attribute choice. In subsequent advance, an element extraction technique is planned for extricating various aspects by higher request client information. By assessment results it is discovered that proposed method improves the churn expectation by oriented ordering pruning method. Qiuhua Shen et al, [39], used feature-based churn expectation development and planned framework of corresponding combination of multilayer includes for increasing spread churn forecast rate. Suggested framework utilized element factorization and aspect developmentby combination of features. This methodology builds churn prediction exactness by settling high dimensions and uneven information issue. Be that as it may, element determination procedure is adequate and consequently uneven information issue reappears.

Sebastián Maldonado et al, [40] suggested a productive feature determination technique utilizing SVM dependent on the benefits model. Its methodology centers on choosing best using the classifier stage. SVM classifier is built on benefit premise when component factors are also chosen by thought of benefit. Methodology adaptable permits bit capacities using the enhanced prediction accuracy. Administrative causes are not fulfilled into SVM like base classifier.Aimee Backiel et al, [41] recommended utilization of a blend of nearby and social features using churn prediction as 2 element models distinguish distinctive arrangement of churners. An outfit approach is utilized by joining two features. Client information and social information of cell phone specialist organizations are utilized for assessment. Proposed model comprises spreading enactment calculation which spreads nearby and social factors between social & neighborhood model & gathering model to consolidate these aspects together. Result of assessment infers that churn prediction is better while utilizing consolidated model of aspects as opposed to utilizing individual models or element models. The principle confinement of this methodology is that exclusion of non-client nodes in production of call diagram because of bigger volume of information decreases adequacy of churn prediction. An additional disadvantage in this methodology is exclusion of bad energies by social network.Social Network analysis may improve CCP as suggested by Aimée Backiel et al, [42]. Authors proposed the framework that integrates social network information into collective churn prediction model by local and real-time attributes. Estimation outcome shows that churn prediction is enhanced in terms of accuracy, AUC (Area Under ROC Curve) and lift percentage.

Pretam Jayaswal et al, [43] recommended ensemble method through forecast of churn. Recommended methodology utilized client use and related data one through investigation of telecommunication client churn. Decision tree and its troupes, Random forest and Gradient boosted trees are used for structure of binary churn classifier. Assessment demonstrates that these ensemble-based methodologies particularly the input improvement built GBT group has better exactness and affectability through client beat expectation. Thus, methodology isn't tried on ongoing information and this confines unwavering quality on this model.Anuj Sharma et al. [17], Marketing writing states that it is more exorbitant to draw in another customer than to hold a current steadfast customer. Churn prediction models are created by scholastics and specialists to adequately oversee and control customer churn keeping in mind the end goal to hold existing customers. As churn management is an imperative action for companies to hold faithful customers, the capacity to accurately anticipate customer churn is fundamental. As the cell network administrations advertise winding up more focused, customer churn management has turned into a vital errand for mobile communication administrators. This paper proposes a neural network (NN) based way to deal with foresee customer churn in membership of cell remote administrations.Adem Karahoca et al. [8], churn management is essential and basic issue for Global Services of Mobile Communications (GSM) administrators to create procedures and strategies to keep its endorsers of pass other GSM administrators. In the first place period of churn management begins with profile creation for the endorsers. Profiling process assesses call detail information, money related data, calls to customer benefit, contract points of interest, showcase subtle elements and geographic and populace information of a given state. In this examination, input features are clustered by x-means and fuzzy c-means clustering algorithms to put the supporters into various discrete classes. Adaptive Neuro Fuzzy Inference System (ANFIS) is executed to build up a delicate prediction demonstrate for churn management by utilizing these classes.

Table I. Shows comparisons of existing methods & its features

Author	Dataset	Features	Methods	Metrics	Advantages	Disadvantage
AdemKarahoca [8]	GSM operator, Turkey 24,900 customers 22 attributes	Demography, Usage pattern, Value added services	x-Means clustering, Adaptive Neuro Fuzzy Inference System	Precision and Recall	The precision and recall values are achieved	The complexity of the system is high
Clement Kirui [9]	European operator 106,405 customers 112 attributes	Contract, usage pattern patterns, and calls pattern	Naïve Bayes, Decision Tree	Confusion matrix, accuracy, precision, recall	The decision tree method will arrange data efficiently	The naïve bayes reduce effectiveness of the system
Ballings, Michel [10]	Unknown 129,892 customers 113 attributes	Demographic, Value added, usage pattern	Logistic regression, Bagging, Decision Tree	AUC	The bagging classification method give good accuracy	Precision, recall can be calculated
Ismail, Mohammad [11]	Unknown, 169 customers 10 attributes	Demographic, Billing data, usage pattern, customer relationship	Neural network, Regression	Confusion matrix, accuracy, precision, recall	The dataset is collected in real time	Regression nature increase execution time
H Lee [12]	Cell2Cell Dataset 100,000 customers 171 attributes	Behavioral information, Customer care and demographics	Stepwise variable selection partial least squares	Proportion of hit records	The behavior of the customers are analyzed	The classification can be applied in future
Anuj Sharma [17]	ML Dataset at UCI 2,427 customers 20 attributes	Demographics, Usage pattern, Value added services	Artificial Neural Network	Confusion matrix	The results are performed on high range dataset	The training time of the system is high
Abbas Keramati [18]	Iranian telecommunication operator 3150 customers 15 attributes	Demographic, call usage pattern, customer care service	Binomial logistic regression model	Statistical hypothesis test	The patterns of the calls are calculated	Statistical method is applied for the analysis
KristofCoussement [19]	Belgian 134, 120 customers 27 attributes	Demographic Usage patter, bill and payment	Generalized additive models (GAM)	AUC top-decile lift	Features are extracted efficiently	The accuracy is low

Author	Dataset	Features	Methods	Metrics	Advantages	Disadvantage
MarcinOwczarczuk [20]	Polish mobile operator 122098 customers 1381 attributes	Demographic, call data records, customer care services	Logistic regression Decision tree	Lift curves	The dataset is collected in real time	The accuracy can be increased
Umayaparvathi [21]	Cell2Cell Dataset 100,000 customers 171 attributes	Behavioral information, Customer care and demographics	Gradient Boosting, Decision Tree, Support Vector Machine, Random Forest, K-NN, Ridge Regression & Logistic Regression	Confusion matrix, accuracy, precision, recall, F1-score	The number of classifiers are applied for the prediction analysis	The complexity of the system is quite high

3. RESEARCH METHODOLOGY

This research work is based on the churn predication using techniques of machine learning. The churn prediction techniques have various phases which include pre-processing, feature extraction and classification. The dataset of the churn prediction is collected from the kaggle. The kaggle is the authentic source for the dataset collection. The collected data has various missing and redundant values which are removed to clean the dataset. In the second phase, features are extracted from the dataset. The feature extraction approach will establish relationship between each attribute and target set. In the last phase the hybrid method is applied for the churn prediction. The hybrid method will be the combination of the KNN classifier and decision tree classifier. The KNN classifier will extract the features and decision tree will generate final results. The voting classifier is the proposed algorithm which is used for the churn prediction.

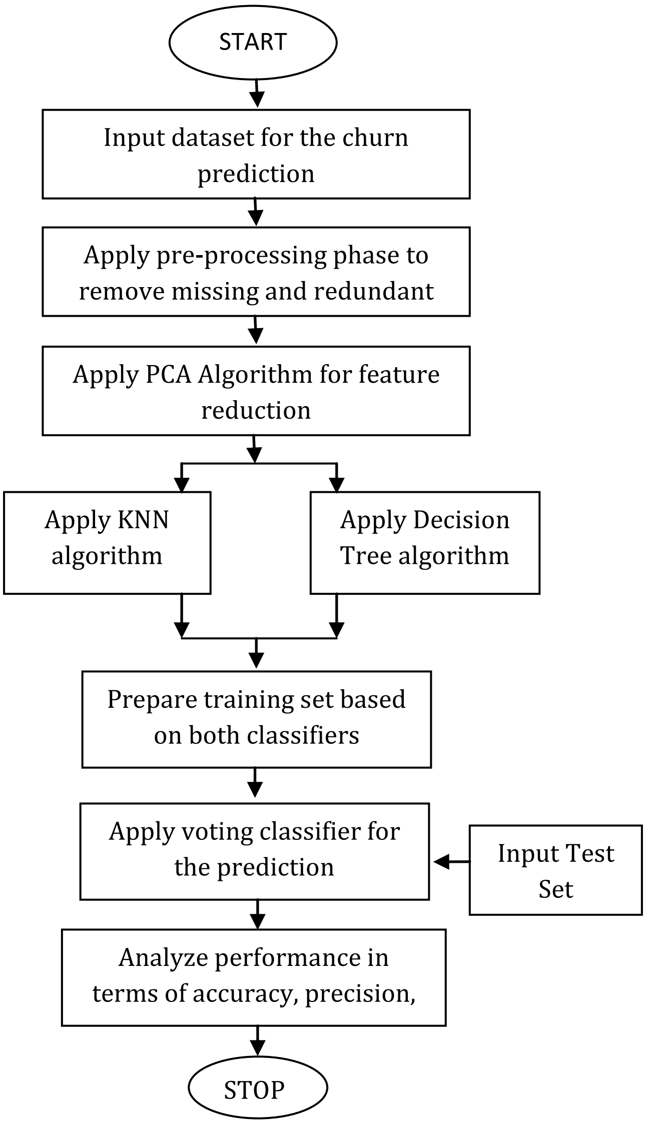

Figure 2: Proposed Flowchart

4. RESULT AND DISCUSSION

The dataset is collected is collected from the kaggle and the results are analyzed in terms of accuracy, precision and recall.

Important metrics considered to analyse the efficiency of these algorithms include:

1. Precision: Precision is the degree to which repeated measurements under static conditions generate similar outcomes.

$$\text{Precision}= (\text{True Positive}) / (\text{True Positive} + \text{False Positive})$$

2. Recall: It is ratio of properly predicted positive observations to the all observations in original class.

$$\text{Recall}= (\text{True Positive}) / (\text{True Positive} + \text{False Negative})$$

3. Accuracy: It is the ratio of the accurately labelled subjects to the entire group of subjects.

$$\text{Accuracy} = \frac{\text{Number of points correctly classified}}{\text{Total Number of points}} * 100$$

Table 1: Performance Analysis

Parameters	KNN Classifier	SVM Classifier	Voting Classifier
Accuracy	92.60 percent	97.40 percent	98.05 percent
Precision	91.34 percent	97 percent	97.12 percent
Recall	93.67 percent	97 percent	98 percent

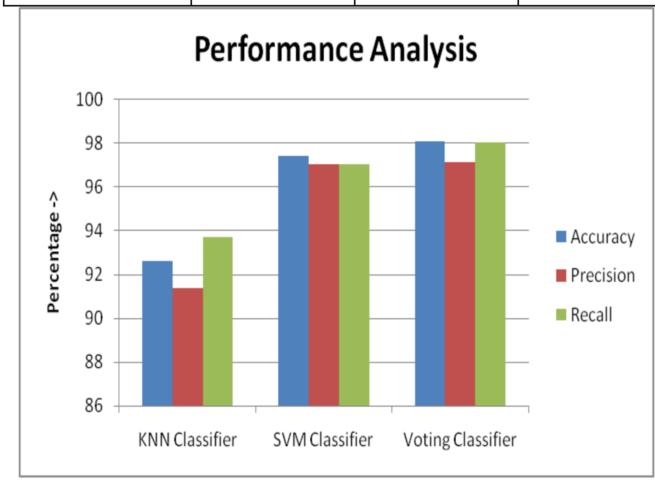

Figure 4.5: Performance Analysis

As depicted in figure 4.5, the efficiency of existing and new algorithm is compared with respect to certain metrics. It is analysed that percentage of all three parameters is higher in the new algorithmic approach.

3. CONCLUSIONS

Customer churn has been accepted like important concern in to aggressive research and the telecommunication industry has been engaged in this by relating several data mining strategies. Various data mining approaches are generally useful in customer churn. Telecommunication trade has proficient great churn rates and gigantic churning misfortune. In unkindness of point that industry trouble is inescapable, however at similar time churn may be administered and saved at acceptable level. This paper appraised diverse classifications of client information available into open datasets, predictive models and performance metrics used such portion of writing through churn prediction into telecommunication industry. The churn prediction has various phases which include pre-processing, feature extraction and classification. The SVM and voting classifiers are implemented for the churn prediction. It is analyzed that voting classifier have high accuracy, precision and recall for the churn prediction as compared to SVM classifier.

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