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## A Dynamic Churn Prediction Model using Soft Computing and Random Forest based Supervised Learning

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**ABSTRACT**: Customer churn is a major problem and one of the most important concerns for large companies. Due to the direct effect on the revenues of the companies, especially in the telecom field, companies are seeking to develop means to predict potential customer to churn. Therefore, finding factors that increase customer churn is important to take necessary actions to reduce this churn. The main contribution of our work is to develop a churn prediction model which assists telecom operators to predict customers who are most likely subject to churn. The model developed in this work uses machine learning techniques on big data platform and builds a new way of features' engineering and selection. In order to measure the performance of the model, This paper also identified churn factors that are essential in determining the root causes of churn. By knowing the significant churn factors from customers' data, CRM can improve productivity, recommend relevant promotions to the group of likely churn customers based on similar behavior patterns, and excessively improve marketing campaigns of the company. The proposed churn prediction model is evaluated using metrics, such as accuracy, precision, recall, f-measure, and receiving operating characteristics (ROC) area. Furthermore, it also provides factors behind the churning of churn customers through the rules generated by using the attribute-selected classifier algorithm

**KEYWORDS**: Receiving Operating Characteristics, Deep learning, Convolution Neural Network, churn prediction, Feature selection.

#### **INTRODUCTION**

Consumers today go through a complex decision making process before subscribing to any one of the numerous Telecom service options. The services provided by the Telecom vendors are not highly differentiated and number portability is commonplace. Customer loyalty becomes an issue. Hence, it is becoming increasingly important for telecommunications companies to proactively identify factors that have a tendency to unsubscribe and take preventive measures to retain customers. To calculate your probable monthly churn, start with the number of users who churn that month. Then divide by the total number of user days that month to get the number of churns per user day. Then multiply by the number of days in the month to get your resulting monthly churn rate. It is found that data mining techniques are more effective in predicting consumer churn from the research conducted over the past few years. Creating an efficient churn prediction model is an essential activity requiring a lot of work right from determining appropriate predictor variables (features) from the large volume of available customer data to choosing an effective predictive data mining technique suitable for the feature set. Telecom Industries collect a large amount of customer-related data such as customer profiling, calling pattern, and democratic data in addition to the network data they generate. Based on the customer's history of calling behaviour and behaviour, there is a possibility to classify their attitude of either going away or not. Data mining techniques are found to be more effective in predicting churn from the research done over the past decade. The predictive modelling techniques in churn prediction are also considered to be more accurate. Churn prediction systems and sentiment analysis using classification as well as clustering techniques to classify churn customers and the reasons behind the churning of telecom customers. In telecom industry should we generate large amount of data on daily basis, it is very tedious task to mine such a kind of last data using specific data mining techniques, while hard to interpret the prediction on classical techniques. Various researchers already described search a work to eliminate churn from large data sets fusion static as well as dynamic approaches, but still such systems are facing many problems actual identification of churn. Sometime such



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telecommunication data may be containing some churn and, it is much necessary to identify search problems. To successful identification of churn from large data is providing effectiveness to customer relationship management (CRM).

In this research we proposed churn identification as well as prediction from large scale telecommunication data set using Natural Language Processing (NLP) and machine learning techniques. First system deals with strategic NLP process which contains data pre-processing, data normalization, feature extraction and feature selection respectively. Feature extraction techniques have been proposed like TF-IDF, Stanford NLP and occurrence correlation techniques. Where machine learning classification algorithms are has used to train and test the entire module.

#### **II.LITERATURE SURVEY**

Telecommunications companies are usually not the most popular companies with consumers and Customer loyalty is the key to profitability in the telecom industry. People often express frustration with the performance of service providers, whether it's complicated billing, spam marketing emails, difficult customer service, internet speed, connectivity, or high plans. As a result, it is not surprising to learn that telecommunications companies have a high customer churn rate. Because telecom providers manage large fixed infrastructures that must be offset by revenue, customer churn (attrition) is particularly problematic in this industry.Companies usually have a greater focus on customer acquisition and keep retention as a secondary priority. 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.Churn is a metric that shows customers who stop doing business with a company or a particular service, also known as customer attrition. By following this metric, what most businesses could do was try to understand the reason behind churn numbers and tackle those factors, with reactive action plans.But what if you could know in advance that a specific customer is likely to leave your business, and have a chance to take proper actions in time to prevent it from happening?

The reasons that lead customers to the cancellation decision can be numerous, coming from poor service quality, delay on customer support, prices, new competitors entering the market, and so on. Usually, there is no single reason, but a combination of events that somehow culminated in customer displeasure. If your company were not capable to identify these signals and take actions prior to the cancel button click, there is no turning back, your customer is already gone. But you still have something valuable: the data. Your customer left very good clues about where you left to be desired. It can be a valuable source for meaningful insights and to train customer churn models. Learn from the past, and have strategic information at hand to improve future experiences, it's all about machine learning. When it comes to the telecommunications segment, there is great room for opportunities. The wealth and the amount of customer data that carriers collect can contribute a lot to shift from a reactive to a proactive position. 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.

Many methods such as machine learning and data mining are used for churn prediction. The decision-tree algorithm is a reliable method for churn prediction [1]. In addition, a neural network method [7], data certainty [8], and particle swarm optimization are used for churn prediction. According to system [2] a current collection of software to increase the standard of detecting possible churners. The roles are extracted from request information and client accounts and are classified as deal, request pattern and call pattern adjustments overview functionality. The characteristics are evaluated using two probabilistic data mining algorithms from Naïve Bayes and Bayesian Network, and their findings compared to those obtained by the use of C4.5 decision tree, an algorithm widely used in many classification and prediction tasks. Among other reasons these have led to the possibility that consumers will quickly turn to competitors. One of the techniques that can be used to do this is to improve churn prediction from large amount of data with extraction in the near future. According to [3] formalization of time-window of the collection process, coupled with literature review. Second, by expanding the duration of consumer events from one to seventeen years using logistic regression, classification trees and bagging together with classification trees, this analysis analyzes the rise in churn model accuracy. The practical result is that researchers may substantially reduce the data-related pressures, such as data collection, preparation, and analysis. The price customers are expected to pay depends on the length and the pro-motional nature of the subscription. The newspaper business is sending a letter telling them that the service is ending. Then ask them if they want to renew their subscription,



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along with guidance on how to do that. Customers are unable to cancel their subscription and have a grace period of four weeks once they have subscribed lapsed.

According to [4] the most efficient consumer engagement strategies can be used to high the client satisfaction level efficiently. The study indicates a Multilaver Perceptron (MLP) neural network method to estimate client turnover in one of Malaysia's leading telecommunications firms. The results were contrasted with the most traditional churn prediction strategies such as Multiple Regression Analysis and Analyzing Logistic Regression. The maximal neural network architecture includes 14 input nodes, 1 concealed node and 1 output node with the learning algorithm Levenberg Marquardt (LM). Multilayer Perceptron (MLP) neural network approach to predict client churn in one of the leading telecommunications companies in Malaysia compared to the most common churn prediction techniques, such as Multiple Regression Analysis and Logistic Regression Analysis. In system [5] on creating an efficient and descriptive statistical churn model utilizing a Partial Least Square (PLS) approach focused on strongly associated intervals in data sets. A preliminary analysis reveals that the proposed model provides more reliable results than conventional forecast models and recognizes core variables in order to better explain churning behaviors. Additionally, network administration, overage administration and issue handling approaches are introduced in certain simple marketing campaigns and discussed. Burez and Van den Poel [6] Unbalance data sets studies in churn prediction models, and contrasts random sampling performance, Advanced Under-Sampling, Gradient Boosting Method, and Weighted Random Forest. The concept was evaluated using Metrics (AUC, Lift). The study shows that the methodology under sampling is preferable to the other techniques evaluated. Gavril et al. [7] Describes an innovative data mining method to explain the broad dataset type of consumer churn detection. About 3500 consumer details isanalyzed based on incoming number as well as outgoing input call and texts. Specific machine learning algorithms were used for training classification and research, respectively. The system's estimated average accuracy is about 90 percent for the entire dataset. He et al. [8] in a with approximately 5.23 million subscribers, a major Chinese telecommunications corporation developed a predictive model focused on the Neural Network method to address the issue of consumer churn. The average degree of precision was the extent of predictability of 91.1%.

Idris [9] suggested a genetic engineering solution to modelingAdaBoost-churning telecommunications problems. Two Standard Data Sets verified the series. With a precision of 89%, one from Orange Telecom and the other from cell2cell and 63% for the other one. Huang et al. [10] the customer churn studied on the big data platform. The researchers ' aim was to show that big data significantly improves the cycle of churn prediction, based on the quantity, variety and pace of the data. A broad data repository for fracture engineering was expected to accommodate data from the Project Support and Business Support Department at China's biggest telecommunications firm. AUC used the forest algorithm at random and assessed. According to [11] with k-means and fuzzy c-means clustering algorithms are clustered input features to place subscribers in separate discrete groups. The Adaptive Neuro Fuzzy Inference System (ANFIS) is introduced using these classes to construct a predictive model for active churn management. The first prediction step begins with Neuro fuzzy parallel classification. FIS then takes Neuro fuzzy classifiers outputs as input to decide on churners activities. Measurements of success can be used to recognize inefficiency problems. Churn management metrics are associated with customer service network services, operations, and efficiency. GSM number versatility is a vital criterion for churner's determination. In System [12] a New set of apps to improve the identification level of potential churners. The features are derived from call details and customer profiles and are categorized as description features related to contract, call pattern, and call pattern changes. The features are tested using two Naïve Bayes and Bayesian Network probabilistic data mining algorithms and their results compared to those obtained from the use of C4.5 decision tree, an algorithm commonly used in many classification and prediction tasks. These have contributed, among other factors, to the risk that customers can easily switch to competitors. One of the techniques that can be used to do this is to improve churn prediction from large amount of data with extraction in the near future.

According to [13] Formalization of the selection method in time window, along with analysis of literature. Second, this study analyzes the increase in churn model consistency by extending the history of customer events from one to seventeen years using logistic regression, classification trees and bagging along with classification trees. The functional consequence is that researchers, such as data storage, planning and research, can significantly reduce data-related burdens. The amount that consumers have to pay depends on the subscription's duration and pro-motional sense. A letter is sent by the newspaper company to remind them that the subscription is coming to an end. Then ask them if they want to renew their subscription,



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along with guidance on how to do that. Customers are unable to cancel their subscription and have a grace period of four weeks once they have subscribed lapsed.

According to [14] the most effective customer retention techniques should be used to effectively reduce customer turnover rates. The research suggests a neural network approach for Multilayer Perceptron (MLP) to predict customer churn in one of Malaysia's leading telecommunications firms. The findings were compared with the most common techniques of churn prediction such as Multiple Regression Analysis and Logistic Regression Analysis. The optimal configuration of the neural network contains 14 input nodes, 1 hidden node and 1 output node with Levenberg Marquardt (LM) learning algorithm. Multilayer Perceptron (MLP) neural network approach to predict client churn in one of the leading telecommunications companies in Malaysia compared to the most common churn prediction techniques, such as Multiple Regression Analysis and Logistic Regression techniques, such as Multiple Regression Analysis and Logistic Regression techniques, such as Multiple Regression Analysis and Logistic Regression techniques, such as Multiple Regression Analysis and Logistic Regression techniques, such as Multiple Regression Analysis and Logistic Regression techniques, such as Multiple Regression Analysis and Logistic Regression Analysis. In system [15] on Building a predictive churn model that is accurate and concise using a Partial Least Square (PLS) methodology based on highly correlated data sets between variables. A preliminary experiment shows that the model presented provides more accurate performance than traditional models of prediction and identifies key variables to better understand churning behaviors. Additionally, there is a range of basic churn marketing strategies— system management, overage management, and complaint management strategies is presented and discussed.

Burez and Van den Poel [16] studied the problem of unbalance datasets in churn prediction models and compared performance of Random Sampling, Advanced Under-Sampling, Gradient Boosting Model, and Weighted Random Forests. They used (AUC, Lift) metrics to evaluate the model. the result showed that under sampling technique outperformed the other tested techniques.

Gavril et al. [17] presented an advanced methodology of data mining to predict churn for prepaid customers using dataset for call details of 3333 customers with 21 features, and a dependent churn parameter with two values: Yes/No. Some features include information about the number of incoming and outgoing messages and voicemail for each customer. The author applied principal component analysis algorithm -PCA to reduce data dimensions. Three machine learning algorithms were used: Neural Networks, Support Vector Machine, and Bayes Networks to predict churn factor. The author used AUC to measure the performance of the algorithms. The AUC values were 99.10%, 99.55% and 99.70% for Bayes Networks, Neural networks and support vector machine, respectively. The dataset used in this study is small and no missing values existed. He et al. [18] proposed a model for prediction based on the Neural Network algorithm in order to solve the problem of customer churn in a large Chinese telecom company which contains about 5.23 million customers. The prediction accuracy standard was the overall accuracy rate, and reached 91.1%. Idris [19] proposed an approach based on genetic programming with AdaBoost to model the churn problem in telecommunications. The model was tested on two standard data sets. One by Orange Telecom and the other by cell2cell, with 89% accuracy for the cell2cell dataset and 63% for the other one. Huang et al. [20] studied the problem of customer churn in the big data platform. The goal of the researchers was to prove that big data greatly enhance the process of predicting the churn depending on the volume, variety, and velocity of the data. Dealing with data from the Operation Support department and Business Support department at China's largest telecommunications company needed a big data platform to engineer the fractures. Random Forest algorithm was used and evaluated using AUC

#### **III.PROPOSED SYSTEM DESIGN**

In the proposed research work to measure identify the churn using text analysis using NLP and machine learning classifier. To identify the customer changing behavior pattern during prediction. To identify the factor which mostly influence to reduce accuracy of churn prediction? To evaluate and calculate churn rate for month wise as well as day wise, which useful for enhance the service quality of system. In the proposed research work to design and develop an approach for churn prediction using NLP and machine learning approaches to enhance the system accuracy. Then we identify the customer changing behavior pattern during prediction. We also evaluate the factor which mostly influences to reduce accuracy of churn prediction and finally evaluate and calculate churn rate for month wise as well as day wise, which useful for enhance the service quality of system. In this research we proposed churn prediction from large scale data, system initially deals with telecommunication synthetic data set which contains some imbalance meta data. To apply data preprocessing, data normalization, feature extraction as well as feature selection respectively. During this execution some Optimization



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The proposed system execution for training and testing. After completion both phases system describe classification accuracy for entire data set.



Figure 1 : Proposed system design

The aim of this such kind of research in the telecommunications industry is to help businesses make more profit. Telecom companies have become known to forecast turnover as one of the most important sources of income. Therefore, this research was aimed at building a system in the Telecom Company that predicts customer churn. Such prediction models will achieve high AUC values. The sample data was divided into 70% for training and 30% for testing to evaluate and develop the model. We chose 10-fold cross-validation for evaluating and optimizing hyper parameters. We used engineering tools, effective function transformation and selection approach. Making the interface fit for machine learning algorithms. Another concern was also found: the data was not balanced. Only about 5% of the entries are customers ' churn. A problem has been solved by under-sampling or using trees algorithms that are not affected by this issue. In detecting the churn in large data and providing accurate prediction, our different classifiers can be more accurate. This work contributes to suggesting a supervised approach to the extraction of dimensional categories, selecting suitable characteristics and avoiding duplication by measuring correlation between characteristics. The results obtained show that there is a comparatively higher f-score in the weighted frequency of the term with the correlation process. In this regard, selecting features using weighted word frequency is more important. The overlap between features in a category of aspect is avoided by measuring the association.

1. Data Acquisition: First of all the information for different Telecom Sector Customer based on certain parameters is extracted data.

2. Preprocessing: Then we will apply various preprocessing steps such as lexical analysis, stop word removal, stemming (Porters algorithm), index term selection and data cleaning in order to make our dataset proper.

3. Lexical analysis: Lexical analysis separates the input alphabet into,



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1) Word characters (e.g. the letters a-z) and 2) Word separators (e.g space, newline, tab).

4. Stop word removal: Stop word removal refers to the removal of words that occur most frequently in documents.

5. Stemming: Stemming replaces all the variants of a word with a single stem word. Variants include plurals, gerund forms (ing forms), third person suffixes, past tense suffixes, etc.).

6. Data Training: We compile artificial as well as real time using online news data and provide training with any machine learning classifier.

7. Testing with machine learning: We predict online news using any machine learning classifier, weight calculator for real time or synthetic input data accordingly.

8. Analysis: We demonstrate the accuracy of proposed system and evaluate with other existing systems

Algorithm Design

1 Bagging Classifier

Input: inp 1.....n all input parameters, Desired Threshold Th.

Output: Executed for output as lable.

Step 1 : Read all records from database (R into DB)

Step 2:Parts [] ← Split(R)

Step 3:

$$CVal = \sum_{k=0}^{n} Parts[k]$$

Step 4: check (Cval with Respective threshold)

Step 5:T  $\leftarrow$  get current state with timestamp

Step 6 : if(T.time> Defined Time)

Read all measure of for TP and FN

Else continue. Tot++

Step 7: calculate score = (TP \* 100 / Tot)

Step 8 : if (score  $\geq$  Th)

Generate event

end for

2 Decision Tree Classifier

Input : Selected feature of all test instances D i...n, Training database policies {T 1 .....T n }



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Output: No. of probable classified trees with weight and label.

Step 1: Read (D into D[i])

V←Extract features (D)

Step 2: N←Count\_Features(D)

Step 3: for each(c into TrainDB)

Step 4:Nc[i] ==Ext\_Features(c)

Step 5: select relevant features of w= {Nc[i], N}

Step 6: Statement (w>t)

Step 9: Return Tree Insatnce { Nc[i], N, w, label }

3Knearest neighbour Classifier

Input: Train\_DatasetFTrF[], Test\_DatesetFTsF[], Threshold T.

Output: Classified label

Step 1: Read R {All attributes} from current parameters.

Step 2: Map with train features with each sample.

Step 3 : Calculate distance of train DB with same evidences

$$distance = \sum_{k=0}^{n} (TrF, TsF)$$

Step 4 : evaluate distance> threshold

Step 5: Return the predicted label

4 Random Forest Classifier

Input: Training Rules Tr[], Test Instances Ts[], Threshold T.

Output: Weight w{0-1}

Step 1 : Read each test instance from (TsInstnace from Ts)

Step 1 : Read each test instance from (TsInstnace from Ts)

Step 2 :TsIns = 
$$\sum_{k=0}^{n} \{Ak \dots An\}$$

Step 3 : Read each train instance from (TrInstnace from Tr)

Step 4 : 
$$TrIns = \sum_{i=0}^{n} \{Aj \dots Am\}$$

Step 5 :w =WeightCalc(TsIns, TrIns)



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Step 6 : if  $(w \ge T)$ 

Step 7 : Forward feed layer to input layer for output OutLayer[]  $\leftarrow$  {Tsf,w}

Step 8 : optimized feed layer weight, Cweigt ← OutLayer [0]

Step 9 : Return Cweight

#### **IV.RESULTS AND DISCUSSIONS**

The below analysis is the system classification graph. The graphs display how system classify the overall inputs into classification various instances. The proposed system is implemented with RNN combination, which gives all results with satisfactory level. For performance evaluation 5000 instances given for training and 1500 reviews given for testing with different cross validation. Here system compares the proposed results with two different existing systems.

#### Table 1 :Comparative analysis of various classification algorithms

No.	Method	Accuracy	Precision	Recall	F-1 score
1	Random Forest	0.95	0.95	1	0.97
2	DT	0.89	0.92	0.96	094
3	BaggingClassifier	0.94	0.96	0.94	0.97
4	Knearestneighbors	0.81	0.86	0.92	0.89

The above Table 5.3 depicts the comapritive analysis of various classification algorithms evaluation for proposed churn prediction module. The KNeighbors provides lowest accuracy thus Random forest classification gives highest accuracy with 95% on varoous cross validation. The similar results has been demonstrated in below Figure 2.



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#### V.CONCLUSION FUTURE WORK

This research mainly focuses on identifying and detecting churn consumers from massive data set of telecommunications, state-of-the-art discusses churn prediction systems produced by different research. Some systems still face problems of conversion of linguistic data, which can occur at high error rate during execution. Many researchers have been putting forward Natural Language Processing (NLP) techniques as well as various machine learning algorithms such a combination is likely to generate good performance when structuring data. If any machine learning algorithm interacts with that kind of a method, it is necessary to test or confirm the entire data set with even sampling techniques that reduce data imbalance problems and provide reliable predictive flow of data. For future direction to implement a proposed system with various machine learning algorithm to achieve better accuracy, as well as the input data contains large size and volume, if we deal the proposed systems with HDFS framework and parallel machine learning algorithm which will provide better result in low computation cost.

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