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AN ORDERED FUZZY RULE INDUCTION BASED CHURN MINING FOR TELECOM INDUSTRY

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Abstract: *Distributed Strategies using outlier mining can result in vast time savings and communication cost while predicting churns in large data sets. However, rule based on the data mining procedure is not obtained with good solutions. Classification Rules based on time series using polynomial modeling was proposed to reduce the churn. But comprehensibility rule set was not addressed while predicting the churns (i.e., faults). In this paper, we propose an Ordered Fuzzy Rule Induction based Churn Mining (OFRI-CM) model to perform the rule mining operation on the clustered churn. The OFRI-CM model develops a system based on the rule that mine the churn from higher order to lower ones. A Fuzzy Data Mining model is first constructed to attain better solution using soft boundaries that perform aggregation operators for combining fuzzy rules, aiming at reducing the true positive rate of churn being detected. Then, we propose a divide and conquer strategy, based on the new sub group pattern of churns (i.e., multiple churns). The final best churns are predicted using divide and conquer strategy that recursively breakdown the churns into two or more churns and are finally aggregated to perform high region of search space with minimal processing time. This process is repeated until a churn mining criterion with comprehensibility rule set is generated. Finally, we present Churn Mining-based Greedy algorithm to improve the accuracy of comprehensibility rule set being generated. Experiments are conducted on Ericson GSM and Nokia Siemens GSM systems and the results show that the Churn Mining-based Greedy algorithm is efficient and that its average processing time of rules scales quite well for an increasing number of subscribers.*

Keywords*:* Classification Rules, Churn Mining, Fuzzy Data Mining model, Divide and Conquer strategy

I. INTRODUCTION

With the rapid increase in the competitive business environment, one of the most important in all Telecom Industries is customer churn. Distributed Strategies for Mining Outliers in Large Datasets (DSMO-LS) [1] was designed to mine outliers. But, rule based on the data mining was not considered that provide good solutions. Mining Comprehensible Classification Rules for Time Series (MCCR-TS) [2] designed efficient classification rule used polynomial modeling to obtain good solutions, but comprehensibility rule set was not considered.

A partial churn detection model was designed in [3] with the motive of improving churn detection rate using classification technique. However, the technique applied was restricted to a specific segment without addressing online market. Another method to detect

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churn rates on financial company was designed in [4] using customer lifetime value based on classification technique. However, the churn prediction was made on the basis of the threshold value, with which the increase in the threshold value, may provide with irrelevant churn factors.

The data mining techniques was applied without fixing any constant value in for obtaining the churn factors in [5]. However, social factors were not considered while measuring the churn factors. Customer churn decisions based on the social factors [6] was designed with the motive of improving the customer retention rate using Hazard rate models, but compromised scalability. Scalability issues were addressed in [7] using flat and hierarchical gossip model. Though scalability was addressed, accuracy was compromised. Two data mining algorithms called, logistic regression and decision was designed to improve the rate of accuracy for credit card companies in [8]. Churn detection using association rule mining has received great attention with the increased attrition rate. Fast Distributed Mining was applied in [9] to measure the churn rate (i.e., multi party) with the objective of reducing computation cost. Various ensemble learning techniques was applied in [10] to learn the churn rates in all industries. Six Sigma Methodology [11] were used to determine the churn rate with the help of Bayesian model to improve the probability of gain being detected.

One of the most debated researches received in the industry for more than ten years is the churn detection model. Prediction model based on the design of data mining techniques was applied in [12] to improve the prediction rate of churn being detected using SVM and Decision tree. However, scalability issues were not addressed. With the increase in the customer, prediction rate also increases. To address this issue, decision support system using data mining was designed in [13] with the objective of improving the scalability factor.

Another method for determining churn factor in telecom industry was designed using decision tree and logistic regression [14] to address scalability and accuracy. However, the model was restricted to cellular industries. A churn prediction model using probability data mining algorithm [15] was designed for financial service sector. Index churn customers that included financial, insurance and telecommunication sector was designed in [16] using classification methods with the objective of improving the accuracy of index churn being detected. A unifying model for determining churn factors [17] was designed to improve the accuracy rate using the poisson distribution model. However, churn detection for online tools was not addressed. Churns related to E-commerce industry [18] was addressed using multiple instance learning. Characterization and prediction related to churn was addressed in [19] using question and answer model, aimed at improving the churn detection rate. Clustering mechanism was applied in [20] to improve the outlier detection using graph clustering.

In this work, an Ordered Fuzzy Rule Induction based Churn Mining (OFRI-CM) model is presented to perform the rule mining operation on the clustered churn, based on the concept of Fuzzy Data Mining model. The contributions are summarized as follows:

(i) The Fuzzy Data Mining model is presented to improve the true positive rate by identifying the key factors based on the soft boundaries and rule set.

(ii) The proposed model exhibits accuracy by applying Divide and Conquer strategy by extensively dividing the problem instance and effectively conquering the sub group patterns using recursive search.

(iii) Other than finding sub group patterns using Divide and Conquer strategy, the proposed OFRI-CM model also aggregates the churns until a churn mining criterion with comprehensibility rule set is generated using the Churn Mining-based Greedy algorithm.

(iv) Experiments also confirm the efficiency of the model in terms of true positive rate, accuracy and processing time compared to the state-of-the-art methods.

II. ORDERED FUZZY RULE INDUCTION BASED CHURN MINING (OFRI-CM) MODEL

One of the most important terms used in the Information and Communication Technology (ICT) is “customer churn”. The customer churn in ICT refers to those subscribers or customers who leave for a new competitor. Predicting this behavior on the clustered churn is very significant for Telecom Industry. In this section, an Ordered Fuzzy Rule Induction based Churn Mining model is described.

The proposed Ordered Fuzzy Rule Induction based Churn Mining model includes three parts, (1) Identifying soft boundaries and discovering rule set using Fuzzy Data Mining model, (2) Dividing the rule set and Conquering the sub group patterns using Divide and Conquer strategy and (3) Churn Mining-based Greedy algorithm to obtain the final solution using rule mining operation on the clustered churn.

The proposed model is divided into three sections namely (i) Fuzzy Data Mining model (ii) Divide and Conquer Strategy and (iii) Churn Mining-based Greedy algorithm. The elaborate description for churn mining is explained in the forthcoming sections.

a. Fuzzy Data Mining model

One of the major obstacles in the Telecom Industry is customer churn. Research focused on Telecom Industry shows that retaining an existing customer is more difficult than obtaining a new customer. Customer retention in Telecom Industry can be measured by understanding the reasons for churn. In this work, an Ordered Fuzzy Rule Induction based Churn Mining (OFRI-CM) model uses Fuzzy Data Mining model to assist Telecom Industry in achieving the effective churn management, that extensively obtains elation analysis to selects the key factors for churn management processes.

The Fuzzy Data Mining model identifies the churn rate key factors for various customers. The Fuzzy Data Mining model obtains soft boundaries based on fuzzy correlation coefficient. Based on the soft boundaries, the rule set is discovered using the correlation coefficient and the proposed data mining rule set are obtained. This, results in reducing the true positive rate of the churns being detected.

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OFRI-CM model concentrates on designing an efficient customer retention mechanism to assist the Telecom Industries for effective churn reduction rate using Fuzzy Data Mining model. The Fuzzy Data Mining model measures the responses obtained from several group of customers by identifying the key factors and therefore improving customer retention rate.

Let us consider that two fuzzy sets (i.e., two different customers) '$X, Y \in FS$', where 'FS' represents the fuzzy space, then, the two fuzzy sets X *and* Y are defined with membership functions, 'μ_X, μ_Y' Then the fuzzy sets X *and* Y is given as follows

$$X = (u, \mu_X(u) | u \in U) \tag{1}$$

$$Y = (u, \mu_Y(u) | u \in U) \tag{2}$$

$$where\ \mu_X, \mu_Y \rightarrow (0,1)$$

In order to obtain better solution, soft boundaries are used to perform the aggregation operators for combining the fuzzy rules. The soft boundaries are evaluated using the correlation coefficient between the fuzzy sets X *and* Y and is given as below

$$SB_{X,Y} = \frac{(\mu_X - \mu_{X'})(\mu_Y - \mu_{Y'})}{SD_X * SD_Y} \tag{3}$$

$$where\ \mu'_X = \sum_{j=1}^{m} \mu_X(u_j), SD_X - Standard\ Deviation\ of\ sample\ X$$

$$where\ \mu'_Y = \sum_{j=1}^{m} \mu_Y(u_j), SD_Y - Standard\ Deviation\ of\ sample\ Y$$

The OFRI-CM model using Fuzzy Data Mining model supports to develop a system with the data mining rule set to mine the churn from higher order to lower order gradually. The combined soft boundaries from (3) help in discovering the new sub group pattern of churn using this proposed data mining rule set (RS_i) as given below

$$RS_1 = if\ SB_{X,Y} \sim 0, then\ fuzzy\ set\ (X, Y)\ are\ high\ churners$$

$$RS_2 = if\ SB_{X,Y} \approx 0, then\ fuzzy\ set\ (X, Y)\ are\ barely\ churners$$

$$RS_3 = if\ SB_{X,Y} > 0, then\ fuzzy\ set\ (X, Y)\ are\ churners$$

$$RS_4 = if\ SB_{X,Y} < 0, then\ fuzzy\ set\ (X, Y)\ are\ non-churners$$

$$RS_5 = if\ SB_{X,Y} = 0, then\ fuzzy\ set\ (X, Y)\ are\ neutral$$

Based on the above rule sets, new subgroup pattern of churn are identified, minimizing the true positive rate of churn being detected. Once the new subgroup pattern of churns is obtained, final best churns are measured using the Divide and Conquer strategy that is discussed in the forthcoming sections.

b. Divide and Conquer strategy

The design of churn mining model should be in such a way that both comprehensibility and accuracy be ensured, developing a more effective retention strategy. So, comprehensibility of the churn mining is one of the important requirements in churn based learning process. In this work, a Divide and Conquer strategy is designed based on the new sub group pattern of churns (i.e., multiple churns). This process is repeated until a churn mining criterion with comprehensibility rule set is generated.

To start with, the rule sets obtained from Fuzzy Data Mining model is divided into sub group patterns. Next, the possible sub group patterns are extracted in a recursive manner, aimed to maximizing the accuracy of the possible sub group patterns being generated. Finally, in order to obtain the final solution (i.e., churn rates), the sub group patterns are aggregated using the Churn Mining-based Greedy algorithm, aimed at minimizing the processing time of churns being detected.

The purpose of Divide and Conquer strategy is to select an attribute (i.e., membership functions) for different rule sets (RS_i) to place at the root node and "divides" the entire structure of the tree by making branches for each possible value of the attribute (i.e., membership functions). The final best churns using Divide and Conquer strategy that recursively breakdown the churns into two or more churns and are finally aggregated to perform high region search space with minimal processing time to be used for mining fuzzy rules.

First, a set of decision rules is built by applying the proposed data mining rule set on the training set. Each data mining rule set contains a number of correlation factors (i.e., high churners, barely churners, churners, non-churners). Let us denote the set of soft boundaries 'SB' where 'SB' = '$SB_1, SB_2, SB_3, \ldots, SB_m$' and a number '$u$'.

The Divide and Conquer strategy in the proposed OFRI-CM model recursively breakdown the churns involves three steps namely Divide problem instance (i.e., rule sets) into sub group patterns of churns as given below,

$$u = SB\left[\frac{m}{2}\right] \tag{4}$$

Conquer the sub group patterns of churns by solving recursively as given below

$$(i) if\ u < SB\left[\frac{m}{2}\right], then\ perform\ recursive\ search$$

$$Recursive\ Search = SB\left[1, \ldots \left[\frac{m}{2}\right] - 1\right] \tag{5}$$

$$(ii) if\ u > SB\left[\frac{m}{2}\right], then\ perform\ recursive\ search$$

$$Recursive\ Search = SB\left[\left[\frac{m}{2}\right] + 1, \ldots, m\right] \tag{6}$$

Finally, the sub group patterns are aggregated to obtain final solution (i.e., churns). The aggregation of sub group patterns in OFRI-CM model is performed using the Churn Mining-based Greedy algorithm which is elaborated in detail in the forthcoming section.

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c. Churn Mining-based Greedy algorithm

The aggregation of sub group patterns in OFRI-CM model is done with the help of Churn Mining-based Greedy algorithm. According to the above description, the proposed Churn Mining-based Greedy algorithm for performing Fuzzy Rule Induction based Churn Mining based on the Divide and Conquer strategy is described next.

INPUT: Training Dataset D, Customer size $Cust_i$, fuzzy sets $X\ and\ Y$, Membership Functions, μ_X, μ_Y, Rule Set RS_i, Number 'u'.
OUTPUT: Finally best churns are mined
Step 1: **Begin**
//Fuzzy Data Mining model
Step 2: Obtain the initial population (i.e., customer size) and membership functions μ_X, μ_Y for each customer
Step 3: Evaluate fuzzy sets $X\ and\ Y$ from (1) and (2)
Step 4: Calculate correlation coefficient between the fuzzy sets $X\ and\ Y$ using (3)
Step 5: Generate data mining rule set RS_i
//Divide and Conquer strategy
Step 6: Divide data mining rule set RS_i into sub group patterns of churns using (4)
Step 7: Perform recursive search
Step 8: $if\ u < SB\ \left[\frac{m}{2}\right]$ then
Step 9: $Recursive\ Search = SB\ \left[1, \dots \left[\frac{m}{2}\right] - 1\right]$
Step 10: else
Step 11: $Recursive\ Search = SB\ \left[\left[\frac{m}{2}\right] + 1, \dots, m\right]$
Step 12: End if
//Greedy solution
Step 13: Repeat
Step 14: Given churn factors $CF = \{CF_1, CF_2, \dots, CR_n\}$, there is an optimal factor CF_i
Step 15: Suppose $Churns\ \subseteq\ CF$
Step 16: $if\ CF_i\ \in\ Churns$, then
Step 17: Optimal churn factors arrived at
Step 18: end if
Step 19: $if\ CF_i\ \notin\ Churns$ then
Step 20: Let first churn in $Churns$ be CF_j
Step 21: Obtain new churn factor by removing CF_j and using CF_i instead
Step 22: end if
Step 23: Until (all churn factors for each customer are validated)

Algorithm 1 - Churn Mining-based Greedy algorithm

The above Churn Mining-based Greedy algorithm is divided into three sections. The first section applies fuzzy data mining model to evaluate the fuzzy sets and obtain the correlation coefficient between the fuzzy sets in order to generate and mine the possible churn factors. Then, divide and conquer strategy is applied to the mined churn factors that efficiently divides the data mining rule set into sub group patterns of churns and perform recursive search in an iterative manner. Finally, greedy solution is applied to the result sets to derive the optimal churn factors based on fuzzy data mining. This greedy solution starts by finding dynamic programming type solution by performing recursion through greedy choice. Finally, the recursive solution for churn mining is identified based on greedy choice.

III. EXPERIMENTAL RESULTS

To check the effectiveness of the proposed model, an Ordered Fuzzy Rule Induction based Churn Mining (OFRI-CM), the performance of Churn Mining-based Greedy algorithm is performed using the JAVA platform. This JAVA platform uses the code to perform the rule mining operation on the clustered churns in telecom industry. Experiments are conducted using the real-world datasets, Ericson GSM systems and Nokia Siemens GSM systems.

Ericson GSM systems provides services to deliver the highest return on partners' network assets, by providing optimal visibility, quality and availability throughout for the effective result. Nokia Siemens GSM systems provide the telecommunication information related to the Nokia Company. The services ensure the assets and track maximum customer services and identify the churns. Ordered Fuzzy Rule Induction based Churn Mining (OFRI-CM) model compares the work with the existing system such as Distributed Strategies for Mining Outliers in Large Datasets (DSMO-LS) [1] framework and Mining Comprehensible Classification Rules for Time Series (MCCR-TS) [2] . Experiment is conducted on factors such as true positive rate of churn being detected, processing time and accuracy of comprehensibility rule set being generated.

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IV. DISCUSSION

To validate the efficiency and theoretical advantages of the proposed Ordered Fuzzy Rule Induction based Churn Mining (OFRI-CM) model with Distributed Strategies for Mining Outliers in Large Datasets (DSMO-LS) [1] framework and Mining Comprehensible Classification Rules for Time Series (MCCR-TS) [2], experimental results using JAVA is presented. The parameters of the OFRI-CM model are chosen as provided in the experiment section.

Scenario 1: Impact of true positive rate

True positive rate using OFRI-CM model is the fraction of positive instances of churn being detected correctly.

$$TPR = \frac{Number_{PCCD}}{Number_{PCCD} + Number_{PCWD}} \quad (7)$$

Where $Number_{PCCD}$ refers to the number of positive churns correctly detected whereas $Number_{PCWD}$ refers to the number of positive churns wrongly detected as negative.

Table 1 Tabulation for true positive rate

No. of subscribers	True positive rate of churn being detected (%)		
	OFRI-CM	DSMO-LS	MCCR-TS
10	70	60	50
20	75	65	55
30	78	69	60
40	83	74	64
50	74	63	54
60	78	65	60
70	80	72	63

The efficiency of true positive rate in OFRI-CM model is obtained using the value from (7). Higher the true positive rate, more efficient the efficiency is said to be. It is measured in terms of percentage (%). To better understand the effectiveness of the OFRI-CM model, extensive experimental results are reported in table 2.

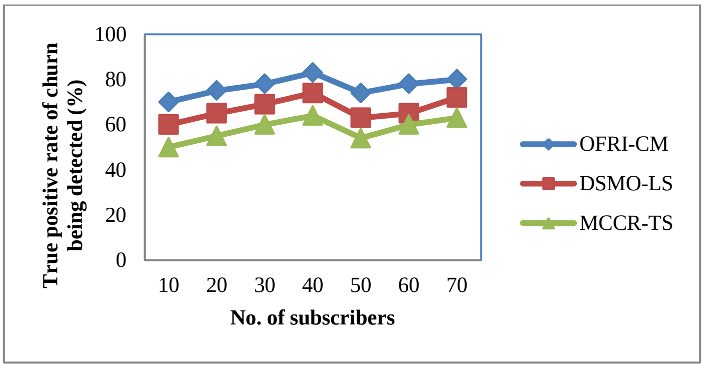

Figure 1 Measure of true positive rate

Figure 1 shows the true positive rate based on the number of subscribers in telecom industry considered for experimental purpose. The proposed OFRI-CM model performs relatively well when compared to two other methods DSMO-LS [1] and MCCR-TS [2]. The true positive rate efficiency is improved in the OFRI-CM model by the application of fuzzy data mining model. With the application of fuzzy data mining model, based on the soft boundaries, the result set are obtained. By using the result set during churn detection, whenever a subscriber enters into the network, the OFRI-CM model correctly analyzes the result set which helps in improving the true positive rate efficiency by 13 % compared to DSMO-LS. The result set based on the correlation coefficient between the fuzzy sets efficiently collects and detects the churn using the result set according to the data mining rule set which then helps in increasing the true positive rate efficiency by 24.5 % compared to MCCR-TS.

Scenario 2: Impact of processing time

Processing time using OFRI-CM model refers to the time taken to divide the rule sets into sub group of churns. The processing time is measured in terms of milliseconds (ms). Lower the milliseconds, more efficient the method is. The formulation for processing time is given as below

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$$Processing_{time} = Time\ ([RS_i] * No_{subscribers}) \quad (8)$$

Where RS_i refers to the rule sets generated and processing time is the time taken to generate the rule set.

Table 2 Tabulation for processing time

No. of subscribers	Processing time (ms)		
	OFRI-CM	DSMO-LS	MCCR-TS
10	120	150	180
20	176	192	202
30	220	235	245
40	235	243	253
50	255	264	274
60	269	279	286
70	292	302	322

The targeting results of processing time using OFRI-CM with two state-of-the-art methods [1], [2] in table 2 presented for comparison based on the number of subscribers in telecom industry.

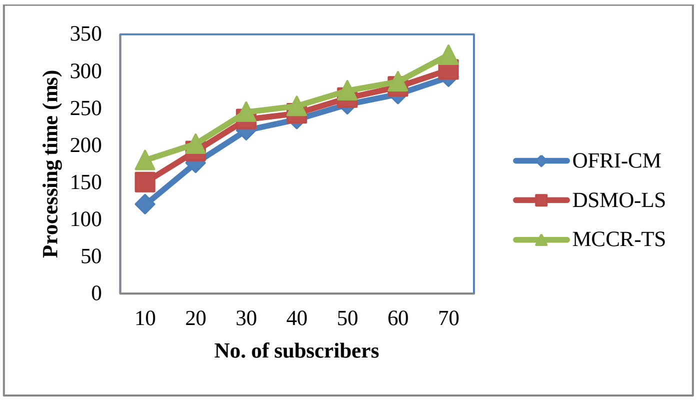

Figure 2 Measure of processing time

From figure 2, it is evident that the processing time is reduced using the proposed OFRI-CM model. The processing time are reduced by applying divide and conquer strategy in OFRI-CM model. The divide and conquer strategy on new sub group pattern of churns repeats a churn mining criterion with comprehensibility rule set is generated. By evaluating the rule set, the optimal churns (i.e., factors to remain the subscriber) are easily measured using OFRI-CM model and accordingly those churn factors are considered while designing a new product in telecom industry. This in turn reduces the processing time for obtaining the rule set using OFRI-CM model by 14.2 % compared to DSMO-LS [1] and 28 % compared to MCCR-TS [2] respectively.

Scenario 3: Impact of accuracy

Accuracy using the proposed OFRI-CM model measures the percentage of correctly detected churns over the total number of instances.

$$A = \frac{Number_{PCCD} + Number_{PCWD}}{Number_{PCCD} + Number_{PCNCD} + Number_{PCWD} + + Number_{PCNWD}} * 100 \quad (9)$$

Where $Number_{PCCD}$ refers to the number of positive churns correctly detected as positive whereas $Number_{PCWD}$ refers to the number of positive churns wrongly detected as negative, $Number_{PCNCD}$ refers to the number of positive churns not correctly detected as positive and $Number_{PCNWD}$ refers to the number of positive churns not wrongly detected as negative.

Table 3 Tabulation for accuracy

No. of subscribers	Accuracy (%)		
	OFRI-CM	DSMO-LS	MCCR-TS
10	58.31	52.13	47.23
20	63.25	58.22	52.17
30	69.22	64.19	60.14
40	66.45	61.42	57.37

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50	71.35	65.32	61.27
60	74.28	69.25	62.20
70	77.29	72.26	67.21

As listed in table 3, OFRI-CM model measures the amount of accuracy of comprehensibility rule set being generated which is measured in terms of percentage (%). The value of accuracy using OFRI-CM model offers comparable values than the state-of-the-art methods.

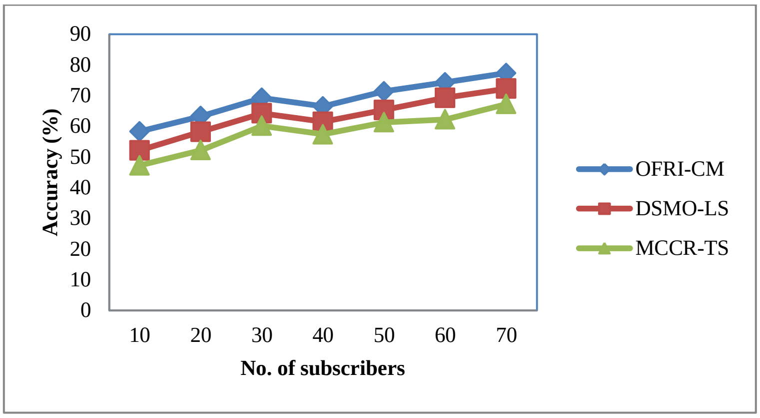

Figure 3 Measure of accuracy

Figure 3 presents the accuracy of OFRI-CM model over different number of subscriber in telecom industry. All the results provided in figure 3 confirm that the proposed OFRI-CM model significantly outperforms the other two methods, DSMO-LS [1] and MCCR-TS [2]. The accuracy is improved in the OFRI-CM model using the Churn Mining-based Greedy algorithm. With the application of Churn Mining-based Greedy algorithm, a greedy method is applied until the optimal factors (i.e., optimal churn factors) are obtained using the dynamic programming through recursive model. In addition, the recursive solution for churn mining is identified based on greedy choice. So, the accuracy obtained using OFRI-CM model is higher and efficient by 8.54% and 16.02% compared to DSMO-LS [1] and MCCR-TS [2] respectively.

V. CONCLUSION

In this paper, an Ordered Fuzzy Rule Induction based Churn Mining (OFRI-CM) model is provided based on the Fuzzy Data Mining model for churn detection in Telecom Industry. This model addresses a system based on the rule that mine the churn from higher order to lower ones. The model uses soft boundaries value in a dynamic manner for combining fuzzy rules which increases the efficiency of true positive rate for the churn rate being detected. The proposed fuzzy data mining model using fuzzy sets and membership functions perform the aggregation operators for combining the fuzzy rules improving the true positive rate. By applying the Divide and Conquer strategy in OFRI-CM model, improves the aggregation of sub group patterns being generated reducing the processing time for detecting churn rates. Finally, with the application of proposed Churn Mining-based Greedy algorithm using Greedy principle, achieves higher rate of accuracy with relatively lower processing time improving the efficiency of the system and the churn rates being detected. Different number of subscribers at different time period using OFRI-CM model carefully analyzes the possible churn factors to significantly reduce the attrition rate of customers. A series of experiments are performed to test the efficiency of true positive rate, accuracy and processing time to measure the effectiveness of OFRI-CM model. Experiments conducted on varied simulation runs shows improvement over the state-of-the-art methods.

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