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# Blended Churn Predictive System for Quadruple-Patterned Churn Classification Towards Effective Customer Behavioural Management

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**Abstract:** The adoption of product centric approach to customer acquisition by many subscriber based companies has become a factor, which influences customer misclassification in existing churn predictive models. While the transaction volume, velocity, and varieties for basic churn processes continues to increase exponentially, every customer remained a potential churner to a certain degree. Although, existing churn prediction models classifies customers as churner or non-churner, many of its approaches assign equal weight to features while the customer's power of influence from socio-transactional data mining are neglected in churn behaviour management. Here, the developed Churn Predictive System is a composite of Recency-Frequency-Monetary-Influence model through customer segmentation management and Fuzzy-Weighted Feature Engineering model, which trained and tested transactional records using Random Forest and Adaboost Ensemble Learning in a 5-fold cross validation protocol. This System was coupled (Customer Segmentation + Ensemble Learning) to achieve a quadrupled customer's churn category as Churner, Potential Churner, Inertia Customer and Premium Customers. The results from the developed system juxtapose the need for a new approach to churn prediction in customer behavioural management.

**Keywords:** Churn Prediction, Fuzzy-weight, Ensemble Machine Learning, Customer Segmentation, Customers' Behavioural Management

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## 1. Introduction

In modern business world, the risk of losing customers to another service provider is so enormous especially for subscriber based organizations. Although, in competitive business cycle where advertisement and promotional offers are used for customers' acquisition, customer churn seems unnoticeable in bits per day, per week [1]. However, when compounded over a period; say a quarter or over a year, a business could be losing a fortune of their customers to competitors. Consequently, instead of using the traditional approach to detect customer churn, machine learning models [2] have been adopted by various researchers to find patterns and relationships in large amount of data. The data, which represents different customers' behavioural traits remained an

important component for effective customer retention.

Thus, as the need for customers' acquisition and retention became a top concern for organizations; aside, machine learning techniques through single or ensemble methods, market/customer segmentation technique have also been used to identify and extract, which parts of the service a customer is using, and how often the customer uses such. The behavioural data through these methods are represented as attributes or features that are manipulated to define a customer and their churn prediction category [3]. While existing Recency-Frequency-Monetary model through customer segmentation neglects the customer's power of influence in community based churn prediction, existing methods in churn prediction via machine learning also assign equal weights to features. This processes as increasing led to

churn misclassification, and less effective targeted decision support in acquiring new customers or retaining existing once. Therefore, in section two, related works in customers' segmentation and machine learning patterns are presented. In section three, the developed blended churn predictive system is presented. Sample experiments and evaluations are documented in section four (4) while the research is concluded in section five (5).

## 2. Related Works

One of the most imperative service aspects in telecommunications industry among other subscriber based organization is churn prediction. It is also an important factor to consider for Customer Relationship Management (CRM) [4]. Churn prediction has become significantly necessary because a business is lost when it cost more to acquire a customer then retaining existing once. Therefore, to measure customers' loyalty for decision support through customer retention, churn prediction algorithms became necessary. While different customers exhibits various behavioural attributes, the quality of a data pre-processing and analyses contributes to churn prediction. Thus, due to the importance of attributes is churn prediction, [5] provided an overview to different types of subscriber attributes that are used for modelling and predicting customer churn. [6] applied Bayesian belief network to discover the most important features that have effects on customer churn in telecommunication industry. Similarly, association rules was used by [7] to extract features from original dataset with the goal of improving the performance of prediction while [8] developed a semi supervised data centric model to cluster high relevant and low redundant feature subset for churn prediction in feature engineering. In addition, [9] introduced a Relative Churn Fuzzy Feature Weight Model as an optimised feature subset for churn prediction. The method assigns fuzzy weights to attributes based on its relevance degree in the cluster as it builds clusters of interdependent relative associations between extracted features for effective churn prediction. By this, high precision and recall interdependent but uniquely weighted feature subset, which is sufficient for churn prediction are extracted. Thus, in reality, the preprocessed data are fed into machine learning algorithms alongside similar technics like customer segmentation for churn prediction.

Subsequently, as churn prediction methods continue to mitigate the demanding nature and high dimensionality issues present in the telecom dataset, [10] used logistic regression and decision tree model for churn prediction. In addition, a cutting-edge method via Support Vector Machine (SVM) algorithm using four kernel functions was introduced to predict the customer churn category by [11] in telecommunications. The research observed that SVM polynomial with four kernel functions outperformed three kernel functions in the prediction of customer churn. Likewise, [12] presented three Hybrid models in telecommunication sector for customer churn prediction. The

designed approaches were based on efficient data clustering and prediction phase. In the analysis, the accuracy, precision and recall values was calculated and matched with other models like C5.0 and MLP-ANN for evaluation. Consequently, with the goal of improving customer churn in the telecom industry for market basket analysis, [13] presented a predictive approach that uses Decision Tree, K-Nearest Neighbor, Naïve Bayes and Random Forest to predict customer churn in Rapid Miner. However, as machine learning algorithms continue to dominate the churn prediction space, customer segmentation approach like Recency-Frequency-Monetary model have been used optimised for churn prediction [14] towards effective customer relationship management. The goal among others is to cluster customers according to how recent (R) they have made a purchase, how frequent (F) they make purchases, and how much, Monetary (M) they have bought. An algorithm for RFM sequential patterns generation using customers' purchasing data was implemented by [15] while [16] extended the RFM model by introducing the customers' influence degree (I). The goal was to harness the socio-transactional network behaviour of customers' through direct point to point relationship towards detecting the customer's power of influence via dependent to targeted customer RFM value analysis in the community. By this, churn misclassification was minimized and churn patterns improved significantly. Despite existing research works as documented, in section four, the developed blended churn predictive system is discussed. The objective of the system is to measure the Accuracy, Precision, Sensitivity of churn classification by harnessing the potency of RFMI churn category model and Ensemble Machine Learning approach through fuzzy weight features to generate four class of churn category i.e. Churner, Potential Churner, Inertia Customer and Premium customer, against existing Two churn categories (Churner and Non-Churner). By this, sample evaluation and experimental results of the research outcomes are presented in section four.

## 3. Methodology: Blended Churn Predictive System

The churn predictive system processes and analyses churn data by using the optimal feature set of customer records alongside customer behavioural segmentation. The developed model logic is represented in figure 1.

Where,  $A_{fd}$  is the automatic feature possessing system,  $Rf_{fw}$  is the Relative Churn Fuzzy-Weight,  $RFMI_p$  is the  $CRFMI_s$  is the customer's RFMI score and  $ccs_i$  is the customer churn score obtained from the general training and learning activities derived from customer's optimal feature analysis via ensemble machine learning. Thus, from figure 1, the churn predictive system performs the following operations:

1. Extract optimal features subset from the raw customer transaction dataset,

2. Assign random fuzzy-weight to features for better churn classification,
3. Generate customer’s churn score using ensemble model (Here, Adaboost and Random Forest),
4. Identify the influence of a customer in a community through socio-transaction network analysis,
5. Generate churn score for customers using the segment based behavioural analysis; here RFMI described in D and,

6. Find the variance of the two independent churn classification result for optimal churn classification.

Thus, from the processing stages, the blended churn predictive system was used to manipulate the raw transactional dataset in order to train and discover patterns that defines the churn category of a customer. The process also helped to define what feature triggers a churn class and when a customer churn may happen.

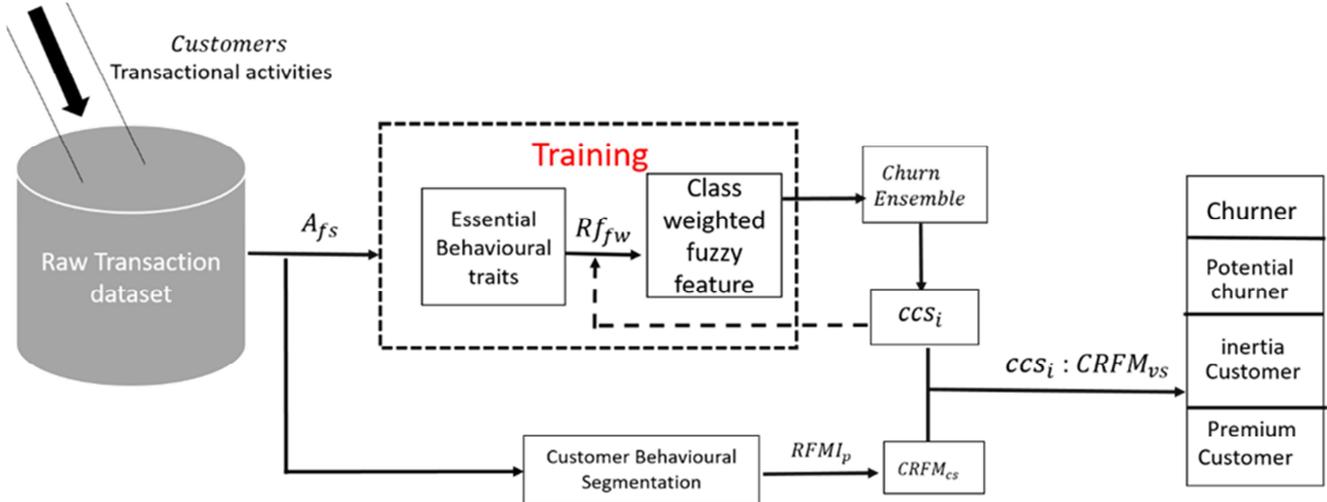


Figure 1. Churn Transaction Predictive System.

### 4. Experiments and Evaluation

In this section, we present a comparative result of the blended churn predictive system via the two ensemble machine learning models; Random Forest Ensemble in Table 1 and Adaboost Ensemble in Table 2. While the overall performance average analysis of the obtained results is also presented in figure 2.

In figure 2, the average performance of Random Forest and Adaboost is presented.

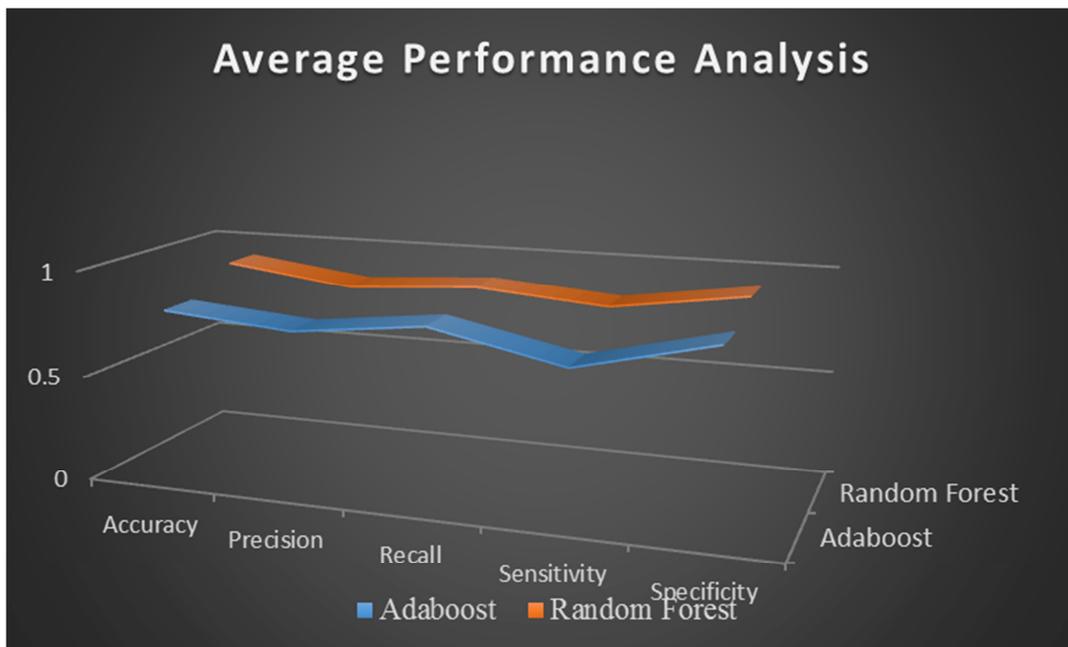


Figure 2. Average performance Analysis (Random Forest VS Adaboost).

**Table 1.** Blended Churn Predictive System (BCPS) with Random Forest Ensemble.

Churn Category	Performance Metrics				
	Accuracy	Precision	Recall	Sensitivity	Specificity
Churner	0.95	0.90	0.86	0.83	0.90
Potential Churner	0.88	0.82	0.92	0.82	0.93
Inertia Customer	0.87	0.78	0.80	0.81	0.91
Premium Customer	0.96	0.84	0.91	0.83	0.92

**Table 2.** Blended Churn Predictive System with Adaboost Ensemble.

Churn Category	Performance Metrics				
	Accuracy	Precision	Recall	Sensitivity	Specificity
Churner	0.81	0.88	0.78	0.55	0.90
Potential Churner	0.76	0.69	0.91	0.74	0.76
Inertia Customer	0.79	0.65	0.72	0.77	0.85
Premium Customer	0.83	0.76	0.84	0.67	0.82

## 5. Conclusion

As consumer centric approach became more imperative in customer relationship management, the approach for churn prediction also needs to be enhanced for better performance. In this research, the blended churn predictive system provided a solution that helped to identify the market segment of a customers while augmenting the ascertained data with relevant customer behavioral patterns through ensemble learning for better churn classification. The system significantly reduced misclassification while improving customer churn categories from the existing binary class to a quadruple class of Churner, Potential Churner, Inertia Customer and Premium Customer respectively. The essence is to enhance targeted decision support for effective customer retention in customer behavior management.

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