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A Study of the Telestatic View

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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.

Keywords-: Telecom, Customer churn, Machine Learning

I. INTRODUCTION

The primary purpose of a churn prediction system is to identify customers at risk of leaving the service provider. By proactively targeting these customers with retention strategies, telecom companies can reduce customer attrition rates and retain valuable subscribers. Acquiring new customers is typically more expensive than retaining existing ones. By identifying potential churners and taking action to retain them, telecom companies can save on marketing and acquisition costs. Churn prediction enables telecom companies to address customer issues and concerns before they lead to defection. By resolving problems and providing personalized offers, customer satisfaction can be significantly improved.ML models can analyze customer data to segment the customer base effectively. This allows telecom companies to tailor marketing campaigns and promotions to specific customer groups, increasing the chances of success. Churn prediction helps telecom companies allocate resources more efficiently. For instance, they can focus their customer service efforts on highrisk customers, allocate retention budgets wisely, and plan network capacity based on expected dema.

II. Literature Survey

Several techniques have been proposed in literaturefir churn prediction. These techniques include datamining, machine learning and hybrid strategies. Thesetechniques help businesses identify, predict, and retainchurn customers, as well as aid decision-making andCRM. Decision trees are the most commonly used method for predicting problems related to customerchurn [11].Decision trees have the limitation thatthey are not suitable for complex nonlinear connectionsbetween attributes, but perform better for linear datawhere attributes are interdependent.However, theaccuracy of decision trees are improved using pruning[12].

In [13], the authors proposed a forecasting approachthat uses a two-phase strategy based on their recency,frequency and monetary value (RFM). The relatedfunctions of the RFM are cclassified into four clustersin the first phase. In the second phase, the churndata collected in the first phase are extracted andevaluated using decision trees,Neural Networks andother machine learning algorithms.Experimentalresults show prediction results are better using hybridapproaches.

In [14], the authors proposed a hybridapproach for churn prediction by combining geneticprogramming with induction algorithm from an existingtree.The proposed algorithm used the behaviourof customers to generate classification rules.Theproposed model is used to predict different customgroups based on time of use, location, and underlyingsocial networks, and represents a practical approachto churn models at the human level rather thanthe mathematical level.

The authors in [15] usedthree models to evaluate the performance of churnmodels.The models include ANN, classificationtrees and logistic regression.They selected tenfeatures based on their exploratory data analysis andbusiness experience. Experimental results show thatthe hybrid models performed better than independentclassification models.

AlShourbaji et al.[16] proposed a novel FeatureSelection strategy ACO-RSA. In this approach twometaheuristicalgorithmsalgorithms(antcolonyoptimization (ACO) and reptile search algorithm (RSA))are integrated for the selection of subset features thatare important for churn prediction. The proposed modelis evaluated using the state- of-the-art test functionsand open-source datasets for churn preductions. Thisis evaluated alongside Standard ACO, Gray WolfOptimiser, Multiverse Optimser and the results showthat ACO-RSA outperforms the compared approaches.Similarly, the authors in [17] propose a new frameworkfor saturated markets. They use an effective churnprediction model for monitoring customer churn basedon Swish Recurrent Neural Network (S-RNN). The proposed model is tuned to classify regular and churn customers based on their network usgae history. In [18], the authors propose a machine learning churningmodel with six phases. Preprocessing and analysisof features are the first two phases while the thirdphase is the feature selection phase using gravitationalsearch algorithm. With ratios of 80% and 20%, thedata is divided inot tensile and test set respectively.Logistic regression, support vector machines,

decisiontrees, naives bayes and random forest were evaluatedand K-fold cross validation was used to optimise thehyperparameters. The results of the experiments showthat Adaboost and XGboost outperformed the otherapproaches compared.
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III. SYSTEM ARCHITECTURE

Telecom companies collect a wide range of customer data, including call records, billing information, customer demographics, usage patterns, customer service interactions, and more. Data Pre-processing: Raw data collected from various sources needs to be cleaned and preprocessed to ensure data quality. This step involves handling missing values, outliers, and data normalization. Feature Engineering: Feature engineering involves creating new variables or transforming existing ones to extract valuable insights. For churn prediction, features might include call drop rates, contract duration, customer tenure, usage trends, and customer complaints.

A feasibility study is a critical evaluation of the practicality and viability of implementing a real time churn Guard Pro model. Churn prediction plays a significant role in the banking industry as it helps identify customers who are likely to close their accounts or stop using banking services. By proactively addressing churn risk, banks can implement targeted retention strategies and enhance customer satisfaction and profitability.

Figure 1. Detail System architecture

The primary objective of a churn prediction system is to reduce customer attrition. Telecom companies can target high-risk customers with retention strategies, leading to reduced churn rates and increased customer loyalty. ML-powered segmentation and predictive analytics enable telecom companies to optimize marketing efforts by tailoring campaigns to specific customer segments,
increasing the effectiveness of marketing spend.

CONCLUSION

Predicting customer churn in the telecommunication industry involves a complex interplay of techniques, data, and ethical considerations. The Customer Churn in Bank web application is designed to predict and manage customer churn in small banks, utilizing Python and various algorithms for accurate churn predictions. The system provides valuable insights and analysis to help banks retain customers effectively.

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