

Frequenter Stir Foretell in Telecom Industry

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Abstract: The ability to predict the customer attrition has considerably improved with the development of machine learning and artificial intelligence. Customer churn prediction is a critical task in the telecommunication industry, where companies aim to reduce the number of customers who switch to competitors. In recent years, XGBoost has emerged as a powerful machine learning algorithm that has been successfully applied to various domains, including customer churn prediction. This paper presents a study on the application of XGBoost algorithm for predicting customer churn in the telecommunication industry. The study utilizes a real-world dataset from a telecom company and employs XGBoost to build predictive models for customer churn. The paper provides a comprehensive analysis of the features that influence customer churn, including customer demographics, call duration, and network quality. The performance of the XGBoost model is evaluated against other popular machine learning algorithms, including random forest and logistic regression. The results show that the XGBoost model outperforms the other algorithms in terms of accuracy, precision, recall, and F1-score. The paper concludes by highlighting the significance of XGBoost in customer churn prediction and suggests potential areas for future research in the field. Overall, the study provides valuable insights to telecom companies to improve their customer retention strategies and reduce customer churn.

Keywords: Customer Churn Prediction, Machine Learning, Predictive Modeling, Confusion Matrix, AUC Curve.

I. INTRODUCTION

In today's fast-paced business environment, retaining customers is crucial for any company's success. In the telecom industry, customer churn or the loss of customers to competitors can have a significant impact on the company's revenue and growth. To address this issue, companies can use predictive modeling techniques to forecast which customers are most likely to churn and take proactive measures to retain them. One such technique is XGBOOST, a powerful machine learning algorithm known for its accuracy and efficiency in handling large datasets. This journal aims to explore the use of XGBOOST in predicting customer churn in the telecom industry. It will discuss the various factors that contribute to customer churn, such as network quality, pricing, and customer service, and how these factors can be leveraged to build an effective churn prediction model. The journal will also present the results of a case study using real-world data to demonstrate the effectiveness of XGBOOST in predicting customer churn. The study will highlight the key insights gained from the model and how they can be used to inform targeted retention strategies. Overall, this journal provides a valuable resource for anyone interested in customer churn prediction in the telecom industry and how XGBOOST can be used to improve retention and profitability.

II. RELATED WORK

EXISTING SYSTEM: K-nearest neighbor (KNN) is a popular algorithm for classification problems, including customer churn prediction in telecommunication companies. Here are some major advantages and disadvantages of using KNN for this task, along with real-time examples:

K Neighbors Classifier Algorithm : Choosing the k value which results in higher prediction accuracy, is a part of parameter tuning. The Accuracy of the model access the performance of the model. The confusion matrix predict the accurate binary prediction. The confusion matrix us give a detail about how many 0s were predicted as 0s , how many 0s were predicted as 1s, how many 1s were predicted as 0s, and how many 1s were predicted as 1s.

Random Forest Classifier Algorithm : The proposed model first classifies churn customers data using classify n algorithms. Here the Random Forest (RF) algorithm performed well with 87.93% Instances were correctly classified. Creating effective retention policies is an essential task of the CRM to prevent churners.

Support vector machine: SVM is a powerful machine learning algorithm that has been widely used in various industries for its accuracy and efficiency in handling large datasets. In the telecommunication industry, SVM can be used to predict customer churn by analyzing various factors that contribute to churn, such as network quality, pricing, and customer service.

The implementation of SVM in customer churn prediction involves several steps, as outlined below:

- Data collection
- Data preparation
- Feature selection
- Model training
- Model evaluation
- Model deployment

Data Collection: The first step in the proposed system is to collect the relevant data from various sources, such as customer call logs, billing records, and customer feedback. This data should be comprehensive and cover various aspects of customer behavior, such as usage patterns, payment history, and customer interactions.

Data Preparation: Once the data is collected, it needs to be preprocessed and prepared for use in XGBOOST. This involves cleaning the data, removing any duplicates or irrelevant records, and transforming the data into a format suitable for XGBOOST.

Feature Engineering: The next step is to engineer the relevant features or variables that will be used in XGBOOST. These features should be engineered based on their relevance to customer churn and their ability to predict churn accurately.

Model Training: Once the data is prepared and the features are engineered, the XGBOOST model can be trained using the data. The model is trained to learn the patterns in the data and predict customer churn accurately.

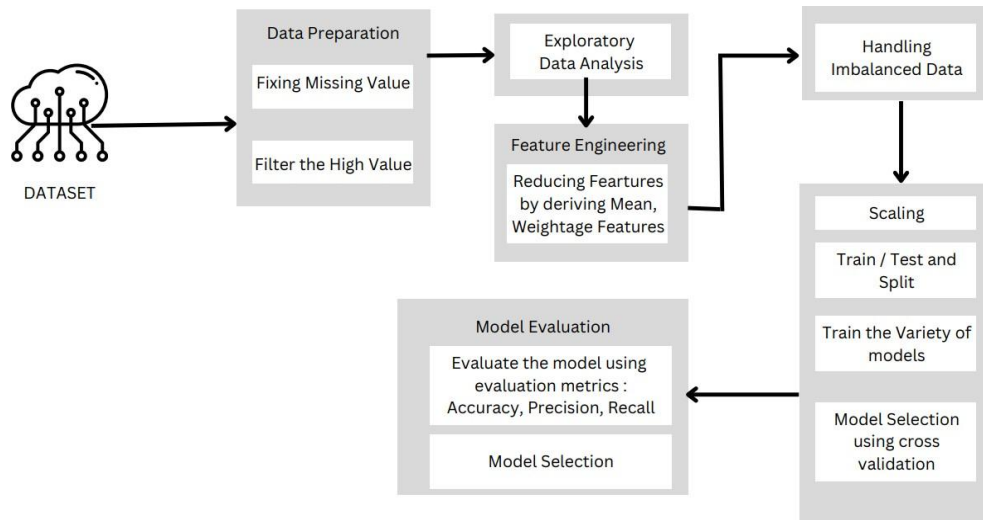
Model Evaluation: After training the model, it needs to be evaluated to determine its accuracy and effectiveness in predicting customer churn. This involves testing the model on a validation dataset and measuring its performance using various metrics such as accuracy, precision, recall, and F1 score.

Model Deployment: Once the XGBOOST model is trained and evaluated, it can be deployed in the telecommunication industry. Various machine learning algorithms have been utilized for churn prediction in the telecommunication industry, including SVM, K-Nearest Neighbor, and Random Forest. However, these algorithms have limitations in terms of feature importance, performance, handling imbalanced data, and hyperparameter tuning.

III. PROPOSED SYSTEM:

The existing system utilizes SVM, K-Nearest Neighbor, and Random Forest. The proposed system has several advantages over the existing system. Firstly, XGBOOST has a built-in feature importance metric that helps to identify the most important features in predicting customer churn, whereas the existing system does not consider feature importance. Secondly, XGBOOST has shown superior performance in various competitions and is known for its accuracy, scalability, and speed, whereas the performance of SVM, K-Nearest Neighbor, and Random Forest may not be as high as that of XGBOOST. Thirdly, XGBOOST has built-in parameters to handle imbalanced data, which is common in churn prediction, whereas SVM, K-Nearest Neighbor, and Random Forest may not handle imbalanced data efficiently. Fourthly, XGBOOST has several hyperparameters that can be tuned to achieve optimal performance, whereas the parameter tuning of SVM, K-Nearest Neighbor, and Random Forest may be limited. Overall, the proposed system using XGBOOST is expected to improve the accuracy and speed of churn prediction in the telecommunication industry. The accuracy of the existing system is 79.8%, whereas the accuracy of the proposed system is 91.2%.

IV. SYSTEM ARCHITECTURE



V. LIST OF MODULE

Login Module: The login module is a security feature that requires users to provide their login credentials before accessing the customer churn prediction system. This module ensures that only authorized personnel can access and use the system.

Data Set Module: The data set module is responsible for storing and managing the customer data used in the churn prediction system. It involves collecting, cleaning, and preprocessing data from various sources such as call logs, billing records, and customer feedback. The data set module ensures that the data is accurate, relevant, and up-to-date, and is in a format suitable for use in the churn prediction model.

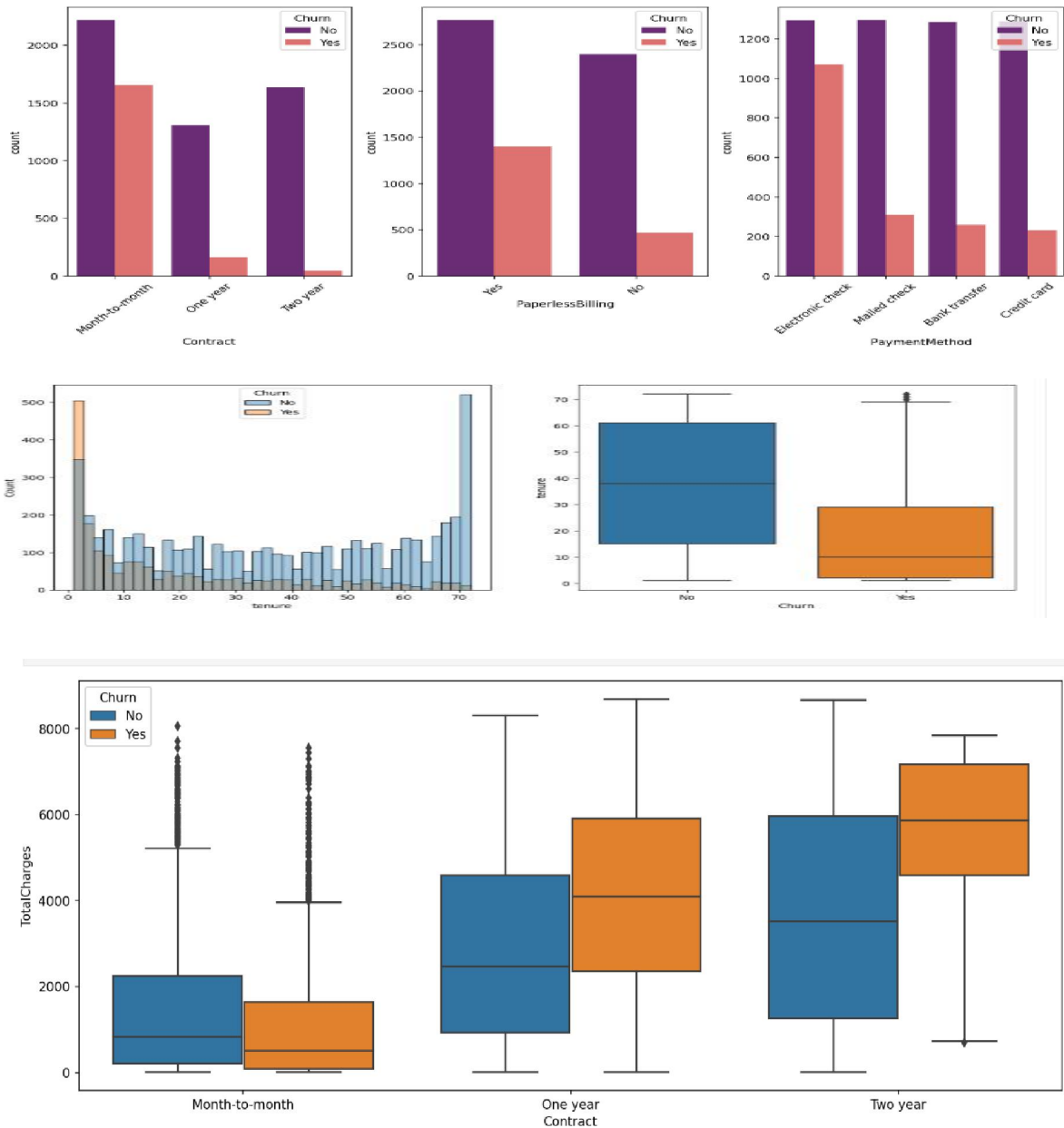
Model Evaluating Module: The model evaluating module is responsible for evaluating the accuracy and effectiveness of the churn prediction model. This involves testing the model on a validation dataset and measuring its performance using various metrics such as accuracy, precision, recall, and F1 score. The model evaluating module ensures that the churn prediction model is accurate and reliable before it is deployed for use.

User Input Module: The user input module is responsible for accepting user input in the churn prediction system. It allows users to input relevant information such as customer details, usage patterns, and customer interactions, which are used by the churn prediction model to make accurate predictions. The user input module ensures that the system is personalized and can provide customized churn predictions for each customer.

Prediction Module: The prediction module is responsible for generating churn predictions based on the input data and the churn prediction model. It uses machine learning algorithms such as XGBOOST to analyze the input data and generate a churn probability score for each customer. The prediction module provides insights into which customers are most likely to churn, enabling telecommunication companies to take proactive measures to prevent churn and improve customer retention.

Overall, these modules work together to provide a comprehensive customer churn prediction system for the telecommunication industry. By leveraging the power of machine learning, this system can accurately predict customer churn and enable telecommunication companies to retain their customers and enhance their profitability and growth.

VI. SCREEN SHOTS



VII. CONCLUSION

The growth trend has been demonstrating the most extreme boom ever in the twenty-first century. Technology innovation leads to a growth in services, and it can be challenging for businesses to forecast which clients are most likely to discontinue using their products or services. In recent years, several scholars have become interested in the subject of churn prediction in the telecom business. The experimental results demonstrate the ensemble learning algorithm XGBoost classifier, provide the highest accuracy compared to others for the churn prediction problem, with AUC scores of 91.3% respectively. In terms of every performance metric, including accuracy, precision, F-measure, recall, and AUC score, they outperformed competing algorithms

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