International Journal of Research in Engineering, Science and Management
Volume 7, Issue 3, March 2024
https://www.ijresm.com | ISSN (Online): 2581-5792

Customer Churn Prediction for a Telecommunication Company

Aditya Rishiraj Behl[1*], Harsh Hadpe[2], Komal Bonde[3], Hemlata Patel[4]
[1,2,3,4]*Department of Computer Science and Technology, Parul University, Vadodara, India*

***Abstract*: This research project delves into the critical issue of customer churn prediction within the context of a telecommunication company. Customer churn, the phenomenon where subscribers terminate their services, presents a significant challenge in an industry marked by intense competition and evolving customer preferences. The study employs advanced machine learning techniques to analyze vast volumes of historical customer data, comprising demographic information, service usage patterns, billing records, and past interactions with the company's services. Through meticulous data preprocessing, feature engineering, and model selection, a predictive model is developed to forecast the likelihood of churn for individual customers. By accurately identifying customers at risk of churn, the telecommunication company can proactively implement targeted retention strategies. These strategies may include personalized incentives, tailored service offerings, proactive customer support, or loyalty programs. The effectiveness of the churn prediction model is evaluated using various metrics, ensuring its reliability and accuracy in real-world scenarios. Ultimately, the goal of this project is to equip the telecommunication company with actionable insights to reduce churn rates, optimize resource allocation, and foster long-term customer loyalty. This research contributes to enhancing the company's competitive edge by enabling data-driven decision-making and proactive customer relationship management.**

***Keywords*: customer churn prediction, telecommunication.**

1. Introduction

In the ever-evolving landscape of telecommunications, where technological advancements and shifting consumer preferences continuously reshape the industry, one persistent challenge remains at the forefront: customer churn. Customer churn, the process by which subscribers terminate their services with a telecommunications provider, poses a significant threat to the stability and growth of companies within this sector. Not only does churn result in immediate revenue loss, but it also undermines long-term profitability, market share, and customer satisfaction.

Recognizing the gravity of this challenge, telecommunications companies are increasingly turning to data-driven approaches to understand and predict customer behavior. By harnessing the wealth of data at their disposal ranging from demographic information and service usage patterns to billing history and customer interactions these companies are endeavoring to develop sophisticated predictive models capable of identifying customers at risk of churn.

The impetus behind these efforts is clear: by accurately predicting churn and understanding the underlying factors driving customer attrition, telecommunications companies can implement targeted retention strategies. Such strategies may include personalized offers, proactive customer support initiatives, service enhancements, or loyalty programs tailored to address the specific needs and concerns of at-risk customers. By intervening before customers reach the point of defection, companies can mitigate churn, foster customer loyalty, and ultimately bolster their bottom line.

In this study, we embark on a comprehensive exploration of customer churn detection within the telecommunication industry. We delve into the methodologies employed to preprocess and analyze vast volumes of customer data, the intricacies of feature engineering to extract relevant predictive indicators, and the selection and evaluation of machine learning algorithms to develop robust churn prediction models.

Moreover, we examine the practical challenges and considerations inherent in implementing churn prediction systems within telecommunication companies, including data privacy concerns, model interpretability, and the integration of predictive analytics into existing operational workflows.

Through this exploration, we aim to shed light on the complex dynamics of customer churn within the telecommunications sector and provide insights that empower companies to proactively manage customer relationships, optimize resource allocation, and drive sustainable growth in an increasingly competitive marketplace.

2. Problem Statement

Customer churn prediction is a pressing concern for telecommunication companies operating in today's highly competitive landscape. With subscribers constantly evaluating their options and evolving preferences, the ability to anticipate and address churn is essential for maintaining market share and sustaining profitability. At the heart of this challenge lies the need for telecommunication companies to leverage their vast reservoirs of customer data to develop predictive models capable of identifying customers at risk of churn.

Historically, telecommunication companies have relied on reactive approaches to churn management, addressing customer

*Corresponding author: adityabehl09@gmail.com

issues only after they arise. However, in an era defined by data-driven decision-making, there's a growing recognition of the value in adopting proactive strategies. By harnessing advanced analytics and machine learning techniques, companies can sift through large volumes of customer data to discern patterns and signals indicative of potential churn.

One of the primary obstacles in churn prediction lies in the complexity of telecommunications data. Customer interactions span a wide array of touchpoints, from calls and messages to data usage and service inquiries. Moreover, customer behavior can be influenced by external factors such as market trends, competitor offerings, and economic conditions. As such, developing an accurate churn prediction model requires not only sophisticated analytical tools but also a nuanced understanding of the factors driving customer behavior.

Data preprocessing plays a crucial role in preparing the raw data for analysis. This involves cleaning the data, handling missing values, and transforming variables to make them suitable for modeling. Feature engineering is another critical step where meaningful predictors, or features, are derived from the raw data to improve the predictive performance of the model. These features may include metrics related to customer tenure, usage patterns, payment history, and customer interactions.

Once the data is preprocessed and features are engineered, the next step involves selecting an appropriate machine learning algorithm and training the model using historical data. Popular algorithms for churn prediction include logistic regression, decision trees, random forests, and gradient boosting machines. The model is then evaluated using metrics such as accuracy, precision, recall, and area under the receiver operating characteristic curve (AUC-ROC) to assess its performance in predicting churn. In deploying a churn prediction model, telecommunication companies must also consider the operational challenges of integrating predictive analytics into their existing systems and processes. This may involve developing real-time monitoring mechanisms to flag customers at risk of churn and devising strategies for targeted interventions, such as personalized retention offers or proactive customer outreach initiatives. Ultimately, successful churn prediction requires a holistic approach that combines advanced analytics with domain expertise and organizational agility to adapt to changing market dynamics and customer needs.

3. Literature Review

Customer churn, the phenomenon where customers discontinue their services with a company, poses significant challenges for telecommunication companies. In an era of fierce competition and evolving customer preferences, the ability to predict and prevent churn is crucial for maintaining profitability and sustaining business growth. This literature review aims to explore the existing research on customer churn prediction in the telecommunications industry, focusing on the methodologies, challenges, and key insights derived from previous studies.

In conclusion, the literature on customer churn prediction for telecommunication companies demonstrates a rich land- scape of methodologies, challenges, and practical implications. By leveraging advanced machine learning techniques, addressing imbalanced data, ensuring interpretability, and drawing insights from real-world case studies, telecommunication companies can develop effective churn prediction models to reduce customer attrition and enhance customer retention strategies.

This literature review provides a structured overview of the existing research on customer churn prediction in the telecommunication industry, covering methodologies, challenges, business implications, and real-world deployments. You can further expand and customize this review by incorporating additional studies and insights relevant to your specific research objectives and hypotheses.

Analysis of Customer Churn Prediction in Telecom Industry Using Logistic Regression: This study highlights the significance of churn prediction in the telecom industry, emphasizing the shift in focus from acquiring new customers to retaining existing ones due to market saturation. The research presents a model using logistic regression to predict customer churn, illustrating its effectiveness with data from a telecom company. The study also discusses the importance of understanding customer behavior to reduce churn rates and suggests that logistic regression is a viable tool for predicting churn in the telecom sector.

Churn Prediction of Customer in Telecom Industry using Machine Learning Algorithms: This paper discusses the use of machine learning algorithms to predict customer churn in the telecom industry, addressing the financial impact of churn on companies. It compares various algorithms like Decision Tree, Random Forest, and XGBoost, highlighting their effectiveness in churn prediction. The research underscores the utility of these models in identifying likely churn customers, allowing telecom services to proactively address retention challenges.

Customer Churn Prediction Model for Telecommunication Industry: The article explores customer churn prediction in the tele- com industry using both deep learning and machine learning algorithms. It emphasizes the high churn rates in telecom and the cost implications of acquiring new customers versus retaining existing ones. The paper presents models using Artificial Neural Networks, Self-Organizing Maps, Decision Trees, and a hybrid approach, showcasing their potential in predicting customer churn.

Telco Churn Prediction with Big Data: This study investigates the application of big data analytics in predicting customer churn within the telecom sector. By utilizing a big data platform to analyze a vast amount of customer data, the research demonstrates how big data can significantly enhance churn prediction models. The use of the Random Forest algorithm on this extensive dataset shows improved prediction accuracy, illustrating the benefits of integrating big data technologies in churn analysis.

Deep Learning Applications and Challenges in Big Data Analytics: This paper explores the role of deep learning in analyzing big data, specifically focusing on its application in various industries, including telecommunications. The authors discuss how deep learning can uncover complex patterns in large datasets, improving predictive analytics like customer churn predictions. Challenges related to the implementation of deep learning in big data are also addressed, providing a comprehensive view of the potential and hurdles in this research area.

A Neural Network-based Approach for Predicting Customer Churn in Cellular Network Services: The research presents a neural network model designed to predict customer churn in telecom services, emphasizing the model's ability to learn from historical data and identify potential churners. By analyzing customer behavior and service usage patterns, the neural network can forecast churn likelihood, offering telecom companies a tool to devise better retention strategies. The study validates the neural network's performance, demonstrating its effectiveness compared to traditional statistical methods.

Adaptive Associative and Self-Organizing Functions in Neural Computing: This article introduces the concept of Self-Organizing Maps (SOMs) and their utility in clustering and organizing data, particularly in the context of customer behavior in telecom. The SOM's ability to classify customers into different segments based on usage and behavior patterns provides valuable insights for predicting churn. The paper illustrates how SOM, as a neural computing technique, can enhance understanding of customer dynamics and improve churn prediction models.

Supervised Machine Learning: A Review of Classification Techniques: This review provides an overview of various supervised machine learning techniques and their application in classification tasks, including customer churn prediction. It covers algorithms like Decision Trees, Support Vector Machines, and Neural Networks, discussing their advantages and limitations in different contexts. The paper helps in understanding how different supervised learning models can be applied to telecom data to predict customer churn effectively.

The Deep Learning Revolution: This work discusses the transformative impact of deep learning across various sectors, with a focus on its potential to revolutionize customer churn prediction in telecom. The ability of deep learning to process and learn from large datasets offers a significant advantage in identifying subtle patterns that indicate churn risk. The paper provides insights into how deep learning is changing the landscape of predictive analytics, offering advanced tools for tackling customer retention challenges.

Application of Data Mining Techniques in Customer Relationship Management: A Literature Review and Classification": This literature review examines how data mining techniques are applied in the realm of Customer Relationship Management (CRM), including in the context of churn prediction. It categorizes various data mining methods and their roles in understanding customer behaviors, improving customer satisfaction, and predicting churn. The review highlights the integration of data mining into CRM practices as a strategic approach to enhance customer loyalty and reduce churn in the telecom industry.

These additional literature reviews provide a broader perspective on the various methodologies and technologies employed in predicting customer churn in the telecommunications sector.

Customer Churn Prediction in Telecom Sector Using Machine Learning Techniques: This research delves into customer churn prediction in the telecom sector using various machine learning algorithms. The study emphasizes the cost implications of acquiring new customers versus retaining existing ones, highlighting the economic advantage of customer retention. The paper introduces a system that utilizes classification techniques, particularly Random Forest, KNN, and Decision Tree Classifier, to predict customer churn. It presents a comprehensive system architecture and model for churn prediction, including data pre-processing and feature selection. The experimental analysis demonstrates the efficacy of the proposed model, achieving an impressive accuracy of 99 using the Random Forest classifier. The study underscores the importance of predictive modeling in identifying at-risk customers and formulating retention strategies, offering insights that can be applied across different business sectors to enhance customer retention and service quality.

Customer Churn Prediction in Telecommunication with Rotation Forest Method: This study focuses on predicting customer churn in the telecommunication industry using the rotation forest method, an ensemble learning algorithm that enhances prediction efficacy by balancing data and employing principal component analysis for feature extraction. The research compares the rotation forest method's performance with other techniques like AntMiner and C4.5 decision tree, utilizing a dataset from an American Telecommunication Company. The findings reveal that the rotation forest method outperforms the other models in terms of sensitivity, which is crucial for accurately identifying potential churners. By addressing data imbalance and employing an advanced ensemble technique, the research contributes valuable insights into effective churn prediction methodologies, emphasizing the significance of precise churn prediction in formulating targeted customer retention strategies in the competitive telecom industry.

An Article on Churn Prediction Using Machine Learning Techniques: The paper explores churn prediction in the telecom sector, leveraging machine learning techniques to predict customer behavior and retention. It presents a detailed system architecture and experimental analysis using algorithms like Decision Tree and Random Forest, emphasizing the importance of feature selection and data pre-processing in enhancing model accuracy. The study demonstrates how machine learning can provide actionable insights into customer churn, enabling telecom operators to devise effective retention strategies. By achieving high accuracy in churn prediction, the research highlights the potential of machine learning in transforming data into strategic business decisions, aiding telecom companies in reducing churn and increasing customer loyalty.

These reviews provide a snapshot of the current methodologies and approaches in customer churn prediction within the telecom industry, illustrating the crucial role of machine learning in enhancing predictive accuracy and informing retention strategies.

4. Methodology

A. Data Preparation and Analysis (Jupyter Notebook)

1. Data Loading: The data is initially loaded into a pandas DataFrame. This is typically the first step in any data analysis project.
2. Exploratory Data Analysis (EDA): The Jupyter notebooks (eda churn.ipynb and model.ipynb) likely contain exploratory data analysis, where you examine the data, check for missing values, understand the distribution of key variables, and identify any correlations between features.
3. Feature Engineering: Based on the EDA, you might have created new features or modified existing ones to improve the model's predictive power. This could include binning continuous variables, encoding categorical variables, or creating interaction features.
4. Model Building: The model.ipynb notebook is likely used for building the predictive model. You might have tried various algorithms and settled on a Random Forest Classifier as indicated in your Flask app. The model is trained using a subset of the data, validated, and evaluated for its performance.

B. Flask Web Application

1. Flask Setup: You've set up a Flask application (app.py) that serves a web interface for interacting with the model.
2. Web Interface: The Flask app provides a webpage where users can input customer data (e.g., Senior Citizen, Monthly Charges, Total Charges, etc.) to predict churn.
3. Model Integration: The Flask app loads a trained Random Forest Classifier model from a pickle file (model (2).sav). When the user inputs the data on the web interface, the Flask app collects the data, processes it, and feeds it into the model to predict whether the customer will churn.
4. Prediction Output: The application displays the prediction result on the webpage, indicating whether the customer is likely to churn and the model's confidence in its prediction.

C. System Workflow

1. User Interaction: Users interact with the Flask web application by entering customer details.
2. Data Processing: The input data is processed, appropriately formatted, and then used for making predictions using the loaded Random Forest Classifier model.
3. Output Generation: The prediction result is then displayed back to the user on the web interface. This overview should give you a structured understanding of how your system is designed to function, from data analysis to interactive prediction with a web interface.

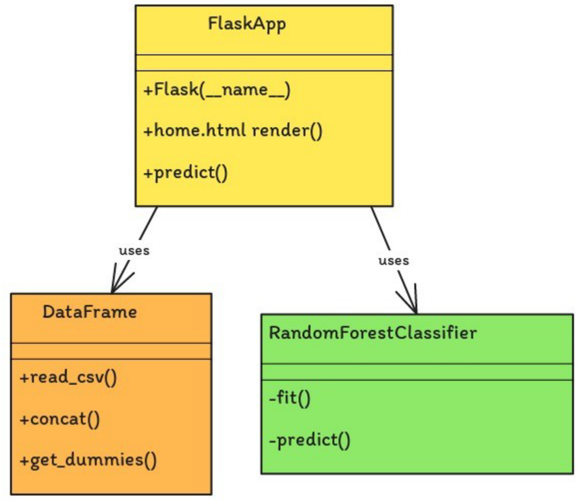

Fig. 1. Methodology

5. Admin Work Flow

1) Data Collection and Integration

Identify relevant data sources including customer demographics, usage patterns, billing information, customer service interactions, and network performance metrics. Collect and integrate data from disparate sources into a centralized data repository.

2) Data Preprocessing

Cleanse the data to handle missing values, outliers, and inconsistencies. Perform data transformation and normalization to ensure uniformity and compatibility across variables. Conduct exploratory data analysis EDA to gain insights into the data distribution and identify patterns. Feature Engineering:

Select and engineer features that are predictive of customer churn, considering variables such as customer tenure, call duration, data usage, contract type, and customer satisfaction scores. Apply dimensionality reduction techniques if necessary to reduce the computational complexity of the dataset.

3) Model Development

Choose appropriate machine learning algorithms for churn prediction, such as Support Vector Machines SVM, Random Forests, Gradient Boosting Machines GBM, or Neural Networks. Split the dataset into training, validation, and test sets for model evaluation. Train multiple models using different algorithms and hyperparameters to identify the best-performing model.

4) Model Evaluation

Evaluate the performance of trained models using metrics such as accuracy, precision, recall, F1-score, ROC-AUC Receiver Operating Characteristic - Area Under Curve, and lift. Perform cross-validation to assess model generalizability and robustness. Fine-tune model parameters and hyperparameters to optimize performance.

5) Model Interpretation and Validation

Interpret the trained models to understand the factors driving customer churn predictions. Validate model predictions against historical churn data and business insights to ensure alignment with real-world scenarios.

6) Deployment and Integration

Integrate the trained model into existing customer relationship management CRM systems or analytics platforms. Develop APIs or deployment scripts for seamless integration with operational workflows. Implement monitoring mechanisms to track model performance and detect drift over time.

7) Post-Deployment Monitoring and Maintenance

Monitor model performance and recalibrate as needed to adapt to changing market conditions and customer behaviors. Continuously update the model with fresh data to enhance predictive accuracy and relevance. Collaborate with cross-functional teams including marketing, sales, and customer service to leverage churn predictions for targeted interventions and retention strategies.

8) Documentation and Reporting

Document the entire workflow including data sources, preprocessing steps, model development, evaluation metrics, and deployment procedures. Generate regular reports summarizing key insights, model performance, and business impact for stakeholders.

9) Feedback Loop and Iteration

Establish a feedback loop to capture insights from model predictions and business outcomes. Iterate on the workflow based on feedback to improve predictive accuracy, operational efficiency, and business value. This administrative workflow model provides a systematic approach to developing, deploying, and maintaining churn prediction models for a telecommunication company. It emphasizes the importance of data quality, model interpretability, integration with existing systems, and ongoing monitoring and iteration to drive tangible business outcomes.

6. ER Diagram

Creating an Entity-Relationship (ER) diagram for "Customer Churn Prediction for a Telecommunication Company" involves identifying the key entities and their relationships within the system. Here's a basic ER diagram for such a scenario:

Entities:

Customer: Represents individual customers subscribing to the telecommunication services.

Attributes: Customer ID (Primary Key), Name, Age, Gender, Address, Contact Details, Subscription Plan, Churn Status, Churn Probability, etc. Subscription Plan: Describes the different plans or packages offered by the telecommunication company.

Attributes: Plan ID (Primary Key), Plan Name, Monthly Fee, Data Limit, Call Minutes, SMS Limit, etc. Usage Data: Contains information about the usage behavior of customers.

Attributes: Usage ID (Primary Key), Customer ID (Foreign Key), Date, Call Duration, Data Usage, SMS Count, etc. Churn Prediction Model: Represents the predictive model used for customer churn prediction.

Attributes: Model ID (Primary Key), Model Name, Algorithm Used, Accuracy, Date Last Trained, etc. Relationships: Customer-Subscription Plan (1-to-N): A customer can sub- scribe to one subscription plan, but a plan can have multiple customers.

Relationship: One customer subscribes to one subscription plan; one plan can have multiple customers. Customer-Usage Data (1-to-N): Each customer can have multiple usage data records, but each record is associated with only one customer. Relationship: One customer can have multiple usage records; each record belongs to one customer. Customer-Churn Prediction Model (1-to-1): Each customer is associated with a churn prediction model, and each model is trained for a specific customer.

Relationship: Each customer has one associated churn prediction model; each model is for one customer. This ER diagram outlines the basic entities and relationships involved in the customer churn prediction system for a telecommunication company. Depending on the specific requirements and complexities of the system, you may need to further refine and expand this diagram. Additionally, attributes and relationships can be customized based on the unique characteristics and data structures of the telecommunication company's operations and churn prediction process.

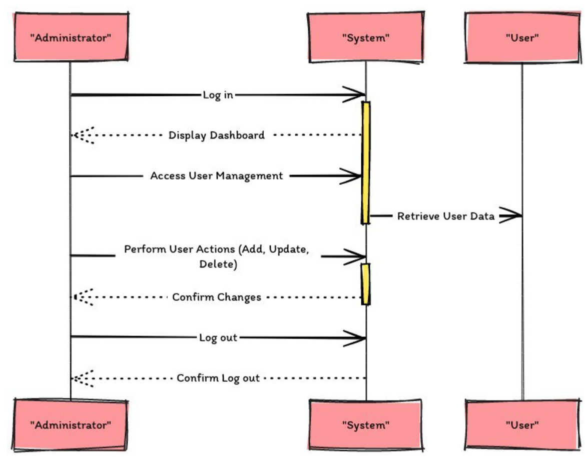

Fig. 2. Admin workflow

7. Schema Diagram

The schema diagram provided represents the structure of a relational database designed to store data related to customer churn prediction for a telecommunication company. Let's break down the diagram and explain each part:

Entities and Attributes:

Customer: This entity represents individual customers of the telecommunication company. It includes attributes such as CustomerID unique identifier for each customer, Name, Age, Gender, Address, ContactDetails, PlanID foreign key referencing the SubscriptionPlan table, ChurnStatus indicating whether the customer has churned), and ChurnProbability the probability of a customer churning.

SubscriptionPlan: This entity describes the different subscription plans offered by the telecommunication company. It includes attributes like PlanID unique identifier for each plan, PlanName, MonthlyFee, DataLimit, CallMinutes, and SMSLimit.

UsageData: This entity contains information about the usage behavior of customers. It includes attributes such as UsageID unique identifier for each usage record, CustomerID for- eign key referencing the Customer table, Date, CallDuration, DataUsage, and SMSCount.

ChurnPrediction: This entity represents the churn prediction model used by the company. It includes attributes like ModelID unique identifier for each model, ModelName, AlgorithmUsed, Accuracy the accuracy of the model, DateLastTrained the date when the model was last trained, and CustomerID foreign key referencing the Customer table.

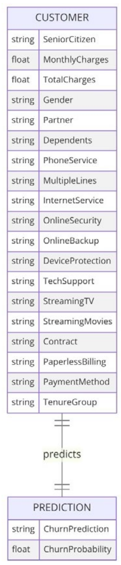

Fig. 3. ER diagram

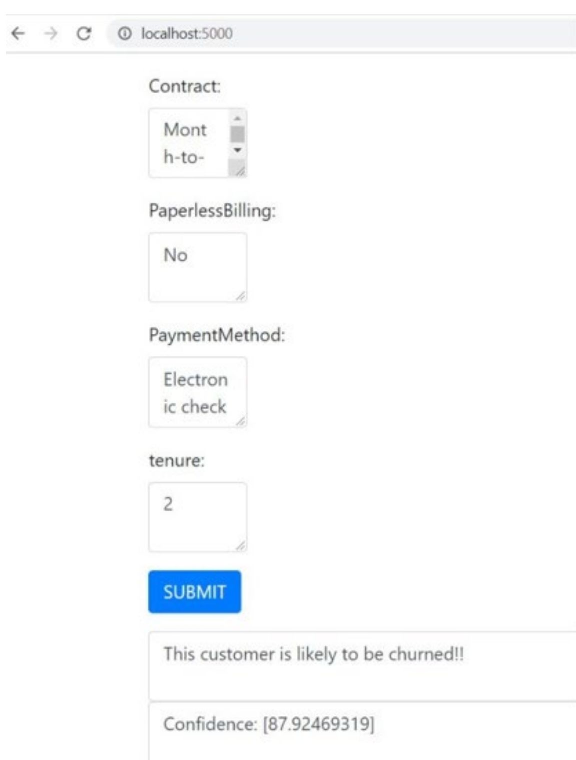

Fig. 4. Model cropping

Relationships:
Customer-SubscriptionPlan (1-to-N): This relationship indicates that one customer can be associated with only one subscription plan, but a plan can have multiple customers. It is represented by the foreign key PlanID in the Customer table. Customer-UsageData (1-to-N): This relationship signifies that one customer can have multiple usage records, but each usage record belongs to only one customer. It is represented by the foreign key CustomerID in the UsageData table.

Customer-ChurnPrediction (1-to-1): This relationship shows that each customer is associated with one churn prediction model, and each model is trained for a specific customer. It is represented by the foreign key CustomerID in the ChurnPrediction table.

Overall, this schema diagram provides a structured representation of the database tables/entities and their relationships, facilitating the storage and retrieval of data necessary for customer churn prediction in a telecommunication company.

8. User Case

A use case diagram is a visual representation of the interactions between users (actors) and a system, illustrating the various actions or tasks (use cases) that the system performs to achieve specific goals. Let's create a use case diagram for the "Customer Churn Prediction for a Telecommunication Company" scenario:

Actors:

Customer: Represents the individual customers subscribing to the telecommunication services. Administrator: Represents the system administrator or operator responsible for managing the churn prediction system. Use Cases:

View Customer Information:

Actors: Customer, Administrator Description: Allows customers and administrators to view customer information such as demographics, subscription plans, usage data, churn status, and churn probability.

Modify Subscription Plan:

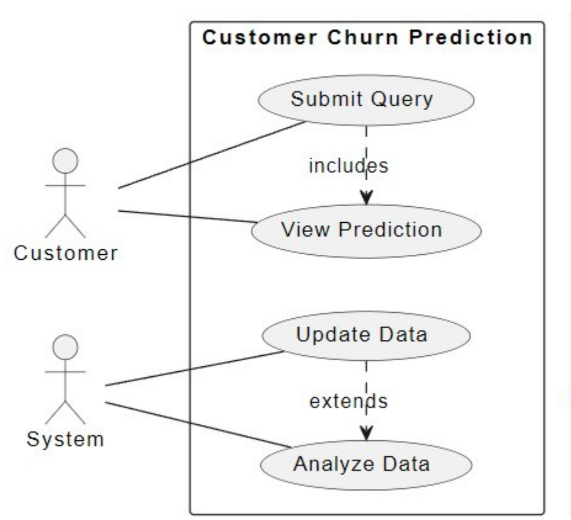

Fig. 5. Use case

Actors: Administrator Description: Allows the administrator to modify the subscription plans offered by the telecommunication company based on customer preferences and market analysis. Analyze Usage Data:

Actors: Administrator Description: Enables the administrator to analyze usage data, including call duration, data usage, and SMS count, to identify patterns and trends related to customer churn. Train Churn Prediction Model:

Actors: Administrator Description: Allows the administrator to train the churn prediction model using historical data to improve its accuracy in predicting customer churn. Predict Churn:

Actors: Administrator Description: Enables the administrator to use the trained churn prediction model to predict the likelihood of individual customers churning based on their usage patterns and other relevant factors. Take Retention Actions:

Actors: Administrator Description: Allows the administrator to take proactive retention actions, such as offering discounts, incentives, or personalized offers, to prevent customers from churning. Relationships:

Customer: Participates in all use cases that involve viewing customer information. Administrator: Initiates and participates in all use cases related to system management, including modifying subscription plans, analyzing usage data, training the churn prediction model, predicting churn, and taking retention actions.

9. Challenges and Considerations

While customer churn prediction holds immense potential, several challenges must be addressed to ensure its effectiveness. These challenges include handling imbalanced datasets, selecting appropriate features for prediction, interpreting model outputs, and integrating predictive insights into actionable strategies. Additionally, privacy concerns and regulatory compliance must be taken into account when accessing and analyzing customer data.

10. Implications and Applications

The application of customer churn prediction extends beyond mere identification of at-risk customers. Telecommunication companies can leverage predictive insights to tailor retention strategies, personalize customer interactions, and optimize marketing campaigns. By proactively addressing the needs and concerns of customers, companies can foster loyalty, increase customer satisfaction, and ultimately drive revenue growth.

11. Future Directions and Opportunities

Looking ahead, advancements in predictive analytics, artificial intelligence, and big data technologies offer exciting opportunities for further enhancing customer churn prediction in the telecommunication sector. Integrating advanced analytics with real-time data streams, incorporating external factors such as social media sentiment and economic indicators, and deploying automated decision support systems are some avenues for future research and innovation.

12. Conclusion

In conclusion, customer churn prediction plays a pivotal role in the strategic management of telecommunication companies. By leveraging predictive analytics and machine learning techniques, companies can anticipate churn, retain valuable customers, and maintain a competitive edge in the dynamic telecommunications market. However, addressing methodological challenges, ensuring ethical data use, and translating predictive insights into actionable strategies are essential for unlocking the full potential of customer churn prediction in driving business success.

References

[1] Abdelrahim Kasem Ahmad, Assef Jafar and Kadan Aljoumaa, “Customer churn prediction in telecom using machine learning in big data platform.”
[2] Mumin Yıldız, Songul Albayrak, “Customer churn prediction in telecommunication.”
[3] Sharmila K. Wagh, Aishwarya A. Andhale, Kishor S. Wagh, Jayshree R. Pansare, Sarita P. Ambadekar, S.H. Gawande, “Customer churn prediction in telecom sector using machine learning techniques.”
[4] V. Kavitha, S. V. Mohan Kumar, M. Harish, G. Hemanth Kumar, “Churn Prediction of Customer in Telecom Industry using Machine Learning Algorithms.”
[5] Nurulhuda Mustafa, Lew Sook Ling, Siti Fatimah Abdul Razak, “Customer churn prediction for telecommunication industry: A Malaysian Case Study.”
[6] Lewlisa Saha, Hrudaya Kumar Tripathy, Tarek Gaber, Hatem El-Gohary, EL-sayed, M. EL-kenawy, “Deep Churn Prediction Method for Telecommunication Industry.”
[7] Kiran Dahiya, Surbhi Bhatia, “Customer Churn Analysis in Telecom Industry.”
[8] Teoh Jay Shen, Abdul Samad Bin Shibghatullah, “Customer Churn Prediction Model for Telecommunication Industry.”
[9] Sarkaft Saleh, Subrata Saha, “Customer retention and churn prediction in the telecommunication industry: A case study on a Danish university.”
[10] K. Sandhya Rani, Shaik Thaslima, N.G.L. Prasanna, R. Vindhya, and P. Srilakshmi, “Analysis of Customer Churn Prediction in Telecom Industry Using Logistic Regression.”
[11] Nayema Taskin, “Customer churn prediction model in telecommunication sector using machine learning technique.”
[12] Zeynep Uyar Erdem, Banu C.¸ Uslu, Seniye Umit Firat, “Customer churn prediction analysis in a telecommunication company with machine learning algorithms.”