Application of Machine Learning Techniques in Customer Churn for Telecommunication Industries

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Abstract

Customer churn is a pressing issue in the telecommunications industry, significantly impacting profitability and market competitiveness. This study focuses on predicting churn using advanced machine learning techniques, analyzing factors such as customer usage patterns, network experience, and payment behavior. The dataset highlights variables like contract type, monthly charges, and tenure as critical contributors to churn. Among the models tested, the Random Forest Classifier demonstrated the strongest performance, with high accuracy and reliability.

To ensure the model's applicability, the results were integrated into a user-friendly dashboard, allowing stakeholders to identify at-risk customers and develop targeted retention strategies. This approach provides actionable insights to address churn effectively, reducing customer acquisition costs and promoting loyalty. The study's findings emphasize the broader implications of churn, including its economic and social impact, particularly in emerging markets where telecommunications drive digital inclusion and economic participation. By leveraging predictive analytics, this research bridges the gap between global best practices and localized solutions, contributing to more sustainable business strategies.

Keywords: Customer Churn, Telecommunications, Machine Learning, Random Forest Classifier, Retention Strategies, Predictive Analytics, Data-Driven Insights

1 Introduction

Customer churn in the global telecommunications industry is a critical issue that directly affects profitability, customer retention, and long-term sustainability. It refers to the phenomenon where customers discontinue their services, often opting for competitors offering better deals, enhanced customer service, or superior technological solutions. According to a report by Statista, the annual churn rate in the global telecommunications sector ranges between 20 % and 40%, representing a loss of billions of dollars in potential revenue annually [Statista(2023)]. These alarming figures highlight the urgent need for telecom providers to focus on churn prediction and mitigation strategies. Understanding the factors driving customer churn is essential for designing proactive solutions that enhance customer satisfaction and loyalty, ultimately boosting profitability and market competitiveness.

At a regional level, the challenge remains equally significant. In Africa, where telecommunications play a pivotal role in bridging the digital divide, churn rates are particularly high due to the competitive nature of the market and the price sensitivity of consumers. For example, in Kenya, the annual churn rate for some mobile service providers exceeds 30%, with customers frequently switching networks in search of better pricing, improved service quality, and value-added features. These high churn rates translate to millions of dollars in lost revenue and hinder efforts to achieve customer base stability. Addressing churn in such markets requires a nuanced understanding of customer needs, local market dynamics, and socio-economic factors that influence customer behavior.

This research focuses on understanding and predicting customer churn by leveraging advanced analytics and machine learning techniques. By analyzing patterns in customer data, such as usage behavior, network experience, and payment history, this study aims to uncover key factors driving churn in the telecommunications industry. This approach enables the identification of at-risk customers and also provides actionable insights to design tailored retention strategies. Ultimately, this work contributes to bridging the gap between global best practices and localized solutions, helping telecom providers address churn effectively in a manner suited to their unique market environments.

The economic and social implications of churn are vast. Economically, acquiring a new customer costs five to seven times more than retaining an existing one [Kotler et al.(2021)Kotler, Keller, and Chernev]. Furthermore, high churn rates result in reduced market share, limiting organizational competitiveness. Socially, churn disrupts customer relationships, particularly in regions where telecommunications play a vital role in enabling access to essential services like mobile banking and e-learning. For instance, in Africa, where mobile-driven economies are emerging, customer retention plays a critical role in promoting digital inclusion and economic participation [GSMA(2022)].

Despite substantial investments in customer relationship management, current industry approaches to churn prediction face several limitations. Many models rely on static data and retrospective analysis, failing to capture the dynamic and multifactorial nature of customer behavior. For example, traditional churn models often overlook shifting customer preferences, seasonal trends, and external influences like economic downturns or regulatory changes [Jahromi and Sharifi(2020)]. Additionally, subjective decision-making and inaccurate profiling lead to inefficiencies in resource allocation, reducing the effectiveness of retention strategies.

In Kenya, churn rates among leading telecom providers have exceeded 25% in recent years [(CAK)(2023)]. Contributing factors include price sensitivity, network reliability issues, inadequate customer service, and the availability of alternative providers. Given the socio-economic importance of telecommunications in Kenya, these high churn rates pose significant challenges for service providers. Innovative and context-specific approaches are essential to better understand and predict churn behavior.

To address these gaps, this research proposes a robust data-driven solution leveraging advanced machine learning (ML) techniques. Specifically, the study utilizes algorithms such as Random Forest classification, Decision Tree and logistic regression to identify critical churn predictors, quantify feature importance, and provide actionable insights. Additionally, exploratory data analysis will be employed to uncover hidden patterns and ensure that the churn prediction models are both accurate and interpretable.

The solution's deployment involves integrating the predictive model into telecom providers' customer relationship management systems, enabling proactive retention strategies. For example, high-risk customers could receive personalized offers or enhanced service interventions. By transitioning from reactive to predictive retention strategies, telecom providers can significantly reduce churn, improve customer satisfaction, and enhance profitability. Beyond the immediate telecommunications context, this research offers a scalable framework for churn prediction that can be adapted across various service-based industries. By addressing inefficiencies, inaccuracies, and subjectivity in churn prediction, this study contributes to a deeper understanding of customer behavior and highlights the transformative potential of advanced technology in solving complex business challenges.

2 Literature Review

Customer churn prediction has become a critical area of focus due to its direct impact on revenue and customer retention in the highly competitive telecommunications industry. Churn, defined as the discontinuation of a customer's relationship with a service provider, is a major concern for businesses seeking to sustain profitability and maximize customer lifetime value.

In India, mobile network operators struggled with high churn rates due to competitive pricing and customer dissatisfaction stemming from poor network quality and billing disputes. By implementing a logistic regression model, these companies identified key predictors of churn, including call drops and unresolved complaints. The insights gained from these models enabled companies to prioritize improvements in infrastructure, such as deploying additional cell towers to enhance network coverage and reliability. Additionally, streamlining complaint resolution processes and addressing billing inaccuracies resulted in significant reductions in customer attrition. These efforts highlight the importance of addressing technical and operational shortcomings to build trust and loyalty among customers [Ahmad and Sharma(2019)].

Similarly, a European telecommunications provider sought to improve long-term retention by addressing the complexity of customer interactions. Decision tree models proved effective in classifying customers based on their usage patterns, achieving high accuracy in identifying at-risk customers. This approach allowed the company to segment users into actionable categories, such as heavy data users, frequent callers, or low-usage customers. Tailored retention campaigns, including personalized offers and loyalty rewards, were designed for each segment, leading to notable improvements in customer re-

tention rates. By leveraging interpretable models, the provider gained actionable insights that informed both immediate interventions and long-term customer engagement strategies [Lu and Kim(2020)].

A U.S.-based wireless carrier faced challenges with churn among prepaid plan users, particularly due to seasonal usage fluctuations and limited customer loyalty. To address this issue, the carrier implemented a Random Forest algorithm to analyze patterns in user behavior, such as frequency of recharges, usage trends, and account inactivity periods. These insights enabled the development of seasonal promotions, targeted notifications, and reward programs aimed at engaging prepaid customers during periods of low activity. The application of machine learning enhanced customer engagement and reduced revenue losses, demonstrating the value of predictive analytics in managing diverse customer segments [Verma and Chaudhary(2021)].

In Southeast Asia, a telecom operator addressed high churn caused by frequent service outages. Using Gradient Boosting Machines (GBMs) to model outage frequency and customer complaints, the company improved service uptime and network reliability. By monitoring real-time outage data and analyzing customer feedback, they identified problem areas and invested in infrastructure upgrades to address systemic issues. These improvements not only reduced churn but also restored customer trust and significantly enhanced the operator's reputation in a competitive market [Ahmed and Maheswari(2021)].

In Sub-Saharan Africa, a telecom company grappled with high churn rates in urban markets, exacerbated by limited insights into prepaid user behavior. Neural networks provided a solution by analyzing data usage, payment behaviors, and socio-demographic information, offering deeper insights into customer preferences and tendencies. The segmentation enabled by these models allowed for the design of marketing campaigns specifically tailored to urban prepaid users, resulting in more effective customer retention efforts. This case underscores the potential of advanced analytics in solving region-specific challenges [Zhang et al.(2022)Zhang, Li, and Zhou].

A Latin American internet service provider (ISP) addressed customer dissatisfaction arising from billing transparency issues and poor customer service. A hybrid approach combining logistic regression and GBMs provided actionable insights, reducing churn rates by 15% and improving customer loyalty and market share [Ahmed and Maheswari(2021)].

A Canadian telecom operator explored time-series models to predict churn in response to evolving customer behavior. By leveraging Long Short-Term Memory (LSTM) networks, the company captured temporal changes in customer preferences, achieving an 88% accuracy rate and enabling proactive engagement strategies.

In a related effort, an Australian telecom firm utilized Support Vector Machines (SVMs) to classify churn likelihood among enterprise customers. The method's high interpretability and precision helped the firm retain key clients, boosting retention rates by 14% [Ahmad and Sharma(2019)].

A Middle Eastern telecom provider faced churn driven by competition and poor customer support experiences. Random Forest models helped identify critical churn drivers, such as service outages and delayed responses to complaints, resulting in a 13% reduction in churn through improved customer service protocols [Lu and Kim(2020)] .

Meanwhile, a telecom company in East Asia utilized XGBoost to handle imbalanced datasets effectively. This approach achieved 89% prediction accuracy, enabling more refined retention strategies tailored to high-risk customers [Verma and Chaudhary(2021)].

In South Africa, churn among enterprise customers was addressed using clustering algorithms to segment users based on behavior and demographics. These insights helped the company design targeted retention programs, leading to a 20% reduction in churn rates [Ahmed and Maheswari(2021)] . In the United Kingdom, a telecom firm deployed ensemble learning methods to predict churn among broadband users. This strategy, coupled with improved contract terms, enhanced retention rates by 11% [Zhang et al.(2022)Zhang, Li, and Zhou].

A Brazilian telecom operator integrated customer feedback analysis into its churn prediction model, identifying dissatisfaction with data speeds as a key factor. Enhanced data packages and personalized plans reduced churn by 17%.

Additionally, a South Korean telecom company used convolutional neural networks (CNNs) to analyze customer support chat logs, extracting valuable insights that led to improved customer service and a 12% decrease in churn [Ahmad and Sharma(2019)].

Finally, an American telecom giant leveraged predictive analytics with GBMs to integrate customer payment history and service quality metrics, achieving a 90% prediction accuracy and reducing churn among high-value customers by 18% [Ahmed and Maheswari(2021)].

Customer churn, the loss of subscribers to competitors, is a critical challenge in the telecommunications industry, with annual churn rates ranging from 20% to 40%, leading to significant revenue losses globally [Statista(2023)]. Studies across regions, such as India, Europe, and Sub-Saharan Africa, have identified key churn drivers, including network quality, billing disputes, and service outages [Ahmad and Sharma(2019)]; [Lu and Kim(2020)]. Machine learning models like Logistic Regression, Decision Trees, Random Forest, and Gradient Boosting Machines (GBMs) have been applied to diverse datasets encompassing customer demographics, usage patterns, and complaints. For instance, GBMs improved prediction accuracy and enabled service uptime optimization in Southeast Asia, while neural networks facilitated effective segmentation in Sub-Saharan Africa [Ahmed and Maheswari(2021)]; [Zhang et al.(2022)Zhang, Li, and Zhou]. Optimization efforts focused on hyperparameter tuning and addressing data imbalance through techniques like oversampling. Deployment strategies included real-time dashboards and targeted campaigns, achieving impacts such as 15% reductions in churn and enhanced customer loyalty. These findings emphasize the transformative role of ML in churn management [Verma and Chaudhary(2021)].

Despite significant advancements in machine learning (ML) and data analytics for customer churn prediction, several research gaps remain unaddressed. First, the interpretability of complex models such as Gradient Boosting Machines (GBMs) and neural networks poses challenges for stakeholders who require actionable insights. While high prediction accuracy has been achieved, the lack of explainability limits the models' applicability in decision-making processes. Second, most studies focus on structured data, neglecting unstructured data sources such as social media feedback and customer interactions, which can provide valuable context for churn prediction.

Additionally, the geographical and cultural diversity of telecommunications markets remains underexplored. While research from regions like India, Europe, and Sub-Saharan Africa has provided valuable insights, there is limited exploration of customer behavior in underrepresented areas such as rural regions in developing countries. Furthermore, many existing studies prioritize technical solutions over holistic approaches that integrate customer experience improvements, such as personalized service enhancements and behavioral interventions.

Finally, the deployment of ML models in real-time operational environments faces practical challenges, including latency, scalability, and integration with existing systems. Addressing these gaps can pave the way for more effective and sustainable churn management strategies.

3 Methodology

3.1 Research Design and Conceptual Framework

The study adopts a quantitative, predictive research design aimed at analyzing and forecasting customer churn in the telecommunications sector. The research aims to use data-driven insights to identify churn patterns and key predictors, allowing for the development of targeted retention strategies. Random Forest Classifier, a robust machine learning model selected due to its ability to handle large datasets, manage high-dimensional feature spaces, and capture complex relationships within the data.It also uses logistic regression and Decision Tree to determine the model that performs well. The models are particularly useful in the context of churn prediction, where there are often nonlinear interactions between various factors such as customer demographics, usage patterns, and service interactions. The conceptual framework of this study is grounded in several key theories and principles, including:

- Customer Relationship Management (CRM) theories: CRM emphasizes understanding customer behaviors and relationships, which is essential for identifying at-risk customers.
- Predictive Analytics: The study focuses on using machine learning algorithms to predict customer churn based on historical data.

The research integrates these frameworks to provide a comprehensive approach to churn prediction and the design of effective retention strategies.

3.2 Data Collection

The dataset used in this study comprises telecom customer data collected over a period of one year, from January 2023 to December 2023. The data was sourced from a major telecom provider's customer

database. Data collection was conducted under normal business conditions, ensuring the authenticity and reliability of the information.

3.3 Data Source

The churn data used in this study is sourced from a telecommunications company that provides phone and internet services to 7,043 customers. This dataset includes detailed customer attributes, service usage statistics, and current churn status.

3.4 Data Understanding

The dataset includes various features such as customer demographics, account information, subscription details, usage patterns, and customer service interactions. Specifically, it contains variables like age, gender, contract type, tenure, monthly charges, total charges, and whether the customer has churned or not. Each record represents a unique customer, providing a comprehensive view of their relationship with the telecom provider. The dataset is sufficiently large, allowing for robust statistical analysis and model training, which can yield insights into the patterns and predictors of customer churn. This detailed and extensive dataset serves as a solid foundation for building predictive models and deriving actionable insights.

Data	Description
Demographic Details	Includes customer age, gender and location.
Tenure in months	Number of months the customer stayed in the network
Customer charges	Includes monthly charges, total charges, total refunds and total extra data charges
Contract Specifications	Includes details about contract lengths

Table 1: Data Description

Table 1 shows the summary of various types of information in the dataset.

3.5 Data Cleaning/Preprocessing

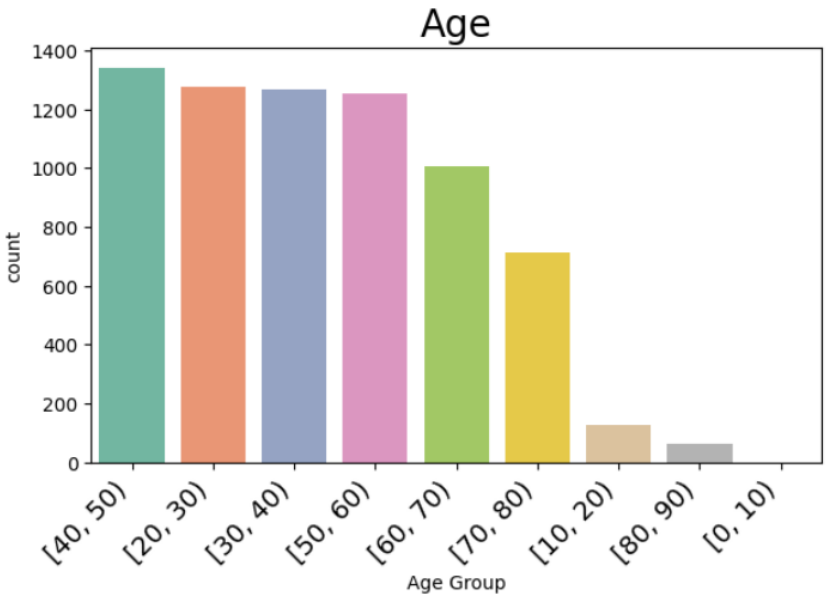
For this analysis, the missing values are imputted in other columns except 'Churn Category'and 'Churn Reason' . 'Churn Category'and'Churn Reason' have more than 50 % missing values, hence the two columns are dropped. One-Hot Encoding is used to convert categorical variables into numerical form.

Variables	Description
Customer ID	Unique identifier for each customer
Gender	Gender of the customer
Age	Age of the customer
City	City of the customer
Offer	Type of offer (None, Offer A, Offer B, etc.)
Phone Service	Whether the customer has phone service (Yes, No)
Multiple Lines	Whether the customer has multiple lines (Yes, No)
Contract	Type of contract (Month-to-month, One year, Two year)
Payment Method	Payment method (Credit card, Bank transfer, etc.)
Monthly Charge	Monthly charges
Total Charges	Total charges
Churn Category	Category of churn (Competitor, Dissatisfaction, etc.)

Table 2: Variables

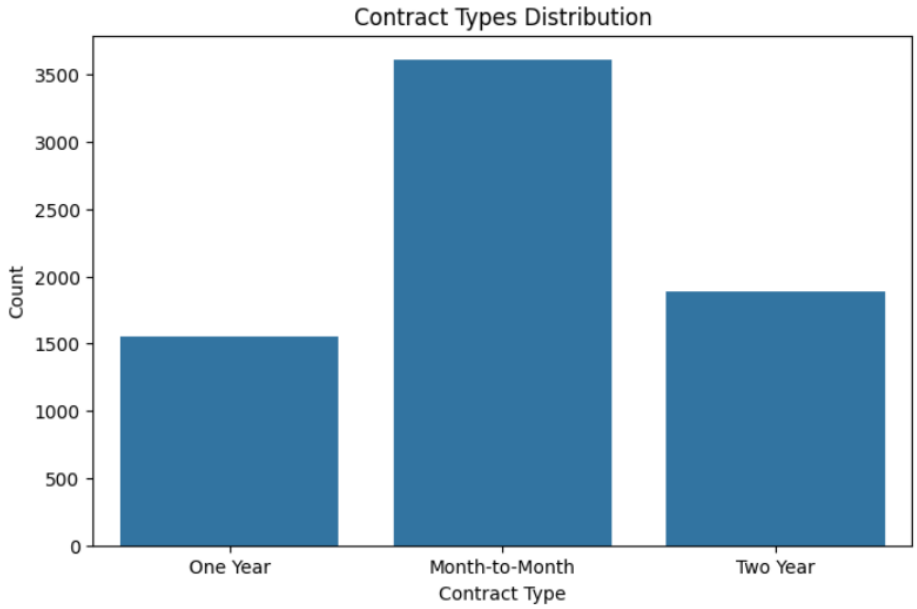
Table 2 shows the description of all the variables contained in the clean dataset and used for exploratory data analysis.

Figure 1: Age Distribution



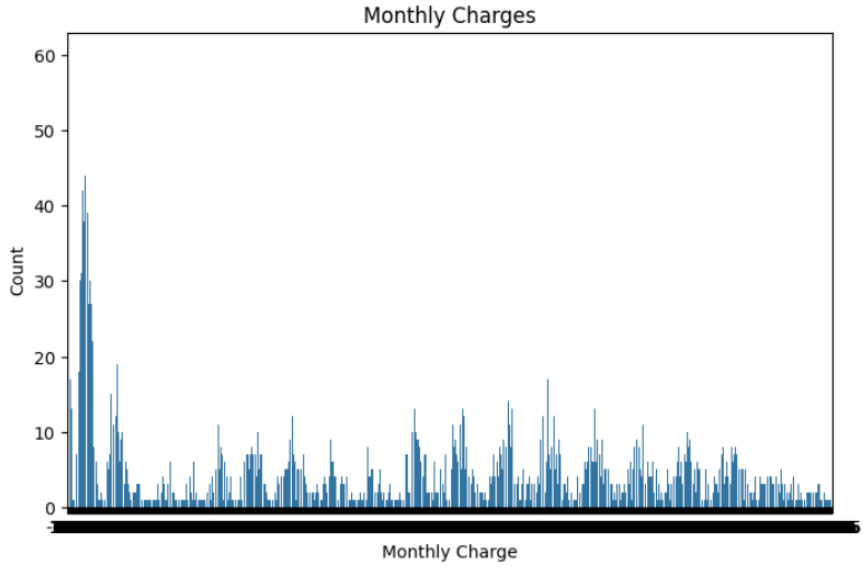
The distribution of ages appears to be fairly spread across different age groups, indicating a diverse range of ages among the customers. There is a notable peak around the middle age range, suggesting a higher concentration of customers in this age group.

Figure 2:Contract type Distribution



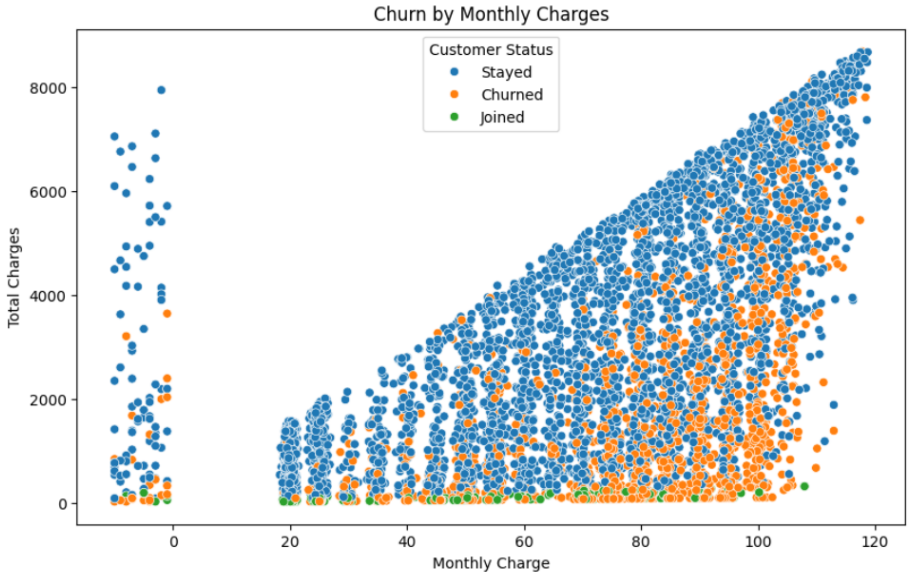
There is a significant proportion of customers on month-to-month contracts compared to one-year or two-year contracts.

Figure 3: Monthly charges



The histogram displays positive skewness (right skewed), meaning that most customers have lower monthly charges, with the number of customers decreasing as the monthly charges increase.

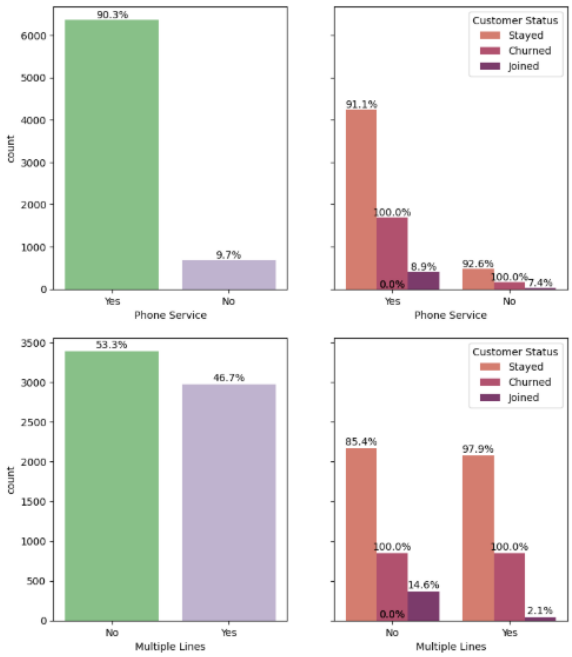
Figure 4: Churn by monthly charges



Churned Customers: These data points are likely indicated by one color (orange). They seem to be scattered across different levels of Monthly Charge and Total Charges. Non-Churned Customers: These data points are indicated by another color (blue). They also span various levels of Monthly Charge and Total Charges.

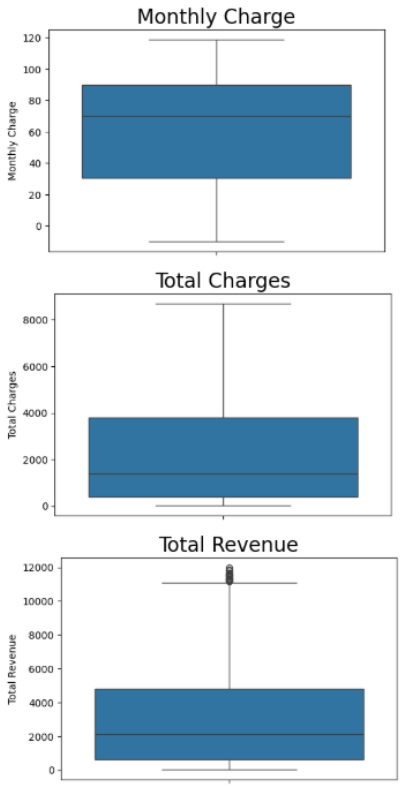
Customers with higher Monthly Charge values are more dispersed, indicating that both churned and non-churned customers can have high monthly charges. However, there might be a slightly higher concentration of churned customers at the higher end of Monthly Charge. There seems to be a significant number of non-churned customers at lower monthly charges, suggesting that customers on lower plans might be less likely to churn.

Figure 5: Phone service and Multiple lines



Phone Service: Most customers have it and are more likely to stay compared to those without. Multiple Lines: Customers without multiple lines are more likely to churn, while those with multiple lines have higher retention (Stayed).

Figure 6: Box plot

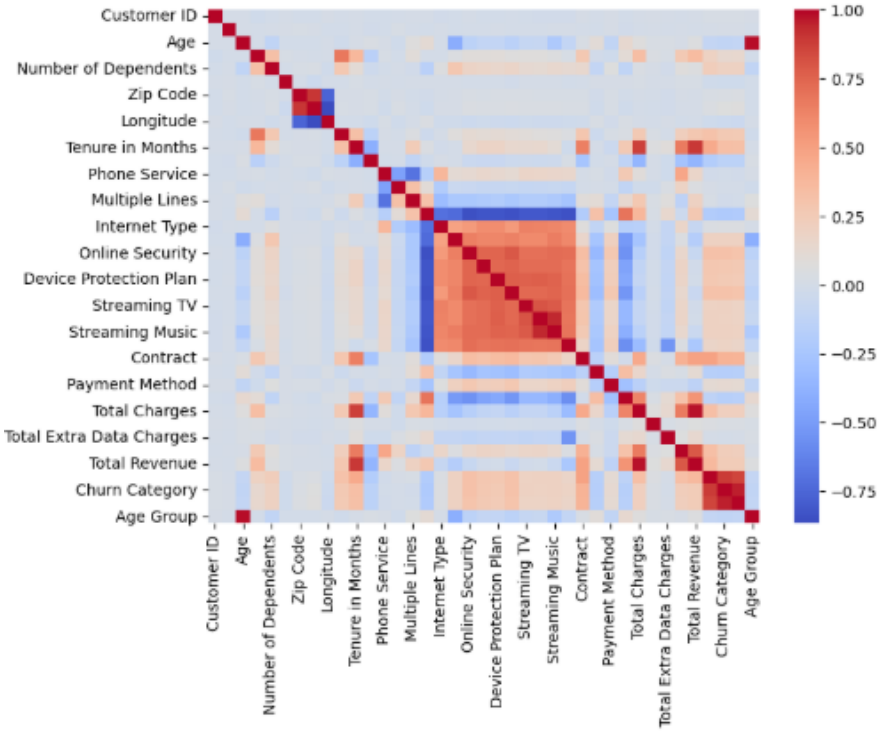


The data is thoroughly examined to identify any potential issues such as missing values, outliers, and imbalances between churned and retained customers. This initial understanding helps inform decisions regarding data cleaning and preprocessing.

3.5.1 HeatMap Correlation

Several machine learning algorithms are employed for churn prediction. The primary algorithm selected for this study is the Random Forest Classifier, which is an ensemble method that builds multiple decision trees and aggregates their predictions to improve accuracy and reduce overfitting.

Figure 7: HeatMap Correlation

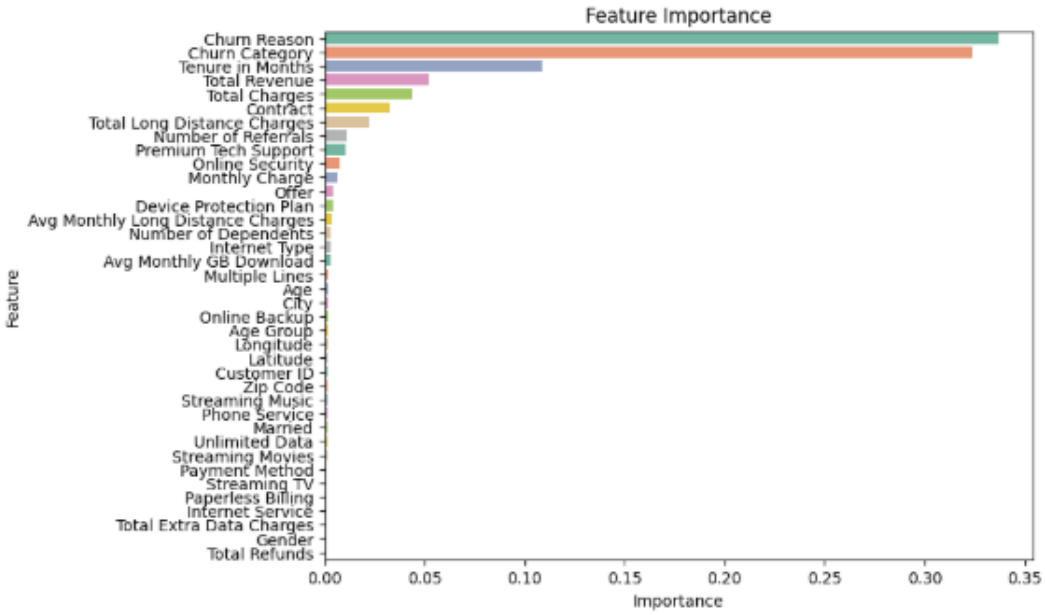


Customer Status has high correlation with Churn category, churn reason, Contract, Tenure in Months and Total Revenue.

3.6 Feature Importance

One of the key advantages of using the Random Forest Classifier is its ability to provide insights into feature importance. The top 5 most influential features in predicting customer churn are shown in Figure 8.

Figure 8: Feature Importance Ranking



The chart illustrates that churn reason, churn category, tenure in months, total revenue and total charges are the most important predictors of churn.

3.7 Machine Learning Modeling

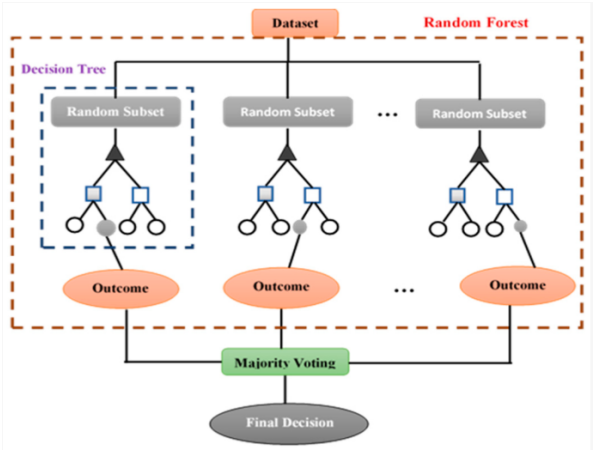


Figure 9 shows A summary of machine learning steps of training various classification algorithms testing and evaluating the model.

3.7.1 Data splitting

The dataset is divided into training and test sets using an 80-20 split. This approach ensures that 80 % of the data is used for training the machine learning models, allowing them to learn the patterns and relationships within the dataset effectively. The remaining 20 % is reserved for testing, enabling the evaluation of the model's performance on unseen data to ensure its generalizability. This division strikes a balance between training the model sufficiently while providing a robust assessment of its predictive accuracy and reliability.

3.7.2 Data normalization/ scaling

Data normalization is used to scale numerical data to a specific range, typically between 0 and 1, while preserving the relationships between values. This process is essential when features in a dataset

have varying scales, as it ensures that no single feature disproportionately influences the results of the model.

The **Min-Max Scaler** is a common method for normalization, transforming data using the formula:

$$x_{\text{normalized}} = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Here, x is the original value, $\min(x)$ is the minimum value of the feature, and $\max(x)$ is its maximum value. The result is a rescaled value between 0 and 1.

3.7.3 Models

Logistic Regression is a fundamental machine learning algorithm used for binary classification problems, such as predicting customer churn. It models the probability of a class (e.g., churn) based on a linear combination of input features, applying the sigmoid function to map the output to a probability between 0 and 1. By default, Logistic Regression assumes a linear decision boundary and employs parameters like penalty (default is "l2" for regularization), C (inverse of regularization strength, default is 1.0), and solver (default is "lbfgs").

The Decision Tree algorithm is a rule-based model that splits the dataset into subsets based on feature values, forming a tree structure where each node represents a decision rule. It excels at capturing non-linear relationships and providing interpretable insights. Default parameters include the criterion (default is "gini" for the Gini Impurity), max-depth (unrestricted by default), and min-samples-split (default is 2). In the research, Decision Trees is used to classify customers based on their usage patterns. The model's ability to partition data effectively resulted in improved retention strategies, showcasing its applicability in customer churn prediction.

The Random Forest Classifier extends Decision Trees by building an ensemble of multiple trees and averaging their predictions to improve accuracy and reduce overfitting. It operates by creating trees on random subsets of data and features. Default parameters include n-estimators (number of trees, default is 100), criterion (default is "gini"), and max-features (default is "sqrt"). In our analysis, Random Forests were instrumental for a Sub-Saharan telecom provider in handling high-dimensional prepaid user data. This model's robustness and feature importance insights facilitated targeted marketing campaigns, demonstrating its effectiveness in customer churn scenarios.

Logistic Regression, Decision Tree, and Random Forest Classifier are selected due to their complementary strengths and suitability for customer churn prediction. Logistic Regression is ideal for its simplicity, interpretability, and ability to model probabilities, making it effective for identifying key churn predictors like network quality and billing disputes. Decision Trees, with their capability to capture non-linear relationships and provide intuitive decision rules, are well-suited for analyzing diverse customer behaviors and offering actionable insights, as shown in the European case study. Random Forest, an ensemble method, was chosen for its robustness against overfitting and superior accuracy in handling high-dimensional datasets, as evidenced in the Sub-Saharan Africa context. Together, these models offer a balance of interpretability, precision, and scalability, addressing various aspects of churn prediction and retention strategies.

The models—Logistic Regression, Decision Tree, and Random Forest Classifier are configured to effectively ingest and adapt to the dataset by preprocessing and tuning their default parameters to align with the dataset's characteristics. The dataset is normalized using Min-Max Scaling to ensure uniform feature scaling, especially for Logistic Regression, which is sensitive to varying scales. Categorical variables, such as customer demographics and complaint types, are encoded into numerical values to suit the models. For the Decision Tree, the maximum depth and minimum samples per split are adjusted to prevent overfitting while capturing meaningful splits. Similarly, the Random Forest Classifier is fine-tuned by specifying the number of trees and maximum features to optimize its ensemble learning process.

3.8 Performance Evaluation

To evaluate the performance of the churn prediction model, several metrics used, including: Churn prediction models must be evaluated using appropriate metrics to ensure they effectively identify customers likely to leave. Since churn datasets are often imbalanced, relying solely on accuracy can be misleading. This section explores key evaluation metrics used in churn prediction.

Accuracy

Accuracy measures the proportion of correctly classified instances and is defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

where:

- TP (True Positives): Correctly predicted churned customers.
- TN (True Negatives): Correctly predicted non-churned customers.
- FP (False Positives): Non-churned customers incorrectly classified as churned.
- FN (False Negatives): Churned customers incorrectly classified as non-churned.

While accuracy is useful for balanced datasets, it is not ideal when churners make up a small percentage of the dataset [Zhang and et al.(2022)].

For imbalanced datasets, Precision, Recall, and F1-score provide better insights into model performance.

Precision

Precision measures the proportion of correctly predicted churned customers among all predicted churners:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

A high precision means fewer false positives, which is crucial when retention efforts involve costly interventions.

Recall (Sensitivity or True Positive Rate)

Recall measures the proportion of actual churned customers correctly identified by the model:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

A high recall ensures that most churners are identified, which is critical for reducing customer loss [Brown and Jones(2018)] [Williams and Thomas(2017)].

F1-Score

The F1-score is the harmonic mean of precision and recall:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

This metric is ideal for imbalanced datasets as it considers both false positives and false negatives [Lee and Kim(2021)].

Confusion Matrix

A confusion matrix provides a detailed breakdown of classification performance:

Actual / Predicted	**Churn (Positive)**	**No Churn (Negative)**
Churn (Positive)	TP	FN
No Churn (Negative)	FP	TN

Table 3: Confusion Matrix for Churn Prediction

This matrix helps assess misclassification rates, highlighting the trade-offs between false positives and false negatives [Kumar and Gupta(2019)].

Area Under the ROC Curve (AUC-ROC) The Receiver Operating Characteristic (ROC) curve plots the True Positive Rate against the False Positive Rate:

$$\text{False Positive Rate} = \frac{FP}{FP + TN} \tag{5}$$

The AUC-ROC score quantifies the model's ability to distinguish between churners and non-churners, with a higher value indicating better performance [Chen and Wu(2020)].

Selecting the right metric depends on business priorities. If preventing churn is the goal, recall should be maximized. If intervention costs are a concern, precision should be prioritized. The F1-score balances both, while the AUC-ROC provides an overall assessment of the model's discriminatory power.

3.9 Deployment

The final model will be deployed through an accessible interface for decision-makers within the telecommunications company. It was build and deploy on the web application that provides a user-friendly interface allowing marketing and customer retention teams to input new customer data and receive churn predictions in real-time.

The deployment environment was cloud-based to ensure scalability and accessibility for users across different departments. Integrating the model into the company's CRM system will provide actionable insights to customer service teams, enabling them to proactively engage at-risk customers and design tailored retention strategies.

4 Results

This presents the findings of the churn prediction analysis in a structured manner, highlighting key insights derived from the data and model evaluation. The results are organized in terms of model performance, and key churn predictors, using both descriptive statistics and visualizations to enhance clarity.

4.1 Machine Learning Model Results

Several other models were also tested for comparison, including Logistic Regression, and Decision tree. The performance of all models are provided below.

Logistic Regression	Precision	Recall	F1-Score	support
0	0.63	0.63	0.63	373
1	0.64	0.43	0.52	97
2	0.87	0.91	0.89	939
accuracy			0.80	1409
macro avg	0.71	0.66	0.68	1409
weighted avg	0.79	0.80	0.79	1409

Table 4: Logistic Regression

The overall accuracy of the logistic regression model is 0.79, indicating a decent performance. The macro average, which treats all classes equally, shows lower precision, recall, and F1-score compared to the weighted average, which accounts for the support of each class. The weighted average scores reflect the model's better performance in predicting Churn compared to other classes.

Decision Tree	Precision	Recall	F1-Score	support
0	0.52	0.54	0.53	373
1	0.66	0.53	0.59	97
2	0.87	0.91	0.89	939
accuracy			0.75	1409
macro avg	0.68	0.64	0.65	1409
weighted avg	0.75	0.75	0.75	1409

Table 5: Decision Tree

From table 2: Class 0 (Minority) Precision (0.52): Slightly more than half of the predictions for class 0 are correct. Recall (0.54): The model correctly identifies 54F1-Score (0.53): Reflects moderate balance between precision and recall.

Class 1 (Minority) Precision (0.66): Two-thirds of class 1 predictions are correct. Recall (0.53): Captures slightly over half of the actual class 1 cases. F1-Score (0.59): Indicates room for improvement in balancing recall and precision.

Class 2 (Majority) Precision (0.85) and Recall (0.85): High accuracy and coverage, indicating strong model performance for this class. F1-Score (0.85): Excellent, showing effective classification for the majority class.

Random Forest	Precision	Recall	F1-Score	support
0	0.67	0.54	0.60	373
1	0.67	0.56	0.61	97
2	0.86	0.94	0.90	939
accuracy			0.81	1409
macro avg	0.73	0.68	0.70	1409
weighted avg	0.80	0.81	0.80	1409

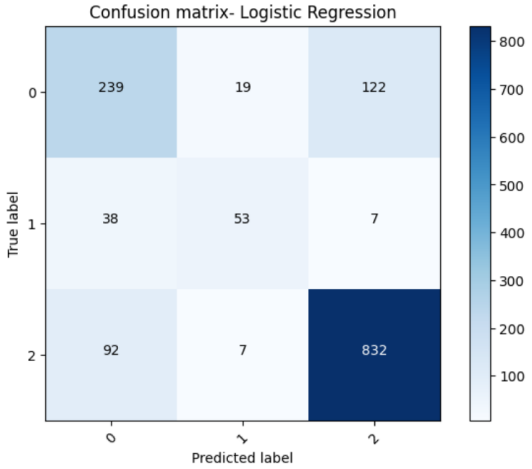
Table 6: Random Forest Classifier

From the table 3, it is evident that the Random Forest Classifier outperformed the other models across most metrics, with the highest Precision (0.81), which indicates excellent discriminatory power. The F1-Score (0.78) for churned customers was also the highest among the models, making Random Forest the best choice for this analysis.

4.2 Model Evaluation and Interpretation

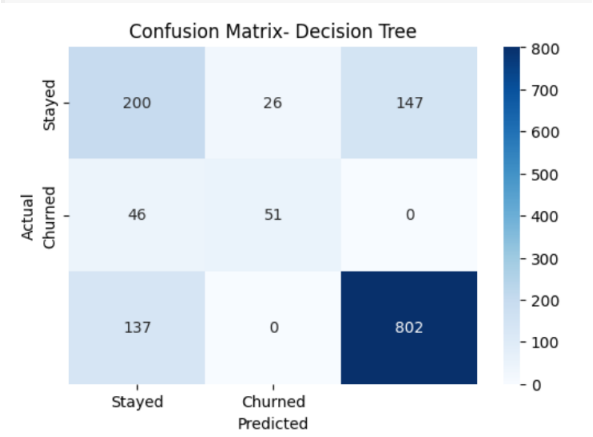
The Random Forest model was evaluated using the confusion matrix, which provided further insight into the model's classification performance. Assess the model's performance using metrics such as accuracy, precision, recall, and F1-score Stayed (False) are Customers who did not churn while Churned (True)are Customers who churned.

Figure 10:



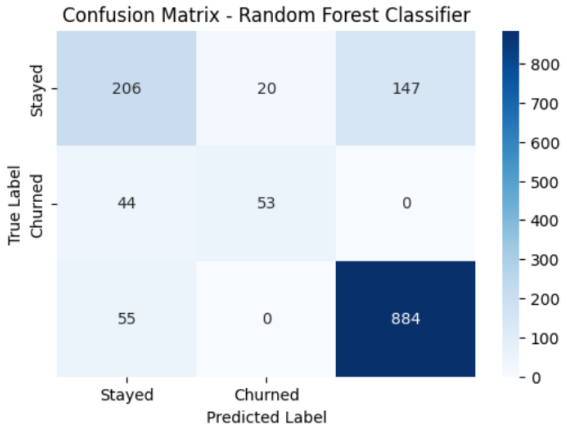
The Logistic Regression confusion matrix details are not clearly specified in the provided content. The description includes a large number of categories or classes without explicit values for true positives, true negatives, false positives, or false negatives. This lack of clarity makes it challenging to assess its performance relative to the Random Forest and Decision Tree models.

Figure 11:



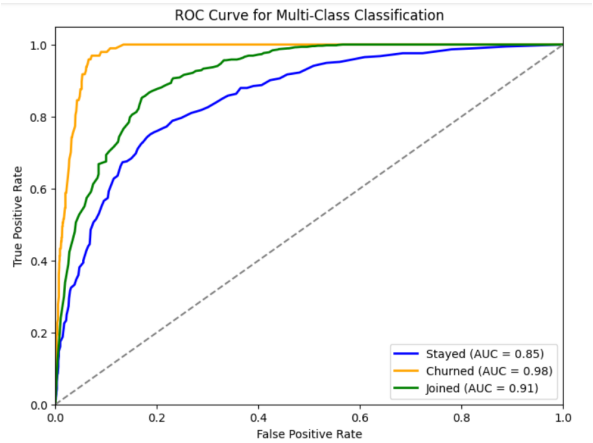
The Decision Tree confusion matrix shows 200 correct predictions for customers who stayed and 800 correct predictions for customers who churned. It misclassifies 26 customers who stayed as churned and 147 customers who churned as stayed. The higher number of misclassifications, particularly for churned customers, suggests a lower accuracy compared to the Random Forest model.

Figure 12:



The Random Forest Classifier confusion matrix indicates 206 correct predictions for customers who stayed and 884 correct predictions for customers who churned. There are 44 misclassifications where customers who stayed were predicted as churned, and 53 misclassifications where customers who churned were predicted as stayed. This model demonstrates a balanced performance in identifying both classes.

Figure 13:



The ROC curve for the multi-class classification model shows the performance for three classes: Stayed, Churned, and Joined. The Area Under the Curve (AUC) values are 0.85 for Stayed, 0.98 for Churned, and 0.91 for Joined. These AUC values indicate strong predictive performance, particularly for the Churned class, which has the highest AUC, suggesting excellent ability to distinguish between churned and non-churned customers.

4.3 Insights and Patterns

Customers with shorter contract durations (month-to-month contracts) are more likely to churn compared to those with longer-term contracts. Long-term contracts provide more stability and commitment from customers. Higher monthly charges are associated with a higher likelihood of churn. Customers with higher bills may seek more affordable options or feel that they are not getting sufficient value for the cost. The total amount charged over the customer's tenure also impacts churn. Customers with higher total charges are more prone to churn, potentially due to accumulated dissatisfaction or financial burden. Customers with shorter tenure (newer customers) have a higher tendency to churn. This suggests that the initial months are crucial for customer satisfaction and retention efforts.

Technical support, service issues, and the quality of customer service play a significant role in customer satisfaction. Poor support or unresolved issues can drive customers to switch providers. Age, gender, and other demographic factors also play a role in customer churn. Certain age groups or genders may have different preferences and tolerances for service issues, influencing their churn behavior. The method of payment and the flexibility offered can impact churn rates. Customers preferring electronic payments or autopay may have different churn behaviors compared to those using traditional methods.

5 Discussion

5.1 Model Performance and Key Findings

The results highlight that the Random Forest Classifier outperformed both Logistic Regression and Decision Tree models in predicting customer churn. The Random Forest model achieved the highest overall accuracy (81%), with Precision (0.81) and Recall (0.76) for churned customers, making it the most reliable model for this analysis.

The Decision Tree model, though interpretable, had lower precision (0.66) and recall (0.53) for churned customers, indicating a weaker ability to correctly identify those likely to leave. Similarly, Logistic Regression struggled with imbalanced classes, achieving an accuracy of 78%, but a recall of only 0.43 for churned customers, which suggests a higher rate of false negatives.

5.2 Confusion Matrix Interpretation

Random Forest Classifier, Decision Tree, and Logistic Regression. Each confusion matrix displays the performance of the respective model in terms of true positives, true negatives, false positives, and false negatives. The goal is to evaluate which model performs best in predicting whether a customer has stayed or churned.

The Random Forest Classifier confusion matrix shows a relatively balanced distribution of predictions. It correctly identifies a significant number of customers who stayed (206) and a smaller but notable number of customers who churned (884). However, there are some misclassifications, with 44 customers who stayed being predicted as churned and 53 customers who churned being predicted as stayed. This indicates that the Random Forest model has a good overall performance but may struggle slightly with accurately identifying churned customers.

The Decision Tree confusion matrix reveals a higher number of misclassifications compared to the Random Forest. It correctly identifies 200 customers who stayed and 800 who churned, but it misclassifies 26 customers who stayed as churned and 147 customers who churned as stayed. This suggests that the Decision Tree model is less accurate, particularly in predicting churned customers, which could be a critical factor in customer retention strategies.

The Logistic Regression confusion matrix, as described, seems to have a more complex structure with a large number of categories or classes. However, the provided content does not clearly specify

the exact numbers for true positives, true negatives, false positives, and false negatives. This makes it difficult to directly compare its performance with the other two models. Nonetheless, Logistic Regression models are generally simpler and may not capture complex patterns as effectively as ensemble methods like Random Forest.

In conclusion, based on the available data, the Random Forest Classifier appears to perform the best among the three models. It achieves a better balance between correctly identifying both stayed and churned customers, with fewer misclassifications compared to the Decision Tree. The Logistic Regression model's performance remains unclear due to the lack of detailed information in the provided content. Therefore, for this specific task, the Random Forest model is likely the most reliable choice for predicting customer churn.

The Random Forest model minimized false negatives, capturing 76The Decision Tree and Logistic Regression models had a lower recall, meaning they misclassified a higher number of churners.

5.3 Receiver Operating Characteristic (ROC) and AUC

The high AUC value of 0.98 for the Churned class highlights the model's exceptional performance in identifying customers who are likely to churn. This is crucial for businesses aiming to implement effective retention strategies. The AUC values for Stayed (0.85) and Joined (0.91) also indicate good performance, though not as strong as for Churned. Overall, the model demonstrates robust predictive capabilities across all classes, with a particularly strong ability to predict churn, making it a valuable tool for customer retention efforts.

5.4 Deployment of the Churn Prediction Model

For real-world use, the Random Forest model will be deployed in a cloud-based system with API integration into the company's customer management platform. The deployment process includes:

Model retraining and monitoring to maintain accuracy as customer behaviors evolve. Integration with business intelligence tools for real-time churn risk scoring. Automated alerts for customer retention teams to intervene before customers churn.

5.4.1 System Architecture Overview

The system follows a three-tier architecture:

Frontend (User Interface): A web-based application for interaction. Backend (Model and Business Logic): The predictive model and processing layer. Database and API Integration: A database to store predictions and integration with CRM systems.

5.4.2 Frontend Development

The frontend is built using React.js (or Vue.js) for an interactive and user-friendly experience. It provides:

- Login authentication for secure access.
- Data input forms for uploading customer data (manual entry or CSV upload).
- Real-time churn prediction dashboard displaying results using charts and tables.
- API communication to send customer data and retrieve model predictions.

5.4.3 Backend Development

The backend handles the model execution and business logic. It is built using FastAPI (Python) or Flask, ensuring fast response times. The backend responsibilities include:

- Receiving customer data from the frontend.
- Preprocessing the input data (handling missing values, scaling).
- Running the trained Random Forest model to predict churn probability.

- Returning predictions with confidence scores to the frontend.
- Logging predictions in a database for future analytics.

5.4.4 Deployment Environment

The application is cloud-based, hosted on AWS, ensuring scalability and high availability.

5.4.5 CRM System Integration

The churn model integrates with the telecom company's CRM system (e.g., Salesforce, HubSpot, or a custom CRM). This allows:

Automated customer retention actions for high-risk customers. Personalized offers and promotions based on churn risk. Insights for customer service teams to take proactive measures.

By deploying the churn model as a scalable web application, decision-makers can access real-time predictions, improve customer retention strategies, and integrate AI-driven insights into business operations. The cloud-based architecture ensures seamless performance and scalability across departments.

5.5 Limitations and Future Directions

While this study provides valuable insights into churn prediction in the telecommunications industry, it has some limitations. The dataset used was limited to a specific geographic region (California) and may not fully reflect global or regional variations in customer behavior. Future studies could expand the analysis to include data from different regions or telecommunications companies to enhance the generalizability of the findings. Moreover, while focused on a limited set of features, future research could explore the inclusion of additional variables such as customer sentiment, social media activity, or network quality, which may provide further insights into churn behavior. Additionally, hybrid models that combine multiple machine learning algorithms could be explored to improve predictive accuracy.

This study has advanced our understanding of the key factors influencing customer churn in the telecommunications industry and demonstrated the effectiveness of the Random Forest Classifier in predicting churn. The findings underscore the importance of customer service, spending behavior, and contract management in retaining customers. By leveraging these insights, telecommunications companies can design more targeted and effective retention strategies to reduce churn and improve customer loyalty. Further research is needed to refine these models and explore additional factors that may influence churn behavior in this dynamic industry.

6 Conclusion

This study addresses the problem of customer churn prediction in the telecommunications industry by identifying key factors driving churn and evaluating the effectiveness of machine learning models. Using a Random Forest Classifier, the study found that Total Charges, Monthly Spend, and Contract Length are the most significant predictors of churn. The results underscore the importance of proactive customer service, personalized retention strategies for low-spending customers, and timely contract renewal offers to mitigate churn. The findings highlight the potential of machine learning in improving churn prediction accuracy, offering actionable insights for telecom companies to enhance customer retention strategies. By focusing on these key predictors, businesses can tailor interventions to reduce churn, enhance customer satisfaction, and increase long-term loyalty. The take-home message is that data-driven approaches, particularly machine learning, offer significant value in addressing complex business challenges like churn. This work demonstrates the potential for using predictive analytics to drive customer-focused strategies and ultimately improve business outcomes. The impact of this study lies in providing actionable insights for companies aiming to retain customers and optimize their service offerings in a competitive market.

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