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Machine Learning Techniques: Predictive Modeling for Customer Churn in Telecommunications

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In the telecommunications industry, customer retention is critical due to the high tendency of customers to switch providers for competitive promotions. This study aims to develop a churn prediction model for an internet service provider to identify at-risk customers by analyzing their usage patterns. The model facilitates targeted retention efforts, allowing the company to focus special offers on high-risk customers, thereby reducing churn rates, enhancing customer satisfaction, and increasing profitability. Evaluating machine learning models for churn prediction, Gradient Boosting emerged as the top performer with the highest AUC and AP scores. AdaBoost and Logistic Regression also showed strong performance. Models like Multi-Layer Perceptron, Light Gradient Boosting, and XGBoost were reliable, while K-Nearest Neighbours and Decision Tree showed lower precision and consistency. Based on these findings, boosting techniques and Logistic Regression are recommended for tasks requiring high recall, with a focus on promoting additional services to at-risk customers to effectively reduce churn.

Keywords: Telecommunications, Gradient Boosting, AdaBoost, Logistic Regression.

1. Introduction

The objective of this analysis is to evaluate the performance of various acquisition channels for an online retailer specializing in consumer electronics. The goal is to identify which channels convert better, cost less, and bring in the most revenue. This will inform budgeting and customer targeting strategies. A comprehensive five-step assessment is recommended to pinpoint underperforming marketing partnerships, as merely relying on basic profitability metrics may not provide an accurate evaluation, according to the company. Inadequately measuring both direct and indirect costs, such as the investment in human resources for partner recruitment and retention, as well as campaign management, can skew the data. Additionally, using gross averages for customer value can be misleading.

Cluster proposes the following practical guidelines for an effective evaluation of marketing channels:

- Reevaluate conventional metrics for channel performance

Traditional metrics like gross additions, average customer value, or quarterly revenue reports may not provide a complete picture of profitability.

- Challenge assumptions regarding channel costs and Customer Lifetime Value (CLV)

Factors such as aggressive competition, emerging efficiencies, and changing performance of channel partners can impact initial assumptions.

- Recalculate the actual costs of marketing efforts

It is crucial to accurately assess both direct and indirect costs to ensure the accuracy of contribution calculations.

- Refine the channel evaluation process

Break down the analysis of aggregate data and trends to generate actionable recommendations incrementally.

- Reallocate resources to high-performing areas

Transform the insights gained from the channel assessment into a detailed action plan. Optimize the utilization of high-performance channels, improve underutilized ones, and discontinue programs or partnerships that do not contribute to profitability.

Machine learning Role in optimizing acquisition channels

Machine learning can play a crucial role in optimizing acquisition channels for an online consumer electronics retailer. Here are several ways in which machine learning can be applied effectively:

Customer Segmentation: Machine learning algorithms can analyze customer data to segment customers based on their behavior, preferences, and purchasing patterns. This segmentation can help in targeting specific customer segments with personalized marketing messages through appropriate acquisition channels.

Predictive Modeling: Machine learning models can predict customer behavior, such as the likelihood of conversion or churn. This information can guide decisions on which acquisition channels to prioritize for different customer segments.

Channel Attribution: Machine learning techniques, such as Markov chains or machine learning attribution models, can help in accurately attributing conversions to different marketing channels. This attribution analysis is essential for understanding the impact of each channel on customer acquisition and optimizing budget allocation.

Campaign Optimization: Machine learning algorithms can optimize marketing campaigns by analyzing vast amounts of data to identify trends, patterns, and optimal strategies. This includes determining the best timing, content, and channels for campaign deployment to maximize conversion rates.

Predictive Customer Lifetime Value (CLV): Machine learning models can predict the CLV of customers acquired through different channels. By understanding the long-term value of customers from each channel, retailers can make informed decisions about resource allocation and customer targeting.

Real-time Personalization: Machine learning enables real-time personalization of marketing messages and offers based on customer interactions and historical data. This personalization enhances the relevance of acquisition channel communications, leading to higher engagement and conversion rates.

Anomaly Detection: Machine learning algorithms can detect anomalies in customer behavior or channel performance. For example, detecting sudden drops in conversion rates or unexpected spikes in acquisition costs can prompt proactive adjustments to marketing strategies.

Recommendation Engines: Recommender systems powered by machine learning can suggest the most relevant acquisition channels or marketing strategies for individual customers based on their preferences and past interactions with the brand.

Sentiment Analysis: Machine learning techniques like natural language processing (NLP) can analyze customer reviews, social media sentiment, and feedback to gauge the perception of different acquisition channels. Positive sentiment can be leveraged, while negative sentiment can signal areas for improvement.

Optimizing Ad Spend: Machine learning algorithms can optimize ad spend by continuously analyzing campaign performance metrics, adjusting bidding strategies, and reallocating budget to channels that drive the highest ROI.

Implementing machine learning in the optimization of acquisition channels for an online consumer electronics retailer comes with several challenges:

Data Quality and Availability: Ensuring that data from various sources (e.g., website analytics, marketing platforms, sales data) is accurate, consistent, and up-to-date can be challenging.

Data may be fragmented or stored in different formats, requiring extensive preprocessing and integration efforts.

Feature Engineering: Creating meaningful features from raw data requires domain knowledge and experimentation. Identifying the most relevant features for predicting customer behavior or channel performance can be complex.

Model Interpretability: Complex machine learning models, such as deep learning algorithms, may lack interpretability, making it challenging to understand how predictions are made. Explainable AI techniques are needed to enhance model transparency.

Data Privacy and Compliance: Handling sensitive customer data and ensuring compliance with data protection regulations (e.g., GDPR, CCPA) adds complexity to machine learning implementation. Anonymization, encryption, and robust data governance practices are essential.

Scalability: Scaling machine learning models to handle large volumes of data and real-time processing can strain computational resources and infrastructure. Distributed computing and cloud-based solutions may be necessary.

Model Overfitting: Overfitting occurs when a model performs well on training data but fails to generalize to unseen data. Regularization techniques and cross-validation are needed to mitigate overfitting risks.

Changing Customer Behavior: Customer preferences and behavior evolve over time, requiring continuous model updates and adaptations. Keeping machine learning models relevant and effective amidst changing market dynamics is a challenge.

Channel Attribution Complexity: Determining the precise contribution of each acquisition channel to customer conversions can be complex, especially in multi-touchpoint customer journeys. Properly attributing conversions and assigning credit accurately is crucial for optimization.

Real-time Decision-making: Making real-time decisions based on machine learning predictions requires low-latency data processing and decision-making frameworks. Delayed responses can lead to missed opportunities or suboptimal outcomes.

Cost Considerations: Implementing and maintaining machine learning infrastructure, hiring skilled data scientists and engineers, and acquiring quality data can incur significant costs. ROI justification and cost-benefit analysis are essential.

2. Related Work:

Valentini et al. (2024) evaluate sales forecasting techniques for Mahram Food Industries, utilizing technical analysis, time series modeling, machine learning, neural networks, and random forest methods to enhance accuracy, although facing complexity in model integration [18]. Theoretical exploration by Tudoran et al. (2024) discusses AI's potential in product management across various lifecycle stages, catalyzing innovation and strategic decision-making but encountering complexity in AI integration and ethical considerations [19]. Mudjahidin et al. (2024) employ principal component analysis, K-means clustering, and random forest methods for financial risk management under machine learning, enhancing risk monitoring but relying on data quality and potentially missing some risk factors [20]. Norouzi (2024) analyzes sales models for new and refurbished products in the secondary market, aiming to maximize manufacturer profits and align with market demand, yet facing challenges in blockchain integration and market demand dependencies [21]. In digital marketing transformation, Kasem et al. (2024) investigate the role of technology (AI, machine learning, big data analytics) in promoting sustainable growth and improving consumer experiences, albeit facing challenges like data privacy, channel integration, and cultural change complexities [22]. Efficient stock price trend prediction is explored by Han et al. (2023) introducing the N-Period Min-Max labeling method and evaluating trading performance using XGBoost, enhancing prediction accuracy but limited to stock price prediction [23]. Durant et al. (2023) examine the resilience of direct market farmers during COVID-19, showcasing adaptation strategies but with a limited focus on a specific market segment [24]. E-commerce channel management from the manufacturers' perspective is investigated by Ballerini et al. (2024), providing insights into manufacturer-retailer dynamics and pricing strategies but highlighting potential gaps in understanding due to fragmented literature [25]. Vemulapalli (2024) investigates information sharing strategies for online platforms, aiming to improve market efficiency but facing potential conflicts between platforms, manufacturers, and sellers [26]. Customer lifetime value prediction using machine learning by Kumar et al. (2023) enhances CRM and targeted marketing but faces data privacy concerns and potential biases in ML algorithms [27]. Lastly, Muradkhanli and Karimov (2023) explore customer behavior analysis with big data analytics and ML, enhancing customer insights and marketing strategies but grappling with data quality challenges and potential biases in predictive models [28].

Table 1: Summary of Related work

Reference	Objective	Methodology	Advantages	Limitations
[18]	Sales forecasting for Mahram Food Industries	Utilizes technical analysis, time series modeling, machine learning, neural networks, and random forest techniques.	Enhanced accuracy in sales forecasting	Complexity in model integration
[19]	AI's theoretical framework in product management	Discusses AI's role across product lifecycle stages: ideation, market research, prototyping, design, quality assurance, launch.	Catalyzes innovation, informs strategic decision-making	Complexity in AI integration, potential ethical considerations
[20]	Exploration of financial risk management under machine learning algorithms	Employs principal component analysis, K-means clustering, and random forest method for financial risk analysis.	Enhances monitoring and evaluation of financial risks	Relies on data quality, may not capture all risk factors
[21]	Sales models for new and refurbished products in the secondary market	Analyzes sales scenarios M, R, and C, considering market demand and blockchain technology's impact.	Maximizes manufacturer profits, aligns with market demand	Dependent on market demand, potential blockchain integration complexities
[22]	Digital marketing transformation for competitive advantage	Investigates technology's role (AI, machine learning, big data analytics) in digital marketing transformation with case studies.	Improves consumer experiences, promotes sustainable growth	Data privacy concerns, channel integration challenges, cultural change complexities
[23]	Efficient stock price trend prediction with machine learning	Introduces N-Period Min-Max labeling method, evaluates trading performance using XGBoost.	Enhances stock price trend prediction, generates trading outperformance	Potential bias in labeling method, limited to stock price prediction
[24]	Resilience of direct market farmers during COVID-19	Examines impacts of COVID-19 on local supply chains and direct market sales channels.	Adapts to market disruptions, increases consumer interest	Limited focus on specific market segment
[25]	E-commerce channel management from manufacturers' perspective	Conducts systematic literature review on online channel management focusing on strategic issues, pricing policies, and supply chain interactions.	Provides insights into manufacturer-retailer dynamics, pricing strategies	Fragmented literature, potential gaps in comprehensive understanding of online channel management
[26]	Information sharing strategies for online platforms	Investigates demand information sharing strategies for online platforms in distribution channels, considering reselling vs. marketplace models.	Improves market efficiency, optimizes information sharing	Potential conflicts between platform, manufacturers, and sellers
[27]	Customer lifetime value prediction using machine learning	Enhances Customer Relationship Management (CRM) with machine learning for CLV predictions, using regression, clustering, neural	Improves CLV accuracy, enhances targeted marketing	Data privacy concerns, potential biases in ML algorithms

Reference	Objective	Methodology	Advantages	Limitations
		networks.		
[28]	Customer behavior analysis with big data analytics and ML	Explores ML algorithms, pipeline development for customer behavior analysis in digital marketing, focusing on churn prediction, prospect identification, communication channel optimization, and sentiment analysis.	Enhances customer insights, optimizes marketing strategies	Data quality challenges, potential biases in predictive models

3. Methodology:

The machine learning workflow begins with acquiring the dataset, followed by conducting exploratory data analysis to understand its characteristics. Next, missing data is handled through imputation or deletion, and the data is normalized to ensure consistent scales across features. The dataset is then split into training and testing sets, typically in an 80/20 ratio. Various models such as Gradient Boosting, AdaBoost, Logistic Regression, Multi-layer Perceptron, Light Gradient Boosting, eXtreme Gradient Boosting, Random Forest, Support Vector Classifier, and K-Nearest Neighbours are trained using the training set. Finally, the models are evaluated as shown in figure 1 [29][30][31].

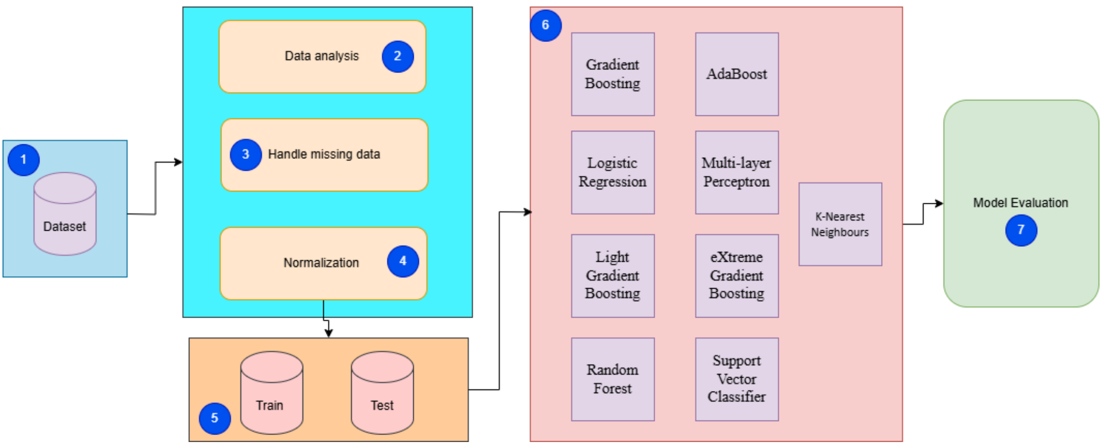

Figure 1: Proposed methodology framework

Datasets: The DataFrame consists of 4930 rows and 11 columns, each representing a customer with 11 attributes, most of which are nominal categorical types currently stored as objects, leading to inefficient memory usage as shown in figure 2. These categorical attributes will be converted to the 'category' data type for optimization. Numerical attributes, such as tenure and Monthly Charges, are stored as int64 and float64, respectively, and can be downcast to more memory-efficient types like int8 and float32. Categorical data is consistently written, indicating no input errors, while numeric data, being measurement results, does not require consistency checks [32][33][34].

attributes	Description
Dependents	Does the customer have dependents or not
tenure	How long the customer has subscribed to the company's services
OnlineSecurity	Does the customer use the *Online Security* service or not
OnlineBackup	Does the customer use the *Online Backup* service or not
InternetService	Does the customer subscribe to *Internet Service* or not
DeviceProtection	Does the customer use the *Device Protection* service or not
TechSupport	Does the customer use *Tech Support* services or not
contracts	The duration of the contract used
PaperlessBilling	Is the bill sent on a *paperless* basis or not
MonthlyCharges	Number of bills charged each month
Churn	Has the customer unsubscribed or not

Figure 2: Dataset attributes Description

Figure 3 provides an overview of Dataset with five records.

	Dependents	tenure	OnlineSecurity	OnlineBackup	InternetService	DeviceProtection	TechSupport	Contract	PaperlessBilling	MonthlyCharges	Churn
624	No	1	No internet service	No internet service	No	No internet service	No internet service	Month-to-month	No	19.65	No
701	No	41	No internet service	No internet service	No	No internet service	No internet service	Two year	No	20.65	No
786	No	1	No	No	Fiber optic	No	No	Month-to-month	Yes	69.65	Yes
951	No	1	No internet service	No internet service	No	No internet service	No internet service	Month-to-month	No	20.15	Yes
1266	No	1	No internet service	No internet service	No	No internet service	No internet service	Month-to-month	No	19.65	No

Figure 3: Sample records of Dataset

The boxplot and histogram (figure 4) illustrate that churn customers typically have shorter tenures compared to non-churn customers, who exhibit a higher median tenure and a broader distribution extending beyond 60 months. Notably, there are significant upper outliers among the churned customers, indicating that some had unusually long tenures before churning. The histogram further highlights this distinction, with churned customers concentrated at lower tenures and non-churned customers more evenly distributed across longer tenures. These anomalies among churned customers necessitate further analysis to determine if the outliers exhibit distinct characteristics from the rest, potentially indicating systemic differences [35].

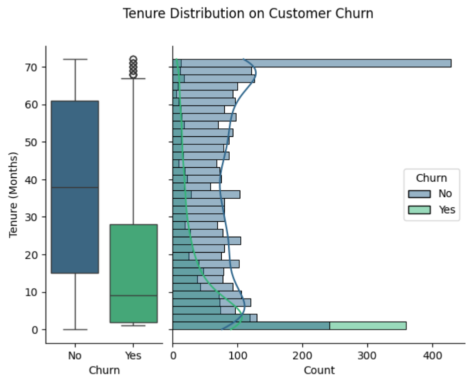

Figure 4:Tenure Distribution on Customer Churn

Figure 5 illustrates the tenure distribution of customers across different features (Online Backup, Device Protection, and Contract type), segmented by churn status. Each box plot highlights the tenure differences between churned and non-churned customers, with a red horizontal line indicating a reference point at a tenure value of 70. In all categories, churned customers consistently show lower median tenures compared to non-churned customers. Specifically, for month-to-month contracts, churned customers have significantly lower tenures, whereas two-year contracts show the highest tenures with non-churned customers having notably higher medians. This trend underscores the impact of contract length and service features on customer retention, with longer tenures generally associated with reduced churn rates.

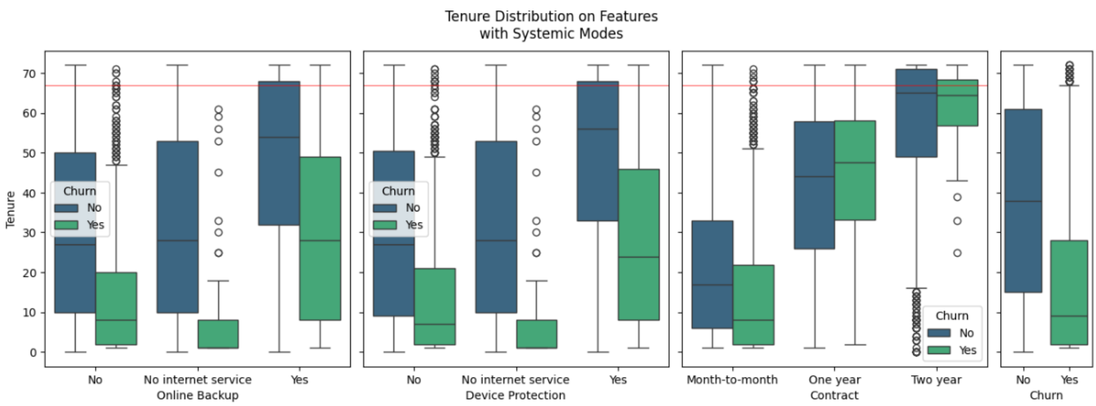

Figure 5: Tenure Distribution on features with systemic modes

The figure 6 displays a density plot of tenure versus monthly charges, differentiated by customer churn status. The plot shows the relationship between tenure (in months) and monthly charges (in dollars) with churned customers in green and non-churned customers in blue. The density distributions along the axes illustrate that churned customers (green) tend to cluster at lower tenures and higher monthly charges. Conversely, non-churned customers (blue) show a more dispersed pattern with higher tenures and a wider range of monthly charges. The red diagonal line indicates a positive correlation between tenure and monthly charges. This visualization highlights that customers with lower tenures and higher monthly charges are more likely to churn, while those with longer tenures are less likely to churn regardless of their monthly charges.

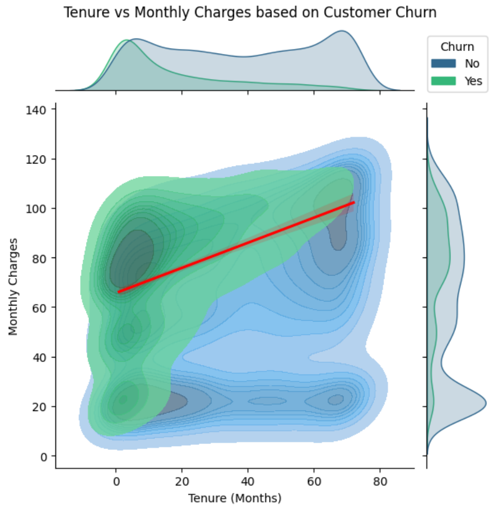

Figure 6: Tenure vs Monthly Charges on customer churn

The figure 7 comprises a pie chart and a bar chart illustrating the distribution of internet service types and their relationship to customer churn. The pie chart reveals that 44.14% of customers use fiber optic, 34.55% use DSL, and 21.31% have no internet service. The bar chart shows churn rates for each service type: fiber optic has the highest churn with 907 churned versus 1256 non-churned customers, DSL follows with 305 churned versus 1388 non-churned customers, and those without internet service have the lowest churn rate with 74 churned versus 970 non-churned customers. These visuals highlight that fiber optic users are more likely to churn compared to DSL users and those without internet service, indicating that internet service type significantly impacts customer retention.

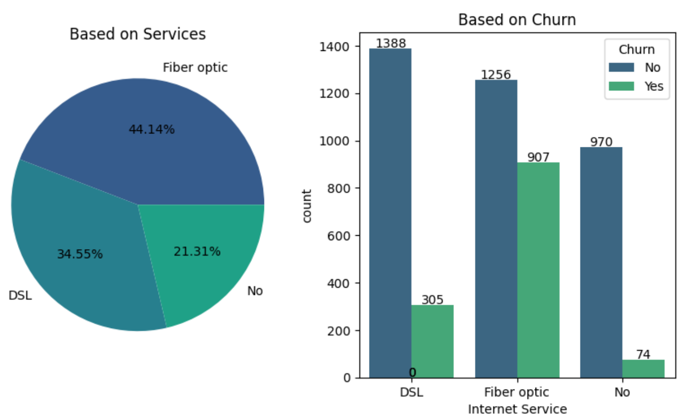

Figure 7: Service report

The bar plots (figure 8) illustrate that customers without services such as Online Security, Online Backup, Device Protection, and Tech Support exhibit higher churn rates compared to those with these services. Specifically, customers without Online Security, Online Backup, Device Protection, and Tech Support have churn rates of 939, 810, 769, and 926 respectively, while those with these services show significantly lower churn rates of 187, 316, 357, and 200 respectively. This pattern suggests that customers with these additional services are more likely to stay, highlighting the potential for reducing churn by encouraging customers to adopt these services.

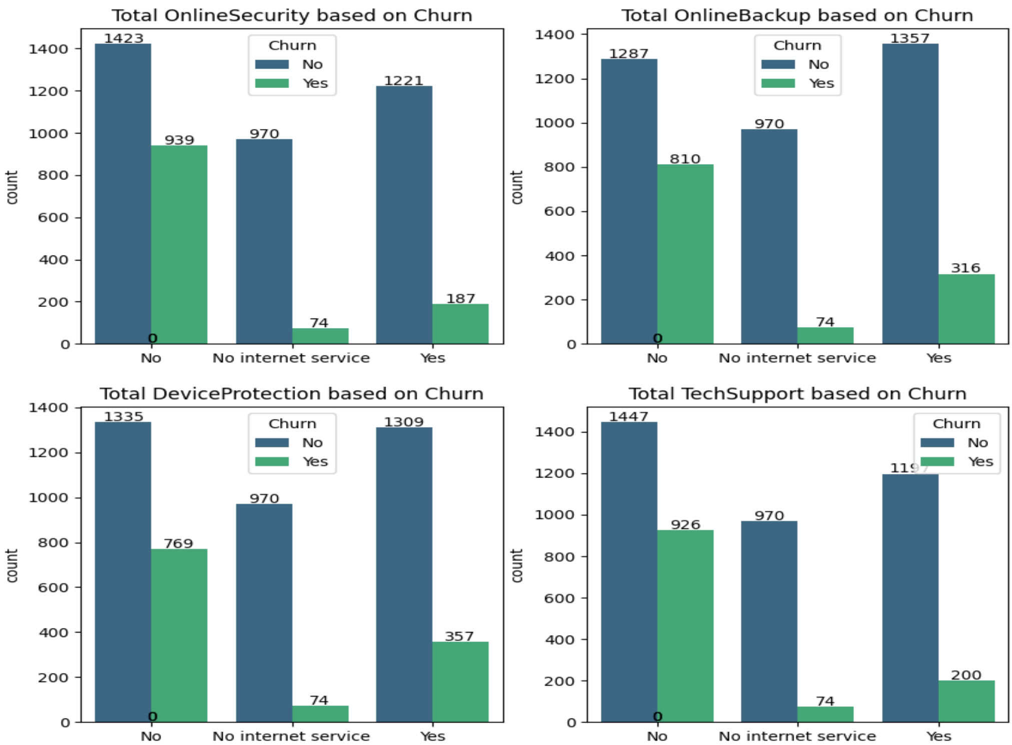

Figure 8:Customers without services

The figure 9 reveals that customers without dependents exhibit higher churn rates (926) compared to those with dependents (176), with a tendency for shorter tenures and higher monthly charges, suggesting these factors contribute to their higher churn. In contrast, customers with dependents are less likely to churn (1259 retained versus 2355 without dependents), with more balanced tenure and monthly charges distributions. This indicates that retention strategies should target customers without dependents by addressing their shorter tenure and higher charges to reduce churn effectively.

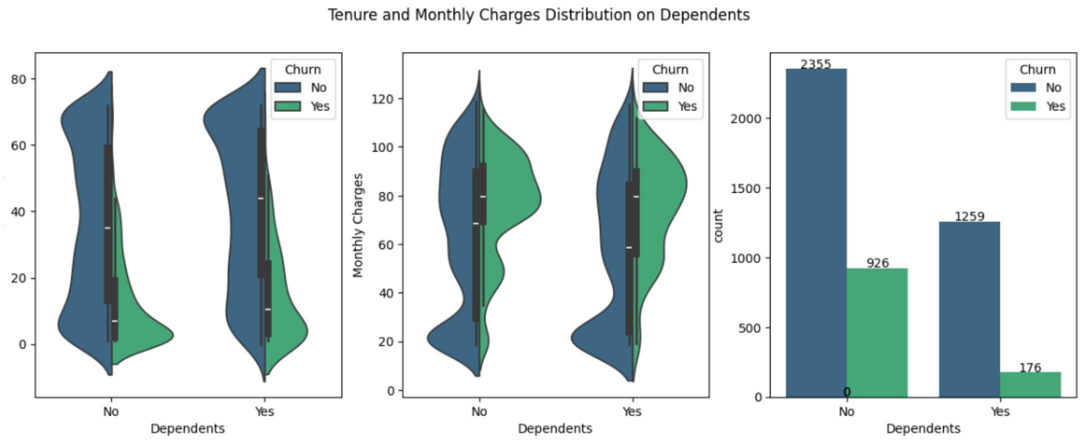

Figure 9: Tenure and Monthly charges distribution on dependents

Figure 10 compares the performance of various machine learning models based on their AUC (Area Under the Curve) and AP (Average Precision) scores, along with their standard deviations (STD). The Gradient Boosting model stands out with the highest AUC score of 89.06 and an AP score of 69.15, indicating excellent capability in distinguishing between classes and maintaining precision. Its relatively low standard deviation (0.82 for AUC and 0.86 for AP) suggests consistent performance across different runs. Similarly, AdaBoost and Logistic Regression follow closely with AUC scores of 88.69 and 88.44, respectively, and AP scores of 68.67 and 68.39. Despite their high performance, AdaBoost shows a slightly higher variability (STD of 1.10 for AUC and 2.08 for AP), which might reflect some instability in certain cases.

Models such as the Multi-Layer Perceptron, Light Gradient Boosting, and eXtreme Gradient Boosting also show strong performance, with AUC scores ranging from 87.18 to 88.20 and AP scores between 64.11 and 68.09. These models have moderate standard deviations, indicating fairly reliable performance. The Random Forest and Support Vector Classifier models demonstrate respectable results with AUC scores around 85 and AP scores in the mid-60s. However, the standard deviations are somewhat higher for the Support Vector Classifier (1.43 for AUC and 2.03 for AP), indicating more fluctuation in their predictive accuracy and precision.

On the lower end of the spectrum, the K-Nearest Neighbours and Decision Tree models perform less effectively, with AUC scores of 81.40 and 74.09, respectively. Their AP scores of 53.83 for K-Nearest Neighbours and 43.19 for Decision Tree are significantly lower, suggesting poorer precision in their predictions. Moreover, these models exhibit higher standard deviations, particularly the Decision Tree (2.19 for AUC and 2.39 for AP), indicating inconsistent performance. Overall, while boosting techniques (Gradient Boosting, AdaBoost) and Logistic Regression emerge as the top-performing models, Decision Tree and K-Nearest Neighbours lag behind, highlighting the importance of model selection based on the specific requirements of precision and consistency in classification tasks.

	AUC Score		AP Score	
	Average	STD	Average	STD
Gradient Boosting	89.06	0.82	69.15	0.86
AdaBoost	88.69	1.10	68.67	2.08
Logistic Regression	88.44	0.90	68.39	2.09
Multi-Layer Perceptron	88.20	0.78	68.09	1.69
Light Gradient Boosting	87.85	0.69	66.79	0.48
eXtreme Gradient Boosting	87.18	0.64	64.01	1.35
Random Forest	85.48	1.00	62.49	0.88
Support Vector Classifier	85.00	1.43	65.62	2.03
K-Nearest Neighbours	81.40	1.10	53.83	2.85
Decision Tree	74.09	2.19	43.19	2.39

Figure 10: Different Machine Learning models result analysis

The bar chart (figure 11) reveals that Gradient Boosting (AP Score: 69.15, AUC Score: 89.06) and AdaBoost (AP Score: 68.67, AUC Score: 88.69) are the top performers, followed closely by Logistic Regression (AP Score: 68.39, AUC Score: 88.44) and Multi-Layer Perceptron (AP Score: 68.09, AUC Score: 88.20), indicating their strong balance of precision and recall. Light Gradient Boosting (AP Score: 66.79, AUC Score: 87.85) and XGBoost (AP Score: 64.01, AUC Score: 87.18) also perform well, though slightly lower. Random Forest (AP Score: 62.49, AUC Score: 85.48) and Support Vector Classifier (AP Score: 65.62, AUC Score: 85.00) are reliable but less effective compared to boosting methods. K-Nearest Neighbors (AP Score: 53.83, AUC Score: 81.40) and Decision Tree (AP Score: 43.19, AUC Score: 74.09) are the least effective, particularly in terms of Average Precision. Overall, boosting methods and Logistic Regression should be prioritized for tasks where recall is crucial, reflecting the F2 Score emphasis.

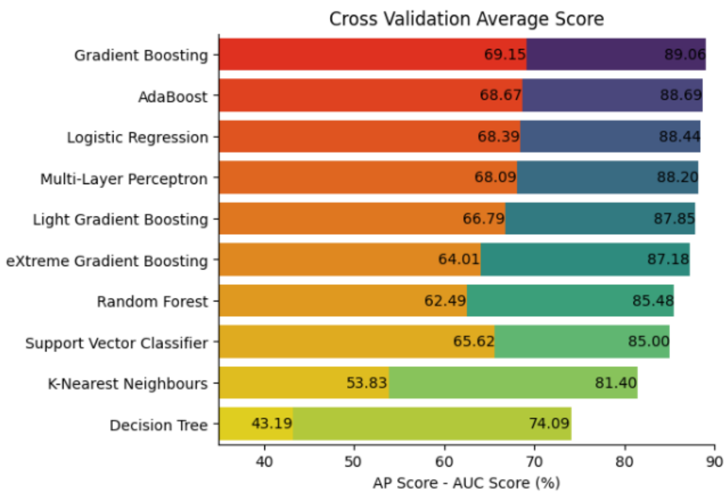

Figure 11: Different Machine Learning models training Cross validation Score

The bar chart (figure 12), showing classifier testing scores, reinforces the performance trends observed in the cross-validation average scores. Gradient Boosting (AP Score: 70.24, AUC Score: 89.96) remains the top performer, followed by AdaBoost (AP Score: 67.90, AUC Score: 89.21), and Multi-Layer Perceptron (AP Score: 72.01, AUC Score: 89.14). Logistic Regression (AP Score: 70.21, AUC Score: 89.09) and Light Gradient Boosting (AP Score: 68.60, AUC Score: 89.01) also demonstrate strong performance. eXtreme Gradient Boosting (AP Score: 65.53, AUC Score: 87.62) and Random Forest (AP Score: 66.28, AUC Score: 86.17) continue to provide solid, albeit slightly lower, results. The Support Vector Classifier (AP Score: 70.07, AUC Score: 85.33) maintains respectable scores, while K-Nearest Neighbors (AP Score: 61.69, AUC Score: 84.98) and Decision Tree (AP Score: 42.41, AUC Score: 73.50) exhibit the lowest performance. Overall, boosting methods and neural networks, alongside logistic regression, are confirmed as the most effective classifiers, particularly in applications prioritizing high recall.

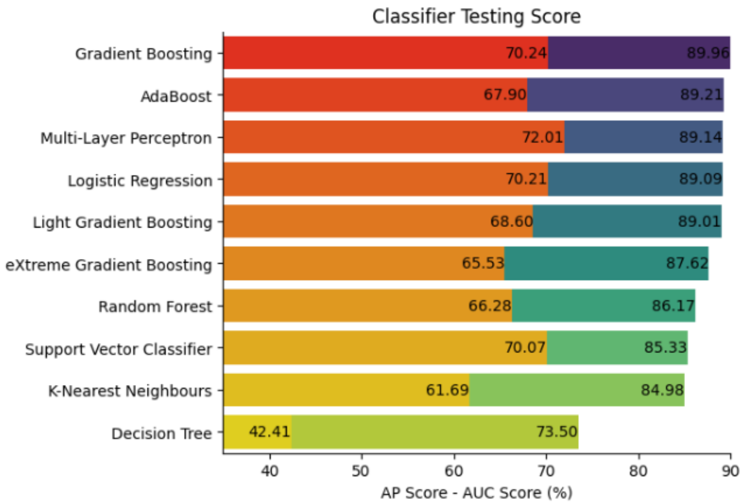

Figure 12: Different Machine Learning models testing Cross validation Score

4. Conclusion:

The analysis of the customer churn dataset, comprising 4930 rows and 11 attributes, revealed critical insights into optimizing data and understanding churn behavior. By converting categorical data to the 'category' type and downcasting numerical attributes to more memory-efficient types, significant improvements in memory usage can be achieved. The dataset shows a clear distinction between churned and non-churned customers, particularly in terms of tenure and monthly charges. Churned customers typically have shorter tenures and higher monthly charges, with significant outliers indicating some had long tenures before churning. In contrast, non-churned customers tend to have longer tenures and more dispersed monthly charges, suggesting a positive correlation between these two factors.

Detailed feature exploration uncovered that churn rates are higher among fiber optic users compared to DSL and customers without internet service. Additionally, customers lacking services such as Online Security, Online Backup, Device Protection, and Tech Support are more likely to churn. This pattern indicates that promoting these additional services could effectively reduce churn. The analysis also highlighted that customers without dependents exhibit higher churn rates and shorter tenures, suggesting that retention strategies should target this demographic to address their specific needs and reduce churn effectively.

Machine learning model performance was evaluated to determine the most effective approaches for predicting churn. Gradient Boosting emerged as the top performer with the highest AUC and AP scores, indicating its strong discrimination and precision capabilities. AdaBoost and Logistic Regression also showed high performance, though with slightly higher variability in AdaBoost's results. Models like Multi-Layer Perceptron, Light Gradient Boosting, and XGBoost displayed strong and reliable performance, while K-Nearest Neighbours and Decision Tree were less effective, showing lower precision and consistency. Based on these findings, boosting techniques and Logistic Regression should be prioritized for tasks where high recall is crucial, with targeted efforts to promote additional services and address factors contributing to churn among customers without dependents.

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