# Churn Ml Dl Business report

## Executive Summary:

This project leveraged advanced Machine Learning (ML) and Deep Learning (DL) techniques to analyze customer data and predict churn. The primary objectives were to identify customers at high risk of leaving and to uncover the underlying factors driving their decision.

Our analysis successfully developed a highly accurate predictive model. More importantly, it translated complex data into actionable business insights. We found that the most significant drivers of churn are contract type, payment method, and tenure. Customers on month-to-month contracts using electronic checks and with lower tenures are at the highest risk.

This report summarizes our methodology, compares the performance of different analytical approaches, and provides concrete, data-driven strategies to improve customer retention and directly impact profitability.

## 2. Project Introduction & Objectives

Customer churn is a critical metric with a direct effect on company revenue and growth. Proactively identifying at-risk customers allows for targeted retention efforts, which is far more cost-effective than acquiring new customers.

## The goals of this project were:

**Predictive Accuracy:** To build and compare ML and DL models for predicting customer churn with high precision.

**Root Cause Analysis:** To move beyond prediction and identify the key factors that influence a customer's decision to leave.

**Actionable Strategy:** To translate these data insights into tangible business strategies for reducing churn.

## 3. Methodology Overview

**We followed a structured machine learning lifecycle:**

**Data Preparation:** Cleaned customer data (e.g., converting TotalCharges to numeric, encoding categorical variables like Contract and PaymentMethod).

**Exploratory Data Analysis (EDA):** Analyzed data distributions and relationships. A correlation heatmap was pivotal in understanding how customer attributes relate to each other and to churn (explained in detail in Section 5).

**Model Development:** Built, trained, and evaluated multiple models.

**Machine Learning (ML):** Utilized classic algorithms like Logistic Regression, Random Forest, and Gradient Boosting.

**Deep Learning (DL):** Implemented a Neural Network model to capture more complex, non-linear patterns in the data.

**Evaluation:** Models were assessed on key metrics like Accuracy, Precision, Recall, and F1-Score to ensure reliability.

## 4. Model Performance: ML vs. DL

Both ML and DL models achieved strong and comparable performance (Accuracy > 80%). The Gradient Boosting model often slightly outperformed or matched the Neural Network in this specific scenario.

**Business Interpretation:** This is excellent news. It means we can achieve top-tier predictive performance using robust, yet more interpretable, ML models. The Random Forest and Gradient Boosting models also provide a clear ranking of feature importance, which is crucial for explaining why a customer might churn, making it highly valuable for business strategy.

**5. Key Business Insights:** The "Why" Behind Churn
Our analysis reveals that churn is not random. It is strongly correlated with specific customer attributes and experiences.

## Understanding the Correlation Heatmap (Business Perspective):

The correlation heatmap is not just a technical chart; it's a visual representation of customer behavior and product relationships. It shows how different factors move together.

**What it shows:** The colored grid displays correlation coefficients between variables. A value close to +1 (dark positive color) means two factors increase together. A value close to -1 (dark negative color) means one factor increases as the other decreases. A value near 0 (light color) means no linear relationship.

**How to use it for business:** We use it to quickly identify the strongest relationships that impact our bottom line. We focus on the row for Churn to see which factors have the strongest positive (red) and negative (blue) relationships with customers leaving.

## Top Drivers of Customer Churn:

**Contract Type (Highest Impact):** The strongest signal. Customers with Month-to-Month contracts have a significantly higher churn rate compared to those with longer-term (One year, Two year) contracts. Long-term contracts create stickiness and reduce churn.

**Tenure (Strong Protective Factor):** This has a strong negative correlation with churn. New customers (low tenure) are the most vulnerable. The longer a customer stays with the company, the less likely they are to leave. This highlights a critical window of risk in the first few months**.**

**Payment Method:** Customers using Electronic Checks are far more likely to churn than those using automated payment methods (Credit Card, Bank Transfer). This suggests friction, inconvenience, or a lack of engagement with automated systems.

**Monthly Charges:** A moderate positive correlation with churn. Customers with higher monthly bills are more sensitive to service value and more likely to explore competitors if they feel they are not getting their money's worth.

**Service Add-ons (Online Security, Tech Support):** These services show a negative correlation with churn. Customers who invest in and use these value-added services are more engaged and satisfied, making them less likely to leave.

## 6. Strategic Recommendations for Customer Retention Based on these insight

**Mitigate Early-Life Churn:**

**Action:** Create a "Welcome Series" and proactive check-ins for customers in their first 3-6 months. Offer dedicated onboarding support to ensure they derive maximum value from the service immediately.

**Goal:** Increase engagement and overcome initial setup hurdles to convert low-tenure customers into long-term loyalists.

### Incentivize Long-Term Commitments:

**Action:** Develop compelling promotional offers for month to month customers to switch to annual contracts. Frame it as a "Lock-in Your Rate" or "Loyalty Discount" program.

**Goal:** Reduce the volatile month-to-month cohort by converting them to more stable long-term contracts.

### Promote Automated & Value-Added Services:

**Action:** Launch a campaign to migrate customers from electronic checks to automated payment methods, offering a small one-time discount or fee waiver. Bundle popular services like Online Security and Tech Support into featured packages for new and at-risk customers.

**Goal:** Reduce friction in payment and increase perceived value, thereby enhancing customer stickiness.

### Implement a Proactive Retention Pipeline:

**Action:** Use the predictive model to generate a weekly list of high-risk customers (e.g., Month-to-Month, using Electronic Check, high charges). Empower the customer success team to reach out with personalized offers or service reviews.

**Goal:** Move from reactive saves to proactive retention, targeting resources efficiently for maximum ROI**.**

## 7. Conclusion and Future Work

This project demonstrates the power of using AI not just for prediction, but for strategic decision-making. By understanding the core reasons behind churn, we can implement precise, effective, and cost-efficient retention strategies.