BESANT TECHNOLOGIES

DATA ANALYSIS PROJECT

Telecom Customer Churn Analysis

SUBMITTED BY

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UNDER THE GUIDANCE OF

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Certificate

This is to certify that the project titled **“Telecom Customer Churn Analysis”** has been successfully completed by **Donal Siby** under the guidance of **Priyanka G** at **Besant Technologies**.

This project fulfills the academic requirements and demonstrates strong knowledge in data analysis, visualization, and business analytics.

Acknowledgement

I express my sincere gratitude to **Besant Technologies** for the opportunity to complete this project.
I thank my trainer **Priyanka G** for her guidance and continuous support.

I also thank my family and friends for their encouragement throughout this project.

Abstract

This project analyzes telecom customer churn using the Telco Customer Churn dataset. The study identifies churn patterns and key factors such as tenure, contract type, and monthly charges that influence customer attrition.

Exploratory Data Analysis and visualization techniques were applied to generate insights that support customer retention strategies.

Contents

Chapter 1

Introduction

Customer churn refers to the process where customers stop using a company's products or services. In the telecommunications industry, customer churn represents a major business challenge due to increasing competition, price sensitivity, and customer expectations.

Telecom companies invest heavily in acquiring new customers through marketing and promotional offers. However, acquiring a new customer is significantly more expensive than retaining an existing one. Therefore, understanding churn behavior and identifying the key reasons why customers leave is crucial for improving profitability and long-term sustainability.

This project focuses on analyzing customer churn using the Telco Customer Churn dataset. The dataset contains information about customer demographics, service subscriptions, billing history, contract types, and payment methods. By applying statistical analysis and data visualization techniques, this study aims to uncover hidden patterns that influence customer churn.

The primary objective is to provide actionable insights that telecom companies can use to improve customer retention strategies. Additionally, the findings of this project can serve as a foundation for developing predictive machine learning models to detect churn risk in advance.

This report presents a detailed walkthrough of the data analysis process, including data cleaning, exploratory analysis, visualization, insights generation, and business recommendations.

Chapter 2

Objectives of the Analysis

The main goal of this project is to analyze telecom customer churn and understand the factors influencing customer retention and attrition.

The specific objectives include:

- To analyze churn distribution across customer segments and demographics
- To identify key service and contract features that influence churn behavior
- To explore customer billing patterns and their impact on churn
- To visualize customer churn trends using statistical charts and plots
- To generate meaningful insights for business decision-making
- To help telecom companies design proactive customer retention strategies
- To support the development of churn prediction models using machine learning
- To understand customer lifetime value and retention patterns

Achieving these objectives will help telecom providers reduce churn rates, improve customer satisfaction, and enhance overall business performance.

Chapter 3

Business Problem and ROI Questions

Customer churn leads to significant financial losses for telecom companies. When customers leave, companies lose recurring revenue and must spend additional resources to attract replacement customers.

3.1 Business Challenges

Telecom companies face several challenges related to churn, including:

- Rising competition from alternative service providers
- Price sensitivity among customers
- Rapid technological changes affecting service expectations
- Increasing customer demand for better service quality

3.2 Key ROI Questions

Which customers churn the most?
Customers with short tenure, month-to-month contracts, higher monthly charges, fiber optic internet service, and manual payment methods show a higher likelihood of churn.

Can churn be predicted early?

Yes. By analyzing contract duration, customer tenure, billing behavior, and service type, companies can predict churn risk before customers terminate their subscriptions.

What factors have the greatest impact on churn?

- Contract type and renewal cycle
- Monthly billing charges and total spending
- Payment method convenience
- Internet and phone service type
- Customer loyalty and tenure

3.3 Expected Business Outcomes

- Reduction in churn rate and improved customer retention
- Better customer segmentation and personalized marketing
- Increased customer lifetime value and long-term profitability
- Optimized pricing and promotional strategies
- Improved service quality and customer experience

Chapter 4

Data Collection

The dataset used for this project is the Telco Customer Churn dataset obtained from Kaggle. It contains real-world telecom customer information designed to simulate customer churn scenarios.

4.1 Dataset Source

The dataset includes customer demographics, subscription services, contract details, billing history, and churn outcomes.

4.2 Dataset Structure

- Total Records: 7,043 customers
- Total Features: 21 columns
- Target Variable: Customer Churn (Yes / No)
- Data Types: Numeric and Categorical

4.3 Key Attributes Description

Important features in the dataset include:

- Gender: Customer gender classification

- SeniorCitizen: Indicates elderly customers
- Tenure: Duration of customer relationship
- Contract Type: Month-to-month, One year, Two year
- MonthlyCharges: Monthly billing amount
- TotalCharges: Total customer spending
- PaymentMethod: Mode of bill payment
- InternetService: Type of internet connection
- Churn: Customer churn status

This dataset provides valuable insights into customer behavior and retention patterns.

Chapter 5

Data Inspection and Initial Analysis

Initial inspection of the dataset revealed a mixture of numerical and categorical variables. The TotalCharges column contained missing or improperly formatted values that required cleaning.

The churn target variable displayed class imbalance, where non-churned customers significantly outnumber churned customers. This imbalance can impact predictive modeling and evaluation metrics.

Duplicate records and inconsistent data formats were identified during the preliminary analysis. Additionally, some columns required transformation before analysis, including encoding categorical variables and normalizing numeric fields.

A summary of descriptive statistics was generated to understand the distribution, range, mean, and standard deviation of numeric attributes. This step helped identify potential outliers and anomalies in the dataset.

Chapter 6

Data Cleaning and Transformation

Data preprocessing is a critical step to ensure the accuracy and reliability of analysis results. Several cleaning operations were performed to improve data quality.

6.1 Cleaning Procedures

- Converted TotalCharges column to numeric data type
- Removed records containing missing or null values
- Eliminated duplicate customer entries
- Encoded categorical variables using label encoding and one-hot encoding
- Standardized column naming conventions
- Treated outliers using Interquartile Range (IQR) method
- Normalized numeric features for consistency

These transformations ensured that the dataset was consistent, complete, and suitable for analysis and visualization.

Chapter 7

Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) was conducted to understand patterns, trends, and relationships within the dataset.

7.1 Class Distribution Analysis

Approximately 73% of customers did not churn, while 27% churned. This imbalance highlights the need for careful evaluation metrics in predictive modeling.

7.2 Tenure Analysis

Customers with shorter tenure exhibited higher churn rates, indicating that early-stage customer engagement is critical for retention.

7.3 Billing Analysis

Higher monthly charges were associated with increased churn risk, suggesting price sensitivity among customers.

7.4 Contract Type Impact

Customers with long-term contracts showed significantly lower churn compared to month-to-month customers.

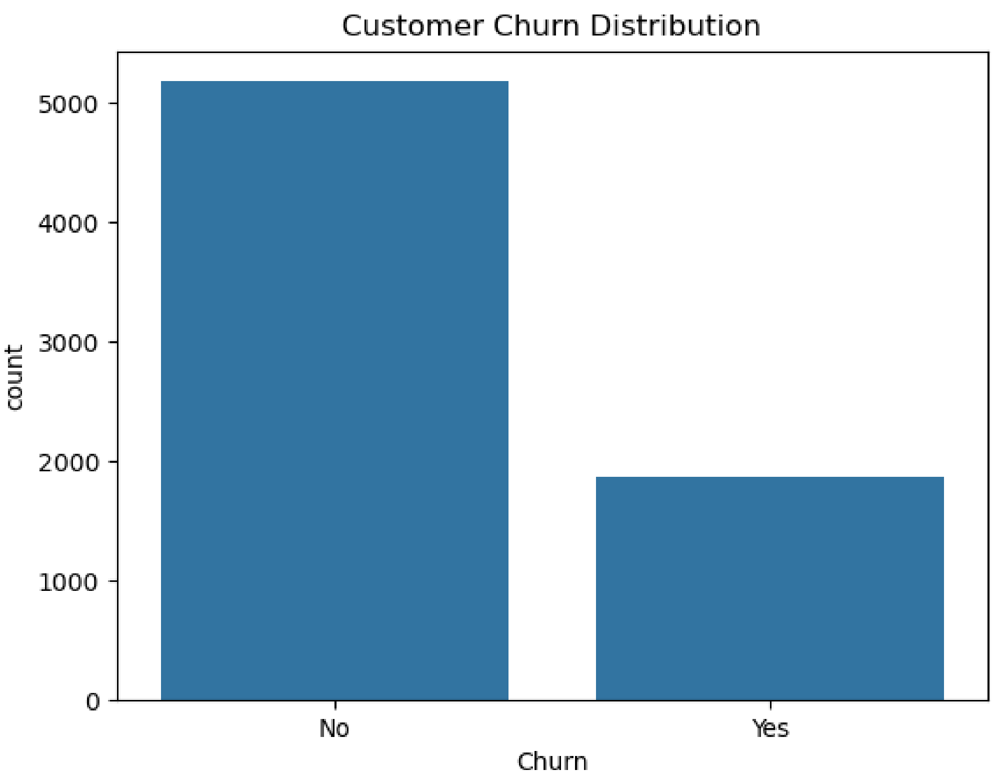
7.5 Payment Behavior

Customers using automatic payment methods demonstrated greater retention than those using manual payment options.

Chapter 8

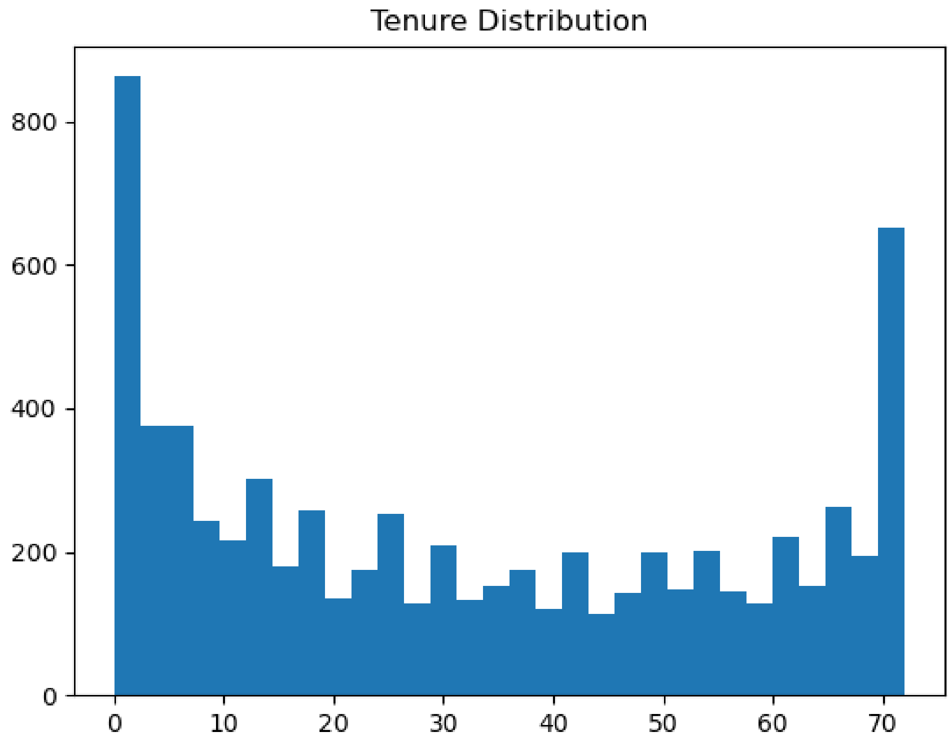
Visualization Results

8.1 Customer Churn Distribution



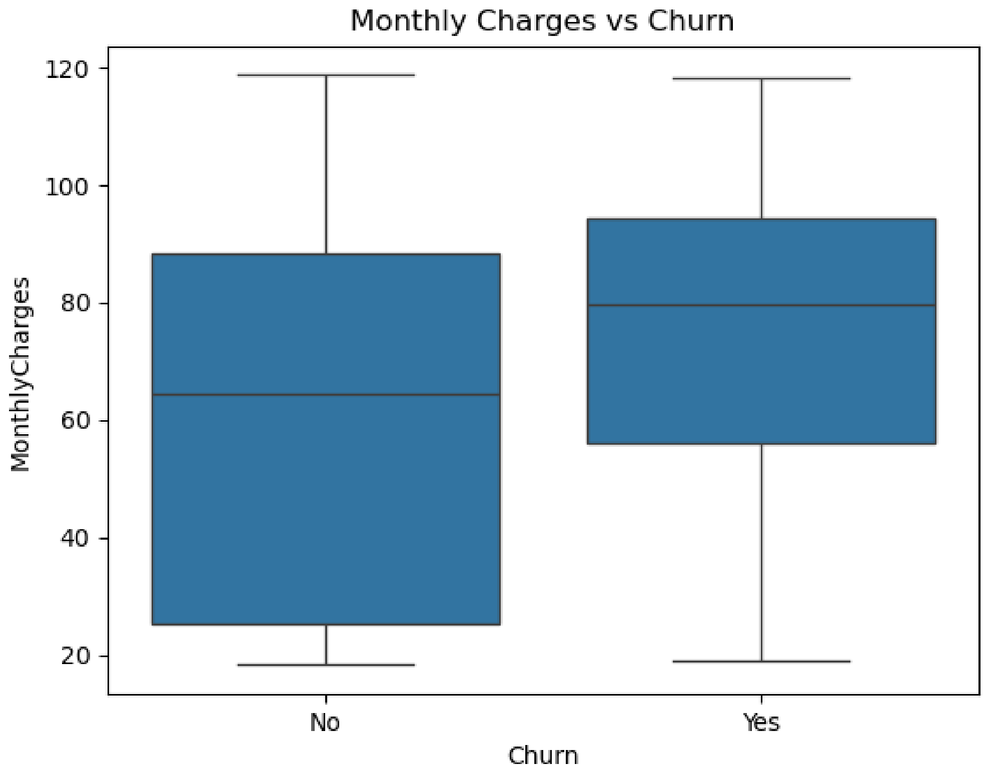
Insights: The class imbalance highlights the importance of specialized churn mitigation strategies.

8.2 Tenure Distribution



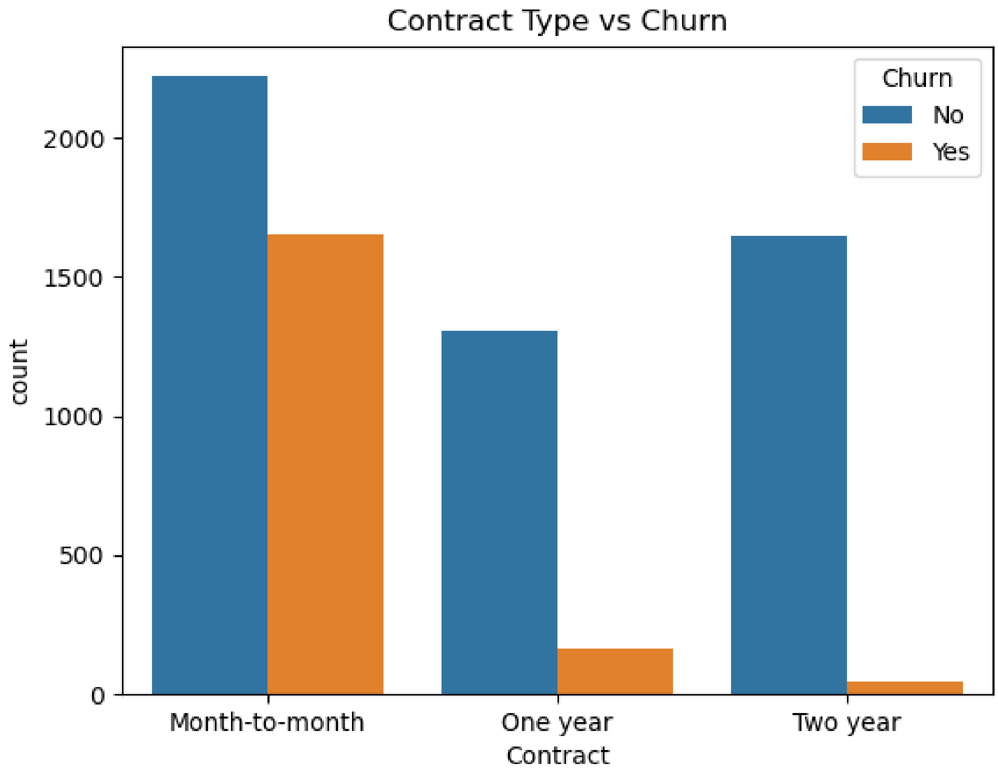
Insights: Customers with longer tenure demonstrate higher loyalty and reduced churn risk.

8.3 Monthly Charges vs Churn



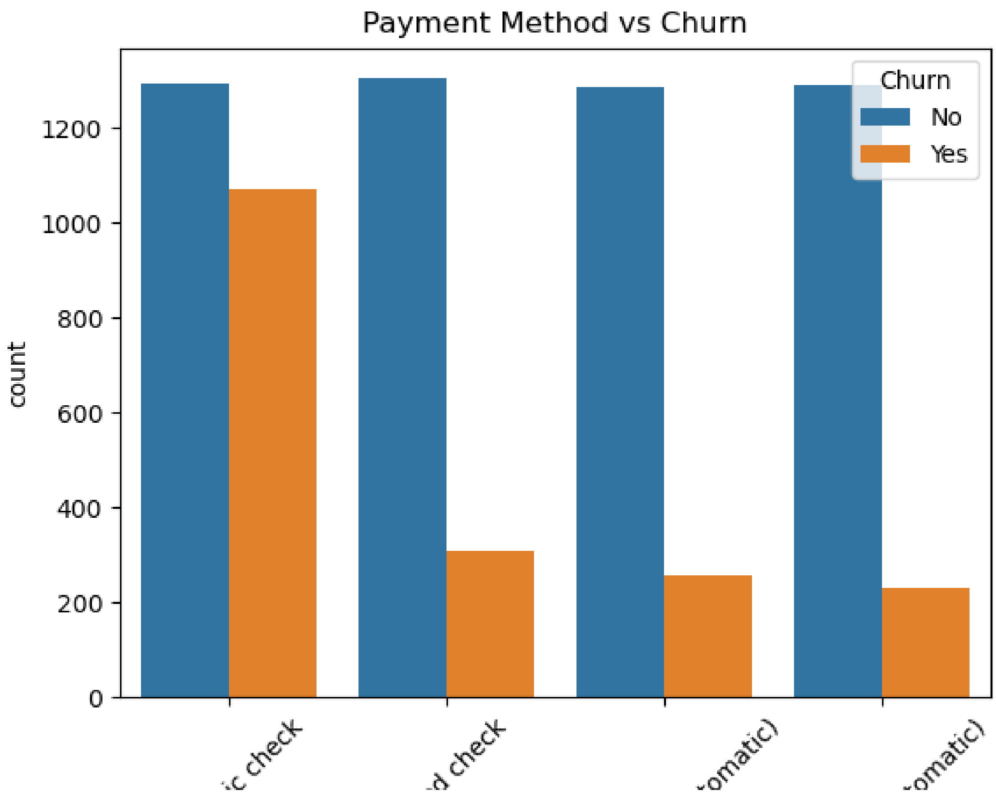
Insights: High monthly charges increase churn probability, emphasizing the need for pricing optimization.

8.4 Contract Type vs Churn



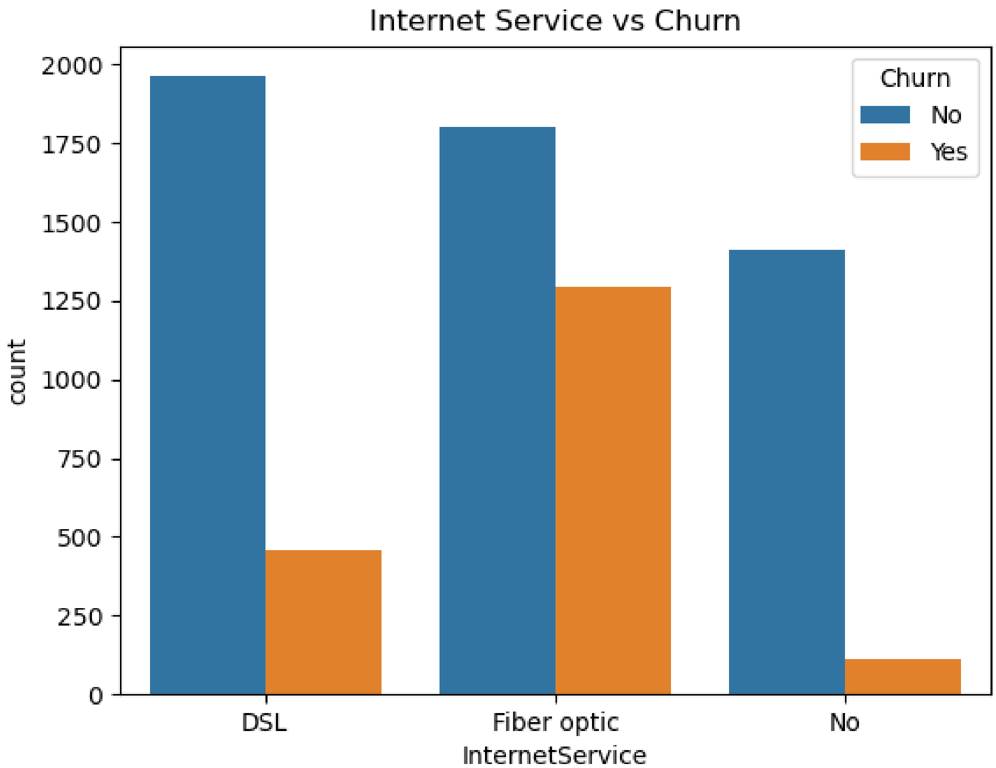
Insights: Long-term contracts significantly reduce churn and improve customer retention.

8.5 Payment Method vs Churn



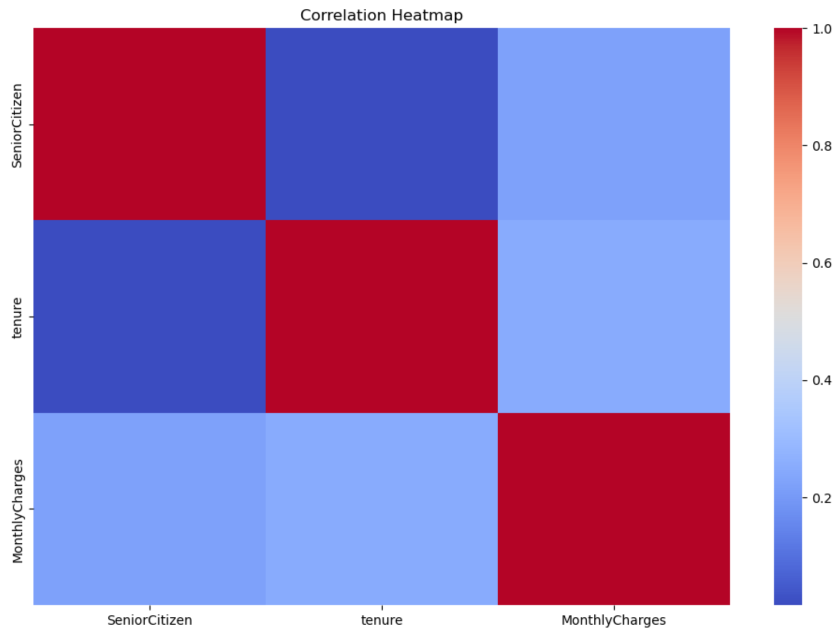
Insights: Automated payment methods encourage customer loyalty.

8.6 Internet Service vs Churn



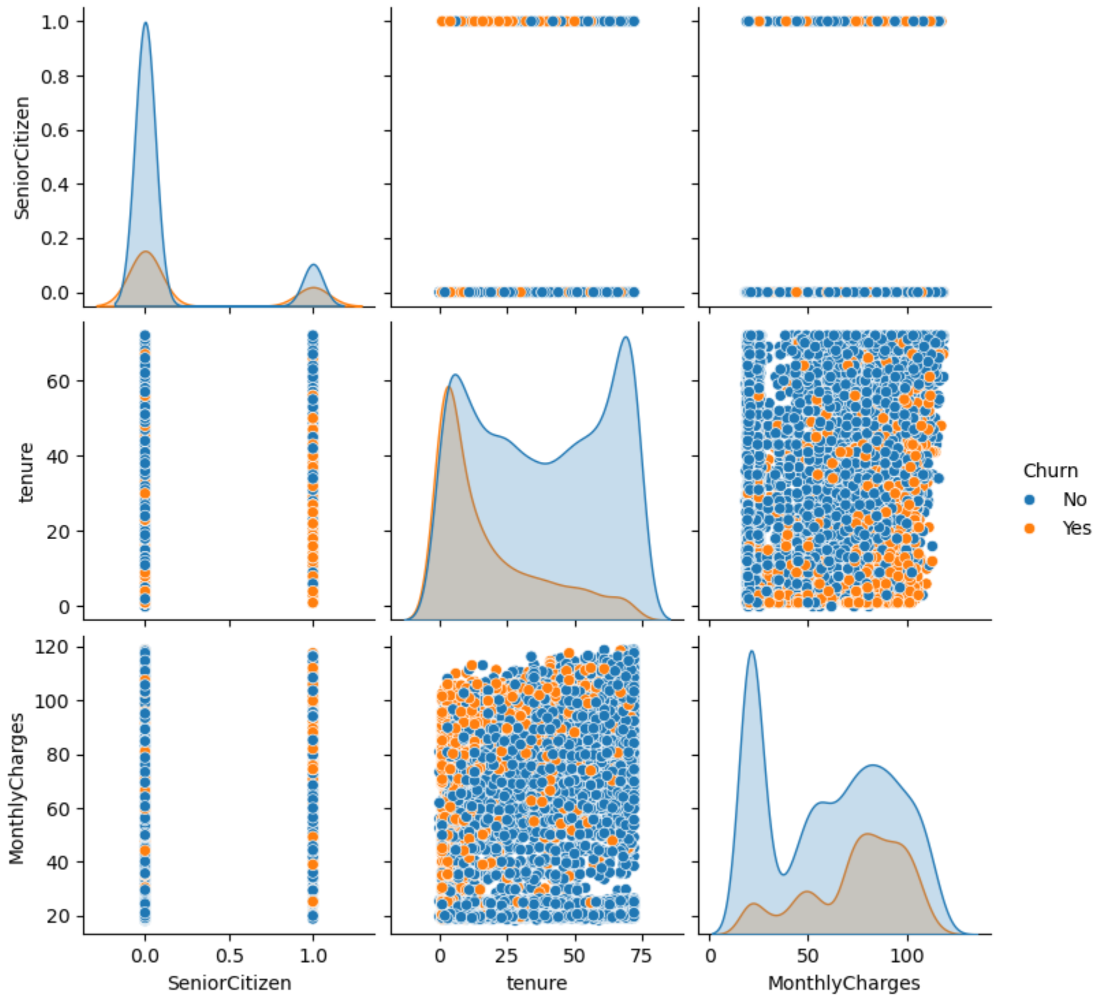
Insights: Fiber optic users show higher churn, possibly due to pricing concerns.

8.7 Correlation Heatmap



Insights: Tenure negatively correlates with churn, while monthly charges show a positive correlation.

8.8 Pairplot



Insights: Tenure and billing features clearly separate churn groups.

Chapter 9

Insights Generation

The analysis produced several important business insights:

- Month-to-month customers have the highest churn rate
- Customers with longer tenure are more loyal
- High monthly charges significantly increase churn probability
- Customers using electronic checks churn more frequently
- Fiber optic customers show higher churn compared to DSL customers
- Automated billing improves customer retention
- Senior citizens require targeted engagement strategies

These insights can help telecom companies implement more effective customer retention programs.

Chapter 10

Technologies Used

This project leveraged multiple tools and technologies:

- Python for data analysis and processing
- Pandas and NumPy for data manipulation
- Matplotlib and Seaborn for data visualization
- Scikit-Learn for predictive modeling foundations
- Jupyter Notebook for interactive analysis
- SQL for optional database integration
- Power BI / Excel for reporting and dashboards

Chapter 11

Conclusion

This project successfully analyzed telecom customer churn using data science techniques. The study identified major churn drivers such as contract type, tenure duration, monthly billing charges, and payment methods.

The insights generated from this project can help telecom companies develop proactive retention strategies, improve customer satisfaction, and increase revenue stability.

Future improvements may include implementing machine learning churn prediction models, developing real-time churn monitoring systems, and integrating additional customer behavioral data.