Customer Churn Analysis Report

📊 Customer Churn Analysis and Prediction Dashboard – Project Report

🔍 Project Overview

This project focuses on analyzing and predicting customer churn using data-driven insights. A Power BI dashboard was developed to visualize key churn metrics, identify patterns, and provide actionable intelligence for customer retention. The project also includes a machine learning model to predict potential churners. The end goal was to help stakeholders understand churn behavior and take proactive measures to reduce it.

⚙️ Technology Stack Used

- **SQL** – Data preprocessing and transformation
- **Python (Scikit-learn)** – Machine Learning model for churn prediction
- **Power BI** – Interactive dashboard for analysis and reporting
- **Excel/CSV** – For data handling and initial loading

🗂️ Dataset Overview

The dataset included customer details like demographics, payment methods, contract types, service subscriptions, internet types, and churn status. It also contained revenue-related columns such as monthly charges, total revenue, and refunds.

🔄 Project Workflow

1. 🧹 Data Preprocessing (Using SQL)

Performed extensive preprocessing and transformation tasks using SQL:

- **Data Cleaning:**
  - Handled missing/null values
  - Removed duplicates
  - Standardized column formats
- **Feature Engineering:**
  - Created tenure categories (<6 Months, 6-12 Months, etc.)
  - Categorized age groups (<20, 20–35, etc.)
  - Created a Churn Category based on reasons for leaving
- **Joins and Aggregations:**
  - Joined demographic data with service and billing information
  - Calculated churn rate by various segments (state, contract type, payment method)

The cleaned and enriched data was exported to Excel for further processing in Power BI and Python.

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2. 🤖 Churn Prediction Model (Python + ML)

A **machine learning model** was developed to identify customers at high risk of churn.

- **Model Used**: Random Forest Classifier
- **Process:**
  - Split data into training and testing sets (80/20)
  - Performed label encoding for categorical features
  - Model trained on customer features like:
    - Monthly Charges
    - Contract Type
    - Payment Method
    - Services Opted
    - Tenure
    - Number of Referrals, etc.
- **Evaluation Metrics:**

  - Accuracy: ~81%
  - Precision, Recall, and F1 Score used to validate performance
- **Prediction Output:**
  - Predicted churners (378 customers)
  - Output included: Customer_ID, Monthly_Charge, Total_Refunds, Total_Revenue, Number_of_Referrals

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3. 📊 Dashboard Design (Power BI)

Created two main dashboard pages:

A. Summary Dashboard

- High-level metrics:
  - Total Customers: 3,223
  - Total Churn: 883
  - Churn Rate: 27.4%
  - New Joiners: 211
- Key Visualizations:
  - **Churn by Age, Tenure, Payment Method, State, Gender**
  - **Churn by Services and Internet Type**
  - **Top Churn Categories** (e.g., Competitor, Dissatisfaction)
  - **Churn Rate by Contract Type** (Month-to-Month had highest at 47.5%)

B. Prediction Dashboard

- Displays predicted churners:
  - 132 Males, 246 Females
  - Churn across tenure groups, age, state, and payment method
  - Customer-wise churn likelihood and business value (e.g., Total Revenue, Monthly Charge)
- Interactive Filters:
  - Monthly Charge Range
  - Marital Status
  - Contract and Payment Method

☑ Key Business Insights

- **High Churn Segments:**
  - Month-to-Month Contracts
  - Mailed Check payments
  - Customers aged over 50
  - Fiber Optic users (41.8% churn)
- **States with High Churn:**
  - Jammu & Kashmir (59.5%)
  - Assam, Jharkhand, Chhattisgarh
- **Customer Services:**
  - Customers without Online Security or Backup services showed higher churn
  - Customers with Unlimited Data were more loyal (81.3% retained)

✅ Conclusion & Impact

By combining SQL for data engineering, Python for predictive modeling, and Power BI for visualization, this project offers both **retrospective analytics** and **forward-looking churn prediction**. It empowers stakeholders to:

- Identify high-risk customers
- Improve service offerings
- Redesign retention strategies for specific segments