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TELECOM CUSTOMER LIFETIME VALUE & CHURN RISK DASHBOARD WITH SERVICE USAGE PATTERN DRILL-THROUGH

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Abstract

This project presents the design and development of a Telecom Customer Lifetime Value (CLV) and Churn Risk Dashboard with advanced service usage pattern drill-through capabilities. The primary objective is to help telecom operators analyze customer behavior, predict churn risk, and estimate the long-term value of customers, enabling data-driven decision-making and improved customer retention strategies.
In the highly competitive telecom industry, retaining existing customers is more cost-effective than acquiring new ones. Traditional analysis methods often fail to provide real-time insights and lack the ability to explore customer behavior at a granular level. To address these challenges, the proposed system leverages data analytics and visualization techniques to build an interactive dashboard that integrates customer demographics, billing information, service usage patterns, and historical interaction data .
The system calculates Customer Lifetime Value using predictive modelling techniques and identifies churn risk through key indicators such as declining usage, payment delays, and service complaints. The dashboard provides intuitive visualizations, including trend analysis, segmentation, and risk categorization, enabling stakeholders to quickly identify high-value and high-risk customers . A key feature of the system is the drill-through functionality, which allows users to navigate from high-level summaries to detailed customer-level insights, such as call, data, and messaging usage patterns. This helps in understanding the root causes of churn and designing targeted retention campaigns .Overall, the solution enhances business intelligence capabilities by providing actionable insights, improving customer satisfaction, and increasing revenue through proactive churn management and optimized customer engagement strategies.

I. Introduction

One of the most significant challenges in the modern telecom industry is understanding customer behavior and effectively predicting customer churn while maximizing customer lifetime value. Telecom companies handle vast amounts of customer data across multiple services such as voice, data, and messaging. However, traditional analysis methods often rely on static reports and fragmented data sources, leading to poor insights, delayed decision-making, and ineffective customer retention strategies.
In a highly competitive market, retaining existing customers is more cost-effective than acquiring new ones. Therefore, it is essential for telecom operators to identify

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high-value customers, detect early signs of churn, and understand service usage patterns. However, analyzing large-scale customer data manually or through basic reporting tools results in inefficiencies, lack of real-time insights, and limited visibility into customer behavior at a granular level.

With the rapid advancement of data analytics and business intelligence tools, interactive dashboards and predictive models have become essential for extracting meaningful insights from telecom data. These systems enable organizations to monitor key performance indicators, forecast customer lifetime value (CLV), and assess churn risk using historical and real-time data. However, building a unified system that combines predictive analytics with intuitive visualization and deep data exploration remains a challenge.

The project titled "Telecom Customer Lifetime Value & Churn Risk Dashboard with Service Usage Pattern Drill-Through" aims to design and develop an interactive analytics solution that provides comprehensive insights into customer behavior. The system integrates multiple data sources, including customer demographics, billing information, service usage records, and historical interactions, to generate meaningful analytics.

The dashboard calculates Customer Lifetime Value using predictive techniques and identifies churn risk based on key indicators such as reduced usage, irregular payments, and service complaints. It presents data through dynamic visualizations, including trend analysis, segmentation, and risk categorization, enabling decision-makers to quickly identify critical business insights.

A key feature of the system is the drill-through functionality, which allows users to navigate from high-level summaries to detailed customer-level data. This includes in-depth analysis of service usage patterns such as call duration, data consumption, and messaging behavior, helping to uncover the root causes of churn.

The system also supports real-time data updates, interactive filtering, and customizable views, improving usability and analytical efficiency. By leveraging advanced analytics and visualization techniques, the solution enhances decision-making, supports targeted marketing campaigns, and improves customer retention.

II. Literature Survey

Machine Learning and Cloud-Based Telecom Customer Analytics for Churn Prediction and CLV Estimation

Authors: Humble, J., & Farley, D.

This study provides a detailed overview of data-driven approaches for analyzing telecom customer behavior using machine learning and cloud-based analytics techniques. The authors emphasize the importance of automation in processing large-scale telecom datasets to improve customer experience, enhance retention strategies, and support data-driven decision-making. The research highlights how predictive models can be used to analyze customer usage patterns, billing history, and service interactions to identify churn risk and estimate Customer Lifetime Value (CLV).

The study explains that integrating multiple telecom data sources such as call detail records, internet usage logs, and customer service records enables a unified view of customer behavior. Machine learning algorithms applied to this integrated dataset improve the accuracy of churn prediction and customer segmentation, allowing telecom companies to take proactive retention actions.

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
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However, the study also identifies several challenges such as handling imbalanced datasets, selecting relevant features from high-dimensional telecom data, and ensuring scalability when processing large volumes of real-time information. It concludes that combining machine learning techniques with cloud-based analytics and interactive visualization dashboards significantly enhances business intelligence and supports better strategic decision-making in the telecom industry.

Cloud-Based Data Analytics and Machine Learning for Telecom Customer Churn and CLV Analysis

Authors: Amazon Web Services (AWS) Architecture Team

This study focuses on best practices for analyzing large-scale telecom customer data using cloud-based analytics and machine learning techniques. The research explains how integrating multiple telecom data sources such as billing systems, call detail records, and service usage logs enables a unified and comprehensive view of customer behavior. This unified data approach helps in identifying churn patterns and estimating Customer Lifetime Value (CLV) more effectively.

The study evaluates the use of cloud-based data processing frameworks and machine learning models for predictive analytics in telecom environments. It highlights how predictive models can classify customers into different risk categories based on usage behavior, payment history, and engagement levels. These insights help telecom organizations improve customer retention strategies and optimize revenue generation.

The authors conclude that combining machine learning techniques with interactive dashboards and cloud-based analytics platforms provides a scalable and efficient solution for telecom customer analysis. However, challenges such as data integration complexity, feature selection from heterogeneous datasets, and scalability issues in handling high-volume telecom data are also highlighted. The study emphasizes the importance of interactive visualization and drill-through capabilities for deeper customer-level insights.

Machine Learning and Cloud-Based Automation for Telecom Customer Analytics

Authors: Sharma, R., & Kumar, S.

This paper discusses the application of automation and machine learning techniques for analyzing telecom customer data in cloud environments. The authors examine the limitations of traditional telecom analytics systems that rely on manual reporting and fragmented data sources. These conventional approaches often fail to provide accurate predictions of customer churn and do not effectively estimate Customer Lifetime Value (CLV).

The proposed approach integrates multiple stages of data processing, including data collection, preprocessing, feature extraction, predictive modeling, and visualization, into a unified analytics framework. This enables telecom organizations to analyze large-scale customer datasets such as call detail records, billing information, and service usage logs in a more structured and efficient manner.

The study demonstrates that automated and machine learning–based analytics systems significantly improve prediction accuracy, reduce manual errors, and enhance decision-making capabilities. It also highlights that integrating predictive models with

International Journal of
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interactive dashboards allows better visualization of churn risk patterns and customer value segmentation.

However, the paper identifies challenges such as handling imbalanced telecom datasets, selecting relevant features from high-dimensional data, and ensuring scalability for real-time analytics. It concludes that combining machine learning techniques with cloud-based analytics and visualization tools provides a more reliable and efficient solution for modern telecom customer analysis systems.

III. System Analysis

The Telecom Customer Lifetime Value & Churn Risk Dashboard with Service Usage Pattern Drill-Through system is designed to analyze telecom customer behavior, predict churn risk, and evaluate customer lifetime value (CLV) using data analytics and visualization techniques. Telecom companies generate massive amounts of data from customer profiles, service usage records, billing details, subscriptions, and customer interactions. Analyzing this data helps organizations understand customer preferences, identify high-value users, and improve customer retention strategies. The system focuses on transforming raw telecom data into meaningful insights through advanced analytics and interactive dashboards. Data preprocessing techniques such as handling missing values, normalization, data cleaning, and feature engineering are applied to improve data quality and accuracy. Customer Lifetime Value analysis helps estimate the long-term profitability and importance of individual customers. Churn risk analysis identifies customers who are likely to discontinue telecom services based on usage patterns and behavioral indicators. Service usage pattern drill-through allows detailed analysis from overall customer summaries to individual service-level insights. Visualization dashboards represent customer segments, churn probability, revenue contribution, and service utilization trends effectively. The system enables telecom providers to improve customer satisfaction, optimize marketing strategies, and increase business profitability through data-driven decision-making.

Existing System

In the existing system, telecom customer analysis mainly depends on traditional reporting tools, manual analysis, and basic customer management systems. Companies usually monitor customer information using simple metrics such as subscription status, monthly revenue, and service usage reports. These traditional approaches provide limited insights and are not effective for analyzing large volumes of customer data generated by modern telecom networks. Existing systems mainly focus on historical customer information rather than predicting future customer behavior and churn possibility. Manual evaluation methods require more time and increase the chances of inaccurate analysis and decision-making. Traditional systems have limited ability to identify hidden patterns related to customer dissatisfaction, service usage changes, and retention risks. Existing approaches often fail to calculate accurate Customer Lifetime Value and prioritize valuable customers. Many systems lack advanced visualization features and drill-through capabilities for detailed customer-level analysis. They also provide limited support for personalized retention strategies and targeted marketing campaigns. As customer data continuously increases, traditional systems face scalability and performance challenges. These limitations

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create the need for an intelligent telecom analytics dashboard with predictive and interactive analysis capabilities.

Disadvantages of Existing System

- Requires high manual effort for customer analysis.
- Time-consuming customer report generation.
- Limited ability to predict customer churn.
- Poor Customer Lifetime Value estimation.
- Difficulty identifying customer behavior patterns.
- Lack of detailed service usage analysis.
- Limited interactive visualization support.
- Inefficient handling of large telecom datasets.
- Reduced accuracy in customer retention planning.
- Lack of personalized marketing and decision support.

Proposed System

The proposed Telecom Customer Lifetime Value & Churn Risk Dashboard with Service Usage Pattern Drill-Through system provides an intelligent analytics solution for predicting customer behavior and improving telecom business performance. The system collects and analyzes customer datasets including demographic details, subscription plans, call records, internet usage, billing information, customer interactions, complaints, and service history. Advanced preprocessing techniques such as data cleaning, missing value handling, normalization, and feature extraction are applied to prepare reliable datasets. Customer Lifetime Value analysis is performed to identify profitable customers and estimate their future contribution to business revenue. Churn prediction models analyze usage patterns, payment behavior, service complaints, and engagement levels to identify customers at risk of leaving. Machine learning algorithms such as Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and K-Nearest Neighbors can be implemented for churn classification and customer segmentation. The drill-through dashboard allows users to move from overall customer statistics to detailed individual service usage insights. Visualization tools represent churn trends, customer value groups, usage behavior, and revenue contribution clearly. The system helps telecom companies create effective retention strategies, improve customer experience, and optimize business decisions. Overall, the proposed system provides a scalable, automated, and data-driven solution for telecom customer analytics.

Advantages of Proposed System

- Automated telecom customer analysis.
- Accurate churn risk prediction.
- Improved Customer Lifetime Value estimation.
- Better customer segmentation.
- Identifies high-value customers effectively.
- Provides detailed service usage insights.
- Interactive dashboard and drill-through analysis.

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- Supports personalized retention strategies.
- Reduces customer loss and improves loyalty.
- Enables data-driven telecom decision-making.

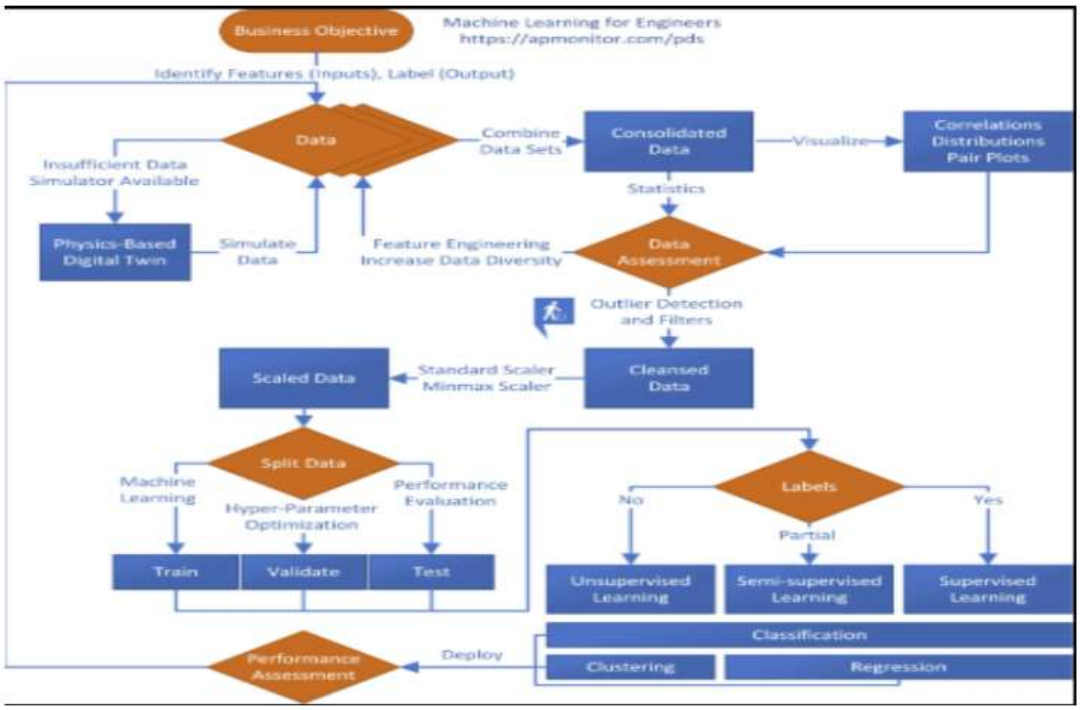
IV. Methodology

The methodology of the Telecom Customer Lifetime Value & Churn Risk Dashboard with Service Usage Pattern Drill-Through system consists of data collection, preprocessing, analysis, prediction, visualization, and insight generation phases. Initially, telecom datasets containing customer profiles, service subscriptions, usage history, billing records, complaints, and customer interaction details are collected from various sources. Data preprocessing techniques such as missing value handling, duplicate removal, normalization, feature selection, and transformation are applied to improve dataset quality. Exploratory Data Analysis is performed to understand customer behavior, usage trends, revenue patterns, and churn-related factors. Customer Lifetime Value analysis calculates customer profitability based on spending behavior, subscription duration, and service usage. Machine learning techniques are applied to predict churn probability and classify customers based on risk levels. Service usage pattern analysis identifies customer preferences, frequently used services, and engagement levels. Visualization dashboards display customer segments, churn rates, CLV scores, and service performance through interactive reports. Model performance can be evaluated using accuracy, precision, recall, F1-score, and confusion matrix. The generated insights help telecom providers improve retention campaigns, pricing strategies, and customer satisfaction. This methodology ensures accurate, scalable, and intelligent telecom customer analytics.

System Architecture

The system architecture of the Telecom Customer Lifetime Value & Churn Risk Dashboard with Service Usage Pattern Drill-Through follows a multi-layer design consisting of data collection, preprocessing, analytics, machine learning, visualization, and storage components. The data collection layer gathers customer details, subscription information, service usage records, billing history, customer feedback, and interaction data from telecom systems. The preprocessing layer performs data cleaning, missing value handling, normalization, encoding, and feature engineering to prepare accurate datasets for analysis. The analytics layer identifies customer behavior patterns, revenue trends, and service utilization insights using exploratory data analysis techniques.

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The churn prediction layer applies machine learning models to identify customers with a high possibility of leaving telecom services. The service usage drill-through layer provides detailed analysis from overall customer groups to individual service activities. The visualization layer generates interactive dashboards, graphs, charts, and analytical reports for business users. The backend layer manages data processing, model execution, and analytical workflows efficiently. The database layer stores raw customer data, processed information, prediction results, and generated insights securely. Overall, the architecture provides a scalable and intelligent framework for improving telecom customer retention, service optimization, and business growth.

V. Result and Output

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VI. Conclusion

The Customer Lifetime Value (CLV) system implemented in this project successfully demonstrates the ability of data-driven techniques to analyze customer behavior and predict long-term customer value. By leveraging data preprocessing, feature engineering, and analytical modeling, the system ensures accurate, consistent, and reliable CLV predictions.

The system efficiently handles customer data collection, cleaning, transformation, and model computation with minimal manual intervention. Its structured design allows seamless integration of multiple data sources, enabling continuous updates

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and real-time analysis of customer activity. The use of Recency, Frequency, and Monetary (RFM) analysis enhances the system's ability to capture meaningful customer insights.

Furthermore, the system demonstrates robustness by handling variations in data quality, customer behavior patterns, and dataset sizes while maintaining consistent prediction performance. Visualization and reporting features improve interpretability, allowing business users to easily identify high-value customers and make informed decisions.

In summary, this project showcases the practical application of Customer Lifetime Value analysis to improve customer segmentation, optimize marketing strategies, and enhance business profitability. The proposed system provides a scalable, efficient, and reliable solution for data-driven customer relationship management.

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