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Customer Churn Prediction And Retention Strategy Optimization For Subscription-Based Services Using Behavioural Data Analytics And Machine Learning Models

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ABSTARCT

This project presents a user-friendly Customer Churn Prediction and Retention Dashboard developed using Streamlit. The tool enables business users and analysts to upload customer datasets in CSV format, preprocess the data, and apply multiple machine learning models to predict customer churn. Supported models include Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, Gradient Boosting, XGBoost, LightGBM, and CatBoost. The dataset is automatically encoded and scaled for compatibility with the models. Once trained, the selected model predicts customer churn and evaluates performance using metrics such as accuracy score, classification report, and confusion matrix. The dashboard also computes churn probabilities and recommends retention actions for high-risk customers (e.g., offering incentives to those with a churn probability > 0.7). It includes visualizations such as churn distribution, retention action breakdown, and feature importance for better interpretability. This approach not only aids in understanding customer behavior but also supports proactive decision-making to improve retention. Users can download the enriched dataset with churn probabilities and retention strategies for further business use.

Key words: Customer Churn Prediction, Retention Strategy, Machine Learning, Streamlit Dashboard, Classification Models, Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, Gradient Boosting, XGBoost, LightGBM, CatBoost, Data Preprocessing, Feature Importance, Churn Probability, Predictive Analytics, Customer Retention, Data Visualization.

1. INTRODUCTION

In the modern era of data-driven economies and customer-centric business models, retaining customers has become a top priority across all service sectors. Among these, the telecommunications industry is particularly affected by customer churn, a phenomenon where existing subscribers discontinue services in favor of competitors. With competition intensifying, companies can no longer rely solely on marketing strategies for customer acquisition. Instead, focus has shifted toward understanding, predicting, and preventing customer attrition through intelligent and data-driven systems. Customer churn is not a new problem, but its implications are becoming increasingly severe. The cost of acquiring a new customer is significantly higher—by as much as five to ten times—than retaining an existing one, making churn prediction a critical component of strategic customer relationship management (CRM) [2], [13]. The telecom industry, in particular, faces high churn rates, with some markets experiencing customer attrition rates exceeding 30% annually [10]. Factors contributing to this include increased competition, changing consumer expectations, pricing pressures, technological advancements, and lack of personalized services. Businesses that can predict and proactively reduce churn stand to gain a significant competitive advantage [8].

What Is Customer Churn

Customer churn, also known as customer attrition or customer turnover, refers to the rate at which customers stop doing business with a company during a given period. It is a crucial metric for evaluating marketing effectiveness, customer satisfaction, and overall business performance [1].

- Definition: Churn rate is calculated as the percentage of customers who discontinue their subscriptions or stop using a product or service within a defined timeframe (e.g., monthly, quarterly, annually).
- Significance:
    - It directly impacts revenue and profitability, especially for businesses with recurring revenue models like Software-as-a-Service (SaaS) or subscription services [1].
    - High churn rates indicate dissatisfaction and potential issues with products, services, or customer support.
    - Acquiring new customers is often significantly more expensive than retaining existing ones, making churn reduction a critical aspect of sustainable growth [2].
- Types:
    - Voluntary Churn: Occurs when customers actively choose to stop using a product or service due to reasons like dissatisfaction, better offers from competitors, or changing needs.
    - Involuntary Churn: Happens due to factors beyond the customer's control, such as payment failures, accidental cancellations, or service disruptions.

- Causes: Churn can stem from various factors, including poor customer service, inadequate product features, high pricing, ineffective onboarding, technical glitches, or a lack of personalized engagement [13], [15]..

Retaining customers is more than a financial imperative; it is a strategic necessity. A loyal customer base contributes to a company's revenue stability and brand advocacy. Studies show that a 5% increase in customer retention can lead to a 25%–95% increase in profits. Moreover, retained Customer churn prediction aims to identify customers likely to discontinue services using historical and behavioral data. Machine learning (ML), a subset of artificial intelligence, provides powerful tools for detecting patterns that traditional analytics may overlook [10], [18]. Common models include Logistic Regression, Decision Trees, Random Forest, Gradient Boosting, XGBoost, LightGBM, CatBoost, Support Vector Machines, and K-Nearest Neighbors, each offering unique advantages in accuracy and interpretability [9], [10].

Customer churn, also known as customer attrition, occurs when a customer discontinues their subscription or service with a company. Churn can be categorized as voluntary or involuntary. Voluntary churn happens when customers actively choose to leave due to dissatisfaction, cost, service quality, etc., whereas involuntary churn occurs due to circumstances beyond their control, such as moving to an area without service coverage. Churn prediction aims to identify customers who are likely to leave, based on historical and behavioral data. Machine learning offers powerful tools to detect patterns and signals that are often imperceptible to traditional analytics. Machine learning (ML) is a subset of artificial intelligence that enables systems to learn from data and improve over time. In the context of churn prediction, ML models can be trained on historical customer data to identify at-risk customers with high accuracy. Commonly used models in churn prediction include Logistic Regression, Decision Trees, Random Forest, Gradient Boosting Machines (GBM), XGBoost, LightGBM, CatBoost, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN). Each model offers unique strengths in terms of interpretability, accuracy, and performance, and can be selected based on the business requirements.

The final step focuses on re-engaging at-risk customers through tailored strategies, ensuring their retention and satisfaction. This process, as highlighted by Leewayhertz, underscores the power of machine learning in transforming raw data into actionable insights. By predicting churn early, companies can implement timely measures, fostering long-term customer loyalty and driving business growth. The integration of pattern recognition and predictive analytics creates a robust framework for sustaining a thriving customer base. While predictive accuracy is crucial, model interpretability is equally important— especially in industries like telecom where business decisions must be transparent. Explainable AI (XAI) addresses the "black box" nature of most machine learning models by providing explanations for why a prediction was made. Two popular tools for XAI are SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations). SHAP uses a game-theoretic approach that assigns importance scores to each feature for a specific prediction. LIME explains individual predictions by approximating the model locally using an interpretable one. These tools help stakeholders understand the key drivers of churn and build trust in the predictive system. The telecom industry has massive datasets covering customer usage patterns, demographics, billing, service issues, and more. Leveraging this data through ML enables telecom companies to identify high-risk customers in real time, implement targeted marketing campaigns, offer personalized discounts or loyalty rewards, reduce operational costs related to customer service, and improve customer satisfaction and brand loyalty. By accurately predicting which customers are likely to churn and why, telecom companies can tailor retention strategies that maximize impact. This project aims to build a robust customer churn prediction model using multiple ML algorithms, evaluate and compare the performance of these models based on accuracy [6], [16], recall, precision, and AUC-ROC, implement an interactive dashboard using Streamlit to visualize and interpret model outputs, integrate SHAP and LIME for explainable predictions, and provide actionable recommendations for customer retention based on predictive insights [10]. The technology stack includes Python as the programming language, libraries and frameworks such as scikit-learn, XGBoost, LightGBM, SHAP, LIME, pandas, matplotlib, and seaborn. Deployment is carried out using Streamlit for dashboard UI. The dataset consists of a telecom customer churn dataset with more than 7000 records. Churn prediction is not without its challenges. Class imbalance is a significant issue since typically, churned customers form a minority, making it difficult for models to learn effectively. Data quality issues such as missing values, noisy data, and inconsistent formats require extensive preprocessing. Feature selection is critical to identify the most relevant predictors from a large set of variables. Model generalization is necessary to ensure models perform well on unseen data without overfitting. Interpretability must be maintained even with high-performing models, which are often less transparent. While the model is built for the telecom industry, the framework is adaptable across various domains like finance, insurance, and e-commerce [19] [20].

However, this project does not include real-time streaming data, handle multilingual customer data, or provide personalized retention messaging (but suggests retention strategies). Future enhancements could integrate deep learning models and real-time prediction systems. Customer churn prediction is a vital application of machine learning that helps businesses retain valuable customers. By integrating explainable AI and user-friendly dashboards, companies can make data-driven decisions that enhance customer loyalty.

This project demonstrates the feasibility, effectiveness, and practical impact of applying machine learning to solve a real-world problem in a high-stakes industry. The continued adoption and enhancement of such models will play a crucial role in helping businesses maintain a competitive edge in dynamic markets. To further elaborate on this perspective, the integration of predictive analytics into customer relationship management practices is not just an innovative advancement but a necessary evolution. Organizations that fail to adopt such solutions risk falling behind in customer satisfaction benchmarks, competitive positioning, and operational efficiency. Beyond prediction, these systems can act as early-warning mechanisms, alerting businesses to declining customer engagement before it culminates in churn. By intervening early, companies can optimize customer retention efforts and improve ROI on marketing and service initiatives.

Objective of the Project

The objective of the Customer Churn Prediction project is to develop a reliable, interpretable, and scalable machine learning system that can accurately identify customers who are likely to discontinue a service or subscription. The system is designed to assist telecom operators in proactively minimizing customer attrition by leveraging historical usage, billing, demographic, and service data. Using advanced classification algorithms and explainable AI methods, the project aims to not only predict churn with high precision but also provide insights into the key drivers of customer behavior. A secondary objective is to present these insights through an interactive dashboard interface (Streamlit), enabling business users to explore churn probabilities, evaluate model performance, and implement strategic retention actions such as personalized offers or loyalty campaigns.

2. LITERATURE SURVEY

[1] Linking Customer Satisfaction to Financial Performance Eklof et al. (2020) conducted a comprehensive empirical study on Scandinavian banks, examining the direct relationship between customer satisfaction and financial performance. The study reveals that higher customer satisfaction scores strongly correlate with increased profitability and reduced customer churn. In industries like banking and telecom, satisfaction serves as a predictive metric for customer loyalty. The authors argue that a structured feedback loop and customer-oriented culture enable organizations to make better strategic decisions, ultimately reducing operational risk and boosting shareholder value.

[2] Enhancing Customer Value with Market Culture: Madhani (2018) proposes a conceptual 7Cs framework focused on enhancing customer value through market-oriented culture. The study emphasizes the integration of core elements such as customer-centricity, communication, customization, and consistency in CRM strategies. The framework aligns well with churn prediction models as it provides a foundation for understanding factors that influence customer retention. In a competitive telecom landscape, adopting a customer-focused approach driven by data analytics can significantly improve churn mitigation efforts.

[3] Deep Learning for Churn Prediction: Chouiekh (2020) explores the application of deep convolutional neural networks (CNNs) for customer churn prediction. The research highlights the ability of CNNs to learn hierarchical data representations, leading to more accurate predictions in complex datasets. Although more computationally expensive than traditional methods, deep learning models have shown superior performance in capturing nonlinear relationships and behavioral patterns. This study supports the use of deep models for telecom churn analytics, especially when working with rich, high dimensional datasets.

[4] The Rise of Explainable Artificial Intelligence (XAI): Duval (2019) introduces Explainable AI (XAI) as a crucial advancement in making machine learning models transparent and accountable. The scholarly report emphasizes the need for interpretability in AI systems, especially in sensitive domains like telecom churn prediction where decisions directly impact customer experience. The work outlines various XAI tools, such as SHAP and LIME, that help bridge the gap between model complexity and business understanding. These tools empower decision-makers by revealing the rationale behind model predictions.

[5] Machine Learning in Telco Churn Use Cases: Reilly (2023) presents a technical overview of how machine learning is revolutionizing churn prediction in the telecom sector. The article discusses real-world implementations using platforms like Akkio and outlines the benefits of automation in identifying at-risk customers. With real-time scoring and proactive intervention, telcos can significantly reduce churn rates. The paper highlights ensemble methods such as XGBoost and LightGBM for their accuracy and scalability, making them ideal for high-volume telecom data.

[6] Sequential Feature Selection with Naive Bayes: Yulianti and Saifudin (2020) focus on improving churn prediction accuracy using sequential feature selection techniques with a Naive Bayes classifier. Their method identifies optimal subsets of features that maximize model performance while reducing dimensionality. This approach aligns well with the telecom domain, where datasets often contain a mix of categorical and continuous variables. Their findings support feature engineering as a critical step in building robust and interpretable predictive systems.

[7] XAI for Data Science in Customer Churn: Leung et al. (2021) discuss the application of Explainable Artificial Intelligence in customer churn modeling. Their research emphasizes that as predictive models become more complex, interpretability becomes vital for adoption in enterprise settings. The study uses case examples from the telecom industry to show how feature importance and local explanations from SHAP can help CRM teams understand churn drivers and formulate actionable strategies. This bridges the gap between data scientists and business managers.

[8] Ensemble-Based Classifiers in Telecom Churn: Mishra and Reddy (2017) conduct a comparative analysis of ensemble classifiers like Bagging, Random Forest, and AdaBoost in the context of telecom churn prediction. Their results show that ensemble models consistently outperform individual classifiers in terms of accuracy and generalization. The paper argues that the combination of multiple weak learners helps in minimizing variance and bias, making ensemble methods a strong fit for imbalanced telecom datasets.

[9] Hybrid Logistic Regression and Decision Trees: De Caigny et al. (2018) propose a hybrid model that combines logistic regression with decision trees to enhance predictive power. This novel approach leverages the interpretability of logistic regression and the non-linear learning capabilities of decision trees. The hybrid model is particularly effective in understanding complex customer behavior in sectors like telecom and banking. The study supports hybrid systems as a viable option when balancing interpretability and accuracy.

[10] ML-Based Customer Churn Systems: Lalwani et al. (2022) present a full-scale customer churn prediction system using machine learning algorithms. The system includes data preprocessing, feature selection, model training, and deployment. The authors demonstrate that integrating multiple classifiers and performance metrics leads to robust systems suitable for telecom operators. They emphasize real-time scoring and decision automation as future advancements for such systems.

[11] BP Network Optimization for Churn: Yu et al. (2018) explore a Particle Swarm Optimization-based backpropagation (BP) network to improve churn prediction in telecommunications. Their model outperforms traditional neural networks in both accuracy and convergence speed. The paper underscores the potential of hybrid optimization techniques in fine-tuning model parameters and improving prediction stability. It highlights the evolving role of metaheuristics in telecom analytics.

[12] Deep Learning in Telecom Churn Prediction: Fujo et al. (2022) apply deep learning architectures, specifically feedforward and recurrent neural networks, to customer churn prediction tasks in telecom. Their results show high precision and recall, demonstrating the models' effectiveness in capturing sequential patterns in customer data. The study supports adopting deep learning when large volumes of customer behavior data are available, such as call logs and billing records.

[13] Role of e-CRM in Customer Retention: Kampani and Jhamb (2020) perform a literature review on the evolution of electronic Customer Relationship Management (e-CRM). They argue that e-CRM plays a crucial role in digital customer retention by enabling personalized communication, loyalty programs, and predictive support. Their study supports integrating predictive churn models within e-CRM frameworks to maximize customer engagement.

[14] Analytical CRM and Competitive Intelligence: Nelson et al. (2020) explore the impact of analytical CRM tools on a salesperson's use of competitive intelligence. The study emphasizes how CRM systems can support churn analysis by providing behavioral insights and competitive benchmarks. In the telecom domain, such integration allows for the early identification of churn risks and competitive threats.

[15] Components of CRM Systems: Al-Homery et al. (2019) outline the core components and typologies of CRM systems, emphasizing the role of operational, analytical, and collaborative CRM in customer management. Their classification provides a foundational understanding for deploying churn prediction systems that align with existing CRM infrastructures. It also highlights how analytical CRM enhances data utilization in churn modeling.

3. PROPOSED SYSTEM

The proposed system aims to develop an intelligent, explainable, and interactive solution for predicting customer churn in the telecom sector using machine learning and data visualization techniques. The system is structured to handle end-to-end processes including data ingestion, preprocessing, feature engineering, model training, evaluation, interpretability, and dashboard deployment.

The system begins by allowing users to upload a telecom customer dataset in CSV format. It preprocesses the data by handling missing values, encoding categorical variables, and normalizing features. This ensures consistency and improves model performance. The system then enables users to select and apply various classification algorithms such as Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, XGBoost, LightGBM, and CatBoost.

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To evaluate model performance, the system provides accuracy, confusion matrix, precision, recall, F1-score, and ROC-AUC. Additionally, the inclusion of SHAP and LIME allows users to interpret the reasoning behind predictions, thus building trust and transparency in the AI model. These interpretability tools help highlight which features most influence a customer's likelihood to churn.

The front-end component is developed using Streamlit, providing an intuitive dashboard where users can select models, visualize churn distribution, explore feature importance, and view customer-specific churn probabilities. A retention recommendation is also generated based on churn probability thresholds (e.g., sending offers to high-risk customers).

Overall, the proposed system not only predicts churn but also empowers telecom service providers to take proactive retention actions through a user-friendly, explainable, and efficient platform.

Advantages of Proposed System

- High prediction accuracy
- Early identification of at-risk customers
- Automated and scalable solution
- User-friendly dashboard
- Supports business decision-making
- Reduces customer churn rate
- Improves customer satisfaction
- Increases company profit

3.1 SYSTEM ARCHITECTURE

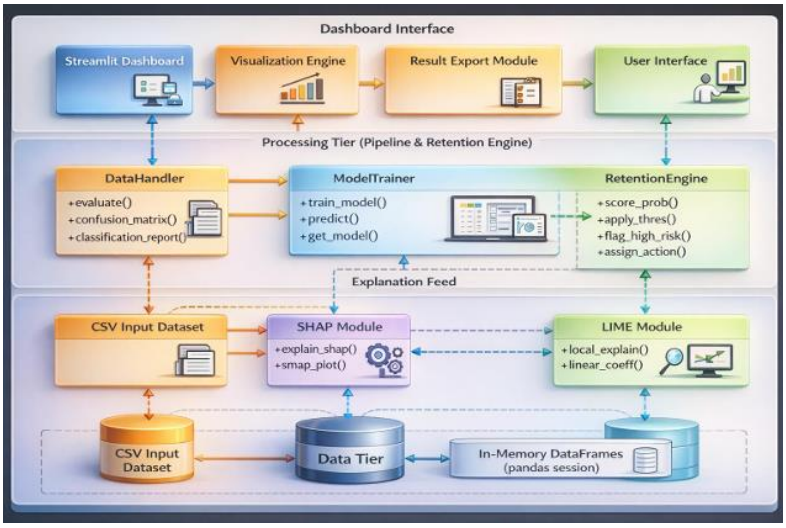

Fig 1: System Architecture

3.2 Use case Diagram

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are

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performed for which actor. Roles of the actors in the system can be depicted. Use case diagrams are considered for high level requirement analysis of a system. When the requirements of a system are analyzed, the functionalities are captured in use cases. The name of a use case is very important. The name should be chosen in such a way so that it can identify the functionalities performed.

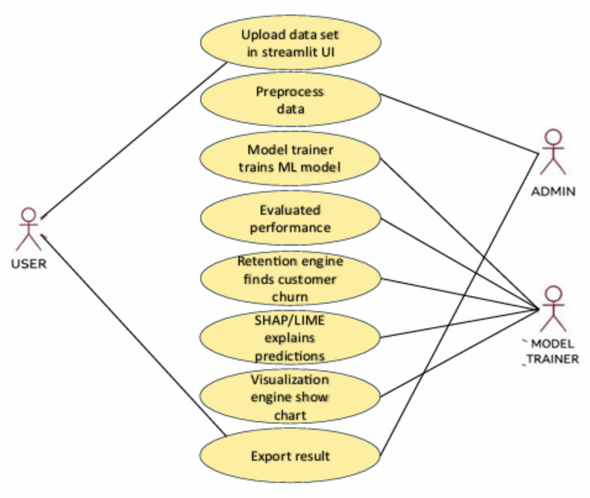

Fig 2: Use Case Diagram

3.3 Class Diagram

In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information. The class diagram is used to refine the use case diagram and define a detailed design of the System. The class diagram classifies the actors defined in the use case diagram into a set of interrelated classes. The relationship or association between the classes can be either an "is-a" Or "has-a" relationship.

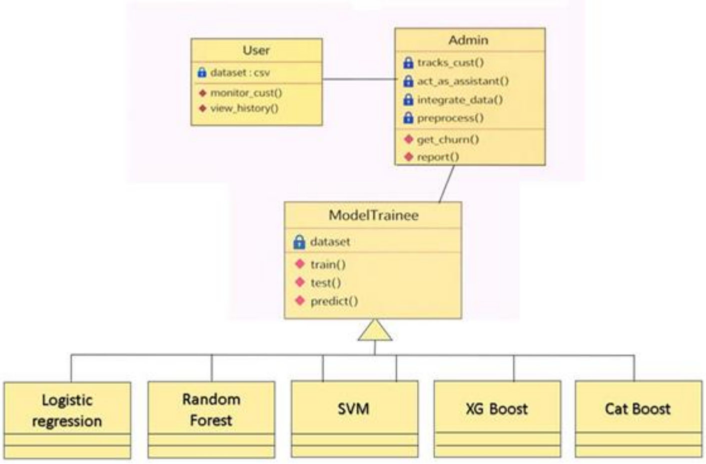

Fig 3: Class Diagram

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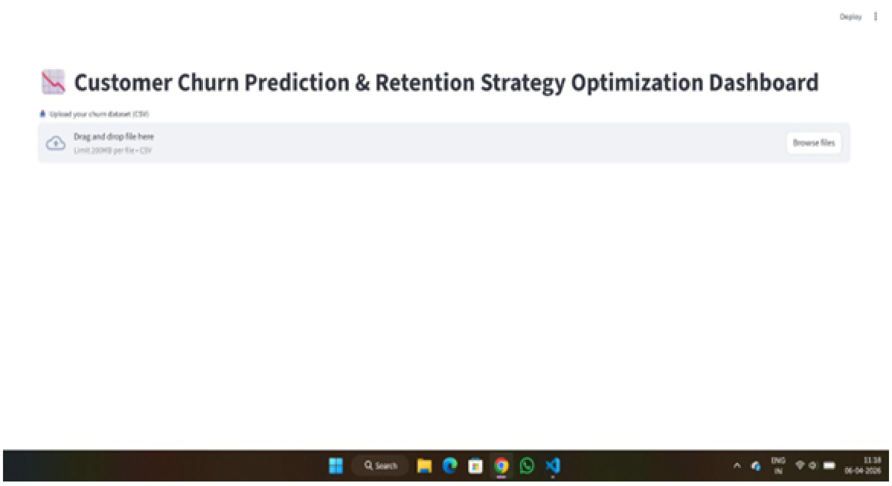
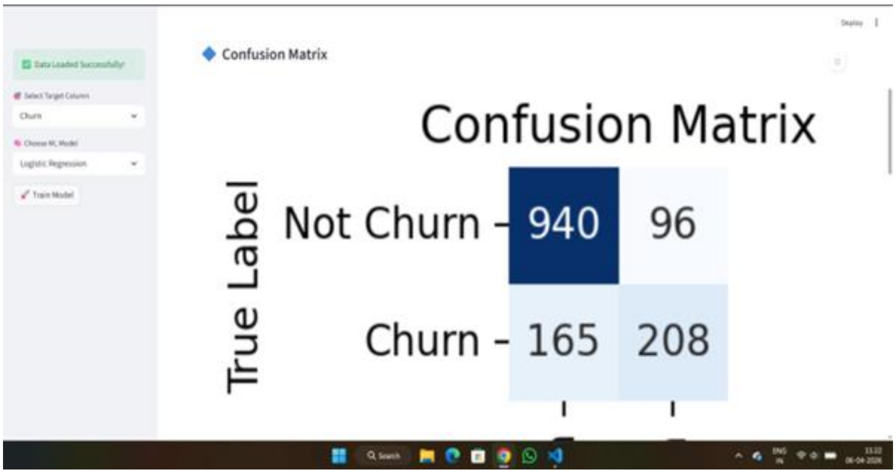
4. RESULTS

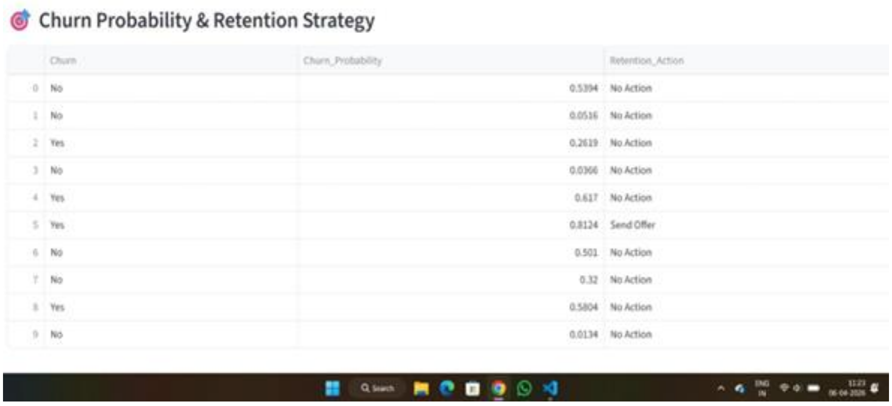
Dashboard Home Page



Confusion Matrix



Churn Probability & Retention Strategy


Churn Probability & Retention Strategy

	Churn	Churn_Probability	Retention_Action
0	No	0.5394	No Action
1	No	0.0516	No Action
2	Yes	0.2619	No Action
3	No	0.0366	No Action
4	Yes	0.617	No Action
5	Yes	0.8124	Send Offer
6	No	0.501	No Action
7	No	0.32	No Action
8	Yes	0.5804	No Action
9	No	0.0134	No Action

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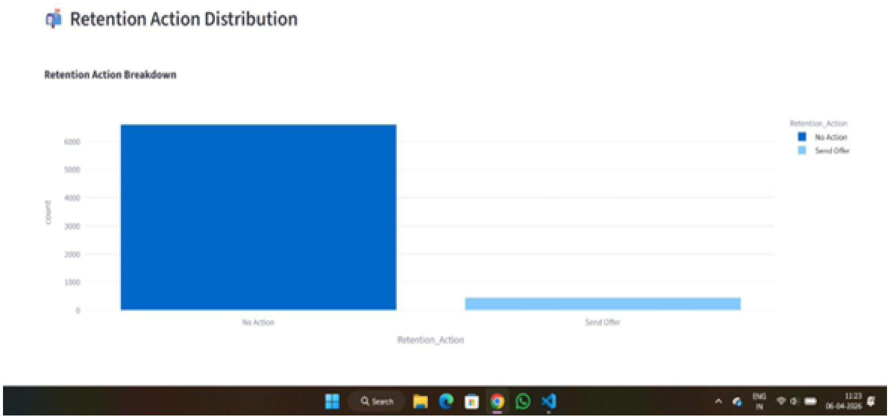
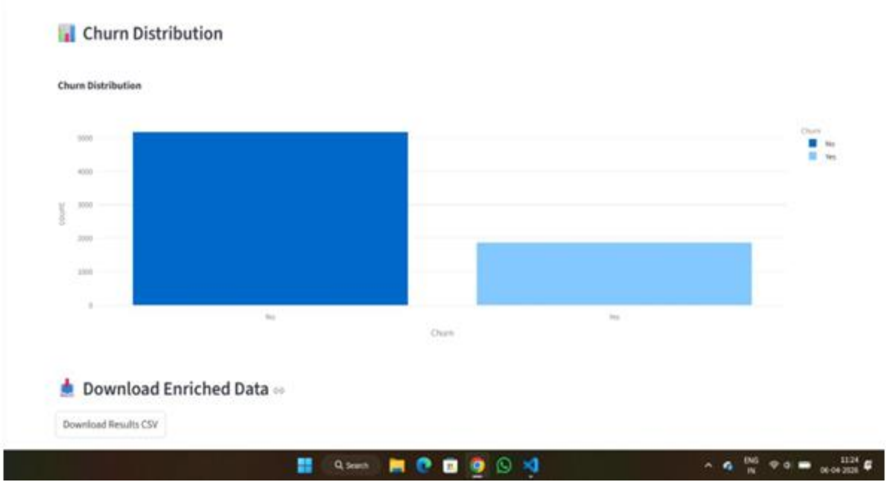
Retention Action Distribution Chart



Churn Distribution Chart and Download Enriched Results



5. CONCLUSION

The Customer Churn Prediction and Retention Dashboard successfully demonstrates how machine learning can solve real-world telecom business challenges by identifying at-risk customers and supporting retention strategies. Using models like Logistic Regression, Random Forest, and XGBoost, along with explainability tools such as SHAP and LIME, the system ensures both accuracy and transparency. The Streamlit dashboard makes it user-friendly for non technical users to analyze data and gain insights. With strong evaluation metrics and features like churn probability and retention recommendations, the system effectively converts data into actionable insights, enabling better decision-making, improved customer satisfaction, and increased profitability.

6. FUTURE SCOPE

The system effectively handles churn prediction and retention but can be further improved for real-time and enterprise use. Integrating real-time streaming tools like Apache Kafka or Apache Spark Streaming can enable instant predictions. Expanding to multiclass and time-series models, along with NLP-based sentiment analysis, can enhance accuracy. Integration with CRM platforms like Salesforce or HubSpot can automate retention actions. Additionally, auto-tuning, model monitoring, and cloud deployment (AWS, GCP, Azure) can improve scalability, while gamified rewards can boost customer engagement and retention.

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