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Development of XAI-Driven Churn Prediction Framework for Proactive Retention in Telecom

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In the telecommunications industry, customer churn is a major problem that has a big influence on profitability and competitiveness. Current systems mostly rely on reactive strategies that are unable to prevent churn proactively. We present an intelligent, explainable AI-driven system, TeleChurnAI, which predicts churn and pinpoints its root causes. The novelty of this research lies in its integration of explainable AI and customer segmentation, providing useful information for retention strategies. To develop TeleChurnAI, a machine learning model, CatBoost, is employed to accurately predict churn, and SHAP (Shapley Additive explanations) is utilized to interpret model results as well as to support predictions. The prediction accuracy and interpretability of the model are assessed after it is trained on the historical telecom customer dataset, "Telco Customer Churn". We found that TeleChurnAI offers transparency through visual explanations of churn risk factors and significantly increases the accuracy of churn predictions. Through an interactive dashboard made for CRM professionals with different levels of technical expertise, using the Shiny framework in Python, the system also divides up the customer base according to demographic and behavioral trends, allowing for targeted retention actions. In addition to helping with early intervention, this dual capability lowers marketing expenses and boosts customer loyalty. In conclusion, TeleChurnAI provides a thorough and user-centered method for telecom churn management. In the future, we aim to integrate sentiment analysis and real-time prediction in our proposed system.

Keywords: Churn Prediction; Explainable AI; Customer Segmentation; Shap Values and Catboost.

Introduction:

In the telecommunication sector, where keeping current clients is far more economical than finding new ones, customer churn is still a major problem. Conventional churn prediction techniques frequently depend on rigid, rule-based methodologies that are unable to adjust to changing consumer behavior and provide little actionable insight for telecommunication professionals. These drawbacks have brought attention to the necessity of data-driven, interpretable, and intelligent systems that can proactively prevent churn.

Over the years, research has shifted towards deep learning and machine learning models, which capture intricate behavioral patterns and provide high prediction accuracy. Neural architectures like CNNs, LSTMs, and hybrid CNN-GBM frameworks have demonstrated good performance, as have ensemble models like Random Forest, Gradient Boosting Machines, and AdaBoost. Additionally, explainable AI (XAI) techniques like SHAP (Shapley Additive exPlanations), which assist in identifying the primary causes of customer churn, and SMOTENC for balancing have been used to address issues like class imbalance and black-box model opacity.

Recent developments have highlighted how crucial it is to divide up your customer base according to their churn risk and behavior. Research indicates that retention rates can be considerably increased by combining customer segmentation with personalized marketing tactics and predictive modeling. Additionally, contemporary systems incorporate visual tools and dynamic dashboards that give CRM professionals easy access to retention actions, insights, and predictions.

In order to meet these demands, we present TeleChurnAI, a complete churn prediction platform that integrates customer segmentation via a dynamic dashboard, machine learning (CatBoost), and SHAP for explainability. CRM professionals can use the system to segment customers for targeted retention, upload data, interpret key influencing features, and create churn predictions. It overcomes the shortcomings of previous models in terms of interpretability and prediction accuracy.

The format of this paper is as follows: Section II represents a literature review, Section III represents the *Materials and Methods*, describing the investigation context, data sources, modeling techniques, and system architecture used to build TeleChurnAI. Section IV provides the *Interface* outlining the design and functionality of the system. Section V outlines the *Results and Discussion*, where experimental findings are analyzed, model performance is evaluated, and the usefulness of explainable AI and segmentation is highlighted. Section VI provides the *Conclusion* along with future work and recommendations.

The goal of this research is to create an understandable and intuitive churn prediction system that enables telecommunication providers to use segmentation and predictive insights to proactively retain customers. Explainable AI, segmentation, and dynamic visualization are all combined into one platform in this work, which fills the gaps in existing churn prediction systems by providing both accuracy and interpretability for well-informed decision-making.

Objectives and Novelty Statement:

Creating TeleChurnAI, an explainable AI-driven framework for proactive churn prediction and customer retention in the telecom industry, is the main goal of this research. By offering precise forecasts, comprehensible outcomes, and actionable insights via an interactive dashboard, the system seeks to empower CRM professionals. It tackles important churn prediction issues like targeted intervention, model transparency, and class imbalance.

The novelty of this research lies in the integration of multiple advanced components into a unified platform, including:

Utilizing the CatBoost classifier because of its exceptional ability to handle imbalanced and categorical data

Using SHAP values to improve decision credibility and model explainability

SMOTENC implementation for reliable mixed-type data resampling

Deployment of a dynamic dashboard for customer segmentation and real-time interaction using Python's Shiny framework.

As a practical and scalable solution for real-world telecom environments, TeleChurnAI offers both predictive power and interpretability, in contrast to other models that operate as black-box systems or lack actionable segmentation.

Literature Review:

In this section, the literature survey provides a comprehensive review of research papers. These papers focus on Machine and Deep Learning based churn systems contributing to churn prediction and reduction in the telecommunication sector. The different research results revealed that customer retention appears to be significantly more cost-effective than attracting new customers. This leads telecom providers to emphasize the importance of understanding customer churn behavior, identifying at-risk customers, planning and implementing tailored marketing campaigns and offers through data-driven insights. The reviewed studies investigated the effectiveness of different approaches in improving customer retention and leading to enhanced decision-making for CRM professionals. It also explores the challenges, including data imbalance, lack of explainability, and how recent innovations are addressing them. This literature review highlights the transition from traditional churn models to more intelligent and explainable approaches. In the latest research, ensemble learning methods, classification algorithms, neural networks, and hybrid models have emerged significantly as powerful tools for predicting churn with high accuracy. Integration of Explainable AI (XAI) has also enabled researchers and businesses to make better interpretations for predictions and to justify their actions taken for customer retention. The development and implementation of efficient and intelligent customer churn prediction systems have a significant impact on how telecom providers develop strategies to identify and retain high-risk customers. Studies have concluded that the traditional churn prediction models usually fall short because of their static nature and limited interpretability, which often leads to scenarios where opportunities for timely intervention are missed [1]. In contrast to these models, modern machine learning models such as ensemble learning, deep neural networks, and hybrid frameworks offer high accuracy and actionable insights. By leveraging a diverse number of features, including customer demographics, service usage, billing history, and behavioral patterns that contribute highly to understanding the churn risk [2]. Explainable AI (XAI) has been widely integrated to handle the black box nature of machine learning models. For instance, studies using SHAP (Shapley Additive exPlanations) values have helped in interpreting predictions, providing explanations on which features influence customers' likelihood to churn the most, empowering CRM professionals to take tailored actions [3]. Several studies have also highlighted the advantages of ensemble models, including Random Forest, Ada Boost, and Gradient Boosting Machine (GBM). The studies suggested that ensemble models had shown consistency in outperforming the single learners in predictive accuracy and generalizability. Moreover, deep learning models like CNN, LSTM, and hybrid CNN-GBM models have shown proven performance in capturing complex patterns within customer behavior data. Alongside these, uplift modeling and hybrid deep learning frameworks such as CN-GBM, LSTM, MLP with SMOTE have been proposed for improving performance and for handling class imbalance issues. Such innovative approaches ultimately contribute to increased precision and accuracy in identifying at-risk customers [4]. Another major aspect studied in the literature review is the integration of customer segmentation in churn prediction systems. Segmenting customers into different customer profiles encourages companies to develop and implement tailored retention strategies, resulting in a high retention rate. Additionally, models helping in early churn prediction have demonstrated potential for proactive interventions, being the most effective when combined with customer segmentation and tailored marketing campaigns, enabling the telecom industries to engage with customers before they decide to leave their service [5]. This literature review examines studies that focus on the impact of an accurate and reliable churn prediction system on customer satisfaction, the quality of service being provided, and actionable insights. Through analysis of different approaches, this section aims to explore the different benefits and limitations that each system has to offer and how they contribute to the telecom industry for improved efficiency.

Over the years of technological advancements, machine learning and deep learning have emerged as a transformative tool for customer churn prediction systems in the telecommunication industry, where retaining customers is highly crucial and more cost-effective than acquiring new ones, resulting in long-term profitability. [6] Machine learning algorithms are intelligent enough to analyze and learn patterns from the provided data to predict churn. They could identify high-risk customers and offer actionable insights for intervention. Such systems enable organizations to identify high-risk customers at an early stage. [1] It also helps them to make data-driven decisions to maximize customer loyalty. As churn prediction has evolved through deep learning, CRM professionals now tend to rely more on such systems, highlighting the importance of the shift from traditional systems to more modern and advanced systems for informed retention strategies in CRM practices.

Traditional models for the prediction of churn usually rely on some basic statistical methods, static reporting, or manual analysis. This ultimately lacks adaptability and the capability of working in real-time scenarios. Such models are inefficient in analyzing and extracting complex patterns and relationships from customer behavior, and in scaling as the size of the dataset increases. [7] They cannot also predict in real time. These models are usually referred to as the black- box models [6] as they don't provide an explanation that supports their prediction, leading to a dilemma for the users to trust in their predictions. These limitations are a driving factor behind the development of more modern systems that can help CRM professionals to meet customer expectations and withstand the competition in the telecom industry. Modern telecom systems require more dynamic and interpretable models like those incorporated in TeleChurnAI to fill this gap.

Various studies have been conducted testing out how machine learning and deep learning models, including Random Forest, Gradient Boosting Machine, CNNs, LSTM, MLPs, and hybrid models, outperform the traditional churn prediction models. [6] These modern and advanced models utilize complex features such as tenure, preferred payment methods, usage history, and interaction with customer support to capture non-linear patterns from customer data to make predictions for customer churn with high accuracy. On the other hand, ensemble models also contribute to further boosting the model performance by combining multiple weak learners to achieve more reliable predictions across diverse datasets and to improve robustness and generalization.

The timely identification of customers at high risk of churn is very crucial for telecom providers. TeleChurnAI works by empowering CRM professionals with flexible, on-demand batch prediction capabilities, enabling them to analyze data and detect patterns whenever needed. This system allows them to upload datasets and get instant churn probabilities against each customer, which can be used to create segments of customers. [3] It also provides the key factors that contribute to churn. These actionable insights through batch processing make the system support timely decision-making without any complexity of handling real-time infrastructure. As CRM professionals can identify customers with a high risk of churn, they can implement customized and personalized retention strategies. This approach helps CRM professionals to work efficiently by allowing them to detect churn more accurately through large and diverse datasets.

The accuracy and reliability of a machine learning model are significantly dependent on how input features are prepared and optimized for the model. [8] Special emphasis has been placed on feature engineering in TeleChurnAI to select input features for model training, resulting in improved predictive performance. Manual feature selection is carried out in the development of this system by selecting the most relevant attributes from the dataset based on domain knowledge. Features including contract type, tenure, payment method, monthly charges, service, subscription type (streaming TV, online security), and customer demographics (senior citizen, dependents) were selected for model training. These were identified as valuable indicators of churn. Furthermore, the performance of the model was improved through model tuning, leading to a high generalizability of the CatBoost classifier.

[9] The process was carried out by manually adjusting the key hyperparameters by experimenting and evaluating different values iteratively. Several iterations was set to control how long the model would keep on training to maintain a balance between overfitting and underfitting. Through the application of feature engineering and model tuning strategies, TeleChurnAI significantly enhances the accuracy and overall effectiveness of the model in churn prediction.

One of the key challenges associated with machine learning models is their lack of interpretability. Different explainable AI (XAI) techniques exist to overcome this issue. TeleChurnAI effectively uses SHAP [4]to bridge this gap and to offer explanations of how much each feature contributes to customer churn. This helps in understanding the predictions made by the model. This approach helps bridge the gap between complex models and human understanding by highlighting the importance of understanding the real reasons behind customer churn. This leads to model transparency, resulting in trust and reliability with CRM professionals.

Clear and easy-to-understand visualizations of the data help to interactively understand customer trends. [4] TeleChurnAI integrates the feature of a dynamic dashboard developed using the Shiny framework in Python to provide a user-friendly interface for CRM professionals by simplifying complex outputs into intuitive visualizations to explore churn trends in the provided data. A dynamic dashboard integrates dynamic filtering and multiple visualizations to analyze customer data while keeping it user-friendly. Multiple value boxes are added to the dashboard to display the key metrics, including total customers, churning customers, loyal customers, churn rate, retention rate, and customer lifetime value (CLV). Moreover, different interactive visualizations, including a data table, ridge plot, pie chart, line chart, and bar chart, are also included. Each of them represents critical information that helps significantly in identifying patterns in churn behavior.

Customer segmentation plays a crucial role in the development and implementation of personalized and customized marketing and retention strategies to minimize churn as much as possible. [10] TeleChurnAI segments the customers using the batch prediction output into high- and low-risk categories. As telecom providers know exactly how many and which customers fall into the category of high risk and the reasons behind it, they can design and implement retention strategies tailored to each group effectively.

As modern machine learning-based churn prediction models offer powerful capabilities, they also come with some practical challenges. Major challenges include data imbalance, model overfitting, [11] the quality and availability of input data for model training, some ethical concerns regarding data privacy, and changes in customer behavior. Other technical issues should also be addressed, such as model interpretability, data imbalance, and feature handling. TeleChurnAI mitigates these challenges through the integration of the explainable AI technique, SMOTENC, to handle the issue of unbalanced data, and utilizing CatBoost's built-in ability to handle categorical features, making the preprocessing steps much easier and simpler.

Implementing machine learning, explainable AI (XAI) [4], and customer segmentation [3] in churn prediction systems has revolutionized how such systems are implemented and trusted in the telecommunications industry. TeleChurnAI integrates data analytics, predictions, and user-friendly visualizations altogether to offer a reliable, transparent, and powerful solution for CRM professionals. This system also helps in developing and implementing tailored campaigns and strategies, appearing as a strong foundation for customer retention. Such systems ultimately help telecom providers to stand out from their competitors by reducing churn effectively and optimizing their relationship with customers.

Material and Methods:

Investigation Site:

Due to the competitive market and high cost of acquiring new users, the telecommunications sector is the focus of this study. The telecom industry is very relevant for predictive analytics research because of the rising churn rate, especially in developing nations like Pakistan. Without transparent customer feedback or regional behavioral datasets, telecom companies find it difficult to understand why customers leave.

We used publicly accessible global datasets to simulate customer behavior and churn scenarios because there aren't many publicly available, localized telecom datasets. Because these datasets replicate the kinds of features commonly found in telecom customer databases, the research is applicable and flexible enough to be used in real-world settings. Further customization of churn factors to regional drivers would be possible if region-specific data from organizations such as the Pakistan Telecommunication Authority (PTA) were made available in the future. The industry's readiness for useful, AI-driven solutions like TeleChurnAI is further demonstrated by the requirement for explainable and interpretable models for CRM decision-makers.

Material and Methods:

Data Collection:

The primary dataset was acquired from a publicly available source on Kaggle [12]. It contains 7,043 records with 21 features, including customer demographics, service usage, billing, and contract data. To enhance model robustness, two additional datasets were integrated, and after cleaning and preprocessing, a final dataset of 14,000 records and 17 relevant features was obtained. Key attributes include:

Table 1. Key Attributes of the Dataset

Customer Demographics	age range, gender, senior citizen
Service Details	multiple lines, phone service, internet service
Billing Information	monthly and total charges, payment method
Contract Tenure	month-to-month, one-year, two-year
Customer Status	churned or active

These features reflect the data typically used in real-world telecom churn models, making the framework practically implementable with minimal customization.

Data Preprocessing and Feature Engineering:

Various preprocessing techniques were applied to clean and transform the data. To ensure the quality of data, missing values were first handled carefully. To detect and replace invalid entries (like blank strings) with NaN, the numerical columns tenure, monthlycharges, and totalcharges were converted to numeric format using pd.to_numeric with errors='coerce'. Forward fill (ffill), which propagates the last valid value downward to ensure continuity without introducing arbitrary imputations, was then used to address these missing values.

To improve the dataset's suitability for machine learning models, feature engineering was then carried out. Contract, internet service, online security, and other categorical columns were all specifically changed to the category data type. This eliminated the need for extra encoding by enabling the CatBoost model to handle these features natively as categorical variables. The target column, churn, was also converted to string format to ensure compatibility with downstream processes such as resampling.

Table 2. Summary of Related Work

Citation	Technique	Strengths	Weaknesses
Panimalar et al. (2025) [6]	MBP-WMLP (Multipath Back Propagation with Weighted Multi-Layer Perceptron)	Offers better accuracy, learns fast, and focuses more on the important features	Risk of overfitting, harder to interpret, and lacks deployment in the real world.
Chang et al. (2024) [13]	Decision Trees, Random Forest, Boosted Trees, Logistic Regression, KNN, Naive Bayes, LIME, SHAP	Offers high accuracy, results are interpretable using explainable AI, ap- appropriate for real-world decision-making.	Restricted access to data, some models are less interpretable, tuning issues, and the problem of the black-box nature of models.
Adeniran et al. (2024) [1]	Decision Trees, SVM, Random Forest, GBM, Logistic Regression, RNN/LSTM (for sequential data)	Able to handle large-scale and complex telecom data, highly accurate and scalable, offers real-time processing, promotes tailored retention and au- automation	Some models lack Interpretability (e.g., deep learning); are computationally intensive; problems in data quality, model tuning, and ethical data use.
[Wagh et al. (2024) [2]	ML classifiers (Random Forest, KNN, Decision Tree, SVM, Naive Bayes, Logistic Regression), SMOTE, Cox Proportional Hazards model	High accuracy, provides reliability with retention timing data	Computational challenges with complex data, over-fitting, possible assumption failures in Cox and Naive Bayes, Class imbalance leading to bias or noise, and feature selection is limited to linear correlation
Poudel et al. (2024) [3]	Gradient Boosting Machine (GBM), SVM, Logistic Regression, Random Forest, Neural Networks, and SHAP	GBM offers the highest accuracy, good predictive performance, and provides explainability with SHAP plots	The model misses out on some churners, leading to revenue loss; some non-churners are wrongly labeled, leading to resource wastage; and the overall performance of the system needs to be improved.
Saha et al. (2024) [14]	Ensemble Learning (RF, ERT, XGB, GBM, Ad- aBoost, Bagging, Stack- ing), Traditional ML (Lo- Logistic Regression, Deci- sion Tree, kNN), (ANN), (CNN)	Behavioral patterns successfully captured in 1D data due to high accuracy (CNN, 99 percent). ANN and CNN outperform other techniques, combine multiple models for prediction, and manage both classification and regression tasks well.	KNN and logistic regression may perform poorly on complex patterns. CNN requires more training time, and DT may overfit withoutpruning. Ensemble techniques may be computationally expensive.
Senthilselvi et al. (2024) [7]	Logistic Regression, KNN, LightGBM, XGBoost, HistGB, CatBoost, Hyperparameter tuning using Optuna	Strong predictive performance, model effectiveness improved by using Optuna	Results may not scale, ignore non-linearities, model complexity, and computational cost,

			resulting in limited generalizability due to the small, fictional dataset.
Thanam et al. (2024) [15]	Logistic Regression, KNN, Decision Tree, Random Forest, SVM	Strong predictive performance achieved by RF, thorough model comparison, and practical churn reduction insights	Limited generalizability due to a small dataset; lacks interpretability, and has high computational costs
Kumar et al. (2024) [9]	Decision Tree, Random Forest, SMOTE-ENN	Offers high accuracy, interpretable models, efficient handling of class imbalance, and identification of the main churn drivers	Without resampling, the initial models' accuracy was low. Decision trees can overfit
Krishna et al. (2024) [10]	Logistic Regression, SVM, Random Forest, Gradient Boosting, SMOTE	Offers comprehensive data insights, enhanced feature scaling, robust accuracy, effective handling of class imbalance, and model interpretability.	Overfitting, heightened complexities, possible noise from artificial data, and restricted capacity to manage non-linear relationships or anomalies.
Rabih et al. (2024) [16]	Multilayer Perceptron (MLP) classification	Provides strong handling of class imbalance, offers high accuracy, and efficient utilization of features.	May encounter difficulties with the interpretability of the model and possible overfitting, requiring additional improvement in transparency and refinement.
R. Seethalak- shmi and B.Swarna Varsha (2024) [11]	GRU (Gated Recurrent Unit), BiLSTM (Bidirectional Long Short-Term Memory), Hybrid GRU + BiLSTM, Hybrid GRU + LSTM	BiLSTM records bidirectional context; GRU-BiLSTM blends efficiency and context; GRU is quick, manages lengthy sequences; GRU-LSTM balances short-term and long-term dependencies with the highest accuracy.	GRU might overlook intricate patterns; BiLSTM requires a lot of computation; GRU-BiLSTM is intricate; and GRU-LSTM requires careful adjustment.
Ouf et al. (2024) [17]	XGBoost, PCA, SMOTE-ENN	High accuracy, robust classification, balanced classes, thorough data handling, and avoidance of overfitting	SMOTE-ENN and XG-Boost need more time and tuning and depend on appropriate preprocessing for optimal performance; PCA may make things less interpretable.
Subaash et al. (2024) [18]	Hybrid CNN, GBM model	Reduces false positives, captures intricate patterns, offers high	Computationally expensive, necessitates deep learning expertise, and is more difficult

		accuracy, and is adaptable to different industries	to interpret.
Satyam Dhariya (2023) [8]	ANN, Random Forest, CNN	Uses ML and DL techniques to manage large and complex telecom data. Implements proactive retention tactics for useful customer insights	High computational resources a r e needed for advanced technologies.
Kumar et al. (2023) [19]	LSTM (LSTM+GRU), FFNN, GRU, CNN, Bi-LSTM, LSTM with Sentiment Analysis, LSTM with Genetic Algorithm, LSTM with Attention Mechanism	High accuracy, efficient with fewer parameters, captures bidirectional context, richer sentiment insights, optimized feature selection, and highlights significant temporal patterns.	Computationally costly, overfits, and is slow, heavy, and complex, requiring labeled sentiment data, weak at long-term dependencies.
Pusto Khina et al. (2023) [20]	ISMOTE (improved SMOTE with optimal, instance-wise sampling rates), MOROA (for optimizing SMOTE sampling rates and WELM parameters), WELM (Weighted Extreme Learning Machine classifier)	Adaptive sampling effectively manages unbalanced data, simultaneously optimizes sampling and model parameters, achieves high performance, lowers the risk of overfitting from SMOTE, and uses WELM for effective classification.	Optimization process's complexity, reliance on MOROA's accurate parameter tuning, possible computational expense from the optimization steps, and performance dependence on the caliber of feature preprocessing and tuning
Saha et al. (2023) [21]	1D CNN, Residual Blocks, SE Block, Spatial Attention, SMOTE, SMOTETomek, SMOTEEN	Robust model integrates attention and residual learning, effectively handles class imbalance, and outperforms state-of-the-art models on three datasets.	Interpretation is difficult due to the model's black-box nature, restricted scalability. Performance improvement possibilities are not investigated.
Buse Demir and Ö vgu¨ Ö ztu¨rk Ergu¨n (2023) [22]	Adaptive Ensemble Learning (Bagging, Boosting, Stacking with classifiers: Random Forest, XGBoost, LightGBM)	Enhances generalization and accuracy; integrates the benefits of several models; and manages imbalance with ensemble diversity	Expensive computational costs and difficult-to-understand models, the risk of overfitting without tuning
Bharambe et al.(2023) [23]	Logistic Regression, Support Vector Machine, Random Forest, and XGBoost	High prediction accuracy; ability to handle numerical and categorical data; suitable for unbalanced data; and model comparison for	Random Forest and XG-Boost can be computationally demanding. Support Vector Machine is sensitive to parameter selection, and logistic regression assumes

		enhanced performance	linearity.
Mengash et al. (2023) [24]	Archimedes Optimization Algorithm (AOA), Convolutional Neural Network - Autoencoder (CNN-AE), (TEO) method	High classification accuracy across different training/testing splits. Model performance improved by hyperparameter tuning using (TEO)	Little discussion of how to deal with outliers and class imbalance; the dataset size being too small can restrict generalization.
Alhaqui et al. (2022) [25]	Random Forest, Uplift Logit Leaf Model (Decision Trees + Logistic Regression)	Focuses on" Persuadable" clients, which results in better churn reduction, helps marketers in determining the ideal number of clients to target to maximize campaign impact, and prevents wasteful spending.	RF has a low uplift because it uses fixed client data and has fewer variables. Needs comprehensive client information, which may not always be available.
Risuna Nkolele and Hairong Wang (2021) [26]	Decision Tree, Random Forest, LightGBM, LIME, SHAP	High predictive performance was attained, par- particularly with LGBM. Explainable AI was incorporated to make black-box models more transparent	Computationally demanding. Overfitting occurs if ensemble models are not tuned. The absence of time-based validation limits the evaluation of real-world deployment performance.
Wu et al. (2021) [5]	Logistic Regression, Decision Tree, Random Forest, Naive Bayes, AdaBoost, Multi-layer Perceptron (MLP), SMOTE-ENN, SMOTE-Tomek, Bayesian Logistic Regression	Random Forest outperforms all others, particularly when SMOTE balancing is used; feature se-selection, such as the chi-square test, helps focus on key elements and reduces dimensionality; helps in analyzing churn risk factors and consumer behavior.	The accuracy of the models varies depending on the dataset. Other sampling techniques could yield better results, but SMOTE was the only one used to deal with unbalanced data; Complex relationships between variables may be overlooked by feature selection; Churn prediction thresholds were not fully optimized; There was room for improvement in limited hyperparameter tuning.
Chowdhury et al. (2021) [4]	SMOTE and Variants (Borderline SMOTE, ADASYN), Random Forest, AdaBoost, Gradient Boost, XGBoost	Predictio robustness is increased. Class imbalance is effectively addressed by SMOTE and its variations. Model performance is improved by hyperparameter tuning. Model generalization is ensured by 10-fold cross-validation.	No feature selection was used, so it might contain noisy or irrelevant features. Oversampling can result in redundant synthetic data or overfitting.

As the data exhibited class imbalance (more retained than churned customers), SMOTENC, which is intended for datasets with both categorical and numerical features, was applied to rectify the class imbalance in the target variable. After identifying the categorical column indices, SMOTENC was used with a sampling strategy of 0.75, which resulted in an oversampling of the minority class (churned customers) to 75% of the size of the majority class. To preserve the integrity of the test data, this resampling was only done on the training set. The robust and balanced dataset produced by these preprocessing and feature engineering procedures allowed the CatBoost model to learn more efficiently and produce predictions that were more accurate.

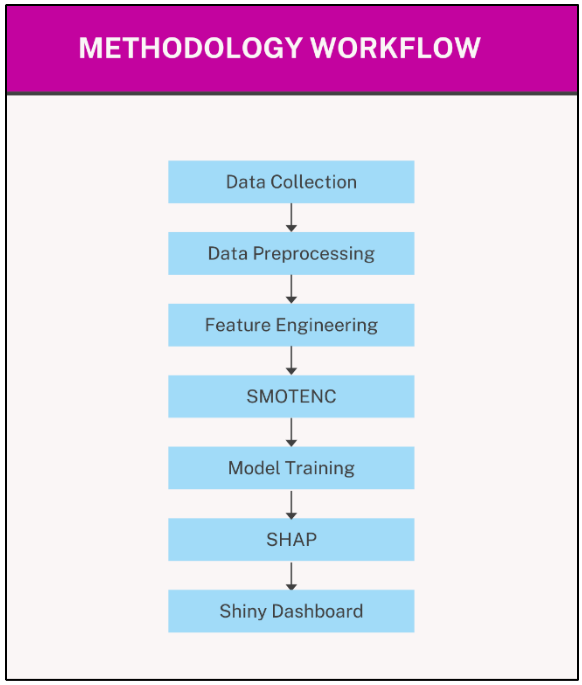

Figure 1. Methodology Workflow

System Design and Architecture:

The four core layers that comprise the system architecture include:

Backend Layer:

Python is used to build the system's backend, which was primarily developed for handling data preprocessing, training machine learning models, utilizing Django and Django REST framework, and creating a dashboard using Shiny for Python (via the *shiny* package in Python).

Frontend Layer:

The frontend is developed using HTML, CSS, and JavaScript. The interface is created to be simple, easy to use, and interactive.

Machine Learning Layer:

CatBoost classifier is used for churn prediction due to its built-in ability to handle categorical data and imbalanced datasets. Joblib is used to save the trained models and is loaded dynamically for predictions. Moreover, for explainable AI (XAI), SHAP is used for generating SHAP values and the prediction of individual features contributing to churn.

Deployment Layer:

The system is developed using Google Colab for backend coding, VS Code for frontend and backend integration by using Rest API. It handles the endpoint for communication with the frontend.

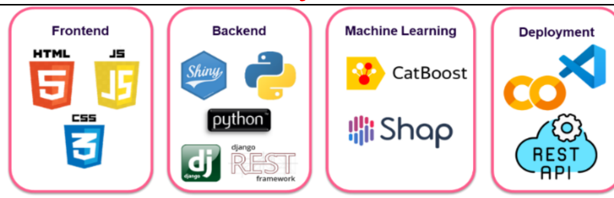

Figure 2. Tech Stack

Interface:

User Interface and Dashboard Integration:

The user interface is made simple, interactive, and easy for users. The use of interactive buttons allows the user to navigate to the desired screen and perform the prediction or view the dashboard for insights. The first screen is a landing page or home page that has 3 buttons. One is single-input prediction, the other is batch prediction, and the last is the dashboard. All three of them have separate functions and provide valuable insight into predicting churn and attribution analysis.

Figure 3. Home Page

Single Prediction:

Input fields are manually filled, either by using the keyboard or by using a drop-down option in the fields. After clicking the prediction button at the bottom, it is followed by the result of the prediction of churn, the probability of churn, a graph with an explanation, and a recommended retention strategy. The input fields include tenure, monthly charges, contract, internet service, online security, online backup, device protection, streaming TV, streaming movies, payment method, paperless billing, partner, dependents, and senior citizen.

The graph highlights the features that most influenced the churn prediction. Features with positive SHAP values increase churn risk, while negative values support retention.
Below the graph, the retention strategy is defined. It tells that working on which feature would help in customer retention.

Batch Prediction:

Batch prediction is used to perform prediction on any telecommunication dataset. It segments the customers into clusters, which can be viewed as high, medium-high, medium, and low risk customers. It displays the predictions, and at the bottom, it has an option to display plots. A new screen appears, as shown in Figure 5, after clicking on it. It has the option for selecting the cluster and visualizing it through a plot. A summary plot is displayed, which can be a beeswarm, bar, or heatmap depending on user selection, along with a key explanation and recommended retention strategy.

Figure 4. Single Prediction Form

Figure 5. Batch Prediction Form (Upload and Predict Screen)

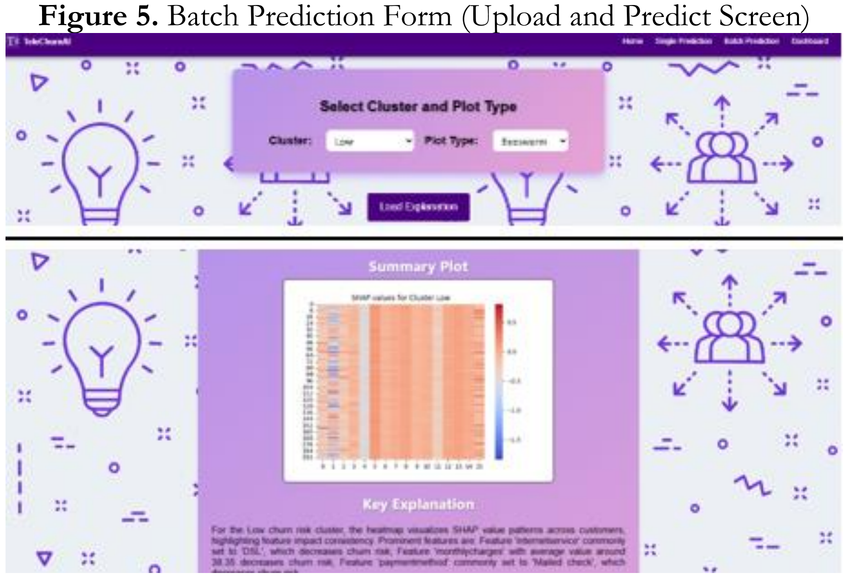

Figure 6. Batch Prediction (Select Cluster, Plot, and Explanation Screen)

Figure 7. Batch Prediction (Recommended Retention Strategies)

Dynamic Visualizations:

The Shiny framework, which was specifically selected to allow for the creation of dynamic and interactive dashboards as opposed to static ones, was used to create the dashboard. Shiny enables responsive data visualization and real-time interactivity, in contrast to basic HTML and CSS, which are restricted to static content. The dynamic dashboard displays customer churn analysis, and filters can be applied to visualize the dataset. Against each important feature or combined features, there is a chart, graph, or plot. This not only helps in understanding churn behavior but also helps in visualizing the data dynamically. The top screen has information about the number of total customers, total churning customers, Loyal customers, Churn Rate, Retention Rate, and Customer Lifetime Value (CLV) as displayed in Figure 7. The top left has filters that can be applied to dynamically visualize the data.

Figure 8. Dynamic Dashboard A

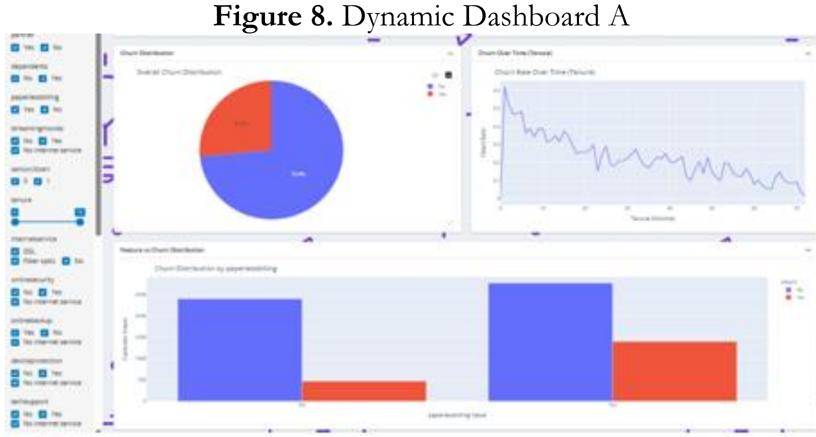

Figure 9. Dynamic Dashboard B

Figure 9 shows that the user visits a landing page to start the process. From there, users have three primary options: visualizing data, making a batch prediction, or making a single prediction. Users enter data directly for individual predictions. Additionally, users supply a CSV file for bulk predictions. A prediction engine is loaded in both instances, after which attribution analysis and retention strategy creation take place. Users have the option to utilize a default dataset or add their own data for data visualization. A default visualization can be created and shown, or filters can be added to the data to produce filtered data for graph production, depending on its intended purpose.

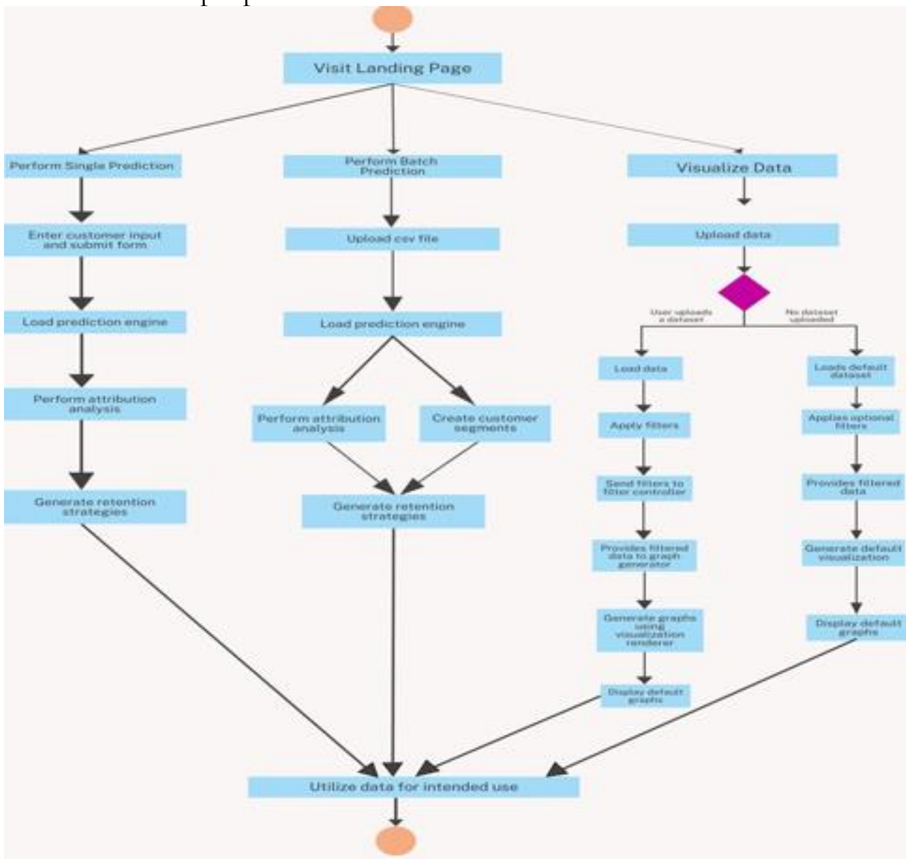

Figure 10. Workflow of TeleChurnAI

Result and Discussion:

This section discusses the results obtained from our proposed framework for proactive customer churn prediction and retention, 'TeleChurnAI'. This system aimed to reduce the number of churning customers and to retain customers using a proactive approach. The TeleChurnAI system demonstrated high potential to identify those customers who would churn, accurately, and provided significant insights to help telecommunication companies and CRM professionals in identifying churn drivers.

Table 3. Classification Report – Stacking Model

Class	Precision	Recall	F1-Score	Support
retained	0.82	0.65	0.73	2316
churned	0.56	0.76	0.64	1348
accuracy	-	-	0.69	3664
macro avg	0.69	0.70	0.68	3664
weighted avg	0.72	0.69	0.69	3664

Table 4. Classification Report – CatBoost Model

Class	Precision	Recall	F1-Score	Support
retained	0.81	0.72	0.76	2316
churned	0.60	0.71	0.65	1348
accuracy	-	-	0.72	3664
macro avg	0.70	0.72	0.71	3664
weighted avg	0.73	0.72	0.72	3664

Following training, we assessed the models' predictive power for customer attrition. With an overall accuracy of 71.7%, the CatBoost model outperformed the Stacking model, which came in at 69%. This suggests that in roughly 72 out of 100 instances, CatBoost produced accurate predictions.

CatBoost achieved 81% precision and 72% recall for non-churning customers and 60% precision and 71% recall for churning customers. This illustrates how well it can identify both churned and retained customers. The Stacking model, on the other hand, had lower recall (65%) for churners but slightly higher precision for non-churners, which is less desirable when proactive retention is the aim.

CatBoost's retained and churned customer F1-scores were 0.76 and 0.65, respectively. These are higher than the Stacking model's scores of 0.73 and 0.64, suggesting a better overall balance between precision and recall.

Basic Testing Overview:

As part of system testing, we used the dataset tested on our system in a controlled environment. As in the system, different actions can be performed, including visualization of the dataset, insights, single and batch predictions. Table 3 displays the test cases.

Table 5. Test Cases Performed

Test Case	Results	Comments
Visit Landing Page	Successful	Page loads correctly with all options visible
Perform Single (Valid Prediction Input)	Successful	Prediction generated based on entered data
Perform Single Prediction (Invalid Input)	Failure Expected	An error message for invalid input was displayed
Perform Batch Prediction (Valid CSV Upload)	Successful	Prediction generated from the uploaded file
Perform Batch Prediction (Invalid CSV Upload)	Failure Expected	Error message for malformed CSV displayed
Visualize (UploadData Valid Dataset)	Successful	Data loaded and graph generation options available
Visualize UploadData (Invalid Dataset)	Failure Expected	Error message for unsupported data format
Visualize (Use Data Default Dataset)	Successful	Default data loaded and default visualization displayed
Apply Filters to Data	Working	Filtered data provided to the graph generator
Generate Retention Strategies	Successful	Strategies generated and displayed/downloadable
Utilize Data for Intended Use	Successful	Data integrated or exported as expected

Discussion of Findings:

Results show that the Catboost Model outperformed the Stacking Model in terms of overall accuracy. Results indicated that the model has a high ability to distinguish between churning and non-churning customers, even with the data having an imbalance issue, making it suitable for telecommunication providers to maximize customer retention.

The high accuracy of churn prediction that TeleChurnAI is able to achieve highlights the power of integrating cutting-edge machine learning methodologies with explainable AI to solve one of the most acute challenges faced by the telecommunication sector. The CatBoost classifier, with its proven capability to deal with categorical variables and class imbalance, produced better performance and was found to be well-suited for capturing the complex patterns in customer data. One of the most important strengths of TeleChurnAI is its incorporation of SHAP for model interpretability. It not only provides transparency by indicating the reason why a customer is going to churn, but also fosters trust among the stakeholders and allows data-driven decision-making with more information. The detection of key drivers of churn allows for actionable insight in developing targeted retention programs. Segmenting customers based on churn probability score is another important feature. In this way, TeleChurnAI goes beyond simple binary predictions and reveals churn root causes to allow businesses to build tailored, successful interventions. It is a high-impact and efficient approach that ensures that customer retention efforts pay off. The platform's intuitive, interactive dashboard is key to democratizing AI-driven insights. It makes sure that even CRM professionals without technical expertise have easy access to dynamic visualizations of churn risk and its causes, turning sophisticated predictions into concise, actionable intelligence. Lastly, the strong and modular design of TeleChurnAI provides reliability and scalability, making it deployable in actual telecom environments. Secure API endpoints and authentication mechanisms protect sensitive customer information, while the flexible design of the system ensures flexibility to accommodate changing business requirements.

Conclusion:

TeleChurnAI demonstrates how integrating advanced machine learning models with additional features can transform the way telecom providers retain their customers, as within the telecommunication sector, customer churn remains a critical business challenge. This system has multiple factors that make it stand out, including:

High accuracy in predicting churning customers makes it highly reliable

The ability to interpret the output of a machine learning model using SHAP values ensures transparency and trust among the stakeholders, as they will feel confident in making decisions based on the system's output.

Providing different segments of customers ultimately revolutionizes the way CRM professionals develop and implement their retention strategies.

Visualizing the trends in customer data using interactive visualizations empowers making timely, data-driven decisions even without having deep technical expertise.

Customer data in the telecom sector typically faces the issue of class imbalance, making it crucial to select a model that will be able to handle such challenges effectively. Implementation of the CatBoost classifier proves to be an effective choice for such cases due to its ability to handle categorical features and how it handles the issue of class imbalance. Along with this model, integration of explainable AI techniques, such as SHAP, not only validates the output provided by the system but also helps in building trust in AI-driven insights, which ultimately encourages its implementation in telecom companies.

The incorporation of the dashboard component acts as a bridge between technical outputs and businesses, helping to translate the complex analytics into actionable insights using a user-friendly interface. This ultimately increases the usability of the system and highly supports its implementation in real-world systems.

In summary, TeleChurnAI stands out as a robust, scalable, and business-aligned solution that effectively addresses the issue of customer churn in the telecommunication sector. It supports the CRM professionals in not only predicting the churning customers but also provides insights and visualizations that ultimately help in developing retention strategies, marketing campaigns, planning, and resource management and allocation. Overall, this system highlights how AI-enabled solutions can revolutionize how the telecom industry operates and lay a strong foundation for future advancements in intelligent customer management systems.

Future enhancements for TeleChurnAI will incorporate real-time prediction capabilities using streaming technologies. Deeper customer insights can be obtained by extending data sources to include unstructured data, such as chat logs and social media, in addition to natural language processing. Scalability and accessibility will be enhanced by implementing the system as a cloud-based service. Large Language Models (LLMs) can also help with automated report generation and more intelligent, customized retention tactics.

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