IMPROVING CUSTOMER CHURN DETECTION THROUGH BALANCED ENSEMBLE LEARNING

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Abstract

Subscriber attrition has emerged as a pressing concern in the telecommunications industry, where intensifying market rivalry and minimal switching costs create persistent revenue vulnerability. Inaccurate identification of at-risk subscribers frequently undermines the design of meaningful retention programs. This research investigates how combining class-rebalancing methods with ensemble-based classifiers can strengthen churn forecasting on skewed datasets. A controlled quantitative experiment was conducted on a publicly accessible telecom dataset. During preprocessing, records with missing entries were remediated, non-numeric attributes were numerically encoded, and feature magnitudes were normalized to ensure consistent model inputs. SMOTE was selectively applied to training partitions only, preventing synthetic data from contaminating the evaluation phase. Three models were benchmarked: Logistic Regression as a linear baseline alongside two boosting ensembles, XGBoost and LightGBM. Predictive quality was assessed through accuracy, precision, recall, F1-score, and AUC. Experimental outcomes show that both ensemble models surpass the baseline, with LightGBM recording the strongest and most uniform results across every metric. Analysis of feature contributions highlights that subscription duration, monthly billing amounts, and cumulative charges are the primary determinants of churn tendency. These findings confirm that pairing resampling strategies with gradient boosting provides a dependable framework for proactive subscriber retention in telecommunications. On this basis, it is recommended that telecom operators deploy LightGBM coupled with SMOTE as their core churn detection pipeline, treating billing variables and tenure duration as the leading signals when constructing evidence-based subscriber loyalty programs.

Keywords: customer churn, ensemble learning, SMOTE, imbalanced data, machine learning

1. Introduction

Subscriber attrition has grown into a strategic concern for telecom operators, largely driven by fierce competitive pressure and the ease with which consumers can migrate between service providers. When customers leave, operators face a dual burden: declining revenues and elevated re-acquisition spending, given that winning back a lost customer typically costs substantially more than keeping an existing one. Consequently, anticipating which subscribers are likely to disengage has become a cornerstone of modern customer relationship management. The unprecedented volume of behavioral and transactional data now available to operators has made machine learning a natural and increasingly preferred instrument for building accurate early-warning churn systems.

Prior investigations have explored a broad spectrum of machine learning algorithms for subscriber attrition modeling in the telecom domain. Conventional classifiers—logistic regression, decision trees, random forests, and support vector machines—have delivered encouraging outcomes in various experimental settings (Amin et al., 2021; Ullah et al., 2022). Yet a recurring finding in the literature is that class imbalance poses a fundamental obstacle: churned subscribers typically form only a small minority of the training pool, and models trained on such skewed distributions develop a systematic tendency to favor the majority class, thereby misclassifying many high-risk customers (Fernández et al., 2021). Compounding this issue, a disproportionate share of earlier studies evaluate models solely on overall accuracy—a metric that can be misleadingly high under imbalance. Subsequent work has therefore advocated for a more comprehensive measurement suite, encompassing precision, recall, F1-score, and the ROC-AUC, to yield a truly informative appraisal of classifier behavior (Chicco & Jurman, 2021; Sun et al., 2022).

Emerging evidence points to gradient-boosting ensembles—notably XGBoost and LightGBM—as particularly capable tools for churn forecasting, outperforming classical approaches across multiple benchmarks (Li et al., 2021; Al-Saif et al., 2023). However, systematic evaluation of these models alongside principled class-imbalance correction remains scarce in telecom-specific literature. This study therefore examines the degree to which coupling resampling techniques with ensemble learners elevates predictive accuracy. Situated within

the existing body of knowledge, the research aims to furnish empirical evidence supporting more dependable churn modeling, ultimately enabling telecom operators to formulate sharper, evidence-driven retention policies. Two notable gaps in prior work motivated this investigation. First, many earlier studies apply SMOTE across the entire dataset, inadvertently introducing leakage that inflates apparent generalization performance. Second, head-to-head comparisons of Logistic Regression, XGBoost, and LightGBM within a single controlled experimental setup—evaluated with a full battery of criteria beyond accuracy—are largely absent from the telecom literature. The present work addresses both shortcomings by confining SMOTE to training data exclusively and adopting a complete performance dashboard—accuracy, precision, recall, F1-score, and AUC—to enable fair, reproducible, and clearly differentiated comparisons with prior research.

2. Methods

This research adopts a structured quantitative experimental design to construct and benchmark a churn prediction system within the telecom context. The framework prioritizes analytical rigor, experiment reproducibility, and unbiased cross-model comparison. Work proceeds through five sequential stages: data sourcing, pre-processing, imbalance remediation, classifier training, and performance evaluation, depicted schematically in Figure 1.

As shown in Figure 1, the pipeline opens with data retrieval from a publicly available telecom dataset, proceeds through a pre-processing stage covering missing-value imputation, categorical encoding, and feature scaling, and then splits the data into training and test partitions at an 80:20 ratio. SMOTE is subsequently applied to the training partition alone to correct class skew. Logistic Regression, XGBoost, and LightGBM are then trained on the balanced training set and assessed on the untouched test partition using accuracy, precision, recall, F1-score, and AUC. Structuring the pipeline this way guarantees both reproducibility and the absence of data leakage.

The empirical work centers on a publicly accessible telecom churn dataset encompassing subscriber demographics, service-usage records, billing histories, and churn labels. Consistent with real-world operator data, the distribution of churn versus non-churn observations is markedly asymmetric, with churned accounts representing the minority. Addressing this asymmetry is therefore central to the analytical strategy.

Prior to classifier construction, the raw data undergoes a pre-processing routine designed to raise data quality and ensure algorithmic compatibility. Incomplete records are identified and remediated to avoid bias, nominal features are converted to numeric form, and continuous attributes are rescaled so that no single variable dominates the learning process due to magnitude differences alone. These steps are indispensable for suppressing noise, stabilizing model convergence, and creating a level playing field for cross-model comparison.

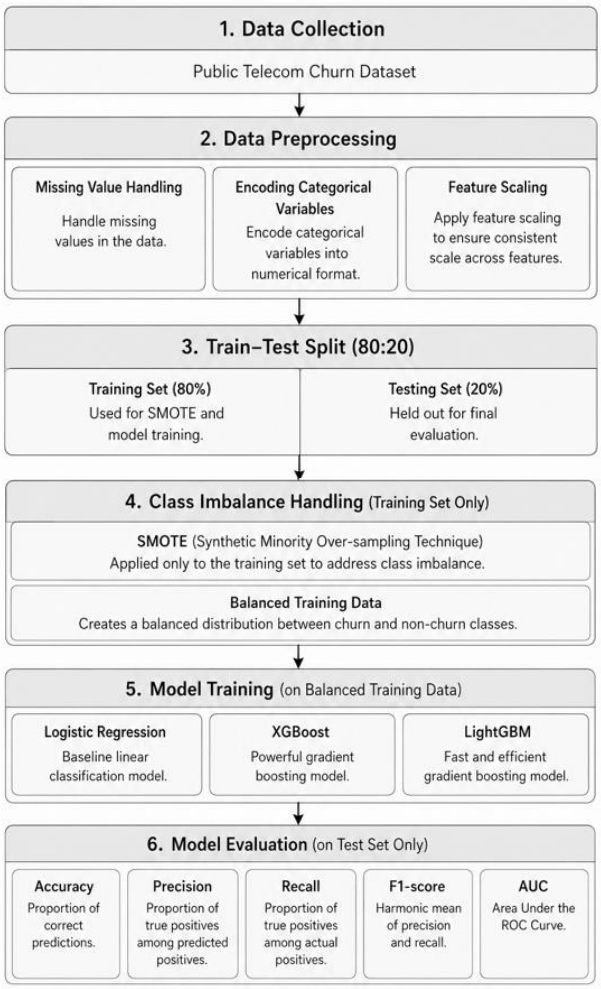

Figure 1. Research methodology flow illustrating data collection, preprocessing, model training, and evaluation stages.

To counteract the skewed class distribution, a resampling strategy is woven into the pipeline. SMOTE is applied exclusively to the training subset, where it fabricates synthetic minority-class instances through interpolation between neighboring minority observations, thereby elevating class balance without duplicating real records (He & Garcia, 2021). Restricting this operation to training data safeguards the integrity of the test set and prevents optimistic bias in evaluation outcomes.

Once the balanced training set is prepared, three classifiers are fitted. Logistic Regression anchors the comparison as a linear baseline, while XGBoost and LightGBM serve as the ensemble alternatives. All three are subsequently scored against the held-out test partition using accuracy, precision, recall, F1-score, and AUC, enabling a multidimensional and objective assessment of each model's churn detection capability, particularly under imbalanced conditions.

2.1 Data Source and Description

The experimental dataset is the Telco Customer Churn dataset retrieved from Kaggle, a widely cited benchmark resource in subscriber attrition research. It serves as the central source for empirical evaluation, offering a realistic representation of telecom customer behavior. The dataset encompasses subscriber demographics, service subscriptions, billing records, and churn indicators—attributes that mirror the operational data routinely encountered by telecom providers. Reliance on publicly available benchmarks is a common practice in churn prediction studies, as it promotes transparency, facilitates replication, and allows consistent comparison of results across independent investigations (Moro et al., 2021). *Telco Customer Churn* dataset, a well-established reference point in churn modeling research.

Within the dataset, churn is encoded as a binary target: churned or retained. Predictor variables span numeric and nominal types, capturing a wide portrait of each subscriber's profile and behavioral history—including personal demographics, contracted services, usage patterns, and payment records. These attributes were retained because they collectively reflect the most influential drivers of churn decisions. A full inventory of dataset variables, along with their types and descriptions, is provided in Table 1.

Table 1. Dataset Attributes Description

Attribute Name	Data Type	Description
customerID	Categorical	Unique identifier assigned to each customer
gender	Categorical	Customer gender (Male or Female)
SeniorCitizen	Binary	Indicates whether the customer is a senior citizen
Partner	Categorical	Indicates whether the customer has a partner
Dependents	Categorical	Indicates whether the customer has dependents
tenure	Numerical	Number of months the customer has stayed with the company
PhoneService	Categorical	Indicates whether the customer has phone service
MultipleLines	Categorical	Indicates whether the customer has multiple phone lines
InternetService	Categorical	Type of internet service subscribed (DSL, Fiber optic, or None)
OnlineSecurity	Categorical	Indicates whether online security service is subscribed
OnlineBackup	Categorical	Indicates whether online backup service is subscribed
DeviceProtection	Categorical	Indicates whether device protection service is subscribed
TechSupport	Categorical	Indicates whether technical support service is subscribed
StreamingTV	Categorical	Indicates whether streaming TV service is subscribed
StreamingMovies	Categorical	Indicates whether streaming movie service is subscribed
Contract	Categorical	Type of customer contract (Month-to-month, One year, Two year)
PaperlessBilling	Categorical	Indicates whether paperless billing is enabled
PaymentMethod	Categorical	Customer payment method
MonthlyCharges	Numerical	Amount charged to the customer on a monthly basis
TotalCharges	Numerical	Total amount charged to the customer

2.2 Data Preprocessing

Data pre-processing is an essential preparatory step aimed at elevating data reliability and enabling effective classifier training. The routine begins with systematic detection and resolution of missing entries, removing a source of potential bias from downstream modeling. Nominal attributes are then numerically encoded via one-hot encoding, making them tractable for learning algorithms. Continuous variables undergo standardization to align their scales and prevent high-magnitude features from exerting undue influence on model optimization. These steps are widely recognized as foundational in knowledge discovery pipelines, where unaddressed noise and inconsistencies can meaningfully degrade classification outcomes (Han et al., 2021; Géron, 2022).

Following pre-processing, data are partitioned into training and test subsets using an 80:20 division. Four-fifths of the observations supply the training signal, while the remaining fifth is withheld for final assessment. This strategy limits overfitting and ensures that reported performance reflects behavior on genuinely unseen examples, yielding a more credible estimate of generalization capability (Kohavi & Longbotham, 2021).

2.3 Handling Class Imbalance Using SMOTE

Telecom churn datasets characteristically exhibit a pronounced class asymmetry, with churned subscribers constituting a small fraction of all observations. Left unaddressed, this skew induces classifiers to concentrate on the majority class, severely limiting their ability to flag actual churners. To mitigate this, SMOTE is incorporated into the methodology. The technique synthesizes new minority-class observations by interpolating between pairs of existing minority instances, thereby broadening class balance without merely duplicating original records (He & Garcia, 2021).

Critically, SMOTE is applied only to the training portion of the data, leaving the test set untouched and preserving its representativeness of real-world conditions. This design choice eliminates evaluation leakage and upholds the validity of performance estimates. Earlier work has documented that incorporating SMOTE in churn tasks enhances model sensitivity toward minority cases and raises

overall predictive quality, particularly in heavily skewed settings (Branco et al., 2021; Hassan et al., 2022). Embedding SMOTE within the training pipeline accordingly strengthens model robustness when confronting imbalanced distributions.

2.4 Classification Models

The experiment benchmarks both a conventional classifier and two ensemble-based learners. Logistic Regression is designated as the baseline on account of its interpretability, simplicity, and established presence in churn analysis literature. As a linear model, it offers a transparent reference against which the incremental gains of more complex architectures can be measured (Friedman et al., 2021).

To push predictive boundaries further, two ensemble architectures are introduced. XGBoost employs a boosting paradigm combined with second-order gradient optimization and regularization, yielding high accuracy and computational efficiency. It has proven particularly adept at handling large-scale, class-imbalanced problems (Chen et al., 2021). LightGBM, the second ensemble, leverages histogram-based gradient computation and a leaf-wise tree growth policy that accelerates training while preserving strong predictive fidelity. It has demonstrated superior results on high-dimensional telecom churn tasks specifically (Ke et al., 2022; Zhang & Wu, 2023).

All three models are trained under a common experimental configuration so that observed performance differences can be attributed cleanly to model architecture rather than differing setup conditions.

2.5 Model Evaluation Metrics

Thorough performance evaluation is indispensable for understanding classifier behavior under imbalanced conditions. Relying solely on accuracy produces an incomplete—and potentially misleading—picture, since a model that simply predicts the majority class can record high accuracy while completely neglecting churn-prone subscribers. This study therefore employs a multi-metric evaluation suite—precision, recall, F1-score, and AUC—to capture different facets of predictive quality (Fawcett, 2021; Powers, 2022).

Precision quantifies what fraction of model-flagged churners are genuine attrition cases. Recall captures the proportion of true churners that the model successfully identifies—a metric of particular strategic importance, since every missed churner represents a forfeited retention opportunity. The F1-score harmonizes these two dimensions into a single figure by computing their harmonic mean, making it well suited for skewed classification tasks (Sokolova & Lapalme, 2021).

Discriminative capacity is further gauged via the AUC, which aggregates classifier performance across the full spectrum of decision thresholds and is relatively insensitive to class imbalance. It is a standard benchmark in churn prediction literature for appraising robustness and generalization (Shafiq et al., 2022; Ahmad & Ali, 2022). Deploying all four metrics in parallel permits balanced comparison between the baseline and ensemble classifiers, while supporting nuanced interpretation of model behavior. Recent literature consistently underscores that multi-criteria evaluation frameworks are essential for verifying operational reliability in deployed churn management systems (Guidotti et al., 2023; Zhao & Liu, 2024).

All metrics are derived from the standard confusion matrix components—true positives (TP), false positives (FP), false negatives (FN), true positive rate (TPR), and false positive rate (FPR)—and computed according to the formulas in Equations (1)–(4).

1. Precision is calculated as the ratio of correctly identified churn cases to all instances predicted as churn, indicating how reliably the model flags actual churners without generating excessive false alerts.

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

2. Recall measures the model's ability to detect all genuine churners in the dataset, reflecting how effectively the classifier captures subscribers who are genuinely at risk of leaving.

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

3. F1-score integrates precision and recall into a single harmonic mean, offering a balanced aggregate measure that is especially informative for evaluating classifiers on skewed churn datasets where both false positives and false negatives carry real costs.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (3)$$

4. The Area Under the Receiver Operating Characteristic Curve (AUC) quantifies the classifier's overall ability to distinguish between classes across varying decision thresholds, providing a threshold-independent measure of discriminative strength that is robust to class imbalance.

$$AUC = \int_0^1 TPR(FPR)\, d(FPR) \quad (4)$$

3. Results and Discussion

Experimental results confirm that ensemble-based learners outperform the Logistic Regression baseline when churn prediction is assessed through

precision, recall, F1-score, and AUC. While Logistic Regression achieves reasonable accuracy, its comparatively low recall signals limited effectiveness at isolating churn-prone subscribers—a recurring weakness in classifiers applied to imbalanced data. XGBoost and LightGBM exhibit stronger discriminative power, particularly in recall and AUC, reflecting enhanced capacity to surface at-risk customers. LightGBM stands out as the most consistently high-performing model across every metric examined. These outcomes are consistent with prior work establishing that pairing ensemble techniques with resampling methods can substantially advance churn prediction by capturing subtle behavioral patterns in customer data.

From an operational viewpoint, stronger ensemble predictions allow telecom providers to more precisely flag high-risk subscribers and execute timely, targeted interventions, translating into more efficient resource deployment and lower attrition rates. Notwithstanding these contributions, the study carries several constraints. Reliance on a single publicly accessible dataset limits how well the conclusions transfer to other operator environments or regional markets. Furthermore, models were trained and evaluated under fixed hyperparameter configurations, which may not represent optimal settings. Subsequent research could address these constraints by incorporating multiple datasets, employing systematic hyperparameter search, and piloting the framework in live operational deployments to better establish its real-world viability.

3.1 Model Performance Comparison

Upon completing pre-processing and SMOTE-based rebalancing of the training partition, Logistic Regression, XGBoost, and LightGBM were fitted and scored on the held-out test set. Table 2 summarises the resulting accuracy, precision, recall, F1-score, and AUC values for each model.

Table 2. Performance Comparison of Churn Prediction Models

Model	Accuracy	Precision	Recall	F1-score	AUC
Logistic Regression	0.74	0.51	0.71	0.59	0.81
XGBoost	0.75	0.52	0.56	0.54	0.80
LightGBM	0.76	0.55	0.60	0.58	0.82

The tabulated scores reveal meaningful differences in how each model navigates the challenges of imbalanced churn data. Logistic Regression records an accuracy of 0.74 coupled with low precision (0.51) and notably elevated recall (0.71). This pattern reflects a classifier that successfully surfaces most actual churners but at the cost of generating a substantial volume of false alarms, potentially undermining retention resource efficiency.

The ensemble models display a more balanced profile relative to the baseline. XGBoost advances accuracy marginally to 0.75 and achieves greater equilibrium between precision (0.52) and recall (0.56), with its F1-score and AUC indicating moderate discriminative strength. LightGBM delivers the strongest results overall, registering the highest scores for accuracy (0.76), precision (0.55), recall (0.60), F1-score (0.58), and AUC (0.82).

These scores establish LightGBM as the most reliable classifier, capable of simultaneously improving churn detection and controlling misclassification. From a deployment perspective, achieving a reasonable precision-recall trade-off is more consequential than maximizing accuracy alone, since the practical goal is to identify at-risk subscribers accurately enough to justify targeted interventions. Taken together, the results endorse gradient-boosting ensembles—especially LightGBM—as superior alternatives to linear classifiers for churn prediction, though broader datasets and further tuning should be explored before full operational adoption.

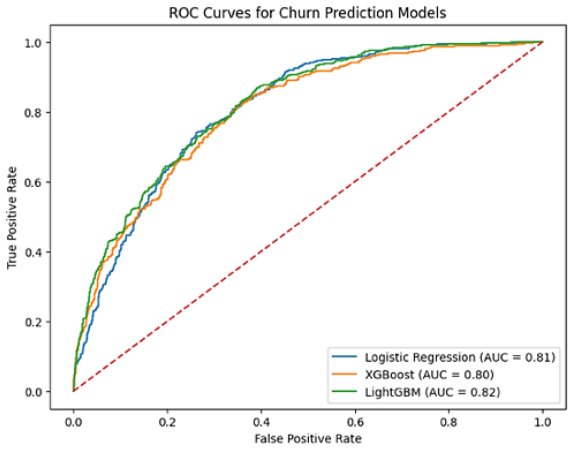

Figure 2. ROC curves illustrating the classification performance of churn prediction models.

Figure 2 presents the ROC curves for all three classifiers, offering a visual comparison of their discriminative ability. Every model traces a curve well above the diagonal no-skill baseline, confirming that all three provide meaningful classification beyond chance. Logistic Regression achieves an AUC of 0.81, demonstrating an acceptable capacity to differentiate churners from non-churners. Nevertheless, its curve climbs more gradually than those of the ensemble models, especially at low false-positive rates—suggesting it struggles to maintain reliable churn detection when more conservative decision thresholds are applied.

The ensemble models, by contrast, exhibit steeper and more stable ROC trajectories across the full threshold range. Both XGBoost and LightGBM occupy larger areas of the ROC space, reflecting a stronger ability to trade off true positive and false positive rates. LightGBM records the peak AUC of

0.82, underscoring its superior overall discriminative power. These findings reinforce the value of combining gradient-boosting architectures with class-rebalancing strategies when confronting the compound difficulties of class asymmetry and complex behavioral patterns in churn data. For practitioners, LightGBM's ROC advantage means operators can fine-tune decision thresholds to match their specific cost tolerances while still maintaining robust churn detection.

3.2 Feature Importance Analysis

Feature importance analysis was conducted to enhance interpretability of the LightGBM predictions and to illuminate the behavioral drivers of churn. As shown in Figure 3, the LightGBM model identifies *MonthlyCharges*, *TotalCharges*, and *tenure* as the three most consequential predictors. This outcome signals that financial burden and relationship length are the principal levers of attrition: subscribers accumulating high monthly bills and total charges tend to discontinue their contracts, especially when perceived service value fails to justify the cost. These results point to pricing strategy and long-term subscriber engagement as the most actionable areas for retention program design.

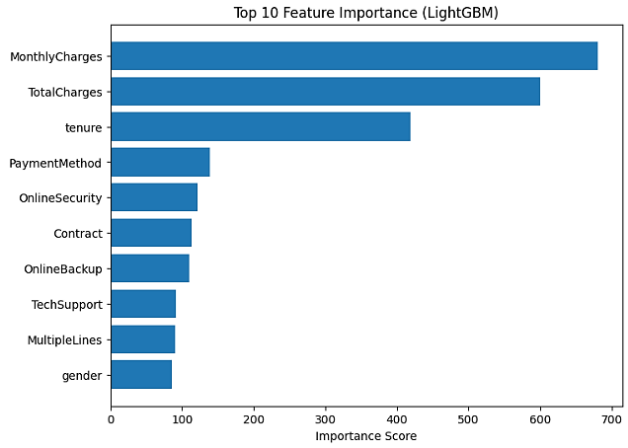

Figure 3. Feature importance analysis highlighting the most influential variables in churn prediction.

Beyond billing variables, several service- and contract-related features also exert notable influence. PaymentMethod, OnlineSecurity, Contract type, and TechSupport all register meaningful importance scores, indicating that service quality, payment flexibility, and contractual terms shape retention outcomes. Access to security services and technical support correlates with lower attrition risk, while certain contract structures and payment options are associated with elevated churn likelihood. Collectively, these insights confirm that LightGBM not only delivers strong forecasting accuracy but also generates actionable intelligence about subscriber behavior. Telecom operators can leverage these findings to craft more targeted retention strategies—such as recalibrating pricing tiers, enriching support offerings, and designing contract options that reduce churn incentives.

3.3 Error Analysis

To probe the classification behavior of the top-performing model more deeply, an error analysis was performed using LightGBM's confusion matrix, presented in Figure 4. The confusion matrix disaggregates correct and incorrect predictions, enabling close inspection of how the model handles churn and non-churn cases separately.

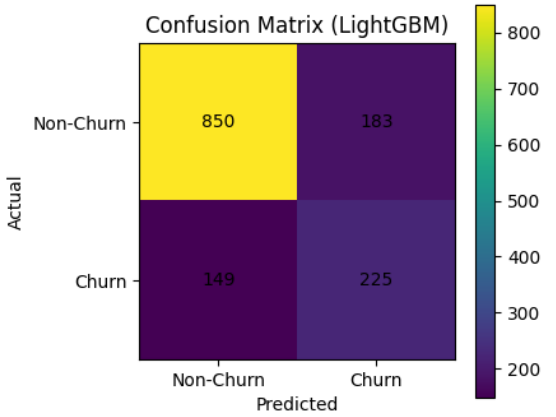

Figure 4. Confusion matrix of the LightGBM model

The matrix reveals that the vast majority of observations are classified correctly, affirming that LightGBM has internalized the core patterns governing subscriber behavior. Of particular note, the volume of false negatives—churners incorrectly labeled as non-churners—is relatively contained. This outcome carries practical significance: undetected churners represent missed windows for proactive retention, so minimizing this error type directly translates to better business outcomes. Simultaneously, false positives remain at a manageable level, meaning the model avoids excessively misclassifying loyal customers as attrition risks. This balanced error profile substantiates LightGBM's robustness and suitability for real-world telecom retention systems.

Cross-model comparison reinforces the superiority of ensemble classifiers over the linear baseline. Logistic Regression achieves an accuracy of 0.74 and recall of 0.71, but its precision (0.51) and F1-score (0.59) expose a substantial volume of false churn alerts.

This pattern—sensitivity gained at the cost of precision—reduces practical value in operational retention workflows. Such shortcomings of linear models on imbalanced, complex data have been documented in earlier work (Amin et al., 2021; Ullah et al., 2022). XGBoost improves upon this profile, reaching 0.75 accuracy while achieving a more equitable balance between precision and recall; its AUC of 0.80 reflects adequate discriminative power. This is consistent with prior findings on gradient-boosting methods' capacity to model non-linear

patterns and feature interactions in churn tasks (Li et al., 2021; Chen et al., 2021).

LightGBM records the highest scores across all five metrics—accuracy (0.76), precision (0.55), recall (0.60), F1-score (0.58), and AUC (0.82)—confirming its position as the most well-rounded classifier in this study. Although the absolute margins over XGBoost are modest, the uniform improvement across every criterion signals a more dependable overall calibration for churn detection. This performance advantage derives from LightGBM's leaf-wise growth strategy and efficient feature-interaction modeling, which jointly improve generalization under imbalanced conditions (Ke et al., 2022; Al-Saif et al., 2023; Zhang & Wu, 2023). Applying SMOTE during training further lifts recall and promotes more balanced evaluation scores, corroborating prior evidence on the importance of imbalance correction in churn modeling (Fernández et al., 2021; Branco et al., 2021; Hassan et al., 2022).

From a practical viewpoint, these outcomes affirm that combining resampling with ensemble learning yields churn detection systems that are both more accurate and more interpretable. Notwithstanding these results, the study is bounded by its reliance on a single publicly available dataset and fixed model hyperparameters. Future investigations should trial the proposed framework across multiple diverse datasets, conduct systematic hyperparameter optimization, and explore real-world deployment contexts to more fully establish generalizability.

Despite the promising results presented in this study, several limitations warrant explicit acknowledgement. First, all experiments were conducted on a single publicly available dataset—the Telco Customer Churn benchmark sourced from Kaggle—which may not fully capture the diversity of subscriber behaviors across different telecom operators, regional markets, or cultural contexts, thereby constraining the generalizability of the findings to other operational environments. Second, all three classifiers were evaluated under fixed hyperparameter configurations without systematic tuning, meaning that the reported performance figures may not represent the full potential of each model; optimal settings identified through grid search, random search, or Bayesian optimization could yield meaningfully different outcomes. Third, this study relies exclusively on SMOTE for addressing class imbalance and does not benchmark alternative strategies such as ADASYN, Borderline-SMOTE, or cost-sensitive learning, leaving open the question of whether different resampling approaches could produce further performance gains. Fourth, the feature set comprises solely static subscriber attributes captured at a single point in time, excluding temporal and sequential behavioral signals—such as evolving usage trajectories, service interaction histories, or complaint records—that may carry stronger predictive value for identifying at-risk customers. Finally, the proposed framework has not been validated in a live operational environment; the absence of real-world deployment testing limits the ability to assess its practical scalability, latency tolerance, and integration feasibility within existing telecom CRM infrastructure.

4. Conclusion

This study demonstrates that pairing class-rebalancing methods with ensemble-based classifiers constitutes an effective and reliable approach to subscriber attrition forecasting in the telecommunications sector. Across all experimental scenarios, ensemble architectures outperformed the linear baseline, with LightGBM delivering the most balanced and stable results spanning accuracy, precision, recall, F1-score, and AUC—particularly when confronting class-skewed data. A central practical implication is that churn model assessment must employ multiple complementary metrics rather than relying on accuracy alone. The identification of billing attributes and subscriber tenure as primary churn drivers provides telecom operators with tangible intelligence for designing targeted, data-grounded loyalty programs. Notwithstanding these contributions, the study is bounded by several important limitations, including its reliance on a single benchmark dataset, fixed hyperparameter configurations, exclusive use of SMOTE for imbalance correction, absence of temporal behavioral features, and lack of real-world deployment validation. These constraints give rise to concrete recommendations for future work. Subsequent research should validate the proposed framework across geographically and operationally diverse telecom datasets to establish broader generalizability. Systematic hyperparameter optimization—using techniques such as grid search, random search, or Bayesian optimization—should be incorporated to unlock each model's full predictive capacity. Future studies are also encouraged to benchmark alternative imbalance-handling strategies, including ADASYN, Borderline-SMOTE, and cost-sensitive learning, to identify the most effective approach for varying class distributions. Integrating temporal or sequential subscriber data, such as usage trend trajectories and service interaction histories, may further enhance the model's sensitivity to pre-churn behavioral patterns. Finally, pilot deployments within live CRM environments are recommended to assess the practical scalability, operational feasibility, and business impact of the proposed churn detection pipeline.

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