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Predicting and Reducing Wireless Customer Churn Using the AI2-Sriya Expert Index (SXI)

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Abstract: The telecommunication sector has experienced swift technological development, with wireless services being the forces of change. One of the key issues in this sector is customer churn that affects profitability and market competitiveness. As customer expectations increase and competition becomes fiercer, telecom providers should be concerned with retaining current customers through better services. This study examines churn prediction in the wireless telecommunication sector via machine learning (ML) methods, focusing on the performance of the AI2-Sriya Expert Index (SXI) model. AI2 (AI Square), launched by Sriya.AI, improves standard AI with a second layer of AI to facilitate adaptive learning. Fundamentally, SXI is a super feature that aggregates outputs from 5–10 ML models into one dynamic score that accurately determines the probability of customer churn. This method condenses complex, multi-dimensional data into two-dimensional data for enhanced decision-making and predictive analysis. In the comparison, conventional models such as XGBoost had 67% accuracy and 0.68 AUC, other research employing LightGBM and CatBoost had AUC values around 0.9, and internal benchmarking showed TabNet and FT-Transformer achieving AUCs of 0.65 and 0.66, respectively. CatBoost with hyperparameter optimization obtained an F1-score of 93% and AUC of 0.91. Nevertheless, the SXI model outperformed all of them with 98% accuracy and a 0.98 AUC value. Aside from predictive accuracy, SXI provides actionable business insights through iterative optimization with deep learning. This study shows that SXI has the capability to decrease customer churn from 49.5% to 39.65% (first 20% improvement). Through optimization, churn can be further reduced to 24.78% (50% reduction) and then eventually to 6.44% (87% reduction), providing long-term strategic advantages. These findings validate that the SXI framework offers a robust, precise, and interpretable solution for customer churn in telecom that is substantially better than that of conventional ML models.

Keywords: SXI, predictive modeling, customer churn, wireless telecommunication industry, churn rate prediction, artificial intelligence

1. Introduction

Every day, the telecom sector generates massive volumes of customer-related data, where acquiring new subscribers is significantly more expensive than retaining existing ones. One of the most critical challenges for operators is customer churn, referring to the tendency of subscribers to switch providers within a defined period [1]. Churn is typically categorized as voluntary, which is driven by service dissatisfaction, poor customer support, or competitive offers, and involuntary, which results from uncontrollable factors such as relocation or financial difficulties [2].

The telecom industry, characterized by intense global competition, pushes providers to expand their market share by offering affordable and attractive services. To remain profitable, operators adopt strategies such as customer acquisition, upselling to existing clients, and retention. Among these, retention is consistently recognized as the most cost-effective approach because it requires substantially fewer resources than acquiring new customers [3, 4]. The sector therefore functions not only as a major revenue generator but also as a driver of socioeconomic growth worldwide [5, 6].

Accurately predicting churn is challenging because of the heterogeneous nature of customer behavior. Although earlier efforts primarily relied on survey-based approaches, recent research increasingly applies data mining and machine learning (ML) techniques to enhance prediction accuracy [7]. Studies have reported area under the curve (AUC) values between 0.70 and 0.91 using algorithms such as decision trees, random forests, logistic regression, support vector machines, and gradient boosting models such as XGBoost, LightGBM, and CatBoost [3, 8–11]. Other techniques, including fuzzy-based systems, have also achieved competitive accuracy, although often with reduced sensitivity for churn cases [12].

Tabular data modeling has progressed beyond typical ML in recent years using a number of deep learning techniques. Although NODE used ensembles of oblivious decision trees optimized end-to-end to beat gradient boosting techniques, TabNet provided an attention-based approach for dynamic feature selection and interpretable learning. Strong benchmarks for tabular prediction tasks were established by transformer-based models such as SAINT and FT-Transformer, which further improved performance by tokenized feature embeddings and row/column attention. Other examples of reinforcement learning include AutoFIS, which automatically chooses feature interactions in factorization models for large-scale applications, and RLBoost, which uses RL to re-weight features and increase robustness [13–18].

Despite these advances, many churn prediction models still lack interpretability, underperform on imbalanced datasets, or fail to leverage the complementary strengths of diverse algorithms [19–23].

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Few studies have explored the integration of ensemble learning with deep learning to simultaneously enhance generalization and accuracy.

To address these gaps, this study introduces the AI2-Sriya Expert Index (SXI), a novel ensemble framework that integrates deep learning with multiple ML models to dynamically optimize outcomes. The goal is to improve both the predictive accuracy and interpretability of churn modeling on real-world telecom datasets.

The specific objectives of this study are the following:

1) To develop a real-time, interpretable churn prediction index (SXI) that integrates ensemble learning and deep learning.
2) To evaluate the performance of SXI against traditional and modern baselines in terms of accuracy, precision, and business interpretability.
3) To demonstrate how SXI can be applied to real-world telecom datasets to reduce churn and improve customer retention strategies.

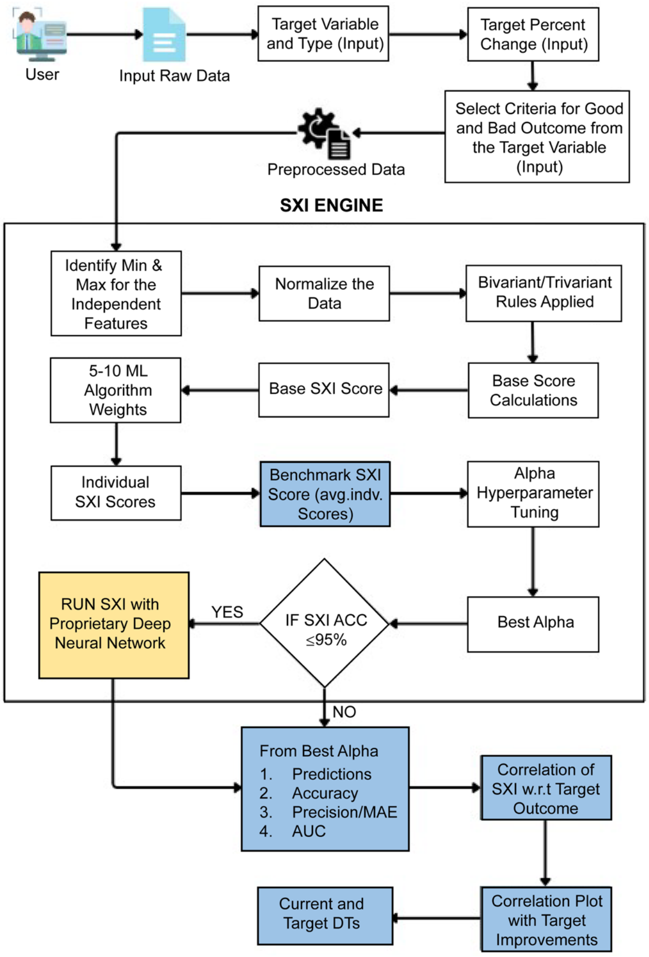
2. Methodology

2.1. Dataset description

This dataset, which has 100,000 records and 100 variables, describes several facets of the telecom sector and important criteria to consider while engaging with telecom clients. There are two distinct values for the goal variable, namely, "customer_churn": "not_churn," which has a count of 50,438 (50.44%), and "churn," which has a count of 49,562 (49.56%). Using the factors at hand, this dataset attempts to forecast which consumers will leave and which will not.

The dataset was preprocessed using the following two methods: feature encoding and missing value treatment. Variables with more than 40% missing values will be eliminated for missing value treatment, but variables with less than 40% missing values will have their values filled in using techniques such as the mean and mode. For feature encoding, variables with fewer than 10 unique values will be encoded using one-hot encoding, and variables with more than 10 unique values will be encoded using label encoding.

Figure 1
SXI framework



2.2. SXI model framework

A proprietary formula composed of weights from 5–10 ML algorithms yields the dynamic score or index known as SXI. SXI is a super feature that transforms a multi-dimensional, challenging problem into a straightforward two-dimensional solution. It is a real weighted representative of all significant features. SXI uses an iterative process in which a deep learning agent dynamically modifies algorithm weights according to the most important weights that the 5–10 ML algorithms supply. The goal of this procedure is to improve accuracy and delineation by strengthening the relationship between SXI scores and business outcomes.

2.3. SXI working

The overall design of the SXI framework shown in Figure 1 has been detailed in our earlier studies [24, 25]. In brief, the model integrates a combination of statistical measures, algebraic operations, and ML weights to generate a robust scoring mechanism. Initially, cleaned data are processed using statistical indicators (e.g., standard deviation and correlations) and proportionality constants to compute a base SXI score. These values capture the relative contribution of each feature, enabling the framework to emphasize influential parameters.

Subsequently, weights derived from multiple ML models—including LASSO, PCA, random forest, and XGBoost—are aggregated with the base score to produce a benchmark SXI score. This benchmark serves as the reference point for further optimization. Key performance indicators such as average SXI values, class distributions, and the ratio of positive to negative outcomes provide insight into the discriminative ability of the framework.

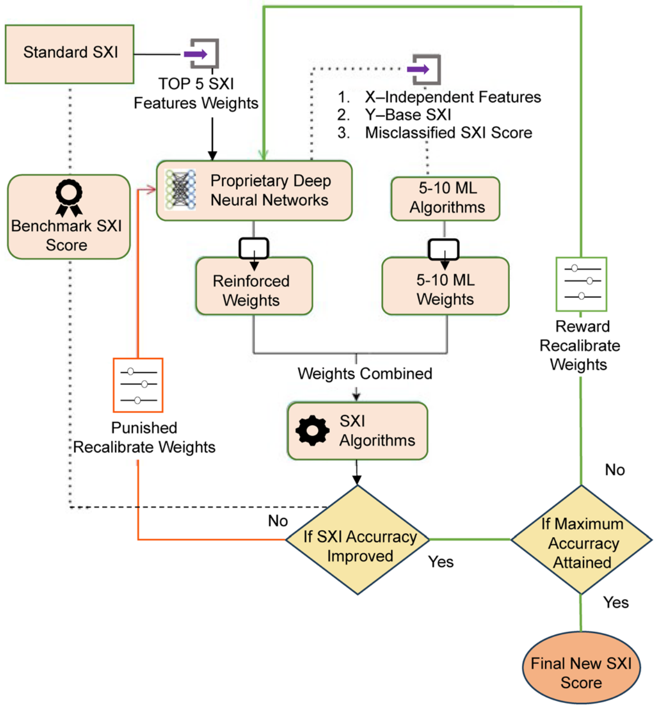
To refine predictions, a proprietary deep neural network (DNN) (Figure 2) module dynamically rebalances feature weights and adapts its architecture through hyperparameter tuning, dataset-aware optimization, and Bayesian search strategies. A 70/20/10 split across training, validation, and test data is employed to ensure both robustness and generalization, with the validation set guiding model selection and overfitting control.

Finally, the SXI incorporates an iterative reinforcement process, where weights are recalibrated using a reward–penalty mechanism until convergence. Positive updates increase delineation accuracy, whereas negative adjustments are applied when improvements plateau. This cycle continues until no further gains are achieved, after which the optimized final SXI scores are stored for decision-making. Unlike our earlier applications [24, 25], this study adapts the same architecture to the telecom churn domain, extending its utility to customer retention analytics.

2.4. Model training and correlation of SXI

The purpose of SXI is to calculate scores by taking into consideration multiple ML algorithms' weightage and their learning on the data. The SXI score is a delineator between sets of business outcomes such as good and bad. On the basis of the scores, we determine

Figure 2
Proprietary DNN architecture



how effectively SXI distinguished the good from the bad and vice versa. The goal is to achieve a high correlation between SXI scores and the business outcomes, which will result in better improvements. The combination of SXI score and correlation will result in the improvement of the outcome.

2.4.1. Model training

Hyperparameter tuning, with an emphasis on the alpha parameter, is the first step in the model training process. This entails changing the alpha value in steps of 0.1 between 0.5 and 1.5 to modify the SXI score. Every iteration allows for fine-tuning to maximize the model's performance by recalculating the SXI score by multiplying the current SXI score by the alpha value.

$$SXI_{new} = \propto * SXI_{Current}, \tag{1}$$

where

1) $\propto$ is the tuning parameter, ranging from 0.5 to 1.5 in increments of 0.1,
2) SXICurrent is the benchmark SXI score, and
3) SXInew is the new SXI score following the alpha correction.

To evaluate the prediction accuracy of customers who churned using various methods—traditional-ML (XGBoost) and Sriya's SXI using target SXI-based random forest trees—the dataset is split into three subsets for training (70%), testing (20%), and validation (10%) purposes. A minimum target decrease of 20% in customer churn rate is set. This deliberate division lowers the possibility of overfitting and permits a precise evaluation of model performance by guaranteeing that the model is well trained and supplying enough data for testing and validation. As a "super feature," the optimized SXI scores are utilized during training and are essential for improving the predicted accuracy of the model.

Several criteria are used to fully assess the model's performance. Although precision focusses on the percentage of real positive findings among all positive forecasts, accuracy gauges how accurate the model's predictions are overall. Deeper insights into the model's classification capabilities are provided by a confusion matrix, which provides a thorough analysis of true positive, true negative, false positive, and false negative results. The model's ability to differentiate between classes is also evaluated using the AUC, which is a reliable measure of its prediction ability. The definitions of accuracy and precision are the following:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}, \tag{2}$$

$$Precision = \frac{TP}{TP+FP}, \tag{3}$$

where

1) TP is the number of true positives,
2) TN is the number of true negatives,
3) FP is the number of false positives, and
4) FN is the number of false negatives.

The classifier's capacity to discriminate between positive and negative classes is gauged by the receiver operating characteristic (ROC) curve's AUC. The ROC curve plots the true positive rate (TPR) versus the false positive rate (FPR) at various threshold values. It is computed using these two metrics. The definitions of TPR, FPR, and AUC are as follows:

$$TPR = \frac{TP}{TP+FN}, \tag{4}$$

$$FPR = \frac{FP}{FP+TN}, \tag{5}$$

$$AUC \approx \sum_{i=1}^{n-1} \left(\frac{TPR_{i+1}+TPR_i}{2} \right) (FPR_{i+1} - FPR_i), \tag{6}$$

where

1) TPRi and TPR(i+1) are the true positive rates at consecutive thresholds and
2) FPRi and FPR(i+1) are the false positive rates at consecutive thresholds.

2.4.2. Correlation of SXI w.r.t target outcome

SXI serves as a proxy for features influencing churn, with each record assigned its own SXI score. These scores act as key indicators, distinguishing between favorable and unfavorable business results. By analyzing the relationship between SXI scores and customer churn, most outcomes are categorized based on whether they fall above or below a benchmark SXI score. Deep learning is then employed to improve SXI's effectiveness in predicting churn, enhancing its correlation, accuracy, and precision compared to the initial model.

Using the SXI scores generated from deep learning, a linear or nonlinear relationship with churn is established through correlation plots. These plots enable the identification of mid-term and long-term compounded improvements in reducing the number of customer churn cases. The new SXI-generated scores from deep learning will be used to fit a linear or nonlinear relationship with customer churn (correlation plot). On the basis of the correlation plot, we will identify the mid-term and long-term compounded improvements in decreasing the number of customers who will churn.

In scenarios where SXI scores positively correlate with outcomes, positive weighted features are adjusted upward and negative weighted features are adjusted downward by user-specified percentages, whereas an opposite adjustment is made in negative correlation scenarios. This adjustment aims to enable initial improvements in the dataset. Then, the random forest model is utilized to analyze the adjusted dataset, identifying the relationships between features and business outcomes by plotting decision trees and identifying the best path for determining the positive and negative sides of the business. Through this scientific methodology, insights into optimizing business performance based on SXI scores and feature adjustments are gained.

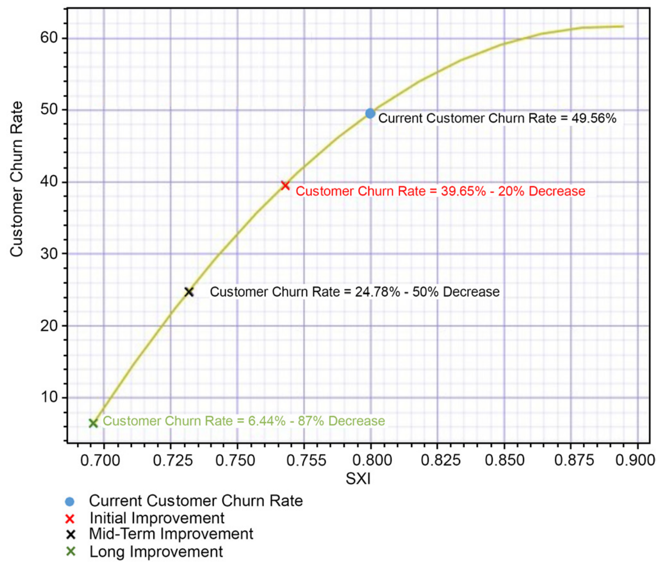
3. Result

3.1. SXI distribution

Figure 3 shows the SXI distribution of the target variable. The current average SXI of the dataset is 0.8, with 52,229 customers having an SXI below the average. Among them, 68.25% are nonchurned customers and 31.75% are churned customers. Conversely, there are 47,771 customers with an SXI above average, among whom 69.0% are churned and 31% are not churned.

This distribution clearly indicates that customers with higher SXI scores are more likely to churn. The left-skewed green bars (nonchurned) and the right-skewed red bars (churned) show a distinguishable separation, supporting the effectiveness of SXI in churn classification. Thus, SXI acts as a reliable indicator, aiding early intervention strategies for high-risk customers.

Figure 4
SXI correlation graph



3.2. Correlation

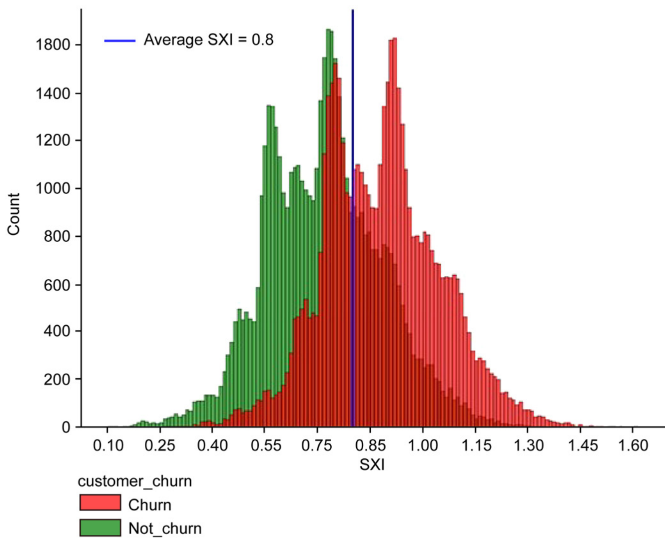
Figure 4 shows the correlation between SXI and customer churn rate, exhibiting a perfect R-squared value of 1.0. This signifies a strong, positive polynomial correlation, indicating that as SXI values increase, the customer churn rate increases accordingly.

As shown, the current churn rate of 49.56% aligns with the existing average SXI. Initial model improvements reduce churn to 39.65% (a 20% decrease), followed by a mid-term improvement to 24.78% (a 50% decrease) and a long-term improvement to 6.44% (an 87% decrease).

3.3. Decision tree

Figure 5 shows the current SXI decision tree, which graphically describes how different input features are used in classifying customer churn. The decision tree indicates the logical process and relevance of different variables in deciding whether a customer will churn or not.

Figure 3
SXI distribution chart of the target variable



One of the most prominent features is the average monthly number of calls over the previous three months (avg3qty). Customers with an average usage of 1 or less are also much more likely to churn, suggesting lower utilization or dissatisfaction with the service. Another powerful churn indicator is a current handset price (hnd_price) of more than $34.99, perhaps suggesting an inconsistency in device price and perceived value of service. If the sum of total service times (months) is over 10.5 months, it is related to higher churn, potentially as a result of contract termination or waning satisfaction over time.

Multiple features indicate a less probable likelihood of churn. Customers with avg3qty over 1 are more likely to stay with the service, which means frequent usage is associated with retention. Further, customers who have been with the service for less than 10.5 months tend to remain, potentially because of their active contract or initial satisfaction period. A second important aspect is the account spending limit flag (asl_flag). "Yes" indicates a managed spending habit that tends to be associated with long-term retention.

This decision tree provides actionable recommendations for telecom operators, allowing them to segment customers across these dimensions and target their retention activities more precisely.

Figure 6 displays the target SXI decision tree that shows the most significant features that lead to customer churn prediction based on optimized SXI scores. This model allows for a detailed segmentation of the drivers that discriminate between customers who are likely to churn and those likely to stay.

Mean monthly minutes of use (mou_mean) is one of the strongest churn indicators. Customers with usage levels below or equal to 0.33 min are likely to churn, and this fact implies low engagement with the service. Adjusted total revenue, adjrev, stands out as a key predictor variable. When adjrev exceeds $150.32, the likelihood of churn increases, possibly because the customers are not satisfied with the service that they received.

The other key churn predictor is the mean number of placed voice calls (plcd_vce_Mean), which if less than 18.2, indicates low interaction and potential lack of interest in continued service. The low interaction measures are consistent with the relationship between lower usage and greater probability of churn.

Figure 5
Current SXI decision tree

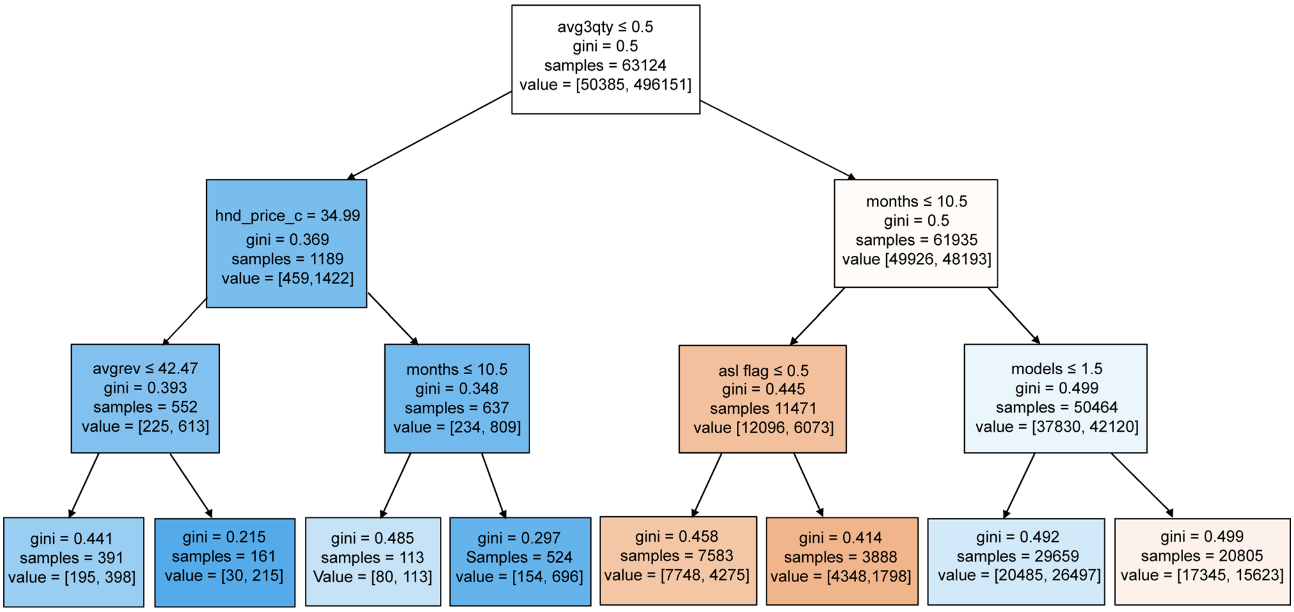
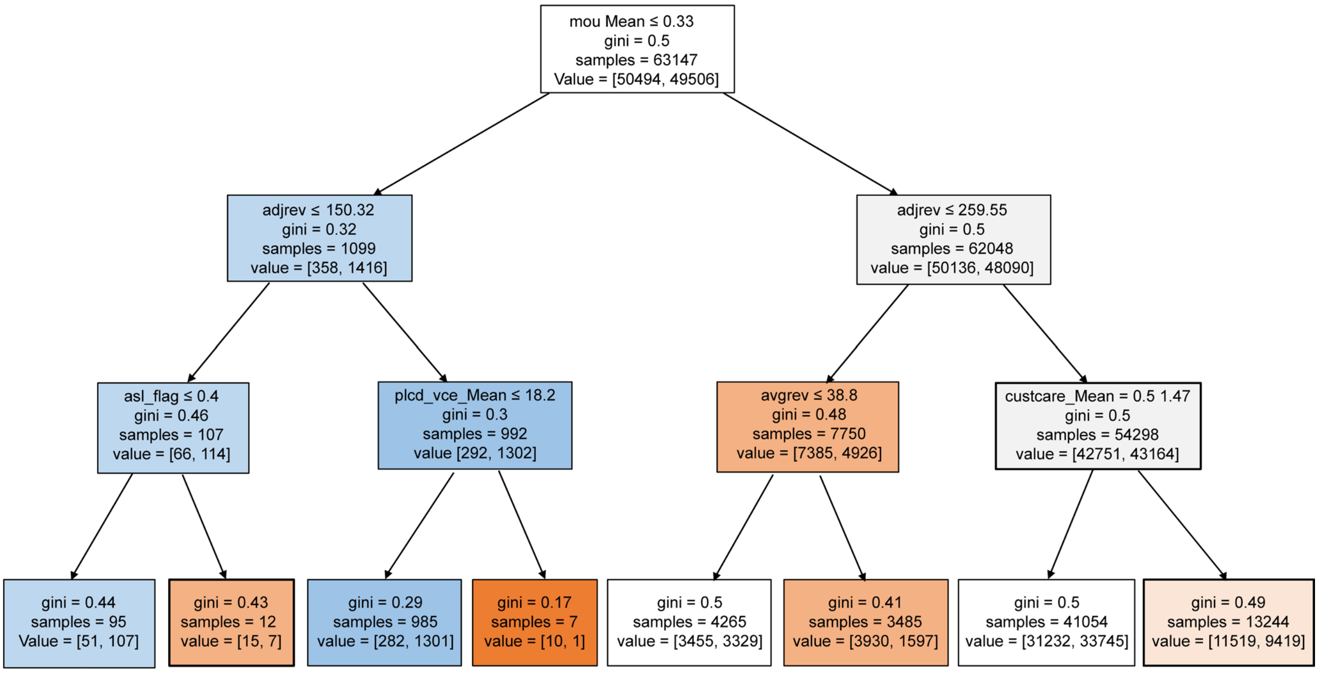


Figure 6
Target SXI decision tree



Conversely, the model finds a number of features that are associated with customer retention. Customers with a mean monthly usage that is greater than 0.33 min and with an adjusted revenue lower than \$259.55 exhibit lower probabilities of churning. Moreover, a greater average monthly revenue (avgrev), especially values greater than \$38.8, relates to greater customer loyalty. Such indicators indicate not just active usage but also a potential congruence between service value and customer expectations.

This decision tree is an important mechanism for converting SXI scores into effective business strategies for reducing churn and enhancing service retention.

3.4. Performance metrics comparison

Table 1 presents a comparative analysis of model performance metrics between traditional ML approaches and the proposed SXI model. The findings clearly demonstrate that the SXI model significantly outperforms the widely used XGBoost algorithm in all three-evaluation metrics: accuracy, precision, and AUC.

Specifically, the SXI achieved an accuracy of 98% (95% CI), compared to 67% (95% CI) in XGBoost, marking a 46.27% improvement. In terms of precision, SXI reached 98%, far surpassing XGBoost's 62.2%. Likewise, the AUC score for SXI was 0.98, which

Table 1
Accuracy comparison of other studies vs. the current study

		Accuracy	Precision	AUC
Other studies	LightGBM	NA	NA	0.9
	XGBoost	NA	NA	0.9
	CatBoost	NA	NA	0.9
	TabNet	61%	61%	0.65
	FT-Transformer	63%	63%	0.66
Current study	XGBoost	67%	62.2%	0.68
	SXI	98%	98%	0.98

is notably higher than XGBoost's 0.68, demonstrating its superior classification capability.

Furthermore, when benchmarked against other deep tabular models, SXI showed substantial gains over TabNet (AUC: 0.65) and FT-Transformer (AUC: 0.66) on this dataset. The relatively modest performance of these models may be attributed to the high dimensionality, sparsity, and complex feature interactions typical of telecom behavioral data, which pose challenges for architectures designed primarily for structured tabular benchmarks.

4. Discussions

The findings of this study demonstrate that the AI²-Sriya Expert Index (SXI) significantly outperforms traditional ML models in predicting wireless customer churn. The results of the comparative analysis between SXI and widely used algorithms such as XGBoost, LightGBM, CatBoost, TabNet, and FT-Transformer show that SXI achieves superior performance across key metrics: 98% accuracy, 98% precision, and an AUC of 0.98. This marked improvement highlights SXI's enhanced ability to model complex behavioral patterns in telecom data.

Unlike conventional models that rely on static training and single-algorithm inference, SXI functions as a dynamic, ensemble-driven super feature. It integrates weighted outputs from 5–10 ML models—including random forest, XGBoost, LASSO, and MI—into a unified score, which is further optimized through a proprietary deep neural network. This hybrid architecture enables SXI to capture both linear and nonlinear relationships more effectively, resulting in higher predictive accuracy and robustness.

Moreover, the iterative optimization process enhanced by deep learning and reward-punishment-based weight calibration ensures the continuous refinement of the SXI score. This real-time adaptability makes SXI particularly effective for dynamic environments where customer behavior evolves rapidly.

In short, SXI offers a robust, scalable, and highly effective solution for churn prediction, with broad potential across industries requiring real-time, interpretable analytics.

5. Conclusion

Traditional ML models are typically trained only once on past data and applied for predictions on unknown data. As opposed to this, the SXI scoring system works in real time, generating scores for each piece of data to calculate the probability of customer churn in real time. This individual-level scoring process enables companies to make more insightful and timely decisions based on the behavior that can be predicted for each customer. The strong relationship between SXI and churn, as indicated by a perfect R-squared value of 1.0, suggests an extremely strong relationship that can be effectively used to drive decision-tree-based customer-retention strategies.

The experimental results discussed in this paper provide actionable insights for crafting data-based business action plans. These findings are especially valuable when creating short-term, mid-term, and long-term actions against customer churn. Through the examination of future data points and the calculation of corresponding SXI scores, the system allows businesses to evaluate churn threats ahead of time, instead of after time.

This study confirms the strong predictive capabilities of the SXI model when applied to telecom datasets aimed at analyzing customer churn patterns. When compared to traditional models such as XGBoost, the SXI consistently delivered substantially higher performance across accuracy, precision, and AUC, highlighting its robustness and practical applicability in real-world churn prediction.

Outside of model performance, this study suggests a holistic framework for dealing with churn reduction at every level. The findings show that customer churn can first be minimized from 49.56% to 39.65% (a drop of 20%) through the SXI model. With further optimization, churn can be minimized to 24.78% in the mid-term and to 6.44% in the long-term. These incremental yet meaningful declines serve to underscore the compounding influence of paying attention to SXI score gains over time. This strongly suggests that ongoing focus on SXI-driven metrics can significantly mitigate customer attrition and improve business continuity.

In conclusion, the results highlight the revolutionary potential of predictive modeling using SXI in the wireless telecommunications industry. The capability of precise churn risk prediction and provision of actionable insights empowers telecom operators with effective instruments to enact strategic retention strategies. This not only enhances customer satisfaction and business performance but also maximizes long-term profitability through minimal revenue loss due to customer churning.

In addition, the telecommunication sector is specifically used in this study, but the SXI framework has a broader application. Its adaptive and modular architecture indicates that it can be expanded and fashioned to address various prediction problems across many other sectors, including finance, healthcare, retail, and insurance, in which decision precision and real-time scoring are critical.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors are employees of Sriya, where the AI² SXI model was developed using the company's resources. The authors declare that this affiliation did not influence the study's results or conclusions.

Data Availability Statement

The data that support the findings of this study are openly available in Kaggle at https://www.kaggle.com/datasets/abhinav89/telecom-customer.

Author Contribution Statement

Nikhil Kakkattu Murugan: Software, Investigation, Data curation, Visualization. **Reeshabh Kumar:** Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Prashant Yadav:** Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Mahesh Banavar:** Conceptualization, Methodology, Resources, Writing – review & editing, Supervision, Project administration. **Srinivas Kilambi:** Conceptualization, Methodology, Resources, Writing – review & editing, Supervision, Project administration.

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