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RESEARCH ARTICLE

## Hybrid AI framework for customer churn classification and business risk assessment

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### ABSTRACT

Customer turnover is a major problem in the telecom sector, Consequently, identifying clients who are most likely to depart might aid in retention decisions. Single-model methods might lack the flexibility to represent complex customer behavior, and class imbalance can impact the identification of churn cases. This study introduces a framework for churn prediction based on machine-learning (ML) techniques that employs CatBoost, LightGBM and XGBoost as base learners and Logistic Regression as a meta-learner in the Stacking Ensemble. The framework utilizes data pre-processing, domain knowledge-based feature engineering, outlier detection, and SMOTE class imbalance techniques for enhancing predictive learning. Feature engineering and SMOTE are incorporated to improve the learning process. Experimental results demonstrate that Stacking Ensemble obtains an accuracy of 81.10%, a recall of 60.86%, an F1-score of 63.08%, and an ROC-AUC of 84.60%, whereas XGBoost scores the best ROC-AUC of 84.63%. Furthermore, churn probabilities are predicted and utilized for customer risk segmentation and financial impact assessment, helping to identify customer groups that have a higher potential revenue exposure. In summary, proposed framework shows the potential of ensemble ML for churn prediction and offers data-driven insights to help companies prioritize customer retention and protect revenue in the telecom industry.

### KEYWORDS

Customer Churn, Telecommunication; Machine Learning, Churn Prediction; Customer Relationship Management, Ensemble Learning, Risk Assessment.

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### 1. Introduction

In the context of business diversification, market saturation and economic globalization, competition among firms has intensified. Due to newer methods of gathering information and the over homogenization offers of their products and services, many firms are experiencing customer churn [1]. Customer churn is the term used to describe the actions of customers who decide not to use a company's goods or services or who switch to competitors. A churned customer base has a high probability of influencing other customers' business decisions in their social networks, which might harm the company's reputation and result in a significant decline in revenue if additional customers decide to unsubscribe [2]. For the long-term growth of enterprises in dynamic, competitive markets, indispensable approach. Enterprises may improve customer satisfaction with Customer Relationship Management (CRM) to establish and maintain long-term connections with their customers and grow their market share and profits [3].

Predicting which customers are at risk of churning enables businesses to implement retention strategies and plans that provide better service to keep customers. A useful method for forecasting client attrition in a variety of sectors is machine learning (ML) [4]. ML models demonstrated noteworthy success in accurately predicting outcomes on complex patterns [5]. This work's primary goal is to develop an ML model that provides telecom firms with reliable customer churn predictions [6]. Customer churn is a major challenge for telecommunications companies due to intensifying competition and evolving customer preferences. Customers who are on the verge of turning into churners can lead to loss of revenue and adversely impact business growth, making it critical to identify them early. Hence, the aim of this research is to develop an efficient ML churn prediction

model to predict customers' churn and enable prompt customer retention initiatives. The highlights of this paper are the following:

- Develops a robust stacking model using complementary gradient-boosting learners to predict customer churn.
- Utilizing imbalance aware learning to improve identification of churned customers which is very important in real-world churn data.
- Introduces domain-informed features capturing customer tenure, charge dynamics, service engagement, business-risk indicators, and their interactions.
- Extends conventional churn classification by translating predicted churn probabilities into customer risk segments and revenue exposure.
- Provides a quantitative basis for prioritizing retention interventions according to customer risk and potential financial impact.

The novelty of this research is to combine the three algorithms Cat Boost, Light GBM, XG Boost in a Stacking Ensemble along with Domain-Informed Feature Engineering and SMOTE Class Imbalance dealing for Customer Churn Prediction. The proposed framework differs from traditional churn classification methods by incorporating predictive probabilities with financial exposure risk assessments and financial impact assessments of customers into financial risk segmentation. The need to better recognize customers at risk of churn makes this approach appropriate and the ability to convert predictive outcomes to actionable retention insights makes this approach appropriate. The framework thus gives a data-driven foundation to prioritize retention actions based on customer risk and the potential financial return.

The rest of the paper is organized as follows: Section II discusses relevant research on the prediction of customer churn. In this study, the materials and methods were elaborated in Section III. In Section IV, Experimental findings are examined. Performance comparison with alternative cutting-edge methods. Section V is followed by a summary and some suggestions for further research.

## 2. Literature Review

The existing studies on customer churn prediction utilizing ML, ensemble learning, DL, and XAI are summarized in Table I.

Raut and Puri (2026) provided a comprehensive ML and explainable artificial intelligence (XAI) customer churn prediction technology for telecom sector. A hyperparameter-optimized XGBoost classifier attains 89.7% accuracy and an ROCAUC of 0.847 on a benchmark telecom dataset. It performs noticeably better than baseline models. Employee attrition is mostly caused by month-to-month contracts, short tenure, electronic cheque payments, and fibre optic service [7].

Dekmak et al. (2025) concentrated on the telecom sector and investigated the potential of data mining and ML to forecast and lower customer attrition. An ensemble voting classifier produced greatest outcomes based on our testing, with 73.19% accuracy and 65.49% recall. The automated process was quicker, required less manual adjustment, and outperformed the baseline model in both accuracy and recall (69.33% accuracy and 53.23% recall). This article uses a publicly available telco dataset that simulates real-world customer activity to demonstrate how AI and ML may make customer retention smarter and lead to a speedier approach to sustaining customers [8].

Singh, Badwal and James (2025) presented a hybrid architecture that combines Reinforcement Learning, XAI, and To develop a comprehensible, reliable, and accurate churn prediction model, ensemble learning. A LightGBM classifier was trained using an e-commerce dataset that included customer churn data based on behavioural characteristics. This resulted in an accuracy of 69.63% for incentive proposals for customer retention and 98.76% for churn prediction [9].

Modupeola et al. (2025) developed predictive models using the cell2cell dataset. For data preparation and feature selection, methods such as principal component analysis, correlation matrices, and RF classifiers were used in conjunction with Python tools. Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are advanced DL techniques used to enhance prediction accuracy and capture temporal correlations in consumer behaviour. The results demonstrated that the RNN achieved accuracies of 0.7108 and AUCs of 0.6107, whereas the LSTM achieved 0.7106 and 0.6026. In order to improve churn prediction systems, paper suggests that future research utilise DL and sophisticated feature engineering techniques [10].

Alteer and Alariyibi (2024) Developed a predictive model to forecast Internet service providers' (ISPs') client attrition. To train the models, a dataset from a Libyan ISP business was used in a number of tests. With only 5% of consumers churning, the dataset was imbalanced. Several oversampling methods were employed to lessen this. 5 different classifiers were employed in the suggested method. In particular, methods Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), Gradient Boosting Machine (GBM), and Extreme Gradient Boosting (XGBoost) are useful in this prediction context. The experiment's findings showed that, with an AUC value of 94%, XGBoost tree model yielded the best results [11].

Aishwarya et al. (2023) In the trials, four ML classifiers are used. These ML classifiers are first used to forecast customers' churn status. It uses the Synthetic Minority Oversampling Technique (SMOTE) to address the imbalance in the dataset. According to experimental inquiry, the best approach is GB Classifier, which has an accuracy of 95.13% [12].

TABLE I. Table 1. Literature Review of Machine Learning-Based Customer Churn Prediction

| Author                          | Dataset                   | Methods                                                  | Findings                                                                                                                                                                    | Recommendation                                                                                            |
|---------------------------------|---------------------------|----------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------|
| Raut and Puri (2026)            | Benchmark Telecom Dataset | Hyperparameter-optimized XGBoost and XAI                 | XGBoost achieved 89.7% accuracy and 0.847 ROC-AUC. The main causes of attrition were fiber-optic services, electronic payments, short tenure, and month-to-month contracts. | Explore advanced ensemble and explainable models for improved churn prediction and retention.             |
| Dekmak et al. (2025)            | Public Telecom Dataset    | ML, data mining, automated workflow, Voting Classifier   | Voting Classifier achieved 73.19% accuracy and 65.49% recall, improving over the baseline.                                                                                  | Reduce manual tuning and investigate stronger ensemble models to improve prediction performance.          |
| Singh, Badwal and James (2025)  | E-commerce Churn Dataset  | Ensemble Learning, XAI, Reinforcement Learning, LightGBM | LightGBM achieved 98.76% accuracy, while reinforcement learning provided retention recommendations with 69.63% reward prediction.                                           | Extend the framework to other domains, particularly telecommunications, and improve retention strategies. |
| Modupeola et al. (2025) [4]     | Cell2cell Dataset         | PCA, correlation analysis, RF, RNN, LSTM                 | RNN achieved 71.08% accuracy and 0.6107 AUC, while LSTM achieved 71.06% accuracy and 0.6026 AUC.                                                                            | Improve churn prediction by utilising cutting-edge DL and feature-engineering approaches.                 |
| Alteer and Alariyibi (2024) [5] | Libyan ISP Dataset        | LR, DT, RF, GBM, XGBoost, oversampling                   | XGBoost produced the best performance with 0.94 AUC despite only 5% churned customers.                                                                                      | Develop more robust approaches for severe class imbalance and ISP-specific churn prediction.              |
| Aishwarya et al. (2023) [6]     | Customer Churn Dataset    | ML classifiers and SMOTE                                 | Gradient Boosting achieved the best accuracy of 95.13%, while SMOTE addressed class imbalance.                                                                              | Investigate advanced ensemble and hybrid approaches with better handling of imbalanced churn data.        |

**Research Gap:** Previous research has reported promising findings for churn prediction; however, there are certain shortcomings in the method. The studies are mainly dedicated to individual machine learning or ensemble models with few studies dedicated to robust hybrid models that use more than one ML techniques. Class imbalance persists, particularly in low-churn datasets such as telecom. Moreover, DL models have demonstrated moderate performance and the capability to incorporate prediction accuracy, interpretability, and actionable customer-retention strategies remain limited. There is a need, therefore, for a more powerful and meaningful churn prediction framework that will enhance prediction accuracy while also giving meaningful insights into the factors that affect customer churn.

### 3. Research Methodology

This study uses a ML based approach to classify customer churn and identify the risk level of customers using Telco Customer Churn dataset. We propose a method that involves data preprocessing, class imbalance and feature engineering. Three ML models—Cat Boost, Light, and Boost—are trained and tested using acc, perc, rec, F1, and ROC-AUC. Stacking is used for prediction and LR is selected as the meta-learner. Finally, churn probabilities are used to guide customer risk segmentation and financial impact assessment to guide retention strategies. The details of each step are provided in following in Figure 1.

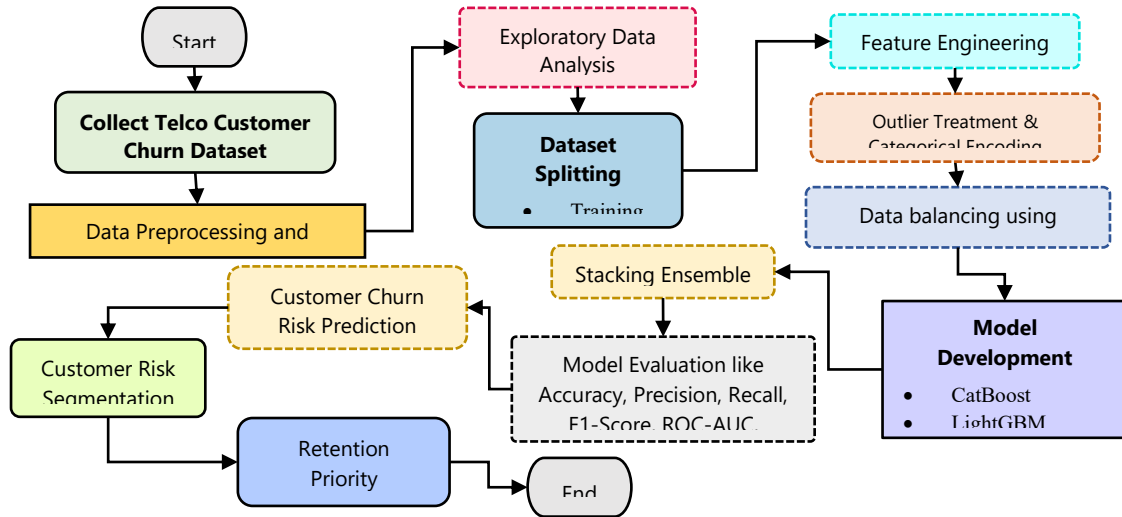


Fig. 1. Figure 1. Proposed Flowchart for Customer Churn Prediction

### 3.1 Data Collection And Analysis

The Telco Customer Churn dataset utilized in this study is publicly available and comprises 7043 customer records and 21 attributes. These features include demographic data, account data, subscribed services, billing data and the target variable Churn. The raw data was first cleaned by filtering out the non-predictive field Customer ID and then making the string Total Charges value into a numeric value as there are 11 missing values for customers who do not have any value in the Total Charges field. In this stage, the target label Churn was also examined to ensure whether the label is distributed according to the class or not before going for further processing. The dataset was moderately imbalanced with 5174 customers in the retained class (73.46%) and 1869 customers in the churned class (26.54%), as shown in Figure 2, typical for churn rate ranges in the telecom industry.

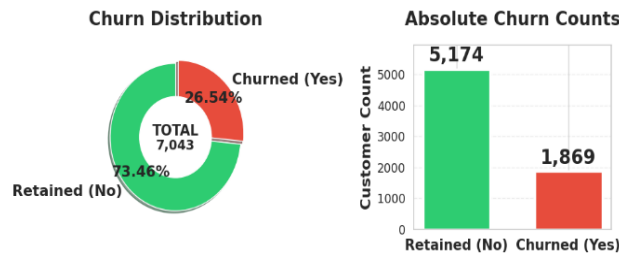


Fig. 2. Figure 2. Pie and Bar Plot for Churn Distribution

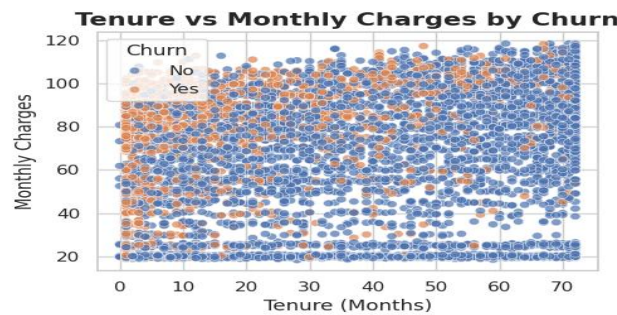


Fig. 3. Figure 3. Tenure vs Monthly Charges by Churn

The scatter plot of customer tenure versus monthly charges, by churn, is displayed in Figure 3. Orange would be churned users, and blue would be retained users. The non-churned customer base is spread over longer tenures and the churned are grouped together with different charges. The lower the lifetime, the higher the churn, the more irregular the charges higher the churn.

### 3.2 Data Splitting

To ensure repeatability, the data is split into training (4,507), validation (1,127), and test (1,409) sets using stratified sampling and a fixed random seed. The validation set is used to fine-tune ensemble, training set is used to fit model, and test set is kept out for ultimate objective assessment.

### 3.3 Feature Engineering

The imputation process is undertaken within a consistent feature-engineering process that produces 13 new features reflecting domain knowledge of the drivers of telecom churn: tenure grouping, charge-dynamics ratios, a service-engagement count,

business-risk flags, and interaction terms between the business-risk factors. The prediction value of the ensemble models is increased since these features capture more information than the raw variables alone.

### 3.4 Outlier Treatment And Encoding

Treatment for outliers is applied to MonthlyCharges, TotalCharges; the IQR method was used, bounds were calculated from the training set only, and the values were clipped (not removed) to minimize impact of the extreme values. The 15 categorical features are one-hot encoded, and the 17 numerical features are fed without any modification. The encoder is applied to validation and test sets without leakage after being employed exclusively on the training set. This creates a set of binary indicator columns for the categorical variables, resulting in 58 columns for model training by combining the 15 categorical variables with the 17 numeric ones.

### 3.5 Class Imbalance Handling

The original dataset is skewed, with significantly more customers churning than remaining. The Synthetic Minority Oversampling Technique (SMOTE) is used only on the training set to get around this. Rather than just copying samples, the SMOTE algorithm creates synthetic minority-class samples by interpolating between existing minority-class samples and their nearest neighbours. The SMOTE algorithm is applied to imbalanced training set to create a fully balanced training set with 6,622 samples (3,311 samples per class), Figure 4 illustrates that neither the validation set nor the test set were impacted, indicating that they would preserve the real-world assessment circumstances and a 1:1 ratio.

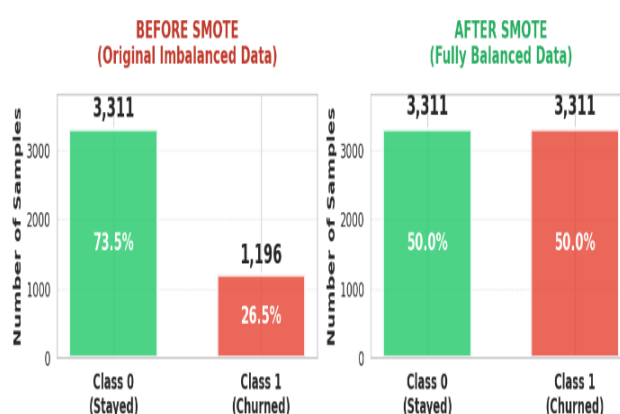


Fig. 4. Figure 4. Data Distribution Before and After SMOTE

### 3.6 Model Development

Three gradient-boosting algorithms are trained independently on the SMOTE-balanced training set to serve as base learners for the ensemble.

- **Cat Boost:** Cat Boost is a gradient-boosting algorithm developed by Yandex, which is unique in its capability to work with categorical features, and in mechanisms that limit overfitting and target leakage typical of other boosting methods. It has 700 iterations, a learning rate of 0.03, tree depth of 5, L2 regularization of 5.0, and is configured to optimize log-loss with the AUROC as the evaluation metric (verbose False, fileLoggingFalse, efficient=False).
- **LightGBM:** LightGBM is a framework of gradient-boosting, it is highly efficient on high dimensional tabular data and keeps the predictive power. It has 500 estimators, a learning rate of 0.025, maximum depth of 5, 24 leaves, 25 minimum child samples, and a subsample rate of 0.85 and column-sample rate of 0.5 to reduce overfitting on the resampled data, along with L1 (0.1) and L2 (0.5) regularization.
- **XGBoost:** XGBoost is an efficient, regularized GB model that has been successfully applied across structured/tabular classification problems for its excellent empirical performance, its efficient computation and its built-in regularization. It has 500 estimators, a learning rate of 0.025, maximum depth of 4, minimum child weight of 2, gamma of 0.1, subsample and column-sample rates of 0.85, binary logistic objective, and histogram-based tree-construction for faster training.

### 3.7 Stacking Ensemble

A stacking ensemble is constructed to stack the three base learners together. To prevent the leakage, at level-0, out-of-fold predictions are made using CatBoost, LightGBM and XGBoost using a training set and 5-fold cross validation. Their outputs directly rely on probability forecasts on the test and validation sets. These are combined into a 3-column meta-feature matrix. At level-1, a logistic regression meta-learner (with L2 penalty and  $C = 1.0$ ) is learned from these meta-features. This performs optimization of weights for the combination of the base models' predictions and constructs the final stacked churn probability. For comparison, a basic weighted averaging ensemble is also tested whose weights are based on validation ROC-AUC of base models. Based on validation results, the model ensemble is selected as the best.

### 3.8 Performance Matrix

A confusion matrix was used to express classification accuracy numerically. Actual and anticipated classes make up the two dimensions of the confusion matrix. TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative values of the confusion matrix, respectively.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

$$f1 - \text{Score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \quad (4)$$

The percentage of correct results in total number of records examined is known as accuracy. The precision measures the percentage of genuine positives among anticipated positives. Recall is another crucial metric that provides additional information when catching every potential positive is essential. Recall is the percentage of all positive samples that were accurately anticipated to be positive. These two metrics can be combined to create a new metric, F1 score, when an ideal balance between accuracy and recall is needed. The F1 score is a number between 0 and 1 that represents the harmonic mean of accuracy and recall. All evaluation formulae for these metrics are provided in Equation (1)–(4).

## 4. Results And Discussion

This experiment makes use of a Jupyter Notebook running Python 3 on an Intel Core i7 CPU running at 4.20 GHz and 48 GB of RAM. Pandas, NumPy, Scikit-learn, CatBoost, LightGBM, and XGBoost were used for data preprocessing, model development, ensemble construction, and evaluation. A comparison of performance of proposed ML models for churn prediction is displayed in Table II. The results showed the best accuracy for the stacked model (0.8110), indicating an appropriate balance between correctly identifying churners and number of churn cases missed. LightGBM has the best result in precision (0.6693) and XGBoost has best result in ROC-AUC (0.8463), showing high overall class discriminatory performance. The accuracy values for CatBoost and Weighted Average are nearly identical (0.8083). Overall, the results suggest that ensemble-based methods are competitive with single classifiers, particularly in terms of increases in rec and F1 on the churn prediction task.

TABLE II. Table 2. Experiment Results of Proposed Models For Churn Prediction

| Algorithm         | Accuracy | Precision | Recall | F1-Score | ROC-AUC |
|-------------------|----------|-----------|--------|----------|---------|
| Cat Boost         | 0.8083   | 0.6614    | 0.5685 | 0.6115   | 0.8431  |
| LightGBM          | 0.8101   | 0.6693    | 0.5618 | 0.6109   | 0.8450  |
| XGBoost           | 0.8083   | 0.6614    | 0.5685 | 0.6115   | 0.8463  |
| Stacking Ensemble | 0.8110   | 0.6546    | 0.6086 | 0.6308   | 0.8460  |
| Weighted Average  | 0.8083   | 0.6640    | 0.5618 | 0.6086   | 0.8458  |

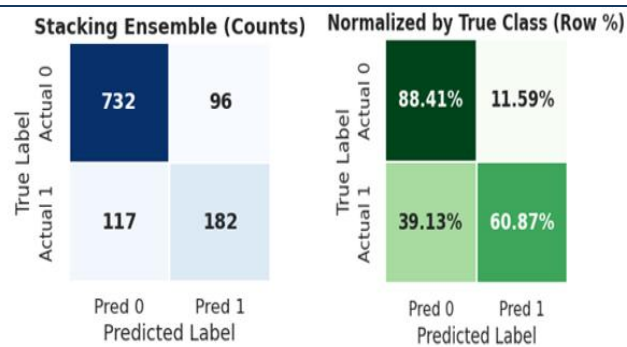


Fig. 5. Figure 5. Confusion Matrices of Stacking Ensemble Model

Figure 5 illustrates confusion matrices of Stacking Ensemble classifier using raw counts and normalized percentages. According to raw matrix, the model correctly identified 732 non-churn instances and 182 churn cases, while misclassifying 96 and 117 non-churn and churn cases, respectively. The normalized matrix shows the model's accuracy for non-churn predictions (88.41%) and churn predictions (60.87%), along with notable churn misclassifications (39.13%). This visualization highlights the ensemble's effectiveness in predicting non-churn customers as opposed to churn customers. Figure 6 shows the ROC and precision-recall curves for the stacking model's classification performance. The ROC curve's AUC value is 0.8461, which reflects good discriminative power, and the precision-recall curve's PR-AUC value is 0.6482, which reflects moderate precision at various recall levels.

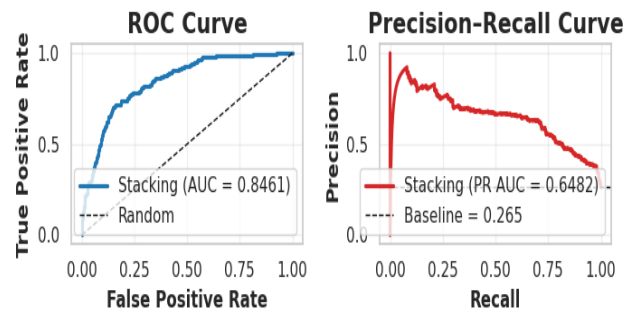


Fig. 6. Figure 6. ROC curve and precision–recall curve for stacking ensemble

#### 4.1 Business Risk Assessment

In addition to classification accuracy, the churn probabilities from the stacking ensemble can be interpreted in terms of business insights on test set. The first segmentation is into four risk tiers depending on the customer's churn likelihood.

Figure 7 demonstrates the distribution of customers by business risk and their monthly revenues at risk. The largest number of customers is in the Low Risk category with 882 customers and the highest Financial Exposure in the Critical Risk category was \$13,629 each month. Overall, the figure highlights the need to focus retention efforts on critical-risk customers to reduce potential revenue loss.

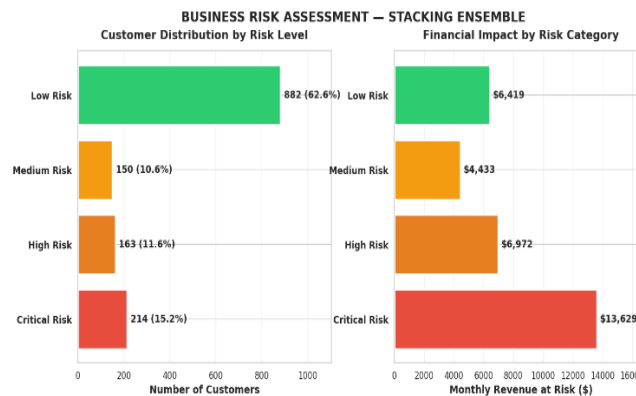


Fig. 7. Figure 7. Customer distribution and monthly revenue at risk by risk category

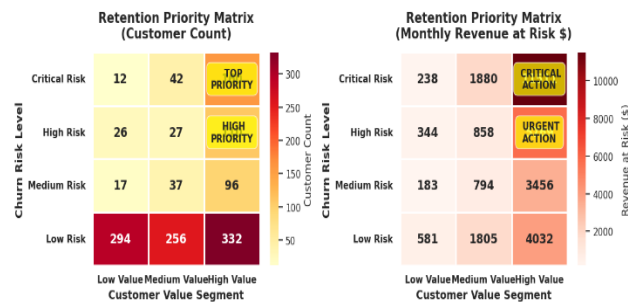


Fig. 8. Figure 8. Customer Retention Priority Matrix of Stacking Ensemble

Figure 8 present the analysis of customer based on churn risk level and customer value segment using stacking ensemble model. The left matrix is the number of customers in each segment and the right matrix is the revenue at risk. Highlighted cells show each of the varying levels of retention action required (Top Priority, High Priority, Critical Action, Urgent Action). Overall, it assists organizations in pinpointing which customer segments to focus on to maximize impact of retention initiatives and preserve revenue.

#### 4.2 Comparison And Discussion

The performance comparison in Table III shows that proposed Stacking Ensemble achieves the highest accuracy among SVM (78.46%), MLP (76.00%), and GNB (77.36%). Comparative results, on the other hand, have to be taken with a pinch of salt because they are calculated using different data sets, preprocessing and experimental pipelines of the proposed approach. Hence, the comparison is more a general one of performance and not a direct comparison of models.

TABLE III. Table 3. Comparison Between Based and Propose Models Performance

| Models                           | Accuracy |
|----------------------------------|----------|
| Support Vector Machine (SVM)[13] | 78.46    |
| Extra Trees[14]                  | 47.56    |
| Multilayer Perceptron (MLP)[15]  | 76       |
| Gaussian Naive Bayes (GNB)[16]   | 77.36    |
| Proposed Stacking Ensemble       | 81.10    |

The research is relevant to the practical use by telecom companies, as it allows them to identify customers at risk of early churn. This study uses Cat Boost, LightGBM and XGBoost algorithms, which when combined in a Stacking Ensemble, increase the success rate of identifying potential churners and deriving concrete churn probabilities. These forecast can be utilized for customer risk segmentation and help businesses classify their clients based on their likelihood of churning. The financial impact assessment also provides an understanding of the financial exposure for various risk groups on a monthly basis. As a result, research may enable organizations to priorities retention strategies, focus resources on their most vulnerable customers, minimize lost revenue and inform their decisions about customer retention through data-driven insights.

#### 4.3 Limitation And Future Work

This study may not be applicable to other telecom datasets or industries due to the specific dataset and models used. The differences between the datasets and experimental pipelines make the comparison to the baseline models not well constrained. Future work can involve the proposed ensemble being tested on larger and wider datasets, new algorithms being added, more sophisticated feature engineering methods and more sophisticated approaches to the development of real-time churn prediction and personalization approaches for real-world implementation.

#### 5. Conclusion And Future Work

In this study, the effectiveness of ML and ensemble approaches in forecasting customer turnover is demonstrated using the Telco Customer turnover dataset. The approach proposed in this article combines data preprocessing, feature engineering, imbalanced data handling with SMOTE, and 3 gradient boosting models – Cat Boost, LightGBM, XGBoost. With 81.10% accuracy, 60.86% recall, 63.08% F1-score, and 84.60% ROC-AUC, the Stacking Ensemble demonstrated competitive predictive performance. Moreover, the churn probabilities were applied in customer risk segmentation and financial impact assessment, helping businesses determine the financial consequences of losing their customers and focus on retention strategies. Overall, the research is supporting data driven churn management and revenue protection.

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