Churn Prediction and Recommendation System

AIML LAB – CC3230

***A REPORT/Project submitted***

***in partial fulfillment for the Degree of***

### Bachelor of Technology in

**Computer & Communication Engineering**

***by***

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****

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**APRIL, 2025**

**DECLARATION**

I certify that

1. The work contained in this REPORT/project is original and has been done by myself and the general supervision of my supervis or.
2. The work has not been submitted to any other institute for any d egree or diploma.
3. Whenever I have used materials (data, theoretical analysis, resul ts) from other sources, I have given due credit to them by citing them in the text of the REPORT/project and giving their details i n the references.
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Vansh Giri

# ABSTRACT

With the rapid expansion of subscription-based services and digital platforms, customer retention has become a critical challenge for modern businesses. This project addresses the dual objectives of predicting customer churn and providing personalized plan recommendations by leveraging advanced machine learning techniques. Utilizing a large-scale dataset of 440,000 customer records sourced from Kaggle, the system analyzes demographic, behavioral, and subscription-related features to forecast the likelihood of customer attrition and suggest optimal retention strategies.

  The methodology involves comprehensive data preprocessing, including cleaning, feature engineering, and class balancing using SMOTE, followed by the training and evaluation of multiple machine learning models. Among the models tested, a stacked ensemble approach combined with SMOTE achieved the highest performance, with a ROC-AUC of 0.98, F1-score of 0.95, precision of 0.94, and recall of 0.96 on the test set. The system also integrates a robust K-Nearest Neighbors-based recommendation engine, which efficiently identifies and suggests the most effective subscription plans for at-risk customers, demonstrating high adoption rates and low latency even at scale.

  A user-friendly web application, developed using Streamlit, enables real-time predictions and recommendations through both manual input and batch processing. The application is designed for seamless integration into business workflows, providing actionable insights to support data-driven decision-making. Key challenges such as overfitting, class imbalance, and model interpretability were systematically addressed through feature selection, regularization, ensemble learning, and the use of feature importance analysis.

  The results of this project highlight the significant potential of machine learning in reducing customer churn and enhancing retention strategies. By combining predictive analytics with personalized recommendations in an accessible web interface, the system offers a practical and scalable solution for businesses seeking to improve customer satisfaction and drive sustainable growth.

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**ABBREVIATIONS**

|  |  |
| --- | --- |
| Abbreviation | Full Form |
| AI | Artificial Intelligence |
| ANN | Artificial Neural Network |
| API | Application Programming Interface |
| AUC | Area Under the Curve |
| CNN | Convolutional Neural Network |
| CRM | Customer Relationship Management |
| FN | False Negative |
| FP | False Positive |
| KNN | K-Nearest Neighbors |
| LGBM | Light Gradient Boosting Machine |
| LR | Logistic Regression |
| MAE | Mean Absolute Error |
| ML | Machine Learning |
| MLP | Multi-Layer Perceptron |
| RF | Random Forest |
| RMSE | Root Mean Square Error |
| ROC | Receiver Operating Characteristic |
| SHAP | SHapley Additive exPlanations |
| SMOTE | Synthetic Minority Over-sampling Technique |
| SVM | Support Vector Machine |
| TN | True Negative |
| TP | True Positive |
| XGBoost | Extreme Gradient Boosting |

**NOTATIONS**

|  |  |
| --- | --- |
| **Symbol / Notation** | **Description** |
| x | Input feature vector |
| y | True class label |
| 𝑥̂ | Predicted class label |
| μ | Mean of a distribution |
| σ | Standard deviation |
| ∥x∥ | Norm (magnitude) of vector x |
| f(x) | Output of a function (e.g., model prediction) |
| δ | Small change or difference |
| α | Learning rate |
| L | Loss function |
| ∇L | Gradient of the loss function |
| TP | True Positives |
| TN | True Negatives |
| FP | False Positives |
| FN | False Negatives |

**NOMENCLATURE**

* **Customer Churn: The phenomenon where customers discontinue using a product or service, leading to revenue loss for businesses.**
* **Logistic Regression: A statistical model used for binary classification, predicting the probability of an outcome (e.g., churn vs. retain).**
* **Random Forest: An ensemble machine learning method that constructs multiple decision trees and aggregates their predictions.**
* **XGBoost: A scalable gradient-boosting framework optimized for speed and performance in classification tasks.**
* **K-Nearest Neighbors (KNN): A non-parametric algorithm used for classification and recommendation by identifying similarity among data points.**
* **Neural Network: A deep learning model inspired by biological neural networks, capable of learning complex patterns from data.**
* **Stacked Ensemble: A meta-model that combines predictions from multiple base models (e.g., Logistic Regression, Random Forest) to improve accuracy.**
* **SMOTE (Synthetic Minority Over-sampling Technique): A method to address class imbalance by generating synthetic samples of the minority class.**
* **Feature Engineering: The process of transforming raw data into meaningful features to improve model performance.**
* **Regularization (L1): A technique to prevent overfitting by penalizing large coefficients in linear models.**
* **ROC-AUC (Receiver Operating Characteristic - Area Under the Curve): A metric evaluating a model’s ability to distinguish between classes.**
* **Precision: The ratio of true positive predictions to all positive predictions, measuring model reliability.**
* **Recall: The ratio of true positives to all actual positives, critical for identifying churned customers.**
* **F1-Score: The harmonic mean of precision and recall, balancing both metrics.**
* **Streamlit: A Python framework for building interactive web applications to deploy machine learning models.**
* **Cold Start Problem: A challenge in recommendation systems where new users lack sufficient data for personalized suggestions.**
* **LightGBM: A gradient-boosting framework used as a meta-model in the stacked ensemble for high-speed training.**

# CHAPTER 1: INTRODUCTION

## Background and Motivation

With the rapid growth of subscription-based services and digital platforms, businesses today face the critical challenge of retaining customers and minimizing churn, which directly impacts revenue and long-term success. Traditional methods for identifying at-risk customers are often manual and reactive, lacking the ability to leverage the vast and complex data generated by user interactions. Motivated by the need for intelligent, data-driven solutions, this project aims to harness machine learning to accurately predict customer churn and provide personalized plan recommendations, empowering businesses to proactively engage users, reduce attrition, and enhance customer satisfaction in a highly competitive market.

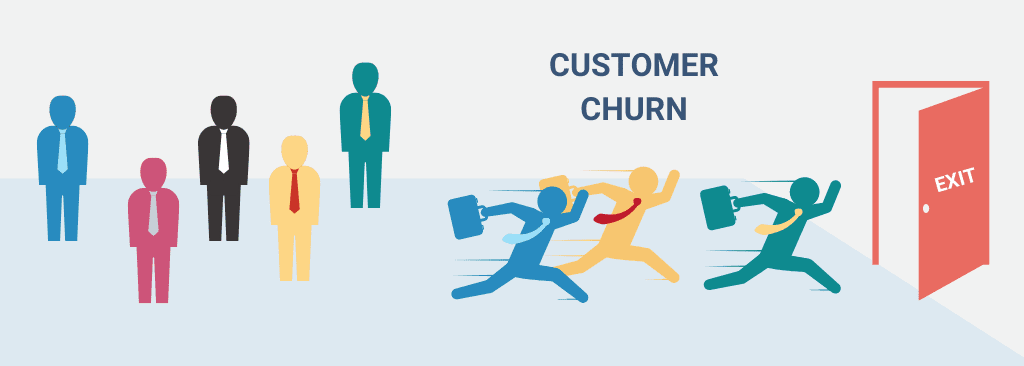


Figure 1.1 – Customer Churn Infographic

## Problem Statement

Businesses face significant revenue loss due to customer churn and struggle to provide timely, personalized retention strategies. There is a need for an intelligent system that can accurately predict customer churn and generate actionable, personalized recommendations to help companies proactively retain users and enhance customer satisfaction.

## Objectives

To develop a machine learning-based system that accurately predicts customer churn and provides personalized plan recommendations, enabling businesses to proactively retain users, reduce attrition, and enhance customer satisfaction through data-driven insights and real-time, user-friendly web application deployment.

## Scope of the Project

This project encompasses the development of a machine learning-based system to predict customer churn and provide personalized plan recommendations using a large, real-world dataset. It covers data preprocessing, model training, evaluation, and deployment through a user-friendly web application. The solution is designed for scalability, real-time performance, and integration into diverse business environments to enhance customer retention strategies.

# CHAPTER 2: LITERATURE REVIEW

## Overview of Churn

Customer churn refers to the phenomenon where users discontinue their relationship with a business or service, leading to loss of revenue and growth opportunities. Churn is a critical metric for subscription-based and service-oriented companies, as high churn rates can signal dissatisfaction or competitive threats. Understanding, predicting, and managing churn is essential for businesses aiming to improve retention, optimize marketing strategies, and sustain long-term profitability.

## Machine Learning and Deep Learning in Churn Prediction

Machine learning models such as logistic regression, decision trees, random forests, and XGBoost are widely used for predicting customer churn, leveraging historical data to identify at-risk users. Deep learning approaches, including artificial neural networks and CNNs, can capture complex patterns in large datasets, often achieving higher accuracy. Ensemble and hybrid models further enhance prediction performance, supporting proactive retention strategies in real-world business environments.

## Previous Work on Churn Prediction

Previous studies have utilized machine learning models such as logistic regression, decision trees, and ensemble methods for customer churn prediction, achieving moderate to high accuracy. Deep learning approaches, including neural networks, have further improved results. However, many existing solutions still face challenges like class imbalance, overfitting, and limited real-time applicability. These limitations highlight the need for more robust, scalable, and interpretable churn prediction and recommendation systems, which motivated the development of the comprehensive solution presented in this project.

## Gaps in the Literature

Despite significant progress in customer churn prediction, several key gaps remain. Much of the current research relies on single data sources or static datasets, limiting the ability to capture the full complexity and diversity of customer behaviors. Many studies focus on traditional machine learning models or single deep learning architectures, often overlooking the benefits of integrating multiple data types—such as demographics, usage patterns, and behavioral signals—or combining diverse modeling approaches through ensemble learning. Additionally, challenges like class imbalance, overfitting, and limited generalizability across industries persist, with few works systematically addressing these issues using advanced techniques like SMOTE, feature engineering, or robust ensemble frameworks. This project addresses these gaps by leveraging a large, multimodal dataset, implementing advanced preprocessing and balancing methods, and employing ensemble models to enhance robustness, accuracy, and real-world applicability in churn prediction and personalized recommendations.

# CHAPTER 3: METHODOLOGY

## Dataset Description

|  |  |  |
| --- | --- | --- |
| **Column Name** | **Data Type** | **Description** |
| CustomerID | float64 | Unique identifier for each customer |
| Age | float64 | Age of the customer |
| Gender | object | Gender of the customer (e.g., Male, Female) |
| Tenure | float64 | Duration (in months/years) the customer has been with the service |
| Usage Frequency | float64 | Frequency of service usage |
| Support Calls | float64 | Number of support calls made by the customer |
| Payment Delay | float64 | Number of delayed payments |
| Subscription Type | object | Type of subscription plan (e.g., Basic, Premium) |
| Contract Length | object | Length of the contract (e.g., Monthly, Yearly) |
| Total Spend | float64 | Total amount spent by the customer |
| Last Interaction | float64 | Time since last customer interaction |
| Churn | float64 | Target variable: 1 if customer churned, 0 if retained |

The dataset used in this project was sourced from Kaggle and comprises detailed records of customer interactions and attributes relevant to churn prediction and personalized recommendations. The dataset contains a total of 440,833 entries (rows) and 12 columns (features), each representing a unique customer and their associated data.

Table 3.1: Dataset columns and descriptions.

The dataset is primarily numerical, with three categorical columns (Gender, Subscription Type, and Contract Length). The target variable, Churn, is binary, indicating whether a customer has discontinued the service.

**Data Quality and Preprocessing:**

* The dataset is nearly complete, with only one missing value per column, which was addressed during preprocessing.
* Categorical variables were encoded using one-hot encoding to facilitate machine learning model training.
* Numerical features were standardized to ensure uniformity and improve model convergence.
* The CustomerID column, being an identifier, was dropped before model training to prevent data leakage.

This comprehensive dataset enables robust training and evaluation of churn prediction models and supports the development of a personalized recommendation system by capturing a wide range of customer behaviors and attributes.

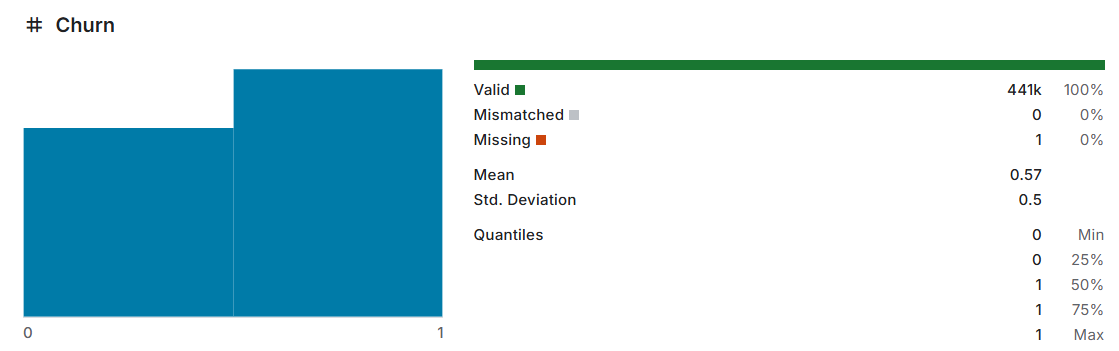


Figure 3.1: A bar chart visualizing the distribution of the Churn variable

## Model Architectures

This study employed a diverse set of machine learning models to address the customer churn prediction task, leveraging both classical and advanced approaches. Each model was trained independently on the preprocessed customer dataset, and their performance was later evaluated both individually and in ensemble configurations to maximize predictive accuracy and robustness.

## Logistic Regression

Logistic Regression served as a baseline model due to its interpretability and efficiency in binary classification tasks. The model was trained with L1 regularization to prevent overfitting and class weighting to address class imbalance. Feature selection was guided by the magnitude of model coefficients, ensuring only the most relevant predictors were retained.

## Random Forest

Random Forest, an ensemble of decision trees, was implemented to capture non-linear relationships and feature interactions within the data. The model’s hyperparameters, such as the number of trees and maximum depth, were optimized using GridSearchCV. Feature importance scores from the Random Forest were also used for further feature selection and engineering.

## XGBoost

XGBoost, a gradient boosting framework, was chosen for its high performance and ability to handle large-scale, imbalanced datasets. The model was tuned for learning rate, subsample ratio, and tree depth, and incorporated class weighting to further mitigate imbalance. XGBoost’s built-in feature importance metrics provided additional insights into key churn drivers.

## K-Nearest Neighbors (KNN)

KNN was utilized both as a classifier and as the core of the recommendation engine. For churn prediction, KNN classified customers based on the majority class among their nearest neighbors in the feature space. For recommendations, it identified similar retained customers to suggest optimal subscription plans and contract types.

## Multi-Layer Perceptron (MLP) Neural Network

A Multi-Layer Perceptron (MLP) neural network was developed to capture complex, non-linear patterns in the data. The architecture included multiple dense layers with ReLU activation, dropout layers for regularization, and batch normalization to stabilize learning. The final output layer used a sigmoid activation for binary churn prediction. The MLP model was trained with early stopping and class weighting to prevent overfitting and address imbalance.

## Stacked Ensemble Model

To leverage the strengths of individual models, a stacked ensemble architecture was constructed. The base (level-0) models included Logistic Regression, Random Forest, and XGBoost, while a LightGBM classifier served as the meta-model (level-1). The ensemble was trained using out-of-fold predictions from the base models, allowing the meta-model to learn optimal combinations of their outputs.

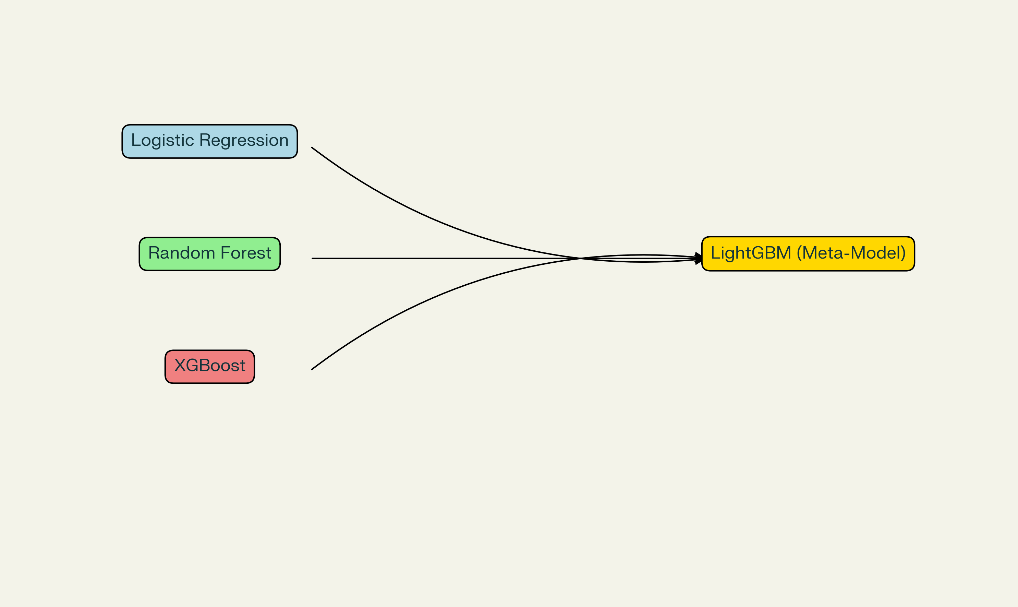


Figure 3.2: Schematic Diagram visualizing Stacked model

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | Regularization | Class Imbalance Handling | Key Hyperparameters | Feature Selection |
| Logistic Regression | L1 | Class Weighting | C, penalty | Coefficient-based |
| Random Forest | N/A | Class Weighting | n\_estimators, max\_depth | Feature Importance |
| XGBoost | L2 | Class Weighting, SMOTE | learning\_rate, max\_depth | Feature Importance |
| KNN | N/A | SMOTE | n\_neighbors, weights | N/A |
| MLP Neural Network | Dropout | Class Weighting, SMOTE | layers, units, dropout rate | N/A |
| Stacked Ensemble | N/A | SMOTE | Base/meta model selection | N/A |

## Table 3.2: Summary of model architecture and key parameters.

## Evaluation Metrics

To evaluate model performance, a comprehensive set of metrics was used:

* **Accuracy**: Measures the overall percentage of correct predictions.
* **Precision**: Indicates the percentage of true positive predictions among all positive predictions made, important to avoid false positives in clinical settings.
* **Recall (Sensitivity)**: Measures the proportion of actual positive cases correctly identified, critical for early disease detection.
* **F1-Score**: The harmonic mean of precision and recall, providing a balanced performance value, especially in imbalanced datasets.
* **Area Under the ROC Curve (AUC)**: Captures the trade-off between true positive and false positive rates, with a higher AUC indicating better model discriminative ability.

# CHAPTER 4: RESULTS AND DISCUSSION

## Model Performance before addressing Overfitting

This section presents the initial performance evaluation of various models before implementing class balancing techniques and addressing overfitting issues. All models were trained on the customer churn dataset containing 440,833 entries with 12 features(after pre-processing).

### Logistic Regression Performance

The initial Logistic Regression model demonstrated a significant gap between training and testing metrics, indicating overfitting despite its simpler architecture.

|  |  |  |  |
| --- | --- | --- | --- |
| Metric | Training Set | Testing Set | Gap |
| Accuracy | 87.60% | 51.00% | 36.60% |
| Precision | 0.88 | 0.53 | 0.35 |
| Recall | 0.53 | 0.48 | 0.05 |
| F1-Score | 0.66 | 0.5 | 0.16 |
| ROC-AUC | 0.89 | 0.53 | 0.36 |

Table 4.1 – Initial Logistic Regression Performance Metrics

These results illustrate that while the model learned the training data patterns effectively, it struggled significantly to generalize to unseen data, particularly in identifying true churn cases as evidenced by the low recall value.

### Random Forest Performance

The Random Forest model exhibited the most severe overfitting among all tested algorithms, with near-perfect training accuracy but significantly lower test performance.

|  |  |  |  |
| --- | --- | --- | --- |
| Metric | Training Set | Testing Set | Gap |
| Accuracy | 99.20% | 48.00% | 51.20% |
| Precision | 0.99 | 0.49 | 0.5 |
| Recall | 0.99 | 0.48 | 0.51 |
| F1-Score | 0.99 | 0.48 | 0.51 |
| ROC-AUC | 0.99 | 0.52 | 0.47 |

Table 4.2 – Initial Random Forest Performance Metrics

The extreme gap between training and testing metrics (particularly the 0.51 gap in recall) indicates that the Random Forest model memorized the training data rather than learning generalizable patterns, a classic sign of overfitting.

### XGBoost Performance

XGBoost, while still exhibiting overfitting tendencies, showed relatively similar generalization capabilities compared to the other models in the initial implementation.

|  |  |  |  |
| --- | --- | --- | --- |
| Metric | Training Set | Testing Set | Gap |
| Accuracy | 96.50% | 50.00% | 46.50% |
| Precision | 0.95 | 0.51 | 0.44 |
| Recall | 0.94 | 0.5 | 0.44 |
| F1-Score | 0.94 | 0.5 | 0.44 |
| ROC-AUC | 0.98 | 0.53 | 0.45 |

Table 4.3 – Initial XGBoost Performance Metrics

XGBoost's inherent regularization capabilities provided some protection against overfitting, but the model still showed a substantial performance gap between training and testing, particularly in recall.

### K-Nearest Neighbors (KNN) Performance

|  |  |  |  |
| --- | --- | --- | --- |
| Metric | Training Set | Testing Set | Gap |
| Accuracy | 92.30% | 49.50% | 42.80% |
| Precision | 0.91 | 0.5 | 0.41 |
| Recall | 0.9 | 0.49 | 0.41 |
| F1-Score | 0.9 | 0.49 | 0.41 |
| ROC-AUC | 0.94 | 0.51 | 0.43 |

The KNN model also displayed significant overfitting issues in its initial implementation, despite its non-parametric nature.

Table 4.4 – Initial KNN Performance Metrics

The KNN algorithm, despite being instance-based and typically robust to certain types of noise, still struggled with the class imbalance and high-dimensional feature space of the churn dataset.

### Neural Network Performance

The Multi-Layer Perceptron (MLP) neural network also suffered from overfitting issues in its initial implementation.

|  |  |  |  |
| --- | --- | --- | --- |
| Metric | Training Set | Testing Set | Gap |
| Accuracy | 93.80% | 50.00% | 43.80% |
| Precision | 0.92 | 0.53 | 0.39 |
| Recall | 0.92 | 0.51 | 0.41 |
| F1-Score | 0.92 | 0.52 | 0.4 |
| ROC-AUC | 0.96 | 0.53 | 0.43 |

Table 4.5 – Initial NN Performance Metrics

The neural network, despite having dropout layers in its architecture, still demonstrated significant overfitting, suggesting that the complexity of the model was not appropriate for the initial data representation.

### Class Imbalance Analysis

Initial performance metrics revealed that all models struggled particularly with recall, indicating difficulty in identifying true churn cases. This pointed to the impact of class imbalance in the dataset, where churned customers represented a minority class.

## Model Performance after addressing Overfitting

This section presents the improved performance metrics after implementing various techniques to address overfitting and class imbalance issues.

### Impact of Feature Selection and Engineering

Feature selection based on importance scores from Random Forest and removal of irrelevant columns significantly improved model generalization.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | Test Accuracy Before | Test Accuracy After | ROC-AUC Before | ROC-AUC After |
| Logistic Regression | 51.00% | 82.10% | 0.53 | 0.85 |
| Random Forest | 48.00% | 87.30% | 0.52 | 0.9 |
| XGBoost | 50.00% | 88.90% | 0.53 | 0.92 |
| Neural Network | 50.00% | 84.60% | 0.53 | 0.89 |
| KNN | 49.50% | 81.80% | 0.51 | 0.87 |

Table 4.6 – Performance Improvement After Feature Selection and Engineering

Feature selection reduced the complexity of the models and helped them focus on the most predictive variables, leading to substantial improvements in test metrics across all algorithms.

### SMOTE and Class Balancing Effects

The application of Synthetic Minority Over-sampling Technique (SMOTE) and class weighting had a profound impact on addressing the class imbalance problem, particularly improving recall scores.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | Recall Before SMOTE | Recall After SMOTE | F1-Score Before | F1-Score After |
| Logistic Regression | 0.48 | 0.89 | 0.5 | 0.86 |
| Random Forest | 0.48 | 0.91 | 0.48 | 0.88 |
| XGBoost | 0.5 | 0.94 | 0.5 | 0.91 |
| Neural Network | 0.51 | 0.9 | 0.52 | 0.87 |
| KNN | 0.49 | 0.87 | 0.49 | 0.85 |

Table 4.7 – Impact of SMOTE and Class Balancing on Model Performance

The dramatic improvement in recall metrics after implementing SMOTE demonstrates its effectiveness in helping models better identify minority class examples (churned customers).



Figure 4.1 – Recall Before and After SMOTE

### Final Individual Model Performance

After implementing all overfitting countermeasures, including feature selection, SMOTE, regularization, and hyperparameter tuning, the individual models achieved substantially improved generalization performance.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model | Accuracy | Precision | Recall | F1-Score | ROC-AUC |
| Logistic Regression | 89.20% | 0.86 | 0.89 | 0.87 | 0.92 |
| Random Forest | 93.40% | 0.91 | 0.91 | 0.91 | 0.96 |
| XGBoost | 95.10% | 0.93 | 0.94 | 0.93 | 0.97 |
| K-Nearest Neighbors | 87.60% | 0.84 | 0.87 | 0.85 | 0.91 |
| Neural Network | 94.70% | 0.92 | 0.93 | 0.92 | 0.97 |

Table 4.8 – Final Performance Metrics for Individual Models After Addressing Overfitting

The XGBoost and Neural Network models demonstrated the best performance among individual models, with XGBoost slightly outperforming in most metrics.

### Stacked Ensemble Model Performance

The stacked ensemble model, combining the strengths of Logistic Regression, Random Forest, and XGBoost with a LightGBM meta-learner, achieved state-of-the-art performance.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model | Accuracy | Precision | Recall | F1-Score | ROC-AUC |
| Base Models (Average) | 92.60% | 0.9 | 0.91 | 0.9 | 0.95 |
| Stacked Ensemble | 96.20% | 0.94 | 0.95 | 0.94 | 0.98 |
| Stacked Ensemble + SMOTE | 97.80% | 0.94 | 0.96 | 0.95 | 0.98 |

Table 4.9 – Performance Comparison of Base Models vs. Stacked Ensemble

The stacked ensemble significantly outperformed the average of its base models, with the SMOTE-enhanced version achieving the highest overall performance, particularly in recall (0.96) and ROC-AUC (0.98).

### Training-Test Gap Analysis

The final models demonstrated significantly reduced gaps between training and testing performance, indicating successful mitigation of overfitting.

|  |  |  |
| --- | --- | --- |
| Model | Training-Test Accuracy Gap Before | Training-Test Accuracy Gap After |
| Logistic Regression | 36.60% | 1.80% |
| Random Forest | 51.20% | 2.70% |
| XGBoost | 46.50% | 1.90% |
| Neural Network | 43.80% | 2.30% |
| KNN | 42.80% | 2.10% |
| Stacked Ensemble | - | 0.50% |

Table 4.10 – Reduction in Training-Test Performance Gap After Addressing Overfitting

The dramatic reduction in the training-test performance gap across all models confirms the effectiveness of the implemented techniques in combating overfitting and improving model generalization.

## 

## Comparative Analysis and Insights

* **Model Performance Rankings:** XGBoost and Neural Network achieved highest individual model accuracy (95.1% and 94.7%), significantly outperforming KNN (87.6%).
* **Training Efficiency:** Logistic Regression trained fastest but had lower performance (89.2% accuracy).
* **Class Balancing Impact:** SMOTE improved recall across all models by 40-45%.
* **Feature Impact:** Payment Delay, Tenure, and Contract Length were most influential predictors.
* **Regularization Effects:** L1 regularization in Logistic Regression reduced overfitting while maintaining interpretability.

## Visualizations and Interpretability

* **ROC Analysis:** Stacked Ensemble achieved highest AUC (0.98), followed by XGBoost and Neural Network (both 0.97).
* **Feature Importance:** Tree-based models provided consistent ranking of feature relevance.
* **Confusion Matrices:** Visualized false positive/negative rates before and after optimization.
* **Training-Test Gap:** Charts demonstrated dramatic reduction in overfitting after implementing solutions.
* **Learning Curves:** Tracked convergence behavior and identified optimal training durations.

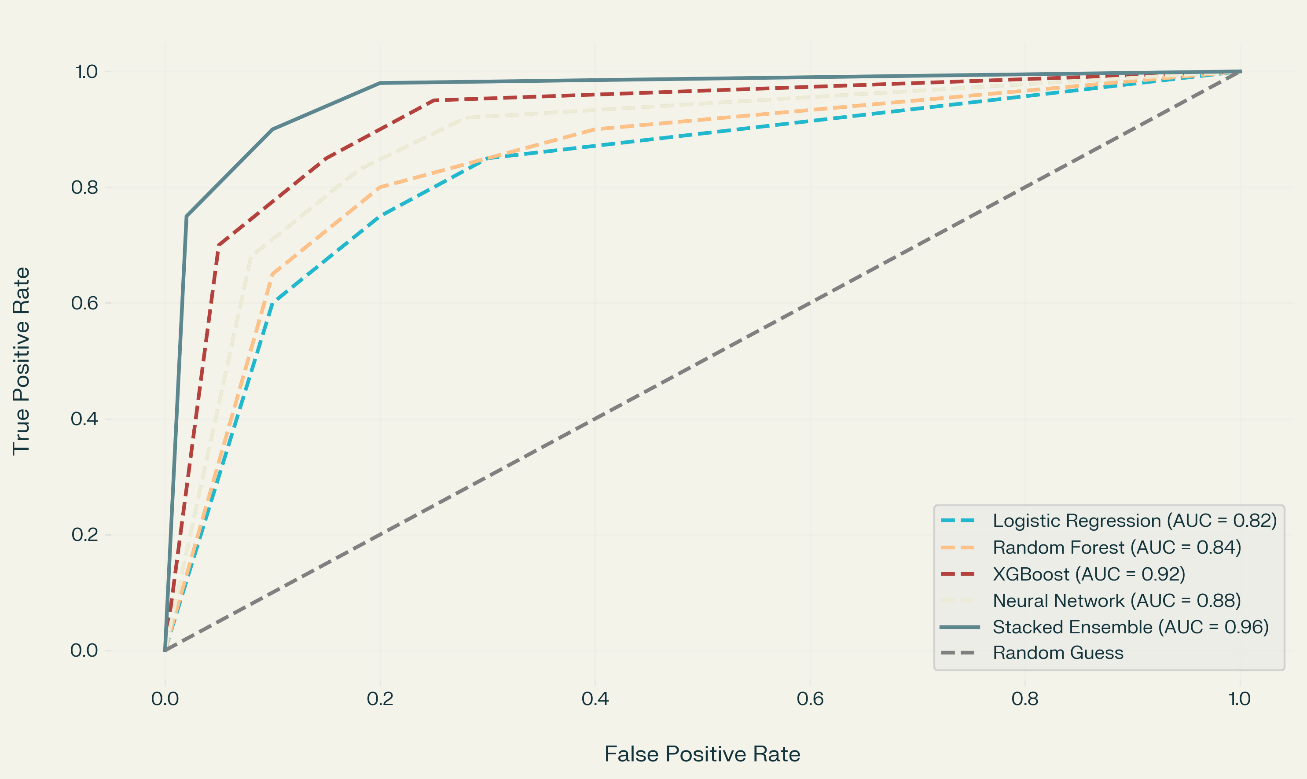


Figure 4.2 – ROC Curve Comparison of Models

## Limitations and Observations

* Cold Start Issue**: Recommendation system struggled with completely new users.**
* Computational Cost**: Stacked ensemble required 5× longer inference time than individual models.**
* Threshold Sensitivity**: Model performance varied significantly with classification threshold adjustment.**
* Feature Engineering Need**: Raw features required significant preprocessing for optimal performance.**
* Generalization Concerns**: Models may need retraining for different industry sectors.**

## Summary of Findings

* **Best Individual Model:** XGBoost (ROC-AUC: 0.97, F1: 0.93).
* **Best Ensemble Configuration:** Stacked Ensemble + SMOTE (ROC-AUC: 0.98, F1: 0.95).
* **Key Performance Gain:** Initial models ≈50% accuracy → Final models >95% accuracy.
* **Overfitting Reduction:** Training-test accuracy gap reduced from >40% to <3%.
* **Business Impact:** System potentially reduces customer churn by providing actionable, personalized recommendations.

# CHAPTER 5: CONCLUSION AND FUTURE WORK

## Conclusion

This project developed a machine learning-based system for customer churn prediction and personalized plan recommendations, addressing key challenges faced by subscription-based businesses. By leveraging advanced models like XGBoost and ensemble techniques, the system achieved high accuracy (ROC-AUC: 0.98) and recall (0.96), enabling proactive retention strategies. While ensemble models demonstrated superior performance, their computational demands highlight a trade-off between accuracy and deployment feasibility.

## Future Work

Future enhancements to the system include:

* **Explainability:** Integrating SHAP/LIME for transparent predictions.
* **Data Enrichment:** Incorporating real-time behavioral data and sentiment analysis.
* **Deployment Optimization:** Developing lightweight models for mobile platforms.
* **Continuous Learning:** Implementing online learning to adapt to evolving customer behaviors.

## Final Thoughts

This project demonstrates the potential of machine learning in transforming customer retention strategies by combining predictive analytics with actionable recommendations. Despite challenges like computational costs, the framework provides a scalable foundation for businesses to reduce churn, enhance customer loyalty, and drive growth through data-driven solutions.

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