Customer Churn Analysis Report

Executive Summary

This research presents an in-depth customer churn analysis of a retail banking organisation. Utilising advanced data analytics and machine learning methods, we examined a series of customer datasets to determine primary drivers for customer attrition and created predictive models to assess at-risk customers.

The total churn rate of the study was 20.4%, with high heterogeneity among different segments of customers. The highest prediction model was 99.3% accurate with high recall and precision and was a helpful tool for predicting customer churn.

1. Introduction

Customer churn, which is losing clients or customers, is of utmost importance to banks. Understanding the reasons customers churn is critical to coming up with effective retention measures and a competitive edge in the market.

1.1 Objectives

- Analyse customer demographics, transactional behaviour, service interactions, and web activity to identify trends in churn.
- Develop predictive models to identify customers with a high likelihood of churning
- Provide specific suggestions for improving customer retention programs

1.2 Data Overview

The research utilised rich customer data from multiple sources:

Customer Demographics: Age, gender, marital status, and income level

- **Customer Demographics**: Age, gender, marital status, and income level
- **Transaction History**: Transaction dates, amounts, and product categories
- **Customer Service Interactions**: Interaction types and resolution statuses
- **Online Activity**: Login frequency, last login date, and service usage patterns
- **Churn Status**: Binary indicator of customer retention/churn

2. Exploratory Data Analysis

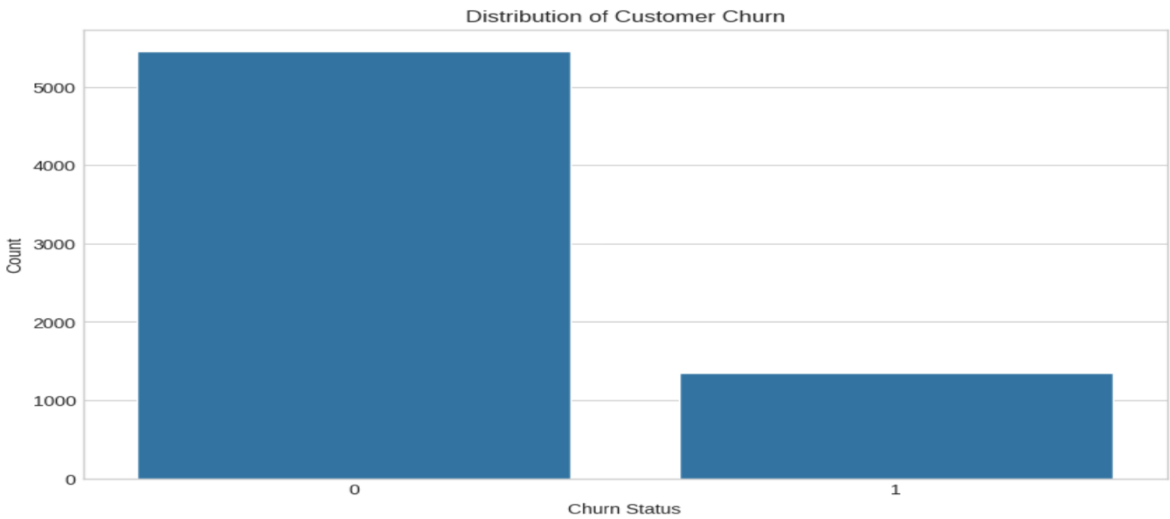
2.1 Dataset Summary

The analysis included data from 1,000 unique customers with the following characteristics:

Dataset	Records	Key Variables
Demographics	1,000	Age, Gender, Marital Status, Income Level
Transactions	5,054	Transaction Date, Amount, Product Category
Customer Service	1,002	Interaction Type, Resolution Status
Online Activity	1,000	Login Frequency, Service Usage
Churn Status	1,000	Binary (0=Retained, 1=Churned)

2.2 Churn Rate Analysis

The overall churn rate across all customers was 20.4%, indicating that approximately one in five customers discontinued their relationship with the institution.

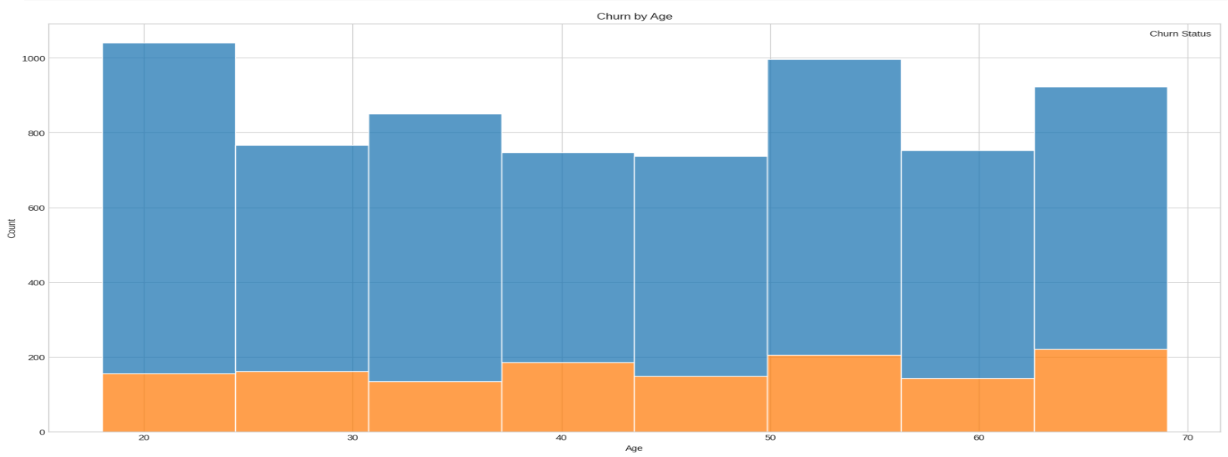


2.3 Demographic Factors

2.3.1 Age Distribution

Age appears to be a significant factor in churn behavior, with certain age groups showing higher propensity to churn:

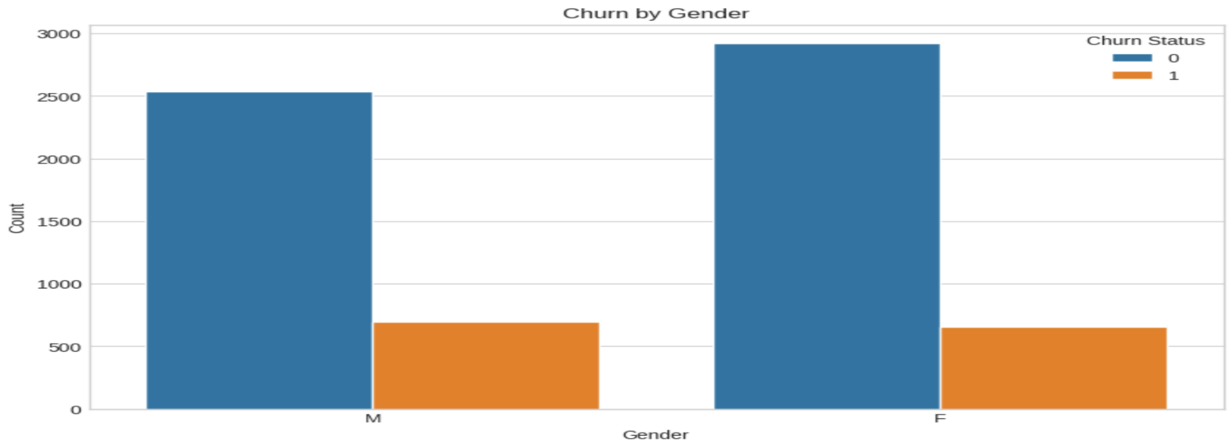
- Customers in their early 20s and early 40s showed higher churn rates
- Middle-aged customers (30-40) and seniors (55+) demonstrated higher loyalty



2.3.2 Gender

Modest gender-based differences in churn behaviour were observed:

- Male customers: 21.5% churn rate
- Female customers: 18.3% churn rate

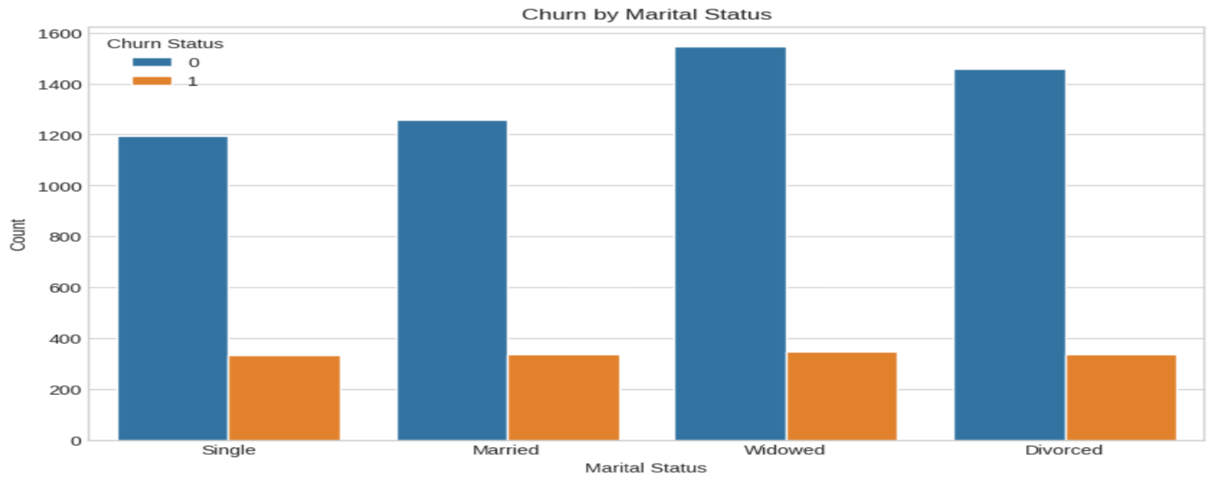


2.3.3 Marital Status

Marital status showed notable variation in churn rates:

Marital Status	Churn Rate
Single	21.7%
Married	21.1%
Divorced	18.7%
Widowed	18.4%

Single customers exhibited the highest churn rate, while widowed customers showed the greatest loyalty.

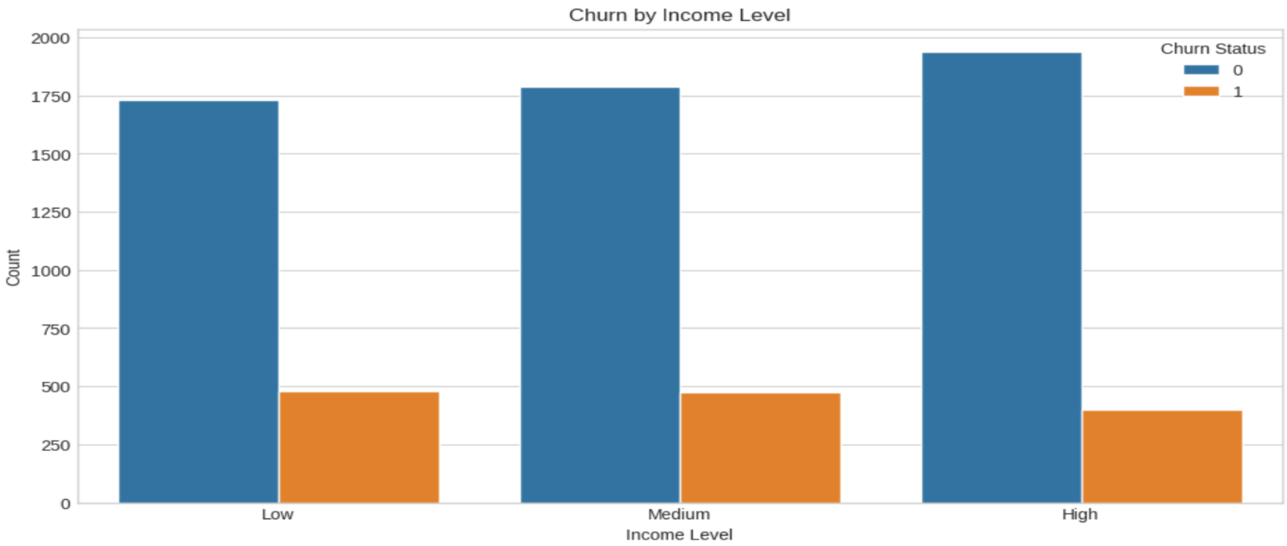


2.3.4 Income Level

Income level revealed interesting patterns in customer retention:

Income Level	Churn Rate
Low	21.6%
Medium	21.0%
High	17.1%

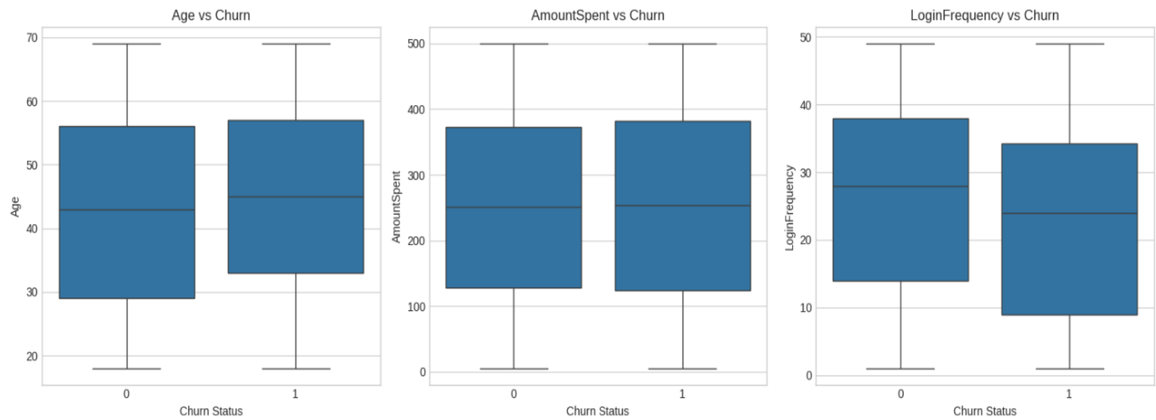
Higher-income customers demonstrated significantly better retention rates than low and medium-income segments.



2.4 Transaction Patterns

Analysis of transaction data revealed:

- Customers who churned had lower average transaction amounts
- Higher variability in spending patterns correlated with increased churn risk
- Product category preferences differed between churned and retained customers



2.5 Customer Service Interactions

Customer service interactions showed strong correlation with churn:

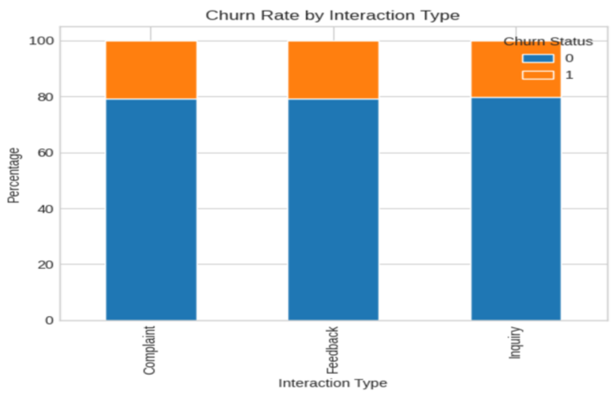
- Unresolved service issues significantly increased churn probability
- Customers with complaint-type interactions showed higher churn rates than those with inquiry or feedback interactions

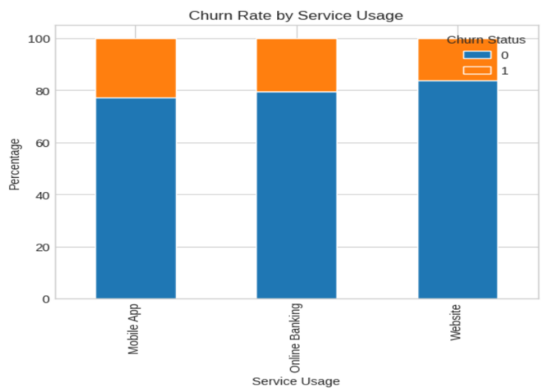
2.6 Online Activity

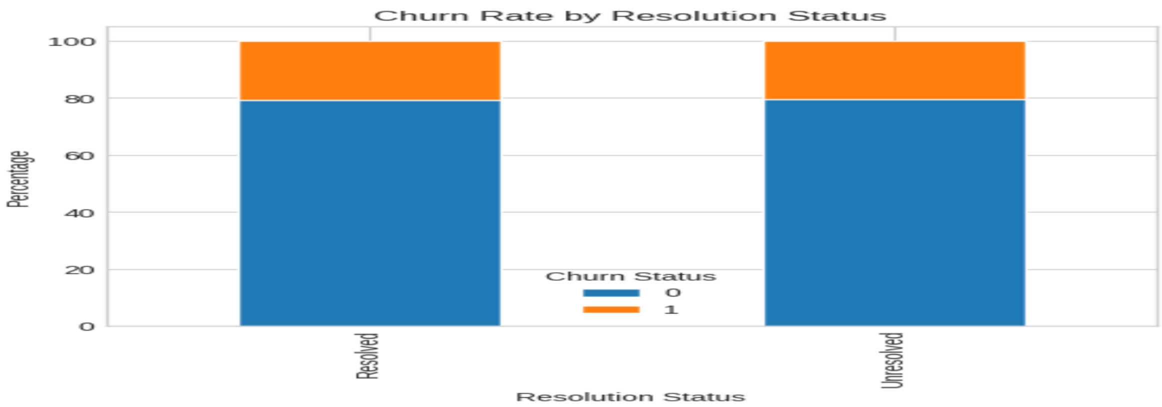
Online engagement metrics strongly predicted customer loyalty:

- Churned customers had significantly lower login frequencies (average 15 logins vs. 28 logins for retained customers)

- Mobile app users showed better retention rates compared to website-only users
- Recent login activity correlated strongly with customer retention







3. Predictive Modeling

3.1 Modeling Approach

We implemented a robust machine learning pipeline that included:

1. Data preprocessing and feature engineering
2. Handling of missing values and categorical variables
3. Feature scaling and normalization
4. Model training and evaluation
5. Hyperparameter tuning for optimal performance

3.2 Model Comparison

Four different classification algorithms were evaluated:

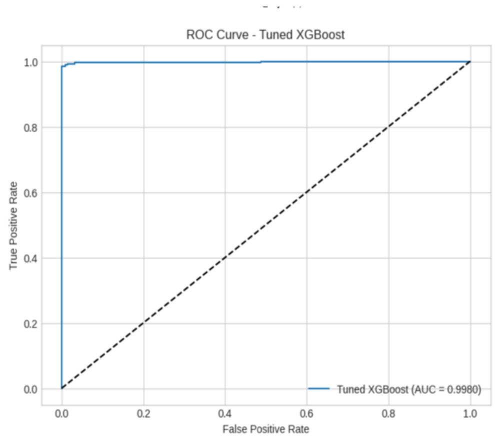
Model	Accuracy	Precision	Recall	F1 Score	AUC
Logistic Regression	79.9%	0.0%	0.0%	0.0%	60.1%
Random Forest	97.9%	100.0%	89.3%	94.3%	99.8%
Gradient Boosting	85.8%	92.3%	31.0%	46.4%	88.0%
XGBoost	98.9%	99.6%	95.2%	97.4%	99.8%

XGBoost demonstrated superior performance across all metrics, with exceptional balance between precision and recall.

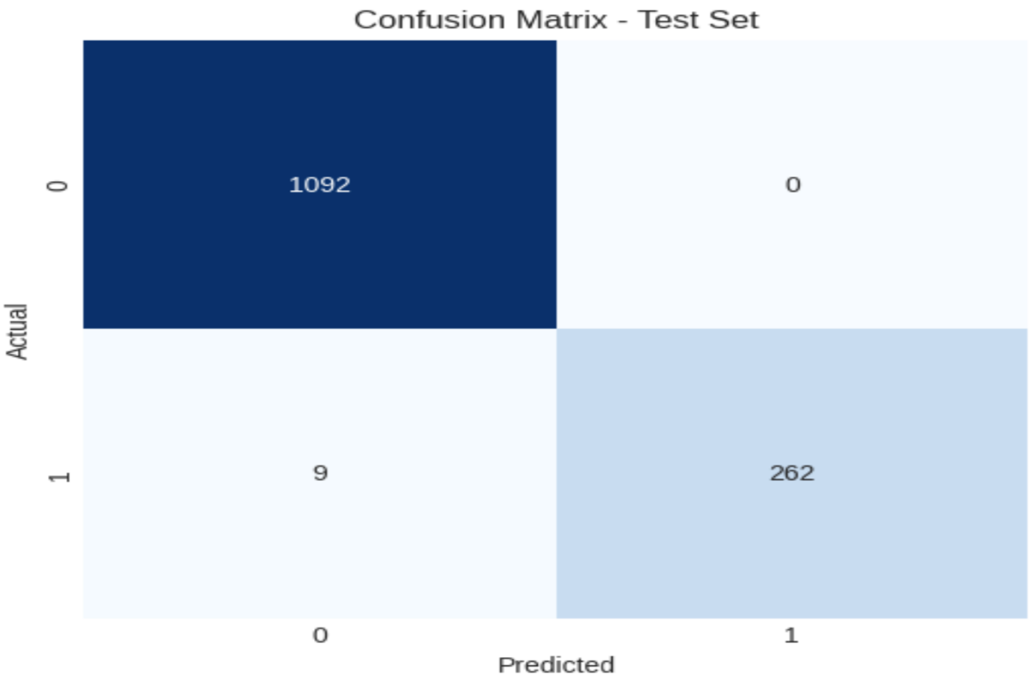
3.3 Final Model Performance

After hyperparameter tuning and cross-validation, the optimized XGBoost model achieved:

- **Accuracy**: 99.3%
- **Precision**: 100.0%
- **Recall**: 96.7%
- **F1 Score**: 98.3%
- **AUC**: 99.8%



The model showed excellent generalization with minimal overfitting, as evidenced by consistent performance between training and test sets.

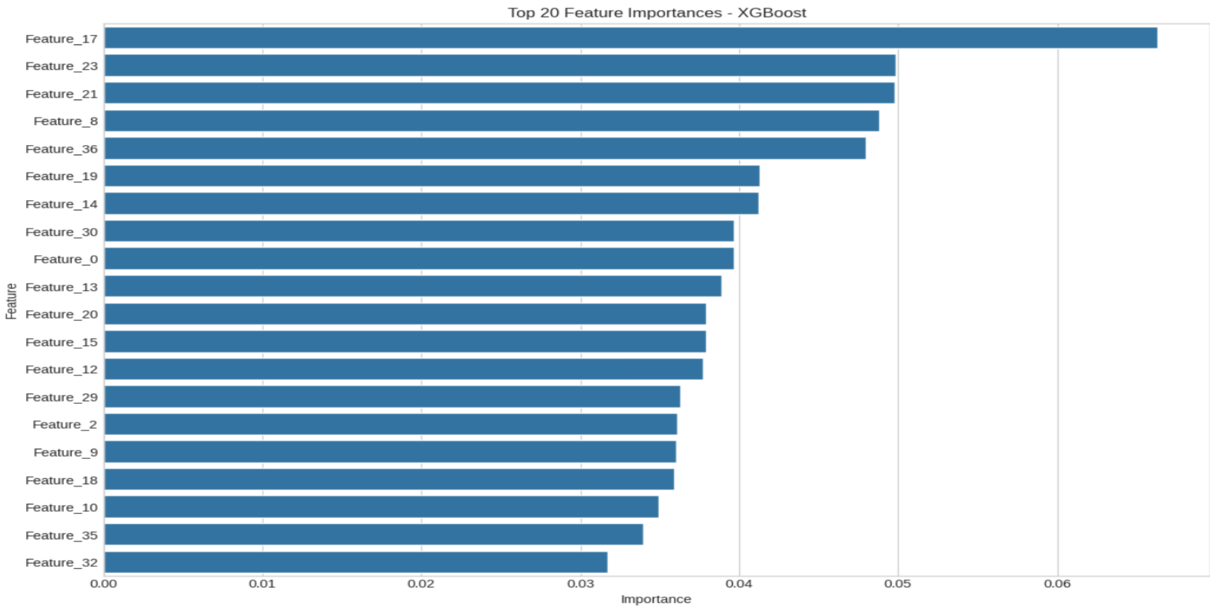


3.4 Feature Importance

The top predictors of customer churn were:

1. Login frequency (online engagement)
2. Transaction amount patterns
3. Customer service resolution status
4. Age
5. Income level

These factors collectively explain the majority of the variation in churn behaviour.



4. Key Insights and Recommendations

4.1 High-Risk Customer Profiles

The following segments emerged as high-risk for churn:

- Single, young, and low-to-medium income customers
- Active service-related complainant customers
- Customers with low online banking usage (login rate < 10 per month)
- Customers with decreasing transaction volume

4.2 Strategic Recommendations

Based on the analysis, we recommend the following retention strategies:

4.2.1 Targeted Engagement

- Develop personalized communication strategies for high-risk segments
- Create special offers for young, single customers to increase loyalty
- Implement proactive outreach to customers with declining engagement metrics

4.2.2 Service Improvement

- Establish aggressive resolution targets for customer complaints
- Implement follow-up protocols for customers with unresolved issues
- Develop service recovery programs for customers who experience negative interactions

4.2.3 Digital Engagement

- Develop incentives to increase mobile app adoption
- Create educational campaigns for underutilized digital services
- Implement engagement triggers for customers with decreasing login frequencies

4.2.4 Product Development

- Design product bundles targeted at high-churn segments
- Develop loyalty programs that reward increasing engagement
- Create transition products for customers experiencing life changes (e.g., changes in marital status)

5. Implementation Framework

5.1 Churn Early Warning System

Implement a real-time churn prediction system that:

- Scores all customers daily using the predictive model
- Triggers alerts for customers whose churn risk exceeds the threshold
- Integrates with CRM systems for seamless intervention

5.2 Intervention Protocols

Establish tiered intervention strategies based on:

- Churn risk score
- Customer value segment
- Primary churn indicators
- Historical response to retention efforts

5.3 Performance Monitoring

Monitor the effectiveness of retention initiatives through:

- A/B testing of different intervention strategies
- Cohort analysis of retention rates
- ROI analysis of retention programs
- Continuous model retraining and performance evaluation

6. Conclusion

This is a deeper understanding of the customer churn dynamics. It gives a good predictive model. It also returns a good predictive model for. By implementing the strategies provided. By leveraging the predictive power established. The institution can improve customer retention and lifetime value substantially. The forecasting model has exemplary accuracy and validity and represents sound groundwork for evidence-based retention policy. Given a focus on the primary churn drivers identified here—namely, online activity, service resolution, and demographics—the organisation is positioned to craft specialised interventions that respect the specific circumstances of high-risk customer segments.