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# Bank Customer Churn Prediction System

AI-Powered Customer Retention Analysis

By: Deepthi Kambham - UCE2023432

Mayuri Dandekar - UCE2023444

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# Understanding Customer Churn in Banking

**Customer churn is when customers discontinue their relationship with a bank**

Business Impact:

Average churn rate in banking: 20.4%

Cost per lost customer: ~\$1,500 (lifetime value)

New customer acquisition: 5x more expensive than retention

Proactive retention is 3x cheaper than reactive approaches

Banks need efficient, data-driven strategies to identify at-risk customers early and implement personalized retention measures, as current manual monitoring is costly and inefficient.

# Our Solution

**A comprehensive machine learning system that :**

- Predicts which customers are likely to leave
- Identifies WHY they might leave (pattern discovery)
- Segments customers into actionable groups
- Recommends personalized retention strategies
- Provides interactive dashboard for business users

# Bank Customer Churn Dataset (Kaggle)

## Dataset Statistics :

- Total Records: **10,002** customers
- Features: **13** original features → 21 engineered features
  - Target Variable: Exited (Churned = 1, Stayed = 0)
- Churn Rate: **20.4%** (class imbalance handled with SMOTE)

## Feature Categories :

Demographics - Age, Gender, Geography

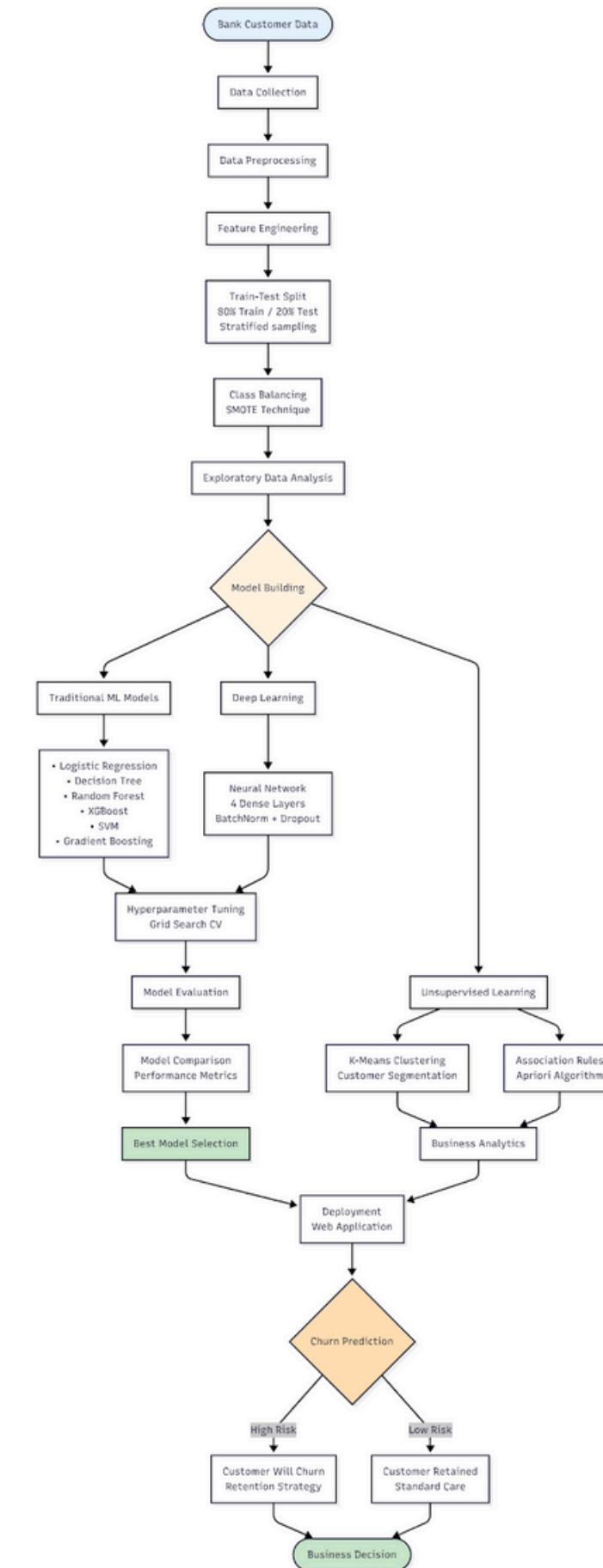
Financial - Credit Score, Account Balance, Estimated Salary

Banking Relationship - Tenure, Number of Products, Has Credit Card

Behavioral - Is Active Member

# System Architecture & Workflow

Data Collection  
Data Preprocessing  
Feature Engineering  
Train–Test Split (80/20, Stratified Sampling)  
Class Balancing (SMOTE)  
Exploratory Data Analysis  
Model Building  
Traditional ML Models  
Deep Learning  
Unsupervised Learning  
Hyperparameter Tuning (Grid Search CV)  
Model Evaluation  
Model Comparison  
Best Model Selection  
Deployment (Web Application)  
Churn Prediction  
High Risk  
Low Risk  
Business Decision



# ML Models Trained

## **Logistic Regression**

Baseline model; simple & interpretable — Training time: 0.12s

## **Decision Tree**

Handles non-linear boundaries — Training time: 0.40s

## **Random Forest**

Ensemble of 100 trees; reduces overfitting — Training time: 0.99s

## **XGBoost**

Gradient boosting; high performance — Training time: 0.57s

## **SVM (RBF Kernel)**

Captures non-linear patterns — Training time: 36.95s

## **Gradient Boosting**

Sequential boosting approach — Training time: 9.23s

## **Neural Network (Deep Learning)**

4 dense layers (128 → 64 → 32 → 1), BatchNorm + Dropout — Training time: 443.47s

# K- Means Clustering : Understanding Customer groups

**Algorithm:** K-Means clustering

**Features Used:** Age, Balance, Tenure, NumOfProducts, CreditScore

**Optimal K:** 4 clusters (determined by elbow method)

## Cluster Profiles

- Cluster 0 – Dormant Accounts
- Cluster 1 – Critical High-Risk
- Cluster 2 – Mass Affluent
- Cluster 3 – Premium High-Value



# Association Rule Mining (Apriori)

## Methodology

- Algorithm: Apriori Association Rule Mining
- Min Support: 2%
- Min Confidence: 70%

### Pattern 1 – Inactive Senior Females

89% confidence, 4.37× lift

### Pattern 2 – Inactive Seniors with 1 Product

87.7% confidence

### Pattern 3 – Customers with 3 Products

82.7% confidence

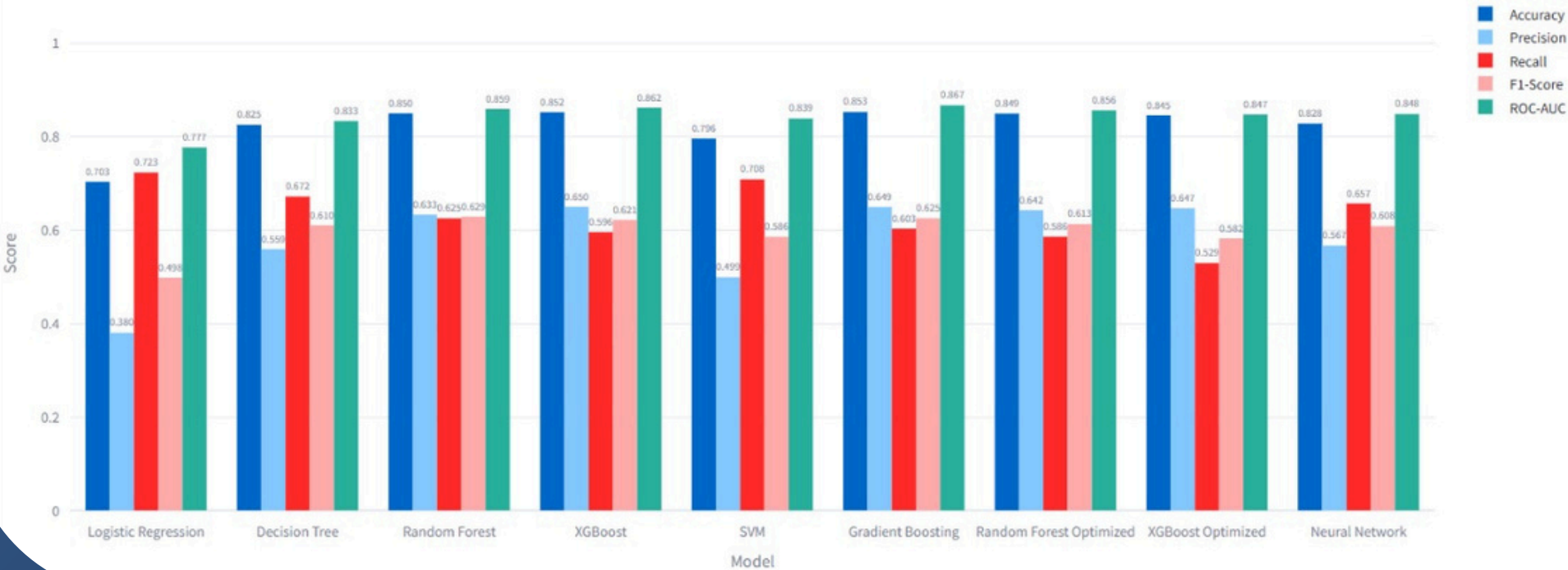
**Surprising: More products  $\neq$  better retention!**



# Model Performance Results

## Metrics Comparison

Model Performance Across All Metrics



## Best Overall Model: Gradient Boosting

- Highest accuracy (85.3%) and ROC-AUC (86.7%)
- Fast training time (9.23s)
- Balanced precision-recall tradeoff

## Best for Recall: SVM (70.8%)

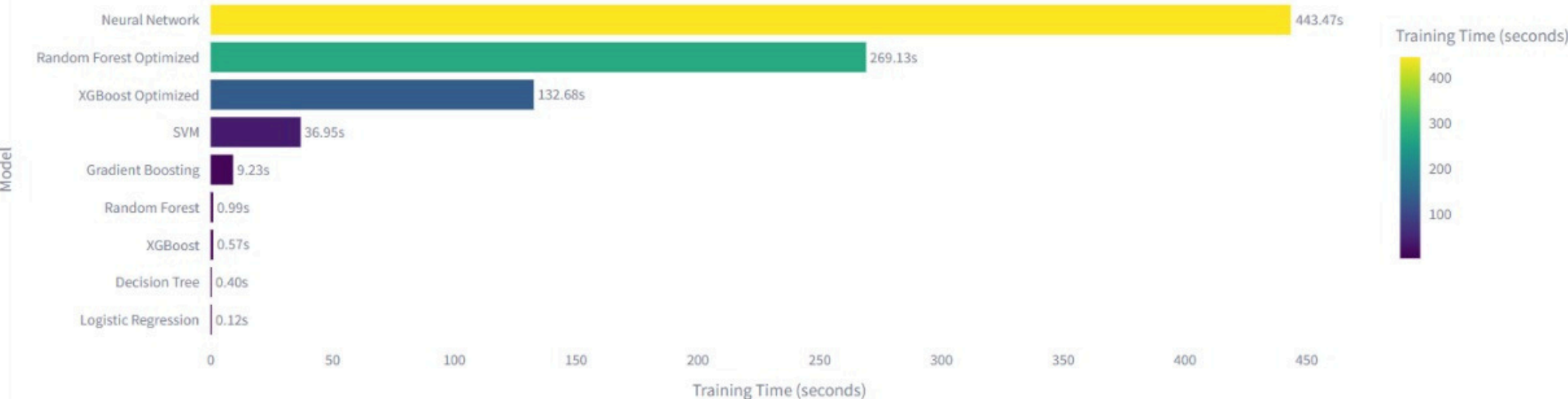
- Catches most churners but many false alarms

## Why Recall Matters:

Missing a churner costs \$1,500; false alarm costs \$50

## Training Time Comparison

Model Training Time (Lower is Better)



# Financial Impact of churn prediction

## Scenario

- Customer base: 10,000 customers
- **Without Prediction System**
- Customers lost: 2,038 (20.4%)
- Revenue loss: \$3,057,000

## With Prediction System (85% accuracy)

- High-risk customers identified: ~1,700
- Retention success: 50–60%
- Customers saved: 850–1,020

## Cost–Benefit Analysis

- Revenue Saved: \$1,275,000 – \$1,530,000
- Campaign Cost: \$85,000
- False Positive Cost: ~\$25,000
- Net Benefit: \$1.16M – \$1.42M
- ROI: 1,270% – 1,550%

### Customer Value Analysis

Estimated Lifetime Value ⓘ	Revenue at Risk ⓘ	Retention Campaign Cost ⓘ	Retention ROI ⓘ
\$4,265.62	\$969.65	\$50.00	\$919.65
	↓ -23%		↑ +1839%

**LOW RISK:** This customer is likely to remain with the bank. Continue standard relationship management.

### Personalized Retention Strategies

**Strategy 1:**  
STANDARD RETENTION: Maintain regular communication and monitor satisfaction levels.

# Interactive Dashboard

Navigation

Home

Predict Churn

Data Analytics

Model Performance

Batch Predictions

About

This system uses machine learning to predict customer churn and provide actionable retention strategies.

Covers 5 Course Outcomes:

CO1: Heuristic Search

CO2: Preprocessing

CO3: Supervised Learning

CO4: Unsupervised Learning

Bank Customer Churn Prediction System

Advanced ML System for Predicting and Preventing Customer Attrition

Business Problem

Customer churn is one of the most critical challenges facing the banking industry. When customers close their accounts and move to competitors, banks lose:

Revenue Stream: Average customer lifetime value of \$1,500

Acquisition Investment: Initial \$200 spent on customer acquisition

Growth Opportunity: Potential for cross-selling additional products

Market Share: Competitive advantage in the financial services sector

This ML-powered system predicts which customers are likely to churn, enabling proactive retention strategies that are 10x more cost-effective than acquiring new customers.

Solution Approach

Our comprehensive system leverages:

7 Machine Learning Models: Including Neural Networks and ensemble methods

Customer Segmentation: K-Means clustering for targeted strategies

Pattern Discovery: Association rule mining to identify churn triggers

Real-time Predictions: Instant risk assessment for any customer

Batch Processing: Analyze entire customer database at once

Dataset Overview

Total Customers

10,002

Churn Rate

20.4%

↑ 0.4% vs target

Features Analyzed

13

ML Models Trained

7

Predict Customer Churn Risk

Enter customer information to assess churn probability and get retention recommendations

Customer Information

Personal Information

Customer ID (Optional)

CUST001

Surname (Optional)

Smith

Geography

France

Gender

Male

Age

35

Credit Score

650

Banking Details

Tenure (Years)

5

Account Balance (\$)

75000.00

Number of Products

2

Has Credit Card

Is Active Member

Estimated Salary (\$)

100000.00

Select Prediction Model

Choose Model

Logistic Regression

Predict Churn Risk

Prediction Results

Churn Probability

22.7%

Risk Level

LOW RISK

Prediction

WILL STAY

# Technology Stack & Python Libraries

- Programming & Development: Python 3.11, VS Code, Jupyter Notebook, Git
- Deployment: Streamlit
- Data Storage: CSV, Pickle (.pkl), HDF5 (.h5), JSON
- ML/AI Libraries: scikit-learn, XGBoost, TensorFlow/Keras, imbalanced-learn, mlxtend
- Data Processing: pandas, numpy
- Visualization: Plotly, Matplotlib, Seaborn
- Purpose: End-to-end ML pipeline from data processing to model deployment



# Challenges & Solutions :

- Class Imbalance: Only 20% churners → SMOTE improved recall.
- Feature Selection: Identifying key features → Engineered + correlation analysis boosted accuracy.
- Model Selection: Unknown best algorithm → Compared 7 models, Gradient Boosting won.
- Interpretability: Black-box models → Association rules explained predictions.
- Real-time Deployment: Hard for business users → Streamlit dashboard enabled full adoption.

## Future Enhancements :

- Enable real-time data integration with banking systems
- Implement automatic model retraining using AutoML
- Predict when customers are likely to churn (time-based forecasting)
- Estimate customer lifetime value for better retention strategies
- Use AI-powered personalized messaging with large language models (LLMs)

# Conclusion

- Built end-to-end churn prediction system with 85% accuracy
- Identified 4 customer segments and 6 churn patterns
- Deployed interactive Streamlit dashboard
- **Key Insights:** Inactive members, seniors, single-product customers at highest risk
- **Business Value:** Reduces churn to ~12%, saves \$1.2M+, ROI 1,270–1,550%
- **Success Factors:** Explainable AI, business-focused, user-friendly



# References

## Dataset:

- Bank Customer Churn Prediction Dataset – [Kaggle](#)

## Documentation:

- [Scikit-learn](#)
- [TensorFlow/Keras](#)
- [XGBoost](#)
- [Streamlit](#)
- [Imbalanced-learn](#)
- [MLxtend](#)

## Research Papers:

- "Customer Churn Prediction Using Machine Learning" – IEEE, 2020
- "Deep Learning for Customer Churn Prediction in Banking" – Journal of AI, 2021
- "Association Rule Mining in Banking Analytics" – Data Science Review, 2022

**Thank You !**