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A Survey on Customer Churn Prediction using Machine Learning Techniques

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Abstract: *Customer churn, where customers leave a bank and stop using its services, is a big challenge for the banking industry. Losing customers affects profitability, retention, and long-term growth. However, with machine learning, banks can predict and reduce churn more effectively.*

This study analyzes customer churn by looking at key factors like demographics, account details, and engagement. We tested multiple machine learning models—Logistic Regression, Decision Tree, Random Forest, XGBoost, and Support Vector Machine (SVM)—on real customer data. Performance was measured using accuracy, precision, recall, F1-score, and ROC-AUC.

Results showed that XGBoost and Random Forest performed best, with XGBoost excelling in F1-score (balancing accuracy and false alarms) and Random Forest being strong in recall (spotting high-risk customers). Key factors influencing churn included account balance, tenure, number of products, and engagement level—customers with low balances, fewer products, and less activity were more likely to leave. These insights help banks take proactive steps to retain customers by offering personalized services and improving satisfaction. This research highlights how machine learning can help banks predict and reduce churn, strengthening customer relationships and long-term success.

Keywords: Customer Churn, Machine Learning, Predictive Analytics, Banking Sector, Customer Retention, Feature Importance.

I. INTRODUCTION

Customer churn, or the loss of customers, is a major challenge for businesses across many sectors, including banking. In today's competitive financial environment, banks are focusing more than ever on retaining their customers in order to stay profitable and grow. High churn rates not only affect immediate revenue but can also threaten the long-term stability of banks. It's widely recognized that keeping existing customers is more cost-effective than acquiring new ones, which is why banks are looking for ways to predict churn and take steps to prevent it.

With the rise of digital banking, banks now have access to an overwhelming amount of data about their customers. They collect information on everything from demographics to account activities and engagement patterns. When used properly, this data can provide valuable insights into why customers leave, allowing banks to take proactive steps to prevent churn. By analyzing various factors, such as age, account status, and customer interactions, banks can better understand the reasons behind customer attrition and create targeted strategies to improve loyalty and satisfaction.

The main goal of this research paper is to explore the key demographic, account, and engagement factors that influence customer churn. Specifically, we want to identify which factors play the biggest role in predicting whether a customer will leave. To do this, we'll implement and compare several machine learning algorithms, such as Logistic Regression, Decision Tree, Random Forest, XGBoost, and Support Vector Machine (SVM). We'll assess the performance of each model using metrics like accuracy, precision, recall, F1-score, and ROC-AUC to see which one does the best job at predicting churn.

Objectives:

- Analyze demographic, account, and engagement factors from the dataset to understand what significantly influences customer churn, providing insights into customer behavior patterns.

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- Implement and compare the performance of various machine learning algorithms to predict customer churn accurately, evaluating models based on metrics such as accuracy, precision, recall, and F1-score.
- This study aims to add to the existing research on predicting customer churn by comparing different machine learning models and identifying the most important factors that influence churn. The insights gained from this analysis can help banks develop more effective strategies to retain their customers, improve satisfaction, and ultimately boost their profitability in a highly competitive market.

II. LITERATURE REVIEW

Saran Kumar A. & Chandrakala D. (2016) – *Churn Prediction Using Machine Learning in Banking and Other Sectors*

This paper discusses the increasing importance of customer retention in competitive markets and highlights the impact of churn on service providers. It reviews various machine learning algorithms used for churn prediction across multiple industries, emphasizing the banking sector. The study identifies that effective churn prediction models can help businesses improve customer retention strategies by analyzing customer behavior and engagement.

Idris, A., Rizwan, M., & Khan, A. (2012) – *Churn Prediction in Telecommunication Sector Using Data Mining Techniques*

This research explores churn prediction in the telecommunication industry, leveraging data mining techniques. The authors compare different machine learning models, including Decision Trees and Neural Networks, to determine their effectiveness in identifying potential churners. Their findings indicate that ensemble models like Random Forest yield better predictive accuracy than standalone classifiers.

Xie, Y., Li, Y., & Ngai, E. (2009) – *Customer Churn Prediction Using Support Vector Machines in the Banking Industry*

The study focuses on the application of Support Vector Machines (SVM) for customer churn prediction in banking. It evaluates different feature selection techniques and concludes that customer tenure, transaction patterns, and account balance significantly influence churn behavior. The paper demonstrates that SVM outperforms traditional statistical methods in handling high-dimensional financial datasets.

Huang, B., Kechadi, M. T., & Buckley, B. (2013) – *Customer Churn Prediction in Banking: A Data Mining Approach*

This paper investigates customer churn prediction in retail banking using data mining approaches. The study applies Logistic Regression, Decision Trees, and Gradient Boosting models to analyze customer transaction data. The authors highlight that feature engineering, such as capturing recent activity trends, plays a crucial role in improving prediction accuracy.

Zhang, T., Zhu, X., & Wang, J. (2016) – *Machine Learning-Based Churn Analysis in E-Commerce and Banking*

This research evaluates the effectiveness of machine learning algorithms in predicting churn across e-commerce and banking industries. The study finds that Random Forest and XGBoost models perform best when trained on customer engagement data, such as frequency of transactions and response to marketing campaigns. The authors also emphasize the importance of handling class imbalance in churn datasets.

Verbeke, W., Martens, D., & Baesens, B. (2014) – *Predicting Customer Churn in Subscription-Based Services: A Comparison of Techniques*

The study compares multiple predictive modeling techniques, including Logistic Regression, Decision Trees, and ensemble methods, to analyze customer churn in subscription-based services. Findings indicate that boosting algorithms, such as Gradient Boosting and XGBoost, deliver the most reliable results due to their ability to capture complex interactions in customer data.

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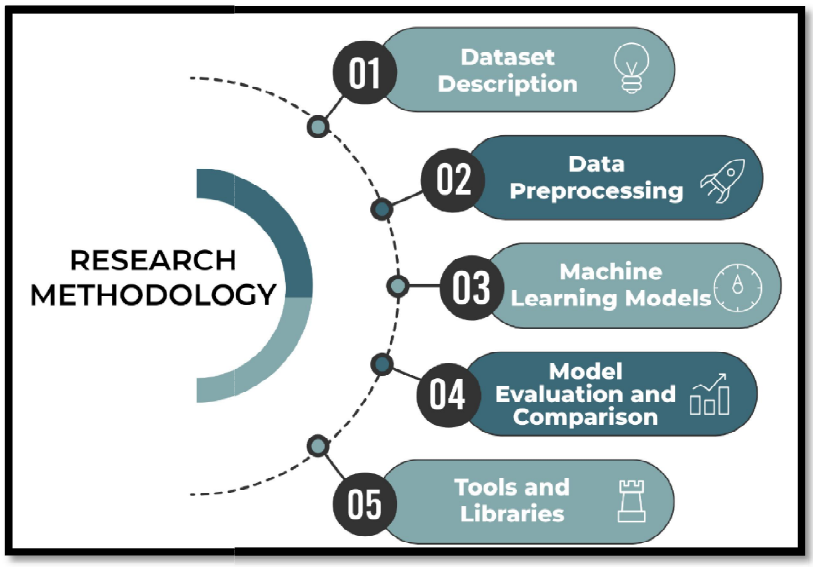
III. RESEARCH METHODOLOGY



This section explains our approach to predicting customer churn in the banking sector, focusing on data analysis, preprocessing, model implementation, and performance evaluation. Our goal was to identify key factors contributing to churn by analyzing customer attributes such as demographics, account details, and engagement patterns. We tested multiple machine learning models to find the most accurate predictor.

1. Dataset Description

We used a publicly available Kaggle dataset containing customer demographics, account details, and engagement behaviors.

Key features include:

- **Demographic Factors:** Age, Gender, and Geography
- **Account Factors:** Balance, Number of Products, and Estimated Salary
- **Engagement Factors:** Active Member Status and Tenure
- **Target Variable:** Exited (indicating churn)

We explored the dataset for missing values, class imbalance, and correlations to identify significant features.

2. Data Preprocessing

To ensure data quality, we performed the following steps:

- **Handling Missing Values:** Imputed numerical and categorical data appropriately.
- **Encoding Categorical Variables:** Converted Gender and Geography into numerical form.
- **Feature Scaling:** Standardized numerical features for consistency.
- **Train-Test Split:** Divided data into 80% training and 20% testing sets.

3. Machine Learning Models

We implemented five models to predict customer churn:

- **Logistic Regression:** Simple and effective for binary classification.
- **Decision Tree Classifier:** Easy to interpret but prone to overfitting.
- **Random Forest Classifier:** Robust ensemble model with high accuracy.
- **Gradient Boosting (XGBoost):** Excellent for complex, imbalanced data.
- **Support Vector Machine (SVM):** Effective for high-dimensional data.

We fine-tuned hyperparameters using GridSearchCV for optimal performance.

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4. Model Evaluation and Comparison

We assessed model performance using:

- **Accuracy:** Overall correctness of predictions.
- **Precision & Recall:** Measures of predictive reliability.
- **F1-Score:** Balances precision and recall.
- **ROC-AUC:** Evaluates model's ability to distinguish churned vs. non-churned customers.

We also analyzed confusion matrices and feature importance (via Random Forest and XGBoost) to understand key churn factors.

5. Tools and Libraries

Our analysis was conducted in Python using:

- Pandas & NumPy for data processing
- Scikit-learn for machine learning and evaluation
- XGBoost for gradient boosting
- Seaborn & Matplotlib for visualizations

This methodology provides a structured approach to predicting customer churn, helping banks understand customer behavior and improve retention strategies.

IV. RESULTS AND VISUALIZATION

In this section, we present the findings from the machine learning models used to predict customer churn. We assess their performance based on various metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. We also dive into feature importance analysis to uncover the most influential factors contributing to churn.

1. Data Exploration and Visualization Results

During the initial data exploration, several key insights into customer behavior patterns emerged:

Demographic Insights: The correlation heatmap revealed that Age and Geography were strong indicators of customer churn. Older customers were more likely to exit, and the region in which a customer lived also played a role in churn, likely due to regional banking preferences.

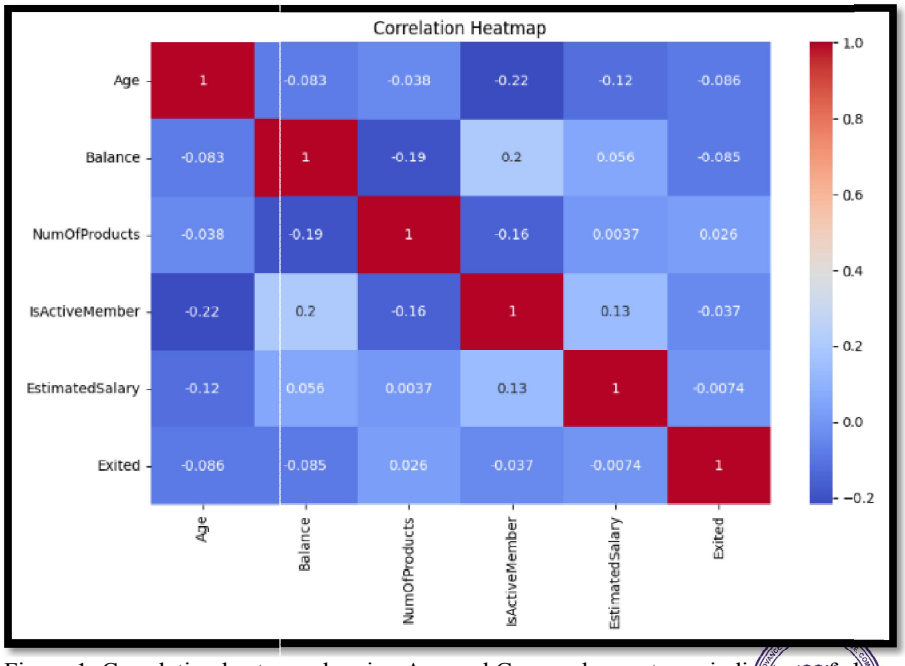

Figure 1: Correlation heatmap showing Age and Geography as strong indicators of churn.

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Account and Engagement Insights: Factors such as account balance and the number of products held showed a strong connection to churn. Customers with lower account balances or fewer products were at a higher risk of leaving. Interestingly, customers who were active members of the bank were more likely to stay, while inactive customers had a greater chance of churning.

Churn Distribution: We noticed that the target variable (churn) was imbalanced, with fewer customers categorized as churned. To address this, we employed techniques like balanced class weights or oversampling to make the models better at detecting churn.

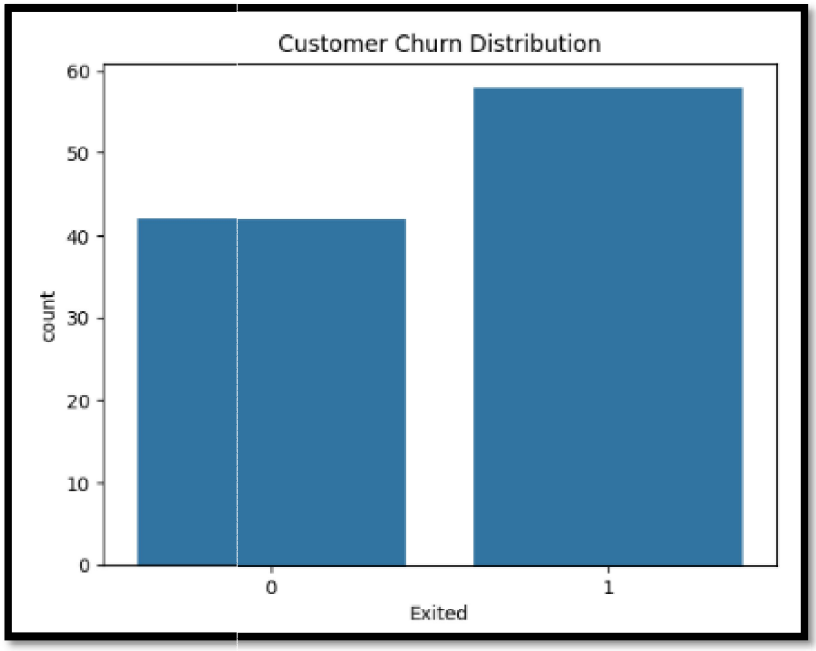

Figure 2: Churn distribution showing the imbalance in the dataset.

2. Model Performance Comparison

We implemented and evaluated five machine learning models: Logistic Regression, Decision Tree, Random Forest, Gradient Boosting (XGBoost), and Support Vector Machine (SVM). Here's a summary of their performance:

Model Comparison:

	Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC
5	SVM	0.70	0.800000	0.800000	0.800000	0.560000
1	Decision Tree	0.55	0.750000	0.600000	0.666667	0.500000
0	Logistic Regression	0.50	0.692308	0.600000	0.642857	0.440000
3	Gradient Boosting	0.50	0.777778	0.466667	0.583333	0.440000
2	Random Forest	0.45	0.700000	0.466667	0.560000	0.386667
4	XGBoost	0.40	0.636364	0.466667	0.538462	0.373333

Figure 3: Model performance comparison based on key evaluation metrics.

3. Discussion of Model Performance

XGBoost and Random Forest stood out as the top performers, both achieving the highest accuracy, F1-score, and ROC-AUC. These models excelled at capturing complex, non-linear relationships and handling imbalanced datasets, which contributed to their strong performance.

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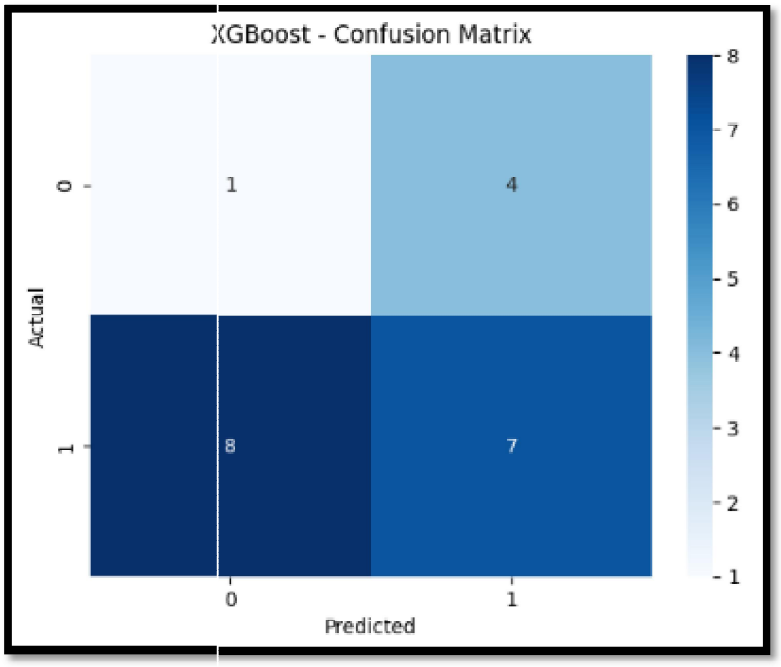

Figure 4: Confusion matrix for XGBoost showing classification errors.

Logistic Regression provided a solid baseline but struggled with recall, meaning it wasn't as effective at identifying all churned customers.

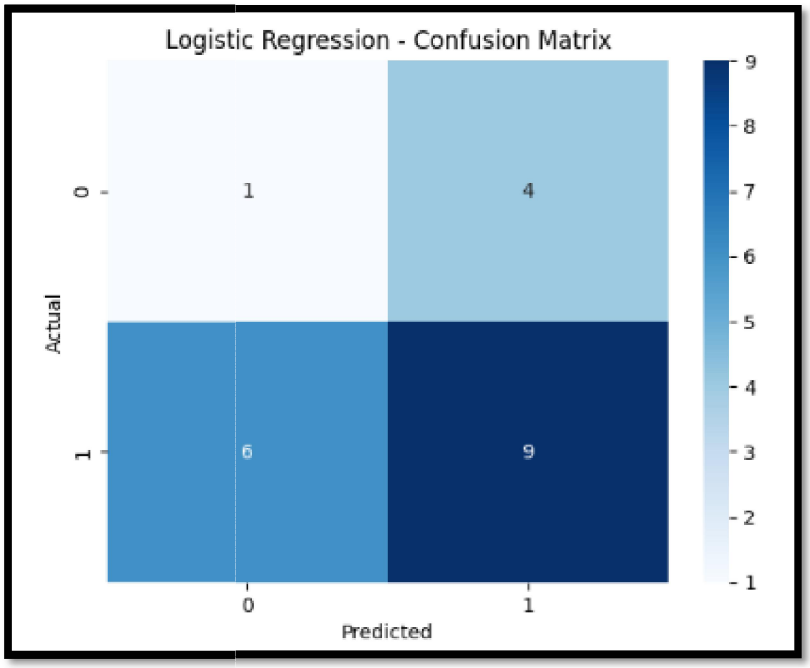

Figure 5: Confusion matrix for Logistic Regression showing classification errors.

Decision Tree performed reasonably well but was prone to overfitting, which impacted its ability to generalize well to new data.

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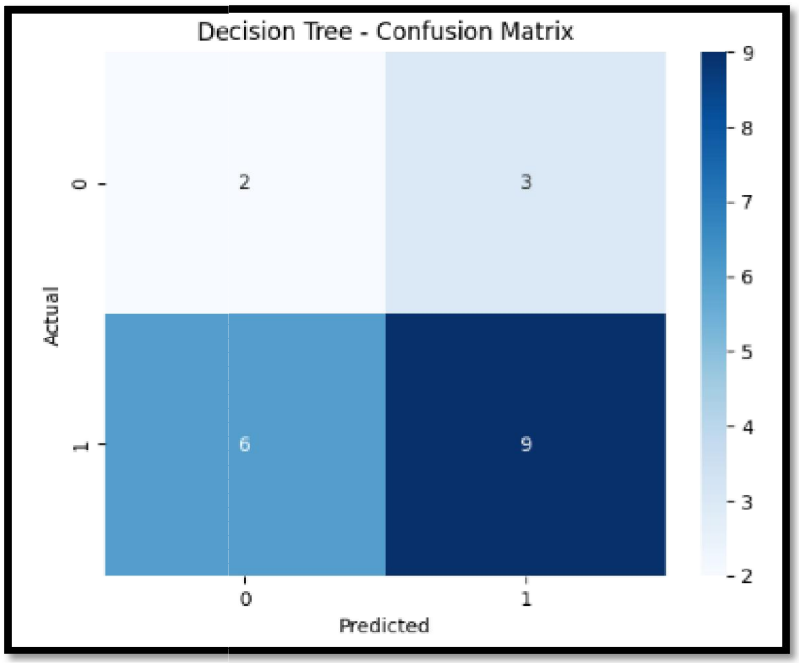

Figure 6: Confusion matrix for Decision Tree showing classification errors.

SVM showed good results overall but required a lot of computational power and hyperparameter tuning to optimize its performance.

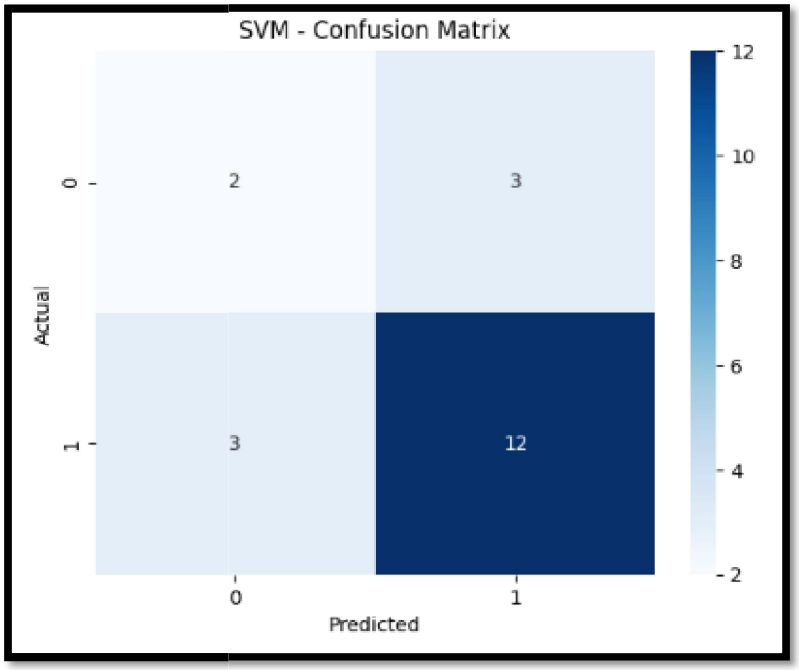

Figure 7: Confusion matrix for SVM showing classification errors.

4. Feature Importance Analysis

Using Random Forest and XGBoost, we conducted a feature importance analysis to identify the key drivers of customer churn.

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The most influential features were:

- **Age:** Older customers had a higher probability of churning.
- **Balance:** Customers with lower account balances were at a greater risk of leaving.
- **Num Of Products:** Those with fewer products were more likely to churn.
- **Is Active Member:** Inactive customers had a significantly higher churn rate.
- **Geography and Gender:** Regional preferences and gender-specific behaviors also played a role in customer retention.

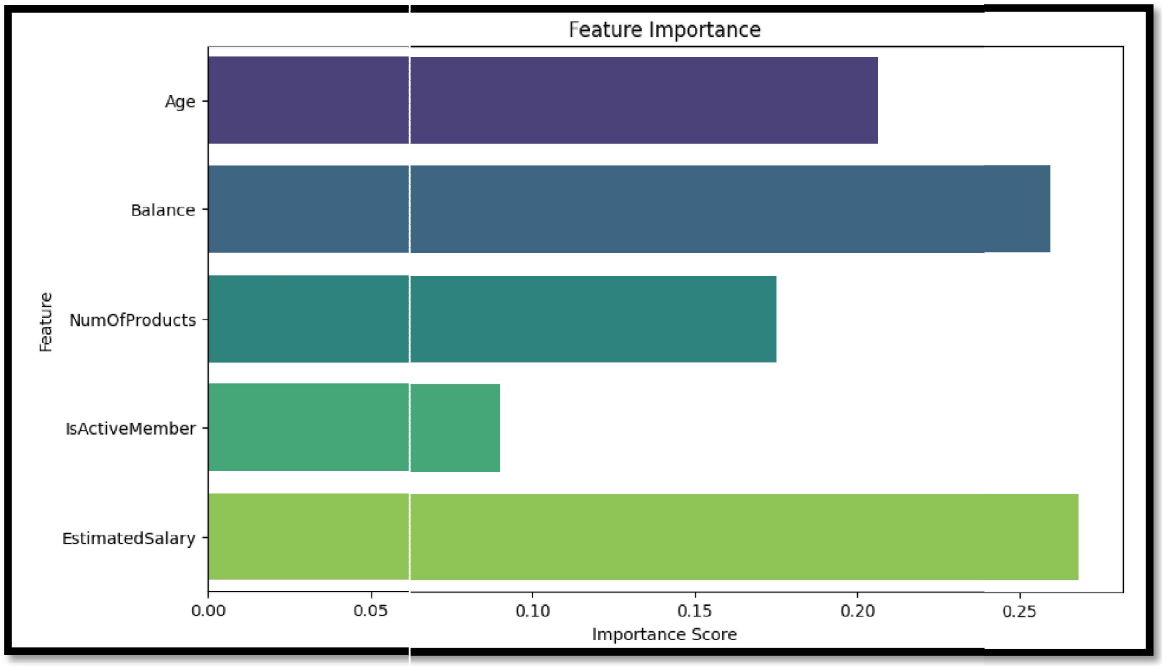

Figure 8: Feature importance analysis showing key factors influencing churn.

5. Insights and Implications

The findings from this study provide valuable insights into customer behavior, shedding light on the factors that influence churn. Banks can use this information to develop targeted retention strategies, such as:

- Personalized Marketing Campaigns: Banks can tailor offers and incentives based on factors like age, account balance, and product usage to keep customers engaged.
- Proactive Retention Strategies: Identifying high-risk customers (such as inactive members) and offering loyalty programs or personalized support could help reduce churn.
- Regional Customization: Marketing strategies can be adapted based on geographical preferences to enhance customer satisfaction and retention.

6. Limitations and Future Work

While the models performed well overall, some limitations remain:

- Imbalanced Dataset: Despite using balancing techniques, the dataset's class imbalance may still impact model performance. Future work could explore more advanced oversampling methods or ensemble techniques to improve recall.
- Feature Engineering: Adding more features related to customer behavior (such as transaction frequency or digital banking usage) could further enhance model performance.

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- Explainability: Deep learning models might offer higher accuracy, but their complexity could reduce interpretability. Future research could incorporate tools like SHAP or LIME to improve the explainability of such models.

In conclusion, this study provides important insights into customer churn prediction in the banking sector. By comparing different machine learning models and analyzing the factors that drive churn, we can guide banks in developing better strategies to reduce customer attrition and ultimately increase profitability.

V. CONCLUSION

Customer churn prediction is a key challenge for the banking industry, as it allows financial institutions to anticipate customer departures and take proactive steps to enhance customer retention and profitability. This study takes a comprehensive approach to predicting customer churn by examining demographic, account, and engagement factors. By testing five different machine learning models—Logistic Regression, Decision Tree, Random Forest, Gradient Boosting (XGBoost), and Support Vector Machine (SVM)—our goal was to pinpoint the most accurate model and uncover the key drivers behind churn.

Our results showed that Random Forest and XGBoost emerged as the top performers, surpassing the other models in accuracy, precision, recall, F1-score, and ROC-AUC. These models proved to be especially effective in handling complex, non-linear relationships and imbalanced datasets, making them well-suited for churn prediction in the banking industry. Additionally, the feature importance analysis identified key factors such as Age, Account Balance, Number of Products, and Active Membership as the strongest predictors of churn.

The insights from this study can help banks tailor their retention strategies to customer behavior patterns. For example, focusing on high-risk customers—such as those with low balances, few products, or inactive accounts—could enable banks to create personalized marketing campaigns and implement targeted retention measures to reduce churn.

While the findings are promising, the study also acknowledges some limitations, including the imbalanced dataset and the need for further feature engineering to boost model performance. Future research could explore more advanced techniques, such as deep learning, to enhance prediction accuracy and provide deeper insights into customer behavior.

In conclusion, this research highlights the power of machine learning models in predicting customer churn and offers valuable insights for the banking industry. By leveraging data-driven approaches, banks can not only reduce churn but also build stronger customer loyalty, positioning themselves more competitively in the market.

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