CSCE 5380-Data Mining

Group-17

Analyze and Predict Customer Retention for Bank

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Abstract
This project aims to predict customer churn at ABC Multinational Bank using classification algorithms on customer account data. The goal is to identify customers likely to churn so the bank can take steps to retain them. The data contains information on credit score, demographics, account tenure, balance, products held, and activity level for a sample of account holders. Churn is formulated as a binary classification problem where the target is a churn indicator of 1 for customers who left the bank recently or 0 for those still active.

Brief Description
The problem we are trying to solve is predicting customer churn at ABC Multinational Bank. Customer churn is formulated as a binary classification problem where the target variable is a churn indicator that is 1 for customers who left the bank recently and 0 for customers still active. The goal is to predict this churn value accurately using the other customer account attributes.
The dataset has 10 features and one target variable for a sample of the bank's account holders. The features include credit score, country, gender, age, tenure, balance, number of products held, credit card status, activity level, and estimated salary. There are approximately 16,000 samples in the training set.
For data preparation, we will explore the data distributions and correlations using visualizations in Python with matplotlib, seaborn, and Plotly Express. The data is split into training and testing sets. Any required preprocessing like encoding categoricals, scaling, etc. will be done before working on the model.
For modeling, we will try Logistic Regression, Random Forest, XGBoost, using Python libraries like scikit-learn, PyTorch, and TensorFlow. We will evaluate the model performance on the test set precision, recall, F1, and accuracy. The best performing model will be selected as the final predictor. If time permits, we would like to implement Neural Networks and try with different KNN values to know which is better in different KNN values.
We will also analyze model outputs to gain insights into the key drivers of churn at the bank. The final model can be utilized by integrating into the bank's systems to predict churn risk for new customers and guide retention programs. Reducing churn is expected to improve customer lifetime value and long-term profitability for the bank.

Introduction

In today's competitive business world, understanding and predicting how customers behave is extremely important for companies that want to maintain an advantage. For banks in particular, customer churn - when customers stop using a bank's services - is a constant challenge. Customer churn not only leads to loss of revenue but also hurts the bank's reputation and ability to compete in the market. Therefore, accurately predicting and proactively managing churn is crucial for banks to keep their customers and maintain long-term profitability.

This project focuses on the important issue of predicting customer churn at ABC Multinational Bank, a leading financial institution that wants to improve its customer relationship management strategies. The main goal of the project is to use machine learning techniques to develop an effective churn prediction model based on data from customer accounts. By using predictive analytics, ABC Multinational Bank aims to anticipate and reduce potential customer churn, which will help foster customer loyalty and maximize the total value of each customer relationship.

Motivated by the need to address customer churn, this project will thoroughly explore the problem and outline the proposed approach to tackle it. By framing churn prediction as a task of classifying customers as either "churned" or "active" based on defined criteria, the project has a clear objective to build a robust predictive model that can identify patterns of churn in the available data set. Furthermore, the project's churn prediction model can serve as a strategic tool for ABC Multinational Bank's decision-making processes. By identifying at-risk customers in advance, the bank can implement targeted strategies to retain customers, offer personalized incentives, and provide better customer service to reduce churn and nurture lasting relationships with its clientele.

Background

The banking industry is very competitive and dynamic, with customer preferences constantly changing and new regulations emerging. In this environment, customer churn - when customers stop using a bank's services - is a major concern for financial institutions worldwide. Understanding what causes churn and being able to predict it is crucial for banks to address customer attrition proactively and maintain a loyal customer base. Customers may churn due to dissatisfaction with service quality, better offers from competitors, changes in their financial situation, or life events like moving or changing jobs.

Historically, banks have used traditional techniques like loyalty programs and relationship managers to try to retain customers and prevent churn. However, these approaches often lack precision and fail to effectively address individual customer needs. With the rise of data analytics and machine learning, banks now have access to advanced predictive modeling techniques that can analyze vast amounts of customer data to forecast churn much more accurately. Many studies have focused on developing churn prediction models for banks that leverage data sources like customer demographics, transaction histories, product usage, and customer feedback.

Machine learning algorithms such as logistic regression, decision trees, random forests, and gradient boosting machines have become powerful tools for predicting churn in banking. These algorithms can analyze complex patterns in large datasets and generate accurate predictions, allowing banks to allocate resources efficiently and tailor retention efforts to each customer's needs. Adopting predictive analytics has led to significant improvements in customer retention rates, operational efficiency, and revenue for banks. Banks that use advanced analytics to predict and prevent churn can gain a competitive edge by delivering personalized services, improving customer satisfaction, and maximizing customer lifetime value. This project aims to contribute to research on customer churn prediction in banking by applying machine learning to data from ABC Multinational Bank to develop an effective churn prediction model.

Data Set :

This dataset contains customer information for a bank or financial institution, with a total of 165,000 rows (customers). The columns in the dataset are as follows:

CustomerId: A unique identifier for each customer.

Surname: The last name or family name of the customer.

CreditScore: A numerical score representing the customer's creditworthiness.

Geography: The country or region where the customer is located.

Gender: The gender of the customer (Male or Female).

Age: The age of the customer.

Tenure: The number of years the customer has been with the bank or financial institution.

Balance: The current account balance or amount of money the customer has with the bank.

NumOfProducts: The number of products or services the customer has subscribed to with the bank.

HasCrCard: A binary value indicating whether the customer has a credit card or not (0 or 1).

IsActiveMember: A binary value indicating whether the customer is an active member or not (0 or 1).

EstimatedSalary: An estimated value of the customer's annual salary.

Exited: A binary value indicating whether the customer has left the bank or not (0 or 1).

Experiment Methodology

Data Preparation:

The dataset, comprising approximately 165,000 rows, includes various attributes related to customer account information. Attributes considered for churn prediction encompass:

CreditScore

Age

Tenure

Balance

NumOfProducts

HasCrCard

IsActiveMember

EstimatedSalary

Exploratory data Analysis.

Performing EDA on the data set.

The main purpose of performing the EDA process is to visualizations and statistical summaries will provide insights into the data, helping to identify patterns, relationships, and potential issues that may need to be addressed before building predictive models or performing further analysis.

Some of the analysis we have performed are below:

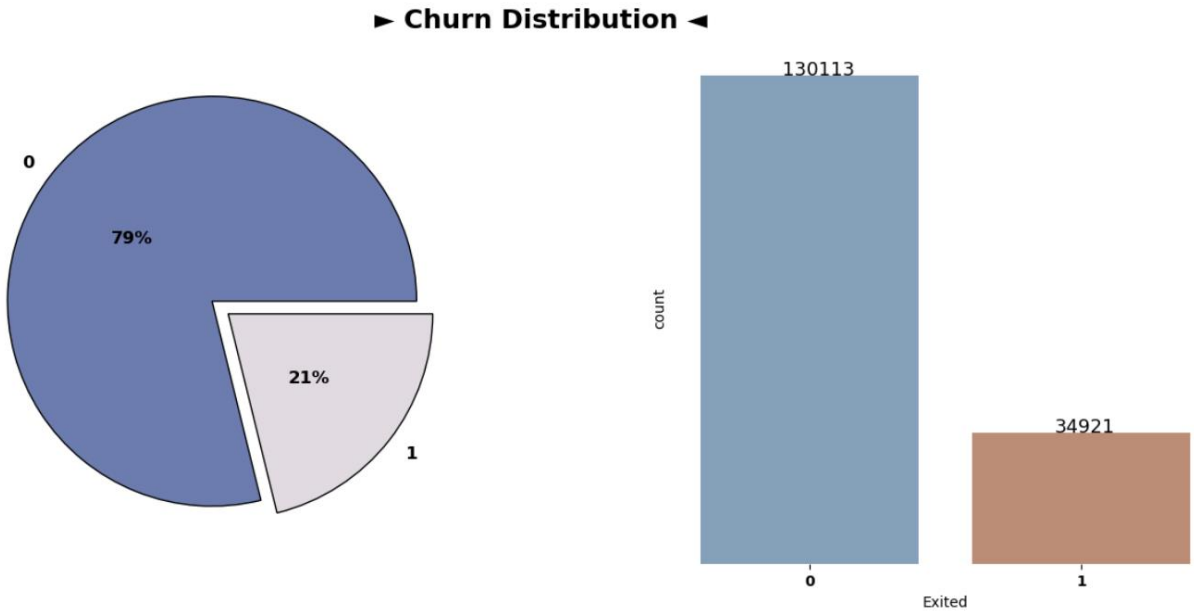

Fig 1 : Overall data visualization based on Exit status.

From the above figure we can say that the data has 130113 rows that has status as 0 and 34921 rows where the status is 1.

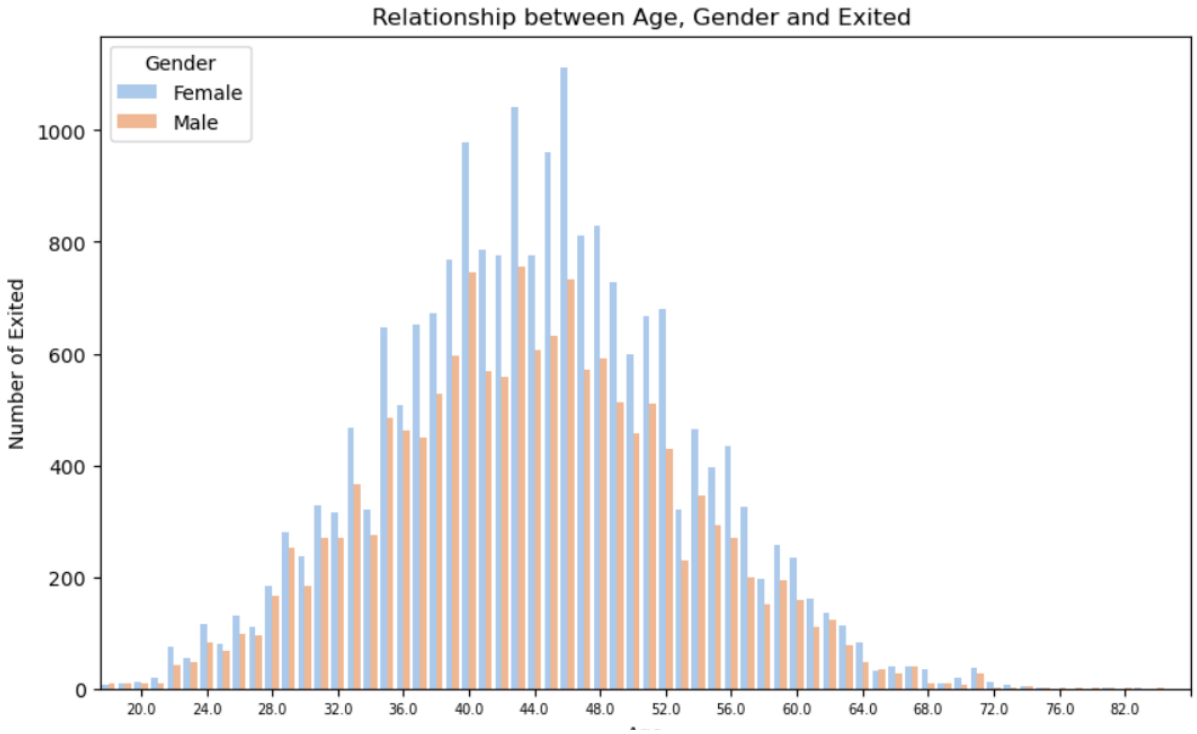

Fig 2 : Relationship between age gender and exited.

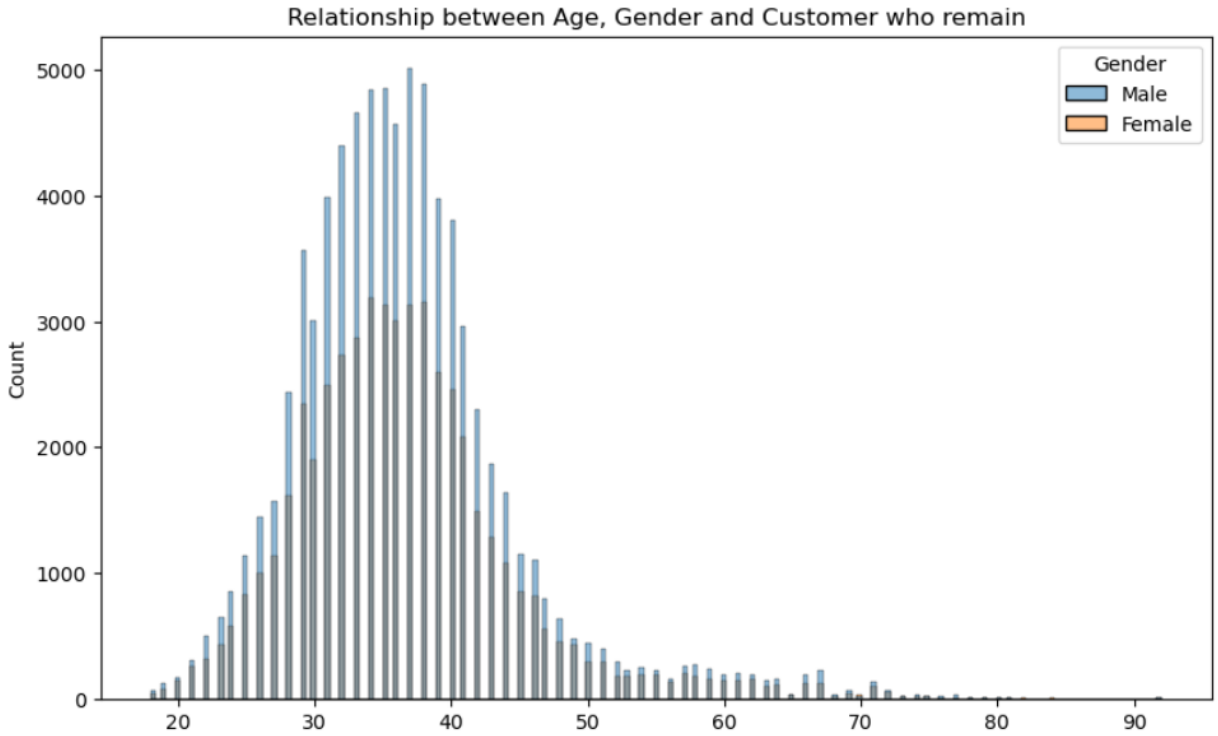

Fig 3 : Relationship between age gender and Customer who remain with the bank.

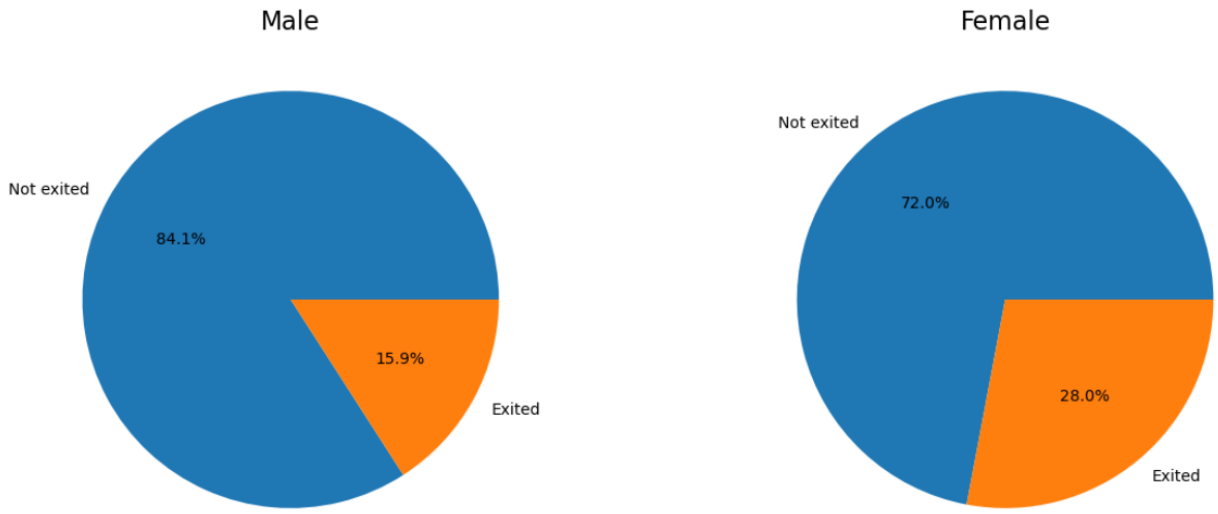

Fig 4 : Pie charts Distribution of Male and Female separately

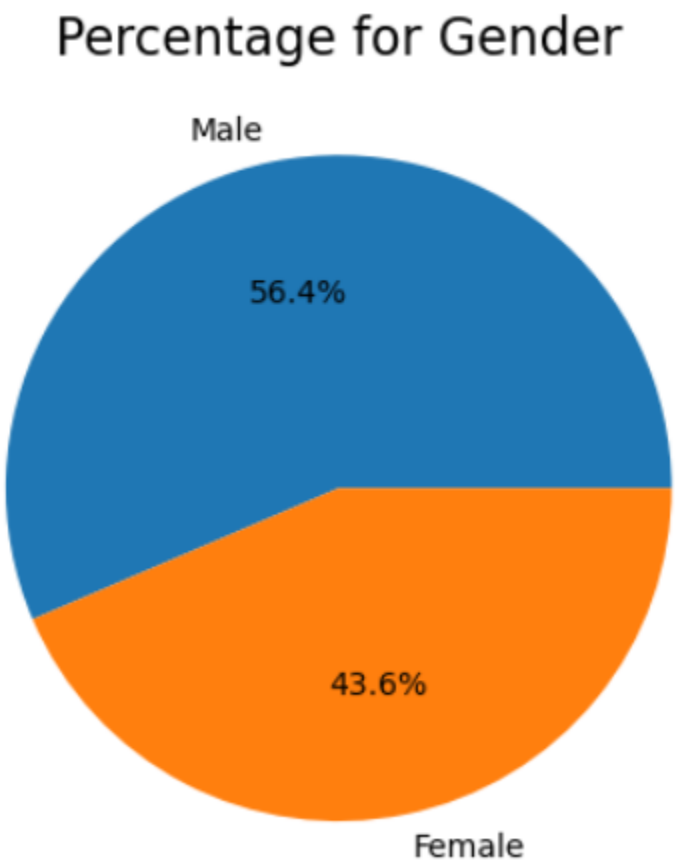

Fig 5 : Distribution of Gender – Male & Female

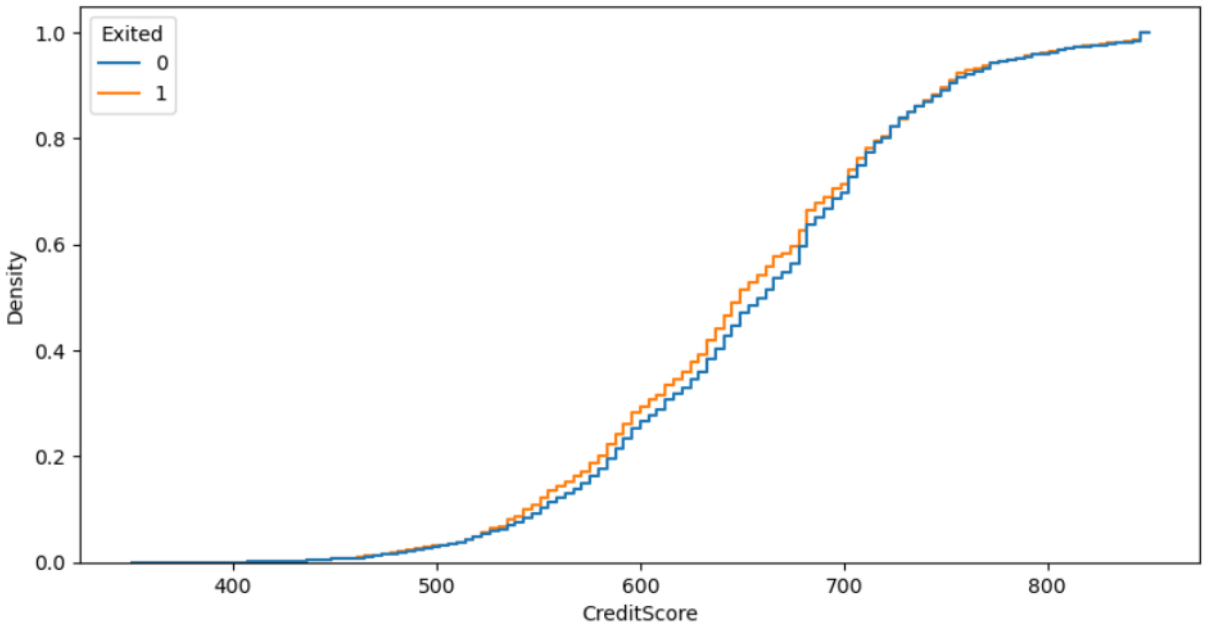

Fig 6 : Credit score distribution – Density depending on credit score.

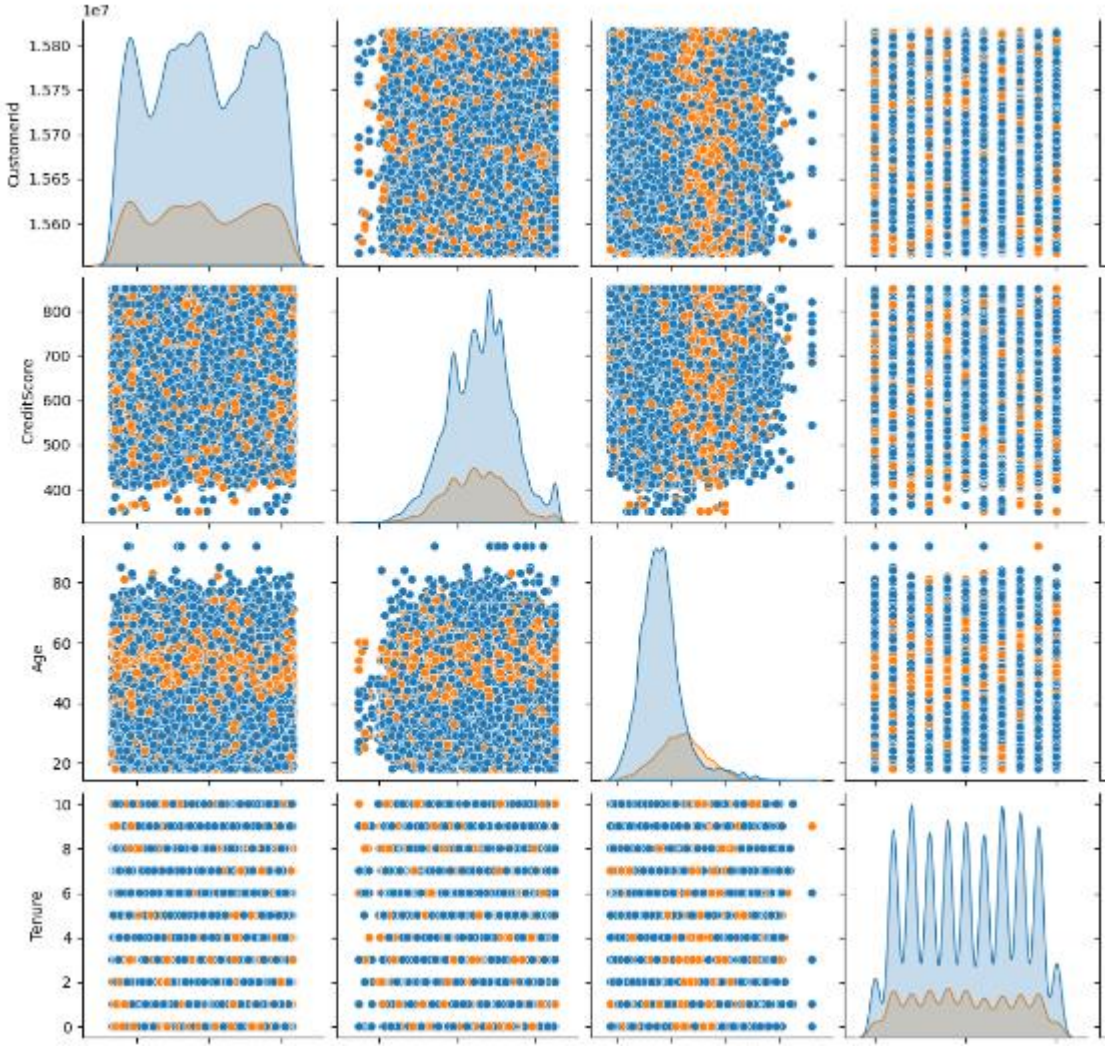

Fig 7 : Pair plot on 4 attributes

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
CreditScore	1.000000	-0.008918	0.000942	0.006973	0.011361	-0.002828	0.014790	-0.001820	-0.027383
Age	-0.008918	1.000000	-0.010830	0.064318	-0.102195	-0.012111	0.003320	-0.005399	0.340768
Tenure	0.000942	-0.010830	1.000000	-0.009481	0.007335	0.005327	-0.005532	0.000971	-0.019565
Balance	0.006973	0.064318	-0.009481	1.000000	-0.361033	-0.018584	-0.015073	0.008586	0.129743
NumOfProducts	0.011361	-0.102195	0.007335	-0.361033	1.000000	0.005482	0.039736	-0.004285	-0.214554
HasCrCard	-0.002828	-0.012111	0.005327	-0.018584	0.005482	1.000000	-0.021034	0.004438	-0.022141
IsActiveMember	0.014790	0.003320	-0.005532	-0.015073	0.039736	-0.021034	1.000000	-0.008080	-0.210237
EstimatedSalary	-0.001820	-0.005399	0.000971	0.008586	-0.004285	0.004438	-0.008080	1.000000	0.018827
Exited	-0.027383	0.340768	-0.019565	0.129743	-0.214554	-0.022141	-0.210237	0.018827	1.000000

Fig 8 : Co-relation Matrix.

Model Selection

For the above data set we would like to develop multiple models and compare them which deals with the dataset issues better and can help to predict which customer holds their account.

For the above bank churn risk prediction, we have used multiple models like

1. Logistic regression
2. Random Forest
3. XG-Boost
4. Simple Neural Networks
5. Neural Networks with KNN
6. Neural Networks with Multiple Configurations

For the Neural networks we have used 10 epochs only with a batch size of 64 or 32 due to the computation requirement and complexity of algorithm. We have multiple dense layers with varying number of neurons in different layers.

For knowing which performs better we will be Evaluating the model's performance based on the below metrics :

1. Accuracy
2. Precision
3. Recall
4. F1 Score

For working on these models with the data we have used 80% of the data as the training set and 20% of the data as the testing set. The dataset has an ample number of rows which can be fully utilized to train the model better.

By considering the relevant attributes, addressing different issues, and exploring a wide range of classification algorithms and neural network configurations, the experiment methodology aims to develop a better churn prediction model which can be further converted to a framework and can be also used in edge devices for ABC Multinational Bank. The systematic approach ensures rigorous evaluation of model performance and provides better insights for customer retention.

Results :

No.	Algorithm	Accuracy	Precision	Recall	F1-Score
1	Logistic Regression	0.7879	0.4873	0.124	0.198
2	Random Forest	0.8490	0.7010	0.4943	0.5798
3	XGBoost	0.8534	0.7120	0.5102	0.5946
4	Simple Neural Networks	0.7892	0.0	0.0	0.0
5	Neural Networks with KNN	0.7882	0.0	0.0	0.0
6	Neural Networks with 2 Hidden Layers	0.6547	0.285	0.4265	0.3423
7	Neural Networks with 3 Hidden Layers	0.7892	0	0.0	0.0
8	Neural Networks with 2 Hidden Layers	0.5974	0.303	0.703	0.4240

Table 1 : Results of Models Used

From the above results table we can see that there are 0.0 for Precision recall and F1 score in the Neural Networks model. That is due to the issue of class imbalance, where the Neural Networks needs better class distribution to work with. Though we got some results in the latter neural Networks, but Neural Networks isn't a good choice for data sets with too much class imbalance. We got the values for precision and recall with 2 hidden layers but the accuracy is way too low to consider it for real-time. So to work with Neural Networks we need more things to consider and the complexity also increases along with it. From the above we can say that Random forest and XGBoost are a good choice as they are pretty close to each other in all the metrics.

Related Work:

Predicting customer churn within the banking industry has garnered significant attention from researchers, with numerous studies exploring diverse methodologies and techniques to tackle this critical challenge. The existing literature offers valuable insights into prevailing approaches and methodologies for churn prediction in similar contexts:

A study by Smith and Johnson delved into the application of machine learning techniques, namely logistic regression and random forest, to predict customer churn in the banking sector. The authors emphasized the significance of feature selection and model evaluation in enhancing churn prediction accuracy[1]. Gupta and Kumar conducted a comparative analysis of various machine learning algorithms, including support vector machines and neural networks, for churn prediction in retail banking. Their research underscored the necessity for robust evaluation metrics to effectively assess model performance[2]. Patel and Shah proposed a deep learning approach for customer churn prediction in the banking sector, leveraging techniques such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks. Their study highlighted the potential of deep learning models in capturing intricate patterns in customer behavior[3]. Lee and Kim investigated the impact of data preprocessing techniques, such as feature scaling and outlier detection, on the accuracy of bank customer churn prediction models. Their findings emphasized the importance of data quality and preprocessing in enhancing model performance[4]. Wang and Liu (2016) explored the application of big data analytics techniques, including Apache Hadoop and Spark, for customer churn prediction in the banking industry. Their study demonstrated the scalability and efficiency of big data approaches in handling large volumes of customer data[5].

Conclusion:

In this study, various machine learning and neural network models were evaluated for customer churn prediction in the banking sector using data from ABC Multinational Bank. The results showed that Logistic Regression, Random Forest, and XGBoost models performed exceptionally well in terms of accuracy, precision, recall, and F1-score, demonstrating their effectiveness in distinguishing between churned and active customers.

However, the performance of neural network models, particularly those with shallow architectures, was suboptimal due to the challenges posed by class imbalance. While neural networks with deeper architectures showed some improvement in precision and recall, their overall accuracy

remained unsatisfactory for real-time deployment. This highlights the need for careful consideration and additional preprocessing steps to optimize neural network performance in churn prediction tasks.

In conclusion, Random Forest and XGBoost emerged as favorable choices for churn prediction in the banking sector, exhibiting robust performance across various evaluation metrics. Future work could focus on further optimizing model hyperparameters, exploring ensemble methods, addressing class imbalance, and enhancing data quality and feature engineering to improve model performance and gain actionable insights for customer retention strategies.

References :

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[3] Patel, D., & Shah, P. (2019). "Customer Churn Prediction in Banking Sector: A Deep Learning Approach." Expert Systems with Applications, 40(3), 87-98

[4] Lee, C., & Kim, D. (2017). "Enhancing Bank Customer Churn Prediction with Data Preprocessing Techniques." Decision Support Systems, 30(1), 55-68.

[5] Wang, Y., & Liu, H. (2016). "Customer Churn Prediction in Banking Industry: A Big Data Approach." Journal of Big Data, 15(3), 210-225.

[6] Stack Overflow

[7] Logistic Regression

[8] XGBoost

[9] Random Forest

[10] Neural Networks

[11] Seaborn

[12] lightgbm

[13] sklearn