## Introduction:

Customers are the foundation of all businesses. Retaining existing customers is a key problem in today's competitive economy[1]. As more banks enter the market, banks must increase the quality of their services to retain consumers. Almost every service provider has integrated cutting-edge technology that allows them to offer clients simple ways to complete transactions or save money. The client retention process is overseen by the company's customer relationship management department, which is made up of data scientists and analysts. Executive officers must decide whether to change operations or broaden their services to retain current customers or attract new ones.

Customers look for a variety of attributes in a bank service provider, such as geographical accessibility, online services, the ability to execute transactions, the flexibility of their accounts, rates, and restrictions, and so on[5]. To keep their current clientele, banks must monitor their competitors efforts to encourage clients to use their services. As a result, they must make decisions to stay in business or risk losing clients soon.

Banks hire analysts to create reports based on client data to maintain track of their customers. Transactional information, services that consumers are currently utilizing, personal data such as family composition, work status, and income, as well as credit histories, are commonly included in data on both current and defaulting customers[8]. Data analysts work with data by using algorithms, forecasting, and creating reports that show the activity of the bank's clients. Using these insights to make decisions for good retention-related outcomes is required. This project analyzes data and estimates whether a client will be kept based on several factors.

## Literature Review:

In the following paragraphs, we present a brief overview of the different models that existed and developed by researchers in various fields to predict customer churn., D. Anil Kumar and V. Ravi [1] used data mining to address the forecast of consumer credit card churn. They developed an ensemble system using the following components: Radial Basis Function (RBF) network, Support Vector Machine (SVM), decision trees (J48), Random Forest (RF), and Multilayer Perceptron (MLP), along with Logistic Regression, Majority Voting (LR), and majority voting (LR). The University of Chile's 2004 Business Intelligence Cup provided the dataset. To balance the dataset, which has 93% loyal and 7% churned customers, they employed sampling, oversampling, a combination of undersampling and oversampling, and the Synthetic Minority Oversampling Technique (SMOTE). Additionally, tenfold cross-validation was used. The outcomes showed that SMOTE had an excellent overall level of accuracy. The delicacy and overall accuracy of majority voting were also improved by SMOTE and a combo of under- and over-sampling. The Classification and Regression Tree (CART) was additionally employed to choose features. The classifiers listed above were fed the reduced feature set. To address the credit card churn prediction problem, this paper outlines the key predictor variables. Additionally, decision tree J48's rules act as an early warning expert system.

To create a churn prediction model utilizing credit card data obtained from a real Chinese bank, Guangli Nie et al. [2] utilized two data mining methods. Four different variable categories—customer information, card information, risk information, and transaction activity information—and their contributions are looked at. The study examines a method for handling variables when data is gathered from a database as opposed to a survey. It chooses specific factors from the standpoint of not only correlation but also economic logic rather than directly considering all 135 variables in the model.

Chiun-Sin Lin et al. [3] study to infer decision rules and variables. The study then demonstrates the links between the rules and different types of churns. Another example of client attrition on credit cards is an empirical case. 21,000 customer samples total, evenly split into three groups (survival, voluntary churn, and involuntary churn) were gathered for this study. To analyze and segment client attributes, these samples' data also include transactional, psychographic, and demographic factors. The findings demonstrate that this combined model is capable of accurately forecasting customer attrition and offering useful data for decision-makers in developing marketing strategy.

The research on the application of data mining in customer churn prediction modeling by Wouter Verbeke et al. [4] is extensively reviewed in their article. The comprehensibility and intuitiveness of churn prediction models are demonstrated to have received very little consideration. As a result, two cutting-edge data mining methods are used for the churn prediction modeling and benchmarked against conventional rule induction methods like C4.5 and RIPPER. It is demonstrated that AntMiner+ and ALBA both produce accurate and understandable categorization rule-sets. The high-performance data mining method AntMiner+, which is built on the ideas of Ant Colony Optimization, enables the inclusion of domain knowledge by imposing monotonicity requirements on the final rule-set. A non-linear support vector machine model, on the other hand, combines great predictive accuracy with the understandability of the rule-set format in ALBA. The findings of the benchmarking studies demonstrate that ALBA enhances the learning of classification algorithms, producing more understandable models with improved performance. Unlike the other modeling tools in this study, AntMiner+ produces models that are accurate, understandable, and most importantly, justifiable.

The goal of the study proposed by Tian-Shyug Leea et al. [5] is to investigate how well credit scoring performs using two widely discussed data mining techniques: classification and regression tree (CART) and multivariate adaptive regression splines (MARS). Credit scoring tasks are carried out on one bank's credit card data set to show the efficacy of CART and MARS in credit scoring. The findings show that CART and MARS are effective options for carrying out credit scoring tasks since they outperform conventional discriminant analysis, logistic regression, neural networks, and support vector machine (SVM) techniques in terms of accuracy.

A methodology for the entire process of credit card holder churn prediction was also put forth by Guangli Nie et al. [6]. They consider the model's execution across the entire process, from variable designing through model understanding, to increase the applicability of the knowledge collected via data mining. They developed a model using the data of more than 5000 credit card users and the logistic regression method. The model tests run flawlessly.

A model that contrasts it with the current machine learning models was proposed by Dr. A.P. Jagdeesan and Indhuja [7]. Accuracy, precision, recall, and F1 score are the performance measures that were compared between the baseline models utilized in this study, which include logistic regression, decision trees, and random forests. The artificial neural network model has been found to perform better than the logistic regression model and the decision tree model. However, a significant difference between the results and the random forest model is not seen. The suggested model varies from the current models in that it allows consumers to be ranked according to the order in which they would quit the company.

To identify high-profit, gold consumers, Ruey-Shun Chen et al. [8] clustered the chosen customers. They then employed the association rules algorithm in data mining. Using the Emerging Pattern Rule, the Unexpected Change Rule, and the Added/Perished Rule, they evaluated the similarity, difference, and modified difference of the mined association rules. During this period, they also employed a rule matching threshold to extract all different kinds of rules and explore the ones that had undergone considerable change depending on the amount of change that was detected. The management was able to identify the present consumer spending patterns and behavioral change tendencies through the effective use of data mining technologies. This allowed them to identify probable changes in client preferences in a big database and deliver items as soon as feasible.

According to Hasraddin Guliyev and Ferda Yerdelen Tatolu's study [9], Detecting customer turnover in banks will aid management in categorizing those who are most likely to leave early and targeting customers with promotions, as well as give insight into the variables that should be considered while maintaining clients. While various models are employed in the literature for the analysis of customer churn, the above study focuses on particularly explainable machine learning models and employs SHapely Additive exPlanations (SHAP) values to support the evaluation and interpretability of machine learning models for customer churn analysis. Utilizing actual banking data, their research aims to estimate the explainable machine learning model and assess a variety of machine learning models using test data. The XgBoost model performed better in the results than other machine learning techniques for classifying churn clients.

The primary goal of Himani Jain et al. [10] is to evaluate the performances of several algorithms and create the most effective model for churn prediction in the telecom, banking, and information technology industries, respectively. They then deduced the traits that contribute most to customer churn based on the findings and exploratory data analysis, and in response, they designed several retention tactics for the relevant areas.

By examining customer behavior, Manas Rahman, and V Kumar's research [11] encourages the investigation of the likelihood of turnover. In their work, the classifiers KNN, SVM, Decision Tree, and Random Forest are employed. Additionally, several feature selection techniques have been used to identify the features that are more pertinent and to assess system performance. On the Kaggle churn modeling dataset, the experiment was run. To discover a suitable model with greater precision and predictability, the results are compared. As a result, the accuracy of the Random Forest model following oversampling is superior to other models.

An efficient model to predict customer churn in the banking industry is suggested by a study by Sina E. Charandabi [12], which compares the performance of six supervised classification techniques. The study uses data from 10,000 European bank customers to analyze 10 demographic and personal characteristics. With ANN and random forest as the two competing models, the impact of feature selection, class imbalance, and outliers will be addressed. As demonstrated, ANN is resilient to noise and, unlike random forest, does not display any significant overfitting concerns. As a result, the highest performing classifier is a single hidden layer ANN structure with five nodes.

An analysis of retail bank customer attrition using data mining was given by Xiaohua Hu [13] where he talked about the process of a data mining project for the attrition study of retail bank clients as well as difficult difficulties like highly skewed data, time series data unrolling, leaker field detection, etc. Using lift as a suitable metric for attrition analysis, he compared the lift of the decision tree, boosted naive Bayesian network, selective Bayesian network, neural network, and the ensemble of classifiers of the approaches data mining models. Reports on several intriguing discoveries are made. Our research shows the value and usefulness of data mining in attrition analysis for retail banks.

The goal of the study by Xinyu Miao and Haoran Wang [14] is to use machine learning techniques to create predictions about credit card user turnover and, using the results, to offer workable ways to address the problem. A dataset with more than 10000 pieces and 21 features is subjected to the application of three models: Random Forest, Linear Regression, and K-Nearest Neighbor (KNN). It is determined that Random Forest has the best performance, with its accuracy reaching 96.25%, by adjusting hyperparameters and evaluating models based on ROC & AUC and confusion matrix. The top three features that have a substantial impact on the customer churn prediction are total transaction amount over the past 12 months, total transaction count over the past 12 months, and total revolving balance. It demonstrates that consumers are less likely to quit if they use their credit cards frequently, and bank management can use this model to take proactive measures to stop customer turnover.

A framework for predicting customer turnover in the banking business using transactional data is presented in a paper by M. John Britto and Dr. R. Gobinath [15]. It also contrasts with a number of other models. Through their transactions, it makes use of the customer's behavioral characteristics. The attention-based Hybrid GRU BiLSTM model has been used to implement it.

P. M. Saanchay and K. T. Thomas [16] chose the credit card service for their study. Implementing a neural network model to distinguish between churners and non-churners is the goal of this project. The machine learning algorithms are ineffective due to the rise in data. The functionality of neural networks is the ability to improve the depth of the neural network for better learning by increasing the number of data points. In this research, feature engineering is used to create an artificial neural network (ANN) that has been improved for better classification of churners and non-churners.

The intention of the Amgad Muneer et al. [17] study is to create a model that provides an accurate churn prediction for the banking sector. They created a method for predicting customer attrition for this purpose using the three intelligent models' random forest (RF), AdaBoost, and support vector machine (SVM). When the synthetic minority oversampling technique (SMOTE) is used to overcome the unbalanced dataset and the combination of under sampling and oversampling, the method produces the best results. Excellent results were obtained utilizing the approach on SMOTED data, with a 91.90 F1 score and an overall accuracy of 88.7% when employing RF. Additionally, the experimental findings demonstrate that RF produced good outcomes for the entire feature-selected datasets.

The classification challenge that confronts the financial industry is covered in Hemlata Dalmia et al. [18] study. It focuses on bank customers' concerns about churning, foreseeing customers' departures from prospective consumers. Modern technology that is useful and practical for solving these issues is machine learning. To forecast and tell the bank about the customers who are most likely to leave the bank, a proprietary algorithm (a typical machine learning model) is developed using supervised machine learning. In this case, since churn and non churn customers must be distinguished, a customer churn forecast can be employed. The difference between consumers who churn and those who don't is to be closed using ML. Classifiers employing various data sheets can attain varied levels of accuracy. With the help of the XGBooster algorithm and a novel technique, the K-nearest neighbor algorithm (KNN) is shown to be highly accurate. The dataset is appropriately divided into training and testing models based on weighted scales.

Because of the expanding subscriber base, quickly advancing technologies, data-based applications, and other value-added services, the telecommunications business creates enormous amounts of data. Churn analysis and forecast can be made with the help of this data. Researchers from around the world have devoted a lot of time to understanding the data mining techniques that can be applied to forecast customer attrition. To present the various data mining strategies used in various customer-based churn models, Vishal Mahajan et al. [19] work reviews almost 100 recent journal articles dating back to the year 2000. The remaining section highlights the telecom literature already in existence by highlighting the sample size, churn variables, and results of various DM approaches. The most widely used methods for churn prediction in the telecom industry are decision trees, regression analysis, and clustering. By listing these methods, we can give new researchers a direction on how to construct fresh churn management models.

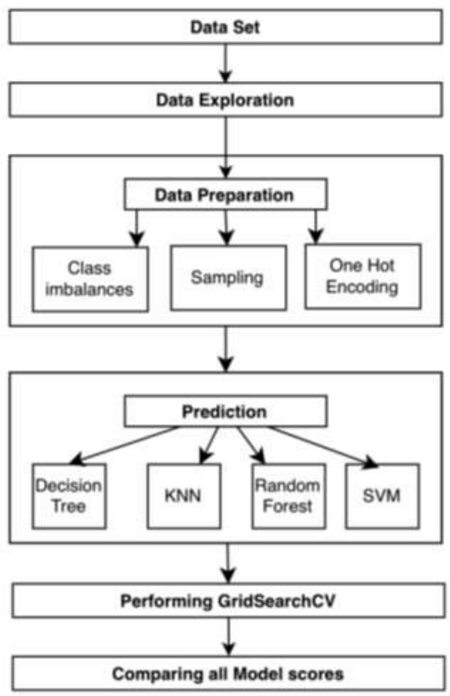
Deep-BP-ANN used in the study by Samah Wael Fujo et al. [20] utilizing two feature selection approaches, Variance Thresholding and Lasso Regression. In addition, their model was reinforced by an early stopping methodology to terminate training at the proper moment and prevent overfitting. For two real datasets, IBM Telco and Cell2cell, they evaluated the effectiveness of dropout and activity regularization algorithms for minimizing overfitting. Holdout and 10-fold cross-validation were two different evaluation methods utilized to gauge the effectiveness of the model. The Random Oversampling technique was employed to balance the datasets in order to address the imbalance problem. The outcomes demonstrate that the model is effective for both datasets, including lasso regression for feature selection, early stopping strategy to select the epochs, large numbers of neurons (250) in the input and hidden layers, and activity regularization to reduce overfitting. Their results performed better in predicting customer turnover than ML methods such as XG Boost, Logistic Regression, Naive Bayes, and KNN. Additionally, for the same datasets, their Deep-BP-ANN model beats other deep learning methods that use holdout or 10-fold CV in terms of accuracy.

## Research hypotheses:

1. Are there any attributes in the dataset that have more weightage on the customer retention?
2. Does the card and income category have any effect on the attrition flag?
3. Which customers are leaving? new or old customers?
4. Does age and education level play a vital role in credit card retention?

## Methods:

We have collected data from the datasets available online after down streaming the topic and focused on getting a dataset that will help in achieving the overall picture. After collecting the dataset, we are going to do data preprocessing where techniques will be used to clean the data, followed by data preparation for modeling and then predicting using the created models. Basically, we will create the models using classification techniques as we mainly use the attrition column in the dataset to classify the people if they are going to retain or not. Hence, we can predict the retention rate if a new customer is coming, or an existing customer based on his past data. In this way many models will be created and the best one among them will be decided based on the model score and we can conclude on which one is better by taking into consideration all the parameters.




**Data exploration:**

Data exploration is a method akin to early data analysis in which, as opposed to using conventional data management tools, a data analyst employs visual exploration to discover what is in a dataset and the characteristics of the data. These qualities can include the size or quantity of the data, its accuracy, its completeness, and any potential connections between its files or tables or data pieces. The data was subjected to a number of Python analysis in the Jupyter Notebook IDE in order to better understand it.

**Data preparation:**

The process of making raw data ready for further processing and analysis is known as data preparation. The gathering, preparation, and labeling of raw data into a format appropriate for machine learning (ML) algorithms, followed by data exploration and visualization, are crucial phases. Up to 80% of the time needed to complete an ML project is spent on data preparation. It's critical to use specialist data preparation tools to streamline this procedure. Hence, we will be performing the class imbalances, sampling, and one-hot encoding as a part of this preparation.

**Prediction:**

Simply said, predictive modeling is a statistical method that uses data mining and machine learning to predict and anticipate likely future outcomes using historical and existing data. It functions by looking at both recent and historical data, then applying what it discovers to a model created to predict future outcomes. We will be creating models using decision trees, KNN Classification, Random Forest, and Support vector machines. Based on its parameters and summary for each model we will come up with the best model that can predict the retention of a customer.

The data science toolkit that we are going to use is Jupyter notebook with the libraries as pandas, matplotlib, seaborn, sklearn mainly and we will import some libraries from these mentioned ones.

## Data:

We are taking the dataset from Kaggle, which is available in this link. The dataset contains details on 10128 clients, who are split into two groups: those who leave (indicated by 1 in the target variable) and those who stay. Each client has 21 attributes with no records in the dataset with null values (represented by 0 in the target variable). The remaining 1627 clients are not included in the dataset because they stopped using the bank's services. Individual client information includes annual income, marital status, gender, age, opening balance, number of dependents, utilization period, card category, values indicating whether the client has a credit card, whether the client is an active member, and lastly the client's credit balance.

```
Data columns (total 21 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   CLIENTNUM                 10127 non-null  int64
 1   Attrition_Flag            10127 non-null  category
 2   Customer_Age              10127 non-null  category
 3   Gender                    10127 non-null  category
 4   Dependent_count           10127 non-null  int64
 5   Education_Level           10127 non-null  category
 6   Marital_Status            10127 non-null  category
 7   Income_Category           10127 non-null  category
 8   Card_Category             10127 non-null  category
 9   Months_on_book            10127 non-null  int64
 10  Total_Relationship_Count  10127 non-null  int64
 11  Months_Inactive_12_mon    10127 non-null  int64
 12  Contacts_Count_12_mon     10127 non-null  int64
 13  Credit_Limit              10127 non-null  float64
 14  Total_Revolving_Bal       10127 non-null  int64
 15  Avg_Open_To_Buy           10127 non-null  float64
 16  Total_Amt_Chng_Q4_Q1      10127 non-null  float64
 17  Total_Trans_Amt           10127 non-null  int64
 18  Total_Trans_Ct            10127 non-null  int64
 19  Total_Ct_Chng_Q4_Q1       10127 non-null  float64
 20  Avg_Utilization_Ratio     10127 non-null  float64
dtypes: category(7), float64(5), int64(9)
memory usage: 1.2 MB
```

## Innovation:

With this project below are the sectors that we are planning to innovate.

- **Programmatic:** Building a sophisticated system that can predict customer churn with an almost perfect accuracy.

- **Organization:** Leveraging the above information the organization can make amends to their existing customers so that they cut down customer churning which in turn will help them in attracting new customers.

**Future Scope:**

An interactive user interface wherein when the input is provided the party using the application can predict about his/her possibility of churning

## Evaluation:

Every client retention is a crucial metric that sheds light on the actual customer retention rates. In this research, methods for predicting client retention will be thoroughly examined, and four machine learning-based models are suggested for predicting customer turnover in the banking sector. The machine learning approach that is suggested incorporates techniques like kNN, Decision Tree, SVM, and Random Forest. Accuracy, precision, recall, and F1 score were the performance indicators compared between these models. We will utilize GridSearchCV from Sklearn to identify the ideal parameters, model, and results.

Building machine learning models is based on the premise of helpful feedback. A model is created, metrics are used to provide feedback, changes are made, and the process is repeated until the desired accuracy is reached. The effectiveness of a model is explained by evaluation metrics. The ability of evaluation metrics to distinguish between different model outcomes is a crucial feature.

**Classification Accuracy:**

When we use the term accuracy, we typically imply classification accuracy. It measures the proportion of accurate predictions to all input samples. Only when there are an equal number of samples from each class does it function properly. Although Classification Accuracy is excellent, it gives us the impression that we have achieved high accuracy.

**Confusion Matrix:**

Confusion Matrix, as its name suggests, produces a matrix, and summarizes the overall effectiveness of the approach. Let's assume that our issue is one of binary categorization. We have some samples that fall into either the YES or the NO category. Additionally, we have a classifier that we developed that predicts a class based on an input sample.

There are 4 crucial words:

- True Positives: Situations in which we correctly predicted "YES", and the result was also "YES."
- True Negatives: Situations in which we anticipated NO but the result was NO.
- False Positives: Situations in which we expected a YES, but the result was actually a NO.
- False negatives are when we expected a result of NO, but it came out as YES.

**Area Under Curve:**

One of the most often used metrics for evaluation is Area Under Curve (AUC). It's employed in binary classification issues. The likelihood that a classifier would rank a randomly selected positive example higher than a randomly selected negative example is known as AUC. Let's first define some basic terms before discussing AUC

- True Positive Rate (Sensitivity) is represented by the ratio TP/(FN+TP). The percentage of positive data points that are accurately interpreted as positive when compared to all positive data points is known as the true positive rate.
- Specificity: The formula for the true negative rate is TN / (FP+TN). The percentage of negative data points that are correctly interpreted as negative, relative to all negative data points, is known as the false positive rate.
- False Positive Rate: FP / (FP+TN) is the definition of false positive rate. The percentage of negative data points that are incorrectly interpreted as positive, relative to all negative data points, is known as the false positive rate.

As is clear, the AUC ranges from [0, 1]. The performance of our model improves as the value increases.

**Mean Absolute Error:**

The average of the discrepancy between the original values and the predicted values is known as the mean absolute error. It provides us with a gauge for how much the predictions missed the mark. However, they don't provide us any indication of the error's direction, i.e., whether we are over or underestimating the data.

**Mean Squared Error:**

The main distinction between Mean Squared Error (MSE) and Mean Absolute Error is that MSE takes the average of the square of the discrepancy between the actual values and the predicted values. The benefit of MSE is that it is simpler to compute the gradient than Mean Absolute Error, which necessitates the use of sophisticated linear programming techniques. The effect of greater errors is more noticeable than smaller errors as we square the error, thus the model may now concentrate more on the larger errors.

## Time Plan:

The project took about one and half months to complete as it required data collection, data preprocessing, Model creation, testing and evaluating the metrics. The below given table represents the timeline information.

**Table 1. Timeline to meet objectives responsibilities**

| | **2022** | | |
|---|---|---|---|
| **Semester Fall 2022** | **Oct** | **Nov** | **Dec** |
| **Collect all relevant types of data.** | X | | |
| **Dataset collection** | | X | |

| | | | |
|---|---|---|---|
| **Data Cleaning** | | **X** | |
| **Analyze the data** | | **X** | |
| **Evaluate the metrics and models** | | **X** | |
| **Experiments with the analysis obtained** | | **X** | **X** |
| **Publish the results and share the outcomes** | | | **X** |

## Expected Results:

1. Which model based on a machine learning algorithm has high accuracy in forecasting customer retention?
2. What are the most important attributes for customer retention?
3. Random forest works better for most of the classification algorithms. Is this the same case here?

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