Project Objective:-

- The **aim** of this project is to train a Machine Learning Model which can find the **key factors** that significantly influence the **customer churn or attrition.**

Project Overview:

- **Churn refers** to customers leaving a bank or discontinuing their banking services.
- **Banking Churn Analysis** is a process of studying customer behavior in the banking industry to predict and understand customer attrition or churn.
- **Banking Churn Modeling** aims to identify patterns and factors that contribute to customer churn, enabling banks to take proactive measures to retain customers and improve customer satisfaction.
- **Importing Libraries & Dataset.**
- **Data Wrangling.**
  - Data Cleaning.
  - Handling Missing Values.
  - Handling Inconsistances.
- **Exploratory Data Analysis (EDA)**
  - Visualizing Dependent Variable.
  - Visualizing Independent Variables.
  - Generating Insights.
- **Data Preprocessing.**
  - Variable Selection and Importance.
  - Feature Transformation and Scaling.
  - Splitting Data for Model Training.
- **Model Training and Evaluation.**
  - Selection of Classification Algorithms.
  - Model Training and Tuning.
  - Model Evaluation and Performance.
  - Confusion Matrix Analysis.
  - Accuracy, Precision, Recall, and F1 Score.
  - Receiver Operating Characteristic (ROC) Curve and AUC.
  - Interpretation of Evaluation Results.
  - Interpretation and Insights.
  - Key Findings and Patterns.
  - Feature Importance and Contribution.

Importing Libraries

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy import stats
import warnings
warnings.filterwarnings("ignore")
sns.set(style="darkgrid",font_scale=1.5)


from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, precision_score,
recall_score ,f1_score,jaccard_score,log_loss
from sklearn.metrics import confusion_matrix, roc_curve, roc_auc_score

from imblearn.over_sampling import SMOTE
```

Loading Dataset

```
df = pd.read_csv("C:\\Users\\kumod sharma\\Desktop\\
Churn_Modelling.csv")

df.head()
```

```
   RowNumber  CustomerId   Surname  CreditScore Geography  Gender  Age
\
0          1    15634602  Hargrave          619    France  Female   42

1          2    15647311      Hill          608     Spain  Female   41

2          3    15619304      Onio          502    France  Female   42

3          4    15701354      Boni          699    France  Female   39

4          5    15737888  Mitchell          850     Spain  Female   43


   Tenure    Balance  NumOfProducts  HasCrCard  IsActiveMember  \
0       2       0.00              1          1               1
1       1   83807.86              1          0               1
2       8  159660.80              3          1               0
3       1       0.00              2          0               0
4       2  125510.82              1          1               1

   EstimatedSalary  Exited
```

```
0        101348.88       1
1        112542.58       0
2        113931.57       1
3         93826.63       0
4         79084.10       0
```

Data Wrangling

- **Data wrangling**, also known as **data munging**, refers to the process of **cleaning, transforming, and preparing raw data for analysis.**
- It involves **handling missing values**, **addressing inconsistencies** and **formatting data** before it can be used for **further analysis**.

1. Generating Basic Information.

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   RowNumber        10000 non-null  int64  
 1   CustomerId       10000 non-null  int64  
 2   Surname          10000 non-null  object 
 3   CreditScore      10000 non-null  int64  
 4   Geography        10000 non-null  object 
 5   Gender           10000 non-null  object 
 6   Age              10000 non-null  int64  
 7   Tenure           10000 non-null  int64  
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64  
 10  HasCrCard        10000 non-null  int64  
 11  IsActiveMember   10000 non-null  int64  
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64  
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

- There is total **10000 records** and ***14 columns** availabe in the dataset.
- **Out of 14 columns** there are **11 numerical columns** and **3 categorical columns.**

---

2. Computing Total No. of Missing Values.

```
df.isnull().sum().to_frame().rename(columns={0:"Total No. of Missing Values"})
```

```
                 Total No. of Missing Values
RowNumber                                  0
CustomerId                                 0
```

```
Surname                  0
CreditScore              0
Geography                0
Gender                   0
Age                      0
Tenure                   0
Balance                  0
NumOfProducts            0
HasCrCard                0
IsActiveMember           0
EstimatedSalary          0
Exited                   0
```

- **None** of the columns is having **missing values.**
- So we **don't** have to use technique of **Data Imputation.**

---

3. Computing Cardinality of Categorical Columns.

```
cat_cols = df.select_dtypes(include="object").columns
df[cat_cols].nunique().to_frame().rename(columns={0:"Total No. of
Unique Values"})
```

```
           Total No. of Unique Values
Surname                          2932
Geography                           3
Gender                              2
```

- **Surname column** is having **very high cardinality.**
- We can also **relate that surname** is **not relevant** for predicting **customer churned or not.** So we can **simply drop this feature.**

4. Dropping "Surname" Column.

```
df.drop(columns=["Surname"],inplace=True)
```

---

5. Showing Random Sample of Data.

```
df.sample(5)
```

```
      RowNumber  CustomerId  CreditScore Geography  Gender  Age
Tenure  \
2220       2221    15806049          714   Germany  Female   49
5
9279       9280    15573854          727    France    Male   62
5
3281       3282    15707634          775    France  Female   32
2
9213       9214    15672216          584    France  Female   40
4
2598       2599    15765812          587     Spain    Male   48
```

```
1

         Balance  NumOfProducts  HasCrCard  IsActiveMember  
EstimatedSalary  \
2220  140510.89              1          1               0  
141914.94   
9279       0.00              2          0               1   
38652.96   
3281  108698.96              2          1               1  
161069.73   
9213   82441.75              1          0               0   
80852.11   
2598       0.00              2          1               1    
8908.00   

      Exited  
2220       0  
9279       0  
3281       0  
9213       0  
2598       0  
```

- We can observe that **RowNumber** and **CustomerId** columns **represents a unique value** for each customer.
- So these features **doesn't seems relevant for predicting customer churned or not.** So we can simply **drop these features.**

6. Dropping "RowNumber" & "CustomerId" Column.

```
df.drop(columns=["RowNumber","CustomerId"],inplace=True)
```

---

7. Renaming Target Column name and its values with more appropirate name for better Analysis.

```
df.rename(columns={"Exited":"Churned"},inplace=True)

df["Churned"].replace({0:"No",1:"Yes"},inplace=True)

df.head()
```

```
   CreditScore Geography  Gender  Age  Tenure    Balance  
NumOfProducts  \
0          619    France  Female   42       2       0.00              
1   
1          608     Spain  Female   41       1   83807.86              
1   
2          502    France  Female   42       8  159660.80              
3   
3          699    France  Female   39       1       0.00              
2   
```

```
4          850     Spain   Female    43        2  125510.82
1

   HasCrCard  IsActiveMember  EstimatedSalary Churned
0          1               1        101348.88     Yes
1          0               1        112542.58      No
2          1               0        113931.57     Yes
3          0               0         93826.63      No
4          1               1         79084.10      No
```

- We have **converted raw data** into **well-structured data** to better analysis.
- So we can perform **Expolatory Data Analysis** and **derive insights from the data.**

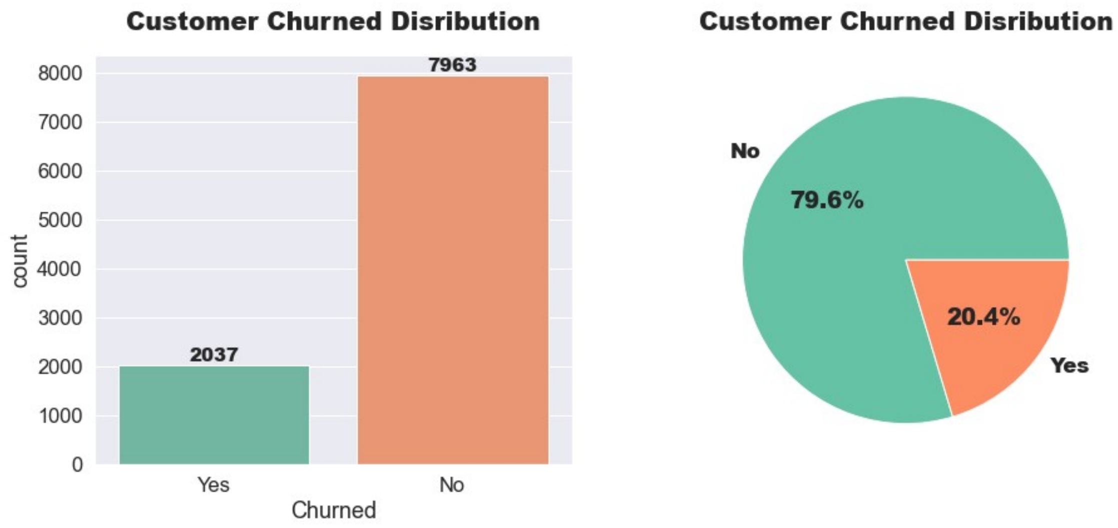
Explorator Data Analysis

1. Visualizing Target Variable.

```
count = df["Churned"].value_counts()

plt.figure(figsize=(15,6))
plt.subplot(1,2,1)
ax=sns.countplot(df["Churned"],palette="Set2")
ax.bar_label(ax.containers[0],fontweight="black",size=15)
plt.title("Customer Churned 
Disribution",fontweight="black",size=20,pad=20)

plt.subplot(1,2,2)
plt.pie(count.values, labels=count.index, autopct="%1.1f%
%",colors=sns.set_palette("Set2"),
        textprops={"fontweight":"black"})
plt.title("Customer Churned 
Disribution",fontweight="black",size=20,pad=20)
plt.show()
```



- There is **huge class-imbalance** which can lead to **bias in model performance.**
- So to **overcome** this **class-imbalance** we have to use technique named **SMOTE.**

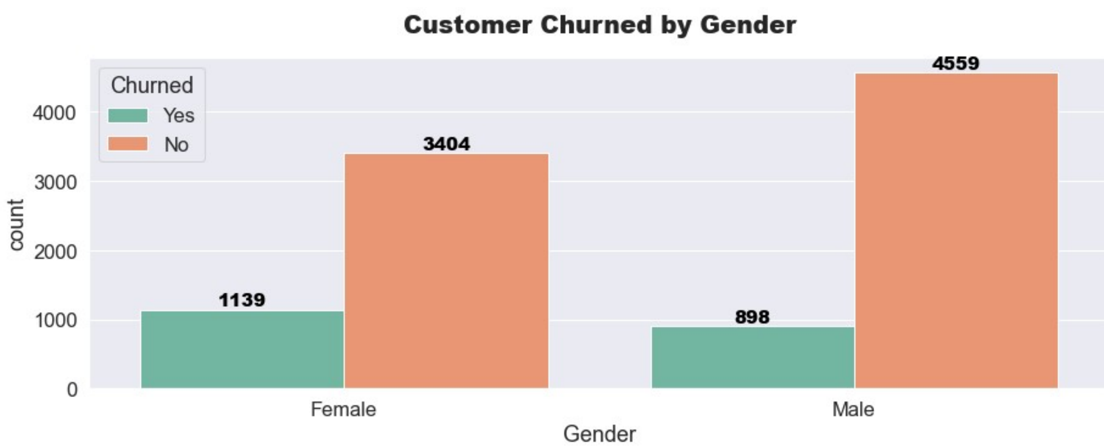
---

2. Visualizing Customer Churned by Gender.

```
def countplot(column):
    plt.figure(figsize=(15,5))
    ax = sns.countplot(x=column, data=df,
hue="Churned",palette="Set2")
    for container in ax.containers:

ax.bar_label(container,size=15,fontweight="black",color="black")
    plt.title(f"Customer Churned by
{column}",fontweight="black",size=20,pad=20)
    plt.show()

countplot("Gender")
```



- The **ratio** of male and female customers is **47: 57**, which suggests that there are **more male customers** than **female customers.**
- **Feamle Customers** have **more churned**, which means **feamle customers** have **more deactivated their bank accounst.**

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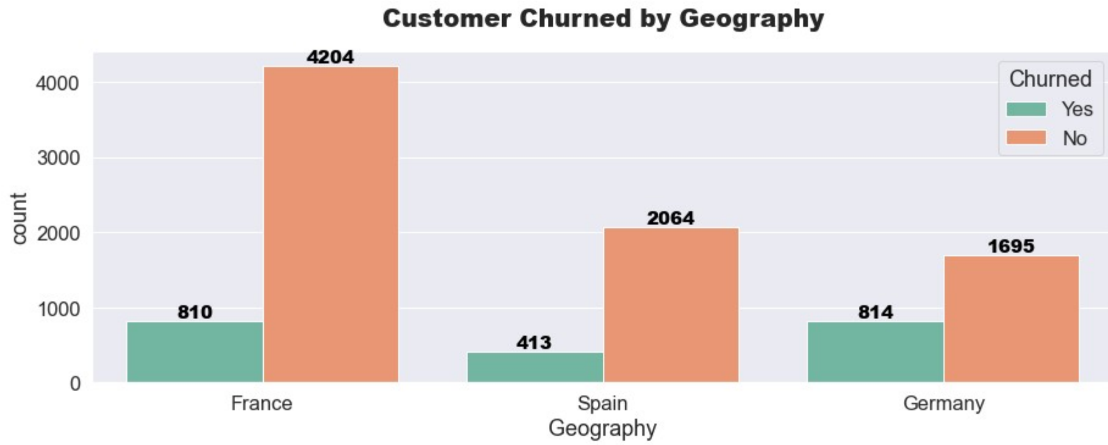
3. Visualizing Customer Churned by Geoprahical Region.

```
countplot("Geography")
```

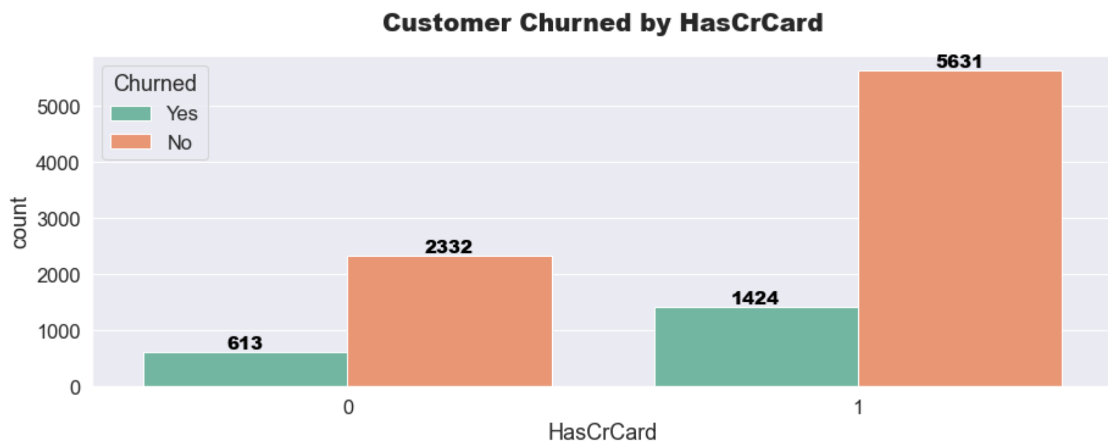


- **Most** of the customers are from **France** and the **churn rate** in **France is low.**
- There are **almost equal customers** from **Spain & Germany** regions.
- But the **Churn rate** is **almost double** in **Germany** when **compared with spain.**

---

4. Visualizing Customer Churn by "HasCrCard".

```
countplot("HasCrCard")
```

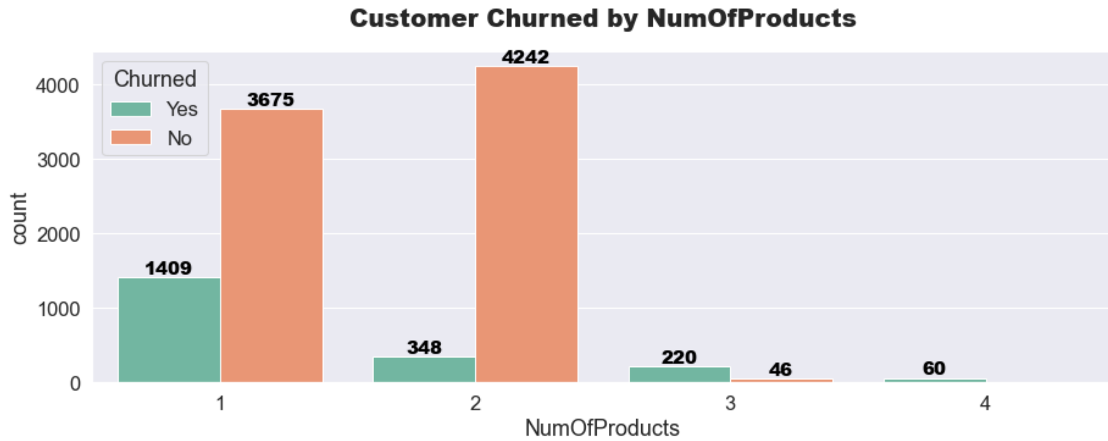


- We have **more than double customers** having **credit card** when compared to customers **not having credit cards.**
- **Churn Rate %** of customers **having credit card is 20.1%** whereas customers **not having credit card is 20.8%**
- So we can say **credit card is not affecting the churn of customers.**

---

5. Visualizing Customer Churned by "NumOfProducts".

```
countplot("NumOfProducts")
```

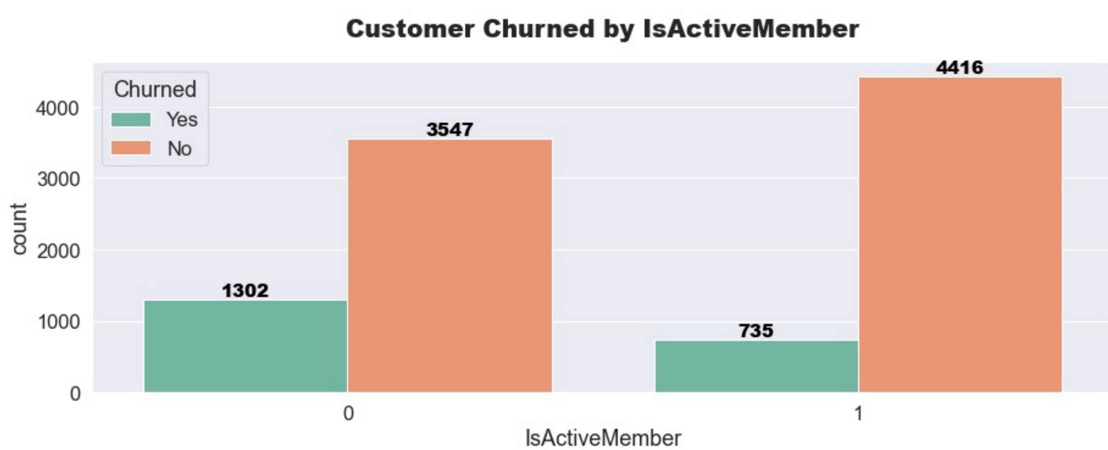


- **Most** of the customers are **having only 1 product** and very few customers are **having more than 2 products.**
- But there is **very high churn rate** in customers **having more than 2 Products.**
- The **lowest chur rate** is in customers with **2 products.**
- **Note:**
    a. We can do **feature engineering** by **grouping the customers having products more than 2 together** to **reduce the class imbalance.**
    b. **Class Imbalance** leads to **bias in model** and **misrepresentation of minority class.**

---

6. Visualizing Customer Churned by "IsActiveMember".

```
countplot("IsActiveMember")
```



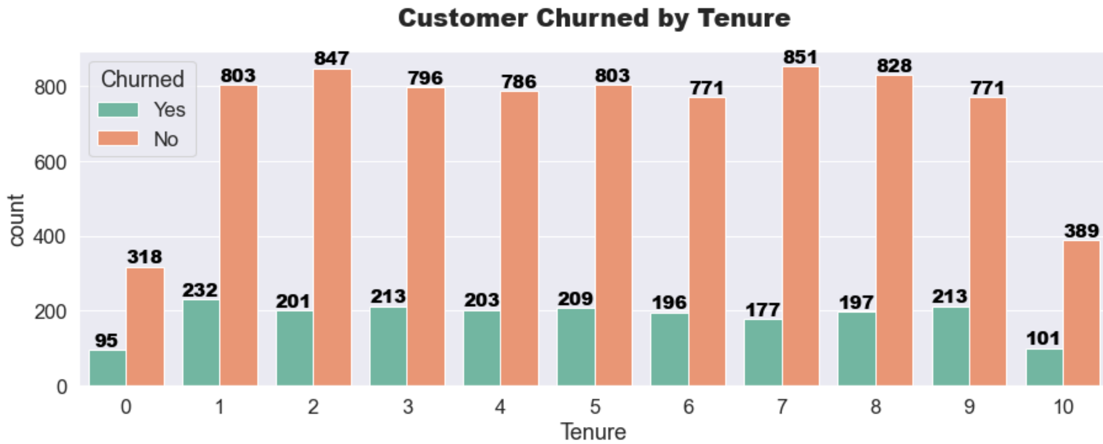
- There is **approxiamately equal customer** who are **either active or not active.**
- But the **churn rate %** in **not active customers is 26.8** whereas in **active customers is 14.2%**

- So we can say **customers which are not active are morely likely to deactivate their accounts.**

---

7. Visualizing Customer Churned by "Tenure".

```
countplot("Tenure")
```



- The **highest tenure is 10 years** which means that those customers have **opened their account 10 years back.**
- Since there is **similar distribution of churned status** we can't make any inference.

---

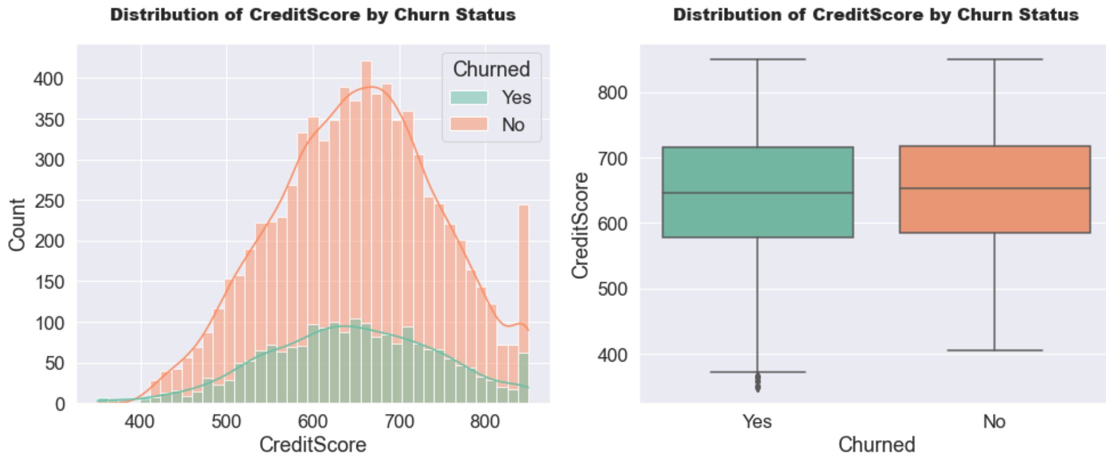
8. Visualizing Customer Churned by "CreditScore".

```
def continous_plot(column):
    plt.figure(figsize=(14,6))
    plt.subplot(1,2,1)

sns.histplot(x=column,hue="Churned",data=df,kde=True,palette="Set2")
    plt.title(f"Distribution of {column} by Churn
Status",fontweight="black",pad=20,size=15)

    plt.subplot(1,2,2)
    sns.boxplot(df["Churned"],df[column],palette="Set2")
    plt.title(f"Distribution of {column} by Churn
Status",fontweight="black",pad=20,size=15)
    plt.tight_layout()
    plt.show()

continous_plot("CreditScore")
```



- The **Median CreditScore** of **both churned** and **not churned** customers are **approxiamately equal.**
- Since the values are approximately equal we **can't generate any inference** for the the churn categoriers.

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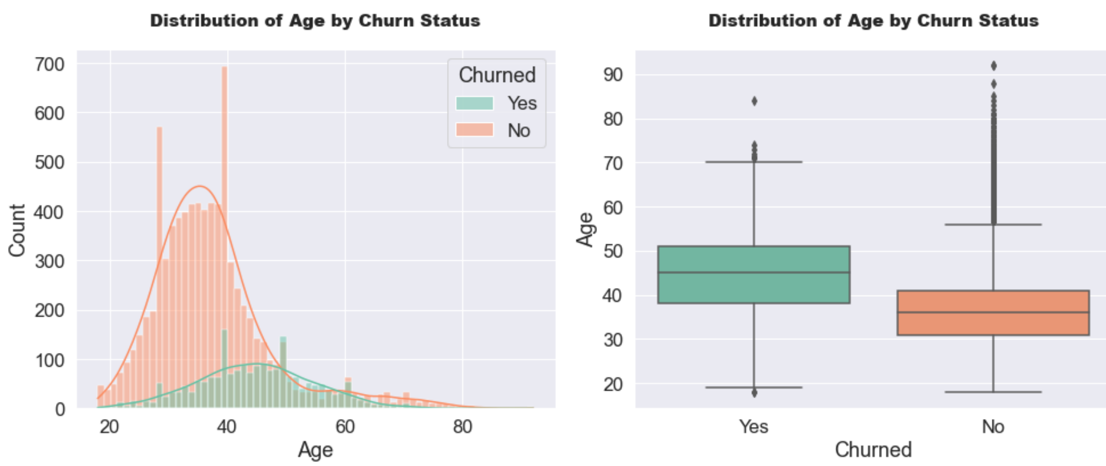
9. Visualizing Customer Churned by "Age".

```
continous_plot("Age")
```

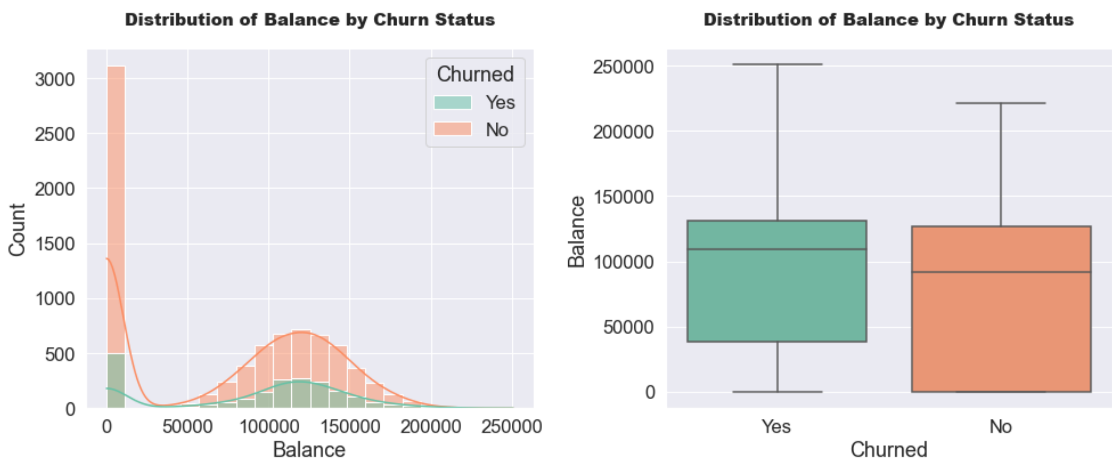


- The **distribution is right skewed** because of **presence of outliers** which can lead to **overfitting in model.**
- To **overcome this right-skewed distribution** we have to **remove those outliers.**

---

10. Visualizing Customer Churned by "Balance."

```
continous_plot("Balance")
```

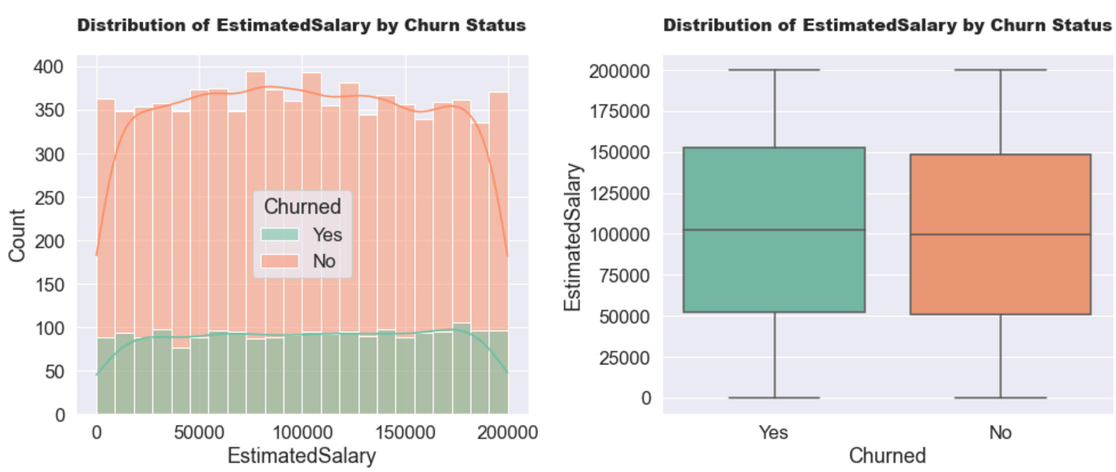


- **More than 3000 customers** are having their **account balance equal to zero.**
- Customers with **zero balance** are more likely to **deactivate their account.**
- **Excluding the zero value** we can observe a **normal distribution.** So don't have to use any other techniques.

---

11. Visualizing Customer Churned by "Estimated Salary".

```
continous_plot("EstimatedSalary")
```



- The **median value of EstimatedSalary** is **approxiamately same** for both the **churned categories.**
- Since the distribution is **kind of similar** for **both churn category** we can make any inference.

Data Preprocessing

1. Detecting Duplicate Records.

```
print("Total duplicate records present in the dataset
is:",df.duplicated().sum())
```

```
Total duplicate records present in the dataset is: 0
```

2. Gathering Descriptive Statistical information of Continous Numerical Features.

```
num_cols = ["CreditScore","Age","Balance","EstimatedSalary"]

df[num_cols].describe().T
```

```
                   count           mean           std     min
25%  \
CreditScore      10000.0     650.528800     96.653299  350.00
584.00
Age              10000.0      38.921800     10.487806   18.00
32.00
Balance          10000.0   76485.889288  62397.405202    0.00
0.00
EstimatedSalary  10000.0  100090.239881  57510.492818   11.58
51002.11

                        50%          75%        max
CreditScore        652.000     718.0000     850.00
Age                 37.000      44.0000      92.00
Balance          97198.540  127644.2400  250898.09
EstimatedSalary  100193.915  149388.2475  199992.48
```

---

3. Computing Unique Values of Categorical Columns.

```
cat_cols = ["Geography","Gender"]

for column in cat_cols:
    print(f"Unique Values in {column} column is:",df[column].unique())
```

```
Unique Values in Geography column is: ['France' 'Spain' 'Germany']
Unique Values in Gender column is: ['Female' 'Male']
```

4. Label Encoding of Categroical Columns.

```
encoder = LabelEncoder()

df[cat_cols] = df[cat_cols].apply(encoder.fit_transform)

df["Churned"].replace({"No":0,"Yes":1},inplace=True)
```

---

5. Removing Outliers Using Z-score in "Age" Column.

```
z_score = np.abs(stats.zscore(df["Age"]))

df = df[(z_score < 3)]

df.shape
```

```
(9867, 11)
```

- Earlier we were having **10000 records** after removing outliers we have **9867 records.**
- Total **23 records** were **conatining outliers** in the **age column.**

---

6. Segregating Features & Labels for Model Training.

```
X = df.drop(columns=["Churned"])
y = df["Churned"]
```

---

7. Splitting Data For Model Training & Testing.

```
x_train,x_test,y_train,y_test = 
train_test_split(X,y,test_size=0.2,random_state=0)
```

```
print("Shape of x_train is:",x_train.shape)
print("Shape of x_test is: ",x_test.shape)
print("Shape of y_train is:",y_train.shape)
print("Shape of y_test is: ",y_test.shape)
```

```
Shape of x_train is: (7893, 10)
Shape of x_test is:  (1974, 10)
Shape of y_train is: (7893,)
Shape of y_test is:  (1974,)
```

- Data is **equally splitted** for **Model Training & Testing.**
- So we can build a **Predictive Model** to find the **key factors** that are significantly influencing **customers churn.**

Model Creation using Decision Tree

1. Performing Grid-Search with cross-validation to find the best Parameters for the Model.

```
dtree = DecisionTreeClassifier(class_weight="balanced")
```

```
param_grid = {"max_depth":[3,4,5,6,7,8],
              "min_samples_split":[2,3,4],
              "min_samples_leaf":[1,2,3,4],
              "random_state":[0,42]}
```

```
grid_search = GridSearchCV(dtree, param_grid, cv=5, n_jobs=-1)
```

```
grid_search.fit(x_train,y_train)
```

```
GridSearchCV(cv=5, 
estimator=DecisionTreeClassifier(class_weight='balanced'),
             n_jobs=-1,
             param_grid={'max_depth': [3, 4, 5, 6, 7, 8],
                         'min_samples_leaf': [1, 2, 3, 4],
```

```
                         'min_samples_split': [2, 3, 4],
                         'random_state': [0, 42]})

print("Best Parameters are:\n")
print(grid_search.best_params_)
```

```
Best Parameters are:

{'max_depth': 5, 'min_samples_leaf': 2, 'min_samples_split': 2,
'random_state': 0}
```

---

2. Creating Model Using Best Parameters.

```
dtree = DecisionTreeClassifier(max_depth=5, min_samples_leaf=2,
min_samples_split=2, random_state=0)

dtree.fit(x_train,y_train)
```

```
DecisionTreeClassifier(max_depth=5, min_samples_leaf=2,
random_state=0)
```

3. Computing Model Accuracy.

```
y_train_pred = dtree.predict(x_train)
y_test_pred = dtree.predict(x_test)

print("Accuracy Score of Model on Training Data is
=>",round(accuracy_score(y_train,y_train_pred)*100,2),"%")
print("Accuracy Score of Model on Testing Data  is
=>",round(accuracy_score(y_test,y_test_pred)*100,2),"%")
```

```
Accuracy Score of Model on Training Data is => 86.0 %
Accuracy Score of Model on Testing Data  is => 83.64 %
```

---

4. Model Evaluation using Different Metrics.

```
print("F1 Score of the Model is
=>",f1_score(y_test,y_test_pred,average="micro"))
print("Recall Score of the Model is
=>",recall_score(y_test,y_test_pred,average="micro"))
print("Precision Score of the Model is
=>",precision_score(y_test,y_test_pred,average="micro"))
print("Jaccard Score of the Model is
=>",jaccard_score(y_test,y_test_pred,average="micro"))
print("Log Loss of the Model is =>",log_loss(y_test,y_test_pred))
```

```
F1 Score of the Model is => 0.8363728470111449
Recall Score of the Model is => 0.8363728470111449
Precision Score of the Model is => 0.8363728470111449
```

```
Jaccard Score of the Model is => 0.7187636047017849
Log Loss of the Model is => 5.651500282187406
```

- The **high values** for **F1 score, recall score, and precision score**, all of which are **approximately 0.84.**
- These **metrics suggest** that the **model achieves good accuracy** in predicting the **positive class.**
- The **Jaccard score**, with a value of **approx 0.72**, indicates a moderate level of **similarity between the predicted and actual sets of instances.**
- A **lower log loss** indicates **better alignment** between the **predicted probabilities and the actual class labels.**

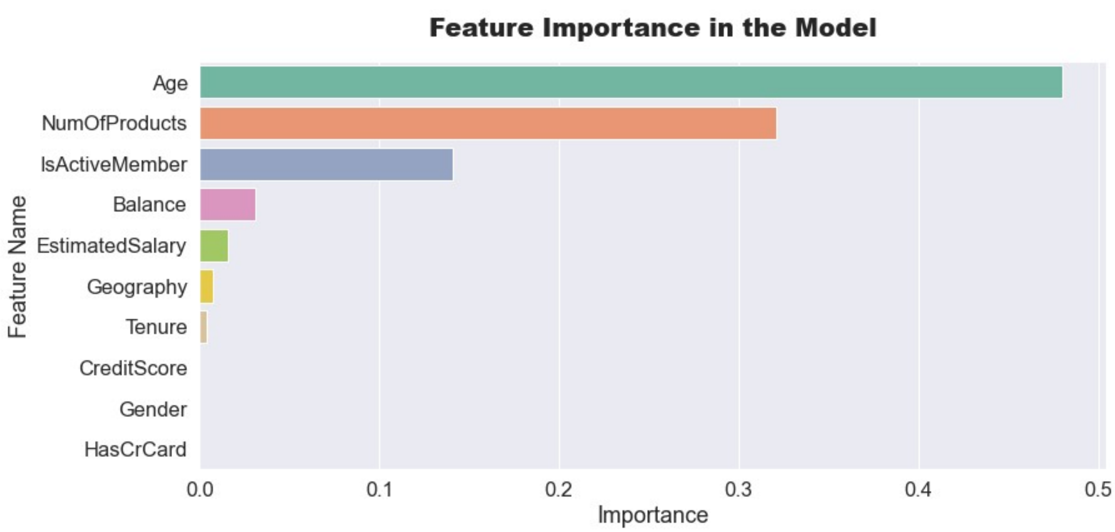
---

5. Finding Importance of Features in DecisionTreeClassifier.

```
imp_df = pd.DataFrame({"Feature Name":x_train.columns,
                       "Importance":dtree.feature_importances_})

features = imp_df.sort_values(by="Importance",ascending=False)

plt.figure(figsize=(13,6))
sns.barplot(x="Importance", y="Feature Name", data=features,
palette="Set2")
plt.title("Feature Importance in the Model", fontweight="black",
size=20, pad=20)
plt.show()
```

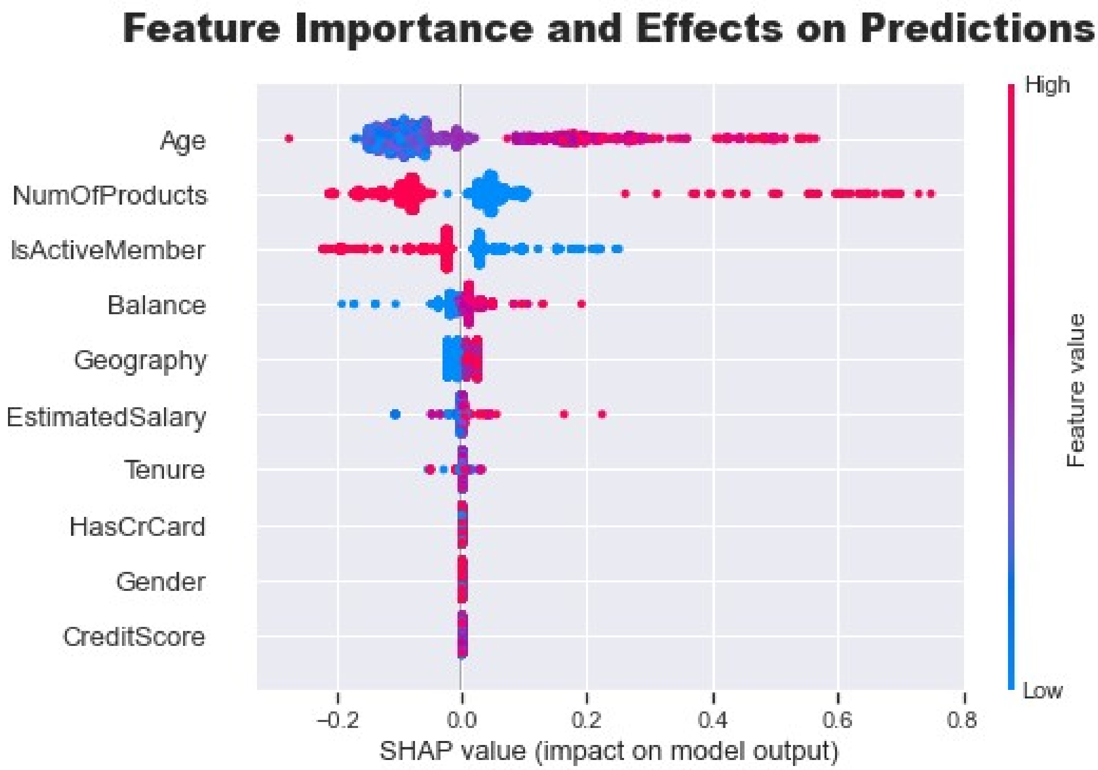


- The **key factors** that significantly influence the **deactivation of customers' bank accounts** are **Age, NumOfProducts, and IsActiveMember.**
- **Gender, HasCard, and CreditScore** have shown to have **minimal impact** on the **deactivation of customers' bank accounts.**

---

6. SHAP Summary Plot: Explaining Model Predictions with Feature Importance.

```
explainer = shap.TreeExplainer(dtree)
shap_values = explainer.shap_values(x_test)
plt.title("Feature Importance and Effects on Predictions",fontweight="black",pad=20,size=18)
shap.summary_plot(shap_values[1], x_test.values, feature_names = x_test.columns)
```



- In **Age** we can observe that **customer with higher age** are **more likely to deactive banking facilites.**
- In **NumOfProducts** we can observe that **customers with either very low products or very high products** are **more likely to deactive banking facilites.**
- In **IsActiveMember** we can clearly observe **customer which are not active** are **more likely to deactive banking facilites.**
- In **Balance** we can observe that **customers with more balance** are **more likely to deactive banking facilites.**

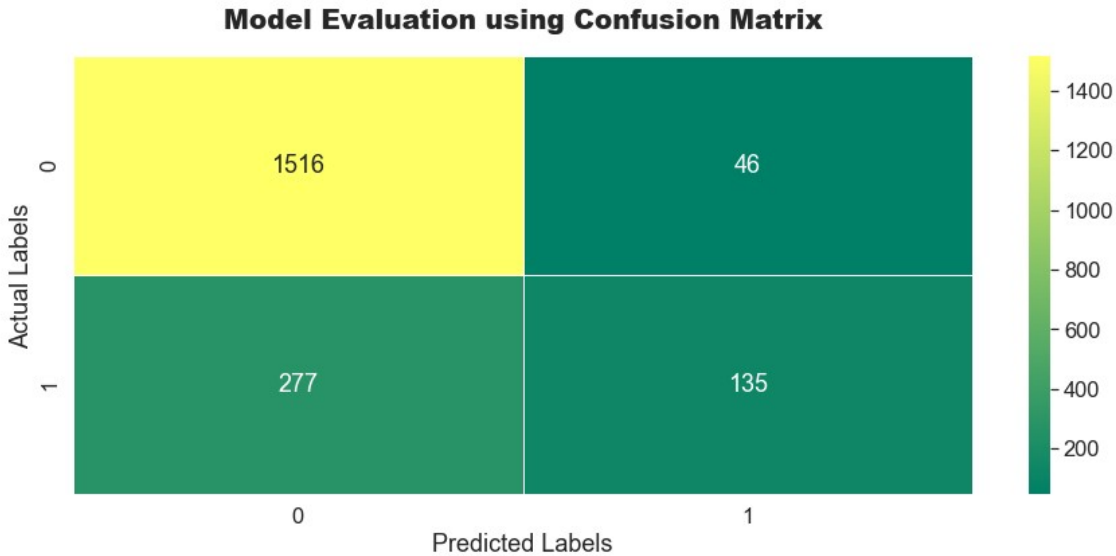
---

7. Model Evaluation using Confusion Matrix.

```
cm = confusion_matrix(y_test,y_test_pred)

plt.figure(figsize=(15,6))
sns.heatmap(data=cm, linewidth=.5, annot=True, fmt="g", cmap="summer")
plt.title("Model Evaluation using Confusion Matrix",fontsize=20,pad=20,fontweight="black")
```

```
plt.ylabel("Actual Labels")
plt.xlabel("Predicted Labels")
plt.show()
```



- **Strong True Positive Rate:** The model achieved a high number of true positive predictions, indicating its ability to correctly identify positive cases. This suggests that the model is effective in accurately classifying the desired outcome.
- **Need of Improvement in False Negative Rate:** The presence of a relatively high number of false negatives suggests that the model may have missed identifying some actual positive cases. This indicates a need for further refinement to enhance the model's ability to capture all positive cases.

---

8. Model Evaluation: ROC Curve and Area Under the Curve (AUC)

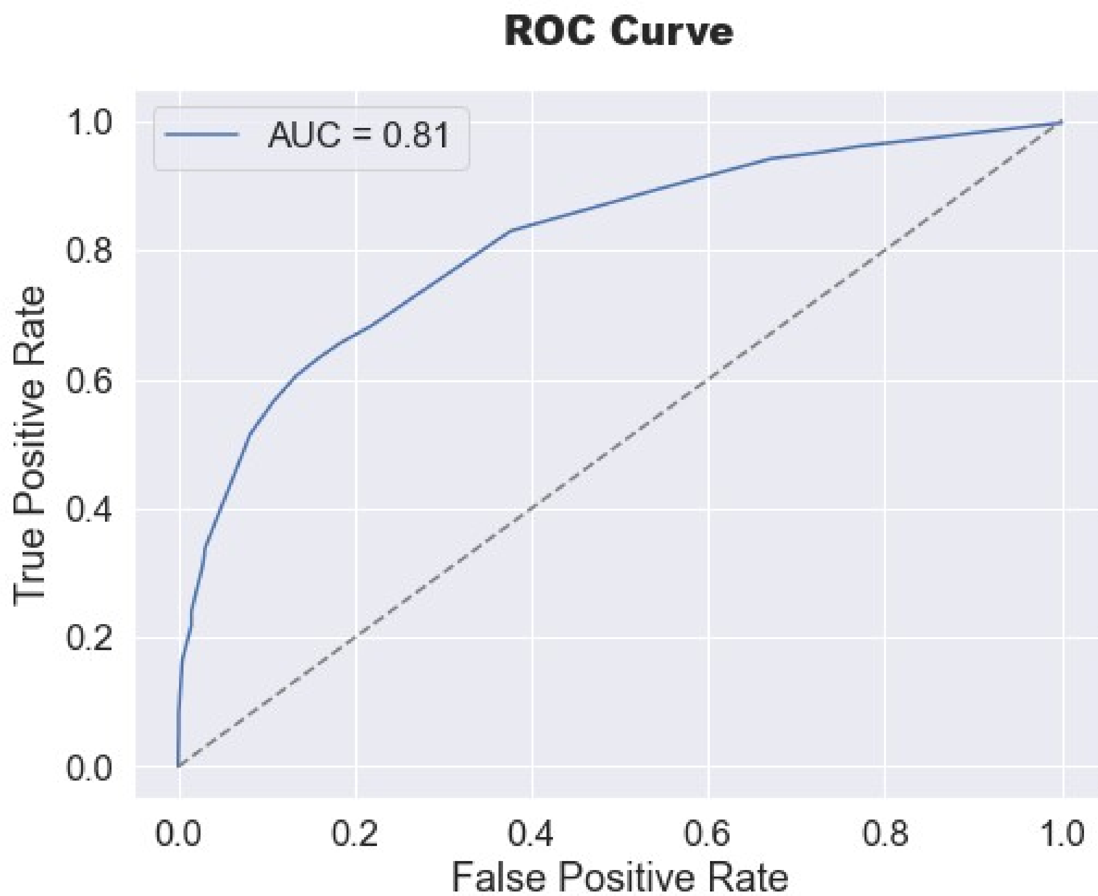
```
y_pred_proba = dtree.predict_proba(x_test)[:][:,1]

df_actual_predicted = pd.concat([pd.DataFrame(np.array(y_test),
columns=["y_actual"])])
df_actual_predicted.index = y_test.index


fpr, tpr, thresholds = roc_curve(df_actual_predicted["y_actual"],
y_pred_proba)
auc = roc_auc_score(df_actual_predicted["y_actual"], y_pred_proba)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f"AUC = {auc:.2f}")
plt.plot([0, 1], [0, 1], linestyle="--", color="gray")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
```

```
plt.title("ROC Curve",pad=20,fontweight="black")
plt.legend()
plt.show()
```



- **Strong Discriminative Power:** The model exhibits a strong discriminative power with an AUC value of 0.81. This suggests that the model has a high ability to distinguish between positive and negative instances, indicating its effectiveness in making accurate predictions.

- **High Training and Testing Accuracies:** The model achieved a high accuracy score of 86.0% on the training data, indicating a good fit to the training instances. Additionally, the model's accuracy score of 83.64% on the testing data suggests its ability to generalize well to unseen instances.
- **High F1 Score, Recall, and Precision:** The model achieved high F1 score, recall, and precision values, all approximately 0.836. This indicates that the model has a strong ability to correctly identify positive cases while minimizing false positives and maximizing true positives.

- **Moderate Jaccard Score:** The Jaccard score, with a value of approximately 0.719, suggests that the model effectively captures the intersection between the predicted and true positive sets, indicating a reasonable level of similarity between them.
- **Acceptable Log Loss:** The model's log loss, with a value of approximately 5.652, indicates that the predicted probabilities align reasonably well with the actual probabilities.
- **Overall Model Performance:** The model demonstrates strong performance across multiple evaluation metrics, indicating its effectiveness in making accurate predictions and capturing the desired outcomes.