1.0 BUSINESS UNDERSTANDING

1.1 Overview

Financial inclusion,access to financial services as well as financial literacy is crucial for economic development as well as poverty eradication. Affordable and accessible financial products and services-such as savings,transactions,credit insurance-is thus an essential tool that helps individuals pull themselves from poverty, manage risk, invest in businesses and build wealth ensuring financial security and freedom.

According to **The World Bank**, financial inclusion is a catalyst to solving **seven(7)** of the **seventeen(17)** Sustainable Development Goals(SDGs). This project is thus looking to solve the problem of access to banking services in East Africa (Kenya,Rwanda, Tanzania, Uganda)

1.2 Objective

The objective of this project is to predict whether an **individual has a bank account to their name** using various demographic and socio-economic features in the data set.

This classification problem, will aim to assist various financial institutions, policy makers or even international entities i.e IMF in identifying unbanked poppulations to promote financial inclusion

1.3 Key Business Questions

1.Who does not have a bank account?

2.What are the factors that influence ownership of a bank account?

3.How best can the model support financial inclusion?

1.4 Success Criteria

1.**Accuracy of the model**- How good is the model in predicting who may or may not have a bank account

2.**Actionable insights**- Providing quality and actionable insights on factors affecting bank account ownership

3.**Business Impact**-Assistance in targeting appropriate audiences for financial inclusion programs.

2.0 DATA UNDERSTANDING

2.1 Overview

The dataset contains 23,524 records from four East African countries: Kenya, Uganda, Tanzania, and Rwanda, and aims to predict whether an individual has a bank account (bank_account-Yes = 1, No = 0).

2.2 Key Features and Data Types

The data set we will be using has a total of 13 features, 12 independent and 1(Bank account) target.Below is a summary of each feature description as well as the data type:

1.**country**: The country in which the respondent resides (Kenya, Uganda, Tanzania, Rwanda) (Categorical)

2.**year**: Year of data collection (numerical)

3.**uniqueid**: A unique identifier for each respondent (categorical)

4.**bank_account**: The target variable (Yes/No) (Binary)

5.**location_type**: Whether the respondent resides in an urban or rural area (Binary)

6.**cellphone_access**: Whether the respondent has access to a cellphone (Binary)

7.**household_size**: Number of people in the household (Numerical)

8.**age_of_respondent**: Age of the respondent (Numerical)

9.**gender_of_respondent**: Gender of the respondent (Binary)

10.**relationship_with_head**: The relationship of the respondent to the head of the household (Categorical)

11.**marital_status**: Marital status of the respondent (Categorical)

12.**education_level**: Education level of the respondent (Categorical)

13.**job_type**: Type of job held by the respondent (Categorical)

2.3 Data Distribution

The target variable (bank_account) could potentially be imbalanced, especially since access to banking services may be limited in rural and less developed regions. A detailed breakdown of the bank_account variable will be necessary to check for imbalance, which can impact model performance.

If imbalanced, techniques like SMOTE (Synthetic Minority Over-sampling Technique) or class weights in the model may be required.

3.0 DATA CLEANING

This is an essential part of the Data Science procedure as the quality of the model is

In [1010]:

```
#importing the necessary libraries

import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
```

In [1011]:

```
#Loading the data set
df=pd.read_csv(r"C:\Users\User\OneDrive\Desktop\Phase 3 Project\Train.c


#make a copy
df_copy=df.copy()
#Viewing the first five rows
df_copy.head()
```

Out[1011]:

	country	year	uniqueid	bank_account	location_type	cellphone_access	householc
0	Kenya	2018	uniqueid_1	Yes	Rural	Yes	
1	Kenya	2018	uniqueid_2	No	Rural	No	
2	Kenya	2018	uniqueid_3	Yes	Urban	Yes	
3	Kenya	2018	uniqueid_4	No	Rural	Yes	
4	Kenya	2018	uniqueid_5	No	Urban	No	

In [1012]:

```
#Looking at the data summary
df_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23524 entries, 0 to 23523
Data columns (total 13 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   country                 23524 non-null  object
 1   year                    23524 non-null  int64 
 2   uniqueid                23524 non-null  object
 3   bank_account            23524 non-null  object
 4   location_type           23524 non-null  object
 5   cellphone_access        23524 non-null  object
 6   household_size          23524 non-null  int64 
 7   age_of_respondent       23524 non-null  int64 
 8   gender_of_respondent    23524 non-null  object
 9   relationship_with_head  23524 non-null  object
 10  marital_status          23524 non-null  object
 11  education_level         23524 non-null  object
 12  job_type                23524 non-null  object
dtypes: int64(3), object(10)
memory usage: 2.3+ MB
```

In [1013]:

```
#Checking for null values
df_copy.isnull().sum()
```

Out[1013]:

```
country                   0
year                      0
uniqueid                  0
bank_account              0
location_type             0
cellphone_access          0
household_size            0
age_of_respondent         0
gender_of_respondent      0
relationship_with_head    0
marital_status            0
education_level           0
job_type                  0
dtype: int64
```

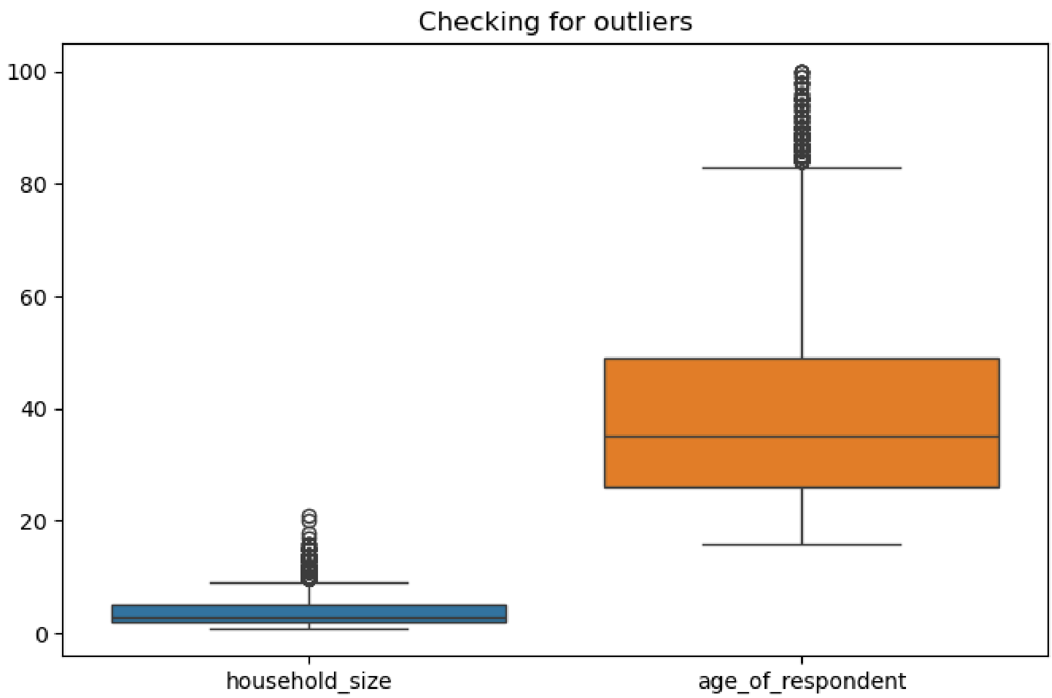
In [1014]:

```
#Checking for any duplicates
df_copy.duplicated().sum()
```

Out[1014]:

```
0
```

In [1015]:
```
#checking for outliers

plt.figure(figsize=(8,5))
sns.boxplot(df_copy[["household_size","age_of_respondent"]])
plt.title("Checking for outliers")
plt.show()
```



In [1016]:
```
#Eliminate outliers using IQR method

#Calculate Q1 & Q3

Q1=df_copy["age_of_respondent"].quantile(0.25)
Q3=df_copy["age_of_respondent"].quantile(0.75)

#Calculate the IQR

IQR=Q3-Q1

#Calculate the lower and upper bounds

lower_bound=Q1-IQR*1.5
upper_bound=Q3+IQR*1.5

#Eliminate outliers
df2=df_copy[(df_copy["age_of_respondent"]>=lower_bound) & (df_copy["age

#Check new shape
df2.shape
```

Out[1016]: (23283, 13)

3.1 FEATURE ENGINEERING

This is an essential part of in improving performance and predictive power of machine learning models.It mainly involves two options i.e Creating new features or modifying existing ones. This will help the model better understand underlying patterns in the data

3.1.1 Creating age_groups and house_hold_groups

In [1017]:

```
#Defining the groups desired
age_bins=[16,25,45,65,100]
age_labels=["Young Adult","Adult","Middle Age","Old"]

#Creating a new column age_group
df2["age_group"]=pd.cut(df2["age_of_respondent"],bins=age_bins,labels=a

df2.head(5)
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_13208\2447590050.py:6: Set
tingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
(https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  df2["age_group"]=pd.cut(df2["age_of_respondent"],bins=age_bins,labe
ls=age_labels,right=True)
```

Out[1017]:

	country	year	uniqueid	bank_account	location_type	cellphone_access	househol
0	Kenya	2018	uniqueid_1	Yes	Rural	Yes	
1	Kenya	2018	uniqueid_2	No	Rural	No	
2	Kenya	2018	uniqueid_3	Yes	Urban	Yes	
3	Kenya	2018	uniqueid_4	No	Rural	Yes	
4	Kenya	2018	uniqueid_5	No	Urban	No	

In [1018]:

```
#Defining the groups desired
household_bins=[0,5,10,15,100]
household_labels=["Small","Average","Large","Very Large"]

#Creating a new column household_group
df2["household_group"]=pd.cut(df2["household_size"],bins=household_bins
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_13208\1382886062.py:6: Set
tingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
(https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  df2["household_group"]=pd.cut(df2["household_size"],bins=household_
bins,labels=household_labels,right=True)
```

3.1.2 Creating Interaction Features

This is a process involving combining two or more features in the data set to capture their effect on the target variable

In [1019]:

```
#Categorical interactions
df2["job_edu_inter"]=df2["job_type"]+"_"+df2["education_level"]
df2["job_cell_inter"]=df2["job_type"]+"_"+df2["cellphone_access"]
df2["edu_cell_inter"]=df2["education_level"]+"_"+df2["cellphone_access'
df2["house_location_inter"]=df2["household_size"].astype(str)+"_"+df2['
df2["job_household_inter"]=df2["job_type"]+"_"+df2["household_size"].as
df2["edu_house_inter"]=df2["education_level"]+"_"+df2["household_size"]

#Numeric interactions
df2["age_household_inter"]=df2["age_of_respondent"]*df2["household_size
df2["age_cell_inter"]=df2["age_of_respondent"]*(df["cellphone_access"]=


pd.set_option("display.max_columns",1000)
df2.head()
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_13208\3383512039.py:2: Set
tingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
(https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  df2["job_edu_inter"]=df2["job_type"]+"_"+df2["education_level"]
C:\Users\User\AppData\Local\Temp\ipykernel_13208\3383512039.py:3: Set
tingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
(https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  df2["job_cell_inter"]=df2["job_type"]+"_"+df2["cellphone_access"]
C:\Users\User\AppData\Local\Temp\ipykernel_13208\3383512039.py:4: Set
tingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
(https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  df2["edu_cell_inter"]=df2["education_level"]+"_"+df2["cellphone_acc
ess"]
C:\Users\User\AppData\Local\Temp\ipykernel_13208\3383512039.py:5: Set
tingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
(https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  df2["house_location_inter"]=df2["household_size"].astype(str)+"_"+d
f2["location_type"]
C:\Users\User\AppData\Local\Temp\ipykernel_13208\3383512039.py:6: Set
tingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
(https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  df2["job_household_inter"]=df2["job_type"]+"_"+df2["household_siz
e"].astype(str)
C:\Users\User\AppData\Local\Temp\ipykernel_13208\3383512039.py:7: Set
tingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
(https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
```

```
l#returning-a-view-versus-a-copy)
  df2["edu_house_inter"]=df2["education_level"]+"_"+df2["household_si
ze"].astype(str)
C:\Users\User\AppData\Local\Temp\ipykernel_13208\3383512039.py:10: Se
ttingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
(https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  df2["age_household_inter"]=df2["age_of_respondent"]*df2["household_
size"]
C:\Users\User\AppData\Local\Temp\ipykernel_13208\3383512039.py:11: Se
ttingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/panda
s-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
(https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  df2["age_cell_inter"]=df2["age_of_respondent"]*(df["cellphone_acces
s"]=="yes").astype(int)
```

Out[1019]:

	country	year	uniqueid	bank_account	location_type	cellphone_access	householc
0	Kenya	2018	uniqueid_1	Yes	Rural	Yes	
1	Kenya	2018	uniqueid_2	No	Rural	No	
2	Kenya	2018	uniqueid_3	Yes	Urban	Yes	
3	Kenya	2018	uniqueid_4	No	Rural	Yes	
4	Kenya	2018	uniqueid_5	No	Urban	No	

In [1020]:

```
df2.isnull().sum()
df2.shape
```

Out[1020]: (23283, 23)

In [1021]:

```
#Dropping null values
df2=df2.dropna()

df2.isnull().sum()

df2.shape
```

Out[1021]: (22821, 23)

4.EXPLORATORY DATA ANALYSIS(EDA)

Exploratory Data analysis is fundamental to the Data Science process as it visualizes the data, uncover patterns thus providing insights

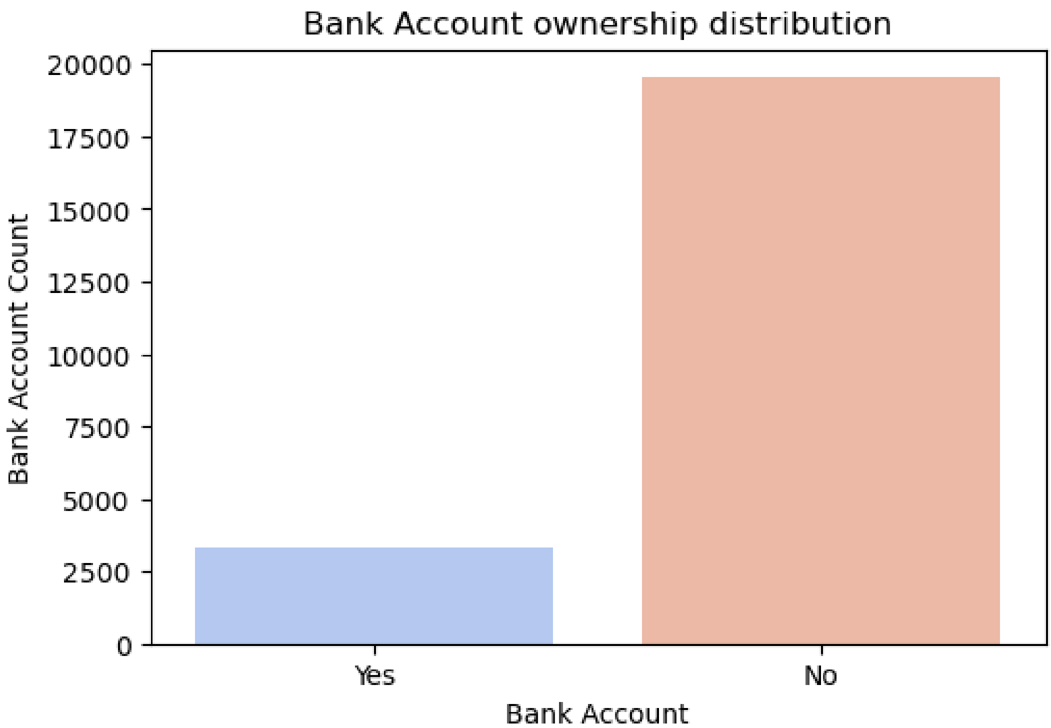
4.1.1 Class Distribution of Target Variable

The below graph will show that the target variable is widely imbalanced. This will skew the model results thus we will have to employ class balancing techniques such as SMOTE

In [1022]:

```
plt.figure(figsize=(6,4))
sns.countplot(x="bank_account",data=df2,palette="coolwarm")
plt.title("Bank Account ownership distribution")
plt.xlabel("Bank Account")
plt.ylabel("Bank Account Count")
plt.show()
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_13208\277013544.py:2: Futu
reWarning:

Passing `palette` without assigning `hue` is deprecated and will be r
emoved in v0.14.0. Assign the `x` variable to `hue` and set `legend=F
alse` for the same effect.

  sns.countplot(x="bank_account",data=df2,palette="coolwarm")
```

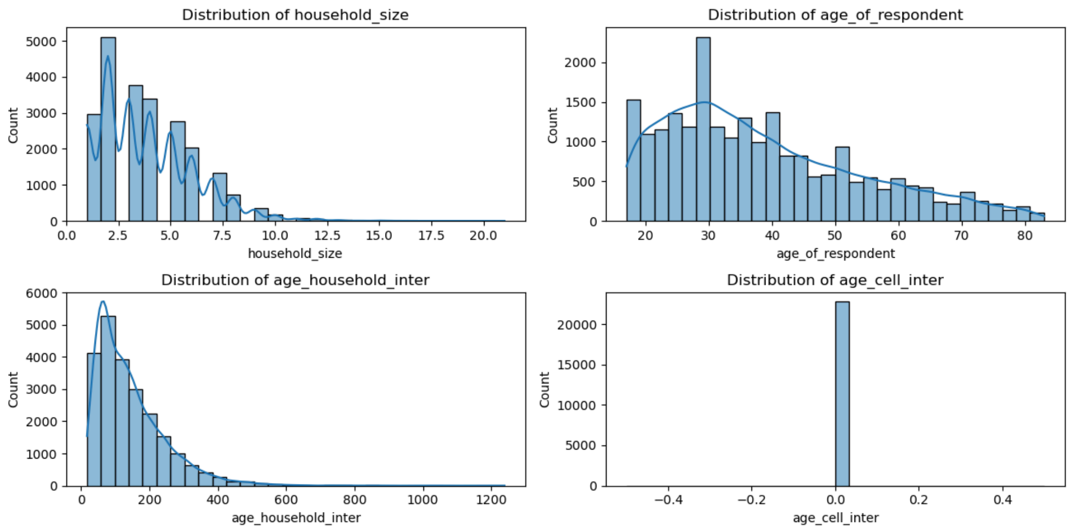


4.1.2 Checking Distribution of Numerical Features

The numerical features are not normally distributed,they are left skewed, thus we will have to do logarithmic transformation to try and normalize them

In [1023]:

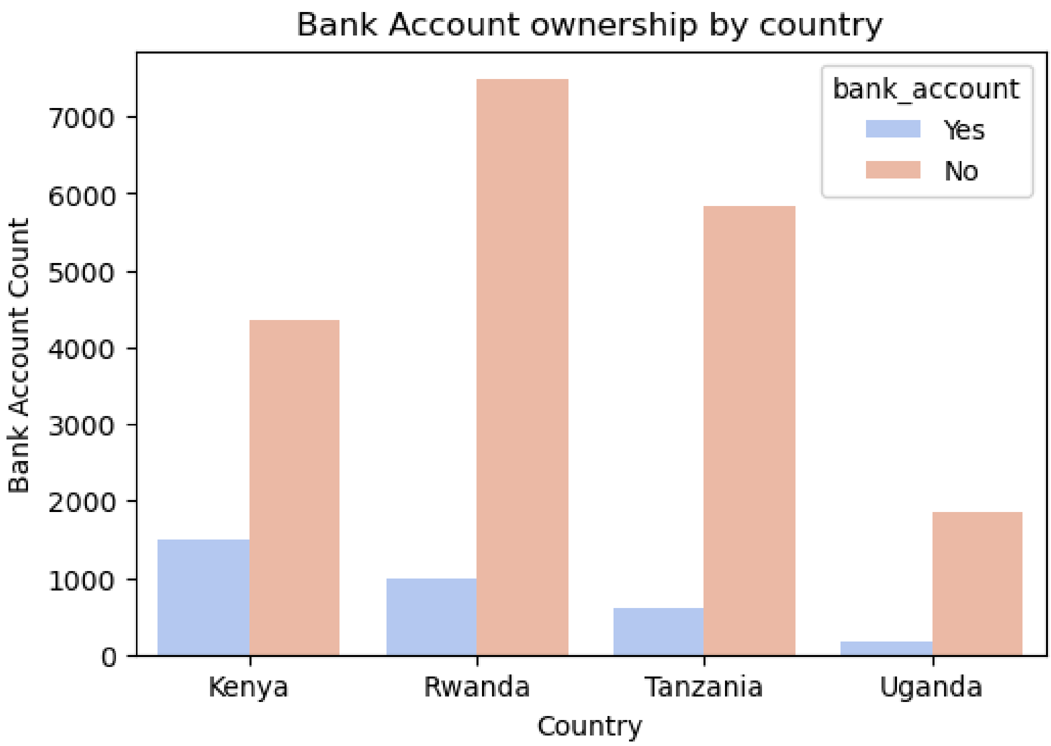
```
num_features=["household_size","age_of_respondent","age_household_inter

plt.figure(figsize=(12,6))
for feature,column in enumerate(num_features):
    plt.subplot(2,2,feature + 1)
    sns.histplot(df2[column],kde=True,bins=30)
    plt.title(f"Distribution of {column}")
plt.tight_layout()
plt.show()
```



4.2.1 Bank Account vs Country

From the plot it shows that Kenya had the most respondents with bank accounts while Rwanda had the most respondents without bank accounts

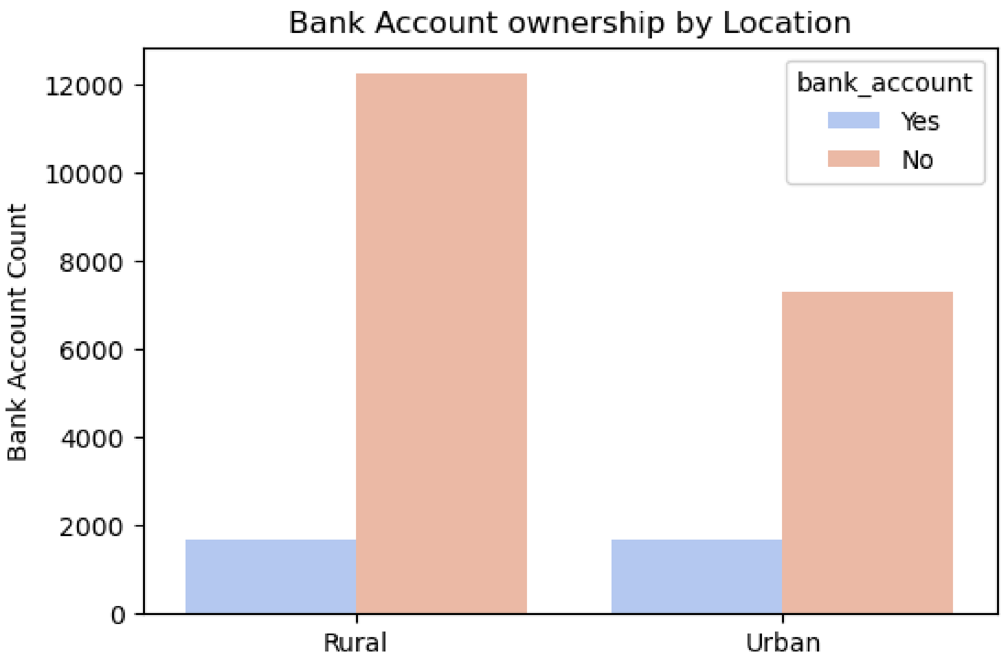
In [1024]:
```
plt.figure(figsize=(6,4))
sns.countplot(x="country",hue="bank_account",data=df2,palette="coolwarm
plt.title("Bank Account ownership by country")
plt.xlabel("Country")
plt.ylabel("Bank Account Count")
plt.show()
```



4.2.2 Bank Account vs Location Type

Majority of Respondents from Rural background had no bank accounts but stunningly around the same number of respondents from Rural and Urban locations had accounts

In [1025]:
```
plt.figure(figsize=(6,4))
sns.countplot(x="location_type",hue="bank_account",data=df2,palette="co
plt.title("Bank Account ownership by Location")
plt.xlabel("Location")
plt.ylabel("Bank Account Count")
plt.show()
```

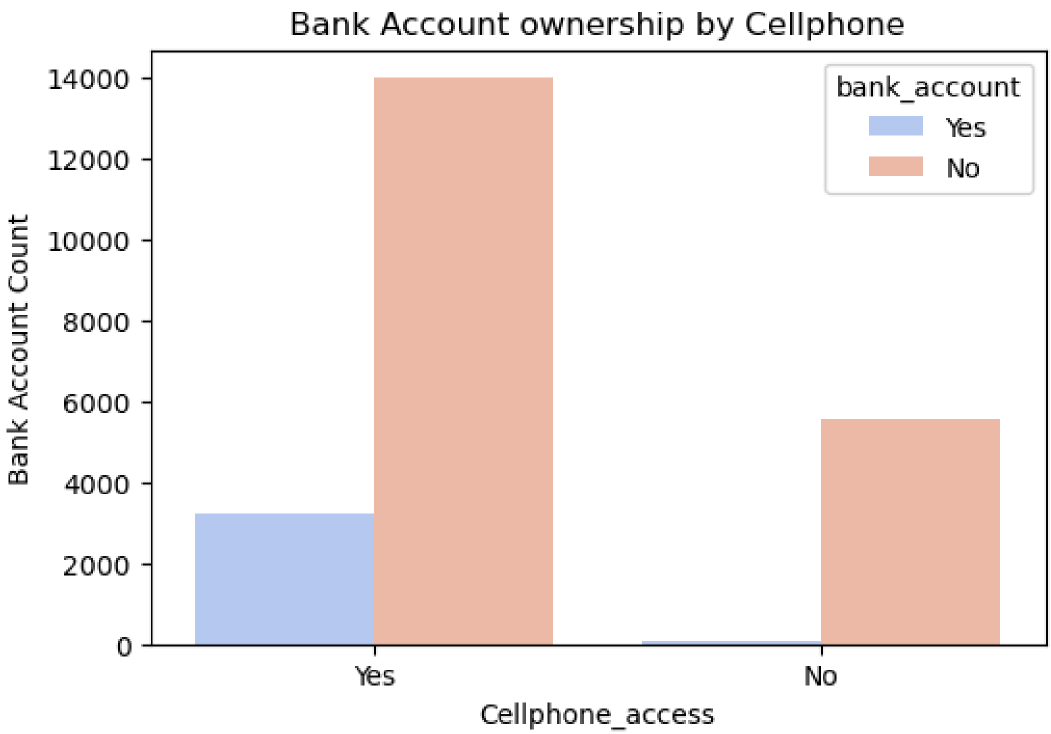


4.2.3 Bank Account by Cellphone access

Unsurprisingly the majority of bank account owners had cellphones

In [1026]:

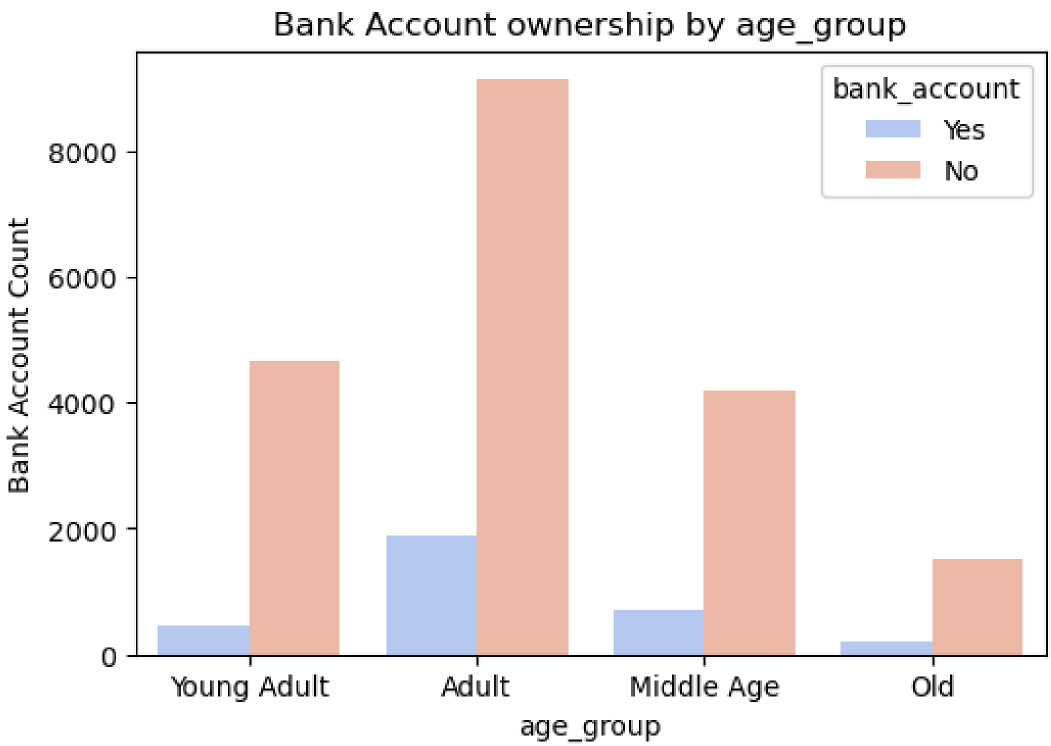
```
plt.figure(figsize=(6,4))
sns.countplot(x="cellphone_access",hue="bank_account",data=df2,palette=
plt.title("Bank Account ownership by Cellphone")
plt.xlabel("Cellphone_access")
plt.ylabel("Bank Account Count")
plt.show()
```



4.2.4 Bank Account by Age group

Adults(26-45) accounted to the majority of bank account ownership

In [1027]:
```
plt.figure(figsize=(6,4))
sns.countplot(x="age_group",hue="bank_account",data=df2,palette="coolwa
plt.title("Bank Account ownership by age_group")
plt.xlabel("age_group")
plt.ylabel("Bank Account Count")
plt.show()
```

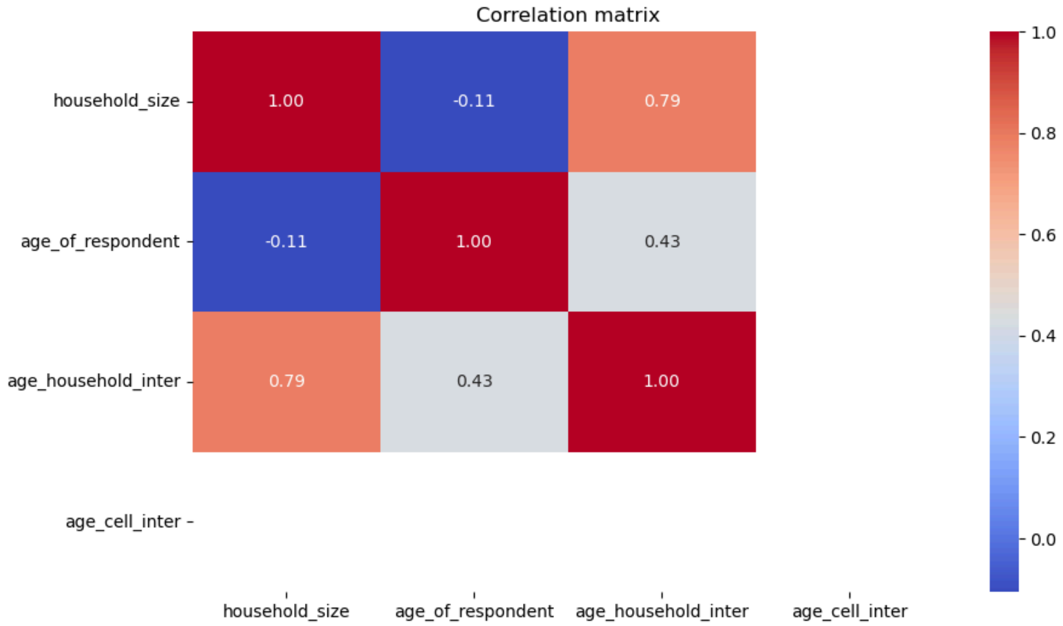


4.3.1 Correlation matrix

Only two of the numerical features are highly correlated, with a correlation of 77%

1.household_size & age_household_inter

In [1028]:
```
num_features2= df2.select_dtypes(include=["int64","float64"]).columns

correlation_matrix=df2[num_features].corr()

plt.figure(figsize=(10,6))
sns.heatmap(correlation_matrix,annot=True,cmap="coolwarm",fmt=".2f")
plt.title("Correlation matrix")
plt.show()
```



4. MODELING

Modeling is essentially the predictive part of the Data Science. In this section, I will look to build a classification model that appropriately predicts whether someone has a bank account and I will tune it to further improve its predictive powers

4.1 Preprocessing

This is the first step of modeling where I further prepare the data needed using methods such as Scaling, Logarithmic transformation, Splitting the data into training and testing as well as Label Encoding/OneHotEncoding

In [1029]:
```
#import necessary libraries
from sklearn.preprocessing import OneHotEncoder, StandardScaler, LabelE
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE
```

In [1030]:
```
df2.shape
```

Out[1030]: (22821, 23)

In [1031]:

```
#Defining categorical and numerical columns
cat=df2.select_dtypes(include=["object","category"]).columns
num=df2.select_dtypes(include=["int64","float64"]).columns

#Exclude target variable & unnecessary
cat=cat.drop(["bank_account","uniqueid"])
df2=df2.drop(["uniqueid","year","country","age_cell_inter"],axis=1)
```

In [1032]:

```
#Label encode the binary columns
le=LabelEncoder()
df2["bank_account"]=le.fit_transform(df2["bank_account"])
df2["location_type"]=le.fit_transform(df2["location_type"])
df2["cellphone_access"]=le.fit_transform(df2["cellphone_access"])
df2["gender_of_respondent"]=le.fit_transform(df2["gender_of_respondent'
df2.head(3)

df2.shape
```

Out[1032]:

```
(22821, 19)
```

In [1033]:

```
# Initialize the OneHotEncoder
ohe = OneHotEncoder(drop="first", sparse_output=False)

# List of columns to encode
columns_to_encode = [
    "relationship_with_head", "marital_status", "education_level", "job
    "age_group", "household_group", "job_edu_inter", "job_cell_inter",
    "edu_cell_inter", "house_location_inter", "job_household_inter", "e
]

# Reset the index of the original DataFrame prevent misalignment during
df2 = df2.reset_index(drop=True)

#Apply OneHotEncoder to the selected columns
encoded_values = ohe.fit_transform(df2[columns_to_encode])

# Get the feature names after encoding
encoded_column_names = ohe.get_feature_names_out(columns_to_encode)

#Create a new DataFrame with the encoded columns and their respective r
encoded_df = pd.DataFrame(encoded_values, columns=encoded_column_names)

#Concatenate the encoded columns with the original DataFrame, ensuring
df2 = pd.concat([df2, encoded_df], axis=1)

#Drop the original columns to avoid duplication
df2.drop(columns=columns_to_encode, inplace=True)

# Verify that no extra rows have been created
print(f"Shape of the DataFrame before OHE: {df2.shape}")
print(f"Shape of the DataFrame after OHE: {encoded_df.shape}")
```

```
Shape of the DataFrame before OHE: (22821, 383)
Shape of the DataFrame after OHE: (22821, 376)
```

In [1034]:

```
X = df2.drop(columns=["bank_account"])  # Features
y = df2["bank_account"]  # Target variable

#Apply scaling only to numerical features
scaler = StandardScaler()

# Identify numerical columns
numerical_cols = X.select_dtypes(include=["float64", "int64"]).columns

# Apply scaling to numerical columns only
X[numerical_cols] = scaler.fit_transform(X[numerical_cols])

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3

#Handle class imbalance using SMOTE
smote = SMOTE(random_state=42)

X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_tr
```

4.2 Modeling

In this step I will build models and tune them to try

In [1035]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report, accuracy_score
```

In [1036]:

```
#Build &Train Logistic Regression model

log_reg=LogisticRegression(max_iter=1000)
log_reg.fit(X_train_resampled,y_train_resampled)

#Making predictions and evaluating the model
log_reg_pred=log_reg.predict(X_test)
print(classification_report(y_test,log_reg_pred))
```

```
              precision    recall  f1-score   support

           0       0.94      0.80      0.87      5850
           1       0.37      0.69      0.48       997

    accuracy                           0.79      6847
   macro avg       0.66      0.75      0.67      6847
weighted avg       0.86      0.79      0.81      6847
```

In [1037]:

```
#Build and Train Decision Tree
dct=DecisionTreeClassifier()
dct.fit(X_train_resampled,y_train_resampled)

#Making predictions and evaluating the model
dct_pred=dct.predict(X_test)
print(classification_report(y_test,dct_pred))
```

```
              precision    recall  f1-score   support

           0       0.90      0.90      0.90      5850
           1       0.39      0.38      0.39       997

    accuracy                           0.82      6847
   macro avg       0.64      0.64      0.64      6847
weighted avg       0.82      0.82      0.82      6847
```

In [1038]:

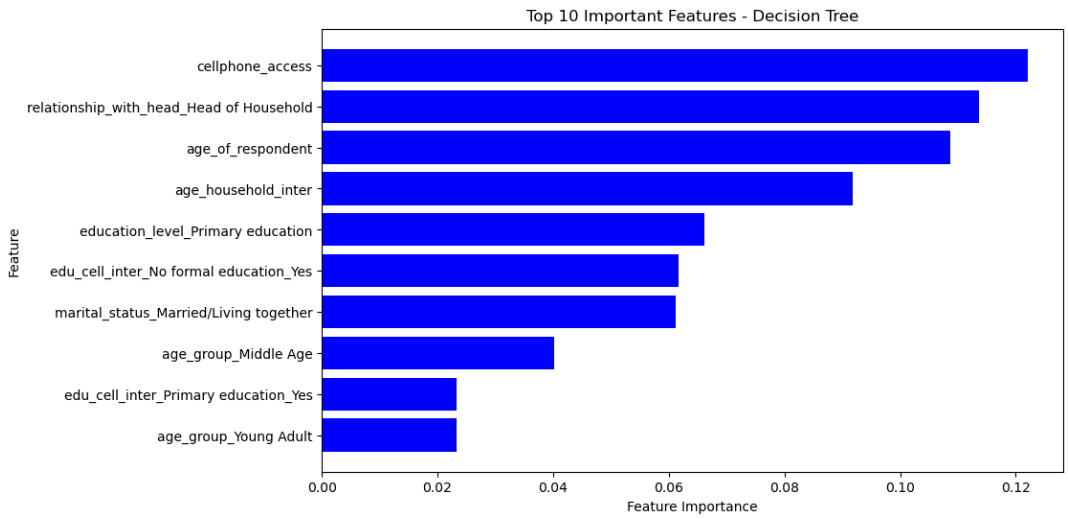
```
#Build and Train XGBoost
xgb_c=XGBClassifier()
xgb_c.fit(X_train_resampled,y_train_resampled)

#Making predictions and evaluating the model
xgb_pred=xgb_c.predict(X_test)
print(classification_report(y_test,xgb_pred))
```

```
              precision    recall  f1-score   support

           0       0.91      0.94      0.92      5850
           1       0.56      0.43      0.49       997

    accuracy                           0.87      6847
   macro avg       0.73      0.69      0.71      6847
weighted avg       0.86      0.87      0.86      6847
```

In [1039]:
```
#Getting most important features for decision tree
dct_feature_importance=pd.DataFrame({"Feature":X_train_resampled.columr

dct_feature_importance=dct_feature_importance.sort_values(by="Importanc

print(dct_feature_importance.head(15))
```

```
                                   Feature  Importance
1                          cellphone_access    0.122128
6     relationship_with_head_Head of Household    0.113716
3                         age_of_respondent    0.108653
5                        age_household_inter    0.091861
16           education_level_Primary education    0.066243
111     edu_cell_inter_No formal education_Yes    0.061764
12      marital_status_Married/Living together    0.061224
29                     age_group_Middle Age    0.040263
115       edu_cell_inter_Primary education_Yes    0.023384
31                      age_group_Young Adult    0.023289
18          education_level_Tertiary education    0.018286
117     edu_cell_inter_Secondary education_Yes    0.016269
4                        gender_of_respondent    0.015039
14                      marital_status_Widowed    0.013946
13         marital_status_Single/Never Married    0.013462
```

In [1040]:
```
#Plot feature importance
# Plot feature importance
plt.figure(figsize=(10, 6))
plt.barh(dct_feature_importance['Feature'][:10], dct_feature_importance
plt.xlabel("Feature Importance")
plt.ylabel("Feature")
plt.title("Top 10 Important Features - Decision Tree")
plt.gca().invert_yaxis()
plt.show()
```



In [1041]:

```
# Selecting the top 10 features
top_10_features = [
    "cellphone_access", "relationship_with_head_Head of Household",
    "age_of_respondent", "age_household_inter", "education_level_Primar
    "edu_cell_inter_No formal education_Yes", "marital_status_Married/L
    "age_group_Middle Age", "age_group_Young Adult", "education_level_T
]

# Subset dataset to include only top 10 features
X_train_top10 = X_train_resampled[top_10_features]
X_test_top10 = X_test[top_10_features]

# Initialize and train Decision Tree model
dct_top10 = DecisionTreeClassifier(random_state=42)
dct_top10.fit(X_train_top10, y_train_resampled)

# Make predictions
dct_top10_pred = dct_top10.predict(X_test_top10)

# Evaluate performance
print(classification_report(y_test, dct_top10_pred))
```

```
              precision    recall  f1-score   support

           0       0.88      0.94      0.91      5850
           1       0.43      0.28      0.33       997

    accuracy                           0.84      6847
   macro avg       0.65      0.61      0.62      6847
weighted avg       0.82      0.84      0.83      6847
```

In [1042]:

```
#Reapply SMOTE
X_train_resampled, y_train_resampled = smote.fit_resample(X_train_top1

# Step 2: Define Hyperparameter Grid
param_grid = {
    'max_depth': [5],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 5],
    'criterion': ['gini', 'entropy']
}

# Step 3: Use GridSearchCV for Hyperparameter Tuning
grid_search = GridSearchCV(dct, param_grid, cv=5, n_jobs=-1)
grid_search.fit(X_train_resampled, y_train_resampled)

# Step 4: Train Decision Tree with Best Parameters
best_params = grid_search.best_params_
best_dct = DecisionTreeClassifier(**best_params, random_state=42)
best_dct.fit(X_train_resampled, y_train_resampled)

# Step 5: Evaluate Performance
y_pred = best_dct.predict(X_test_top10)
print("Best Parameters:", best_params)
print(classification_report(y_test, y_pred))
```

```
Best Parameters: {'criterion': 'gini', 'max_depth': 5, 'min_samples_l
eaf': 1, 'min_samples_split': 2}
              precision    recall  f1-score   support

           0       0.91      0.92      0.91      5850
           1       0.49      0.45      0.47       997

    accuracy                           0.85      6847
   macro avg       0.70      0.69      0.69      6847
weighted avg       0.85      0.85      0.85      6847
```

In [ ]: