Introduction to Neural Networks: Bank Churn prediction

Problem Statement

Context

Businesses like banks which provide service have to worry about problem of 'Customer Churn' i.e. customers leaving and joining another service provider. It is important to understand which aspects of the service influence a customer's decision in this regard. Management can concentrate efforts on improvement of service, keeping in mind these priorities.

Objective

You as a Data scientist with the bank need to build a neural network based classifier that can determine whether a customer will leave the bank or not in the next 6 months.

Data Dictionary:

- **CustomerId: Unique ID which is assigned to each customer**
- **Surname: Last name of the customer**
- **CreditScore: It defines the credit history of the customer.**
- **Geography: A customer's location**
- **Gender: It defines the Gender of the customer**
- **Age: Age of the customer**
- **Tenure: Number of years for which the customer has been with the bank**
- **NumOfProducts: refers to the number of products that a customer has purchased through the bank.**
- **Balance: Account balance**
- **HasCrCard: It is a categorical variable which decides whether the customer has credit card or not.**
- **EstimatedSalary: Estimated salary**
- **isActiveMember: Is is a categorical variable which decides whether the customer is active member of the bank or not (Active member in the sense, using bank products regularly, making transactions etc)**
- **Exited : whether or not the customer left the bank within six month. It can take two values 0=No (Customer did not leave the bank) 1=Yes (Customer left the bank)**

Importing necessary libraries

In [2]:

```
# Importing essential libraries for data manipulation
import pandas as pd
import numpy as np

# Importing libraries for data visualization
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set_theme()

# Importing libraries for data preprocessing and scaling
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

```python
# Importing libraries for various metric scores and analysis
from sklearn.metrics import (
    accuracy_score,  # Accuracy metric
    confusion_matrix,  # Confusion matrix metric
    precision_score,  # Precision metric
    recall_score,  # Recall metric
    f1_score,  # F1 score metric
    precision_recall_curve,  # Precision-Recall curve
    auc,  # Area Under the Curve metric
    roc_auc_score,  # ROC-AUC score metric
    roc_curve,  # ROC curve
)
from sklearn.decomposition import PCA  # Principal Component Analysis


import warnings  # Suppressing warnings for cleaner output
warnings.filterwarnings("ignore")
warnings.filterwarnings("ignore", category=DeprecationWarning)
import os
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '1'  # or any {'0', '1', '2', '3'}


# Importing TensorFlow and Keras for neural network modeling
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras import optimizers
from tensorflow.keras.optimizers import Adam,RMSprop
from scikeras.wrappers import KerasClassifier

import keras
from keras import backend as K
from keras.models import Sequential
from keras.layers import Dense, Dropout, BatchNormalization
```

Loading the dataset

In [3]:

```python
df = pd.read_excel(r"C:\Users\SHREYA\Downloads\Churn.xlsx")
```

Data Overview

In [4]:

```python
df.head(10)
```

Out[4]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCar
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	
5	6	15574012	Chu	645	Spain	Male	44	8	113755.78	2	
6	7	15592531	Bartlett	822	France	Male	50	7	0.00	2	
7	8	15656148	Obinna	376	Germany	Female	29	4	115046.74	4	
8	9	15792365	He	501	France	Male	44	4	142051.07	2	
9	10	15592389	H?	684	France	Male	27	2	134603.88	1	

In [5]:

```
#checking the shape of the dataset
df.shape
```

Out[5]:

```
(10000, 14)
```

There are 10000 rows and 14 columns in the dataset.

In [6]:

```
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
```

Observations:
-Every variable is numerical, with the exception of Surname, Geography, and Gender.

In [7]:

```
#checking for missing values
df.isnull().sum()
```

Out[7]:

```
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
dtype: int64
```

Observations:
There are no missing values in the dataset

In [8]:

```
# checking for duplicate values
df.duplicated().sum()
```

Out[8]:

```
0
```

Observations:
There are no duplicate values in the dataset

In [9]:

```
# dropping `RowNumber`, `CustomerId`, and `Surname`
df.drop(["RowNumber", "CustomerId", "Surname"], axis=1, inplace=True)
```

Observations:
We drop columns "RowNumber", "CustomerId", "Surname" as they don't give us any additional information in the dataset.

In [10]:

```
# Converting 'Gender' and 'Geography' columns to categorical
df[['Gender', 'Geography']] = df[['Gender', 'Geography']].astype('category')
```

In [11]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CreditScore      10000 non-null  int64
 1   Geography        10000 non-null  category
 2   Gender           10000 non-null  category
 3   Age              10000 non-null  int64
 4   Tenure           10000 non-null  int64
 5   Balance          10000 non-null  float64
 6   NumOfProducts    10000 non-null  int64
 7   HasCrCard        10000 non-null  int64
 8   IsActiveMember   10000 non-null  int64
 9   EstimatedSalary  10000 non-null  float64
 10  Exited           10000 non-null  int64
dtypes: category(2), float64(2), int64(7)
memory usage: 723.0 KB
```

Observations:
There are 9 numerical columns in the dataset, and two categorical columns.

In [12]:

```
df.describe().T
```

Out[12]:

	count	mean	std	min	25%	50%	75%	max
CreditScore	10000.0	650.528800	96.653299	350.00	584.00	652.000	718.0000	850.00
Age	10000.0	38.921800	10.487806	18.00	32.00	37.000	44.0000	92.00

	count	mean	std	min	25%	50%	75%	max
Age	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Tenure	10000.0	5.012800	2.892174	0.00	3.00	5.000	7.0000	10.00
Balance	10000.0	76485.889288	62397.405202	0.00	0.00	97198.540	127644.2400	250898.09
NumOfProducts	10000.0	1.530200	0.581654	1.00	1.00	1.000	2.0000	4.00
HasCrCard	10000.0	0.705500	0.455840	0.00	0.00	1.000	1.0000	1.00
IsActiveMember	10000.0	0.515100	0.499797	0.00	0.00	1.000	1.0000	1.00
EstimatedSalary	10000.0	100090.239881	57510.492818	11.58	51002.11	100193.915	149388.2475	199992.48
Exited	10000.0	0.203700	0.402769	0.00	0.00	0.000	0.0000	1.00

Observations:
-The average consumer credit score is roughly 650, indicating a comparatively good credit standing.
-37 is the median age, indicating a somewhat younger clientele.
-With a 25th percentile value of 0, the "Balance" variable indicates that a sizable percentage of clients have a balance of 0.There is a possibility of right-skewness.
-The boolean variables HasCrCard, IsActiveMember, and Exited have values of either 0 or 1.
-With a mean of 0.2037, "Exited" shows a class imbalance, meaning that only about 20.37% of consumers have left.

In [13]:

```
df.describe(exclude="number").T
```

Out[13]:

	count	unique	top	freq
Geography	10000	3	France	5014
Gender	10000	2	Male	5457

Observations:
-The majority of customers in the dataset are from 'France,' which appears 5014 times.
-Most customers in the dataset is 'Male,' with a frequency of 5457.

Exploratory Data Analysis

Questions:

1. What is the distribution of the credit score of customers? Are there any noticeable patterns or outliers in the distribution?
2. How many active members are there with the bank?
3. How are the different customer attributes correlated to each other?
4. Who is churning more when compared to males and females?
5. Customers from which geographical part are churning more?

In [14]:

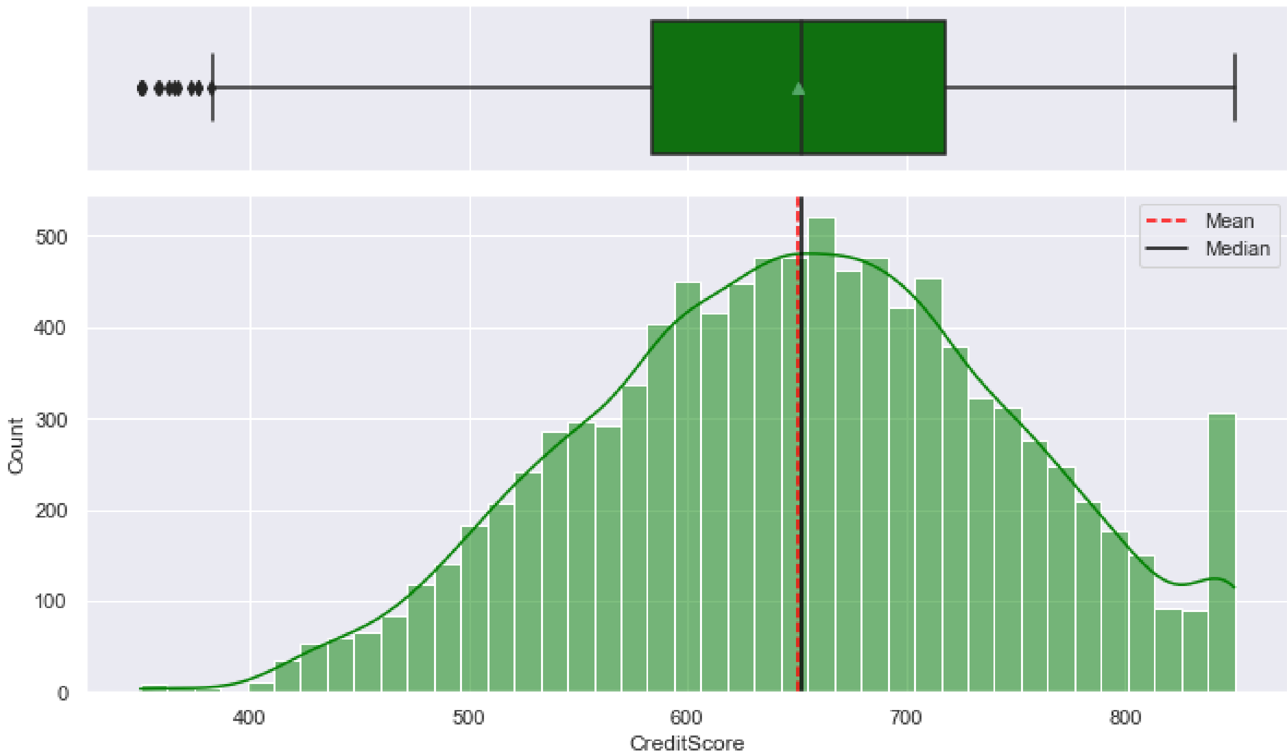
```
def histogram_boxplot(data, feature, figsize=(10,6)):
    """
    Boxplot and histogram combined with KDE curve

    data: dataframe
    feature: dataframe column
    figsize: size of figure (default (10, 6))
    """
    # Create subplots with shared x-axis
```

```
    f, (ax_box, ax_hist) = plt.subplots(
        nrows=2,
        sharex=True,
        gridspec_kw={"height_ratios": (0.25, 0.75)},
        figsize=figsize,
    )

    # Creating Boxplot
    sns.boxplot(data=data, x=feature, ax=ax_box, showmeans=True, color="green")

    # Creating Histogram with KDE curve
    sns.histplot(data=data, x=feature, color="green", kde=True, ax=ax_hist)

    # Adding mean and median lines to the histogram
    ax_hist.axvline(data[feature].mean(), color="red", linestyle="--", label="Mean")
    ax_hist.axvline(data[feature].median(), color="black", linestyle="-", label="Median"
)


    ax_box.set(xlabel='')
    ax_hist.set_xlabel(feature)
    ax_hist.legend()


    plt.tight_layout()


    plt.show()
```

Q1-What is the distribution of the credit score of customers?

In [15]:

```
histogram_boxplot(df, "CreditScore")
```

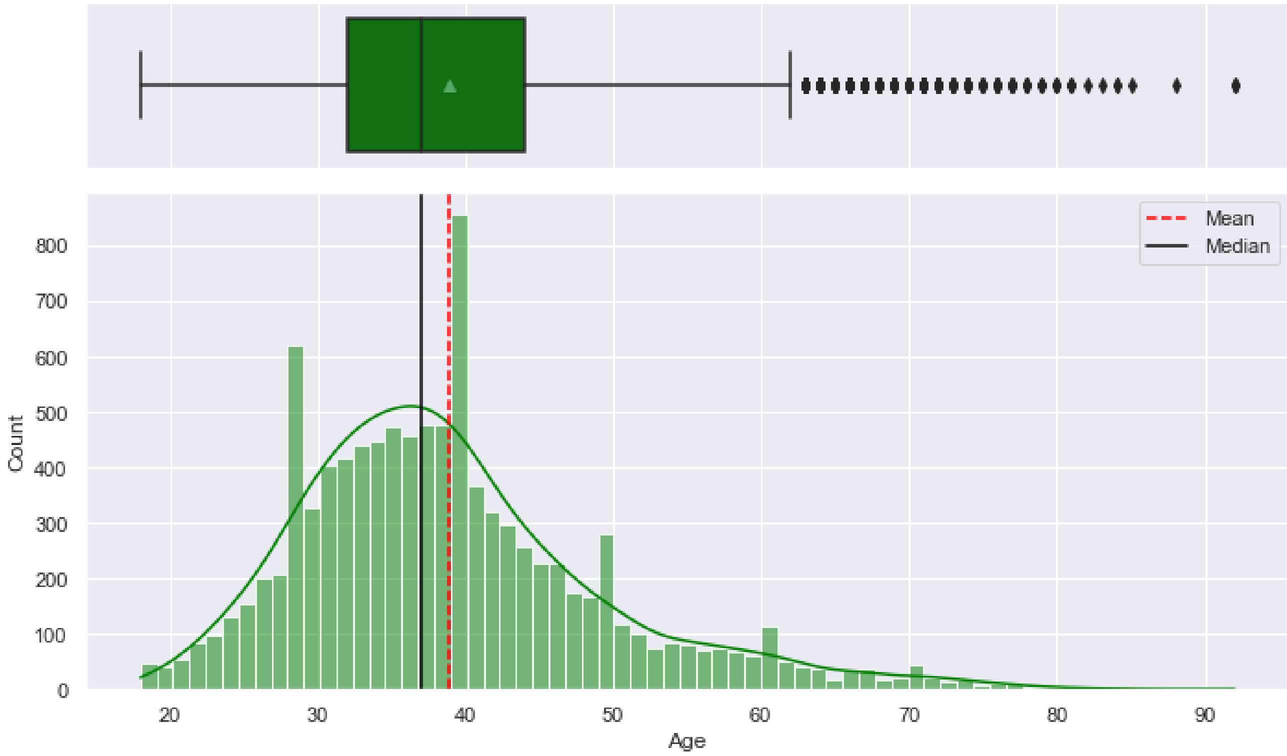


Observations:
-The distribution of credit score is approximately normal.
-It has a few outliers on the left

In [16]:

```
histogram_boxplot(df, "Age")
```

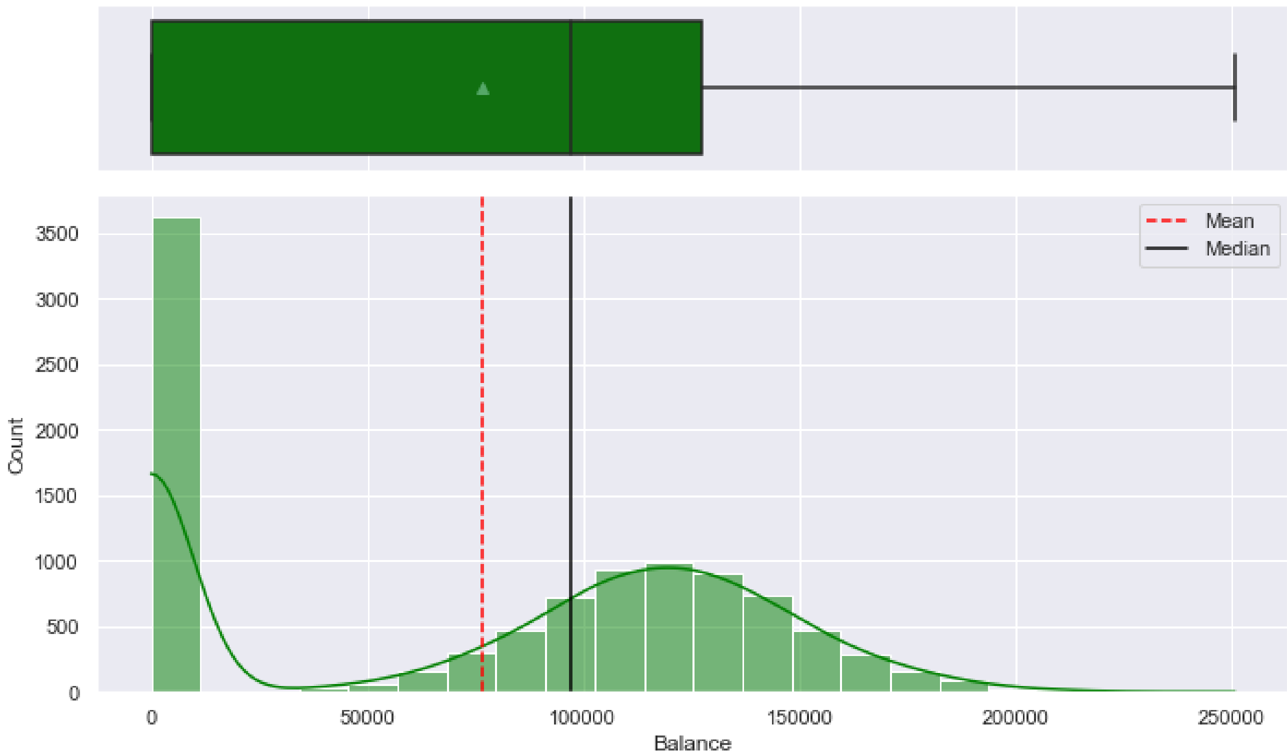
```
histogram_boxplot(df, "Age")
```



Observations:
-The distribution of age shows a right skew with the mean greater than the median.
-There are outliers on the right.

In [17]:

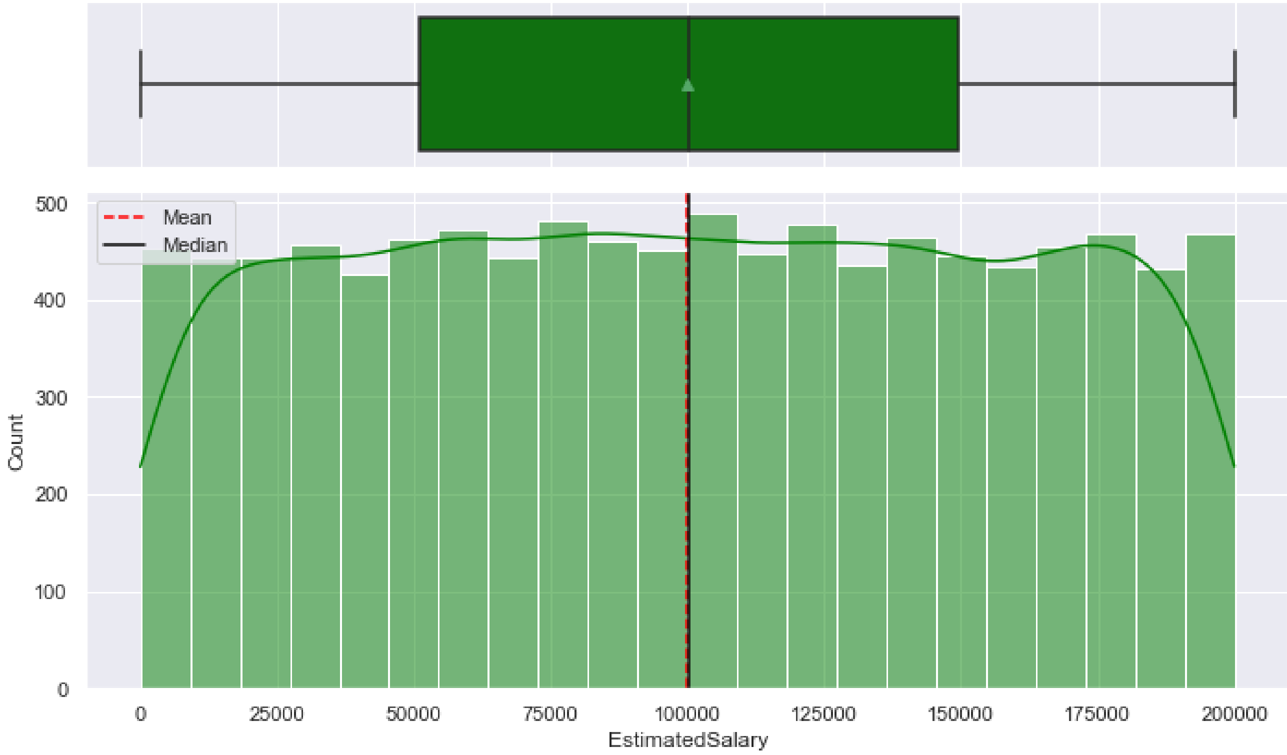
```
histogram_boxplot(df, "Balance")
```



Observations:
The distribution of Balance has a left skew due to the presence of high number of 0 balance accounts.

In [18]:

```
histogram_boxplot(df, "EstimatedSalary")
```



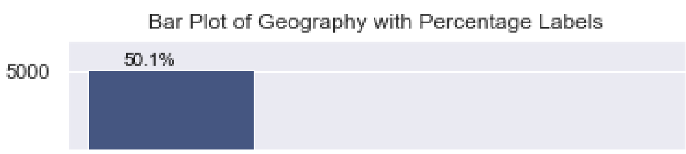
Observations:
-The distribution of salary is approximately uniform ranging from 0 to 200000.
-The mean and median are approximately equal at 10,000

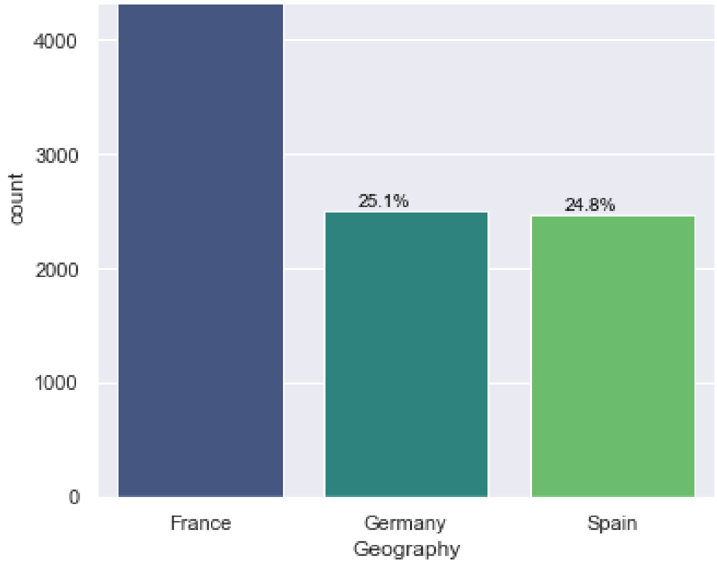
In [19]:

```
def categorical_barplot(data, categorical_column):
    """
    Function to generate a bar plot with percentage labels.

    Parameters:
    - data: DataFrame
    - categorical_column: Categorical column name
    """
    plt.figure(figsize=(6, 6))


    sns.countplot(x=categorical_column, data=data, palette='viridis')


    total_entries = len(data[categorical_column])
    for p in plt.gca().patches:
        percentage = '{:.1f}%'.format((p.get_height() / total_entries) * 100)
        x_position = p.get_x() + p.get_width() / 2 - 0.1
        y_position = p.get_height() + 0.05
        plt.text(x_position, y_position, percentage, ha='center', va='bottom', fontsize=
10, color='black')

    plt.title(f'Bar Plot of {categorical_column} with Percentage Labels')
    plt.show()
```

In [20]:

```
categorical_barplot(df, 'Geography')
```

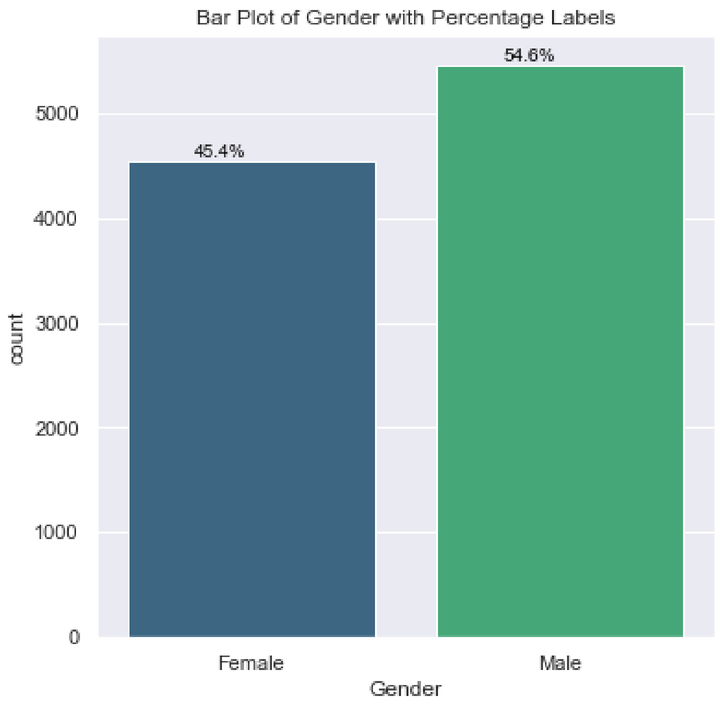




Observations:
Approximately 50% of the Customers in the dataset are from France.

In [21]:

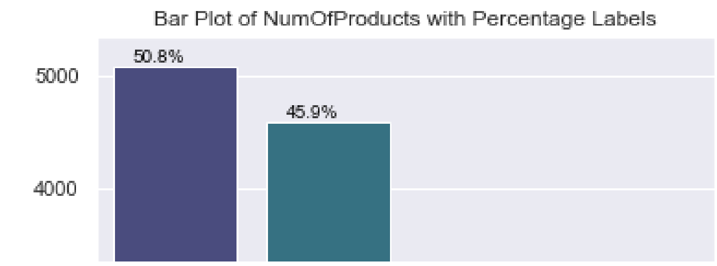
```
categorical_barplot(df, 'Gender')
```

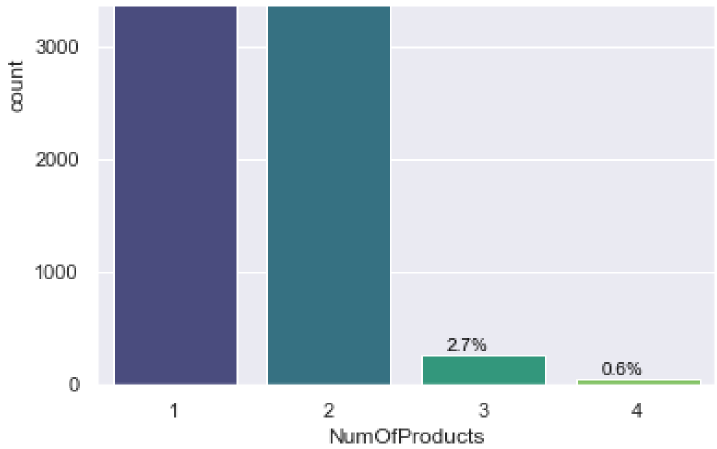


Observations:
Males have higher representation than females in the dataser at 54.6%

In [22]:

```
categorical_barplot(df, 'NumOfProducts')
```

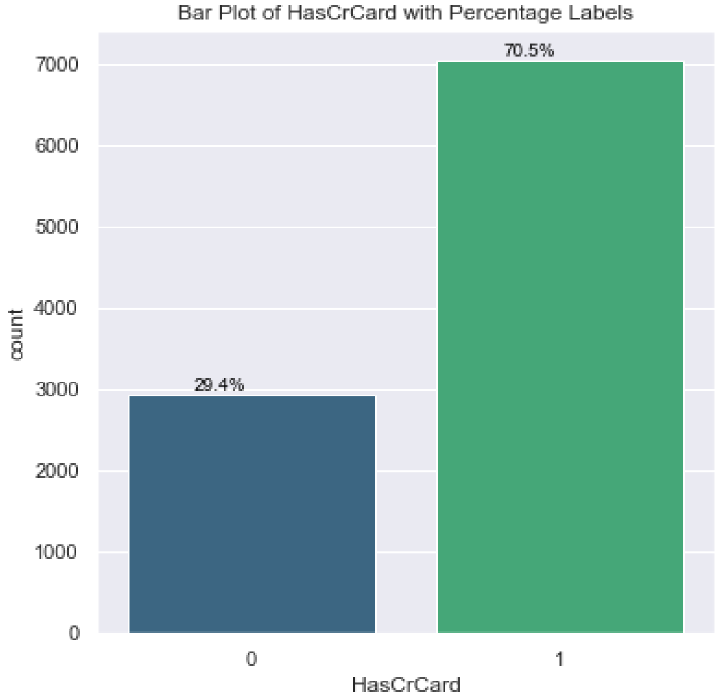




Observations:
Around 51% of the customers in the dataset possess a single product from the bank, while 46% own two products.

In [23]:

```
categorical_barplot(df, 'HasCrCard')
```

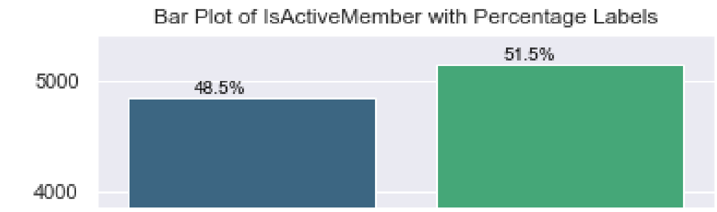


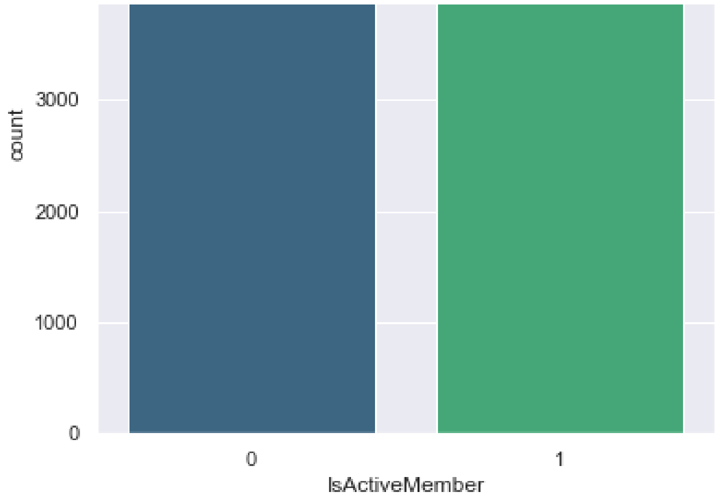
Observations:
70.5% of the customers in dataset own a credit card.

Q-2How many active members are there with the bank

In [24]:

```
categorical_barplot(df, 'IsActiveMember')
```





In [25]:

```
df['IsActiveMember'].value_counts()
```

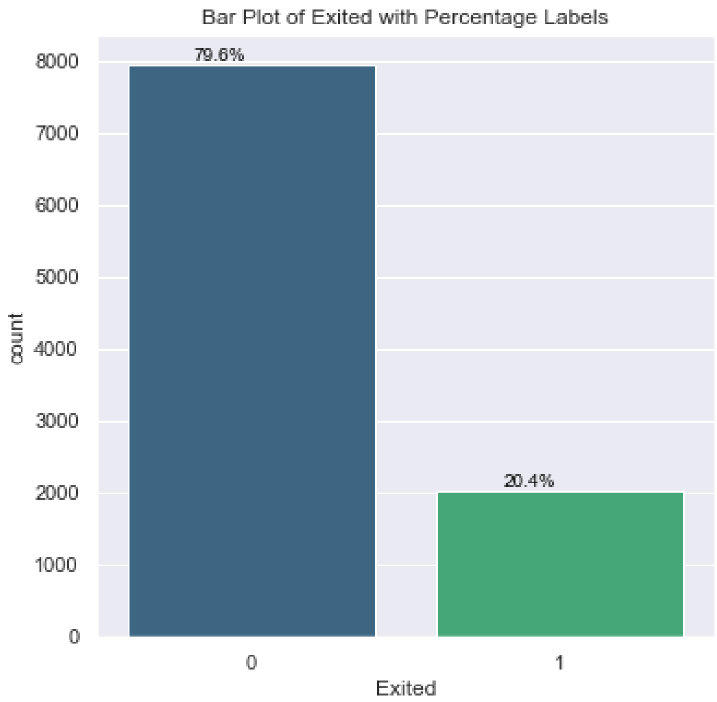
Out[25]:

```
1    5151
0    4849
Name: IsActiveMember, dtype: int64
```

Observations:
51.5%(5151) of customers can be considered an active of the bank compared to 48.5% (4849) who aren't.

In [26]:

```
categorical_barplot(df, 'Exited')
```

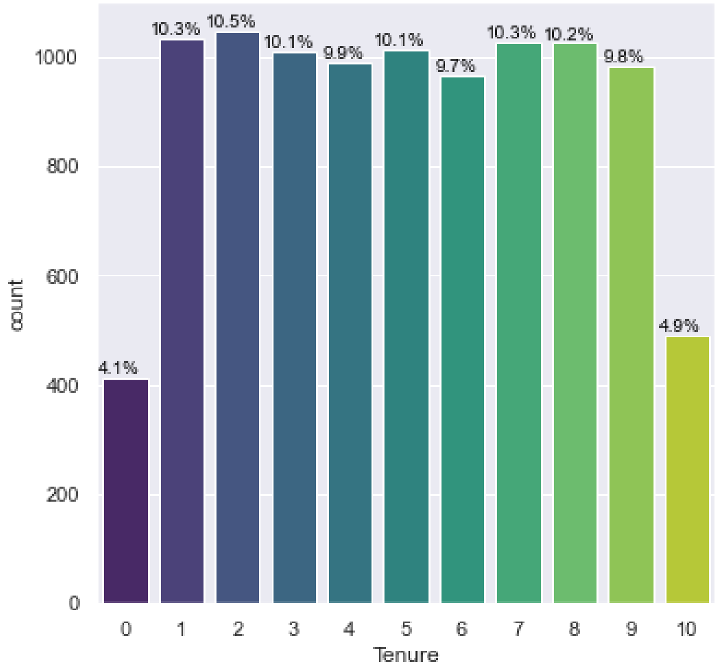


Observations:
20.4% of the customers in the bank have exited the bank, while 79.6% are still part of the bank.

In [27]:

```
categorical_barplot(df,'Tenure')
```

Bar Plot of Tenure with Percentage Labels

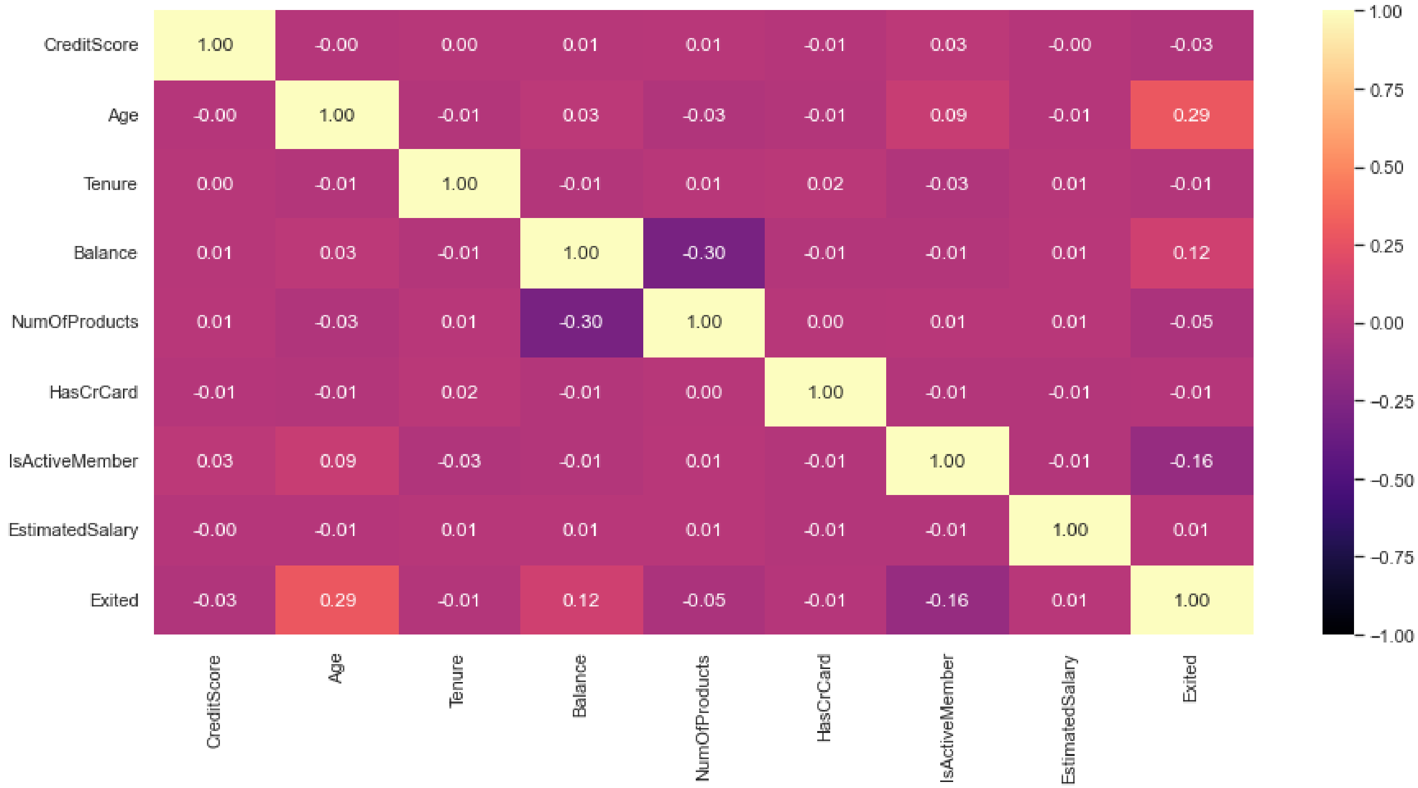


Observations:
Merely 4% of the customers have a tenure of 0, and 6% have a tenure of 10. Additionally, each of the tenures from 1 to 9 years. is represented by approximately 10% of the customers.

Q-3 How are the different customer attributes correlated to each other?

In [28]:

```
# checking for correlations
plt.figure(figsize=(15, 7))
sns.heatmap(df.corr(), annot=True, vmin=-1, vmax=1, fmt=".2f", cmap="magma")
plt.show()
```



Observations:

-There is a slight positive correlation of 0.29 between age and the likelihood of leaving the bank (Exited = 1).
-There is a negative correlation between balance and the number of products a customer has purchased through the bank.
-Overall, the dataset exhibits low correlations between its variables.

In [29]:

```
def bar_plot(data, x_col, hue_col, title):
    """
    Function to generate a bar plot for two categorical variables.

    Parameters:
    - data: DataFrame
    - x_col: Column name for the x-axis
    - hue_col: Column name for color differentiation (hue)
    - title: Title of the plot
    """
    plt.figure(figsize=(12, 8))
    ax = sns.countplot(x=x_col, hue=hue_col, data=data, palette='viridis', edgecolor='wh
ite')


    total_entries = len(data)
    for p in ax.patches:
        percentage = '{:.1f}%'.format((p.get_height() / total_entries) * 100)
        x_position = p.get_x() + p.get_width() / 2
        y_position = p.get_height() + 0.02  # Adjusted y_position to place labels above
bars
        ax.annotate(percentage, (x_position, y_position), ha='center', va='bottom', font
size=12, color='black')


    plt.xlabel(x_col.capitalize())
    plt.ylabel('Count')
    plt.title(title)
    plt.legend(title=hue_col.capitalize(), loc='upper right')


    plt.show()
```

Q-4 Who is churning more when compared to males and females?

In [30]:

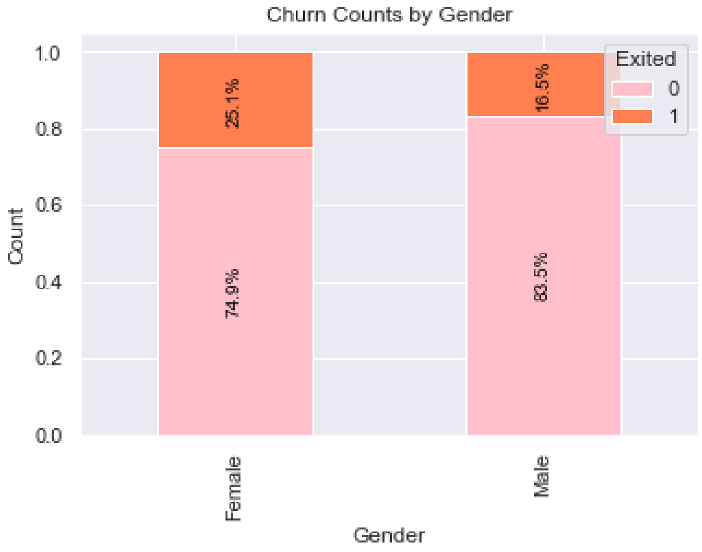
```
def stacked_bar_plot(data, x_col, hue_col, title):
    """
    Function to generate a stacked bar plot for two categorical variables with percentage
labels.

    Parameters:
    - data: DataFrame
    - x_col: Column name for the x-axis
    - hue_col: Column name for color differentiation (hue)
    - title: Title of the plot
    """

    cross_tab = pd.crosstab(data[x_col], data[hue_col], normalize='index')

    plt.figure(figsize=(12, 8))


    cross_tab.plot(kind='bar', stacked=True, color=['pink', 'coral'], edgecolor='white')

    # percentage labels
    for i in range(len(cross_tab)):
        total_entries = cross_tab.sum(axis=1).iloc[i]
        for j in range(len(cross_tab.columns)):
            percentage = '{:.1f}%'.format(cross_tab.iloc[i, j] * 100)
```

```
            x_position = i
            y_position = cross_tab.iloc[i, :j].sum() + cross_tab.iloc[i, j] / 2
            plt.text(x_position, y_position, percentage, ha='center', va='center', fonts
ize=10, color='black',rotation=90)


    plt.xlabel(x_col.capitalize())
    plt.ylabel('Count')
    plt.title(title)
    plt.legend(title=hue_col.capitalize(), loc='upper right')


    plt.show()
```

In [31]:

```
stacked_bar_plot(df, 'Gender', 'Exited', 'Churn Counts by Gender')
```

<Figure size 864x576 with 0 Axes>



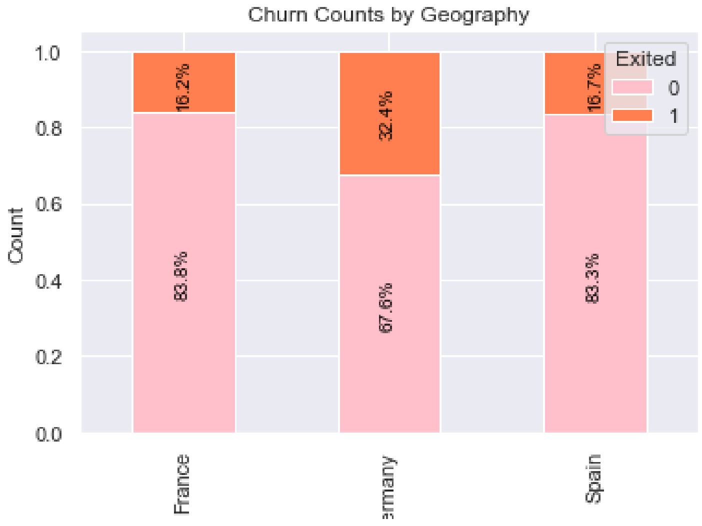
Observations:
More women have exited(25%) as compared to men(16.4%) from the bank.

Q-5 Customers from which geographical part are churning more?

In [32]:

```
stacked_bar_plot(df, 'Geography', 'Exited', 'Churn Counts by Geography')
```

<Figure size 864x576 with 0 Axes>



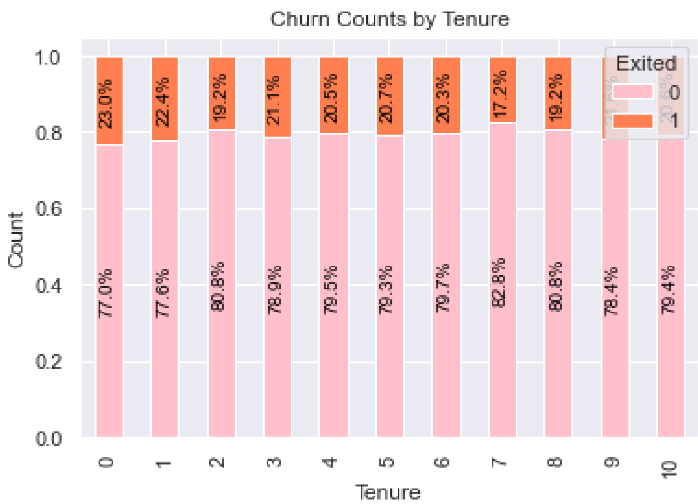
Geography

Observations:
Germany has the highest number of customers who have churned(32%) compared to France(16.1%) and Spain(16.6%).

In [33]:

```
stacked_bar_plot(df, 'Tenure', 'Exited', 'Churn Counts by Tenure')
```

```
<Figure size 864x576 with 0 Axes>
```

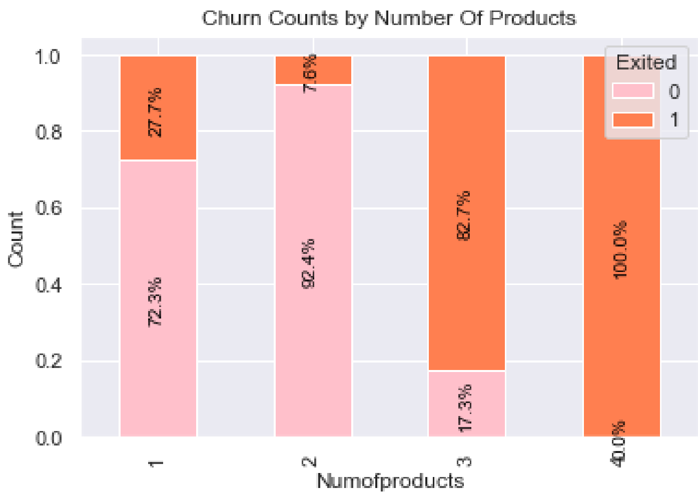


Observations:
Customers with a tenure of 1 year and 0 year have a higher churn count compared to others.

In [34]:

```
stacked_bar_plot(df, 'NumOfProducts', 'Exited', 'Churn Counts by Number Of Products')
```

```
<Figure size 864x576 with 0 Axes>
```

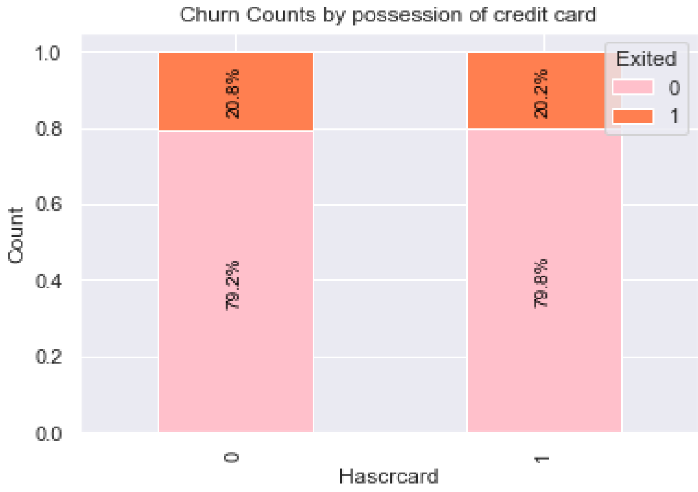


Observations:
-All the customers who purchased 4 products left the bank.
-Lowest churn percentage was among the customers who purchased 2 products.

In [35]:

```python
stacked_bar_plot(df, 'HasCrCard', 'Exited', 'Churn Counts by possession of credit card')
```

<Figure size 864x576 with 0 Axes>

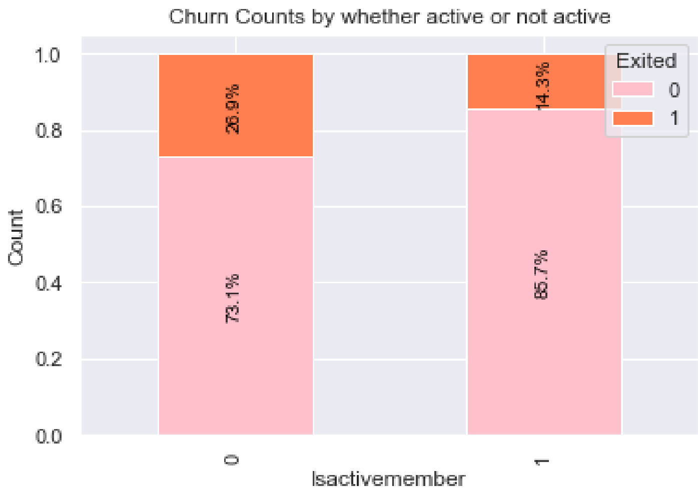


Observations:
Churn count is approximately similar for customers who own a credit and those who don't.

In [36]:

```python
stacked_bar_plot(df, 'IsActiveMember', 'Exited', 'Churn Counts by whether active or not a
ctive')
```

<Figure size 864x576 with 0 Axes>



Observations:
Non-Active members of the bank have a higher churn count.

Data Preprocessing

- **Missing value treatment**
- **Feature engineering (if needed)**
- **Outlier detection and treatment (if needed)**
- **Preparing data for modeling**
- **Any other preprocessing steps (if needed)**

Missing Value and Duplicate Data Treatment:

There are no missing and duplicated values in the dataset, and hence it doesn't require any treatment.

Outlier Removal

Outliers are present in Age and CreditScore. However, people with ages or credit ratings that differ greatly from the average are frequently encountered in real-world situations, and these differences can offer important insights into the complexity and diversity of the data. Hence we will keep the outliers

In [37]:

```
data = df.copy()
```

In [38]:

```
# Splitting the Data
X_data = data.drop(["Exited"], axis=1)

# target variable
y_data = data["Exited"]   # target variable
```

In [39]:

```
# Creating dummy variables for the 2 the categorical variables
X_data = pd.get_dummies(X_data, columns=["Geography", "Gender"],drop_first=True)
X_data.head(10)
```

Out[39]:

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Geography_Germany
0	619	42	2	0.00	1	1	1	101348.88	0
1	608	41	1	83807.86	1	0	1	112542.58	0
2	502	42	8	159660.80	3	1	0	113931.57	0
3	699	39	1	0.00	2	0	0	93826.63	0
4	850	43	2	125510.82	1	1	1	79084.10	0
5	645	44	8	113755.78	2	1	0	149756.71	0
6	822	50	7	0.00	2	1	1	10062.80	0
7	376	29	4	115046.74	4	1	0	119346.88	1
8	501	44	4	142051.07	2	0	1	74940.50	0
9	684	27	2	134603.88	1	1	1	71725.73	0

In [40]:

```
X_data.shape
```

Out[40]:

```
(10000, 11)
```

The predictor(X) dataframe has 10,000 rows and 11 columns.

In [41]:

```
# Splitting the data up in train, validation and test sets


X_temp, X_test, y_temp, y_test = train_test_split(X_data, y_data, test_size=0.2, random_
state=1, stratify=y_data)

X_train, X_val, y_train, y_val = train_test_split(X_temp, y_temp, test_size=0.2, random_
```

```
state=1, stratify=y_temp)
```

In [42]:

```
print("Shape of X_train:", X_train.shape)
print("Shape of X_val:", X_val.shape)
print("Shape of X_test:", X_test.shape)
print("Shape of y_train:", y_train.shape)
print("Shape of y_val:", y_val.shape)
print("Shape of y_test:", y_test.shape)
```

```
Shape of X_train: (6400, 11)
Shape of X_val: (1600, 11)
Shape of X_test: (2000, 11)
Shape of y_train: (6400,)
Shape of y_val: (1600,)
Shape of y_test: (2000,)
```

In [43]:

```
# Specifying columns to scale
columns_to_scale = ["CreditScore", "Age", "Tenure", "Balance", "EstimatedSalary"]

# Create a scaler
scaler = StandardScaler()

# Fiting on the training set
scaler.fit(X_train[columns_to_scale])

# Transforming the training set
X_train[columns_to_scale] = scaler.transform(X_train[columns_to_scale])

# Transforming the validation and test sets
X_val[columns_to_scale] = scaler.transform(X_val[columns_to_scale])
X_test[columns_to_scale] = scaler.transform(X_test[columns_to_scale])
```

In [44]:

```
X_train.head(10)
```

Out[44]:

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Geography_G
5292	0.976155	-1.047381	0.347046	-1.212523	2	1	0	0.939366	
3879	1.316949	-0.572048	1.377238	1.214872	2	0	0	1.389376	
6118	-0.190810	0.949016	0.003649	1.473810	1	0	0	0.692477	
4044	0.077695	-0.667115	1.033841	-1.212523	1	1	1	-0.347954	
3202	-0.893054	-0.572048	-0.339749	0.961751	1	1	0	-0.647963	
6142	1.079426	-0.096715	-1.369941	-1.212523	2	1	0	-1.386390	
7804	0.346200	1.899682	1.377238	0.746234	1	0	1	-1.472138	
9731	-0.448988	-0.952314	0.690443	0.428567	1	1	0	1.093685	
9086	-0.035903	-0.952314	-1.026544	-1.212523	2	1	0	1.368194	
2539	-0.686511	0.663817	0.347046	0.184697	2	1	0	0.347509	

Model Building

Model Evaluation Criterion

Recall is important when the cost of false negatives is high.In the case of customer churn prediction, reducing false negatives is crucial since it minimizes the situations in which the model is unable to identify customers who are most likely to depart. False negatives are the result of missed chances to take preventative measures, such as providing incentives to keep consumers and stop them from leaving.

Model Building: Neural Network

In [46]:

```
# initializing the model
model = Sequential()

#input layer
model.add(Dense(units=32, activation='relu', input_dim=11))

#hidden layer
model.add(Dense(units=64, activation='relu'))

#output layer
model.add(Dense(1, activation='sigmoid'))
```

In [48]:

```
# Creating the model with SGD optimizer with default learning rate and recall as the metr
ic
model.compile(optimizer='sgd',
              loss='binary_crossentropy',
              metrics=[tf.keras.metrics.Recall()])
```

In [49]:

```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_3 (Dense)             (None, 32)                384

 dense_4 (Dense)             (None, 64)                2112

 dense_5 (Dense)             (None, 1)                 65

=================================================================
Total params: 2561 (10.00 KB)
Trainable params: 2561 (10.00 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [50]:

```
X_train = X_train.astype(int)
X_val = X_val.astype(int)
X_test = X_test.astype(int)

y_train = y_train.astype(int)
y_val = y_val.astype(int)
y_test = y_test.astype(int)
```

In [51]:

```
history = model.fit(X_train, y_train, epochs=50,validation_data=(X_val, y_val), batch_si
ze=32)
```

```
Epoch 1/50
```

```
WARNING:tensorflow:From C:\Users\SHREYA\AppData\Roaming\Python\Python39\site-packages\ker
as\src\utils\tf_utils.py:492: The name tf.ragged.RaggedTensorValue is deprecated. Please
use tf.compat.v1.ragged.RaggedTensorValue instead.

200/200 [==============================] - 2s 6ms/step - loss: 0.5593 - recall_1: 0.0667
- val_loss: 0.4920 - val_recall_1: 0.0000e+00
Epoch 2/50
200/200 [==============================] - 1s 3ms/step - loss: 0.4904 - recall_1: 0.0000e
+00 - val_loss: 0.4829 - val_recall_1: 0.0000e+00
Epoch 3/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4832 - recall_1: 0.0000e
+00 - val_loss: 0.4766 - val_recall_1: 0.0000e+00
Epoch 4/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4771 - recall_1: 0.0000e
+00 - val_loss: 0.4715 - val_recall_1: 0.0000e+00
Epoch 5/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4723 - recall_1: 0.0000e
+00 - val_loss: 0.4668 - val_recall_1: 0.0000e+00
Epoch 6/50
200/200 [==============================] - 1s 3ms/step - loss: 0.4680 - recall_1: 7.6687e
-04 - val_loss: 0.4631 - val_recall_1: 0.0031
Epoch 7/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4646 - recall_1: 0.0031
- val_loss: 0.4598 - val_recall_1: 0.0061
Epoch 8/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4615 - recall_1: 0.0077
- val_loss: 0.4572 - val_recall_1: 0.0153
Epoch 9/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4588 - recall_1: 0.0169
- val_loss: 0.4551 - val_recall_1: 0.0153
Epoch 10/50
200/200 [==============================] - 1s 3ms/step - loss: 0.4569 - recall_1: 0.0261
- val_loss: 0.4528 - val_recall_1: 0.0276
Epoch 11/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4550 - recall_1: 0.0368
- val_loss: 0.4512 - val_recall_1: 0.0368
Epoch 12/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4536 - recall_1: 0.0475
- val_loss: 0.4496 - val_recall_1: 0.0429
Epoch 13/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4522 - recall_1: 0.0544
- val_loss: 0.4484 - val_recall_1: 0.0583
Epoch 14/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4510 - recall_1: 0.0629
- val_loss: 0.4471 - val_recall_1: 0.0583
Epoch 15/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4496 - recall_1: 0.0698
- val_loss: 0.4466 - val_recall_1: 0.0798
Epoch 16/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4488 - recall_1: 0.0767
- val_loss: 0.4452 - val_recall_1: 0.0706
Epoch 17/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4478 - recall_1: 0.0775
- val_loss: 0.4450 - val_recall_1: 0.0798
Epoch 18/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4472 - recall_1: 0.0844
- val_loss: 0.4435 - val_recall_1: 0.0767
Epoch 19/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4462 - recall_1: 0.0844
- val_loss: 0.4428 - val_recall_1: 0.0798
Epoch 20/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4455 - recall_1: 0.0890
- val_loss: 0.4420 - val_recall_1: 0.0798
Epoch 21/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4446 - recall_1: 0.0943
- val_loss: 0.4413 - val_recall_1: 0.0736
Epoch 22/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4437 - recall_1: 0.0951
- val_loss: 0.4404 - val_recall_1: 0.0828
Epoch 23/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4427 - recall_1: 0.1089
- val_loss: 0.4397 - val_recall_1: 0.0767
```

```
Epoch 24/50
200/200 [==============================] - 1s 3ms/step - loss: 0.4420 - recall_1: 0.1028
- val_loss: 0.4387 - val_recall_1: 0.0859
Epoch 25/50
200/200 [==============================] - 1s 3ms/step - loss: 0.4410 - recall_1: 0.1120
- val_loss: 0.4379 - val_recall_1: 0.0828
Epoch 26/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4400 - recall_1: 0.1196
- val_loss: 0.4373 - val_recall_1: 0.0828
Epoch 27/50
200/200 [==============================] - 1s 3ms/step - loss: 0.4391 - recall_1: 0.1143
- val_loss: 0.4362 - val_recall_1: 0.0920
Epoch 28/50
200/200 [==============================] - 1s 3ms/step - loss: 0.4380 - recall_1: 0.1219
- val_loss: 0.4353 - val_recall_1: 0.1135
Epoch 29/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4368 - recall_1: 0.1273
- val_loss: 0.4343 - val_recall_1: 0.1135
Epoch 30/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4358 - recall_1: 0.1342
- val_loss: 0.4334 - val_recall_1: 0.1227
Epoch 31/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4345 - recall_1: 0.1419
- val_loss: 0.4325 - val_recall_1: 0.1166
Epoch 32/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4334 - recall_1: 0.1472
- val_loss: 0.4316 - val_recall_1: 0.1196
Epoch 33/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4321 - recall_1: 0.1457
- val_loss: 0.4302 - val_recall_1: 0.1258
Epoch 34/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4306 - recall_1: 0.1503
- val_loss: 0.4290 - val_recall_1: 0.1442
Epoch 35/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4293 - recall_1: 0.1595
- val_loss: 0.4278 - val_recall_1: 0.1472
Epoch 36/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4281 - recall_1: 0.1656
- val_loss: 0.4266 - val_recall_1: 0.1564
Epoch 37/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4263 - recall_1: 0.1702
- val_loss: 0.4259 - val_recall_1: 0.1718
Epoch 38/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4250 - recall_1: 0.1718
- val_loss: 0.4242 - val_recall_1: 0.1380
Epoch 39/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4234 - recall_1: 0.1733
- val_loss: 0.4226 - val_recall_1: 0.1564
Epoch 40/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4216 - recall_1: 0.1833
- val_loss: 0.4210 - val_recall_1: 0.1595
Epoch 41/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4199 - recall_1: 0.1802
- val_loss: 0.4196 - val_recall_1: 0.1902
Epoch 42/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4181 - recall_1: 0.1902
- val_loss: 0.4180 - val_recall_1: 0.1626
Epoch 43/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4162 - recall_1: 0.1863
- val_loss: 0.4167 - val_recall_1: 0.1963
Epoch 44/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4148 - recall_1: 0.2025
- val_loss: 0.4152 - val_recall_1: 0.1810
Epoch 45/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4131 - recall_1: 0.1986
- val_loss: 0.4135 - val_recall_1: 0.1963
Epoch 46/50
200/200 [==============================] - 1s 3ms/step - loss: 0.4111 - recall_1: 0.2040
- val_loss: 0.4134 - val_recall_1: 0.2515
Epoch 47/50
200/200 [==============================] - 1s 3ms/step - loss: 0.4099 - recall_1: 0.2193
- val_loss: 0.4107 - val_recall_1: 0.1933
```

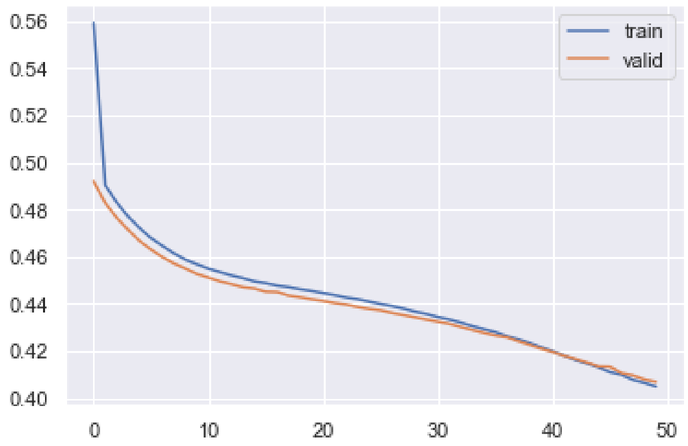
```
Epoch 48/50
200/200 [==============================] - 1s 3ms/step - loss: 0.4078 - recall_1: 0.2124
- val_loss: 0.4097 - val_recall_1: 0.2454
Epoch 49/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4065 - recall_1: 0.2362
- val_loss: 0.4079 - val_recall_1: 0.2025
Epoch 50/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4049 - recall_1: 0.2362
- val_loss: 0.4069 - val_recall_1: 0.2055
```

In [52]:

```
# Capturing learning history per epoch
hist = pd.DataFrame(history.history)
hist["epoch"] = history.epoch

# Plotting accuracy at different epochs
plt.plot(hist["loss"])
plt.plot(hist["val_loss"])
plt.legend(("train", "valid"), loc=0)
```

Out[52]:

```
<matplotlib.legend.Legend at 0x159399120d0>
```

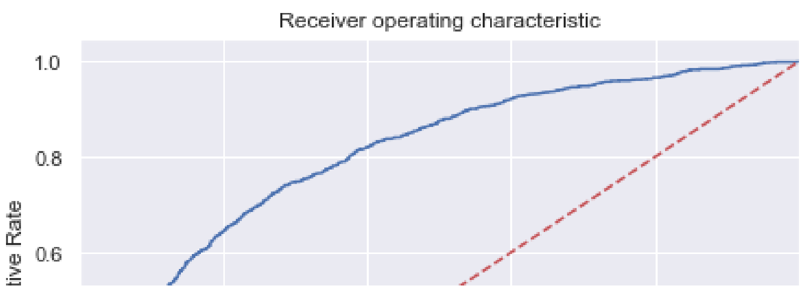


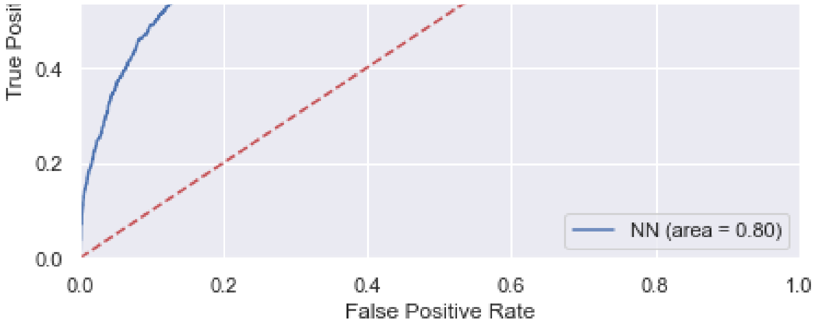
Since the learning curves (training and validation) closely follow each other across epochs, it indicates that the model is likely generalizing well to both the training and validation datasets.

In [53]:

```
# ROC-AUC on training set
NN_roc_auc_train= roc_auc_score(y_train.astype(float), model.predict(X_train))
fpr, tpr, thresholds = roc_curve(y_train.astype(float), model.predict(X_train))
plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, label="NN (area = %0.2f)" % NN_roc_auc_train)
plt.plot([0, 1], [0, 1], "r--")
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic")
plt.legend(loc="lower right")
plt.show()
```

```
200/200 [==============================] - 1s 2ms/step
200/200 [==============================] - 1s 2ms/step
```

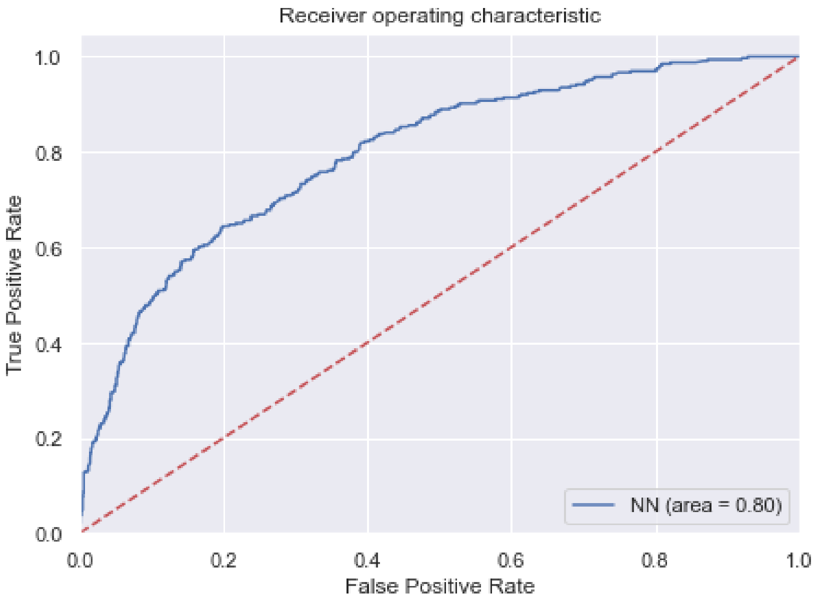




In [54]:

```
# ROC-AUC on validation set
NN_roc_auc_val = roc_auc_score(y_val.astype(float), model.predict(X_val))
fpr, tpr, thresholds = roc_curve(y_val.astype(float), model.predict(X_val))
plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, label="NN (area = %0.2f)" % NN_roc_auc_train)
plt.plot([0, 1], [0, 1], "r--")
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic")
plt.legend(loc="lower right")
plt.show()
```

```
50/50 [==============================] - 0s 2ms/step
50/50 [==============================] - 0s 1ms/step
```



In [55]:

```
# Optimal threshold using AUC-ROC curve
# The optimal cut off would be where tpr is high and fpr is low
fpr, tpr, thresholds = roc_curve(y_train.astype(float), model.predict(X_train))

optimal_idx = np.argmax(tpr - fpr)
optimal_threshold_auc_roc = thresholds[optimal_idx]
print(optimal_threshold_auc_roc)
```

```
200/200 [==============================] - 0s 2ms/step
0.20008567
```

In [56]:

```
def make_confusion_matrix(
    cf,
    group_names=None,
    categories="auto",
    count=True,
```

```
    percent=True,
    cbar=True,
    xyticks=True,
    xyplotlabels=True,
    sum_stats=True,
    figsize=None,
    cmap="Blues",
    title=None,
):
    """
    This function will make a pretty plot of an sklearn Confusion Matrix cf using a Seaborn heatmap visualization.

    """

    blanks = ["" for _ in range(cf.size)]

    if group_names and len(group_names) == cf.size:
        group_labels = ["{}\n".format(value) for value in group_names]
    else:
        group_labels = blanks

    if count:
        group_counts = ["{0:0.0f}\n".format(value) for value in cf.flatten()]
    else:
        group_counts = blanks

    if percent:
        group_percentages = [
            "{0:.2%}".format(value) for value in cf.flatten() / np.sum(cf)
        ]
    else:
        group_percentages = blanks

    box_labels = [
        f"{v1}{v2}{v3}".strip()
        for v1, v2, v3 in zip(group_labels, group_counts, group_percentages)
    ]
    box_labels = np.asarray(box_labels).reshape(cf.shape[0], cf.shape[1])

    # CODE TO GENERATE SUMMARY STATISTICS & TEXT FOR SUMMARY STATS
    if sum_stats:
        # Accuracy is sum of diagonal divided by total observations
        accuracy = np.trace(cf) / float(np.sum(cf))

        # if it is a binary confusion matrix, show some more stats
        if len(cf) == 2:
            # Metrics for Binary Confusion Matrices
            precision = cf[1, 1] / sum(cf[:, 1])
            recall = cf[1, 1] / sum(cf[1, :])
            f1_score = 2 * precision * recall / (precision + recall)
            stats_text = "\n\nAccuracy={:0.3f}\nPrecision={:0.3f}\nRecall={:0.3f}\nF1 Score={:0.3f}".format(
                accuracy, precision, recall, f1_score
            )
        else:
            stats_text = "\n\nAccuracy={:0.3f}".format(accuracy)


    else:
        stats_text = ""

    # SET FIGURE PARAMETERS ACCORDING TO OTHER ARGUMENTS
    if figsize is None:
        # Get default figure size if not set
        figsize = plt.rcParams.get("figure.figsize")

    if not xyticks:
        # Do not show categories if xyticks is False
        categories = False

    # MAKE THE HEATMAP VISUALIZATION
```

```
    plt.figure(figsize=figsize)
    sns.heatmap(
        cf,
        annot=box_labels,
        fmt="",
        cmap=cmap,
        cbar=cbar,
        xticklabels=categories,
        yticklabels=categories,
    )

    if xyplotlabels:
        plt.ylabel("True label")
        plt.xlabel("Predicted label" + stats_text)
    else:
        plt.xlabel(stats_text)

    if title:
        plt.title(title)

    # Creating a DataFrame for metrics

    metrics_df = pd.DataFrame({
        'Metric': ['Accuracy', 'Precision', 'Recall', 'F1 Score'],
        'Score': [accuracy, precision, recall, f1_score]
    })

    return metrics_df.T
```

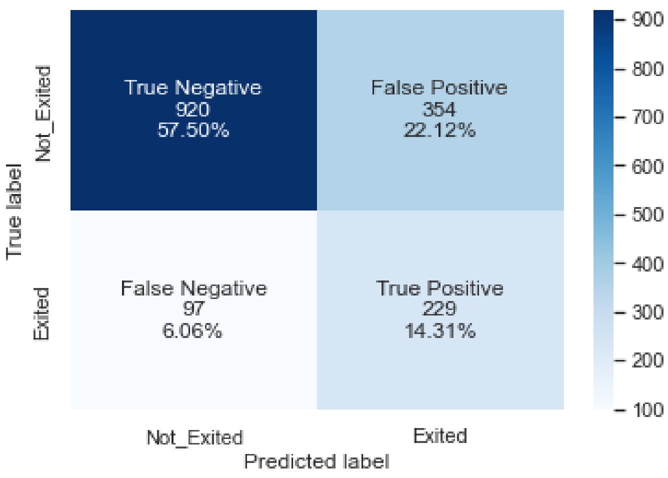
In [57]:

```
# Predictions on validation set
y_pred_val = model.predict(X_val)

# Applying the optimal threshold
y_pred_val_binary = (y_pred_val > optimal_threshold_auc_roc).astype(int)

# Creating confusion matrix
cm_val = confusion_matrix(y_val, y_pred_val_binary)

# Define labels and categories
labels = ["True Negative", "False Positive", "False Negative", "True Positive"]
categories = ["Not_Exited", "Exited"]

# Plotting confusion matrix
make_confusion_matrix(cm_val, group_names=labels, categories=categories, cmap="Blues")
```

```
50/50 [==============================] - 0s 2ms/step
```

Out[57]:

	0	1	2	3
Metric	Accuracy	Precision	Recall	F1 Score
Score	0.718125	0.392796	0.702454	0.50385



Accuracy=0.718
Precision=0.393
Recall=0.702
F1 Score=0.504

1. **Accuracy (0.718125): This is the proportion of total predictions that the model got right. In this case, the model correctly predicted whether a customer will leave the bank or not about 71.81% of the time.**
2. **Precision (0.392796): This is the proportion of positive identifications (i.e., a customer will leave the bank) that were actually correct.When the model predicted that a customer will leave the bank, it was correct only about 39.28% of the time.**
3. **Recall (0.702454): This is the proportion of actual positives that were identified correctly. In this case, the model correctly identified 70.25% of the customers who actually left the bank.**
4. **F1 Score (0.50385): F1 Score is approximately 0.50, which is not very high.**

Model Building: Neural Network model with Adam Optimizer

In [58]:

```
model1 = Sequential()

# Adding the input layer
model1.add(Dense(units=32, activation='relu', input_dim=11))

#Adding the hidden layer
model1.add(Dense(units=16, activation="relu"))

# Adding the output layer
model1.add(Dense(1, activation='sigmoid'))
```

In [59]:

```
# Compiling the model

model1.compile(optimizer='Adam',
               loss='binary_crossentropy',
               metrics=[tf.keras.metrics.Recall()])
```

In [60]:

```
model1.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_6 (Dense)             (None, 32)                384

 dense_7 (Dense)             (None, 16)                528

 dense_8 (Dense)             (None, 1)                 17

=================================================================
Total params: 929 (3.63 KB)
Trainable params: 929 (3.63 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [61]:

```
history1 = model1.fit(X_train, y_train, epochs=50,validation_data=(X_val, y_val), batch_
size=32)
```

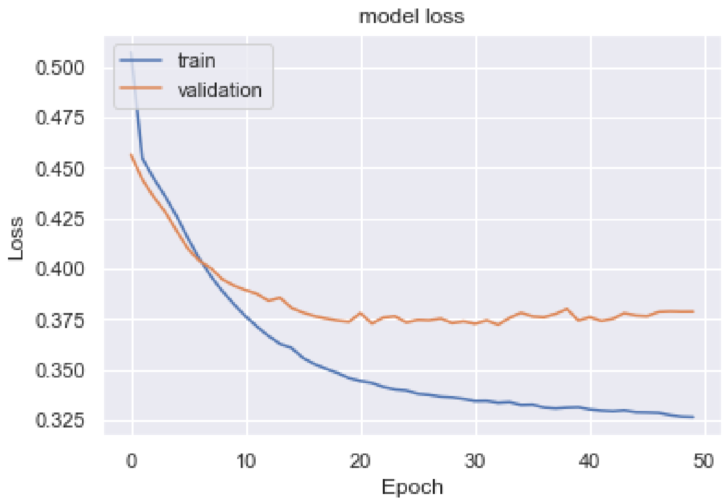
```
Epoch 1/50
200/200 [==============================] - 3s 6ms/step - loss: 0.5072 - recall_2: 0.1035
- val_loss: 0.4564 - val_recall_2: 0.0460
Epoch 2/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4547 - recall_2: 0.0897
- val_loss: 0.4442 - val_recall_2: 0.1043
```

```
Epoch 3/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4446 - recall_2: 0.1288
- val_loss: 0.4354 - val_recall_2: 0.1595
Epoch 4/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4357 - recall_2: 0.1687
- val_loss: 0.4280 - val_recall_2: 0.1534
Epoch 5/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4259 - recall_2: 0.2032
- val_loss: 0.4186 - val_recall_2: 0.1718
Epoch 6/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4148 - recall_2: 0.2408
- val_loss: 0.4096 - val_recall_2: 0.2086
Epoch 7/50
200/200 [==============================] - 1s 3ms/step - loss: 0.4046 - recall_2: 0.2646
- val_loss: 0.4038 - val_recall_2: 0.2638
Epoch 8/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3961 - recall_2: 0.3044
- val_loss: 0.4000 - val_recall_2: 0.2147
Epoch 9/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3887 - recall_2: 0.3152
- val_loss: 0.3946 - val_recall_2: 0.2791
Epoch 10/50
200/200 [==============================] - 1s 3ms/step - loss: 0.3823 - recall_2: 0.3344
- val_loss: 0.3916 - val_recall_2: 0.3098
Epoch 11/50
200/200 [==============================] - 1s 3ms/step - loss: 0.3764 - recall_2: 0.3482
- val_loss: 0.3893 - val_recall_2: 0.2822
Epoch 12/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3712 - recall_2: 0.3566
- val_loss: 0.3874 - val_recall_2: 0.3436
Epoch 13/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3666 - recall_2: 0.3765
- val_loss: 0.3840 - val_recall_2: 0.3160
Epoch 14/50
200/200 [==============================] - 1s 3ms/step - loss: 0.3626 - recall_2: 0.3888
- val_loss: 0.3856 - val_recall_2: 0.3190
Epoch 15/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3607 - recall_2: 0.3811
- val_loss: 0.3806 - val_recall_2: 0.3957
Epoch 16/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3558 - recall_2: 0.4064
- val_loss: 0.3782 - val_recall_2: 0.3221
Epoch 17/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3527 - recall_2: 0.4080
- val_loss: 0.3765 - val_recall_2: 0.3466
Epoch 18/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3504 - recall_2: 0.4003
- val_loss: 0.3753 - val_recall_2: 0.3221
Epoch 19/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3483 - recall_2: 0.4164
- val_loss: 0.3743 - val_recall_2: 0.3344
Epoch 20/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3458 - recall_2: 0.4248
- val_loss: 0.3736 - val_recall_2: 0.3528
Epoch 21/50
200/200 [==============================] - 1s 3ms/step - loss: 0.3443 - recall_2: 0.4310
- val_loss: 0.3779 - val_recall_2: 0.2975
Epoch 22/50
200/200 [==============================] - 0s 2ms/step - loss: 0.3434 - recall_2: 0.4233
- val_loss: 0.3728 - val_recall_2: 0.3957
Epoch 23/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3414 - recall_2: 0.4371
- val_loss: 0.3757 - val_recall_2: 0.3129
Epoch 24/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3401 - recall_2: 0.4279
- val_loss: 0.3764 - val_recall_2: 0.3773
Epoch 25/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3396 - recall_2: 0.4356
- val_loss: 0.3733 - val_recall_2: 0.3436
Epoch 26/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3380 - recall_2: 0.4310
- val_loss: 0.3746 - val_recall_2: 0.3160
```

```
Epoch 27/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3374 - recall_2: 0.4394
- val_loss: 0.3744 - val_recall_2: 0.3834
Epoch 28/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3365 - recall_2: 0.4363
- val_loss: 0.3752 - val_recall_2: 0.3160
Epoch 29/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3361 - recall_2: 0.4425
- val_loss: 0.3731 - val_recall_2: 0.4110
Epoch 30/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3354 - recall_2: 0.4363
- val_loss: 0.3739 - val_recall_2: 0.4356
Epoch 31/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3344 - recall_2: 0.4456
- val_loss: 0.3727 - val_recall_2: 0.3681
Epoch 32/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3344 - recall_2: 0.4379
- val_loss: 0.3744 - val_recall_2: 0.3313
Epoch 33/50
200/200 [==============================] - 1s 3ms/step - loss: 0.3335 - recall_2: 0.4425
- val_loss: 0.3721 - val_recall_2: 0.3865
Epoch 34/50
200/200 [==============================] - 1s 3ms/step - loss: 0.3339 - recall_2: 0.4509
- val_loss: 0.3756 - val_recall_2: 0.3405
Epoch 35/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3325 - recall_2: 0.4425
- val_loss: 0.3781 - val_recall_2: 0.4785
Epoch 36/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3326 - recall_2: 0.4525
- val_loss: 0.3763 - val_recall_2: 0.3313
Epoch 37/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3312 - recall_2: 0.4417
- val_loss: 0.3759 - val_recall_2: 0.3896
Epoch 38/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3308 - recall_2: 0.4471
- val_loss: 0.3775 - val_recall_2: 0.3344
Epoch 39/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3312 - recall_2: 0.4433
- val_loss: 0.3801 - val_recall_2: 0.3129
Epoch 40/50
200/200 [==============================] - 1s 3ms/step - loss: 0.3314 - recall_2: 0.4479
- val_loss: 0.3743 - val_recall_2: 0.4018
Epoch 41/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3302 - recall_2: 0.4371
- val_loss: 0.3760 - val_recall_2: 0.3436
Epoch 42/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3296 - recall_2: 0.4471
- val_loss: 0.3740 - val_recall_2: 0.3405
Epoch 43/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3293 - recall_2: 0.4486
- val_loss: 0.3751 - val_recall_2: 0.3712
Epoch 44/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3297 - recall_2: 0.4563
- val_loss: 0.3779 - val_recall_2: 0.3896
Epoch 45/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3289 - recall_2: 0.4624
- val_loss: 0.3767 - val_recall_2: 0.3742
Epoch 46/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3287 - recall_2: 0.4509
- val_loss: 0.3764 - val_recall_2: 0.3957
Epoch 47/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3286 - recall_2: 0.4640
- val_loss: 0.3786 - val_recall_2: 0.3773
Epoch 48/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3274 - recall_2: 0.4601
- val_loss: 0.3789 - val_recall_2: 0.3282
Epoch 49/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3266 - recall_2: 0.4678
- val_loss: 0.3787 - val_recall_2: 0.3497
Epoch 50/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3264 - recall_2: 0.4571
- val_loss: 0.3787 - val_recall_2: 0.3620
```

In [62]:

```
plt.plot(history1.history['loss'])
plt.plot(history1.history['val_loss'])
plt.title('model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```



Observations:
-The increasing gap validation loss curve between train and suggests that the model is continuing to improve its fit to the training data, but these improvements are not translating to the validation data.
-This could be a sign of overfitting.

In [63]:

```
#Training the model to early stop

model_e = Sequential()
model_e.add(Dense(units=32, activation='relu', input_dim=11))
model_e.add(Dense(units=16, activation='relu'))
model_e.add(Dense(units=1, activation='sigmoid'))


# Compile the model
model_e.compile(optimizer='Adam',
              loss='binary_crossentropy',
              metrics=[tf.keras.metrics.Recall()])
```

In [64]:

```
#Importing classback API
from keras import callbacks


# Define early stopping
early_stopping = callbacks.EarlyStopping(monitor='val_loss', min_delta=0.001, patience=5)

# Train the model with early stopping
history_e = model_e.fit(X_train, y_train, epochs=50, validation_data=(X_val, y_val),
                    batch_size=32, callbacks=[early_stopping], verbose=1)
```

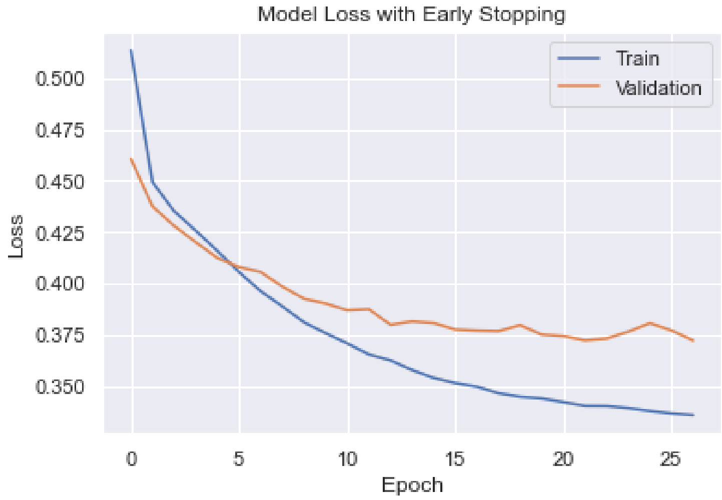
```
Epoch 1/50
200/200 [==============================] - 3s 6ms/step - loss: 0.5134 - recall_3: 0.0176
- val_loss: 0.4606 - val_recall_3: 0.0123
Epoch 2/50
200/200 [==============================] - 1s 3ms/step - loss: 0.4493 - recall_3: 0.0989
- val_loss: 0.4375 - val_recall_3: 0.0951
Epoch 3/50
```

```
Epoch 3/50
200/200 [==============================] - 1s 3ms/step - loss: 0.4352 - recall_3: 0.1327
- val_loss: 0.4280 - val_recall_3: 0.1718
Epoch 4/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4257 - recall_3: 0.1741
- val_loss: 0.4200 - val_recall_3: 0.1871
Epoch 5/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4158 - recall_3: 0.2109
- val_loss: 0.4124 - val_recall_3: 0.2454
Epoch 6/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4055 - recall_3: 0.2446
- val_loss: 0.4079 - val_recall_3: 0.2485
Epoch 7/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3962 - recall_3: 0.2669
- val_loss: 0.4056 - val_recall_3: 0.3190
Epoch 8/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3889 - recall_3: 0.3075
- val_loss: 0.3985 - val_recall_3: 0.2577
Epoch 9/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3811 - recall_3: 0.3267
- val_loss: 0.3926 - val_recall_3: 0.3282
Epoch 10/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3758 - recall_3: 0.3397
- val_loss: 0.3903 - val_recall_3: 0.2853
Epoch 11/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3708 - recall_3: 0.3443
- val_loss: 0.3870 - val_recall_3: 0.3374
Epoch 12/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3655 - recall_3: 0.3620
- val_loss: 0.3875 - val_recall_3: 0.2607
Epoch 13/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3626 - recall_3: 0.3704
- val_loss: 0.3799 - val_recall_3: 0.3344
Epoch 14/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3578 - recall_3: 0.3719
- val_loss: 0.3815 - val_recall_3: 0.2945
Epoch 15/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3540 - recall_3: 0.3957
- val_loss: 0.3807 - val_recall_3: 0.2945
Epoch 16/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3515 - recall_3: 0.4095
- val_loss: 0.3776 - val_recall_3: 0.3374
Epoch 17/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3497 - recall_3: 0.4026
- val_loss: 0.3771 - val_recall_3: 0.3374
Epoch 18/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3466 - recall_3: 0.4164
- val_loss: 0.3768 - val_recall_3: 0.3313
Epoch 19/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3448 - recall_3: 0.4118
- val_loss: 0.3797 - val_recall_3: 0.3804
Epoch 20/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3440 - recall_3: 0.4195
- val_loss: 0.3751 - val_recall_3: 0.3497
Epoch 21/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3422 - recall_3: 0.4187
- val_loss: 0.3744 - val_recall_3: 0.3681
Epoch 22/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3404 - recall_3: 0.4310
- val_loss: 0.3723 - val_recall_3: 0.4141
Epoch 23/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3404 - recall_3: 0.4363
- val_loss: 0.3732 - val_recall_3: 0.3497
Epoch 24/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3393 - recall_3: 0.4363
- val_loss: 0.3766 - val_recall_3: 0.4049
Epoch 25/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3379 - recall_3: 0.4440
- val_loss: 0.3807 - val_recall_3: 0.2883
Epoch 26/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3367 - recall_3: 0.4402
- val_loss: 0.3771 - val_recall_3: 0.3344
Epoch 27/50
```

```
200/200 [==============================] - 1s 3ms/step - loss: 0.3359 - recall_3: 0.4363
- val_loss: 0.3722 - val_recall_3: 0.3865
```

In [65]:

```python
# Plot training loss and validation loss
plt.plot(history_e.history['loss'])
plt.plot(history_e.history['val_loss'])
plt.title('Model Loss with Early Stopping')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper right')
plt.show()
```



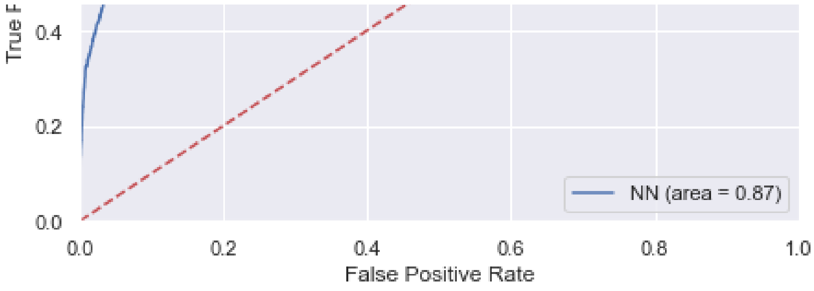
Observations:

-Training loss decreases steadily as the number of epochs increases. This indicates that the model is learning and improving its performance on the training data over time.
-The validation loss, which also decreases initially but starts to plateau and diverge from the training loss around epoch 10. This could suggest that the model is beginning to overfit the training data.

In [66]:

```python
# ROC-AUC on training set
NN_roc_auc_train= roc_auc_score(y_train.astype(float), model_e.predict(X_train))
fpr, tpr, thresholds = roc_curve(y_train.astype(float), model_e.predict(X_train))
plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, label="NN (area = %0.2f)" % NN_roc_auc_train)
plt.plot([0, 1], [0, 1], "r--")
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic")
plt.legend(loc="lower right")
plt.show()
```

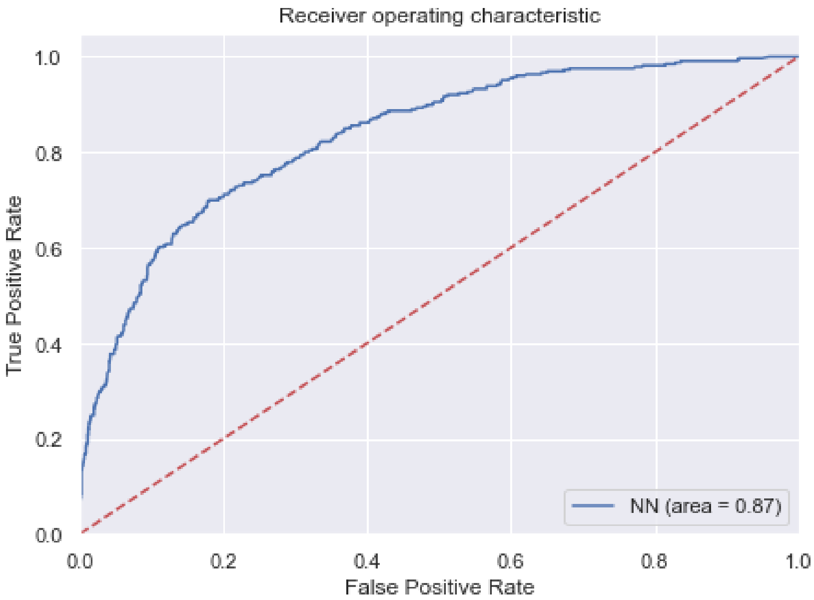
```
200/200 [==============================] - 1s 2ms/step
200/200 [==============================] - 1s 2ms/step
```



In [67]:

```
# ROC-AUC on validation set
NN_roc_auc_val = roc_auc_score(y_val.astype(float), model_e.predict(X_val))
fpr, tpr, thresholds = roc_curve(y_val.astype(float), model_e.predict(X_val))
plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, label="NN (area = %0.2f)" % NN_roc_auc_train)
plt.plot([0, 1], [0, 1], "r--")
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic")
plt.legend(loc="lower right")
plt.show()
```

```
50/50 [==============================] - 0s 2ms/step
50/50 [==============================] - 0s 2ms/step
```



In [68]:

```
# Optimal threshold using AUC-ROC curve
# The optimal cut off would be where tpr is high and fpr is low
fpr, tpr, thresholds = roc_curve(y_train.astype(float), model_e.predict(X_train))

optimal_idx = np.argmax(tpr - fpr)
optimal_threshold_auc_roc = thresholds[optimal_idx]
print(optimal_threshold_auc_roc)
```

```
200/200 [==============================] - 1s 2ms/step
0.21540754
```

The optimal threshold found using ROC-AUC curve is 0.17

In [69]:

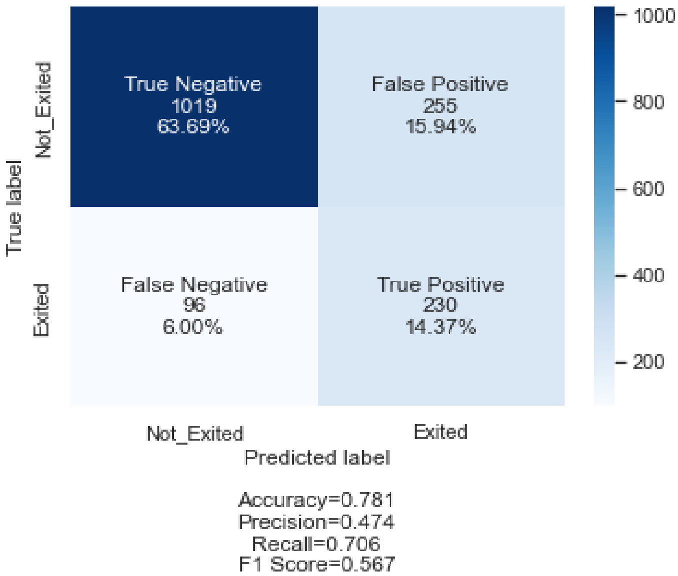
```
# Predictions on validation set
y_pred_val = model_e.predict(X_val)

# Applying the optimal threshold
```

```
y_pred_val_binary = (y_pred_val > optimal_threshold_auc_roc).astype(int)

# Creating confusion matrix
cm_val = confusion_matrix(y_val, y_pred_val_binary)

# Define labels and categories
labels = ["True Negative", "False Positive", "False Negative", "True Positive"]
categories = ["Not_Exited", "Exited"]

# Plotting confusion matrix
make_confusion_matrix(cm_val, group_names=labels, categories=categories, cmap="Blues")
```

```
50/50 [==============================] - 0s 2ms/step
```

Out[69]:

	0	1	2	3
Metric	Accuracy	Precision	Recall	F1 Score
Score	0.780625	0.474227	0.705521	0.567201



- **Accuracy (0.780625): This indicates that the model1 correctly predicted the customer churn for about 78.0625% of the customers in the dataset.**
- **Precision (0.474227): This score suggests that when the model1 predicts a customer will churn, it is correct about 47.4227% of the time.**
- **Recall (0.705521): This score tells us that the model1 correctly identified 70.5521% of the customers who actually churned.**
- **F1 Score (0.567201)**

Model Improvement: Neural Network model with Dropout

In [70]:

```
#Initializing the neural network
model2 = Sequential()

#Adding the input layer with 32 neurons and relu as activation function
model2.add(Dense(32,activation='relu',input_dim = 11))

# Adding dropout with ratio of 0.2
model2.add(Dropout(0.2))

# Adding the first hidden layer with 16 neurons with relu as activation functions
model2.add(Dense(16,activation='relu'))

# Adding dropout with ratio of 0.2
model2.add(Dropout(0.2))
```

```
# Adding the second hidden layer with 8 neurons with relu as activation functions
#model2.add(Dense(8,activation='relu'))

# Adding the output layer
model2.add(Dense(1, activation = 'sigmoid'))
```

In [71]:

```
model2.compile(optimizer='Adam',
               loss='binary_crossentropy',
               metrics=[tf.keras.metrics.Recall()])
```

In [72]:

```
# Summary of the model
model2.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_12 (Dense)            (None, 32)                384

 dropout (Dropout)           (None, 32)                0

 dense_13 (Dense)            (None, 16)                528

 dropout_1 (Dropout)         (None, 16)                0

 dense_14 (Dense)            (None, 1)                 17

=================================================================
Total params: 929 (3.63 KB)
Trainable params: 929 (3.63 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [73]:

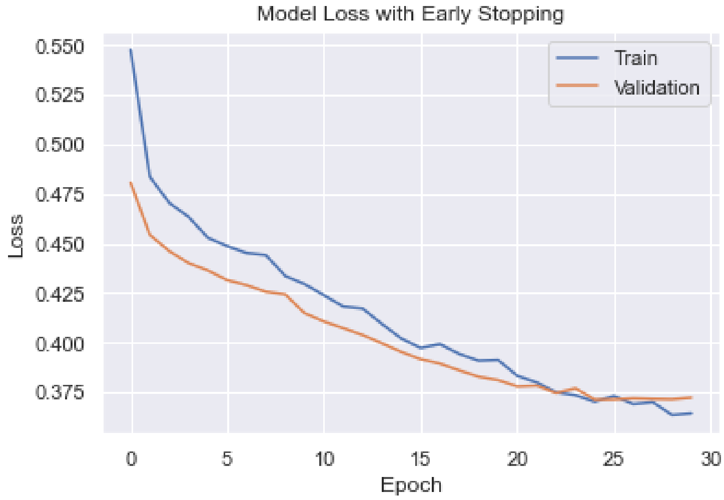
```
history2 = model2.fit(X_train,y_train,batch_size=32,epochs=50,verbose=1,validation_data=
(X_val,y_val),callbacks=[early_stopping])
```

```
Epoch 1/50
200/200 [==============================] - 2s 4ms/step - loss: 0.5476 - recall_4: 0.0521
- val_loss: 0.4807 - val_recall_4: 0.0000e+00
Epoch 2/50
200/200 [==============================] - 1s 3ms/step - loss: 0.4837 - recall_4: 0.0207
- val_loss: 0.4544 - val_recall_4: 0.0337
Epoch 3/50
200/200 [==============================] - 1s 5ms/step - loss: 0.4705 - recall_4: 0.0805
- val_loss: 0.4462 - val_recall_4: 0.1104
Epoch 4/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4635 - recall_4: 0.1127
- val_loss: 0.4401 - val_recall_4: 0.1012
Epoch 5/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4528 - recall_4: 0.1204
- val_loss: 0.4364 - val_recall_4: 0.1564
Epoch 6/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4486 - recall_4: 0.1541
- val_loss: 0.4315 - val_recall_4: 0.1503
Epoch 7/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4452 - recall_4: 0.1817
- val_loss: 0.4290 - val_recall_4: 0.1656
Epoch 8/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4442 - recall_4: 0.1825
- val_loss: 0.4257 - val_recall_4: 0.2025
Epoch 9/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4336 - recall_4: 0.2025
- val_loss: 0.4243 - val_recall_4: 0.2270
Epoch 10/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4295 - recall_4: 0.2193
- val_loss: 0.4149 - val_recall_4: 0.2362
```

```
Epoch 11/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4239 - recall_4: 0.2354
- val_loss: 0.4107 - val_recall_4: 0.2546
Epoch 12/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4183 - recall_4: 0.2515
- val_loss: 0.4073 - val_recall_4: 0.2117
Epoch 13/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4172 - recall_4: 0.2699
- val_loss: 0.4038 - val_recall_4: 0.2546
Epoch 14/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4095 - recall_4: 0.2592
- val_loss: 0.3997 - val_recall_4: 0.2485
Epoch 15/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4021 - recall_4: 0.2853
- val_loss: 0.3953 - val_recall_4: 0.2730
Epoch 16/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3974 - recall_4: 0.3098
- val_loss: 0.3917 - val_recall_4: 0.2853
Epoch 17/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3993 - recall_4: 0.3029
- val_loss: 0.3894 - val_recall_4: 0.2822
Epoch 18/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3943 - recall_4: 0.3229
- val_loss: 0.3860 - val_recall_4: 0.2914
Epoch 19/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3909 - recall_4: 0.3367
- val_loss: 0.3829 - val_recall_4: 0.2914
Epoch 20/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3913 - recall_4: 0.3298
- val_loss: 0.3811 - val_recall_4: 0.2853
Epoch 21/50
200/200 [==============================] - 1s 3ms/step - loss: 0.3833 - recall_4: 0.3344
- val_loss: 0.3779 - val_recall_4: 0.3190
Epoch 22/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3800 - recall_4: 0.3574
- val_loss: 0.3783 - val_recall_4: 0.3160
Epoch 23/50
200/200 [==============================] - 1s 3ms/step - loss: 0.3750 - recall_4: 0.3650
- val_loss: 0.3746 - val_recall_4: 0.3221
Epoch 24/50
200/200 [==============================] - 1s 5ms/step - loss: 0.3735 - recall_4: 0.3581
- val_loss: 0.3770 - val_recall_4: 0.3528
Epoch 25/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3703 - recall_4: 0.3811
- val_loss: 0.3713 - val_recall_4: 0.3650
Epoch 26/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3731 - recall_4: 0.3627
- val_loss: 0.3713 - val_recall_4: 0.3344
Epoch 27/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3691 - recall_4: 0.3735
- val_loss: 0.3719 - val_recall_4: 0.3374
Epoch 28/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3701 - recall_4: 0.3673
- val_loss: 0.3716 - val_recall_4: 0.3221
Epoch 29/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3635 - recall_4: 0.3773
- val_loss: 0.3714 - val_recall_4: 0.3528
Epoch 30/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3644 - recall_4: 0.3880
- val_loss: 0.3723 - val_recall_4: 0.3528
```

In [74]:

```
# Plot training loss and validation loss
plt.plot(history2.history['loss'])
plt.plot(history2.history['val_loss'])
plt.title('Model Loss with Early Stopping')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper right')
plt.show()
```

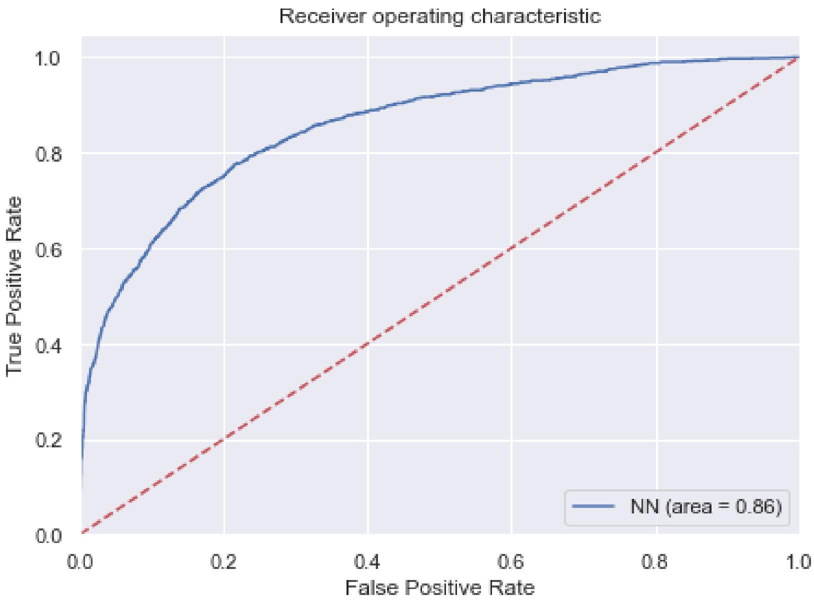


Observations:
Towards the end, the training loss continues to decrease slightly while the validation loss remains relatively stable. This could suggest that the model is starting to overfit.

In [75]:

```
# ROC-AUC on training set
NN_roc_auc_train= roc_auc_score(y_train.astype(float), model2.predict(X_train))
fpr, tpr, thresholds = roc_curve(y_train.astype(float), model2.predict(X_train))
plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, label="NN (area = %0.2f)" % NN_roc_auc_train)
plt.plot([0, 1], [0, 1], "r--")
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic")
plt.legend(loc="lower right")
plt.show()
```

```
200/200 [==============================] - 0s 2ms/step
200/200 [==============================] - 0s 2ms/step
```

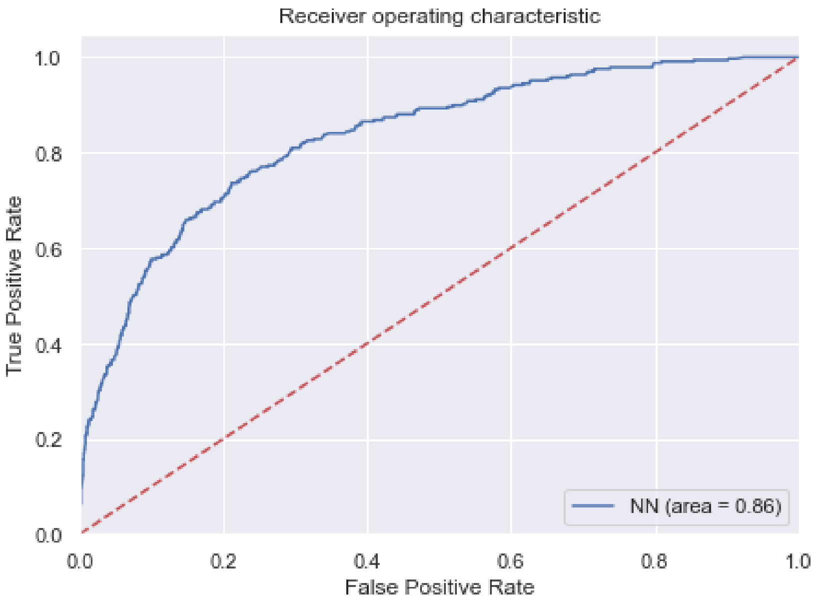


In [76]:

```
# ROC-AUC on validation set
NN_roc_auc_val = roc_auc_score(y_val.astype(float), model2.predict(X_val))
fpr, tpr, thresholds = roc_curve(y_val.astype(float), model2.predict(X_val))
plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, label="NN (area = %0.2f)" % NN_roc_auc_train)
```

```
plt.plot([0, 1], [0, 1], "r--")
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic")
plt.legend(loc="lower right")
plt.show()
```

```
50/50 [==============================] - 0s 2ms/step
50/50 [==============================] - 0s 3ms/step
```



In [77]:

```
# Optimal threshold using AUC-ROC curve
# The optimal cut off would be where tpr is high and fpr is low
fpr, tpr, thresholds = roc_curve(y_train.astype(float), model2.predict(X_train))

optimal_idx = np.argmax(tpr - fpr)
optimal_threshold_auc_roc = thresholds[optimal_idx]
print(optimal_threshold_auc_roc)
```

```
200/200 [==============================] - 1s 2ms/step
0.18691029
```

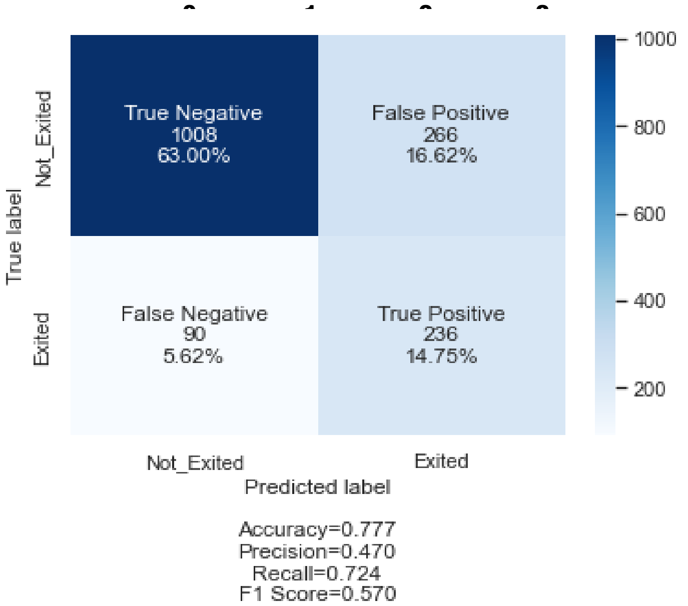
In [78]:

```
# Predictions on validation set
y_pred_val = model2.predict(X_val)

# Applying the optimal threshold
y_pred_val_binary = (y_pred_val > optimal_threshold_auc_roc).astype(int)

# Creating confusion matrix
cm_val = confusion_matrix(y_val, y_pred_val_binary)

# Define labels and categories
labels = ["True Negative", "False Positive", "False Negative", "True Positive"]
categories = ["Not_Exited", "Exited"]

# Plotting confusion matrix
make_confusion_matrix(cm_val, group_names=labels, categories=categories, cmap="Blues")
```

```
50/50 [==============================] - 0s 3ms/step
```

Out[78]:

	0	1	2	3
Metric	Accuracy	Precision	Recall	F1 Score
Score	0.7775	0.47012	0.723926	0.570048



1. **Accuracy:** Model 2 has an accuracy of 0.7775, which is higher than the 0.718125 of Model 1.Model 2 is correctly predicting whether a customer will leave the bank or not more often than Model 1.
2. **Precision:** The precision of Model 2 is 0.47012, which is also higher than the 0.392796 of Model 1.Model 2, when predicting that a customer will leave the bank, is correct more often than Model 1.
3. **Recall:** The recall of Model 2 is 0.723926, which is slightly higher than the 0.702454 of Model 1. This means Model 2 is slightly better at correctly identifying customers who will actually leave the bank.
4. **F1 Score:** The F1 score of Model 2 is 0.570048, which is higher than the 0.50385 of Model 1.

Model Improvement: Neural Network model with Hyperparameter tuning

In [79]:

```
def create_model(layer_1=32, layer_2=16, lr=0.001, dropout_rate1=0.0, dropout_rate2=0.0)
:
    # Initializing the neural network
    model_3 = Sequential()

    # Adding the input layer (by specifying input dimension)
    model_3.add(Dense(layer_1, activation='relu', input_dim=X_train.shape[1]))
    # Adding dropout before the hidden layer
    model_3.add(Dropout(dropout_rate1))

    # Adding the hidden layer
    model_3.add(Dense(layer_2, activation='relu'))
    # Adding dropout after the hidden layer
    model_3.add(Dropout(dropout_rate2))

    # Adding the output layer
    # We have an output of 1 node, which is the desired dimensions of our output (stay wi
th the bank or not)
    # We use the sigmoid because we want probability outcomes
    model_3.add(Dense(1, activation='sigmoid'))

    # Adding Adam initializer
    optimizer = tf.keras.optimizers.Adam(learning_rate=lr)

    # Compile model
    model_3.compile(optimizer=optimizer, loss='binary_crossentropy', metrics=[tf.keras.m
etrics.Recall()])

    return model_3
```

In [80]:

```
keras_estimator = KerasClassifier(build_fn=create_model, verbose=1,dropout_rate1=0.0,drop
out_rate2=0.0,lr=0.001)
```

In [81]:

```
from sklearn.model_selection import GridSearchCV
# Define the grid search parameters
param_grid = {
    'batch_size': [32, 64, 128],
    'lr': [0.01, 0.001, 0.1],
    'dropout_rate1': [0.0, 0.1, 0.2],
    'dropout_rate2': [0.0, 0.1, 0.2]
}

kfold_splits = 3

# Applying GridSearchCV
grid = GridSearchCV(estimator=keras_estimator,
                    verbose=1,
                    cv=kfold_splits,
                    param_grid=param_grid,
                    n_jobs=-1)
```

In [82]:

```
## Fitting Grid model
grid_result = grid.fit(X_train, y_train,validation_data = (X_val,y_val),verbose=1)

# Summarize results
print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
# Printing mean
means = grid_result.cv_results_['mean_test_score']
# Printing standard deviation
stds = grid_result.cv_results_['std_test_score']
# Printing best parameters
params = grid_result.cv_results_['params']
```

```
Fitting 3 folds for each of 81 candidates, totalling 243 fits
200/200 [==============================] - 5s 11ms/step - loss: 0.4738 - recall_5: 0.0667
- val_loss: 0.4353 - val_recall_5: 0.1472
Best: 0.811719 using {'batch_size': 32, 'dropout_rate1': 0.0, 'dropout_rate2': 0.1, 'lr':
0.01}
```

Observations:
The best combination found from Grid Search is a batch size of 32 and a learning rate (lr) of 0.01.

In [83]:

```
# Creating the model
model3=create_model(lr=grid_result.best_params_['lr'])
# Printing model summary
model3.summary()
```

```
Model: "sequential_6"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_18 (Dense)            (None, 32)                384

 dropout_4 (Dropout)         (None, 32)                0

 dense_19 (Dense)            (None, 16)                528

 dropout_5 (Dropout)         (None, 16)                0

 dense_20 (Dense)            (None, 1)                 17

=================================================================
Total params: 929 (3.63 KB)
Trainable params: 929 (3.63 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

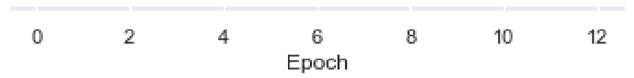
In [84]:

```
# Fitting the model
history3= model3.fit(X_train, y_train, epochs=50, batch_size = grid_result.best_params_[
'batch_size'], verbose=1,validation_data=(X_val,y_val),callbacks=[early_stopping])
```

```
Epoch 1/50
200/200 [==============================] - 3s 7ms/step - loss: 0.4611 - recall_6: 0.0936
- val_loss: 0.4328 - val_recall_6: 0.1411
Epoch 2/50
200/200 [==============================] - 1s 4ms/step - loss: 0.4127 - recall_6: 0.2876
- val_loss: 0.4004 - val_recall_6: 0.3620
Epoch 3/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3859 - recall_6: 0.3451
- val_loss: 0.3827 - val_recall_6: 0.2945
Epoch 4/50
200/200 [==============================] - 1s 3ms/step - loss: 0.3694 - recall_6: 0.3880
- val_loss: 0.3771 - val_recall_6: 0.3160
Epoch 5/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3659 - recall_6: 0.4011
- val_loss: 0.3747 - val_recall_6: 0.3436
Epoch 6/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3625 - recall_6: 0.4210
- val_loss: 0.3761 - val_recall_6: 0.3436
Epoch 7/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3607 - recall_6: 0.4172
- val_loss: 0.3788 - val_recall_6: 0.3558
Epoch 8/50
200/200 [==============================] - 1s 5ms/step - loss: 0.3556 - recall_6: 0.4248
- val_loss: 0.3726 - val_recall_6: 0.3067
Epoch 9/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3564 - recall_6: 0.4057
- val_loss: 0.3747 - val_recall_6: 0.4632
Epoch 10/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3517 - recall_6: 0.4371
- val_loss: 0.4019 - val_recall_6: 0.2454
Epoch 11/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3538 - recall_6: 0.4279
- val_loss: 0.3876 - val_recall_6: 0.2822
Epoch 12/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3522 - recall_6: 0.4080
- val_loss: 0.3761 - val_recall_6: 0.3374
Epoch 13/50
200/200 [==============================] - 1s 4ms/step - loss: 0.3497 - recall_6: 0.4126
- val_loss: 0.3723 - val_recall_6: 0.3436
```

In [85]:

```
# Plot training loss and validation loss
plt.plot(history3.history['loss'])
plt.plot(history3.history['val_loss'])
plt.title('Model Loss with Early Stopping')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper right')
plt.show()
```



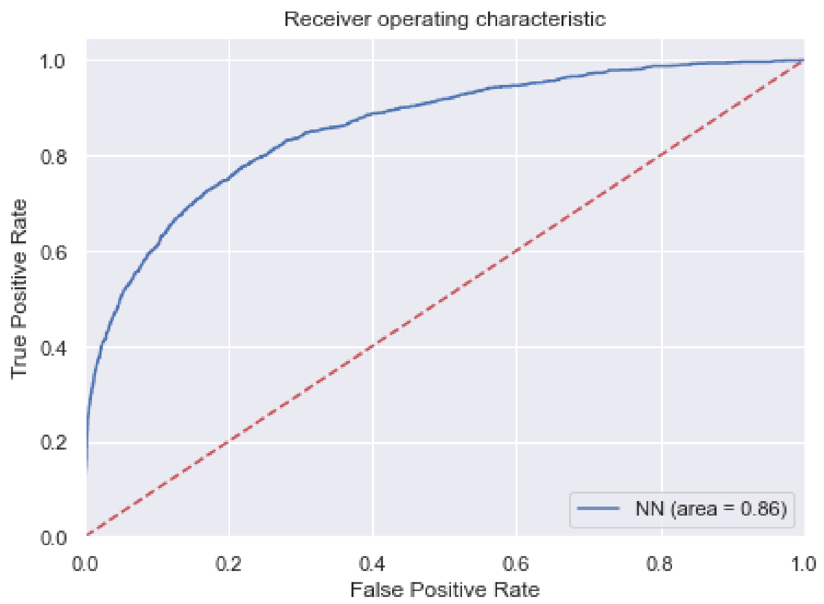
Observations:

The validation loss decreases initially but starts fluctuating after around epoch 6, which could be an indication of overfitting.

In [86]:

```
# ROC-AUC on training set
NN_roc_auc_train= roc_auc_score(y_train.astype(float), model3.predict(X_train))
fpr, tpr, thresholds = roc_curve(y_train.astype(float), model3.predict(X_train))
plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, label="NN (area = %0.2f)" % NN_roc_auc_train)
plt.plot([0, 1], [0, 1], "r--")
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic")
plt.legend(loc="lower right")
plt.show()
```

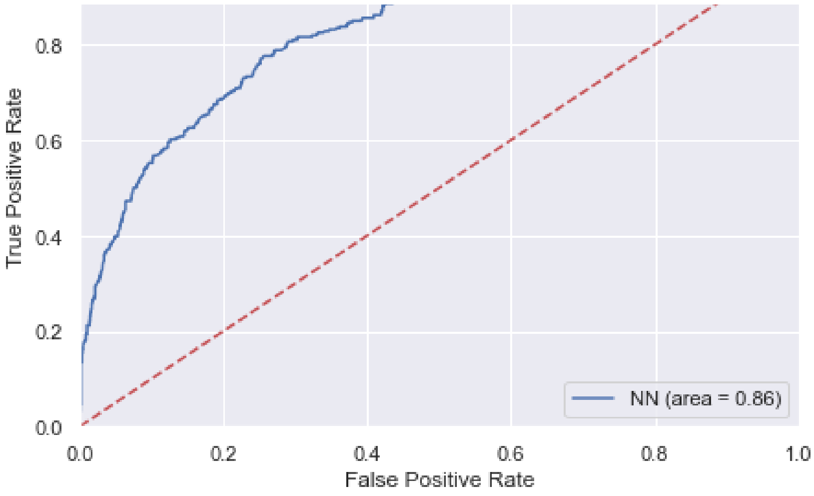
```
200/200 [==============================] - 1s 2ms/step
200/200 [==============================] - 0s 2ms/step
```



In [87]:

```
# ROC-AUC on validation set
NN_roc_auc_val = roc_auc_score(y_val.astype(float), model3.predict(X_val))
fpr, tpr, thresholds = roc_curve(y_val.astype(float), model3.predict(X_val))
plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, label="NN (area = %0.2f)" % NN_roc_auc_train)
plt.plot([0, 1], [0, 1], "r--")
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic")
plt.legend(loc="lower right")
plt.show()
```

```
50/50 [==============================] - 0s 3ms/step
50/50 [==============================] - 0s 2ms/step
```



In [88]:

```
# Optimal threshold using AUC-ROC curve
# The optimal cut off would be where tpr is high and fpr is low
fpr, tpr, thresholds = roc_curve(y_train.astype(float), model3.predict(X_train))

optimal_idx = np.argmax(tpr - fpr)
optimal_threshold_auc_roc = thresholds[optimal_idx]
print(optimal_threshold_auc_roc)
```

```
200/200 [==============================] - 1s 2ms/step
0.18877062
```

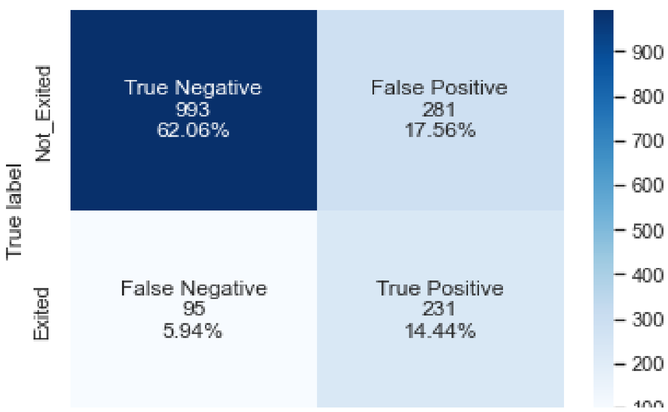
In [89]:

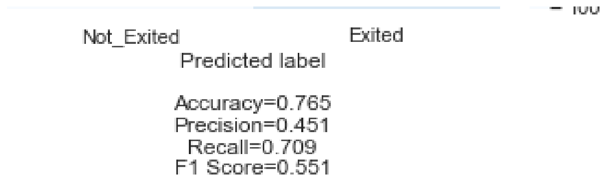
```
# Predictions on validation set
y_pred_val = model3.predict(X_val)

# Applying the optimal threshold
y_pred_val_binary = (y_pred_val > optimal_threshold_auc_roc).astype(int)

# Creating confusion matrix
cm_val = confusion_matrix(y_val, y_pred_val_binary)

# Define labels and categories
labels = ["True Negative", "False Positive", "False Negative", "True Positive"]
categories = ["Not_Exited", "Exited"]

# Plotting confusion matrix
<h4>Observations:</h4>make_confusion_matrix(cm_val, group_names=labels, categories=categ
ories, cmap="Blues")
```

```
50/50 [==============================] - 0s 2ms/step
```

Out[89]:

	0	1	2	3
Metric	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Score	**0.765**	**0.451172**	**0.708589**	**0.551313**





Observations:

1. **Accuracy (0.765): Model3 correctly predicted whether a customer will leave the bank or not about 76.5% of the time.**
2. **Precision (0.451172): Model3 predicted that a customer will leave the bank, it was correct only about 45.12% of the time.**
3. **Recall (0.708589): Model3 correctly identified 70.86% of the customers who actually left the bank.**
4. **F1 Score (0.551313): The F1 Score is approximately 0.55, which is not very high.**

Model Improvement: Neural Network model with balanced data[SMOTE]

In [90]:

```
from imblearn.over_sampling import SMOTE
sm  = SMOTE(random_state=1)
X_train_over, y_train_over = sm.fit_resample(X_train, y_train)
print('After OverSampling, the shape of train_X: {}'.format(X_train_over.shape))
print('After OverSampling, the shape of train_y: {} \n'.format(y_train_over.shape))
```

```
After OverSampling, the shape of train_X: (10192, 11)
After OverSampling, the shape of train_y: (10192,)
```

In [91]:

```
Oversampled_count = y_train_over.value_counts()
Oversampled_count
```

Out[91]:

```
0    5096
1    5096
Name: Exited, dtype: int64
```

In [92]:

```
#Initializing the neural network
model4 = Sequential()

#Adding the input layer with 32 neurons and relu as activation function
model4.add(Dense(32,activation='relu',input_dim = 11))

# Adding dropout with ratio of 0.2
model4.add(Dropout(0.2))

# Adding the first hidden layer with 16 neurons with relu as activation functions
model4.add(Dense(16,activation='relu'))

# Adding dropout with ratio of 0.2
model4.add(Dropout(0.2))

# Adding the second hidden layer with 8 neurons with relu as activation functions
#model2.add(Dense(8,activation='relu'))

# Adding the output layer
model4.add(Dense(1, activation = 'sigmoid'))
```

In [93]:

```
model4.summary()
```

```
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_21 (Dense)            (None, 32)                384

 dropout_6 (Dropout)         (None, 32)                0

 dense_22 (Dense)            (None, 16)                528

 dropout_7 (Dropout)         (None, 16)                0

 dense_23 (Dense)            (None, 1)                 17

=================================================================
Total params: 929 (3.63 KB)
Trainable params: 929 (3.63 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

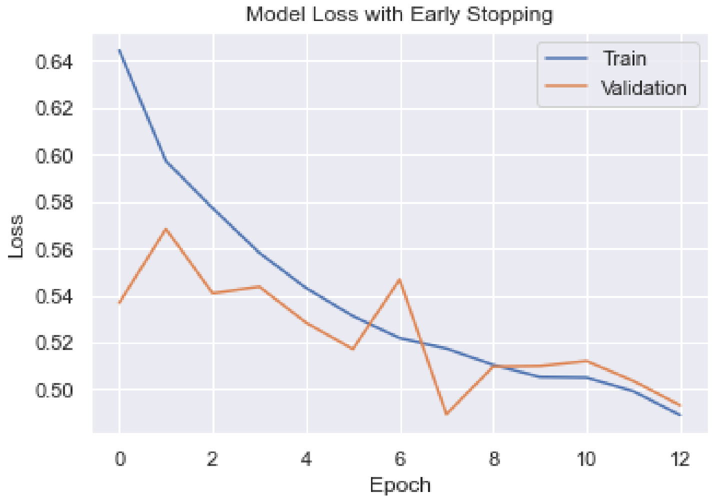
In [95]:

```
# Complining the model with binary cross entropy as loss and recall. as metrics
model4.compile(optimizer='Adam',
              loss='binary_crossentropy',
              metrics=[tf.keras.metrics.Recall()])

# Fitting the model on train and test with batch_size of 32, and early stopping
history4 = model4.fit(X_train_over,y_train_over,batch_size=32,epochs=50,verbose=1,valida
tion_data=(X_val,y_val),callbacks=[early_stopping])
```

```
Epoch 1/50
319/319 [==============================] - 4s 5ms/step - loss: 0.6445 - recall_8: 0.5500
- val_loss: 0.5368 - val_recall_8: 0.5061
Epoch 2/50
319/319 [==============================] - 1s 3ms/step - loss: 0.5973 - recall_8: 0.6576
- val_loss: 0.5684 - val_recall_8: 0.6380
Epoch 3/50
319/319 [==============================] - 1s 4ms/step - loss: 0.5772 - recall_8: 0.6797
- val_loss: 0.5409 - val_recall_8: 0.6227
Epoch 4/50
319/319 [==============================] - 1s 4ms/step - loss: 0.5581 - recall_8: 0.7019
- val_loss: 0.5437 - val_recall_8: 0.6748
Epoch 5/50
319/319 [==============================] - 1s 4ms/step - loss: 0.5432 - recall_8: 0.7208
- val_loss: 0.5284 - val_recall_8: 0.6472
Epoch 6/50
319/319 [==============================] - 1s 4ms/step - loss: 0.5312 - recall_8: 0.7296
- val_loss: 0.5172 - val_recall_8: 0.6442
Epoch 7/50
319/319 [==============================] - 1s 4ms/step - loss: 0.5219 - recall_8: 0.7308
- val_loss: 0.5468 - val_recall_8: 0.6933
Epoch 8/50
319/319 [==============================] - 1s 4ms/step - loss: 0.5174 - recall_8: 0.7398
- val_loss: 0.4894 - val_recall_8: 0.6074
Epoch 9/50
319/319 [==============================] - 1s 4ms/step - loss: 0.5105 - recall_8: 0.7394
- val_loss: 0.5097 - val_recall_8: 0.6472
Epoch 10/50
319/319 [==============================] - 1s 4ms/step - loss: 0.5053 - recall_8: 0.7488
- val_loss: 0.5100 - val_recall_8: 0.6626
Epoch 11/50
319/319 [==============================] - 1s 4ms/step - loss: 0.5051 - recall_8: 0.7516
- val_loss: 0.5121 - val_recall_8: 0.6902
Epoch 12/50
319/319 [==============================] - 1s 4ms/step - loss: 0.4992 - recall_8: 0.7545
- val_loss: 0.5036 - val_recall_8: 0.6748
Epoch 13/50
319/319 [==============================] - 1s 4ms/step - loss: 0.4890 - recall_8: 0.7688
- val_loss: 0.4932 - val_recall_8: 0.6626
```

In [96]:

```
# Plot training loss and validation loss
plt.plot(history4.history['loss'])
plt.plot(history4.history['val_loss'])
plt.title('Model Loss with Early Stopping')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper right')
plt.show()
```

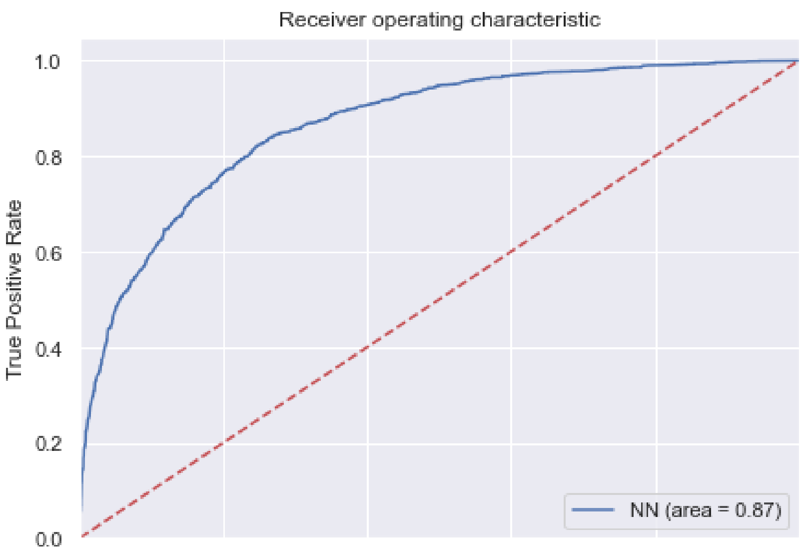


Observations:
The validation loss is fluctuating which could be an indication of overfitting.

In [97]:

```
# ROC-AUC on training set
NN_roc_auc_train= roc_auc_score(y_train_over.astype(float), model4.predict(X_train_over)
)
fpr, tpr, thresholds = roc_curve(y_train_over.astype(float),model4.predict(X_train_over)
)
plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, label="NN (area = %0.2f)" % NN_roc_auc_train)
plt.plot([0, 1], [0, 1], "r--")
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic")
plt.legend(loc="lower right")
plt.show()
```

```
319/319 [==============================] - 1s 2ms/step
319/319 [==============================] - 1s 2ms/step
```



In [98]:

```
# ROC-AUC on validation set
NN_roc_auc_val = roc_auc_score(y_val.astype(float), model4.predict(X_val))
fpr, tpr, thresholds = roc_curve(y_val.astype(float), model4.predict(X_val))
plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, label="NN (area = %0.2f)" % NN_roc_auc_train)
plt.plot([0, 1], [0, 1], "r--")
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic")
plt.legend(loc="lower right")
plt.show()
```

```
50/50 [==============================] - 0s 2ms/step
50/50 [==============================] - 0s 3ms/step
```

In [99]:

```
# Optimal threshold using AUC-ROC curve
# The optimal cut off would be where tpr is high and fpr is low
fpr, tpr, thresholds = roc_curve(y_train_over.astype(float), model4.predict(X_train_over
))

optimal_idx = np.argmax(tpr - fpr)
optimal_threshold_auc_roc = thresholds[optimal_idx]
print(optimal_threshold_auc_roc)
```

```
319/319 [==============================] - 1s 2ms/step
0.45771956
```

In [100]:

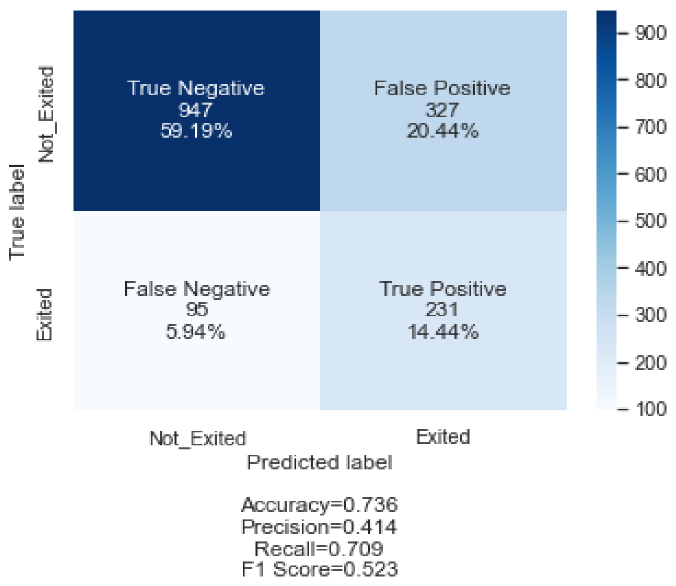
```
# Predictions on validation set
y_pred_val = model4.predict(X_val)

# Applying the optimal threshold
y_pred_val_binary = (y_pred_val > optimal_threshold_auc_roc).astype(int)

# Creating confusion matrix
cm_val = confusion_matrix(y_val, y_pred_val_binary)

# Define labels and categories
labels = ["True Negative", "False Positive", "False Negative", "True Positive"]
categories = ["Not_Exited", "Exited"]
```

```python
# Plotting confusion matrix
make_confusion_matrix(cm_val, group_names=labels, categories=categories, cmap="Blues")
```

```
50/50 [==============================] - 0s 2ms/step
```

Out[100]:

	0	1	2	3
Metric	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Score	0.73625	0.413978	0.708589	0.522624



Observations:

- **Accuracy (0.73625): Model4 correctly predicted whether a customer will leave the bank or not for about 73.625% of the customers.**
- **Precision (0.413978):Out of all the customers that your model4 predicted would leave the bank, only about 41.3978% actually left.**
- **Recall (0.708589): Model4 correctly identified 70.8589% of the total customers who actually left the bank.**
- **F1 Score (0.522624)**

Final Model

Observations:
We determine that the model incorporating the Adam optimizer and dropout rate of 0.2 (model2) exhibited the highest recall value among all considered models. In the context of our specific problem statement, where correctly identifying customers who are likely to leave is crucial, recall serves as an important metric.

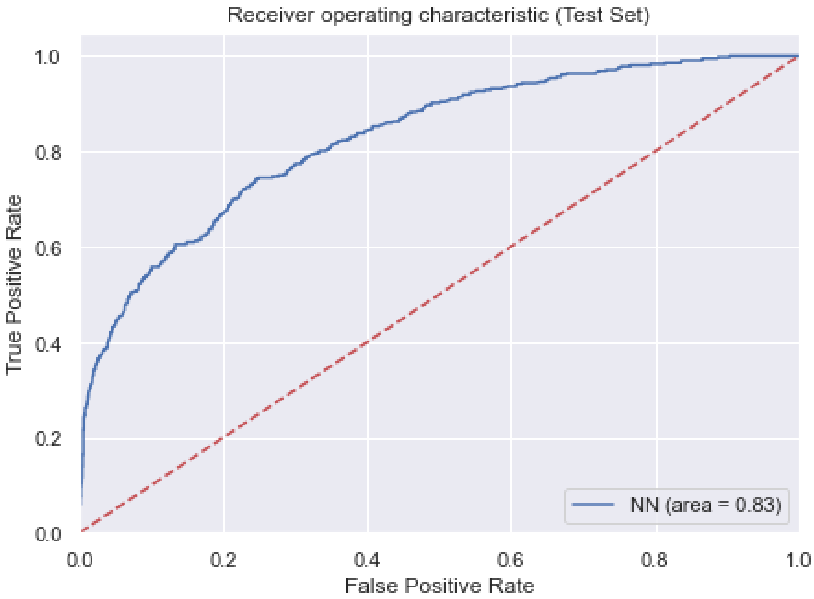
So we select model2 as our final model for predicting values on the test set.

In [101]:

```python
# ROC-AUC on test set using model incorporating the Adam optimizer and dropout rate of 0.
2 (model2)
NN_roc_auc_test = roc_auc_score(y_test.astype(float), model2.predict(X_test))
fpr_test, tpr_test, thresholds_test = roc_curve(y_test.astype(float), model2.predict(X_t
est))
plt.figure(figsize=(7, 5))
plt.plot(fpr_test, tpr_test, label="NN (area = %0.2f)" % NN_roc_auc_test)
plt.plot([0, 1], [0, 1], "r--")
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
```

```
plt.title("Receiver operating characteristic (Test Set)")
plt.legend(loc="lower right")
plt.show()
```

```
63/63 [==============================] - 0s 2ms/step
63/63 [==============================] - 0s 2ms/step
```



Observations:

-An AUC score of 0.83 on the test set indicates a relatively good performance of the model in distinguishing between positive and negative instances.
-Therfore the model has a high probability of ranking a randomly chosen positive instance higher than a randomly chosen negative instance.

In [102]:

```
# Optimal threshold using AUC-ROC curve on test set
optimal_idx_test = np.argmax(tpr_test - fpr_test)
optimal_threshold_auc_roc_test = thresholds_test[optimal_idx_test]
print("Optimal Threshold (Test Set):", optimal_threshold_auc_roc_test)
```

```
Optimal Threshold (Test Set): 0.1763247
```

In [104]:

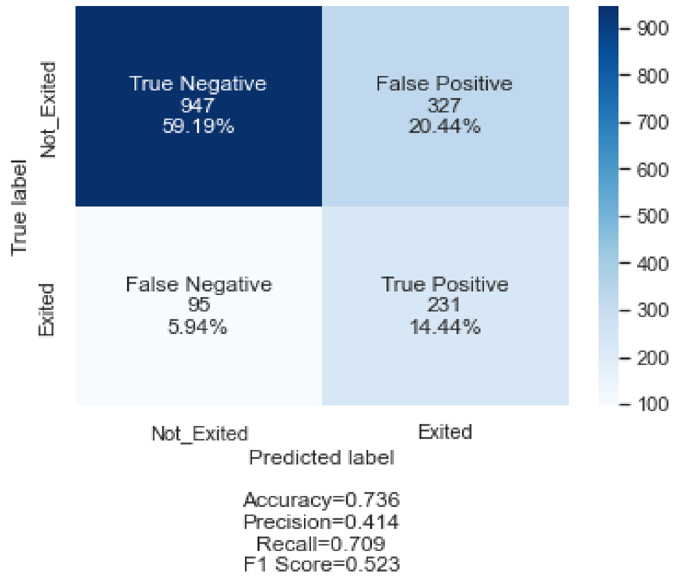
```
# Predictions on test set
y_pred_test = model2.predict(X_test)

# Applying the optimal threshold on test set
y_pred_test_binary = (y_pred_test > optimal_threshold_auc_roc_test).astype(int)

# Creating confusion matrix for test set
cm_test = confusion_matrix(y_test, y_pred_test_binary)

labels = ["True Negative", "False Positive", "False Negative", "True Positive"]
categories = ["Not_Exited", "Exited"]

# Plotting confusion matrix
make_confusion_matrix(cm_val, group_names=labels, categories=categories, cmap="Blues")
```

```
63/63 [==============================] - 0s 2ms/step
```

Out[104]:

	0	1	2	3
Metric	**Accuracy**	**Precision**	**Recall**	**F1 Score**

	0	1	2	3
Score	0.73625	0.413978	0.708589	0.522624



Observations:

Accuracy (0.73625): The model correctly predicted the customer churn for about 73.625% of the customers in the test set.

Precision (0.413978): When the model predicts a customer will churn, it is correct about 41.3978% of the time. Te model may be overestimating customer churn, which could lead to unnecessary retention efforts.

Recall (0.708589): The model correctly identified 70.8589% of the customers who actually churned. This is important to identify as many churning customers as possible.

F1 Score (0.522624): An F1 score of 52.2624% indicates that there is room for improvement in achieving a better balance.

Actionable Insights and Recommendations

What recommedations would you suggest to the bank?

*

Engagement of dormant Members: The bank might launch a campaign to turn dormant members into active clients. To help these clients get the most out of their accounts, this can entail contacting them with exclusive deals or incentives or offering them individualized financial guidance.

Product Retention and Diversification: There is a chance to encourage customers to diversify their product holdings because the minority of customers who only own one product (51%). Create retention techniques to hold on to clients that possess numerous items, like incentives or packaged services.

Services That Consider Age: Given that quitting a bank is positively correlated with age, you should think about offering age-specific services or incentives to keep customers in particular age ranges. Customizing services to fit various stages of life could increase client retention.

Retention based on Tenure: Higher rates of customer churn are seen among those with shorter tenures—one year and zero years. Use promotions, individualized services, or onboarding programs to win over more customers throughout the early years of their bank relationship.

In [ ]: