Churn Prediction

In [33]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split , cross_val_score, RandomizedSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
```

In [2]:
```
df=pd.read_csv(r"F:\projects\banking\churn_prediction 01\Churn_Modelling.csv")
```

In [3]:
```
df.head()
```

Out[3]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSal
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084

In [4]:
```
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
```

In [5]:
```
df.shape
```

Out[5]:
```
(10000, 14)
```

In [6]:
```
# no missing values
```

In [7]:
```
df.select_dtypes(include="object")
```

Out[7]:

	Surname	Geography	Gender
0	Hargrave	France	Female
1	Hill	Spain	Female
2	Onio	France	Female
3	Boni	France	Female
4	Mitchell	Spain	Female
...	...	...	...
9995	Obijiaku	France	Male
9996	Johnstone	France	Male
9997	Liu	France	Female
9998	Sabbatini	Germany	Male
9999	Walker	France	Female

10000 rows × 3 columns

In [8]:
```
df.select_dtypes(include=["int64","float64"])
```

Out[8]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	1	15634602	619	42	2	0.00	1	1	1	101348.88	1
1	2	15647311	608	41	1	83807.86	1	0	1	112542.58	0
2	3	15619304	502	42	8	159660.80	3	1	0	113931.57	1
3	4	15701354	699	39	1	0.00	2	0	0	93826.63	0
4	5	15737888	850	43	2	125510.82	1	1	1	79084.10	0
...	...	...	...	...	...	...	...	...	...	...	...
9995	9996	15606229	771	39	5	0.00	2	1	0	96270.64	0
9996	9997	15569892	516	35	10	57369.61	1	1	1	101699.77	0
9997	9998	15584532	709	36	7	0.00	1	0	1	42085.58	1
9998	9999	15682355	772	42	3	75075.31	2	1	0	92888.52	1
9999	10000	15628319	792	28	4	130142.79	1	1	0	38190.78	0

10000 rows × 11 columns

In [9]:
```
df.describe()
```

Out[9]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSal
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.239
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.492
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.247
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.480

Data cleaning

In [10]:
```
df.head()
```

Out[10]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSal
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084

In [11]:
```
# we will be removing rownumber,surname as it seems that we have no use of them in future
```

In [12]:
```
df.drop(columns=["RowNumber","Surname"],inplace=True)
```

In [13]:
```
df.select_dtypes(include="object")
```

Out[13]:

	Geography	Gender
0	France	Female
1	Spain	Female
2	France	Female
3	France	Female
4	Spain	Female
...	...	...
9995	France	Male
9996	France	Male
9997	France	Female
9998	Germany	Male
9999	France	Female

10000 rows × 2 columns

In [14]:
```
df.select_dtypes(include=["int64","float64"])
```

Out[14]:

	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	15634602	619	42	2	0.00	1	1	1	101348.88	1
1	15647311	608	41	1	83807.86	1	0	1	112542.58	0
2	15619304	502	42	8	159660.80	3	1	0	113931.57	1
3	15701354	699	39	1	0.00	2	0	0	93826.63	0
4	15737888	850	43	2	125510.82	1	1	1	79084.10	0
...	...	...	...	...	...	...	...	...	...	...
9995	15606229	771	39	5	0.00	2	1	0	96270.64	0
9996	15569892	516	35	10	57369.61	1	1	1	101699.77	0
9997	15584532	709	36	7	0.00	1	0	1	42085.58	1
9998	15682355	772	42	3	75075.31	2	1	0	92888.52	1
9999	15628319	792	28	4	130142.79	1	1	0	38190.78	0

10000 rows × 10 columns

In [15]:
```
df["Geography"].value_counts()
```

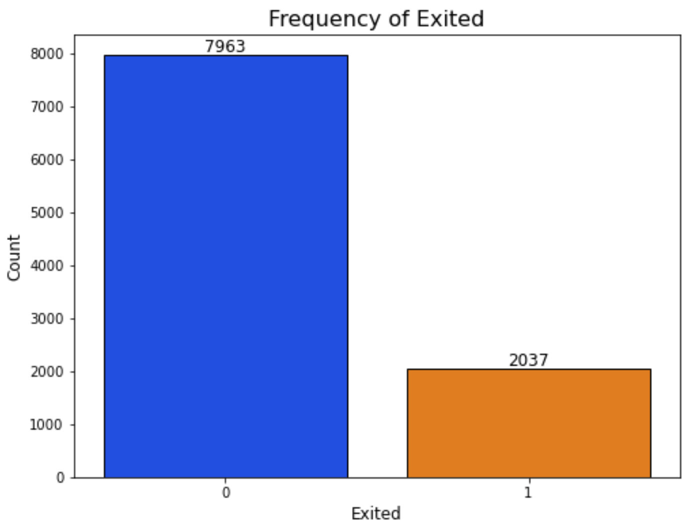
Out[15]:
```
France     5014
Germany    2509
Spain      2477
Name: Geography, dtype: int64
```

In [16]:
```
df["Gender"].value_counts()
```

Out[16]:
```
Male      5457
Female    4543
Name: Gender, dtype: int64
```

In [17]:
```
#Plotting a Countplot to Explore the Label column
plt.figure(figsize=(8, 6))
sns.countplot(df['Exited'], palette='bright', edgecolor='black')

# Adding a title and labels to the plot
plt.title('Frequency of Exited', fontsize=16)
plt.xlabel('Exited', fontsize=12)
plt.ylabel('Count', fontsize=12)

# Adding annotations to the bars
for i in range(len(df['Exited'].value_counts())):
    count = df['Exited'].value_counts()[i]
    label = count
    plt.annotate(label, (i, count), ha='center', va='bottom', fontsize=12)


plt.show()

#Getting the total values
print(f'Total Values:',  df.Exited.count())
```

```
F:\anacponda main\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword a
rg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an expl
icit keyword will result in an error or misinterpretation.
  warnings.warn(
```



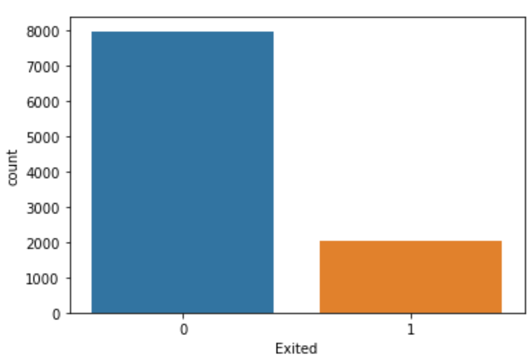

```
Total Values: 10000
```

In [18]:
```
df.Exited.value_counts()
```

Out[18]:
```
0    7963
1    2037
Name: Exited, dtype: int64
```

In [19]:
```
sns.countplot(df['Exited'])
plt.show()
```

```
F:\anacponda main\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword a
rg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an expl
icit keyword will result in an error or misinterpretation.
  warnings.warn(
```



Corelation

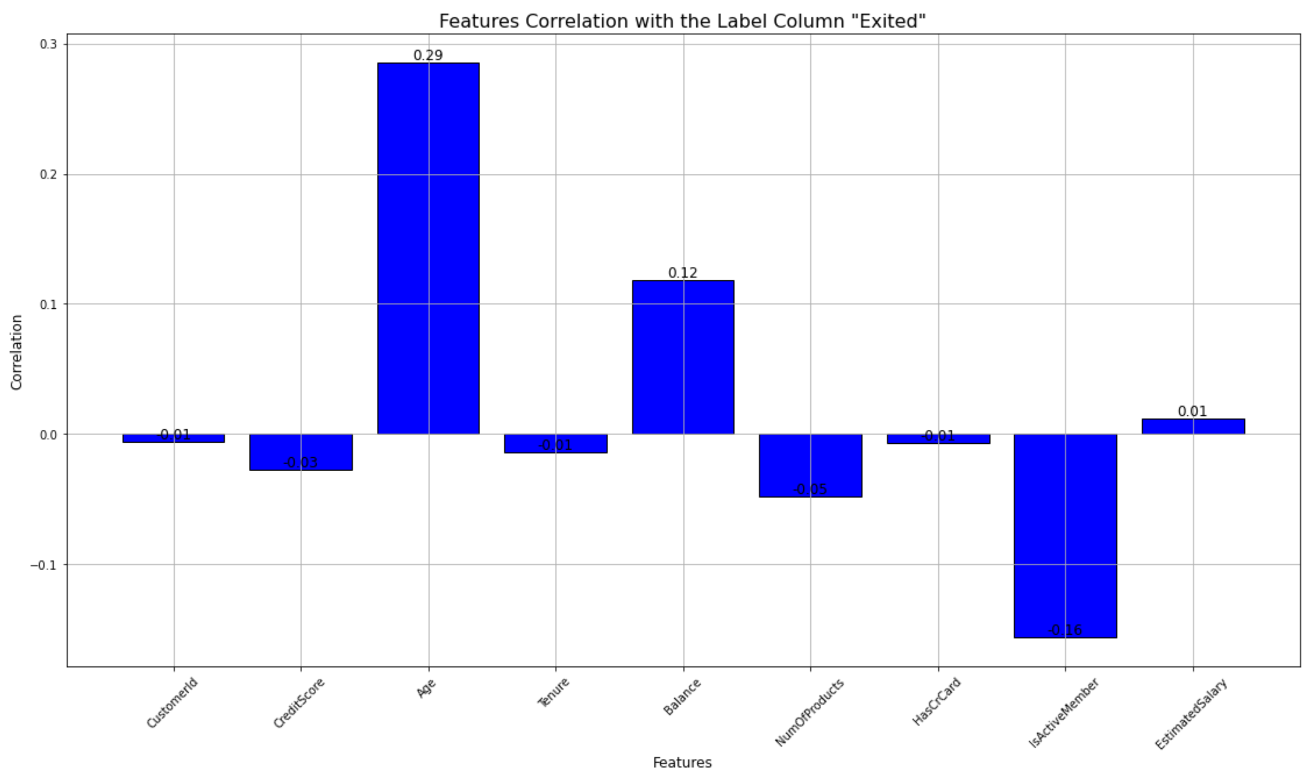
In [20]:
```
df2=df.drop(columns=['Exited'])  #droping the unnecessary columns
df2
```

Out[20]:

	CustomerId	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	15634602	619	France	Female	42	2	0.00	1	1	1	101348.88
1	15647311	608	Spain	Female	41	1	83807.86	1	0	1	112542.58
2	15619304	502	France	Female	42	8	159660.80	3	1	0	113931.57
3	15701354	699	France	Female	39	1	0.00	2	0	0	93826.63
4	15737888	850	Spain	Female	43	2	125510.82	1	1	1	79084.10
...	...	...	...	...	...	...	...	...	...	...	...
9995	15606229	771	France	Male	39	5	0.00	2	1	0	96270.64
9996	15569892	516	France	Male	35	10	57369.61	1	1	1	101699.77
9997	15584532	709	France	Female	36	7	0.00	1	0	1	42085.58
9998	15682355	772	Germany	Male	42	3	75075.31	2	1	0	92888.52
9999	15628319	792	France	Female	28	4	130142.79	1	1	0	38190.78

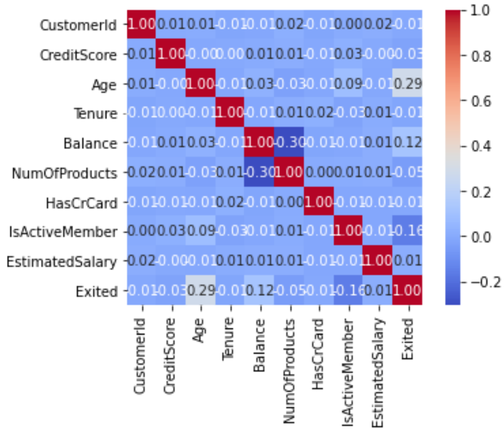
10000 rows × 11 columns

In [21]:
```
corrw = df2.corrwith(df['Exited'])
plt.figure(figsize=(19, 10))
plt.bar(corrw.index, corrw.values, color='blue', edgecolor='black')
plt.title('Features Correlation with the Label Column "Exited"', fontsize=16)
plt.xlabel('Features', fontsize=12)
plt.ylabel('Correlation', fontsize=12)
plt.xticks(rotation=45)
plt.grid(True)
for i, value in enumerate(corrw.values):
    label = f"{value:.2f}"
    plt.annotate(label, (i, value), ha='center', va='bottom', fontsize=12)

# Displaying the plot
plt.show()
```



In [22]:
```
corr=df.corr()
sns.heatmap(corr,square=True,annot=True,cmap='coolwarm',fmt='.2f',cbar=True)
```

Out[22]: <AxesSubplot:>



Splitting the data into train,test

In [23]:
```
x=df.drop(columns=['Exited','Geography','Gender'])
y=df["Exited"]
```

In [24]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=1234)
```

In [25]:
```
x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

Out[25]:
```
((8000, 9), (2000, 9), (8000,), (2000,))
```

In [26]:
```
#standarizing the data
from sklearn.preprocessing import StandardScaler
ss=StandardScaler()
x_train=ss.fit_transform(x_train)
x_test=ss.transform(x_test)
```

In [27]:
```
#model building

lr=LogisticRegression(random_state=0)
lr.fit(x_train,y_train)
pred=lr.predict(x_test)

#testing the accuracy score with different parameters

from sklearn.metrics import confusion_matrix, recall_score, f1_score, accuracy_score, precision_score

acc=accuracy_score(y_test,pred)
f1=f1_score(y_test,pred)
recal=recall_score(y_test,pred)
prec=precision_score(y_test,pred)
cnf_mat=confusion_matrix(y_test,pred)

result=pd.DataFrame([{'model':"Logistic Regression",'accuracy_score':acc,"f1_score":f1,"recall_score":recal,"precissiojn_
```

In [28]:
```
result
```

Out[28]:

	model	accuracy_score	f1_score	recall_score	precissiojn_score
0	Logistic Regression	0.8075	0.263862	0.167476	0.621622

In [29]:
```
cnf_mat
```

Out[29]:
```
array([[1546,   42],
       [ 343,   69]], dtype=int64)
```

In [37]:
```
#cross validation

accuricies=cross_val_score(estimator=lr,X=x_train,y=y_train,cv=10)
print('accuricies is: ',format(accuricies.mean()*100))
print(f"standard deviation is:",format(accuricies.std()*100))
```

```
accuricies is:  80.72500000000001
standard deviation is: 0.8584142356694688
```

In [49]:
```
# building the XGB model
xgb=XGBClassifier()
xgb.fit(x_train,y_train)
pred=xgb.predict(x_test)

#Testing the model accuracy with different paramtes
acc  = accuracy_score(y_test, pred)   # Getting the Accuracy Score
f1   = f1_score(y_test, pred)         # Getting the f1 Score
rec  = recall_score(y_test, pred)     # Getting the recall Score
prec = precision_score(y_test, pred)  # Getting the Precision Score
cm   = confusion_matrix(y_test, pred) # Getting the confusion Matrix

#Defining a DataFrame
rf_result=pd.DataFrame([{'model':"XGB boost",'accuracy_score':acc,"f1_score":f1,"recall_score":recal,"precissiojn_score":
result1 = result.append(rf_result, ignore_index=True)
```

In [50]:
```
result1
```

Out[50]:

	model	accuracy_score	f1_score	recall_score	precissiojn_score
0	Logistic Regression	0.8075	0.263862	0.167476	0.621622
1	XGB boost	0.8455	0.531108	0.167476	0.708502

In [51]:
```
#cross validation

accuricies=cross_val_score(estimator=xgb,X=x_train,y=y_train,cv=10)
print('accuricies is: ',format(accuricies.mean()*100))
print(f"standard deviation is:",format(accuricies.std()*100))
```

```
accuricies is:  84.7875
standard deviation is: 0.901474486605138
```

In [ ]: