In [2]:
```
import pandas as pd
import numpy as np
from sklearn import preprocessing
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
data = pd.read_csv("Churn.csv",na_values='Nan')
data
```

Out[3]:

	Unnamed: 0	state	area.code	account.length	voice.plan	voice.messages	intl.plan	intl.mins	intl.calls	intl.charge	...	da
0	1	KS	area_code_415	128	yes	25	no	10.0	3	2.70	...	
1	2	OH	area_code_415	107	yes	26	no	13.7	3	3.70	...	
2	3	NJ	area_code_415	137	no	0	no	12.2	5	3.29	...	
3	4	OH	area_code_408	84	no	0	yes	6.6	7	1.78	...	
4	5	OK	area_code_415	75	no	0	yes	10.1	3	2.73	...	
...	...	...	...	...	...	...	...	...	...	...	...	
4995	4996	HI	area_code_408	50	yes	40	no	9.9	5	2.67	...	
4996	4997	WV	area_code_415	152	no	0	no	14.7	2	3.97	...	
4997	4998	DC	area_code_415	61	no	0	no	13.6	4	3.67	...	
4998	4999	DC	area_code_510	109	no	0	no	8.5	6	2.30	...	
4999	5000	VT	area_code_415	86	yes	34	no	9.3	16	2.51	...	

5000 rows × 21 columns

In [4]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Unnamed: 0      5000 non-null   int64  
 1   state           5000 non-null   object 
 2   area.code       5000 non-null   object 
 3   account.length  5000 non-null   int64  
 4   voice.plan      5000 non-null   object 
 5   voice.messages  5000 non-null   int64  
 6   intl.plan       5000 non-null   object 
 7   intl.mins       5000 non-null   float64
 8   intl.calls      5000 non-null   int64  
 9   intl.charge     5000 non-null   float64
 10  day.mins        5000 non-null   float64
 11  day.calls       5000 non-null   int64  
 12  day.charge      4993 non-null   float64
 13  eve.mins        4976 non-null   float64
 14  eve.calls       5000 non-null   int64  
 15  eve.charge      5000 non-null   float64
 16  night.mins      5000 non-null   float64
 17  night.calls     5000 non-null   int64  
 18  night.charge    5000 non-null   float64
 19  customer.calls  5000 non-null   int64  
 20  churn           5000 non-null   object 
dtypes: float64(8), int64(8), object(5)
memory usage: 820.4+ KB
```

In [5]:
```
data.isna().sum()
```

Out[5]:
```
Unnamed: 0         0
state              0
area.code          0
account.length     0
voice.plan         0
voice.messages     0
intl.plan          0
intl.mins          0
intl.calls         0
intl.charge        0
day.mins           0
day.calls          0
day.charge         7
eve.mins          24
eve.calls          0
eve.charge         0
night.mins         0
night.calls        0
night.charge       0
customer.calls     0
churn              0
dtype: int64
```

In [6]:
```
data.dropna(inplace=True)
```

In [7]:
```
data.columns
```

Out[7]:
```
Index(['Unnamed: 0', 'state', 'area.code', 'account.length', 'voice.plan',
       'voice.messages', 'intl.plan', 'intl.mins', 'intl.calls', 'intl.charge',
       'day.mins', 'day.calls', 'day.charge', 'eve.mins', 'eve.calls',
       'eve.charge', 'night.mins', 'night.calls', 'night.charge',
       'customer.calls', 'churn'],
      dtype='object')
```

In [8]:
```
data.rename(columns={'area.code':'area_code','account.length':'account_length','voice.plan':'voice_plan',
                     'voice.messages':'voice_messages','intl.plan':'intl_plan','intl.mins':'intl_mins',
                    'intl.calls':'intl_calls','intl.charge':'intl_charge','day.mins':'day_mins','day.calls':'day
                    'day.charge':'day_charge','eve.mins':'eve_mins','eve.calls':'eve_calls','eve.charge':'eve_cl
                    'night.mins':'night_mins','night.calls':'night_calls','night.charge':'night_charge','custome
                    },inplace=True)
data
```

Out[8]:

	Unnamed: 0	state	area_code	account_length	voice_plan	voice_messages	intl_plan	intl_mins	intl_calls	intl_charge	...
0	1	KS	area_code_415	128	yes	25	no	10.0	3	2.70	...
1	2	OH	area_code_415	107	yes	26	no	13.7	3	3.70	...
2	3	NJ	area_code_415	137	no	0	no	12.2	5	3.29	...
3	4	OH	area_code_408	84	no	0	yes	6.6	7	1.78	...
4	5	OK	area_code_415	75	no	0	yes	10.1	3	2.73	...
...	...	...	...	...	...	...	...	...	...	...	...
4995	4996	HI	area_code_408	50	yes	40	no	9.9	5	2.67	...
4996	4997	WV	area_code_415	152	no	0	no	14.7	2	3.97	...
4997	4998	DC	area_code_415	61	no	0	no	13.6	4	3.67	...
4998	4999	DC	area_code_510	109	no	0	no	8.5	6	2.30	...
4999	5000	VT	area_code_415	86	yes	34	no	9.3	16	2.51	...

4969 rows × 21 columns

In [9]:
```
data.drop('Unnamed: 0',axis=1,inplace=True)
data
```

Out[9]:

	state	area_code	account_length	voice_plan	voice_messages	intl_plan	intl_mins	intl_calls	intl_charge	day_mins	da
0	KS	area_code_415	128	yes	25	no	10.0	3	2.70	265.1	
1	OH	area_code_415	107	yes	26	no	13.7	3	3.70	161.6	
2	NJ	area_code_415	137	no	0	no	12.2	5	3.29	243.4	
3	OH	area_code_408	84	no	0	yes	6.6	7	1.78	299.4	
4	OK	area_code_415	75	no	0	yes	10.1	3	2.73	166.7	
...	...	...	...	...	...	...	...	...	...	...	
4995	HI	area_code_408	50	yes	40	no	9.9	5	2.67	235.7	
4996	WV	area_code_415	152	no	0	no	14.7	2	3.97	184.2	
4997	DC	area_code_415	61	no	0	no	13.6	4	3.67	140.6	
4998	DC	area_code_510	109	no	0	no	8.5	6	2.30	188.8	
4999	VT	area_code_415	86	yes	34	no	9.3	16	2.51	129.4	

4969 rows × 20 columns

In [10]:

```
le = preprocessing.LabelEncoder()
objlist = ['area_code','intl_plan','voice_plan','churn','state']
data[objlist] = data[objlist].apply(le.fit_transform)
```

In [11]:

```
data
```

Out[11]:

	state	area_code	account_length	voice_plan	voice_messages	intl_plan	intl_mins	intl_calls	intl_charge	day_mins	day_ca
0	16	1	128	1	25	0	10.0	3	2.70	265.1	1
1	35	1	107	1	26	0	13.7	3	3.70	161.6	1
2	31	1	137	0	0	0	12.2	5	3.29	243.4	1
3	35	0	84	0	0	1	6.6	7	1.78	299.4	
4	36	1	75	0	0	1	10.1	3	2.73	166.7	1
...	...	...	...	...	...	...	...	...	...	...	
4995	11	0	50	1	40	0	9.9	5	2.67	235.7	1
4996	49	1	152	0	0	0	14.7	2	3.97	184.2	
4997	7	1	61	0	0	0	13.6	4	3.67	140.6	
4998	7	2	109	0	0	0	8.5	6	2.30	188.8	
4999	46	1	86	1	34	0	9.3	16	2.51	129.4	1

4969 rows × 20 columns

In [12]:

```
data.columns
```

Out[12]:

```
Index(['state', 'area_code', 'account_length', 'voice_plan', 'voice_messages',
       'intl_plan', 'intl_mins', 'intl_calls', 'intl_charge', 'day_mins',
       'day_calls', 'day_charge', 'eve_mins', 'eve_calls', 'eve_charge',
       'night_mins', 'night_calls', 'night_charge', 'customer_calls', 'churn'],
      dtype='object')
```

In [13]:

```
data = data[[ 'account_length', 'voice_plan', 'voice_messages',
       'intl_plan', 'intl_calls', 'intl_charge',
       'day_calls', 'day_charge', 'eve_calls', 'eve_charge',
       'night_calls', 'night_charge', 'customer_calls', 'churn']]
data
```

Out[13]:

	account_length	voice_plan	voice_messages	intl_plan	intl_calls	intl_charge	day_calls	day_charge	eve_calls	eve_charge
0	128	1	25	0	3	2.70	110	45.07	99	16.78
1	107	1	26	0	3	3.70	123	27.47	103	16.62
2	137	0	0	0	5	3.29	114	41.38	110	10.30
3	84	0	0	1	7	1.78	71	50.90	88	5.26
4	75	0	0	1	3	2.73	113	28.34	122	12.61
...	...	...	...	...	...	...	...	...	...	...
4995	50	1	40	0	5	2.67	127	40.07	126	18.96
4996	152	0	0	0	2	3.97	90	31.31	73	21.83
4997	61	0	0	0	4	3.67	89	23.90	128	14.69
4998	109	0	0	0	6	2.30	67	32.10	92	14.59
4999	86	1	34	0	16	2.51	102	22.00	104	22.70

4969 rows × 14 columns

In [14]:
```
data['Total_Charge'] =  data['day_charge'] + data['eve_charge'] + data['night_charge']
```

In [15]:
```
data
```

Out[15]:

	account_length	voice_plan	voice_messages	intl_plan	intl_calls	intl_charge	day_calls	day_charge	eve_calls	eve_charge
0	128	1	25	0	3	2.70	110	45.07	99	16.78
1	107	1	26	0	3	3.70	123	27.47	103	16.62
2	137	0	0	0	5	3.29	114	41.38	110	10.30
3	84	0	0	1	7	1.78	71	50.90	88	5.26
4	75	0	0	1	3	2.73	113	28.34	122	12.61
...	...	...	...	...	...	...	...	...	...	...
4995	50	1	40	0	5	2.67	127	40.07	126	18.96
4996	152	0	0	0	2	3.97	90	31.31	73	21.83
4997	61	0	0	0	4	3.67	89	23.90	128	14.69
4998	109	0	0	0	6	2.30	67	32.10	92	14.59
4999	86	1	34	0	16	2.51	102	22.00	104	22.70

4969 rows × 15 columns

In [16]:
```
data.drop(['day_charge','eve_charge','night_charge'],axis=1,inplace=True)
```

In [17]:
```
data=data.iloc[:,[10,0,1,2,3,4,5,6,7,8,9,11]]
```

In [18]:
```
data
```

Out[18]:

	churn	account_length	voice_plan	voice_messages	intl_plan	intl_calls	intl_charge	day_calls	eve_calls	night_calls	custo
0	0	128	1	25	0	3	2.70	110	99	91	
1	0	107	1	26	0	3	3.70	123	103	103	
2	0	137	0	0	0	5	3.29	114	110	104	
3	0	84	0	0	1	7	1.78	71	88	89	
4	0	75	0	0	1	3	2.73	113	122	121	
...	...	...	...	...	...	...	...	...	...	...	
4995	0	50	1	40	0	5	2.67	127	126	116	
4996	1	152	0	0	0	2	3.97	90	73	113	
4997	0	61	0	0	0	4	3.67	89	128	97	
4998	0	109	0	0	0	6	2.30	67	92	89	
4999	0	86	1	34	0	16	2.51	102	104	100	

4969 rows × 12 columns

In [19]:
```python
x = data.iloc[:,1:]
x
```

Out[19]:

	account_length	voice_plan	voice_messages	intl_plan	intl_calls	intl_charge	day_calls	eve_calls	night_calls	customer_ca
0	128	1	25	0	3	2.70	110	99	91	
1	107	1	26	0	3	3.70	123	103	103	
2	137	0	0	0	5	3.29	114	110	104	
3	84	0	0	1	7	1.78	71	88	89	
4	75	0	0	1	3	2.73	113	122	121	
...	...	...	...	...	...	...	...	...	...	
4995	50	1	40	0	5	2.67	127	126	116	
4996	152	0	0	0	2	3.97	90	73	113	
4997	61	0	0	0	4	3.67	89	128	97	
4998	109	0	0	0	6	2.30	67	92	89	
4999	86	1	34	0	16	2.51	102	104	100	

4969 rows × 11 columns

In [20]:
```python
y = data.iloc[:,0:1]
y
```

Out[20]:

	churn
0	0
1	0
2	0
3	0
4	0
...	...
4995	0
4996	1
4997	0
4998	0
4999	0

4969 rows × 1 columns

In [21]:
```python
from sklearn.preprocessing import RobustScaler
```

In [22]:
```python
transformer = RobustScaler().fit(x)
x=transformer.transform(x)
```

In [23]:
```python
x
```

Out[23]:
```
array([[ 0.51851852,  1.        ,  1.47058824, ..., -0.34615385,
         0.        ,  1.16008615],
       [ 0.12962963,  1.        ,  1.52941176, ...,  0.11538462,
         0.        , -0.08327351],
       [ 0.68518519,  0.        ,  0.        , ...,  0.15384615,
        -1.        ,  0.16511127],
       ...,
       [-0.72222222,  0.        ,  0.        , ..., -0.11538462,
         0.        , -0.6137832 ],
       [ 0.16666667,  0.        ,  0.        , ..., -0.42307692,
        -1.        ,  0.00646088],
       [-0.25925926,  1.        ,  2.        , ...,  0.        ,
        -1.        , -0.36109117]])
```

In [24]:
```python
from sklearn.model_selection import train_test_split, cross_val_score
```

In [25]:
```python
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.3, random_state=15)
```

In [26]:
```python
#Logistic Regression
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
from sklearn import preprocessing
```

```
from sklearn import metrics
```

In [27]:
```
model=LogisticRegression()
model.fit(x_train,y_train)
y_pred=model.predict(x_test)
```

In [28]:
```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score as ac
confusion_matrix=confusion_matrix(y_test,y_pred)
print(confusion_matrix)
```

```
[[1254   39]
 [ 156   42]]
```

In [29]:
```
print(classification_report(y_test,y_pred))
from sklearn.metrics import precision_recall_fscore_support as score
precision,recall,fscore,support = score(y_test,y_pred,average='macro')
LR=fscore
LR
```

```
              precision    recall  f1-score   support

           0       0.89      0.97      0.93      1293
           1       0.52      0.21      0.30       198

    accuracy                           0.87      1491
   macro avg       0.70      0.59      0.61      1491
weighted avg       0.84      0.87      0.84      1491
```

Out[29]: 0.6144666022221427

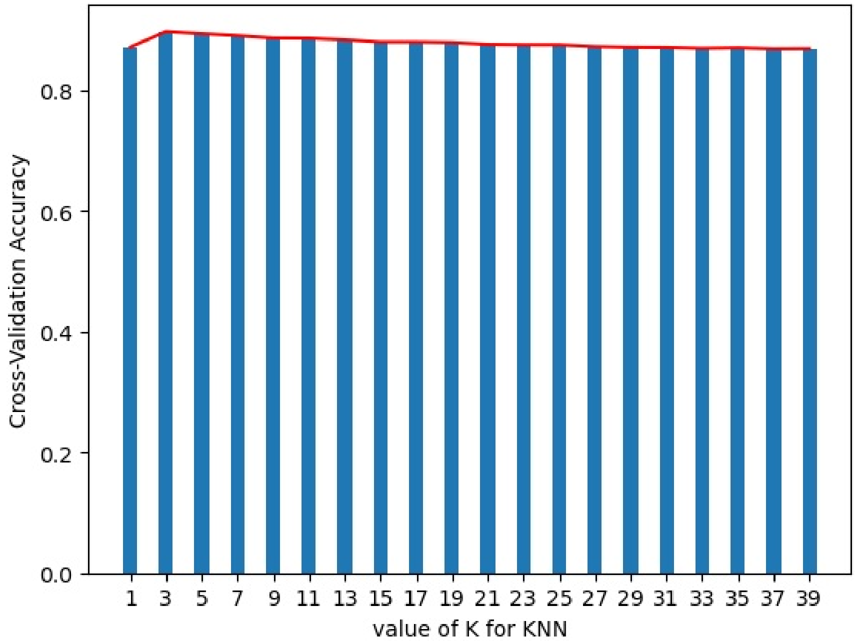
In [30]:
```
#KNN
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.neighbors import KNeighborsClassifier
import matplotlib.pyplot as plt
%matplotlib inline
k_range = [2*i+1 for i in range(0,20)]
k_scores = []
for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn,x_train , y_train, cv = 10)
    k_scores.append(scores.mean())
    print("K value=",k)
    model = KNeighborsClassifier(n_neighbors=k)
    model.fit(x_train,y_train)
    pred = model.predict(x_test)
    print(classification_report(y_test,pred))
```

```
K value= 1
              precision    recall  f1-score   support

           0       0.92      0.94      0.93      1293
           1       0.56      0.48      0.52       198

    accuracy                           0.88      1491
   macro avg       0.74      0.71      0.73      1491
weighted avg       0.87      0.88      0.88      1491

K value= 3
              precision    recall  f1-score   support

           0       0.91      0.98      0.95      1293
           1       0.75      0.40      0.52       198

    accuracy                           0.90      1491
   macro avg       0.83      0.69      0.73      1491
weighted avg       0.89      0.90      0.89      1491

K value= 5
              precision    recall  f1-score   support

           0       0.91      0.99      0.95      1293
           1       0.84      0.38      0.52       198

    accuracy                           0.91      1491
   macro avg       0.88      0.68      0.74      1491
weighted avg       0.90      0.91      0.89      1491

K value= 7
              precision    recall  f1-score   support

           0       0.91      0.99      0.95      1293
```

```
           1       0.90      0.33      0.49       198

    accuracy                           0.91      1491
   macro avg       0.91      0.66      0.72      1491
weighted avg       0.91      0.91      0.89      1491

K value= 9
              precision    recall  f1-score   support

           0       0.90      0.99      0.94      1293
           1       0.87      0.27      0.42       198

    accuracy                           0.90      1491
   macro avg       0.89      0.63      0.68      1491
weighted avg       0.90      0.90      0.87      1491

K value= 11
              precision    recall  f1-score   support

           0       0.90      1.00      0.94      1293
           1       0.91      0.26      0.40       198

    accuracy                           0.90      1491
   macro avg       0.90      0.63      0.67      1491
weighted avg       0.90      0.90      0.87      1491

K value= 13
              precision    recall  f1-score   support

           0       0.89      1.00      0.94      1293
           1       0.88      0.22      0.35       198

    accuracy                           0.89      1491
   macro avg       0.89      0.61      0.65      1491
weighted avg       0.89      0.89      0.86      1491

K value= 15
              precision    recall  f1-score   support

           0       0.89      1.00      0.94      1293
           1       0.87      0.21      0.33       198

    accuracy                           0.89      1491
   macro avg       0.88      0.60      0.64      1491
weighted avg       0.89      0.89      0.86      1491

K value= 17
              precision    recall  f1-score   support

           0       0.89      1.00      0.94      1293
           1       0.89      0.21      0.34       198

    accuracy                           0.89      1491
   macro avg       0.89      0.60      0.64      1491
weighted avg       0.89      0.89      0.86      1491

K value= 19
              precision    recall  f1-score   support

           0       0.89      1.00      0.94      1293
           1       0.85      0.18      0.29       198

    accuracy                           0.89      1491
   macro avg       0.87      0.59      0.62      1491
weighted avg       0.88      0.89      0.85      1491

K value= 21
              precision    recall  f1-score   support

           0       0.89      0.99      0.94      1293
           1       0.83      0.17      0.28       198

    accuracy                           0.89      1491
   macro avg       0.86      0.58      0.61      1491
weighted avg       0.88      0.89      0.85      1491

K value= 23
              precision    recall  f1-score   support

           0       0.89      0.99      0.94      1293
           1       0.84      0.18      0.30       198

    accuracy                           0.89      1491
```

```
   macro avg       0.86      0.59      0.62      1491
weighted avg       0.88      0.89      0.85      1491

K value= 25
              precision    recall  f1-score   support

           0       0.89      1.00      0.94      1293
           1       0.86      0.18      0.30       198

    accuracy                           0.89      1491
   macro avg       0.87      0.59      0.62      1491
weighted avg       0.88      0.89      0.85      1491

K value= 27
              precision    recall  f1-score   support

           0       0.89      1.00      0.94      1293
           1       0.85      0.17      0.28       198

    accuracy                           0.89      1491
   macro avg       0.87      0.58      0.61      1491
weighted avg       0.88      0.89      0.85      1491

K value= 29
              precision    recall  f1-score   support

           0       0.88      1.00      0.94      1293
           1       0.86      0.15      0.26       198

    accuracy                           0.88      1491
   macro avg       0.87      0.57      0.60      1491
weighted avg       0.88      0.88      0.85      1491

K value= 31
              precision    recall  f1-score   support

           0       0.89      1.00      0.94      1293
           1       0.89      0.16      0.27       198

    accuracy                           0.89      1491
   macro avg       0.89      0.58      0.60      1491
weighted avg       0.89      0.89      0.85      1491

K value= 33
              precision    recall  f1-score   support

           0       0.89      1.00      0.94      1293
           1       0.89      0.16      0.27       198

    accuracy                           0.89      1491
   macro avg       0.89      0.58      0.60      1491
weighted avg       0.89      0.89      0.85      1491

K value= 35
              precision    recall  f1-score   support

           0       0.88      1.00      0.94      1293
           1       0.84      0.14      0.23       198

    accuracy                           0.88      1491
   macro avg       0.86      0.57      0.59      1491
weighted avg       0.88      0.88      0.84      1491

K value= 37
              precision    recall  f1-score   support

           0       0.88      1.00      0.94      1293
           1       0.87      0.14      0.24       198

    accuracy                           0.88      1491
   macro avg       0.88      0.57      0.59      1491
weighted avg       0.88      0.88      0.84      1491

K value= 39
              precision    recall  f1-score   support

           0       0.88      1.00      0.94      1293
           1       0.90      0.13      0.23       198

    accuracy                           0.88      1491
   macro avg       0.89      0.56      0.58      1491
weighted avg       0.88      0.88      0.84      1491
```

In [31]:
```
plt.bar(k_range, k_scores)
plt.plot(k_range, k_scores, color = "red")

plt.xlabel('value of K for KNN')
plt.ylabel('Cross-Validation Accuracy')
plt.xticks(k_range)
plt.show()
```



In [32]:
```
model = KNeighborsClassifier(n_neighbors=3)
model.fit(x_train,y_train)
pred = model.predict(x_test)
```

In [33]:
```
print(classification_report(y_test,pred))
precision,recall,fscore,support = score(y_test,pred,average='macro')
KNN=fscore
KNN
```

```
              precision    recall  f1-score   support

           0       0.91      0.98      0.95      1293
           1       0.75      0.40      0.52       198

    accuracy                           0.90      1491
   macro avg       0.83      0.69      0.73      1491
weighted avg       0.89      0.90      0.89      1491
```

Out[33]: 0.7336637359144649

In [34]:
```
#Decision Tree
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
model = DecisionTreeClassifier(criterion='gini',min_samples_split=5)
model.fit(x_train,y_train)
pred = model.predict(x_test)
metrics.accuracy_score(pred,y_test)
print(classification_report(y_test,pred))
precision,recall,fscore,support = score(y_test,pred,average='macro')
DT=fscore
DT
```

```
              precision    recall  f1-score   support

           0       0.97      0.98      0.97      1293
           1       0.85      0.80      0.83       198

    accuracy                           0.96      1491
   macro avg       0.91      0.89      0.90      1491
weighted avg       0.95      0.96      0.95      1491
```

Out[34]: 0.9000875135646025

In [35]:
```
#Decision Tree
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
model = DecisionTreeClassifier(criterion='entropy',min_samples_split=5)
model.fit(x_train,y_train)
```

```
pred = model.predict(x_test)
metrics.accuracy_score(pred,y_test)
print(classification_report(y_test,pred))
```

```
              precision    recall  f1-score   support

           0       0.97      0.97      0.97      1293
           1       0.83      0.80      0.82       198

    accuracy                           0.95      1491
   macro avg       0.90      0.89      0.89      1491
weighted avg       0.95      0.95      0.95      1491
```

In [36]:
```
# Random Forest Classification

from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier

x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25,random_state=7)

num_trees = 140
max_features = 6

model = RandomForestClassifier(n_estimators=num_trees,max_samples=0.8, max_features=max_features, random_state =

model.fit(x_train,y_train)

pred = model.predict(x_test)

print(classification_report(y_test,pred))
precision,recall,fscore,support = score(y_test,pred,average='macro')
RD=fscore
RD
```

```
              precision    recall  f1-score   support

           0       0.98      1.00      0.99      1074
           1       0.98      0.85      0.91       169

    accuracy                           0.98      1243
   macro avg       0.98      0.92      0.95      1243
weighted avg       0.98      0.98      0.98      1243
```

Out[36]: 0.9492445896284197

In [37]:
```
#SVM
from sklearn import svm
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV

# clf = SVC()
# param_grid = [{'kernel':["rbf"],'gamma':[50,5,10,0.5,1,0.001,0.0001,0.00001],'C':[1,15,14,13,12,11,10,0.1] }]
# gsv = GridSearchCV(clf,param_grid,cv=10)
# gsv.fit(x_train,y_train)
```

In [38]:
```
#gsv.best_params_ , gsv.best_score_
```

In [39]:
```
clf = SVC(C= 1, gamma = 0.5,kernel="rbf")
clf.fit(x_train,y_train)
y_pred = clf.predict(x_test)
print(classification_report(y_test, y_pred))
precision,recall,fscore,support = score(y_test,y_pred,average='macro')
SVM=fscore
SVM
```

```
              precision    recall  f1-score   support

           0       0.93      0.99      0.96      1074
           1       0.92      0.51      0.66       169

    accuracy                           0.93      1243
   macro avg       0.92      0.75      0.81      1243
weighted avg       0.93      0.93      0.92      1243
```

Out[39]: 0.8092934293429344

In [40]:
```
#ANN
import tensorflow as tf
model = tf.keras.models.Sequential()
model.add(tf.keras.layers.Dense(15,input_dim=11,activation = 'sigmoid'))
model.add(tf.keras.layers.Dense(10,activation='sigmoid'))
```

```
model.add(tf.keras.layers.Dense(1,activation='sigmoid'))
```

In [41]:
```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 15)	180
dense_1 (Dense)	(None, 10)	160
dense_2 (Dense)	(None, 1)	11

Total params: 351 (1.37 KB)

Trainable params: 351 (1.37 KB)

Non-trainable params: 0 (0.00 B)

In [42]:
```
# Compile model
model.compile(loss ='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

In [43]:
```
history = model.fit(x,y,validation_split=0.20, epochs=50, batch_size=100)
```

```
Epoch 1/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 2s 11ms/step - accuracy: 0.8581 - loss: 0.4515 - val_accuracy: 0.8581 - val_loss: 0.4
249
Epoch 2/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8581 - loss: 0.4150 - val_accuracy: 0.8581 - val_loss: 0.40
78
Epoch 3/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8581 - loss: 0.4055 - val_accuracy: 0.8581 - val_loss: 0.40
26
Epoch 4/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8581 - loss: 0.4015 - val_accuracy: 0.8581 - val_loss: 0.39
90
Epoch 5/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8581 - loss: 0.3983 - val_accuracy: 0.8581 - val_loss: 0.39
54
Epoch 6/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8581 - loss: 0.3947 - val_accuracy: 0.8581 - val_loss: 0.39
17
Epoch 7/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8581 - loss: 0.3910 - val_accuracy: 0.8581 - val_loss: 0.38
78
Epoch 8/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8581 - loss: 0.3869 - val_accuracy: 0.8581 - val_loss: 0.38
33
Epoch 9/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8581 - loss: 0.3826 - val_accuracy: 0.8581 - val_loss: 0.37
88
Epoch 10/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8581 - loss: 0.3781 - val_accuracy: 0.8581 - val_loss: 0.37
41
Epoch 11/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8581 - loss: 0.3734 - val_accuracy: 0.8581 - val_loss: 0.36
90
Epoch 12/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8581 - loss: 0.3684 - val_accuracy: 0.8581 - val_loss: 0.36
37
Epoch 13/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8581 - loss: 0.3633 - val_accuracy: 0.8581 - val_loss: 0.35
84
Epoch 14/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8581 - loss: 0.3583 - val_accuracy: 0.8581 - val_loss: 0.35
32
Epoch 15/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8581 - loss: 0.3534 - val_accuracy: 0.8581 - val_loss: 0.34
85
Epoch 16/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8581 - loss: 0.3490 - val_accuracy: 0.8581 - val_loss: 0.34
37
Epoch 17/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8581 - loss: 0.3446 - val_accuracy: 0.8581 - val_loss: 0.33
93
Epoch 18/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8581 - loss: 0.3410 - val_accuracy: 0.8581 - val_loss: 0.33
54
Epoch 19/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8584 - loss: 0.3376 - val_accuracy: 0.8622 - val_loss: 0.33
20
Epoch 20/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8594 - loss: 0.3348 - val_accuracy: 0.8632 - val_loss: 0.32
```

```
87
Epoch 21/50
40/40 0s 5ms/step - accuracy: 0.8601 - loss: 0.3319 - val_accuracy: 0.8652 - val_loss: 0.32
60
Epoch 22/50
40/40 0s 5ms/step - accuracy: 0.8604 - loss: 0.3296 - val_accuracy: 0.8652 - val_loss: 0.32
33
Epoch 23/50
40/40 0s 5ms/step - accuracy: 0.8634 - loss: 0.3276 - val_accuracy: 0.8612 - val_loss: 0.32
13
Epoch 24/50
40/40 0s 5ms/step - accuracy: 0.8624 - loss: 0.3262 - val_accuracy: 0.8632 - val_loss: 0.31
93
Epoch 25/50
40/40 0s 6ms/step - accuracy: 0.8626 - loss: 0.3245 - val_accuracy: 0.8632 - val_loss: 0.31
76
Epoch 26/50
40/40 0s 5ms/step - accuracy: 0.8626 - loss: 0.3234 - val_accuracy: 0.8632 - val_loss: 0.31
59
Epoch 27/50
40/40 0s 4ms/step - accuracy: 0.8636 - loss: 0.3223 - val_accuracy: 0.8622 - val_loss: 0.31
50
Epoch 28/50
40/40 0s 5ms/step - accuracy: 0.8621 - loss: 0.3215 - val_accuracy: 0.8612 - val_loss: 0.31
38
Epoch 29/50
40/40 0s 5ms/step - accuracy: 0.8636 - loss: 0.3208 - val_accuracy: 0.8632 - val_loss: 0.31
26
Epoch 30/50
40/40 0s 5ms/step - accuracy: 0.8629 - loss: 0.3202 - val_accuracy: 0.8652 - val_loss: 0.31
16
Epoch 31/50
40/40 0s 6ms/step - accuracy: 0.8667 - loss: 0.3196 - val_accuracy: 0.8652 - val_loss: 0.31
04
Epoch 32/50
40/40 0s 5ms/step - accuracy: 0.8654 - loss: 0.3191 - val_accuracy: 0.8672 - val_loss: 0.31
02
Epoch 33/50
40/40 0s 6ms/step - accuracy: 0.8674 - loss: 0.3187 - val_accuracy: 0.8662 - val_loss: 0.30
91
Epoch 34/50
40/40 0s 6ms/step - accuracy: 0.8674 - loss: 0.3181 - val_accuracy: 0.8662 - val_loss: 0.30
86
Epoch 35/50
40/40 0s 6ms/step - accuracy: 0.8657 - loss: 0.3178 - val_accuracy: 0.8662 - val_loss: 0.30
80
Epoch 36/50
40/40 0s 5ms/step - accuracy: 0.8664 - loss: 0.3175 - val_accuracy: 0.8672 - val_loss: 0.30
74
Epoch 37/50
40/40 0s 6ms/step - accuracy: 0.8667 - loss: 0.3173 - val_accuracy: 0.8652 - val_loss: 0.30
68
Epoch 38/50
40/40 0s 6ms/step - accuracy: 0.8674 - loss: 0.3172 - val_accuracy: 0.8662 - val_loss: 0.30
62
Epoch 39/50
40/40 0s 5ms/step - accuracy: 0.8657 - loss: 0.3174 - val_accuracy: 0.8632 - val_loss: 0.30
59
Epoch 40/50
40/40 0s 4ms/step - accuracy: 0.8669 - loss: 0.3166 - val_accuracy: 0.8642 - val_loss: 0.30
55
Epoch 41/50
40/40 0s 5ms/step - accuracy: 0.8669 - loss: 0.3165 - val_accuracy: 0.8632 - val_loss: 0.30
52
Epoch 42/50
40/40 0s 4ms/step - accuracy: 0.8672 - loss: 0.3163 - val_accuracy: 0.8632 - val_loss: 0.30
46
Epoch 43/50
40/40 0s 4ms/step - accuracy: 0.8662 - loss: 0.3161 - val_accuracy: 0.8632 - val_loss: 0.30
44
Epoch 44/50
40/40 0s 4ms/step - accuracy: 0.8667 - loss: 0.3160 - val_accuracy: 0.8632 - val_loss: 0.30
42
Epoch 45/50
40/40 0s 3ms/step - accuracy: 0.8664 - loss: 0.3158 - val_accuracy: 0.8642 - val_loss: 0.30
36
Epoch 46/50
40/40 0s 3ms/step - accuracy: 0.8667 - loss: 0.3155 - val_accuracy: 0.8632 - val_loss: 0.30
33
Epoch 47/50
40/40 0s 5ms/step - accuracy: 0.8659 - loss: 0.3154 - val_accuracy: 0.8632 - val_loss: 0.30
30
Epoch 48/50
```

```
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8662 - loss: 0.3154 - val_accuracy: 0.8612 - val_loss: 0.30
29
Epoch 49/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8669 - loss: 0.3149 - val_accuracy: 0.8632 - val_loss: 0.30
23
Epoch 50/50
40/40 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8662 - loss: 0.3149 - val_accuracy: 0.8622 - val_loss: 0.30
21
```

In [44]:
```
model.save_weights("mywt.weights.h5")
```

In [45]:
```
#evaluate the model
scores = model.evaluate(x,y)
print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
ANN=model.metrics_names[1], scores[1]*100
ANN=ANN[1]
ANN
```

```
156/156 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8658 - loss: 0.3120
compile_metrics: 86.58%
```

Out[45]:
```
86.5767776966095
```

In [46]:
```
#Naive_Bayes
from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()
nb.fit(x_train, y_train)
```

Out[46]:
```
▾ GaussianNB
GaussianNB()
```

In [47]:
```
y_pred =  nb.predict(x_test)
```

In [48]:
```
from sklearn.metrics import confusion_matrix
conf_matrix1=confusion_matrix(y_test, y_pred)
conf_matrix1
```

Out[48]:
```
array([[980,  94],
       [ 91,  78]])
```

In [49]:
```
import seaborn as sns
%matplotlib inline
fig, ax= plt.subplots(1,1, figsize=(4,4),dpi=100)

xlabels=['0-Less than 50K','1-Above 50K']
ylabels=['0-Less than 50K','1-Above 50K']

sns.heatmap(conf_matrix1,annot=True, cbar=None, cmap="Purples",xticklabels=xlabels,yticklabels=ylabels,
            linewidths=1,linecolor='black')
ax.set_xlabel('Predicted Class')
ax.set_ylabel('True Class')
```

Out[49]:
```
Text(20.722222222222214, 0.5, 'True Class')
```

In [50]:
```
from sklearn.metrics import classification_report
names=['0-Less than 50K','1-Above 50K']
print(classification_report(y_test, y_pred,target_names=names))
precision,recall,fscore,support = score(y_test,y_pred,average='macro')
NB=fscore
NB
```

```
                 precision    recall  f1-score   support

0-Less than 50K       0.92      0.91      0.91      1074
    1-Above 50K       0.45      0.46      0.46       169

       accuracy                           0.85      1243
      macro avg       0.68      0.69      0.69      1243
   weighted avg       0.85      0.85      0.85      1243
```

Out[50]:
```
0.6856154598090082
```

In [51]:
```
#Bagging

from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import BaggingClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=2)
```

```python
num_trees = 100
model = BaggingClassifier(max_samples=0.8, n_estimators=num_trees,random_state=8)

model.fit(x_train,y_train)
pred = model.predict(x_test)
print(classification_report(y_test,pred))
precision,recall,fscore,support = score(y_test,pred,average='macro')
BG=fscore
BG
```

```
              precision    recall  f1-score   support

           0       0.98      0.99      0.99      1290
           1       0.95      0.88      0.91       201

    accuracy                           0.98      1491
   macro avg       0.97      0.93      0.95      1491
weighted avg       0.98      0.98      0.98      1491
```

Out[51]: 0.9494100130132448

In [52]:
```python
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.model_selection import GridSearchCV

param_grid = {
    'estimator__max_depth': [1, 2, 3, 4, 5],   # FIXED HERE
    'max_samples': [0.05, 0.1, 0.2, 0.5]
}

bag = BaggingClassifier(
    estimator=DecisionTreeClassifier(),  # FIXED HERE
    n_estimators=100,
    max_features=0.5,
    random_state=42
)

clf = GridSearchCV(
    bag,
    param_grid,
    cv=5,
    n_jobs=-1
)

clf.fit(x_train, y_train)
```

Out[52]:

▸ **GridSearchCV**

▸ **best_estimator_: BaggingClassifier**

▸ **estimator: DecisionTreeClassifier**

▸ DecisionTreeClassifier

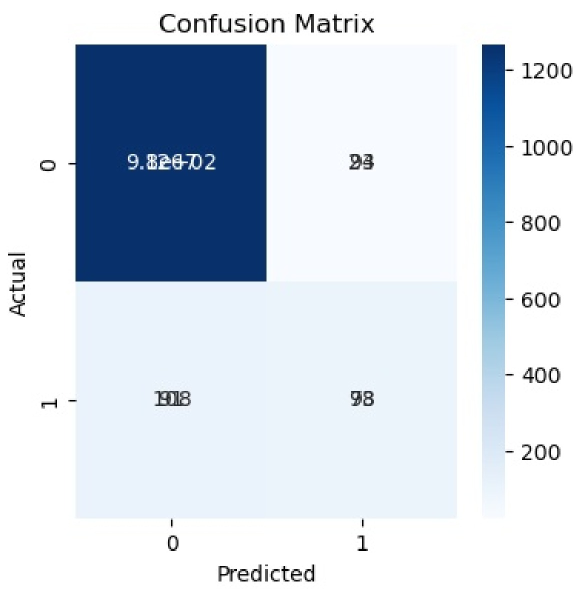
In [53]:
```python
clf.best_params_ , clf.best_score_
```

Out[53]:
```
({'estimator__max_depth': 5, 'max_samples': 0.5},
 np.float64(0.8723397833457373))
```

In [54]:
```python
#AdaBoost Classifier

from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier

ada = AdaBoostClassifier(
    estimator=DecisionTreeClassifier(max_depth=1),  # weak learner
    n_estimators=200,
    learning_rate=0.05,
    random_state=42
)

ada.fit(x_train, y_train)

y_pred = ada.predict(x_test)
from sklearn.metrics import accuracy_score

#Accuracy (quick check)
acc = accuracy_score(y_test, y_pred)
```

```python
print("Accuracy:", acc)

#Confusion Matrix (MOST IMPORTANT)
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n", cm)

import seaborn as sns
import matplotlib.pyplot as plt

sns.heatmap(cm, annot=True, fmt="d", cmap="Blues")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()

#Precision, Recall, F1-score (INTERVIEW FAVORITE)
from sklearn.metrics import classification_report

print(classification_report(y_test, y_pred))

#ROC–AUC Score (BEST METRIC for churn)
from sklearn.metrics import roc_auc_score

y_prob = ada.predict_proba(x_test)[:, 1]
roc_auc = roc_auc_score(y_test, y_prob)

print("ROC-AUC Score:", roc_auc)
```

```
Accuracy: 0.9121395036887995
Confusion Matrix:
 [[1267   23]
 [ 108   93]]
```




```
              precision    recall  f1-score   support

           0       0.92      0.98      0.95      1290
           1       0.80      0.46      0.59       201

    accuracy                           0.91      1491
   macro avg       0.86      0.72      0.77      1491
weighted avg       0.91      0.91      0.90      1491

ROC-AUC Score: 0.9133036368544872
```

Accuracy Sacores All Models

In [55]:

```python
# initialize list elements
data1 = [['Logistic Regression',LR],['KNearest Nighbour',KNN],
        ['Decision Tree',DT],['Random Forest',RD],['Support Vector Machine',SVM],['Artificial Neural Network',AI
        ['Navie Bais',NB],['Bagging',BG],['AdaBoosting',ada]]
# Create the pandas DataFrame with column name is provided explicitly
df = pd.DataFrame(data1, columns=['Algorithm Names','Accuracy'])
df
```

Out[55]:

	Algorithm Names	Accuracy
0	Logistic Regression	0.614467
1	KNearest Nighbour	0.733664
2	Decision Tree	0.900088
3	Random Forest	0.949245
4	Support Vector Machine	0.809293
5	Artificial Neural Network	86.576778
6	Navie Bais	0.685615
7	Bagging	0.94941
8	AdaBoosting	(DecisionTreeClassifier(max_depth=1, random_st...

In [56]:

```
y_test = y_test.to_numpy()
y_test
```

Out[56]:

```
array([[0],
       [0],
       [0],
       ...,
       [0],
       [0],
       [0]])
```

In [60]:

```
import numpy as np
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

x_train, x_test, y_train, y_test = train_test_split(
    x, y, test_size=0.3, random_state=15
)

clf = MLPClassifier(
    hidden_layer_sizes=(10,),
    max_iter=1000,
    random_state=15
)

clf.fit(x_train, y_train)

y_pred = clf.predict(x_test)

print(len(y_pred))
print(len(y_test))
print(y_pred)

accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")
```

```
1491
1491
[0 0 1 ... 0 0 0]
Accuracy: 94.43%
```

In [58]:

```
data
```

Out[58]:

	churn	account_length	voice_plan	voice_messages	intl_plan	intl_calls	intl_charge	day_calls	eve_calls	night_calls	custc
0	0	128	1	25	0	3	2.70	110	99	91	
1	0	107	1	26	0	3	3.70	123	103	103	
2	0	137	0	0	0	5	3.29	114	110	104	
3	0	84	0	0	1	7	1.78	71	88	89	
4	0	75	0	0	1	3	2.73	113	122	121	
...	...	...	...	...	...	...	...	...	...	...	
4995	0	50	1	40	0	5	2.67	127	126	116	
4996	1	152	0	0	0	2	3.97	90	73	113	
4997	0	61	0	0	0	4	3.67	89	128	97	
4998	0	109	0	0	0	6	2.30	67	92	89	
4999	0	86	1	34	0	16	2.51	102	104	100	

4969 rows × 12 columns

In [59]:
```
x
```

Out[59]:
```
array([[ 0.51851852,  1.        ,  1.47058824, ..., -0.34615385,
         0.        ,  1.16008615],
       [ 0.12962963,  1.        ,  1.52941176, ...,  0.11538462,
         0.        , -0.08327351],
       [ 0.68518519,  0.        ,  0.        , ...,  0.15384615,
        -1.        ,  0.16511127],
       ...,
       [-0.72222222,  0.        ,  0.        , ..., -0.11538462,
         0.        , -0.6137832 ],
       [ 0.16666667,  0.        ,  0.        , ..., -0.42307692,
        -1.        ,  0.00646088],
       [-0.25925926,  1.        ,  2.        , ...,  0.        ,
        -1.        , -0.36109117]])
```

In [61]:
```
y
```

Out[61]:

	churn
0	0
1	0
2	0
3	0
4	0
...	...
4995	0
4996	1
4997	0
4998	0
4999	0

4969 rows × 1 columns

In [ ]:
```
import numpy as np
from sklearn.datasets import load_breast_cancer
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import train_test_split



X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2)

# Create an instance of the MLPClassifier
clf = MLPClassifier(hidden_layer_sizes=(10,), max_iter=1000, random_state=0)

# Fit the classifier to the training data
clf.fit(X_train, y_train)

# Predict on the test data
y_pred = clf.predict(X_test)
```

```python
# Calculate the accuracy of the classifier
accuracy = np.mean(y_pred == y_test)
print("Accuracy: {:.2f}%".format(accuracy * 100))
```

In [63]:
```python
import pickle

final_artifacts = {
    "model": model,                    # trained Random Forest
    "scaler": transformer,              # RobustScaler
    "label_encoder": le,                # LabelEncoder
    "feature_order": [
        'account_length',
        'voice_plan',
        'voice_messages',
        'intl_plan',
        'intl_calls',
        'intl_charge',
        'day_calls',
        'eve_calls',
        'night_calls',
        'customer_calls',
        'Total_Charge'
    ]
}

with open("churn_complete_pipeline.pkl", "wb") as f:
    pickle.dump(final_artifacts, f)

print("✅ Full project pipeline saved successfully!")
```

```
✅ Full project pipeline saved successfully!
```

In [65]:
```python
import os
print(os.getcwd())
print(os.listdir())
```

```
C:\Users\Agnel Sharon Jerald\Machine learning
['.ipynb_checkpoints', 'boosting.ipynb', 'Cars.csv', 'Churn.csv', 'churn_complete_pipeline.pkl', 'churn_coustome
r_prediction.zip', 'CHURN_CUSTOMER_PREDICTION_WITH_FEATURE_ENGINEERING.ipynb', 'CHURN_CUSTOMER_WITHOUT_FEATURE_E
NGINEERING.ipynb', 'claimants.csv', 'Data Visualisations.ipynb', 'Decision Tree Classifier.ipynb', 'Decision Tre
e_C5.0_CART.ipynb', 'Iris Species decicision Tree.ipynb', 'KNN_updated.ipynb', 'Linear_Regression.ipynb', 'Logis
tic Regression.ipynb', 'Machine Learning basics.ipynb', 'Multi Linear Regression.ipynb', 'mywt.weights.h5', 'Num
py.ipynb', 'pima-indians-diabetes.csv', 'polynomial Regression.ipynb', 'Practice libraries.ipynb', 'Predicting C
ustomer Purchase Behavior in the Travel Industry.ipynb', 'Random Forest Regression Implementation.ipynb', 'Trave
l.csv']
```

In [ ]: