Import Libraries & Load Data

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import joblib
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import confusion_matrix, classification_report,
accuracy_score, roc_auc_score, roc_curve
import warnings
warnings.filterwarnings('ignore')

# Load data
df = pd.read_csv("WA_Fn-UseC_-Telco-Customer-Churn.csv")
df.head()
```

```
   customerID  gender  SeniorCitizen Partner Dependents  tenure
PhoneService  \
0  7590-VHVEG  Female              0     Yes         No       1
No
1  5575-GNVDE    Male              0      No         No      34
Yes
2  3668-QPYBK    Male              0      No         No       2
Yes
3  7795-CFOCW    Male              0      No         No      45
No
4  9237-HQITU  Female              0      No         No       2
Yes

      MultipleLines InternetService OnlineSecurity  ...
DeviceProtection  \
0  No phone service             DSL             No  ...
No
1                No             DSL            Yes  ...
Yes
2                No             DSL            Yes  ...
No
3  No phone service             DSL            Yes  ...
Yes
4                No     Fiber optic             No  ...
No

  TechSupport StreamingTV StreamingMovies        Contract
PaperlessBilling  \
0          No          No              No  Month-to-month
Yes
1          No          No              No        One year
```

```
No
2          No          No               No  Month-to-month
Yes
3         Yes          No               No        One year
No
4          No          No               No  Month-to-month
Yes

              PaymentMethod MonthlyCharges  TotalCharges Churn
0          Electronic check          29.85         29.85    No
1              Mailed check          56.95        1889.5    No
2              Mailed check          53.85        108.15   Yes
3  Bank transfer (automatic)          42.30       1840.75    No
4          Electronic check          70.70        151.65   Yes

[5 rows x 21 columns]
```

Data Cleaning

```
# Check info
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   gender            7043 non-null   object
 2   SeniorCitizen     7043 non-null   int64
 3   Partner           7043 non-null   object
 4   Dependents        7043 non-null   object
 5   tenure            7043 non-null   int64
 6   PhoneService      7043 non-null   object
 7   MultipleLines     7043 non-null   object
 8   InternetService   7043 non-null   object
 9   OnlineSecurity    7043 non-null   object
 10  OnlineBackup      7043 non-null   object
 11  DeviceProtection  7043 non-null   object
 12  TechSupport       7043 non-null   object
 13  StreamingTV       7043 non-null   object
 14  StreamingMovies   7043 non-null   object
 15  Contract          7043 non-null   object
 16  PaperlessBilling  7043 non-null   object
 17  PaymentMethod     7043 non-null   object
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object
 20  Churn             7043 non-null   object
```

```
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB

# Convert TotalCharges to numeric
df['TotalCharges']=pd.to_numeric(df['TotalCharges'],errors='coerce')
'''errors : {'ignore', 'raise', 'coerce'}, default 'raise'
    - If 'raise', then invalid parsing will raise an exception.
    - If 'coerce', then invalid parsing will be set as NaN.
    - If 'ignore', then invalid parsing will return the input'''

"errors : {'ignore', 'raise', 'coerce'}, default 'raise'\n    - If
'raise', then invalid parsing will raise an exception.\n    - If
'coerce', then invalid parsing will be set as NaN.\n    - If 'ignore',
then invalid parsing will return the input"

#check null value
df.isnull().sum()

customerID           0
gender               0
SeniorCitizen        0
Partner              0
Dependents           0
tenure               0
PhoneService         0
MultipleLines        0
InternetService      0
OnlineSecurity       0
OnlineBackup         0
DeviceProtection     0
TechSupport          0
StreamingTV          0
StreamingMovies      0
Contract             0
PaperlessBilling     0
PaymentMethod        0
MonthlyCharges       0
TotalCharges        11
Churn                0
dtype: int64

#fill null value with median
df['TotalCharges']=df['TotalCharges'].fillna(df['TotalCharges'].median
())

df.head(20)

    customerID  gender  SeniorCitizen Partner Dependents  tenure
PhoneService  \
0   7590-VHVEG  Female              0     Yes         No       1
No
```

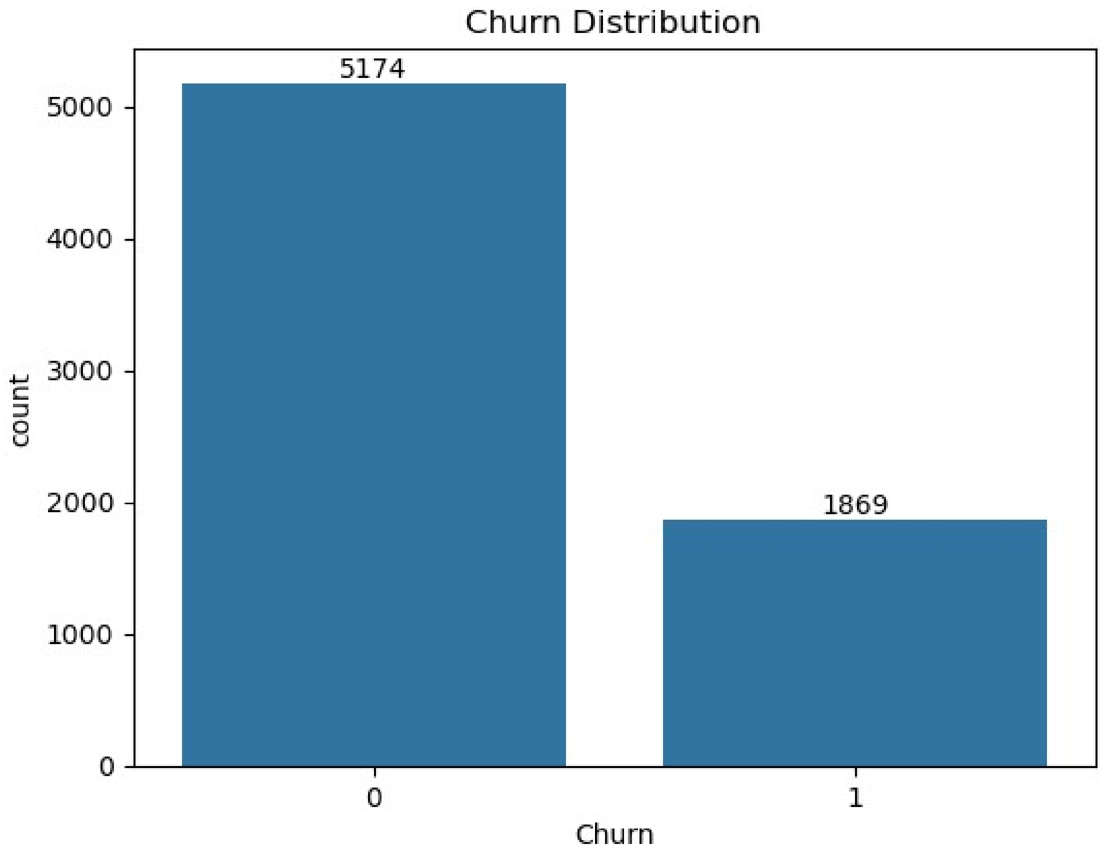
```
1   5575-GNVDE    Male              0      No          No      34
Yes
2   3668-QPYBK    Male              0      No          No       2
Yes
3   7795-CFOCW    Male              0      No          No      45
No
4   9237-HQITU  Female              0      No          No       2
Yes
5   9305-CDSKC  Female              0      No          No       8
Yes
6   1452-KIOVK    Male              0      No         Yes      22
Yes
7   6713-OKOMC  Female              0      No          No      10
No
8   7892-POOKP  Female              0     Yes          No      28
Yes
9   6388-TABGU    Male              0      No         Yes      62
Yes
10  9763-GRSKD    Male              0     Yes         Yes      13
Yes
11  7469-LKBCI    Male              0      No          No      16
Yes
12  8091-TTVAX    Male              0     Yes          No      58
Yes
13  0280-XJGEX    Male              0      No          No      49
Yes
14  5129-JLPIS    Male              0      No          No      25
Yes
15  3655-SNQYZ  Female              0     Yes         Yes      69
Yes
16  8191-XWSZG  Female              0      No          No      52
Yes
17  9959-WOFKT    Male              0      No         Yes      71
Yes
18  4190-MFLUW  Female              0     Yes         Yes      10
Yes
19  4183-MYFRB  Female              0      No          No      21
Yes

       MultipleLines InternetService       OnlineSecurity  ...  \
0   No phone service             DSL                   No  ...
1                 No             DSL                  Yes  ...
2                 No             DSL                  Yes  ...
3   No phone service             DSL                  Yes  ...
4                 No     Fiber optic                   No  ...
5                Yes     Fiber optic                   No  ...
6                Yes     Fiber optic                   No  ...
7   No phone service             DSL                  Yes  ...
8                Yes     Fiber optic                   No  ...
```

```
9                   No             DSL                  Yes  ...
10                  No             DSL                  Yes  ...
11                  No              No  No internet service  ...
12                 Yes     Fiber optic                   No  ...
13                 Yes     Fiber optic                   No  ...
14                  No     Fiber optic                  Yes  ...
15                 Yes     Fiber optic                  Yes  ...
16                  No              No  No internet service  ...
17                 Yes     Fiber optic                  Yes  ...
18                  No             DSL                   No  ...
19                  No     Fiber optic                   No  ...

       DeviceProtection          TechSupport          StreamingTV  \
0                    No                   No                   No
1                   Yes                   No                   No
2                    No                   No                   No
3                   Yes                  Yes                   No
4                    No                   No                   No
5                   Yes                   No                  Yes
6                    No                   No                  Yes
7                    No                   No                   No
8                   Yes                  Yes                  Yes
9                    No                   No                   No
10                   No                   No                   No
11  No internet service  No internet service  No internet service
12                  Yes                   No                  Yes
13                  Yes                   No                  Yes
14                  Yes                  Yes                  Yes
15                  Yes                  Yes                  Yes
16  No internet service  No internet service  No internet service
17                  Yes                   No                  Yes
18                  Yes                  Yes                   No
19                  Yes                   No                   No

        StreamingMovies        Contract PaperlessBilling  \
0                    No  Month-to-month              Yes
1                    No        One year               No
2                    No  Month-to-month              Yes
3                    No        One year               No
4                    No  Month-to-month              Yes
5                   Yes  Month-to-month              Yes
6                    No  Month-to-month              Yes
7                    No  Month-to-month               No
8                   Yes  Month-to-month              Yes
9                    No        One year               No
10                   No  Month-to-month              Yes
11  No internet service        Two year               No
12                  Yes        One year               No
13                  Yes  Month-to-month              Yes
```

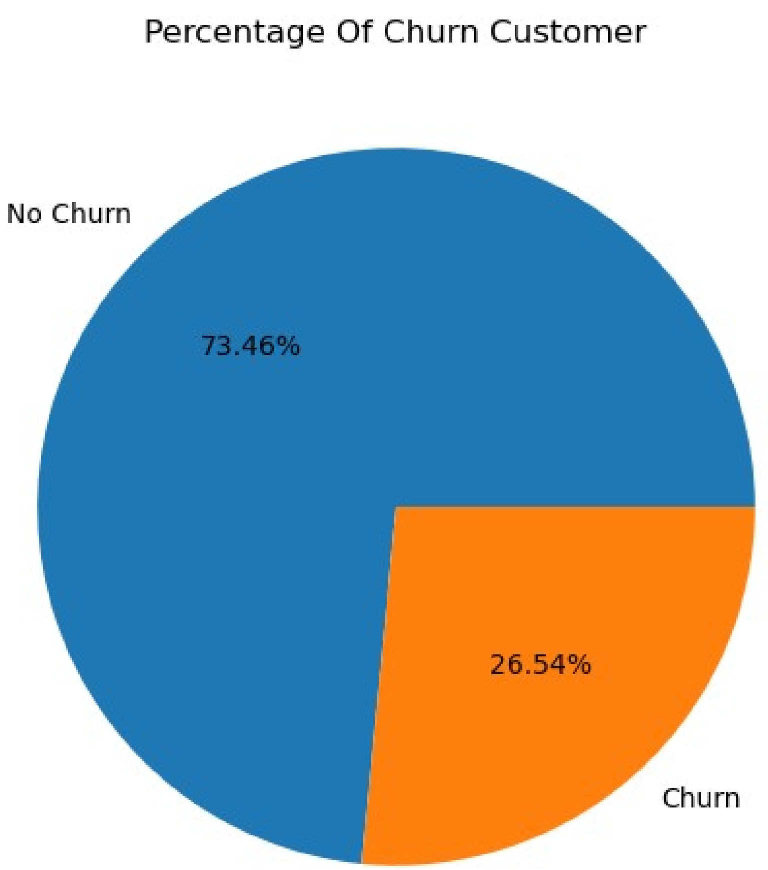
```
14                    Yes  Month-to-month             Yes
15                    Yes        Two year              No
16  No internet service        One year              No
17                    Yes        Two year              No
18                     No  Month-to-month              No
19                    Yes  Month-to-month             Yes

                PaymentMethod MonthlyCharges  TotalCharges  Churn
0            Electronic check          29.85         29.85     No
1                Mailed check          56.95       1889.50     No
2                Mailed check          53.85        108.15    Yes
3   Bank transfer (automatic)          42.30       1840.75     No
4            Electronic check          70.70        151.65    Yes
5            Electronic check          99.65        820.50    Yes
6     Credit card (automatic)          89.10       1949.40     No
7                Mailed check          29.75        301.90     No
8            Electronic check         104.80       3046.05    Yes
9   Bank transfer (automatic)          56.15       3487.95     No
10               Mailed check          49.95        587.45     No
11    Credit card (automatic)          18.95        326.80     No
12    Credit card (automatic)         100.35       5681.10     No
13  Bank transfer (automatic)         103.70       5036.30    Yes
14           Electronic check         105.50       2686.05     No
15    Credit card (automatic)         113.25       7895.15     No
16               Mailed check          20.65       1022.95     No
17  Bank transfer (automatic)         106.70       7382.25     No
18    Credit card (automatic)          55.20        528.35    Yes
19           Electronic check          90.05       1862.90     No

[20 rows x 21 columns]

# Drop customerID
df=df.drop('customerID',axis=1)
#axis : {0 or 'index', 1 or 'columns'}, default 0

# change target variable in binary format
df['Churn']=df['Churn'].map({'Yes':1,'No':0})

#df.to_excel("churn_cleaned_data_powerbi.xlsx", index=False)
```

Exploratory Data Analysis (EDA)

```
# Check churn balance
ax=sns.countplot(x='Churn',data=df)
ax.bar_label(ax.containers[0])
plt.title('Churn Distribution')
plt.show()
```

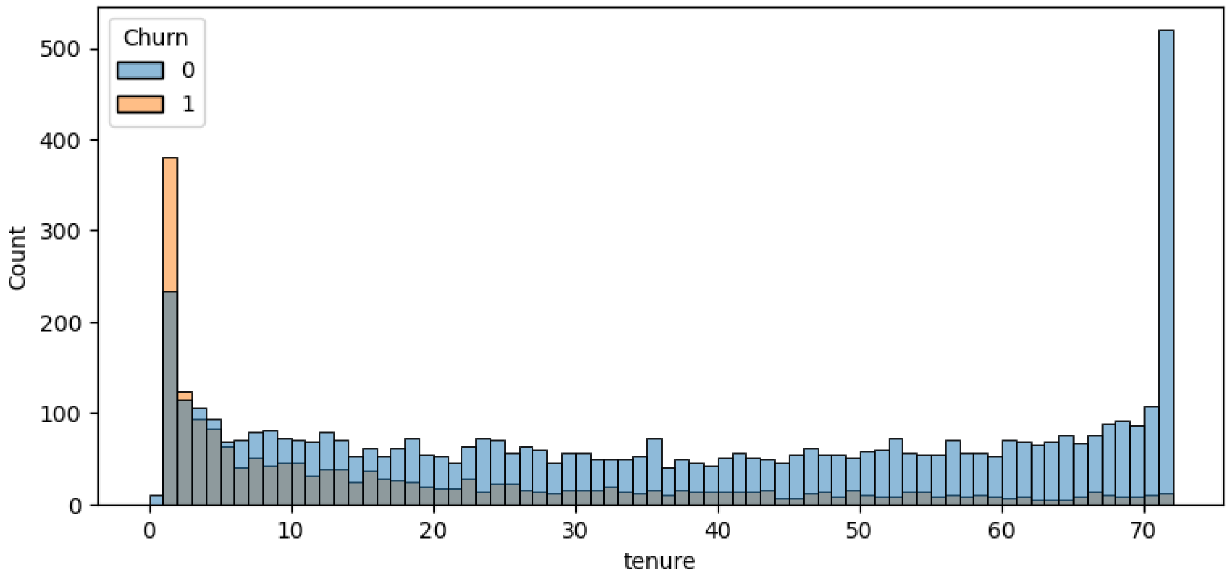



```
chrn_count=df['Churn'].value_counts()
chrn_count

Churn
0    5174
1    1869
Name: count, dtype: int64

plt.figure(figsize=(6,6))
plt.pie(chrn_count, labels=['No Churn', 'Churn'],autopct='%1.2f%%')
plt.title('Percentage Of Churn Customer')

Text(0.5, 1.0, 'Percentage Of Churn Customer')
```



in above we undestand 73% people is not chrn and 27% people is chrun out

```
plt.figure(figsize=(9,4))
sns.histplot(x='tenure',data=df,bins=72,hue='Churn')
plt.show()
```



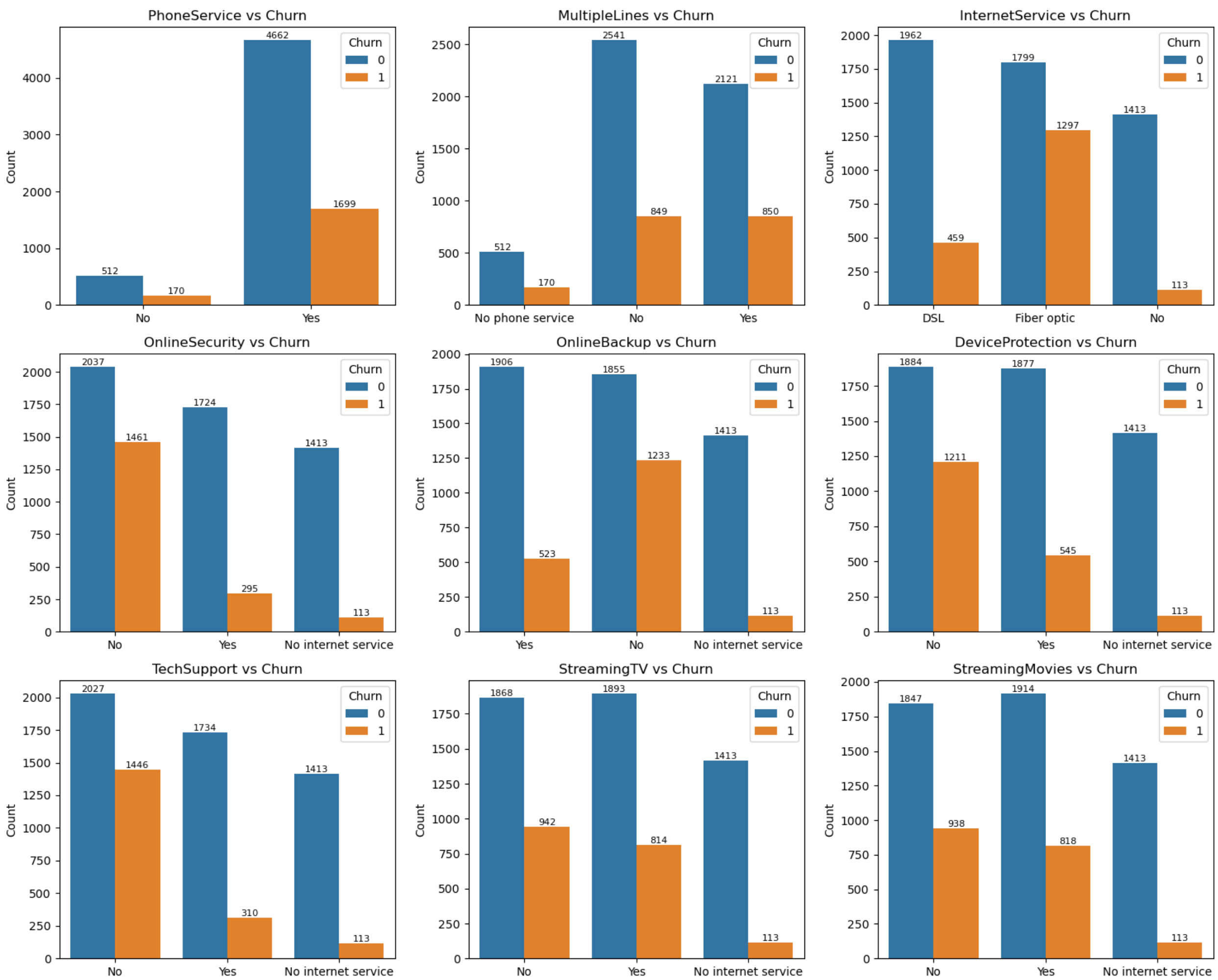
in above we undestand who have used servcies is long time its stay who using only 1 and 2 month is churned

```
df.columns
```

```
Index(['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
       'PhoneService', 'MultipleLines', 'InternetService',
'OnlineSecurity',
       'OnlineBackup', 'DeviceProtection', 'TechSupport',
'StreamingTV',
       'StreamingMovies', 'Contract', 'PaperlessBilling',
'PaymentMethod',
       'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

```
# Columns to plot
cols = [
    'PhoneService', 'MultipleLines', 'InternetService',
'OnlineSecurity',
    'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV',
    'StreamingMovies'
]

# Create subplot grid (3 rows × 3 columns)
fig, axes = plt.subplots(3, 3, figsize=(15, 12))
axes = axes.flatten()  # Flatten 2D array of axes for easy iteration

# Loop through columns
for i, col in enumerate(cols):
    sns.countplot(x=col, data=df, hue='Churn', ax=axes[i])
    axes[i].set_title(f'{col} vs Churn', fontsize=12)
    axes[i].bar_label(axes[i].containers[0], fontsize=8)
```

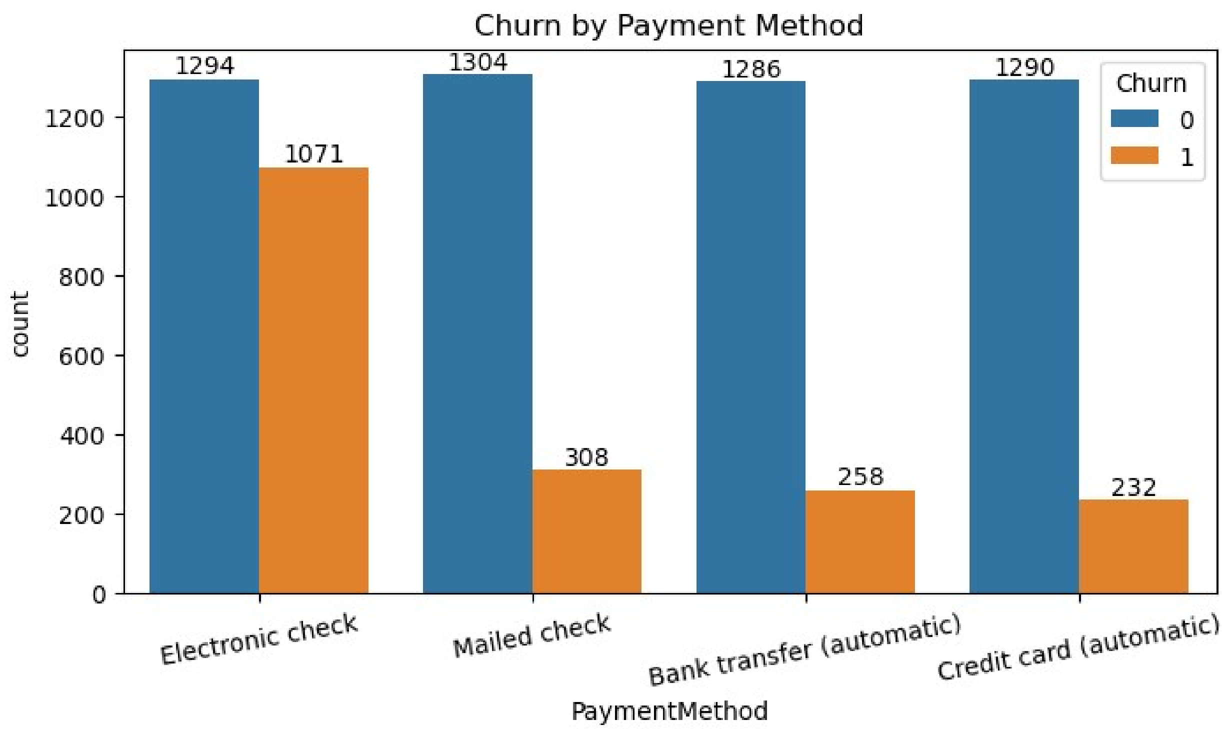
```python
    if len(axes[i].containers) > 1:
        axes[i].bar_label(axes[i].containers[1], fontsize=8)
    axes[i].set_xlabel('')
    axes[i].set_ylabel('Count')

# Remove extra empty plots (if any)
for j in range(len(cols), len(axes)):
    fig.delaxes(axes[j])

plt.tight_layout()
plt.show()
```



in above Customers without internet-based add-ons (like OnlineSecurity, TechSupport, or DeviceProtection) tend to churn more frequently. Fiber optic users also exhibit higher churn rates compared to DSL users. Overall, having additional services (security, backup, or protection) is linked with lower churn

```python
# analysis using paymnet method
plt.figure(figsize=(8,4))
```

```python
ax=sns.countplot(x='PaymentMethod',hue='Churn',data=df)
for containers in ax.containers:
    ax.bar_label(containers)
#ax.bar_label(ax.containers[0])
plt.title("Churn by Payment Method")
plt.xticks(rotation=10)
plt.show()
```

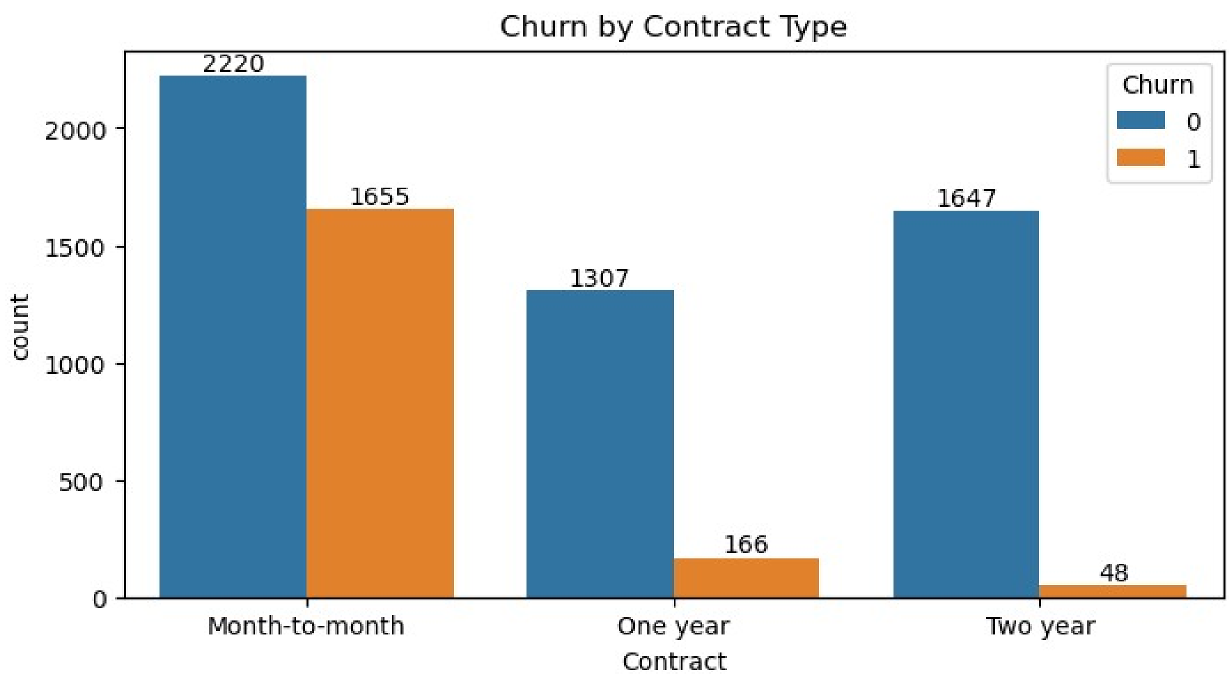


Customer is churn out when they are using Electronic Check

```python
# Numeric summary
df.describe()
```

```
       SeniorCitizen       tenure  MonthlyCharges  TotalCharges
Churn
count    7043.000000  7043.000000     7043.000000   7043.000000
7043.000000
mean        0.162147    32.371149       64.761692   2281.916928
0.265370
std         0.368612    24.559481       30.090047   2265.270398
0.441561
min         0.000000     0.000000       18.250000     18.800000
0.000000
25%         0.000000     9.000000       35.500000    402.225000
0.000000
50%         0.000000    29.000000       70.350000   1397.475000
0.000000
```

```
75%          0.000000    55.000000       89.850000    3786.600000
1.000000
max          1.000000    72.000000      118.750000    8684.800000
1.000000

# Categorical distribution example
plt.figure(figsize=(8,4))
ax=sns.countplot(x='Contract',hue='Churn',data=df)
for containers in ax.containers:
    ax.bar_label(containers)
#ax.bar_label(ax.containers[0])
plt.title("Churn by Contract Type")
plt.show()
```



in above you can say month to month contrcat base customert is chrun more and for log term one year and 2 year customer is stay. for that we need to convey to customer contract for long time

Feature Encoding & Scaling

```
# Encode categorical columns(in this categorical columns store in 1
variable)
cat_col=df.select_dtypes(include='object').columns
cat_col

Index(['gender', 'Partner', 'Dependents', 'PhoneService',
'MultipleLines',
       'InternetService', 'OnlineSecurity', 'OnlineBackup',
'DeviceProtection',
```

```
       'TechSupport', 'StreamingTV', 'StreamingMovies', 'Contract',
       'PaperlessBilling', 'PaymentMethod'],
      dtype='object')

#in this we convert categorical columns in True False Format and drop
firt orignal column df =
df =pd.get_dummies(df,columns=cat_col,drop_first=True)
df

      SeniorCitizen  tenure  MonthlyCharges  TotalCharges  Churn
gender_Male  \
0                 0       1           29.85         29.85      0
False
1                 0      34           56.95       1889.50      0
True
2                 0       2           53.85        108.15      1
True
3                 0      45           42.30       1840.75      0
True
4                 0       2           70.70        151.65      1
False
...             ...     ...             ...           ...    ...
...
7038              0      24           84.80       1990.50      0
True
7039              0      72          103.20       7362.90      0
False
7040              0      11           29.60        346.45      0
False
7041              1       4           74.40        306.60      1
True
7042              0      66          105.65       6844.50      0
True

      Partner_Yes  Dependents_Yes  PhoneService_Yes  \
0            True           False             False
1           False           False              True
2           False           False              True
3           False           False             False
4           False           False              True
...           ...             ...               ...
7038         True            True              True
7039         True            True              True
7040         True            True             False
7041         True           False              True
7042        False           False              True

      MultipleLines_No phone service  ...  StreamingTV_No internet
service  \
0                               True  ...
```

```
False
1                                  False  ...
False
2                                  False  ...
False
3                                   True  ...
False
4                                  False  ...
False
...                                  ...  ...
...
7038                               False  ...
False
7039                               False  ...
False
7040                                True  ...
False
7041                               False  ...
False
7042                               False  ...
False

      StreamingTV_Yes  StreamingMovies_No internet service  \
0               False                                False
1               False                                False
2               False                                False
3               False                                False
4               False                                False
...               ...                                  ...
7038             True                                False
7039             True                                False
7040            False                                False
7041            False                                False
7042             True                                False

      StreamingMovies_Yes  Contract_One year  Contract_Two year  \
0                   False              False              False
1                   False               True              False
2                   False              False              False
3                   False               True              False
4                   False              False              False
...                   ...                ...                ...
7038                 True               True              False
7039                 True               True              False
7040                False              False              False
7041                False              False              False
7042                 True              False               True

      PaperlessBilling_Yes  PaymentMethod_Credit card (automatic)  \
0                     True                                  False
```

```
1                     False                                      False
2                      True                                      False
3                     False                                      False
4                      True                                      False
...                     ...                                        ...
7038                   True                                      False
7039                   True                                       True
7040                   True                                      False
7041                   True                                      False
7042                   True                                      False

      PaymentMethod_Electronic check  PaymentMethod_Mailed check
0                               True                       False
1                              False                        True
2                              False                        True
3                              False                       False
4                               True                       False
...                              ...                         ...
7038                           False                        True
7039                           False                       False
7040                            True                       False
7041                           False                        True
7042                           False                       False

[7043 rows x 31 columns]
```

```
# Split data in x and y
x = pd.get_dummies(df.drop('Churn', axis=1), drop_first=True)
feature_names = x.columns.tolist()
joblib.dump(feature_names, "feature_names.pkl")
y = df['Churn']

x.columns
```

```
Index(['SeniorCitizen', 'tenure', 'MonthlyCharges', 'TotalCharges',
       'gender_Male', 'Partner_Yes', 'Dependents_Yes',
'PhoneService_Yes',
       'MultipleLines_No phone service', 'MultipleLines_Yes',
       'InternetService_Fiber optic', 'InternetService_No',
       'OnlineSecurity_No internet service', 'OnlineSecurity_Yes',
       'OnlineBackup_No internet service', 'OnlineBackup_Yes',
       'DeviceProtection_No internet service', 'DeviceProtection_Yes',
       'TechSupport_No internet service', 'TechSupport_Yes',
       'StreamingTV_No internet service', 'StreamingTV_Yes',
       'StreamingMovies_No internet service', 'StreamingMovies_Yes',
       'Contract_One year', 'Contract_Two year',
'PaperlessBilling_Yes',
       'PaymentMethod_Credit card (automatic)',
       'PaymentMethod_Electronic check', 'PaymentMethod_Mailed
```

```
check'],
      dtype='object')

# Train-test split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,rando
m_state=42,stratify=y)
'''random_state : default=None
    Controls the shuffling applied to the data before applying the
split.
shuffle : default=True
    Whether or not to shuffle the data before splitting. If
shuffle=False
    then stratify must be None.'''

'random_state : default=None\n    Controls the shuffling applied to
the data before applying the split.\nshuffle : default=True\n
Whether or not to shuffle the data before splitting. If shuffle=False\
n    then stratify must be None.'

# Scale
scaler=StandardScaler()
x_train=scaler.fit_transform(x_train)
x_test=scaler.transform(x_test)
```

Model Training (Logistic Regression & Random Forest)

```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier

models={'Logistic Regression':LogisticRegression(),
   'Random
Forest':RandomForestClassifier(n_estimators=100,random_state=42)}
'''n_estimators : int, default=100
    The number of trees in the forest.
random_state :default=None
    Controls both the randomness of the bootstrapping of the samples
used
    when building trees (if ``bootstrap=True``) and the sampling of
the
    features to consider when looking for the best split at each
node'''

'n_estimators : int, default=100\n    The number of trees in the
forest.\nrandom_state :default=None\n    Controls both the randomness
of the bootstrapping of the samples used\n    when building trees (if
``bootstrap=True``) and the sampling of the\n    features to consider
when looking for the best split at each node'

for name,model in models.items():
    model.fit(x_train,y_train)
```

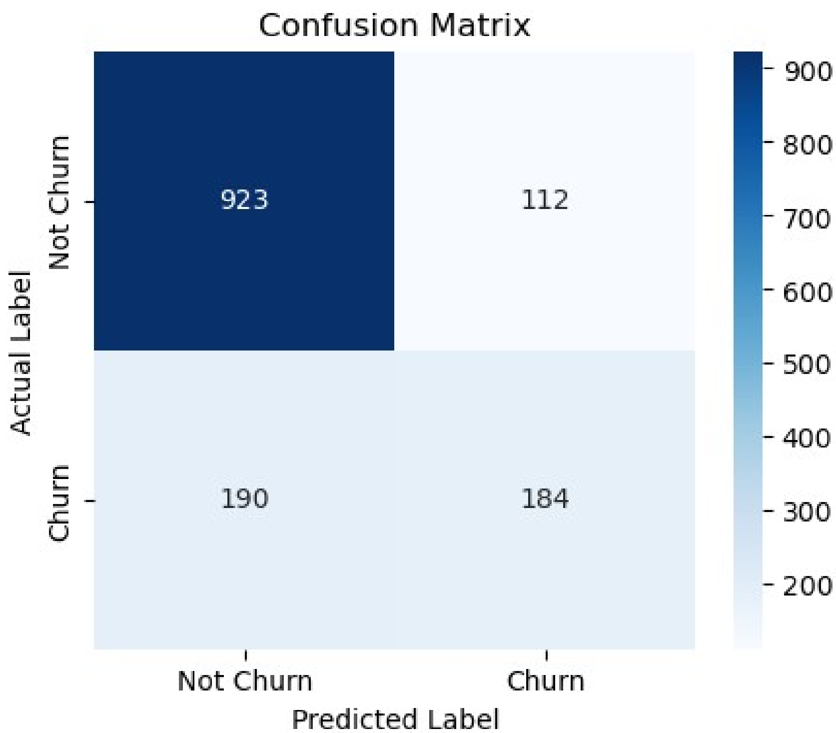
```
    y_pred=model.predict(x_test)
    print(f"=== {name} ===")
    print('acurracy score',accuracy_score(y_test,y_pred))
    print("ROC-AUC:", roc_auc_score(y_test, y_pred))
    print("Classification Report:\n", classification_report(y_test, 
y_pred))
    print("-" * 40)
```

```
=== Logistic Regression ===
acurracy score 0.8069552874378992
ROC-AUC: 0.7302823632746905
Classification Report:
               precision    recall  f1-score   support

           0       0.85      0.89      0.87      1035
           1       0.66      0.57      0.61       374

    accuracy                           0.81      1409
   macro avg       0.75      0.73      0.74      1409
weighted avg       0.80      0.81      0.80      1409

----------------------------------------
=== Random Forest ===
acurracy score 0.7856635911994322
ROC-AUC: 0.6918830246195975
Classification Report:
               precision    recall  f1-score   support

           0       0.83      0.89      0.86      1035
           1       0.62      0.49      0.55       374

    accuracy                           0.79      1409
   macro avg       0.73      0.69      0.70      1409
weighted avg       0.77      0.79      0.78      1409

----------------------------------------
```

in above Logistic Regression outperforms Random Forest in this case, with higher accuracy, ROC-AUC, and recall.Therfore Logistic Regression It's the better choice for predicting churn in this dataset.

```
cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(5,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Not Churn', 'Churn'],
            yticklabels=['Not Churn', 'Churn'])

plt.xlabel('Predicted Label')
plt.ylabel('Actual Label')
```

```
plt.title('Confusion Matrix')
plt.show()
```



Feature Importance (for Random Forest)

```
x.columns

Index(['SeniorCitizen', 'tenure', 'MonthlyCharges', 'TotalCharges',
       'gender_Male', 'Partner_Yes', 'Dependents_Yes',
'PhoneService_Yes',
       'MultipleLines_No phone service', 'MultipleLines_Yes',
       'InternetService_Fiber optic', 'InternetService_No',
       'OnlineSecurity_No internet service', 'OnlineSecurity_Yes',
       'OnlineBackup_No internet service', 'OnlineBackup_Yes',
       'DeviceProtection_No internet service', 'DeviceProtection_Yes',
       'TechSupport_No internet service', 'TechSupport_Yes',
       'StreamingTV_No internet service', 'StreamingTV_Yes',
       'StreamingMovies_No internet service', 'StreamingMovies_Yes',
       'Contract_One year', 'Contract_Two year',
'PaperlessBilling_Yes',
       'PaymentMethod_Credit card (automatic)',
       'PaymentMethod_Electronic check', 'PaymentMethod_Mailed
check'],
      dtype='object')
```

```
rf = RandomForestClassifier(random_state=42)
rf.fit(x, y)
```

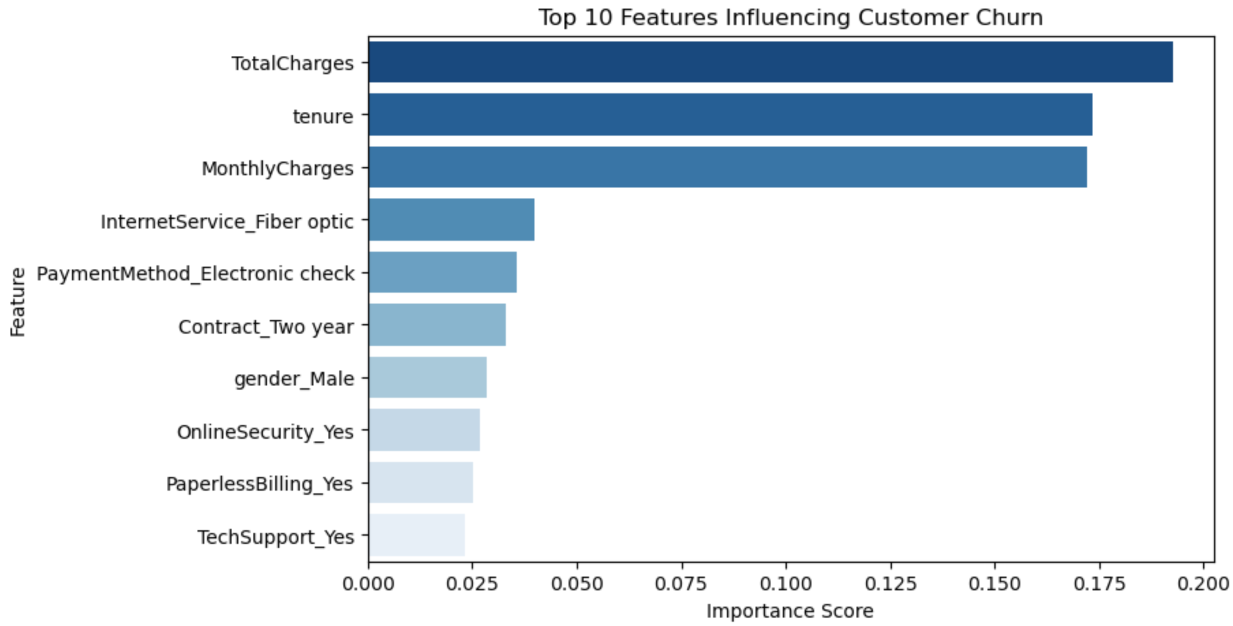
```
RandomForestClassifier(random_state=42)
```

```
importances = pd.Series(rf.feature_importances_, index=x.columns)
importances.sort_values(ascending=False).head(10)
```

```
TotalCharges                        0.192846
tenure                              0.173395
MonthlyCharges                      0.172255
InternetService_Fiber optic         0.039823
PaymentMethod_Electronic check      0.035774
Contract_Two year                   0.032939
gender_Male                         0.028368
OnlineSecurity_Yes                  0.026899
PaperlessBilling_Yes                0.025229
TechSupport_Yes                     0.023075
dtype: float64
```

its tell you how important each feature was in making predictions.

```
plt.figure(figsize=(8,5))
sns.barplot(
    x=importances.nlargest(10),
    y=importances.nlargest(10).index,
    palette='Blues_r'
)
plt.title("Top 10 Features Influencing Customer Churn")
plt.xlabel("Importance Score")
plt.ylabel("Feature")
plt.show()
```



Financial factors (charges) and customer tenure are the strongest churn drivers.Service experience (security, support) helps retain customers. Payment and internet type also influence behavior, showing that both pricing and service quality matter.In short: High charges + short tenure + fiber optic users + electronic check payments = higher churn risk

improving recall for churn class

Use Class Weights

RandomForest supports class_weight='balanced' that forces model to pay more attention to minority class

```
rf = RandomForestClassifier(class_weight='balanced', random_state=42)
rf.fit(x_train, y_train)
y_pred = rf.predict(x_test)

print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.83      0.89      0.86      1035
           1       0.63      0.50      0.56       374

    accuracy                           0.79      1409
   macro avg       0.73      0.70      0.71      1409
weighted avg       0.78      0.79      0.78      1409
```

The use of class weights did not result in any significant improvement in recall.

Now We Are Using SMOTE Oversampling

```python
from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=42)

X_resampled, y_resampled = sm.fit_resample(x_train, y_train)

rf = RandomForestClassifier(random_state=42)
rf.fit(X_resampled, y_resampled)

y_pred = rf.predict(x_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.85      0.84      0.85      1035
           1       0.57      0.60      0.59       374

    accuracy                           0.78      1409
   macro avg       0.71      0.72      0.72      1409
weighted avg       0.78      0.78      0.78      1409
```

Using SMOTE results are better than before — especially recall for churn (class 1) improving from 0.50 → 0.60. But we can still push churn recall higher

Now Try To Use Both SMOTE + Class Weight Together

```python
sm = SMOTE(random_state=42)
x_train_res, y_train_res = sm.fit_resample(x_train, y_train)

rf = RandomForestClassifier(
    n_estimators=300,
    class_weight='balanced',
    random_state=42
)
rf.fit(x_train_res, y_train_res)

y_pred = rf.predict(x_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.85      0.84      0.85      1035
           1       0.58      0.60      0.59       374

    accuracy                           0.78      1409
   macro avg       0.72      0.72      0.72      1409
weighted avg       0.78      0.78      0.78      1409
```

Using Both SMOTE + class_weight results are almost the same as pure SMOTE

Now we are using Threshold Tuning By default, prediction threshold = 0.50 So values like 0.40 or 0.35 are treated as NON-churn So we LOWER the threshold to 0.35 to catch more churn customers.

```
y_prob = rf.predict_proba(x_test)[:, 1]
```

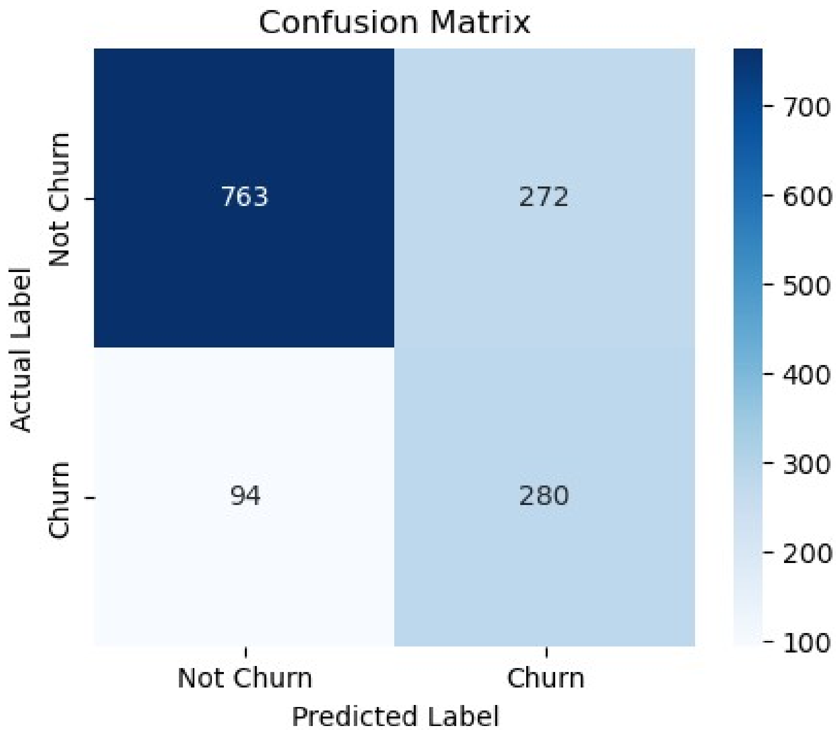
in this only take the probability of class 1

```
y_pred_35 = (y_prob >= 0.35).astype(int)
print("Threshold = 0.35")
print(classification_report(y_test, y_pred_35))
```

```
Threshold = 0.35
              precision    recall  f1-score   support

           0       0.89      0.74      0.81      1035
           1       0.51      0.75      0.60       374

    accuracy                           0.74      1409
   macro avg       0.70      0.74      0.71      1409
weighted avg       0.79      0.74      0.75      1409
```

So Improved churn recall from 0.50 to 0.75 using probability threshold tuning (0.35)

```
cm = confusion_matrix(y_test, y_pred_35)

plt.figure(figsize=(5,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Not Churn', 'Churn'],
            yticklabels=['Not Churn', 'Churn'])

plt.xlabel('Predicted Label')
plt.ylabel('Actual Label')
plt.title('Confusion Matrix')
plt.show()
```




```
import joblib
joblib.dump(rf, "churn_model.pkl")
joblib.dump(scaler, "scaler.pkl")
```

```
['scaler.pkl']
```

```
import os
print(os.getcwd())
```

```
C:\Users\Admin
```