Import Libraries & Load Data

```
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
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"
```

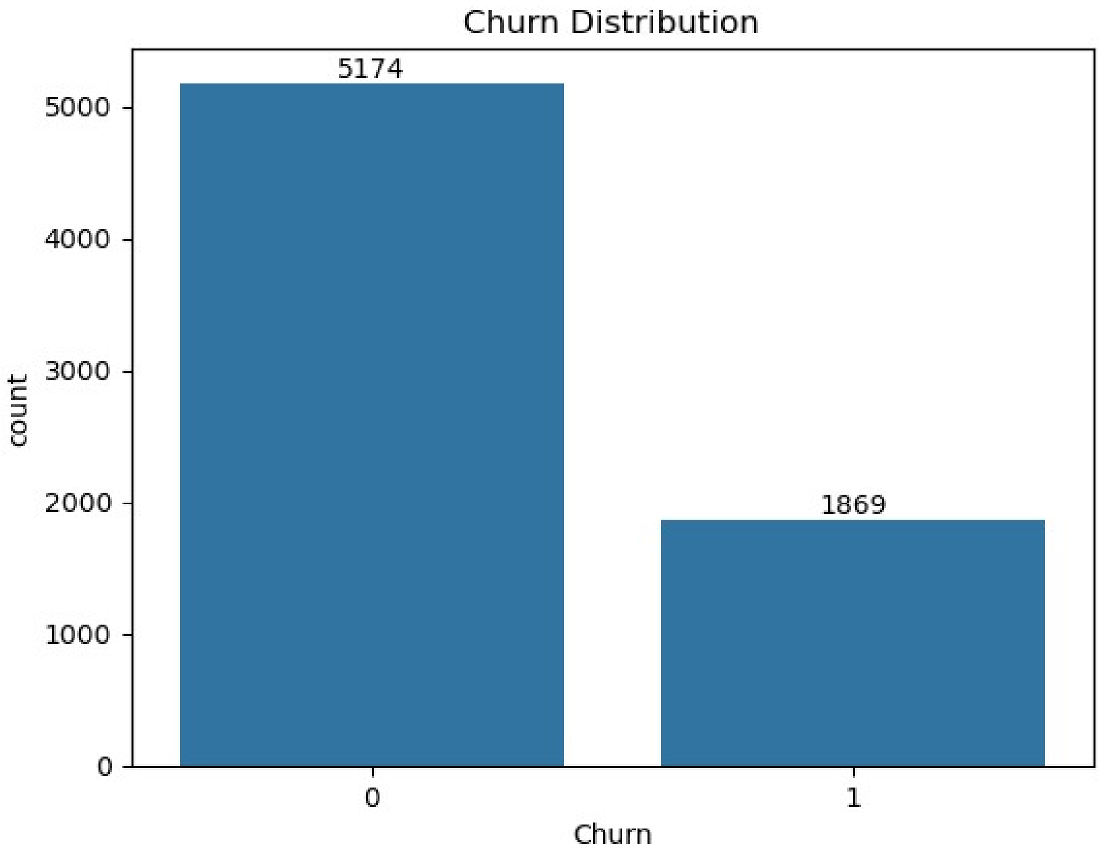
```
#check null value
df.isnull().sum()
```

```
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
())

# 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})
```

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()
```

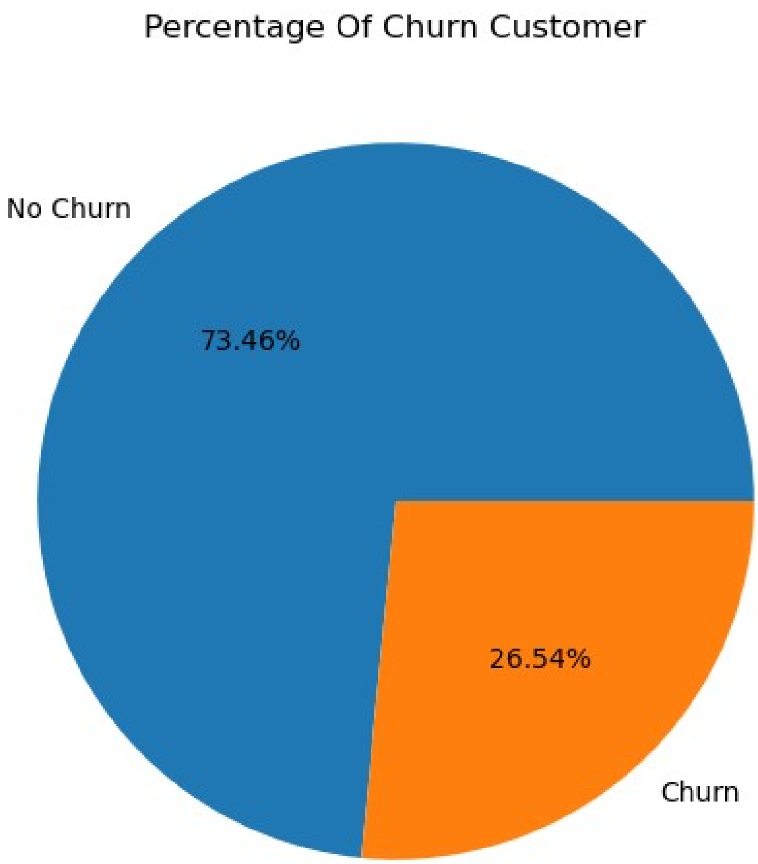



```
chrn_count=df['Churn'].value_counts()
chrn_count
```

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

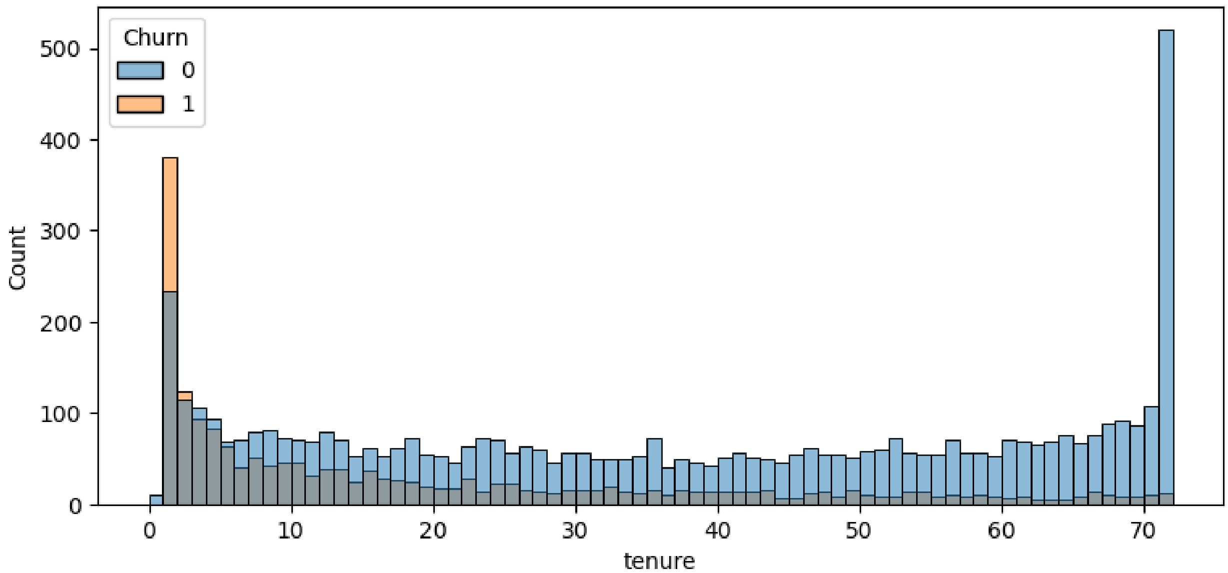
```
plt.figure(figsize=(6,6))
plt.pie(chrn_count, labels=['No Churn', 'Churn'],autopct='%1.2f%%')
plt.title('Percentage Of Churn Customer')
```

```
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()
```



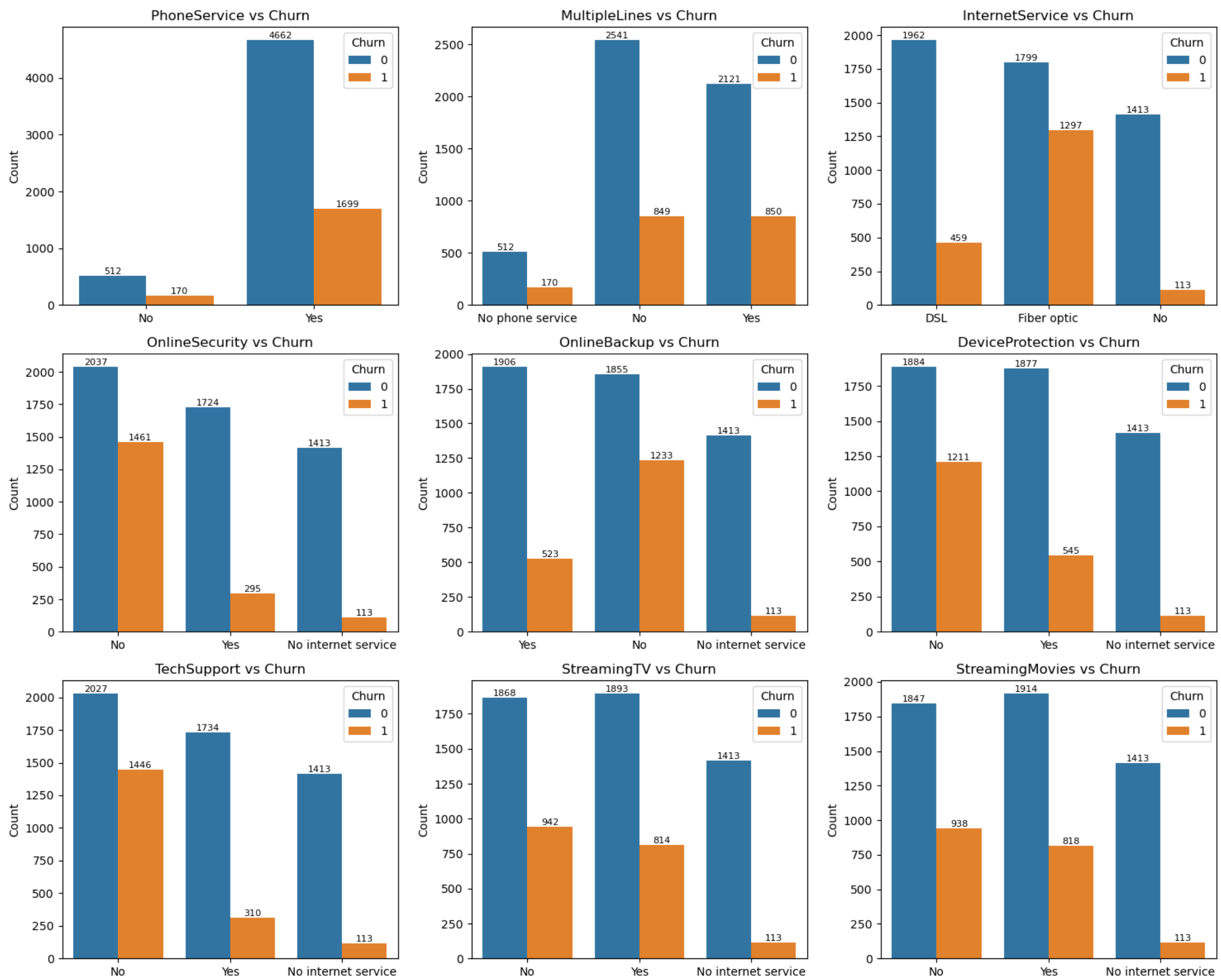
in above we undestand who have used servcies is long time its stay who using only 1 and 2 month is churned

```
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)
```

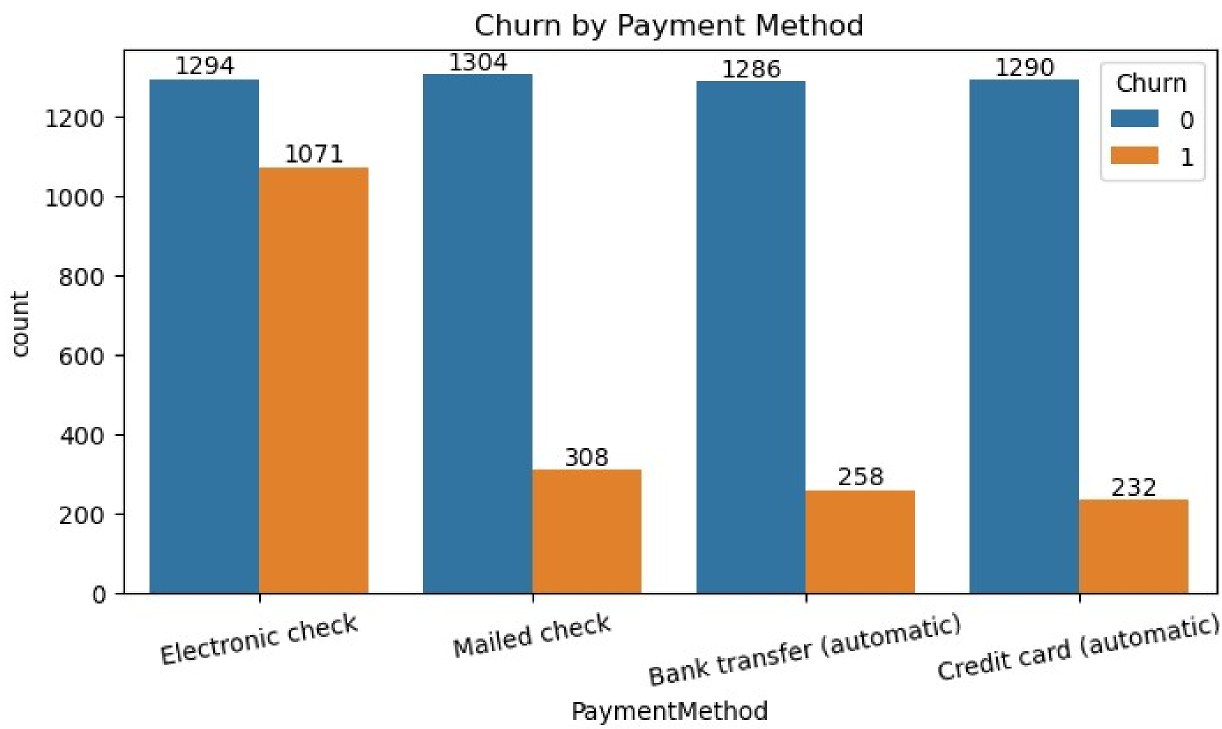
```
    if len(axes[i].containers) > 1:
        axes[i].bar_label(axes[i].containers[1], fontsize=8)
    axes[i].set_xlabel('')
    axes[i].set_ylabel('Count')

# 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

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

```
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()
```

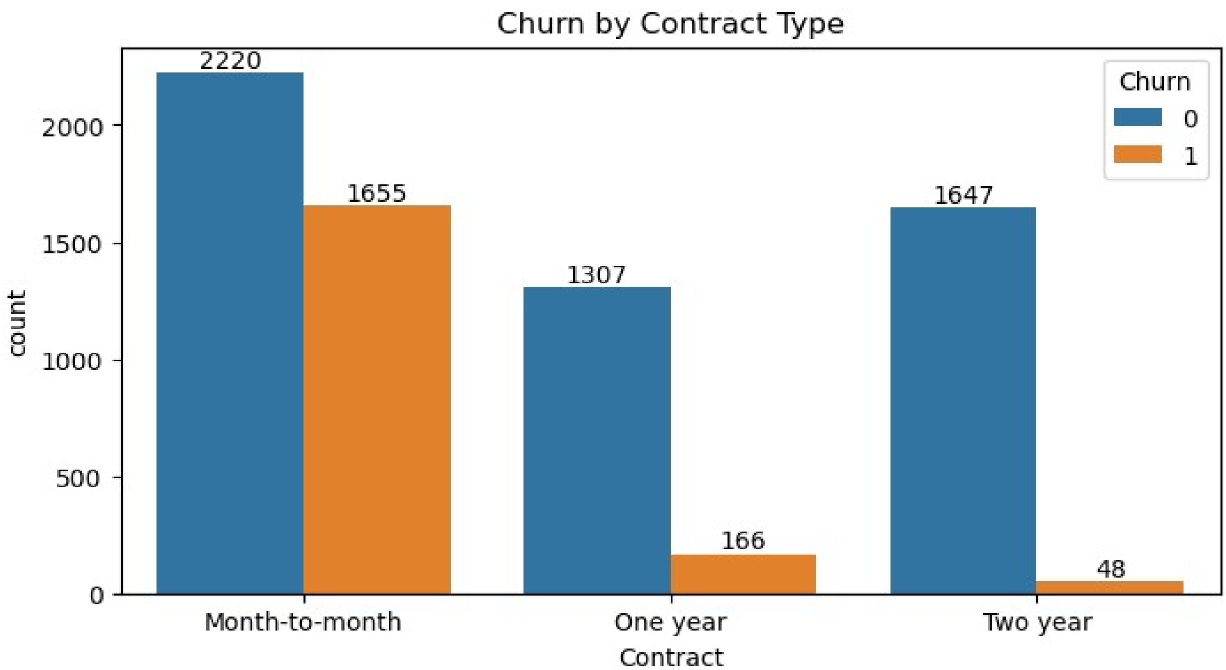


Customer is churn out when they are using Electronic Check

```
# 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)
```

```
[col for col in x.columns if 'Churn' in col]
```

```
[]
```

```
# Split data in x and y
x = pd.get_dummies(df.drop('Churn', axis=1), drop_first=True)
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.

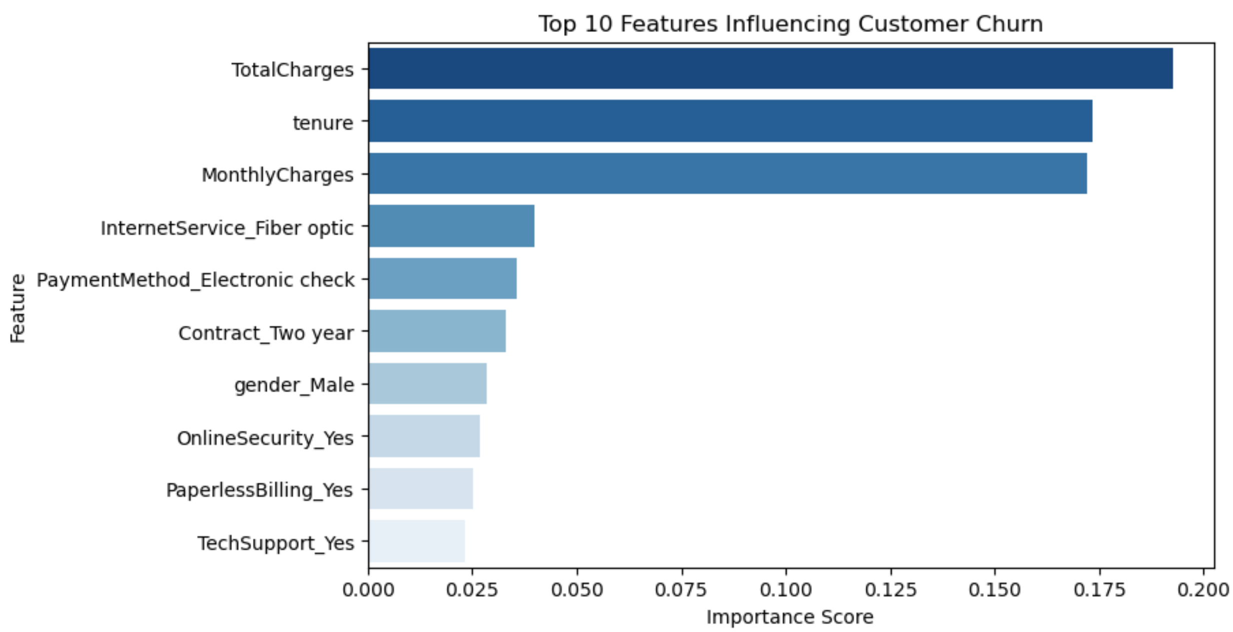
Feature Importance (for Random Forest)

```
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)
```

```python
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
```

```python
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

```python
df.groupby('gender_Male')['Churn'].value_counts(normalize=True)
```

```
gender_Male  Churn
False        0        0.730791
             1        0.269209
True         0        0.738397
             1        0.261603
Name: proportion, dtype: float64
```

```python
[col for col in df.columns if 'Churn' in col]
```

```
['Churn']
```