Customer Churn Prediction

Objective: Build a predictive model to identify customers at high risk of churn for a telecom company based on synthetically generated customer data

Step 1: Import all Libraries required for the project

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier,
GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV,
train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, roc_auc_score, roc_curve, auc
from sklearn.pipeline import Pipeline
import pandas as pd
import numpy as np

# Set random seed for reproducibility in np
np.random.seed(90)
```

Task1 : Data Generation

I created a synthetic dataset with 5,000 customer records, including the specified features. Here's how each feature was generated.

CustomerID: A unique identifier for each customer, such as "cust1", "cust2",etc

```
no_records = 5000

customer_ids = [f"Cust{i}" for i in range(1, no_records + 1)]
customer_ids[:5]

['Cust1', 'Cust2', 'Cust3', 'Cust4', 'Cust5']
```

Age: Ages will be normally distributed with an average of 35 and a standard deviation of 9, with values capped between 18 and 80 for realism.

```
ages = np.clip(np.random.normal(35, 9, no_records), 18,
80).astype(int)
ages[:5]
```

```
array([26, 27, 23, 18, 39])
```

Gender: Randomly chosen with an equal 50/50 split between 'Male' and 'Female'.

```
genders = np.random.choice(['Male', 'Female'], no_records)


print(genders[:15])
```

```
['Female' 'Female' 'Female' 'Male' 'Female' 'Male' 'Female' 'Female'
 'Male' 'Female' 'Female' 'Female' 'Female' 'Male' 'Male']
```

ContractType: Categorical distribution with probabilities:

Month-to-month: 60% One year: 25% Two years: 15%

```
contract_options = ['Month-to-month', 'One year', 'Two year']
probabilities = [0.6, 0.25, 0.15]


contract_types = np.array([np.random.choice(contract_options,
p=probabilities) for _ in range(no_records)])



contract_types[:15]
```

```
array(['One year', 'Month-to-month', 'One year', 'Month-to-month',
       'One year', 'One year', 'Month-to-month', 'Month-to-month',
       'Month-to-month', 'Month-to-month', 'Month-to-month', 'Two
year',
       'Month-to-month', 'Two year', 'Month-to-month'], dtype='<U14')
```

MonthlyCharges: Normally distributed charges with a mean of ₹800 and a standard deviation of ₹400. The charges are capped between ₹200 and ₹1500.

```
mean_charge = 800
std_dev = 400


monthly_charges_raw = np.random.normal(loc=mean_charge, scale=std_dev,
```

```
size=no_records)

monthly_charges = np.maximum(np.minimum(monthly_charges_raw, 1500), 200)

monthly_charges[:9]

array([1020.0794104 , 1310.89973764,  679.60689755,  200.        ,
        821.85985682,  612.58147911,  862.58878409,  530.79845716,
        266.24569379])
```

InternetService: Categorical distribution:

- DSL: 35%
- Fiber optic: 50%
- No: 15%

```
service_options = ['DSL', 'Fiber optic', 'None']
probabilities = [0.35, 0.50, 0.15]


internet_services = np.random.choice(service_options, size=no_records, p=probabilities)

internet_services[:4]

array(['Fiber optic', 'Fiber optic', 'None', 'Fiber optic'], dtype='<U11')
```

TechSupport: Randomly chosen with a distribution favoring no tech support:

- Yes: 40%
- No: 60%

```
tech_support = np.random.choice(['Yes', 'No'], no_records, p=[0.4, 0.6])

tech_support[:5]

array(['No', 'Yes', 'Yes', 'No', 'Yes'], dtype='<U3')
```

Tenure:Uniformly distributed tenures ranging from 1 to 99 months.

```
tenures = np.random.randint(1, 100, no_records)

tenures[:8]

array([19, 51, 77,  9, 91, 81, 86, 71])
```

PaperlessBilling: 60% of customers use paperless billing.

```
paperless_billing = np.random.choice(['Yes', 'No'], no_records, 
p=[0.6, 0.4])

paperless_billing

array(['Yes', 'Yes', 'No', ..., 'Yes', 'Yes', 'No'], dtype='<U3')
```

PaymentMethod: Random selection among:

- Electronic check: 25%
- Mailed check: 15%
- Bank transfer: 30%
- Credit card: 30%

```
payment_methods = np.random.choice(['Electronic check', 'Mailed 
check', 'Bank transfer', 'Credit card'], no_records, p=[0.25, 0.15, 
0.30, 0.30])

payment_methods

array(['Credit card', 'Credit card', 'Mailed check', ..., 'Mailed 
check',
       'Mailed check', 'Credit card'], dtype='<U16')


calculated_charges = monthly_charges * tenures


noise = np.random.normal(loc=10, scale=25, size=no_records)
total_charges = calculated_charges + noise


total_charges = np.maximum(total_charges, monthly_charges * 1.1)

print("Total Charges =",total_charges[:10])

Total Charges = [ 7164.59597083  9148.02575347  3387.22325908 
6019.01261472
 63330.03006328 52696.08068662 67306.19571854 21235.19092055
 22108.88030258 39370.4363925 ]
```

Churn: The goal is to achieve a 20% churn rate, with churn likelihood influenced by factors such as contract type, tenure, and internet service.

```


churn_probs = np.where(contract_types == 'Month-to-month', 0.40, 0.10)

# Generate churn labels with adjusted probabilities
churn = np.random.choice(['Yes', 'No'], size=no_records, p=[0.25, 
0.75])
```

```
print(churn_probs[:5])
print(churn)

[0.1 0.4 0.1 0.4 0.1]
['No' 'No' 'No' ... 'Yes' 'Yes' 'No']
```

Creating Derived Features

average_monthly_charges: Calculated as `TotalCharges / Tenure`, with proper handling of cases where tenure is zero.

customer_lifetime_value: Estimated using `MonthlyCharges × Tenure × RetentionFactor`, where `RetentionFactor` is 1 for non-churned customers and less than 1 for churned customers.

```
average_monthly_charges = total_charges / tenures

# customer_lifetime_value
retention_factor = np.where(churn == 'No', 1.0, 0.9)
customer_lifetime_value = monthly_charges * tenures * retention_factor

customer_lifetime_value[:8]

array([ 7140.55587281,  9176.29816347,  3398.03448777,  6000.        ,
       56954.88807774, 47413.80648318, 60553.73264321,
19108.74445759])
```

Creating data frame

```
df = pd.DataFrame({
    'CustomerID': customer_ids,
    'Age': ages,
    'Gender': genders,
    'ContractType': contract_types,
    'MonthlyCharges': monthly_charges,
    'TotalCharges': total_charges,
    'TechSupport': tech_support,
    'InternetService': internet_services,
    'Tenure': tenures,
    'PaperlessBilling': paperless_billing,
    'PaymentMethod': payment_methods,
    'Churn': churn,
    'AverageMonthlyCharges': average_monthly_charges,
    'CustomerLifetimeValue': customer_lifetime_value
})
```

```
df.head()
```

```
  CustomerID  Age  Gender    ContractType  MonthlyCharges
TotalCharges  \
0      Cust1   26  Female        One year     1020.079410
7164.595971
1      Cust2   27  Female  Month-to-month     1310.899738
9148.025753
2      Cust3   23  Female        One year      679.606898
3387.223259
3      Cust4   18    Male  Month-to-month      200.000000
6019.012615
4      Cust5   39  Female        One year      821.859857
63330.030063

  TechSupport InternetService  Tenure PaperlessBilling
PaymentMethod  \
0          No     Fiber optic       7              Yes       Credit
card
1         Yes     Fiber optic       7              Yes       Credit
card
2         Yes            None       5               No      Mailed
check
3          No     Fiber optic      30              Yes     Bank
transfer
4         Yes     Fiber optic      77               No  Electronic
check

  Churn  AverageMonthlyCharges  CustomerLifetimeValue
0    No            1023.513710            7140.555873
1    No            1306.860822            9176.298163
2    No             677.444652            3398.034488
3    No             200.633754            6000.000000
4   Yes             822.467923           56954.888078
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 14 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   CustomerID             5000 non-null   object
 1   Age                    5000 non-null   int64
 2   Gender                 5000 non-null   object
 3   ContractType           5000 non-null   object
 4   MonthlyCharges         5000 non-null   float64
 5   TotalCharges           5000 non-null   float64
 6   TechSupport            5000 non-null   object
 7   InternetService        5000 non-null   object
```

```
 8   Tenure                 5000 non-null   int64
 9   PaperlessBilling       5000 non-null   object
 10  PaymentMethod          5000 non-null   object
 11  Churn                  5000 non-null   object
 12  AverageMonthlyCharges  5000 non-null   float64
 13  CustomerLifetimeValue  5000 non-null   float64
dtypes: float64(4), int64(2), object(8)
memory usage: 547.0+ KB
```

Creating Data Quality Issues

Missing Values: Introduce missing values in approximately 9% of the MonthlyCharges and Tenure fields.

```
missing_values = np.random.choice(no_records, size=int(no_records *
0.09), replace=False)


df.loc[missing_values, 'MonthlyCharges'] = np.nan

# Apply missing values to 'Tenure'
df.loc[missing_values, 'Tenure'] = np.nan

df.isna().sum()

CustomerID                 0
Age                        0
Gender                     0
ContractType               0
MonthlyCharges           450
TotalCharges               0
TechSupport                0
InternetService            0
Tenure                   450
PaperlessBilling           0
PaymentMethod              0
Churn                      0
AverageMonthlyCharges      0
CustomerLifetimeValue      0
dtype: int64
```

Outliers: Introduce outliers in TotalCharges by randomly inflating the values for 2% of the data.

```
outliers = np.random.choice(no_records, size=int(no_records * 0.02),
replace=False)
df.loc[outlier_indices, 'TotalCharges'] *= np.random.uniform(1.5, 3.0,
size=len(outliers))
```

Adding inconsistencies (TotalCharges lower than MonthlyCharges * Tenure)

```
inconsistent_indices = np.random.choice(no_records,
size=int(no_records * 0.01), replace=False)
df.loc[inconsistent_indices, 'TotalCharges'] =
df.loc[inconsistent_indices, 'MonthlyCharges'] *
np.random.uniform(0.5, 1.0, size=len(inconsistent_indices))

df.TotalCharges[:5]
```

```
0     7164.595971
1     9148.025753
2     3387.223259
3     6019.012615
4    63330.030063
Name: TotalCharges, dtype: float64
```

```
expect_total_charges = df['MonthlyCharges'] * df['Tenure']

# Identify inconsistencies
inconsis_rows = df.loc[(df['TotalCharges'] < expect_total_charges ) |
                             (df['TotalCharges'] >
expect_total_charges)]

len(inconsis_rows)
```

```
4550
```

TASK2 : Exploratory Data Analysis (EDA)

Summary statistics for df(sample)

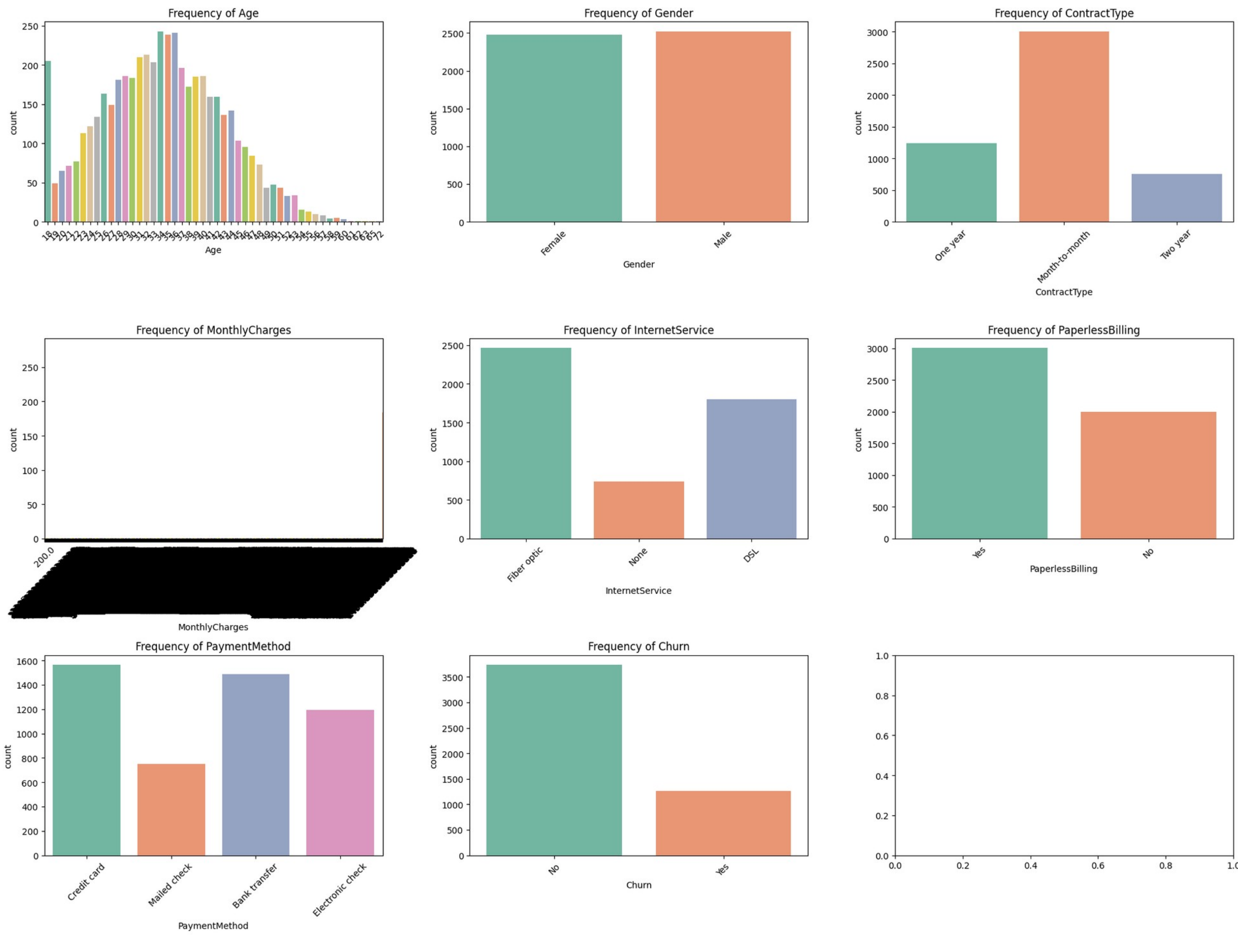
```
df.describe()
```

```
               Age  MonthlyCharges    TotalCharges       Tenure  \
count  5000.000000     4550.000000     5000.000000  4550.000000
mean     34.291200      807.051782    40251.681617    49.850769
std       8.665715      358.791800    31136.648162    28.748413
min      18.000000      200.000000      220.000000     1.000000
25%      28.000000      543.969962    15085.283626    25.000000
50%      34.000000      799.440390    33072.923380    49.000000
75%      40.000000     1068.925168    60032.494352    75.000000
max      72.000000     1500.000000   148493.731428    99.000000

       AverageMonthlyCharges  CustomerLifetimeValue
count            5000.000000            5000.000000
mean              806.995874           39199.267749
std               358.717046           30401.324890
min               192.723072             200.000000
```

```
25%              545.506772          14720.198462
50%              799.355265          32354.422778
75%             1067.380365          58430.666521
max             1650.000000         148500.000000
```

categorical features

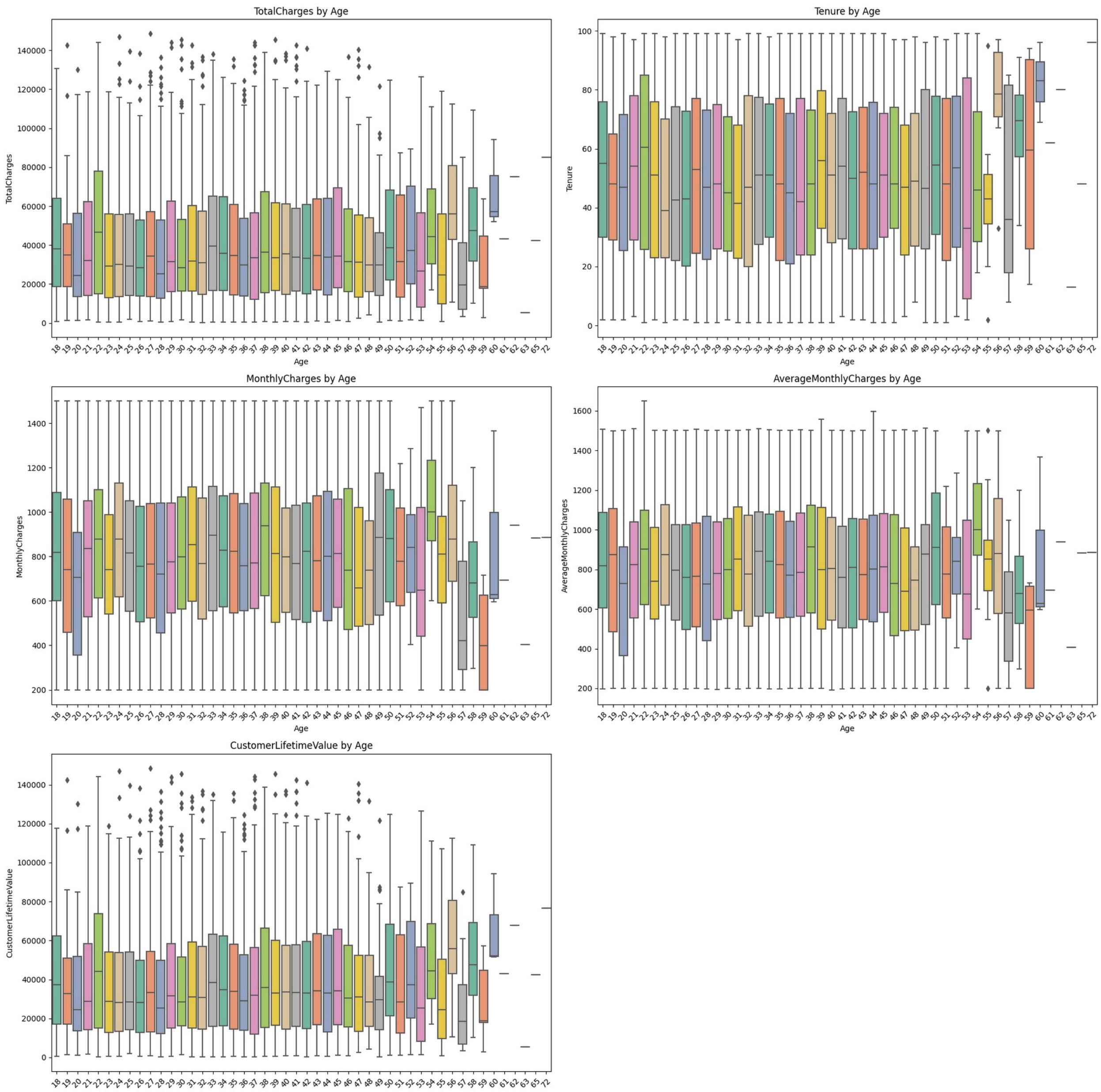
```
categorical_features = ["Age", 'Gender', 'ContractType',
'MonthlyCharges', 'InternetService', 'PaperlessBilling',
'PaymentMethod', 'Churn']


fig, axes = plt.subplots(3, 3, figsize=(20, 15))


axes = axes.flatten()

# Plot each categorical feature
for idx, feature in enumerate(categorical_features):
    sns.countplot(x=feature, data=df, palette='Set2', ax=axes[idx])
    axes[idx].set_title(f'Frequency of {feature}')
    axes[idx].tick_params(axis='x', rotation=45)


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



Relationship between numerical features and churn

```
num_features = ['TotalCharges', 'Tenure', 'MonthlyCharges',
'AverageMonthlyCharges', 'CustomerLifetimeValue']


plt.figure(figsize=(20, 20))


for i, feature in enumerate(num_features):
    plt.subplot(3, 2, i + 1)

    # Check if feature is numeric, if not, convert it or handle
accordingly
    if pd.api.types.is_numeric_dtype(df[feature]):
        sns.boxplot(x='Age', y=feature, data=df, palette='Set2')
    else:
```

```
        print(f"Warning: '{feature}' is not numeric and will not be
plotted.")

    plt.title(f'{feature} by Age')
    plt.xticks(rotation=45)


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



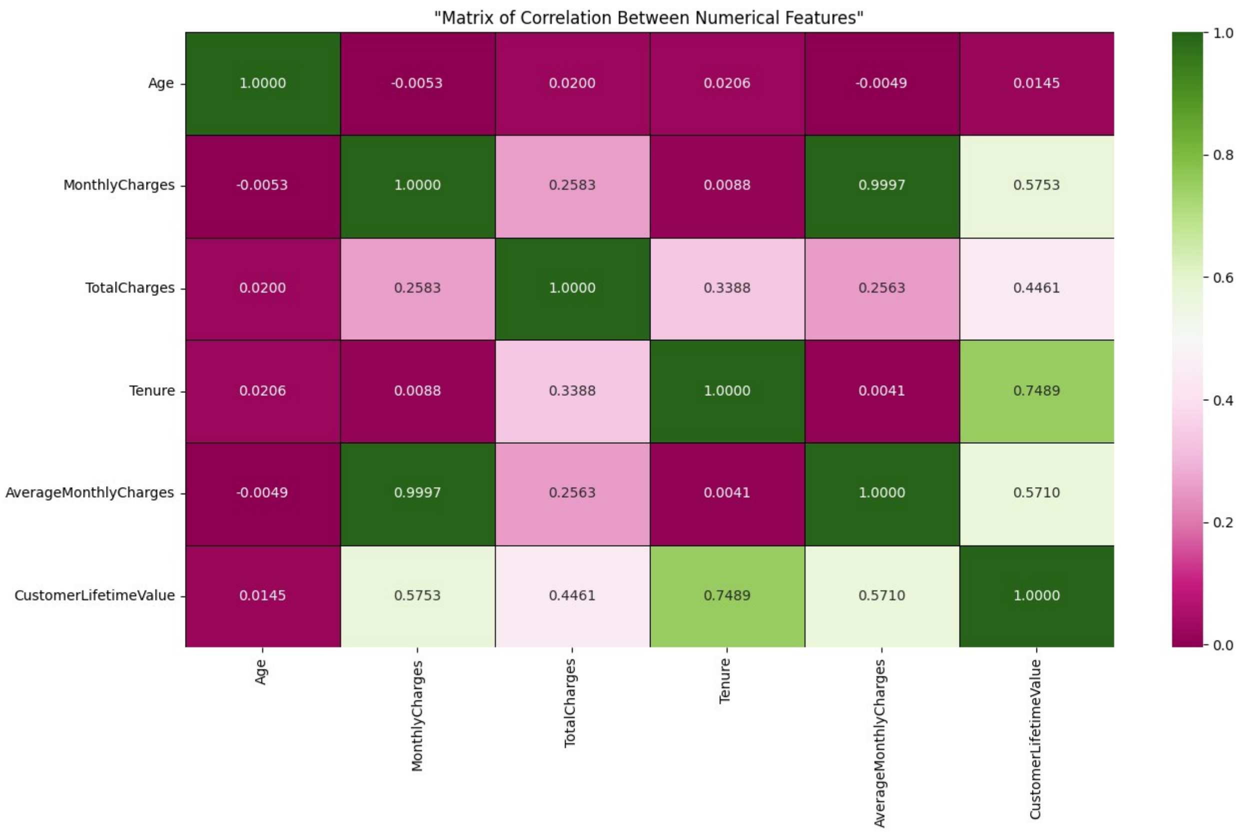
Correlation matrix

```
num_features = ['Age', 'MonthlyCharges', 'TotalCharges', 'Tenure',
'AverageMonthlyCharges', 'CustomerLifetimeValue']

# Calculate the correlation matrix
correlation_matrix = data[num_features].corr()


correlation_matrix
```

```
                            Age  MonthlyCharges  TotalCharges
Tenure  \
Age                    1.000000       -0.005250      0.019996
0.020570
MonthlyCharges        -0.005250        1.000000      0.258294
0.008776
TotalCharges           0.019996        0.258294      1.000000
0.338796
Tenure                 0.020570        0.008776      0.338796
1.000000
AverageMonthlyCharges -0.004866        0.999692      0.256263
0.004059
CustomerLifetimeValue  0.014541        0.575313      0.446093
0.748895

                       AverageMonthlyCharges  CustomerLifetimeValue
Age                                -0.004866               0.014541
MonthlyCharges                      0.999692               0.575313
TotalCharges                        0.256263               0.446093
Tenure                              0.004059               0.748895
AverageMonthlyCharges               1.000000               0.570976
CustomerLifetimeValue               0.570976               1.000000
```

** Visualize the Correlation Matrix with a Heatmap**

```
plt.figure(figsize=(15, 8))
#headmap
sns.heatmap(correlation_matrix, annot=True, fmt='.4f', cmap='PiYG',
linewidths=0.5, linecolor='black')

plt.title('"Matrix of Correlation Between Numerical Features"')

plt.show()
```



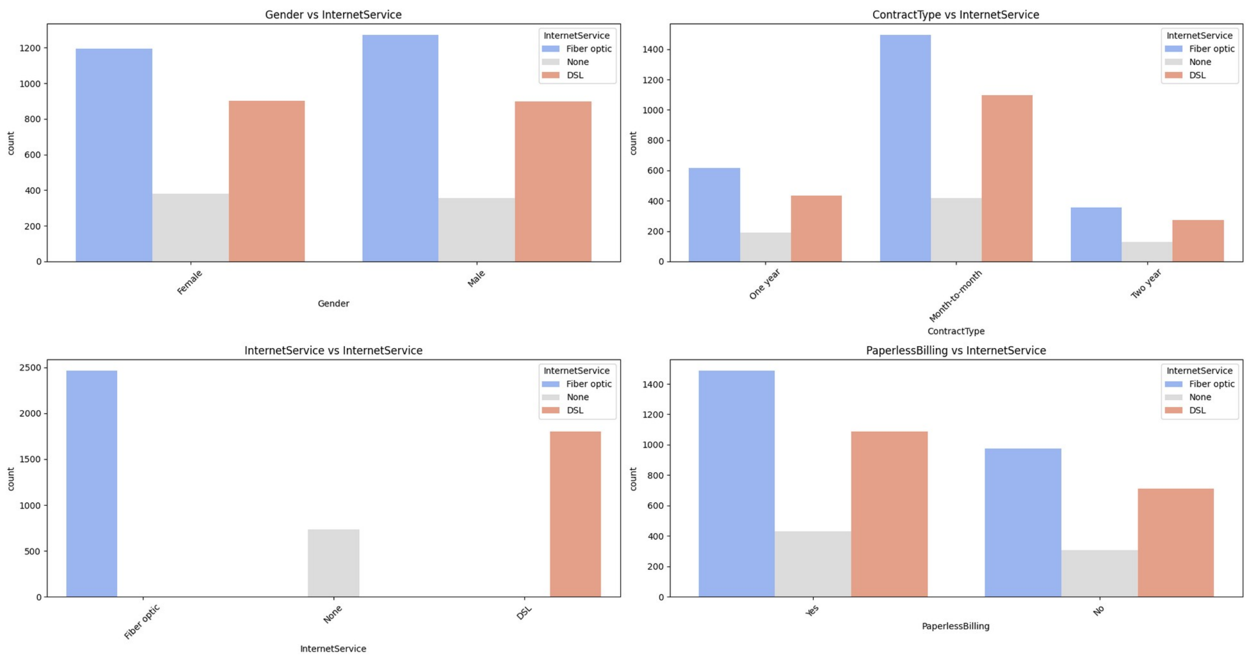

```
correlation_matrix[(correlation_matrix > 0.7) & (correlation_matrix !=
1.0)].dropna(how='all', axis=0).dropna(how='all', axis=1)
```

```
                       MonthlyCharges    Tenure  AverageMonthlyCharges  \
MonthlyCharges                    NaN       NaN               0.999692

Tenure                            NaN       NaN                    NaN

AverageMonthlyCharges        0.999692       NaN                    NaN

CustomerLifetimeValue             NaN  0.748895                    NaN


                       CustomerLifetimeValue
MonthlyCharges                           NaN
Tenure                              0.748895
AverageMonthlyCharges                    NaN
CustomerLifetimeValue                    NaN
```

Visualize Categorical Features vs. Churn

```
categorical_features = ['Gender', 'ContractType', 'InternetService',
'PaperlessBilling', 'PaymentMethod']
```

```
plt.figure(figsize=(20, 15))

# Subplots for feature comparisons
for i, feature in enumerate(categorical_features[:-1]):  # Exclude the
last feature if needed
    plt.subplot(3, 2, i + 1)
    sns.countplot(x=feature, hue='InternetService', data=df,
palette='coolwarm')
    plt.title(f'{feature} vs InternetService')
    plt.xticks(rotation=45)


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



TASK3 : Data Preprocessing

Handle Missing Values

```
missing_values = df.isnull().sum()
print("Missing values before handling:")
print(missing_values[missing_values > 0])

Missing values before handling:
MonthlyCharges    450
```

```
Tenure            450
dtype: int64
```

```python
# Fill missing values in 'MonthlyCharges' with mean
df['MonthlyCharges'].fillna(df['MonthlyCharges'].mean(), inplace=True)
```

```
/tmp/ipykernel_36/1085292209.py:2: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment
using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.


  df['MonthlyCharges'].fillna(df['MonthlyCharges'].mean(),
inplace=True)
```

```python
df.MonthlyCharges.info()
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 5000 entries, 0 to 4999
Series name: MonthlyCharges
Non-Null Count  Dtype
--------------  -----
5000 non-null   float64
dtypes: float64(1)
memory usage: 39.2 KB
```

```python
# Fill missing values in 'Tenure' with median
df['Tenure'].fillna(df['Tenure'].median(), inplace=True)
```

```
/tmp/ipykernel_36/3563801387.py:2: FutureWarning: A value is trying to
be set on a copy of a DataFrame or Series through chained assignment
using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never
work because the intermediate object on which we are setting values
always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try
using 'df.method({col: value}, inplace=True)' or df[col] =
df[col].method(value) instead, to perform the operation inplace on the
original object.


  df['Tenure'].fillna(df['Tenure'].median(), inplace=True)
```

```
df.Tenure.info()
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 5000 entries, 0 to 4999
Series name: Tenure
Non-Null Count  Dtype
--------------  -----
5000 non-null   float64
dtypes: float64(1)
memory usage: 39.2 KB
```

Encode Categorical Features

```
encoder = LabelEncoder()


cat_features = ['Gender', 'ContractType', 'TechSupport',
'InternetService', 'PaperlessBilling', 'PaymentMethod', 'Churn']

# Apply label encoding to each categorical feature
for feature in cat_features:
    df[feature] = encoder.fit_transform(df[feature])

# Display the first few rows of the DataFrame after encoding
df.head()
```

```
  CustomerID  Age  Gender  ContractType  MonthlyCharges  TotalCharges  \
0      Cust1   26       0             1     1020.079410   7164.595971

1      Cust2   27       0             0     1310.899738   9148.025753

2      Cust3   23       0             1      679.606898   3387.223259

3      Cust4   18       1             0      807.051782   6019.012615

4      Cust5   39       0             1      821.859857  63330.030063


   TechSupport  InternetService  Tenure  PaperlessBilling
PaymentMethod  \
0            0                1     7.0                 1
1
1            1                1     7.0                 1
1
2            1                2     5.0                 0
3
3            0                1    49.0                 1
0
```

```
4            1                1    77.0                0
2

   Churn  AverageMonthlyCharges  CustomerLifetimeValue
0      0            1023.513710            7140.555873
1      0            1306.860822            9176.298163
2      0             677.444652            3398.034488
3      0             200.633754            6000.000000
4      1             822.467923           56954.888078
```

TASK4 : Feature Engineering:

```
df['AvgMonthlyCharges'] = df['TotalCharges'] / (df['Tenure'] + 1)

df['CustLifetimeValue'] = df['MonthlyCharges'] * df['Tenure']


df['AgeGroup'] = pd.cut(df['Age'], bins=[0, 30, 40, 50, 60, np.inf],
labels=['<30', '30-40', '40-50', '50-60', '60+'])


df['LogTotalCharges'] = np.log1p(df['TotalCharges'])

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 18 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   CustomerID             5000 non-null   object
 1   Age                    5000 non-null   int64
 2   Gender                 5000 non-null   int64
 3   ContractType           5000 non-null   int64
 4   MonthlyCharges         5000 non-null   float64
 5   TotalCharges           4996 non-null   float64
 6   TechSupport            5000 non-null   int64
 7   InternetService        5000 non-null   int64
 8   Tenure                 5000 non-null   float64
 9   PaperlessBilling       5000 non-null   int64
 10  PaymentMethod          5000 non-null   int64
 11  Churn                  5000 non-null   int64
 12  AverageMonthlyCharges  5000 non-null   float64
 13  CustomerLifetimeValue  5000 non-null   float64
 14  AvgMonthlyCharges      4996 non-null   float64
 15  CustLifetimeValue      5000 non-null   float64
 16  AgeGroup               5000 non-null   category
 17  LogTotalCharges        4996 non-null   float64
```

```
dtypes: category(1), float64(8), int64(8), object(1)
memory usage: 669.3+ KB
```

Data Volume: Reduce the dataset size to simulate real-world constraints.

```
features = [
    'Age', 'MonthlyCharges', 'TotalCharges', 'Tenure',
'AverageMonthlyCharges',
    'CustomerLifetimeValue', 'LogTotalCharges', 'AgeGroup'
]

df.head()

  CustomerID  Age  Gender  ContractType  MonthlyCharges  TotalCharges
\
0      Cust1   26       0             1     1020.079410   7164.595971

1      Cust2   27       0             0     1310.899738   9148.025753

2      Cust3   23       0             1      679.606898   3387.223259

3      Cust4   18       1             0      807.051782   6019.012615

4      Cust5   39       0             1      821.859857  63330.030063


   TechSupport  InternetService  Tenure  PaperlessBilling
PaymentMethod  \
0            0                1     7.0                 1
1
1            1                1     7.0                 1
1
2            1                2     5.0                 0
3
3            0                1    49.0                 1
0
4            1                1    77.0                 0
2

   Churn  AverageMonthlyCharges  CustomerLifetimeValue
AvgMonthlyCharges  \
0      0            1023.513710            7140.555873
895.574496
1      0            1306.860822            9176.298163
1143.503219
2      0             677.444652            3398.034488
564.537210
3      0             200.633754            6000.000000
120.380252
4      1             822.467923           56954.888078
```

```
811.923462

   CustLifetimeValue AgeGroup  LogTotalCharges
0        7140.555873      <30         8.877047
1        9176.298163      <30         9.121403
2        3398.034488      <30         8.128061
3       39545.537304      <30         8.702845
4       63283.208975    30-40        11.056131
```

```
data = df[features]


data['AgeGroup'] = encoder.fit_transform(data['AgeGroup'])
```

```
/tmp/ipykernel_36/177443646.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  data['AgeGroup'] = encoder.fit_transform(data['AgeGroup'])
```

```
X = data.drop('Churn', axis=1, errors='ignore')
y = df['Churn']

X.head()
```

```
   Age  MonthlyCharges  TotalCharges  Tenure  AverageMonthlyCharges  \
0   26     1020.079410   7164.595971     7.0            1023.513710
1   27     1310.899738   9148.025753     7.0            1306.860822
2   23      679.606898   3387.223259     5.0             677.444652
3   18      807.051782   6019.012615    49.0             200.633754
4   39      821.859857  63330.030063    77.0             822.467923

   CustomerLifetimeValue  LogTotalCharges  AgeGroup
0            7140.555873         8.877047         4
1            9176.298163         9.121403         4
2            3398.034488         8.128061         4
3            6000.000000         8.702845         4
4           56954.888078        11.056131         0
```

```
y.head()
```

```
0    0
1    0
2    0
3    0
4    1
Name: Churn, dtype: int64
```

```
X_all, X_test, y_all, y_test = train_test_split(X, y, test_size=0.25,
random_state=42, stratify=y)
X_train, X_val, y_train, y_val = train_test_split(X_all, y_all,
test_size=0.33, random_state=42, stratify=y_all)

print(f"Train shape: {X_train.shape}")
print(f"Validation shape: {X_val.shape}")
print(f"Test shape: {X_test.shape}")
```

```
Train shape: (2512, 8)
Validation shape: (1238, 8)
Test shape: (1250, 8)
```

Task5: Model Building

Experiment with various classification algorithms (Logistic Regression, Random Forest, Gradient Boosting, XGBoost, etc.)

```
models = {
    'Logistic Regression': LogisticRegression(max_iter=500),
    'Random Forest': RandomForestClassifier(n_estimators=100,
random_state=42),
    'Gradient Boosting': GradientBoostingClassifier(n_estimators=100,
random_state=42),
    'XGBoost': XGBClassifier(use_label_encoder=False,
eval_metric='mlogloss')
}

imputer = SimpleImputer(strategy='median')
X_train_imputed = imputer.fit_transform(X_train)
X_val_imputed = imputer.transform(X_val)
X_test_imputed = imputer.transform(X_test)


results = {}
for name, model in models.items():
    model.fit(X_train_imputed, y_train)  # Fit model
    y_pred = model.predict(X_val_imputed)  # Predict

    # Calculate metrics
    results[name] = {
        'Accuracy': accuracy_score(y_val, y_pred),
        'Precision': precision_score(y_val, y_pred, zero_division=0),
        'Recall': recall_score(y_val, y_pred, zero_division=0),
        'F1 Score': f1_score(y_val, y_pred, zero_division=0)
    }
```

```python
for i in results:
    print(i)
    print(results[i])
```

```
Logistic Regression
{'Accuracy': 0.7366720516962844, 'Precision': 0.18181818181818182,
'Recall': 0.01282051282051282, 'F1 Score': 0.023952095808383232}
Random Forest
{'Accuracy': 0.8012924071082391, 'Precision': 0.7946428571428571,
'Recall': 0.28525641025641024, 'F1 Score': 0.41981132075471694}
Gradient Boosting
{'Accuracy': 0.8053311793214862, 'Precision': 0.8585858585858586,
'Recall': 0.2724358974358974, 'F1 Score': 0.41362530413625304}
XGBoost
{'Accuracy': 0.9369951534733441, 'Precision': 0.8979591836734694,
'Recall': 0.8461538461538461, 'F1 Score': 0.8712871287128713}
```

Optimize model hyperparameters using techniques like Grid Search or Randomized Search.

```python
param_grids = {
    'Logistic Regression': {
        'C': [0.05, 0.5, 5, 50]
    },
    'Random Forest': {
        'n_estimators': [150, 250],
        'max_depth': [10, 25, 40]
    },
    'Gradient Boosting': {
        'n_estimators': [150],
        'learning_rate': [0.05, 0.2],
        'max_depth': [3, 6]
    },
    'XGBoost': {
        'n_estimators': [150],
        'learning_rate': [0.05, 0.15],
        'max_depth': [4, 6]
    }
}


best_models = {}
for name, model in models.items():
    grid_search = GridSearchCV(model, param_grids[name], cv=5,
scoring='f1', n_jobs=-1)
    grid_search.fit(X_train_imputed, y_train)
    best_models[name] = grid_search.best_estimator_

# Show best hyperparameters
```

```
for name, model in best_models.items():
    print(f"Best parameters for {name}: {model.get_params()}\n")
```

```
Best parameters for Logistic Regression: {'C': 5, 'class_weight':
None, 'dual': False, 'fit_intercept': True, 'intercept_scaling': 1,
'l1_ratio': None, 'max_iter': 500, 'multi_class': 'auto', 'n_jobs':
None, 'penalty': 'l2', 'random_state': None, 'solver': 'lbfgs', 'tol':
0.0001, 'verbose': 0, 'warm_start': False}

Best parameters for Random Forest: {'bootstrap': True, 'ccp_alpha':
0.0, 'class_weight': None, 'criterion': 'gini', 'max_depth': 25,
'max_features': 'sqrt', 'max_leaf_nodes': None, 'max_samples': None,
'min_impurity_decrease': 0.0, 'min_samples_leaf': 1,
'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0,
'n_estimators': 250, 'n_jobs': None, 'oob_score': False,
'random_state': 42, 'verbose': 0, 'warm_start': False}

Best parameters for Gradient Boosting: {'ccp_alpha': 0.0, 'criterion':
'friedman_mse', 'init': None, 'learning_rate': 0.2, 'loss':
'log_loss', 'max_depth': 6, 'max_features': None, 'max_leaf_nodes':
None, 'min_impurity_decrease': 0.0, 'min_samples_leaf': 1,
'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0,
'n_estimators': 150, 'n_iter_no_change': None, 'random_state': 42,
'subsample': 1.0, 'tol': 0.0001, 'validation_fraction': 0.1,
'verbose': 0, 'warm_start': False}

Best parameters for XGBoost: {'objective': 'binary:logistic',
'base_score': None, 'booster': None, 'callbacks': None,
'colsample_bylevel': None, 'colsample_bynode': None,
'colsample_bytree': None, 'device': None, 'early_stopping_rounds':
None, 'enable_categorical': False, 'eval_metric': 'mlogloss',
'feature_types': None, 'gamma': None, 'grow_policy': None,
'importance_type': None, 'interaction_constraints': None,
'learning_rate': 0.15, 'max_bin': None, 'max_cat_threshold': None,
'max_cat_to_onehot': None, 'max_delta_step': None, 'max_depth': 6,
'max_leaves': None, 'min_child_weight': None, 'missing': nan,
'monotone_constraints': None, 'multi_strategy': None, 'n_estimators':
150, 'n_jobs': None, 'num_parallel_tree': None, 'random_state': None,
'reg_alpha': None, 'reg_lambda': None, 'sampling_method': None,
'scale_pos_weight': None, 'subsample': None, 'tree_method': None,
'validate_parameters': None, 'verbosity': None, 'use_label_encoder':
False}
```

Evaluate model performance using metrics like accuracy, precision, recall, F1-score, ROC curve, AUC.

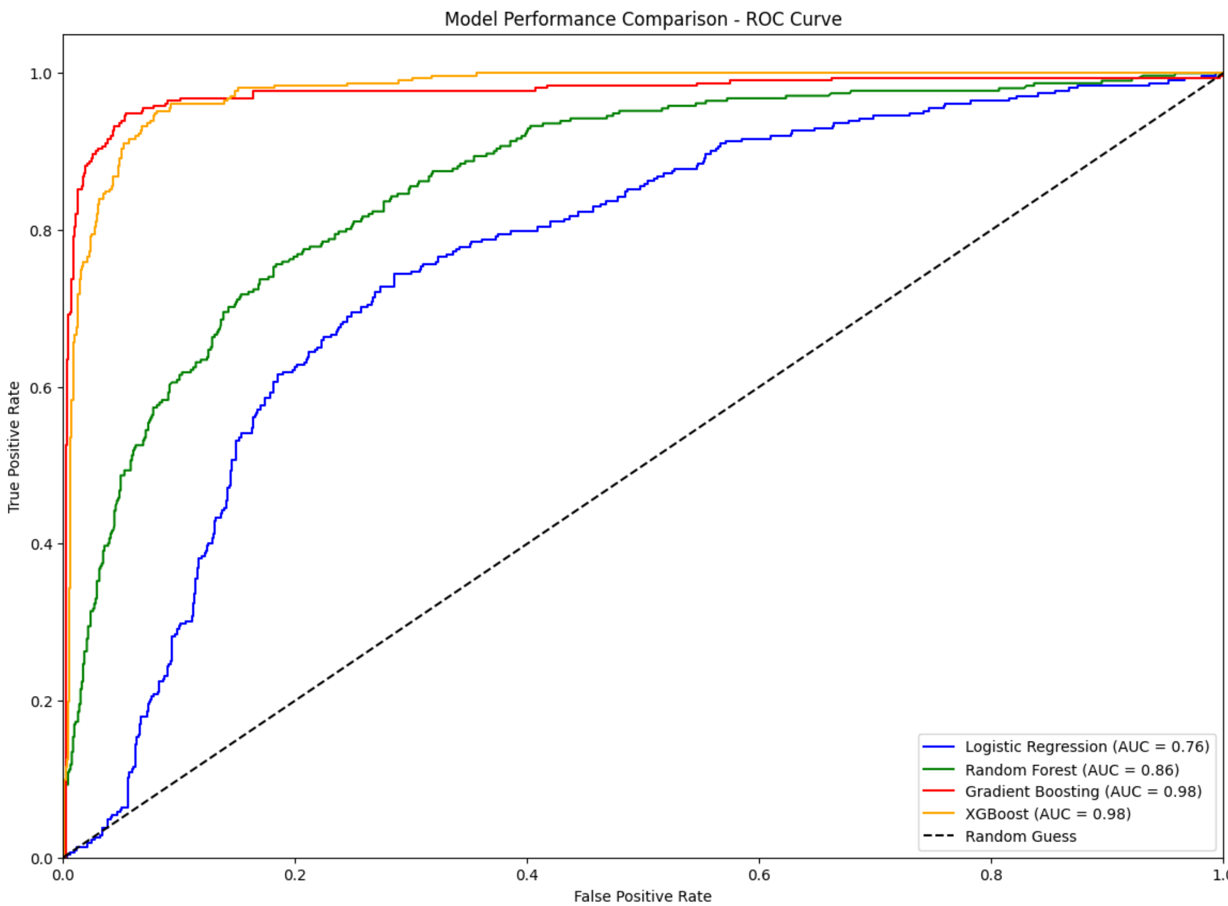
```
imputer = SimpleImputer(strategy='median')
```

```python
X_train_imputed = imputer.fit_transform(X_train)
X_val_imputed = imputer.transform(X_val)

model_results = {}

# Evaluate each best model
for name, model in best_models.items():
    y_pred = model.predict(X_val_imputed)

    # Compute metrics
    metrics = {
        'Accuracy': accuracy_score(y_val, y_pred),
        'Precision': precision_score(y_val, y_pred),
        'Recall': recall_score(y_val, y_pred),
        'F1 Score': f1_score(y_val, y_pred)
    }


    model_results[name] = metrics


results_df = pd.DataFrame(model_results).T


print(results_df)
```

```
                     Accuracy  Precision    Recall  F1 Score
Logistic Regression  0.736672   0.181818  0.012821  0.023952
Random Forest        0.805331   0.819820  0.291667  0.430260
Gradient Boosting    0.953958   0.938144  0.875000  0.905473
XGBoost              0.930533   0.909420  0.804487  0.853741
```

```python
colors = ['blue', 'green', 'red', 'orange']
fig_size = (14, 10)
title_name = 'Model Performance Comparison - ROC Curve'

# Plot ROC Curve
plt.figure(figsize=fig_size)

for (name, model), color in zip(best_models.items(), colors):
    y_pred_proba = model.predict_proba(X_val_imputed)[:, 1]  # Use
imputed data
    fpr, tpr, _ = roc_curve(y_val, y_pred_proba)
    roc_auc = auc(fpr, tpr)
    plt.plot(fpr, tpr, color=color, label=f'{name} (AUC =
{roc_auc:.2f})')

plt.plot([0, 1], [0, 1], 'k--', label='Random Guess')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
```

```
plt.ylabel('True Positive Rate')
plt.title(title_name)
plt.legend(loc='lower right')
plt.show()
```



Ensemble methods for improved performance

```
from sklearn.ensemble import VotingClassifier
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score

voting_model = VotingClassifier(
    estimators=[
        ('LR', best_models['Logistic Regression']),
        ('RF', best_models['Random Forest']),
        ('GB', best_models['Gradient Boosting']),
        ('XGB', best_models['XGBoost'])
    ],
    voting='soft'
)

voting_model.fit(X_train_imputed, y_train)  # Ensure X_train_imputed
```

```
is used if missing values were handled


y_pred = voting_model.predict(X_val_imputed)  # Ensure X_val_imputed
is used if missing values were handled

# Compute metrics
ensemble_metrics = {
    'Accuracy': accuracy_score(y_val, y_pred),
    'Precision': precision_score(y_val, y_pred),
    'Recall': recall_score(y_val, y_pred),
    'F1 Score': f1_score(y_val, y_pred)
}


print("Ensemble Model Performance:")
for metric, score in ensemble_metrics.items():
    print(f"{metric}: {score:.2f}")
```

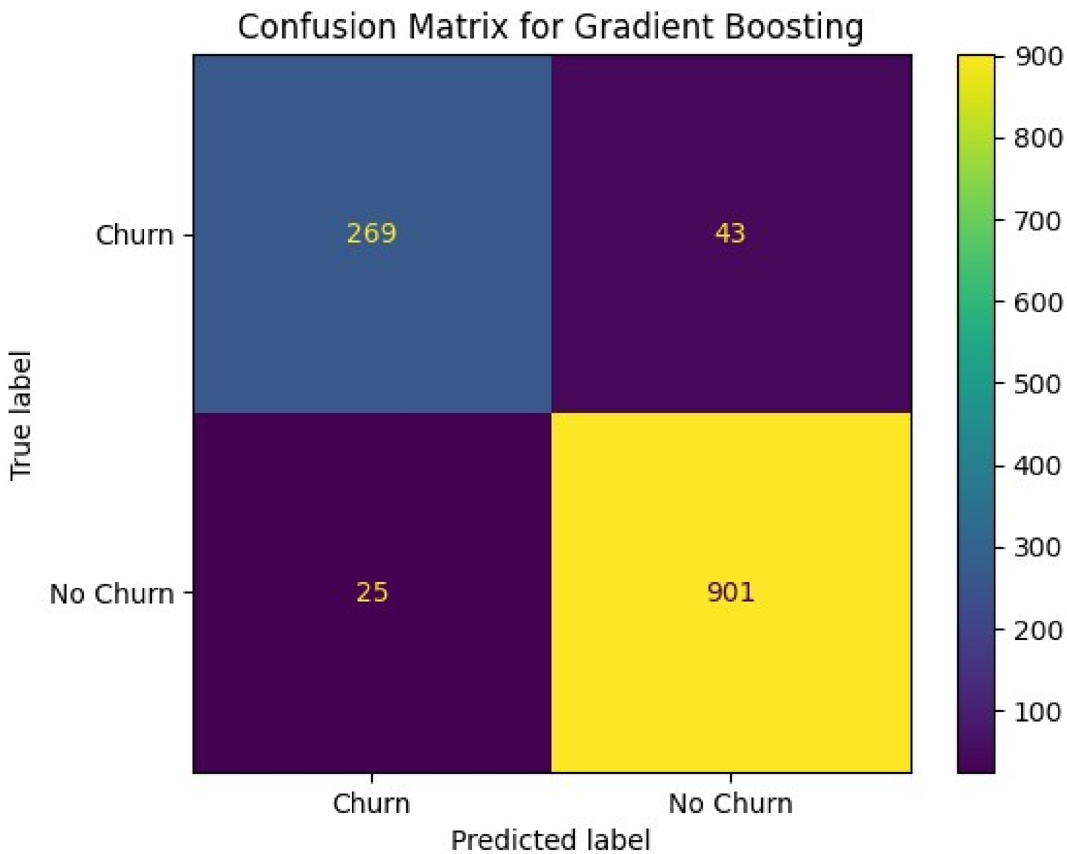
```
Ensemble Model Performance:
Accuracy: 0.93
Precision: 0.94
Recall: 0.76
F1 Score: 0.84
```

Task6 :Model Selection and Evaluation

best-performing model based on evaluation metrics

```
from sklearn.impute import SimpleImputer
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt


model_name = 'Gradient Boosting'
selected_model = best_models[model_name]


imputer = SimpleImputer(strategy='mean')
X_val_imputed = imputer.fit_transform(X_val)


predictions = selected_model.predict(X_val_imputed)

# Create confusion matrix
cm = confusion_matrix(y_val, predictions, labels=[1, 0])  # Assuming
'1' for churn and '0' for no churn
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
```

```
display_labels=['Churn', 'No Churn'])

# Plot confusion matrix
plt.figure(figsize=(10, 7))
disp.plot(cmap='viridis', values_format='d')
plt.title(f'Confusion Matrix for {model_name}')
plt.show()

<Figure size 1000x700 with 0 Axes>
```

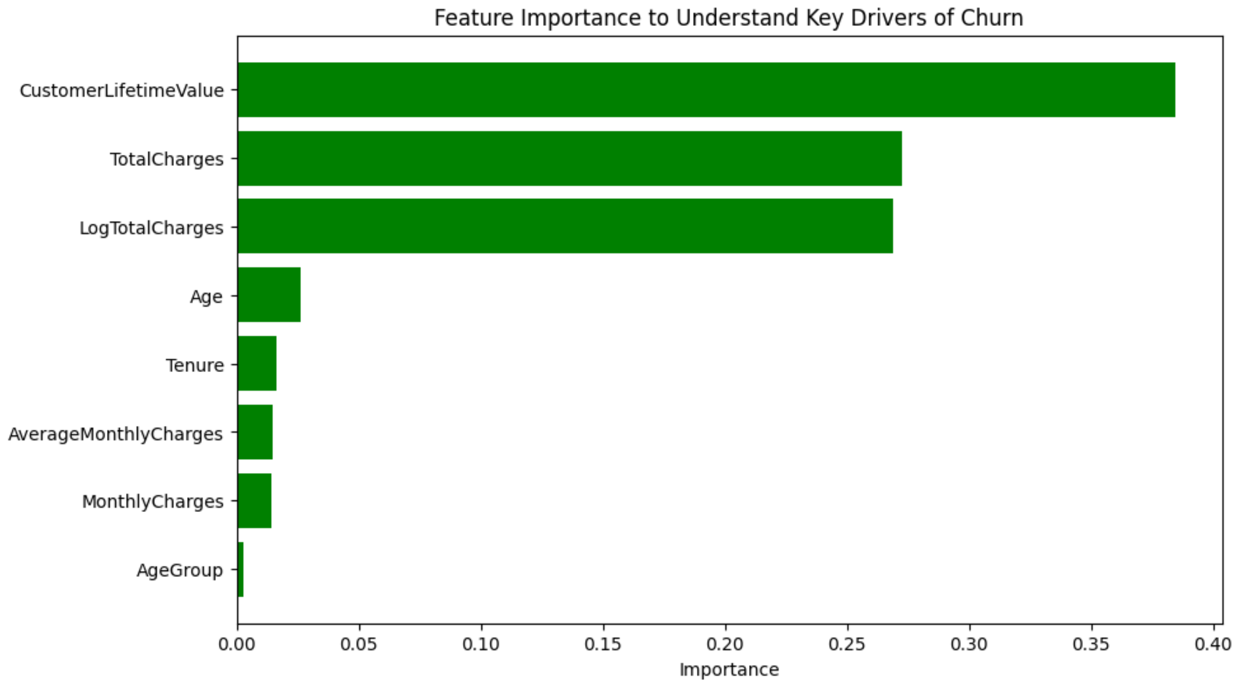


Calculate Feature Importance

```
from sklearn.ensemble import GradientBoostingClassifier
import matplotlib.pyplot as plt


best_model_name = 'Gradient Boosting'  # Change this to your selected
model name
best_model = best_models.get(best_model_name)  # Retrieve the model
from best_models

if best_model and hasattr(best_model, 'feature_importances_'):
```

```python
    importances = best_model.feature_importances_
    features = X_train.columns
    sorted_importances = sorted(zip(features, importances), key=lambda
x: x[1], reverse=True)


    print("Feature Importance to Understand Key Drivers of Churn:")
    for feature, importance in sorted_importances:
        print(f"{feature}: {importance:.3f}")

    # Plot feature importances
    plt.figure(figsize=(10, 6))
    plt.barh([f[0] for f in sorted_importances], [f[1] for f in
sorted_importances], color='green')
    plt.xlabel('Importance')
    plt.title('Feature Importance to Understand Key Drivers of Churn')
    plt.gca().invert_yaxis()
    plt.show()
else:
    print("Selected model does not support feature importances. Use a
tree-based model for this analysis.")
```

```
Feature Importance to Understand Key Drivers of Churn:
CustomerLifetimeValue: 0.384
TotalCharges: 0.273
LogTotalCharges: 0.269
Age: 0.026
Tenure: 0.016
AverageMonthlyCharges: 0.015
MonthlyCharges: 0.014
AgeGroup: 0.003
```


Feature Importance to Understand Key Drivers of Churn
CustomerLifetimeValue
TotalCharges
LogTotalCharges
Age
Tenure
AverageMonthlyCharges
MonthlyCharges
AgeGroup
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
Importance