In [1]:
```
# Import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import classification_report, roc_auc_score, confusion_matrix,
```

In [2]:
```
# Load data
data = pd.read_csv('customerchurn.csv')
data.head()
```

Out[2]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	Multipl
0	7590-VHVEG	Female	0	Yes	No	1	No	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	No
4	9237-HQITU	Female	0	No	No	2	Yes	

5 rows × 21 columns

In [3]:
```
# Check dimension of data
data.shape
```

Out[3]:
```
(7043, 21)
```

In [4]:
```
# Understand column types
data.dtypes
```

Out[4]:
```
customerID           object
gender               object
SeniorCitizen         int64
Partner              object
Dependents           object
tenure                int64
PhoneService         object
MultipleLines        object
InternetService      object
OnlineSecurity       object
OnlineBackup         object
DeviceProtection     object
TechSupport          object
StreamingTV          object
StreamingMovies      object
Contract             object
PaperlessBilling     object
PaymentMethod        object
MonthlyCharges      float64
TotalCharges         object
Churn                object
dtype: object
```

In [5]:
```
# Understand numerical data
data.describe()
```

Out[5]:

	SeniorCitizen	tenure	MonthlyCharges
count	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692
std	0.368612	24.559481	30.090047
min	0.000000	0.000000	18.250000
25%	0.000000	9.000000	35.500000
50%	0.000000	29.000000	70.350000
75%	0.000000	55.000000	89.850000
max	1.000000	72.000000	118.750000

Note that this is a classification problem due to lack of numerical data.

In [6]:
```
# Check for missing values
data.isna().sum()
```

Out[6]:
```
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        0
Churn               0
dtype: int64
```

There are no missing values in the dataset.

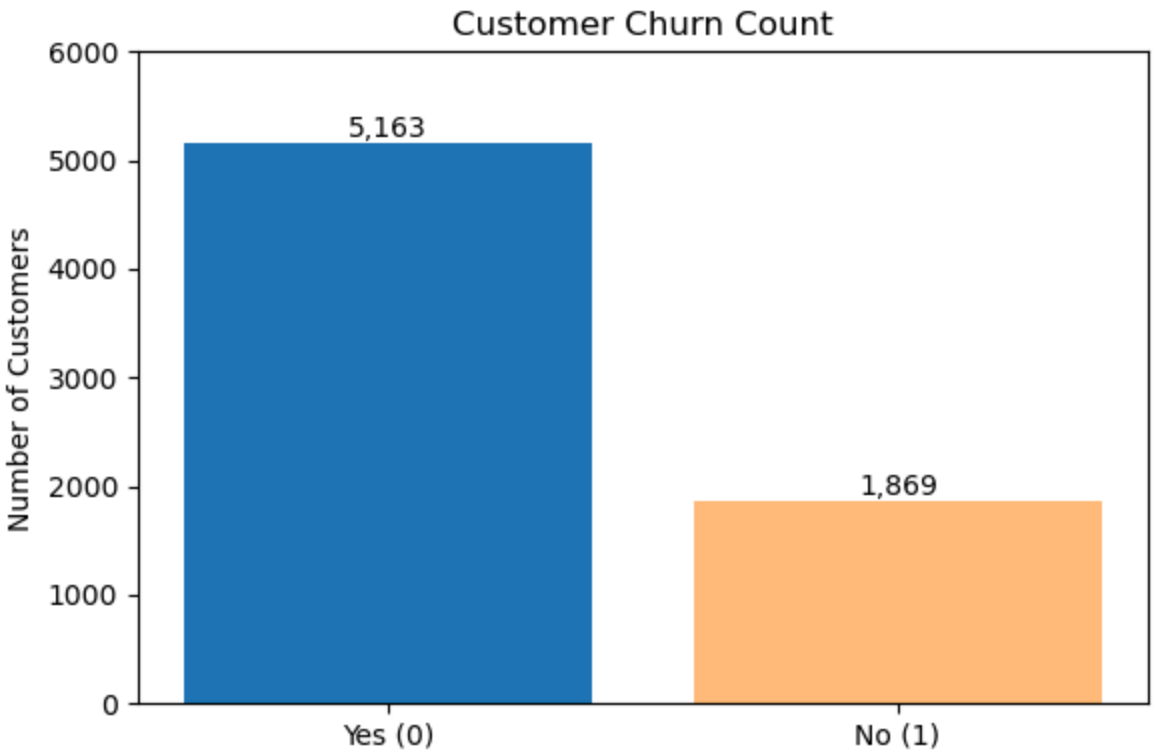
In [7]:
```
# Check for duplicates
data.duplicated().sum()
```

Out[7]:
```
0
```

In [8]:
```
# Drop unneeded ID column
data.drop('customerID', axis=1, inplace=True)

# Convert TotalCharges to numeric and handle errors
data['TotalCharges'] = pd.to_numeric(data['TotalCharges'], errors='coerce')
data.dropna(inplace=True)
```

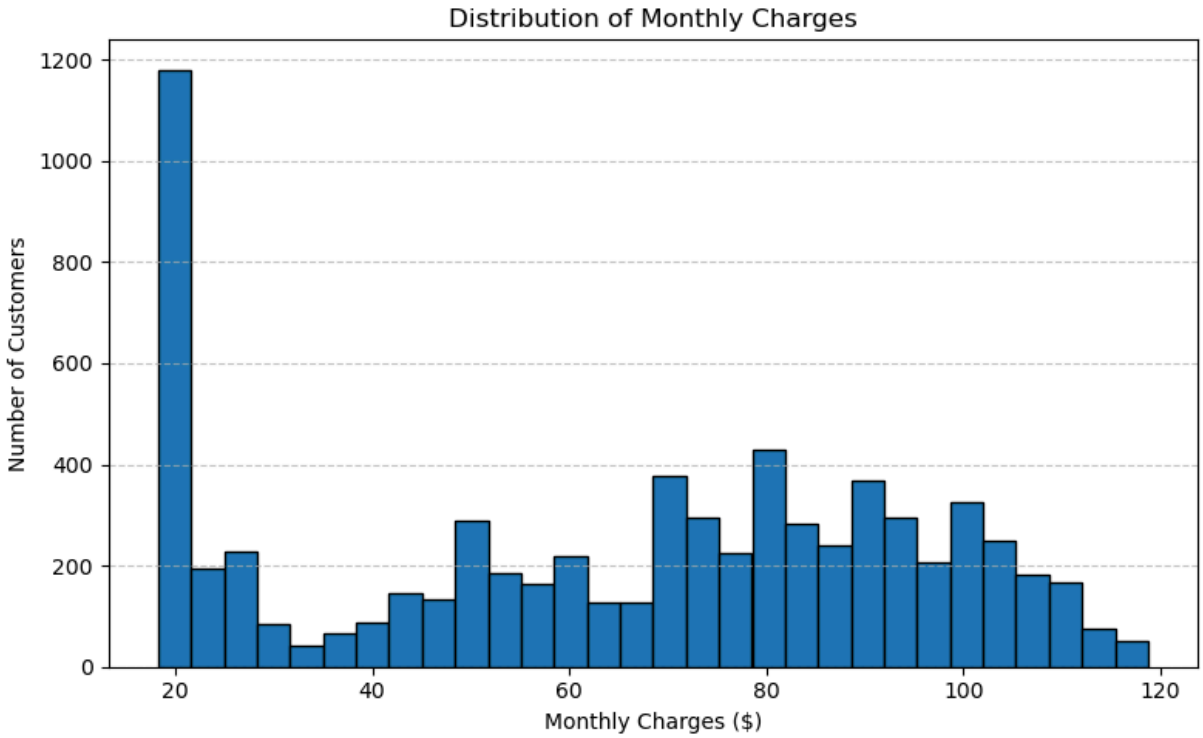
In [9]:
```
#Check imbalance within the dataset

# Count of each class
class_counts = data['Churn'].value_counts()

# Bar chart
plt.figure(figsize=(6, 4))
bars = plt.bar(class_counts.index, class_counts.values, color=['#1f77b4', '#ffbb78'

# Set labels and ticks
plt.xticks([0, 1], ['Yes (0)', 'No (1)'])
plt.ylabel('Number of Customers')
plt.title('Customer Churn Count')

# Set y-axis increments to 1000
max_count = max(class_counts.values)
plt.yticks(range(0, int(max_count + 1000), 1000))
```

```
# Add value labels
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2, height, f'{int(height):,}',
             ha='center', va='bottom', fontsize=10)

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

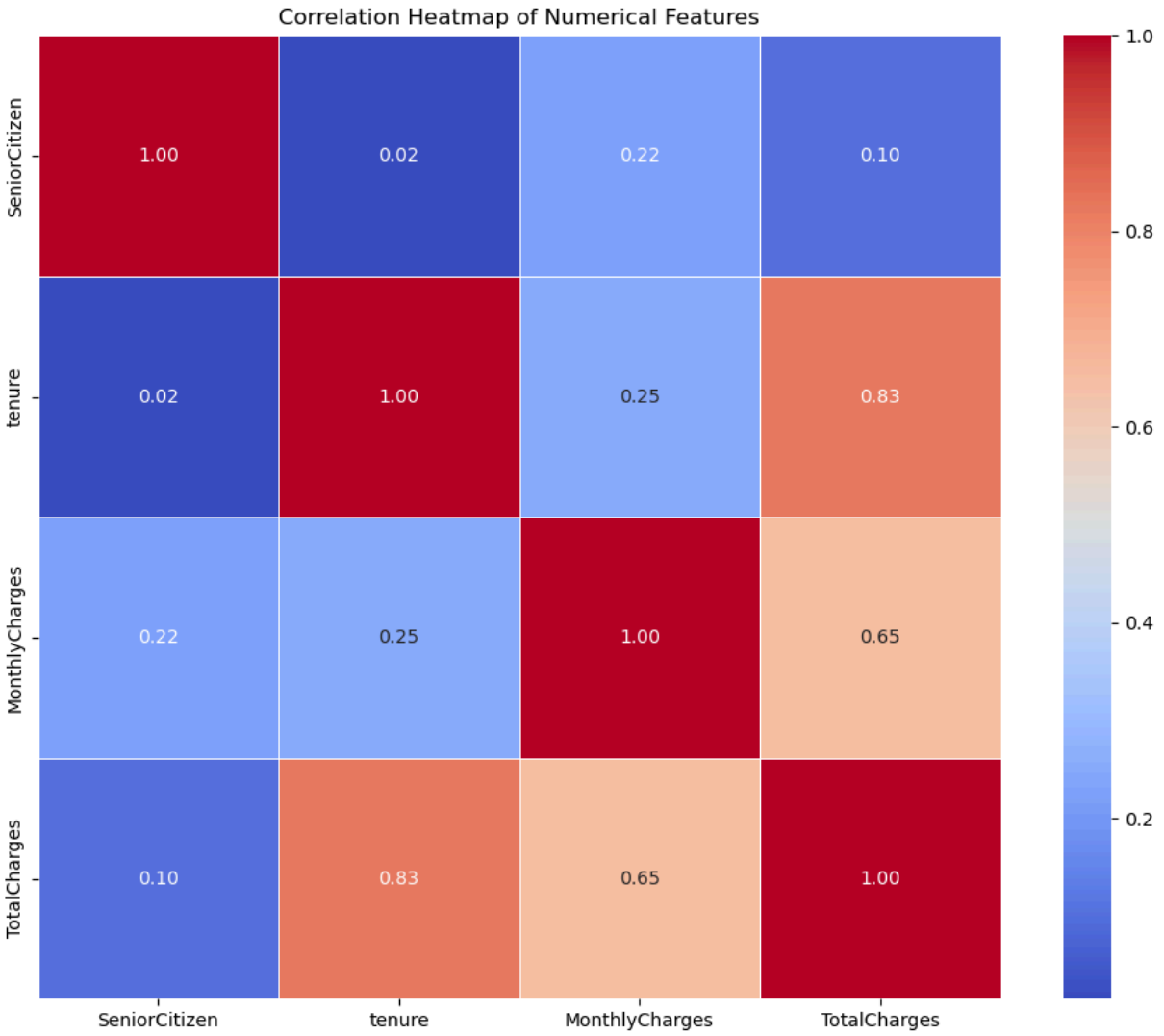


In [10]:
```
# One-hot encode categorical features (including 'Churn')
categorical_cols = data.select_dtypes(include='object').columns.tolist()
data_encoded = pd.get_dummies(data, columns=categorical_cols, drop_first=True)
```

In [11]:
```
# Distribution chart for Monthly Charges
plt.figure(figsize=(8, 5))
plt.hist(data['MonthlyCharges'], bins=30, color='#1f77b4', edgecolor='black')  # Da
plt.title('Distribution of Monthly Charges')
plt.xlabel('Monthly Charges ($)')
plt.ylabel('Number of Customers')
plt.grid(axis='y', linestyle='--', alpha=0.7)

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



In [12]:
```
# Compute correlation matrix (only numerical columns)
corr_matrix = data.corr(numeric_only=True)

# Plot the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap='coolwarm', square=True, linew

plt.title('Correlation Heatmap of Numerical Features')
plt.tight_layout()
plt.show()
```



In [13]:
```
# Split features and target variables

X = data_encoded.drop('Churn_Yes', axis=1)
y = data_encoded['Churn_Yes']

# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.2
```

In [14]:
```
# Apply SMOTE to balance the training data
smote = SMOTE(random_state=42)
X_train_res, y_train_res = smote.fit_resample(X_train, y_train)
```

In [15]:
```
# Define Models
# Logistic Regression
lr = LogisticRegression(max_iter=1000, random_state=42)
lr.fit(X_train_res, y_train_res)

# Random Forest
rf = RandomForestClassifier(n_estimators=50, max_depth=5, random_state=42, n_jobs=-
rf.fit(X_train_res, y_train_res)

# XGBoost
```

```
xgb = XGBClassifier(n_estimators=50, max_depth=3, use_label_encoder=False, eval_met
xgb.fit(X_train_res, y_train_res)
```

```
C:\Users\chris\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:458: Co
nvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
C:\Users\chris\anaconda3\Lib\site-packages\xgboost\training.py:183: UserWarning: [2
1:21:07] WARNING: C:\actions-runner\_work\xgboost\xgboost\src\learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```

Out[15]:

XGBClassifier

```
XGBClassifier(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='logloss',
              feature_types=None, feature_weights=None, gamma=None,
              grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=
None,
```

In [16]:

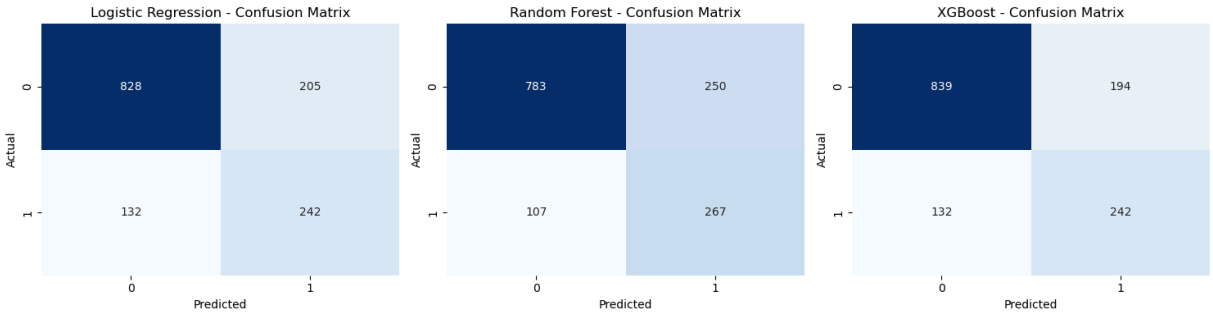
```
# Evaluate models

# Store results
results = []

models = {'Logistic Regression': lr, 'Random Forest': rf, 'XGBoost': xgb}

for name, model in models.items():
    y_pred = model.predict(X_test)
    y_proba = model.predict_proba(X_test)[:, 1]  # Get probability for ROC AUC

    report = classification_report(y_test, y_pred, output_dict=True, zero_division=
    roc_auc = roc_auc_score(y_test, y_proba)

    results.append({
        'Model': name,
        'Precision': report['True']['precision'],
        'Recall': report['True']['recall'],
        'F1-Score': report['True']['f1-score'],
        'ROC AUC': roc_auc
    })

# Convert to DataFrame
results_df = pd.DataFrame(results).round(4)
```

```
# Display the table
results_df
```

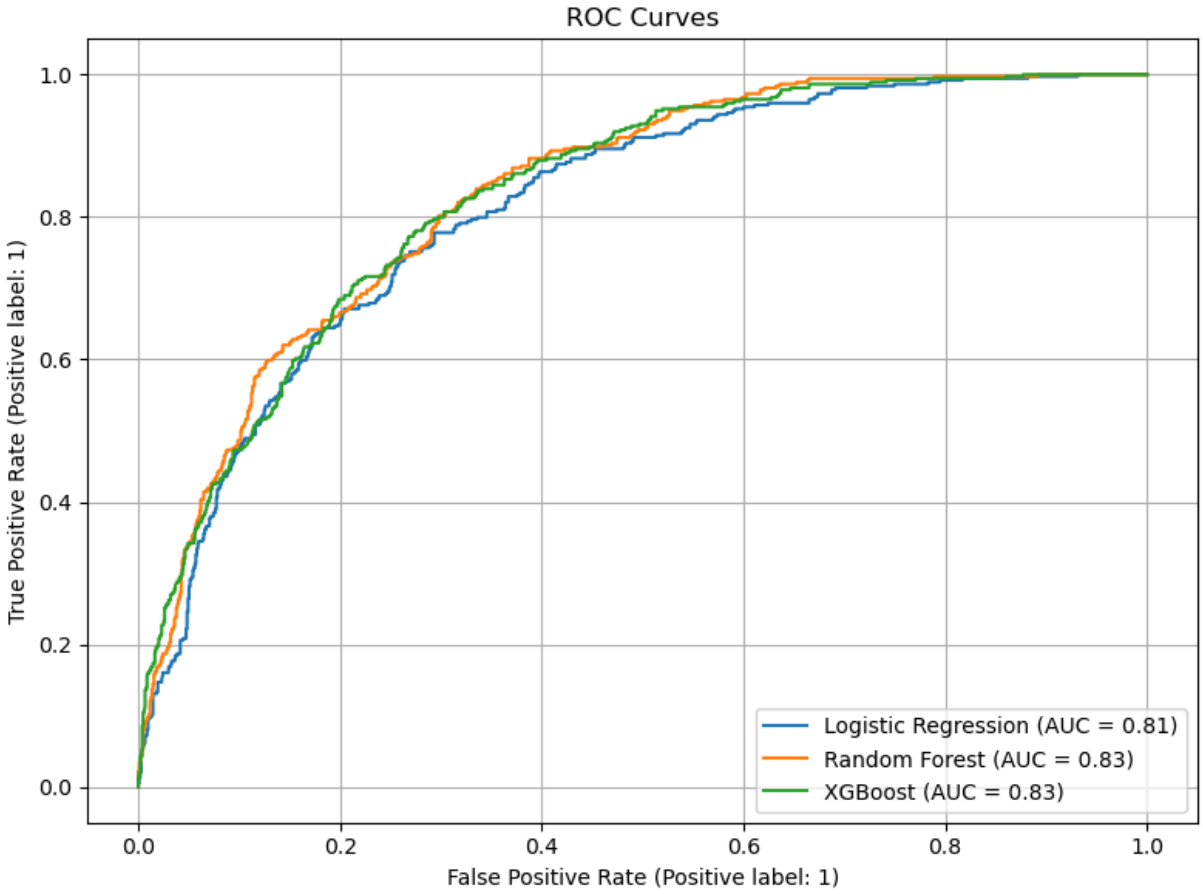
Out[16]:

	Model	Precision	Recall	F1-Score	ROC AUC
0	Logistic Regression	0.5414	0.6471	0.5895	0.8124
1	Random Forest	0.5164	0.7139	0.5993	0.8319
2	XGBoost	0.5550	0.6471	0.5975	0.8291

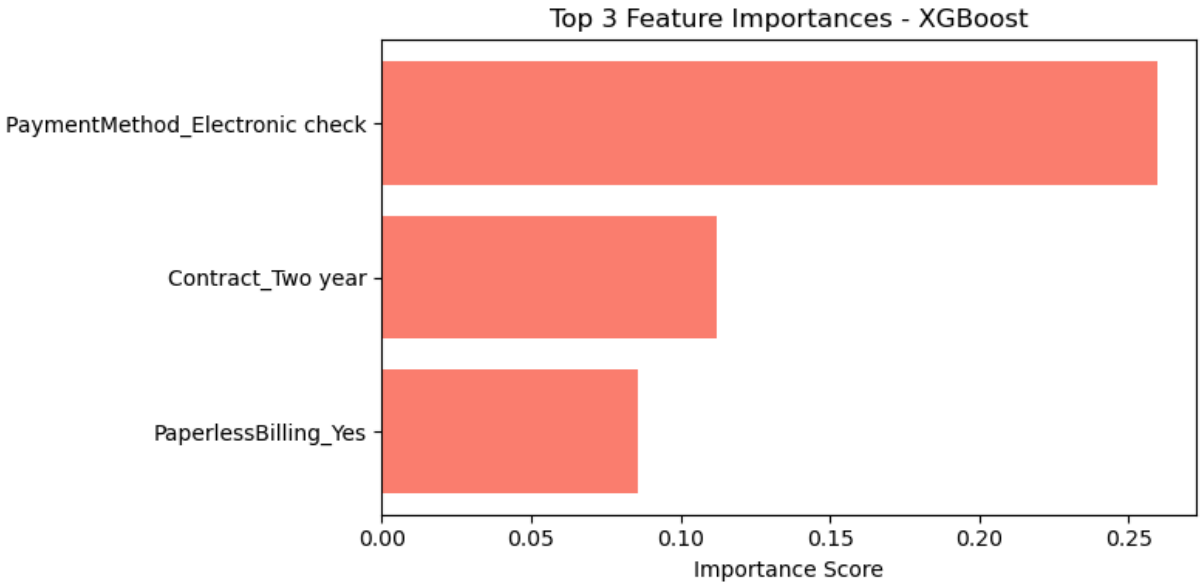
In [17]:
```
# Confusion matrices for each model
models = {'Logistic Regression': lr, 'Random Forest': rf, 'XGBoost': xgb}

# Plot confusion matrices
plt.figure(figsize=(15, 4))
for i, (name, model) in enumerate(models.items(), 1):
    y_pred = model.predict(X_test)
    cm = confusion_matrix(y_test, y_pred)

    plt.subplot(1, 3, i)
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False)
    plt.title(f'{name} - Confusion Matrix')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')

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



In [18]:
```
# ROC curves
plt.figure(figsize=(8, 6))
for name, model in models.items():
    RocCurveDisplay.from_estimator(model, X_test, y_test, name=name, ax=plt.gca())

plt.title('ROC Curves')
plt.grid(True)
plt.tight_layout()
plt.show()
```



In [19]:
```python
# Calculate and prepare feature importances for XGBoost
xgb_importances = pd.Series(xgb.feature_importances_, index=X.columns)
top3 = xgb_importances.sort_values(ascending=False).head(3)

# Convert to DataFrame for plotting
xgb_df = top3.reset_index()
xgb_df.columns = ['Feature', 'Importance']

# Plot
plt.figure(figsize=(8, 4))
plt.barh(xgb_df['Feature'], xgb_df['Importance'], color='salmon')
plt.gca().invert_yaxis()
plt.title('Top 3 Feature Importances - XGBoost')
plt.xlabel('Importance Score')
plt.tight_layout()
plt.show()
```


Top 3 Feature Importances - XGBoost
PaymentMethod_Electronic check
Contract_Two year
PaperlessBilling_Yes
0.00
0.05
0.10
0.15
0.20
0.25
Importance Score

In [ ]: