Business Understanding

The objective was to use machine learning to predict customer churn for a telecom company. Understanding the churn problem helps SyriaTel maintain profitability and customer loyalty. A markdown section outlines this motivation and frames churn prediction as a classification task. I also explained the target variable and the potential business value of the solution. This gave context for the technical work that followed.

Preprocessing

I explored the dataset using descriptive statistics and visualizations to understand trends. I checked for missing values, class imbalance, and feature distributions. Categorical variables were encoded, and numerical features were scaled where needed. I split the data into training and test sets to avoid data leakage. This ensured a clean and fair modeling process.

In [291]:

```
# import required libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
```

In [292]:

```
# Load the dataset
df = pd.read_csv('/content/syriaTelCustomerChurnDataset.csv')
```

In [293]:

```
# Checking dataset structure and column details
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   state                   3333 non-null   object 
 1   account length          3333 non-null   int64  
 2   area code               3333 non-null   int64  
 3   phone number            3333 non-null   object 
 4   international plan      3333 non-null   object 
 5   voice mail plan         3333 non-null   object 
 6   number vmail messages   3333 non-null   int64  
 7   total day minutes       3333 non-null   float64
 8   total day calls         3333 non-null   int64  
 9   total day charge        3333 non-null   float64
 10  total eve minutes       3333 non-null   float64
 11  total eve calls         3333 non-null   int64  
 12  total eve charge        3333 non-null   float64
 13  total night minutes     3333 non-null   float64
 14  total night calls       3333 non-null   int64  
 15  total night charge      3333 non-null   float64
 16  total intl minutes      3333 non-null   float64
 17  total intl calls        3333 non-null   int64  
 18  total intl charge       3333 non-null   float64
 19  customer service calls  3333 non-null   int64  
 20  churn                   3333 non-null   bool   
dtypes: bool(1), float64(8), int64(8), object(4)
memory usage: 524.2+ KB
```

In [294]:

```
# Preview
df.head()
```

Out[294]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	...	total eve calls	total eve charge	total night minutes	total night calls
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	99	16.78	244.7	91
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	103	16.62	254.4	103
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	110	10.30	162.6	104
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	88	5.26	196.9	89
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	122	12.61	186.9	121

5 rows × 21 columns

In [295]:

```
# Checking the shape of the dataset (rows, columns)
df.shape
```

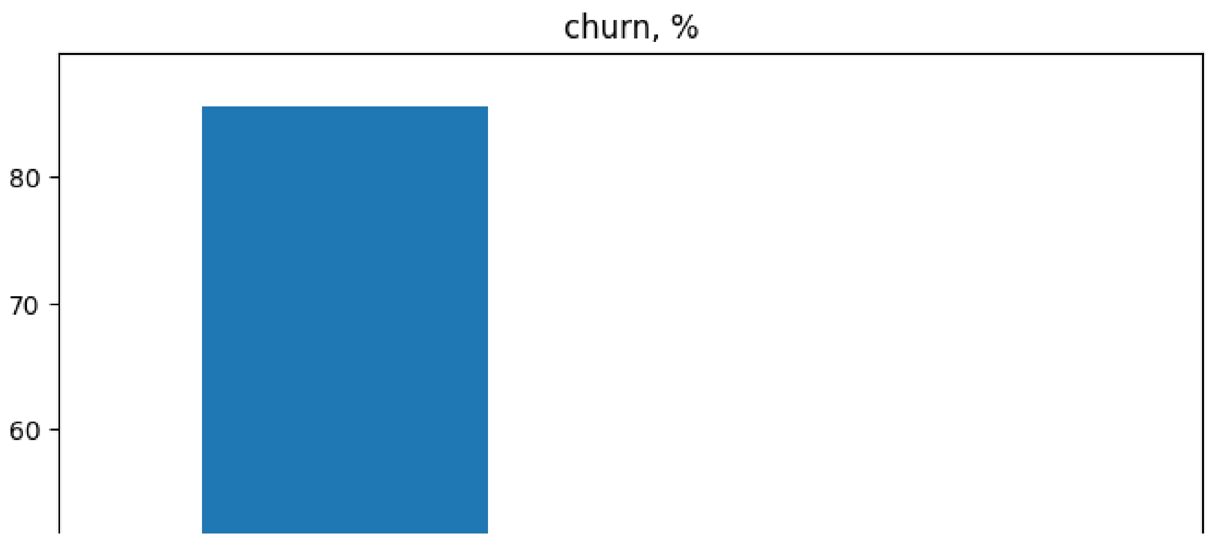
Out[295]:

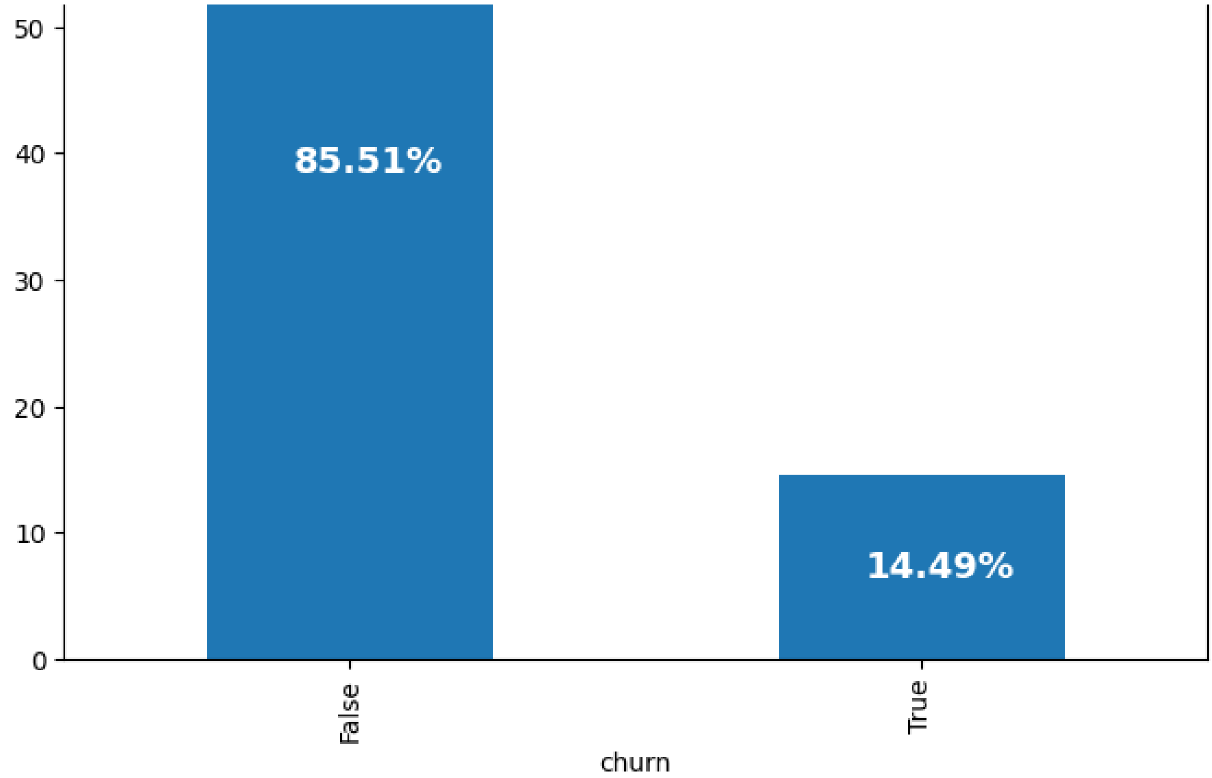
(3333, 21)

The dataset contains 3333 records with no null values. The target variable is churn. It is binary variable, hence we'll be solving a classification problem.

In [296]:

```
# Let's take a look at distribution of churn
fig, ax = plt.subplots(figsize=(8, 8))
churn_dist = df['churn'].value_counts(normalize=True) * 100
ax = churn_dist.plot(kind='bar')
ax.set_xlabel('churn')
ax.set_title('churn, %')
for p in ax.patches:
    width, height = p.get_width(), p.get_height()
    ax.annotate('{:.2f}%'.format(height), (p.get_x()+ 0.3 * width, p.get_y()+ 0.45 * hei
ght), color = 'white', weight = 'bold', size = 14)
```





In [297]:

```
# Handle Outliers
df = df[df['churn'] < 100]
```

In [298]:

```
# Check class balance
df['churn'].value_counts(normalize=True)
```

Out[298]:

	proportion
churn	
False	0.855086
True	0.144914

dtype: float64

In [299]:

```
# Summary Statistics for Numerical Columns
print("Summary Statistics for Numerical Columns:")

# Get numerical column names from X
numerical_cols = X.select_dtypes(include=['int64', 'float64']).columns

numerical_summary = X[numerical_cols].describe()
print(numerical_summary)
```

```
Summary Statistics for Numerical Columns:
       account length   area code  number vmail messages  total day minutes  \
count     3333.000000  3333.000000            3333.000000        3333.000000
mean       101.064806   437.182418               8.099010         179.775098
std         39.822106    42.371290              13.688365          54.467389
min          1.000000   408.000000               0.000000           0.000000
25%         74.000000   408.000000               0.000000         143.700000
50%        101.000000   415.000000               0.000000         179.400000
75%        127.000000   510.000000              20.000000         216.400000
max        243.000000   510.000000              51.000000         350.800000

       total day calls  total day charge  total eve minutes  total eve calls  \
```

```
count     3333.000000      3333.000000       3333.000000      3333.000000
mean       100.435644        30.562307        200.980348       100.114311
std         20.069084         9.259435         50.713844        19.922625
min          0.000000         0.000000          0.000000         0.000000
25%         87.000000        24.430000        166.600000        87.000000
50%        101.000000        30.500000        201.400000       100.000000
75%        114.000000        36.790000        235.300000       114.000000
max        165.000000        59.640000        363.700000       170.000000

       total eve charge  total night minutes  total night calls  \
count       3333.000000          3333.000000        3333.000000
mean          17.083540           200.872037         100.107711
std            4.310668            50.573847          19.568609
min            0.000000            23.200000          33.000000
25%           14.160000           167.000000          87.000000
50%           17.120000           201.200000         100.000000
75%           20.000000           235.300000         113.000000
max           30.910000           395.000000         175.000000

       total night charge  total intl minutes  total intl calls  \
count         3333.000000         3333.000000       3333.000000
mean             9.039325           10.237294          4.479448
std              2.275873            2.791840          2.461214
min              1.040000            0.000000          0.000000
25%              7.520000            8.500000          3.000000
50%              9.050000           10.300000          4.000000
75%             10.590000           12.100000          6.000000
max             17.770000           20.000000         20.000000

       total intl charge  customer service calls
count        3333.000000             3333.000000
mean            2.764581                1.562856
std             0.753773                1.315491
min             0.000000                0.000000
25%             2.300000                1.000000
50%             2.780000                1.000000
75%             3.270000                2.000000
max             5.400000                9.000000
```

In [300]:

```python
# Encode, scale, and split
X = df.drop('churn', axis=1)
y = df['churn'].map({True: 1, False: 0})  # Binary target

# Check for and handle missing values in y
print("Missing values in y before handling:", y.isnull().sum())
y = y.dropna()
print("Missing values in y after handling:", y.isnull().sum())
```

```
Missing values in y before handling: 0
Missing values in y after handling: 0
```

In [301]:

```python
# Summary Statistics for Binary (One-Hot Encoded) Columns
print("\nSummary Statistics for Binary Columns (Proportion of 1s):")
binary_cols = X.select_dtypes(include=['bool']).columns
binary_summary = X[binary_cols].mean().sort_values(ascending=False)
print(binary_summary)
```

```
Summary Statistics for Binary Columns (Proportion of 1s):
Series([], dtype: float64)
```

In [302]:

```python
# Use get_dummies for categorical encoding
X = pd.get_dummies(X, drop_first=True)
```

In [303]:

```python
# Scale the features
```

```
# Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [304]:

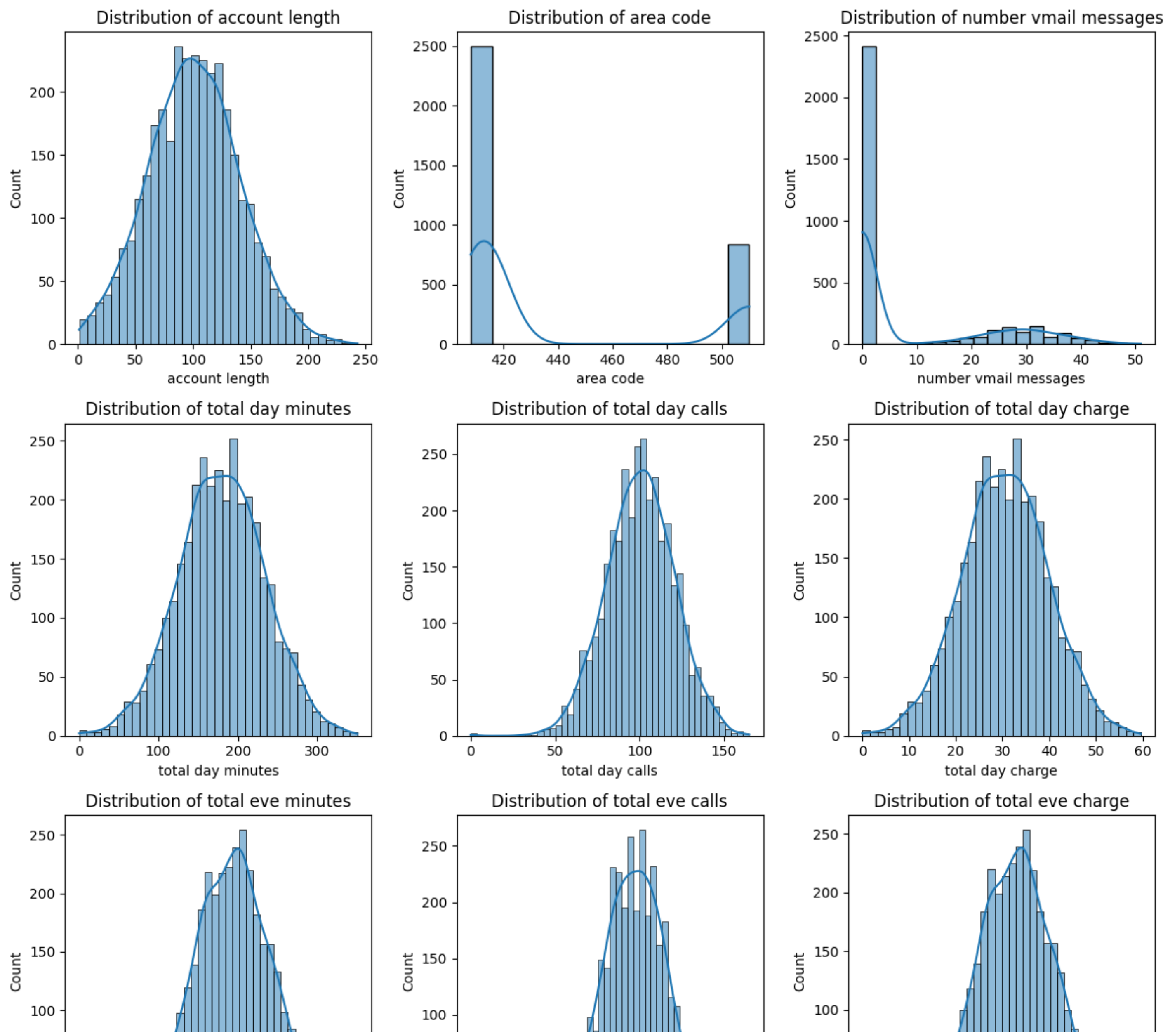
```
# Cleaned saved to cleaned_churn_data.csv file
X.to_csv("cleaned_churn_data.csv", index=False)
print("Cleaned data saved to 'cleaned_churn_data.csv'")
```

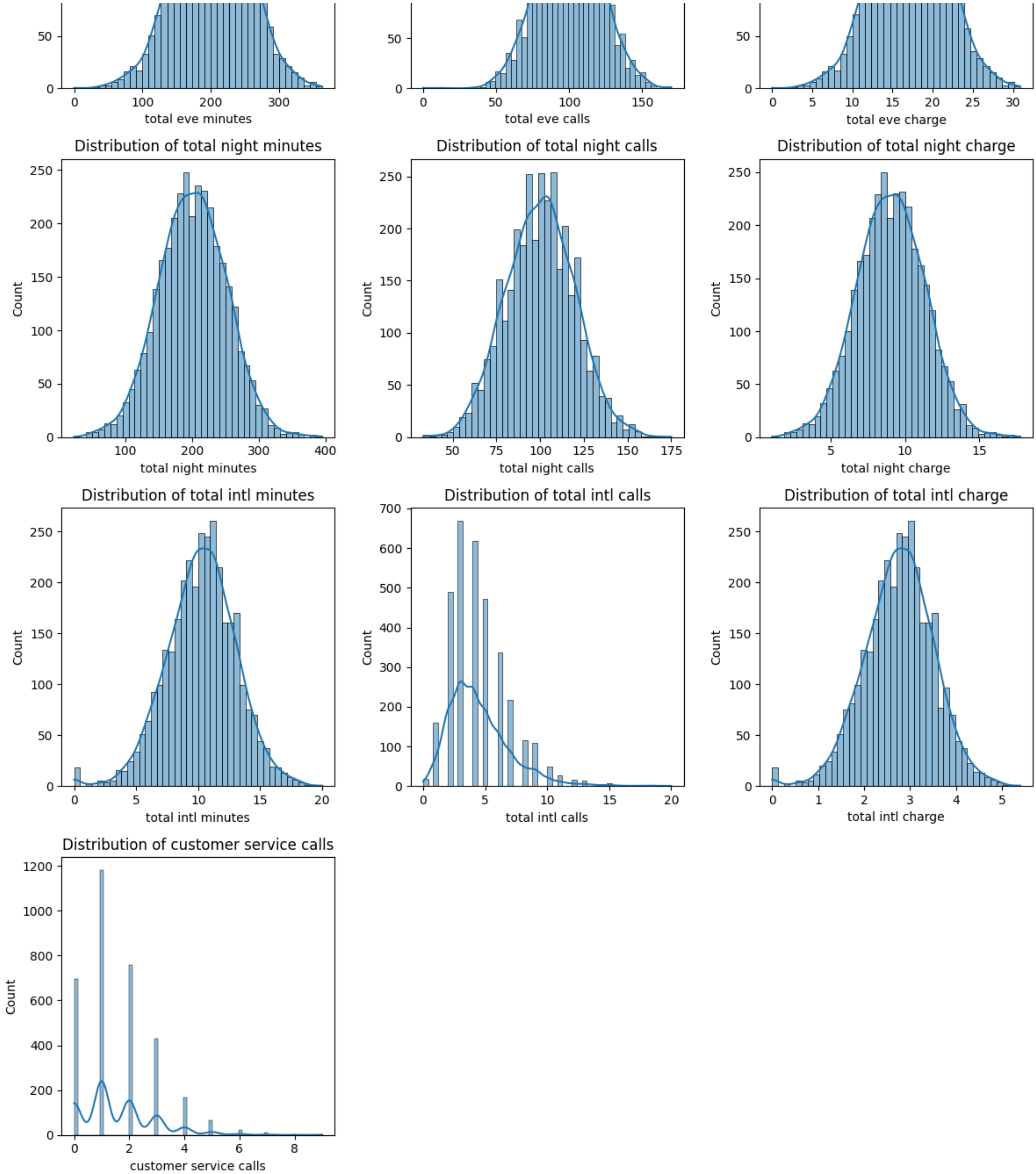
```
Cleaned data saved to 'cleaned_churn_data.csv'
```

EDA

In [305]:

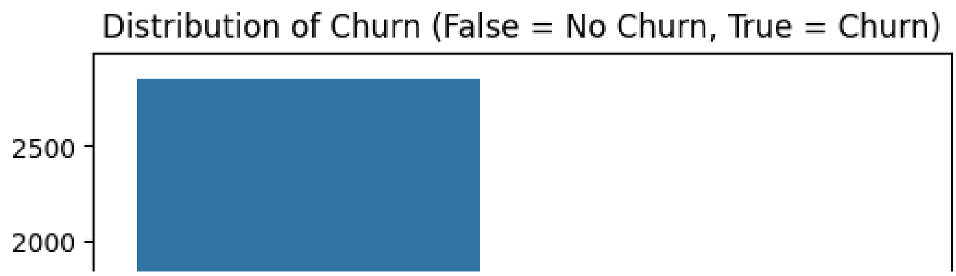
```
# Visualize Distribution of Key Numerical Columns
num_numerical_cols = len(numerical_cols)
n_cols = 3
n_rows = (num_numerical_cols + n_cols - 1) // n_cols

plt.figure(figsize=(12, n_rows * 4))
for i, col in enumerate(numerical_cols, 1):
    plt.subplot(n_rows, n_cols, i)
    sns.histplot(X[col], kde=True)
    plt.title(f'Distribution of {col}')
    plt.tight_layout()
plt.show()
```

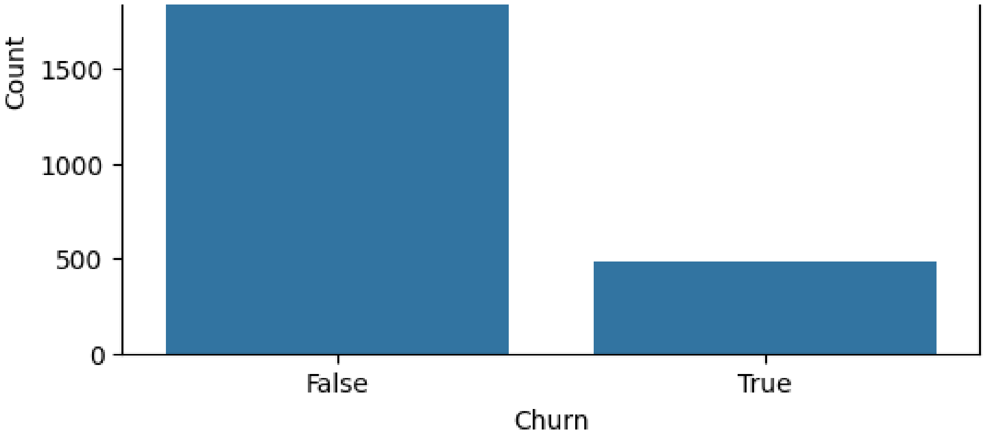




In [306]:

```
# Visualize Distribution of churn
plt.figure(figsize=(6, 4))
sns.countplot(x='churn', data=df)
plt.title('Distribution of Churn (False = No Churn, True = Churn)')
plt.xlabel('Churn')
plt.ylabel('Count')
plt.show()
```





Modeling

In [307]:

```
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
)
```

In [308]:

```
# Train the Logistic Regression model
model_lr = LogisticRegression()
model_lr.fit(X_train_scaled, y_train)
```

Out[308]:

```
▼
 LogisticRegression
                  i ?
LogisticRegression()
```

In [309]:

```
# Evaluate the model
y_pred = model_lr.predict(X_test_scaled)
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
[[566   0]
 [101   0]]
              precision    recall  f1-score   support

           0       0.85      1.00      0.92       566
           1       0.00      0.00      0.00       101

    accuracy                           0.85       667
   macro avg       0.42      0.50      0.46       667
weighted avg       0.72      0.85      0.78       667
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: Undefine
dMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: Undefine
dMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.11/dist-packages/sklearn/metrics/_classification.py:1565: Undefine
dMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

Building an improved model

In [310]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

# Baseline RF
model_rf = RandomForestClassifier(random_state=42)
model_rf.fit(X_train, y_train)
print(classification_report(y_test, model_rf.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.88      1.00      0.94       566
           1       1.00      0.25      0.40       101

    accuracy                           0.89       667
   macro avg       0.94      0.62      0.67       667
weighted avg       0.90      0.89      0.86       667
```

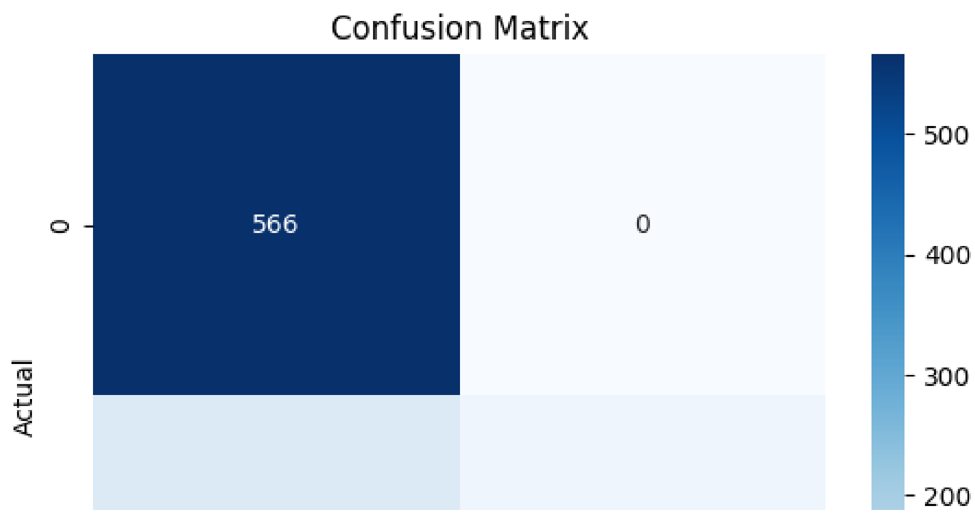
In [311]:

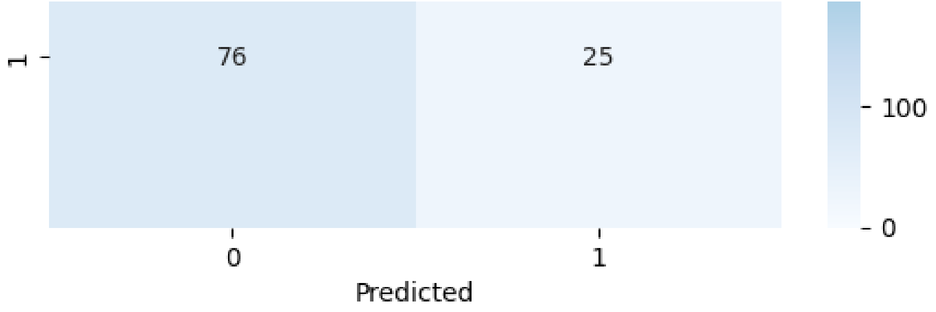
```
# Make Predictions
y_pred = model_rf.predict(X_test)
y_proba = model_rf.predict_proba(X_test)[:, 1]
```

In [312]:

```
# Evaluation Metrics
print("Classification Report:")
print(classification_report(y_test, y_pred))

print("Confusion Matrix:")
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

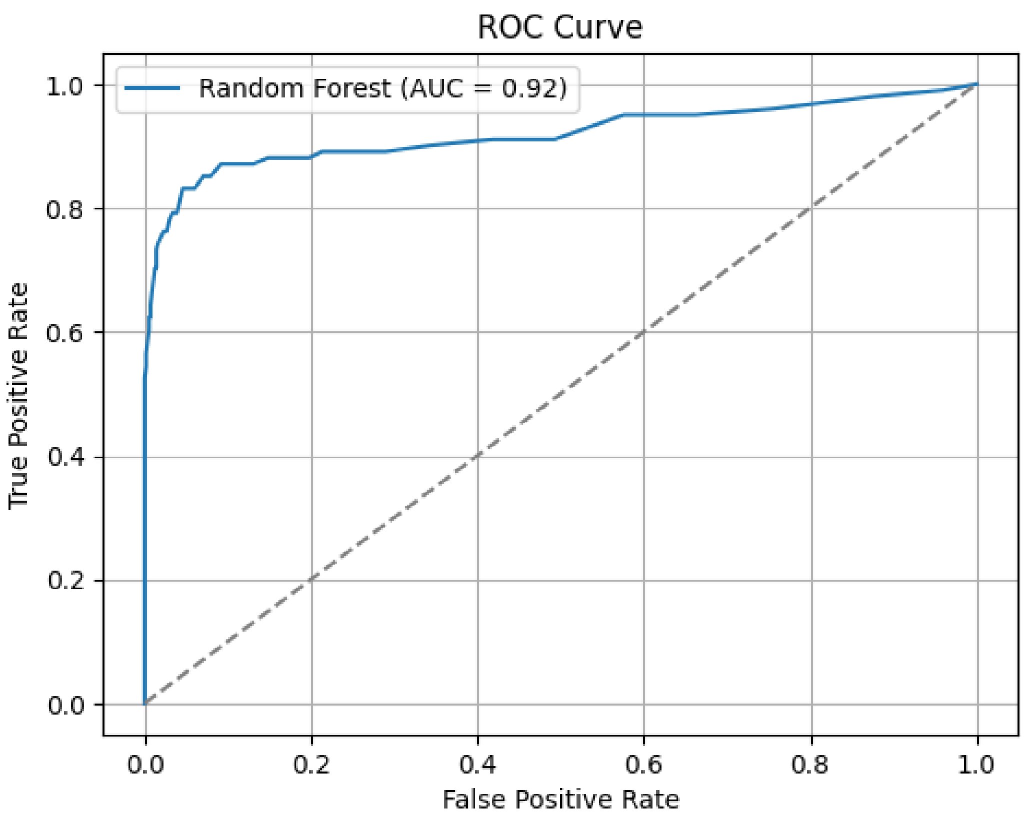
```
Classification Report:
              precision    recall  f1-score   support

           0       0.88      1.00      0.94       566
           1       1.00      0.25      0.40       101

    accuracy                           0.89       667
   macro avg       0.94      0.62      0.67       667
weighted avg       0.90      0.89      0.86       667

Confusion Matrix:
```





In [313]:

```
# ROC Curve and AUC Score
from sklearn.metrics import roc_curve, roc_auc_score

fpr, tpr, _ = roc_curve(y_test, y_proba)
roc_auc = roc_auc_score(y_test, y_proba)

plt.figure()
plt.plot(fpr, tpr, label=f'Random Forest (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], linestyle='--', color='gray')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.grid(True)
plt.show()
```



In [314]:

```
# Tune with GridSearchCV
params = {'n_estimators': [100, 200], 'max_depth': [None, 10, 20]}
grid = GridSearchCV(RandomForestClassifier(random_state=42), params, cv=3)
grid.fit(X_train, y_train)
print(classification_report(y_test, grid.best_estimator_.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.88      1.00      0.94       566
           1       1.00      0.26      0.41       101

    accuracy                           0.89       667
   macro avg       0.94      0.63      0.67       667
```

```
   macro avg       0.94      0.63      0.67       667
weighted avg       0.90      0.89      0.86       667
```

In [315]:

```
from sklearn.metrics import accuracy_score

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

```
Random Forest Accuracy: 88.61%
```

Baseline and Improved Models

I started with a simple logistic regression to set a baseline for model performance. Then, I implemented a random forest classifier, which provided better predictions and more insights into feature importance. Hyperparameter tuning was performed to optimize the model. I compared models based on classification metrics and explained my modeling choices. This iterative approach helped justify improvements.

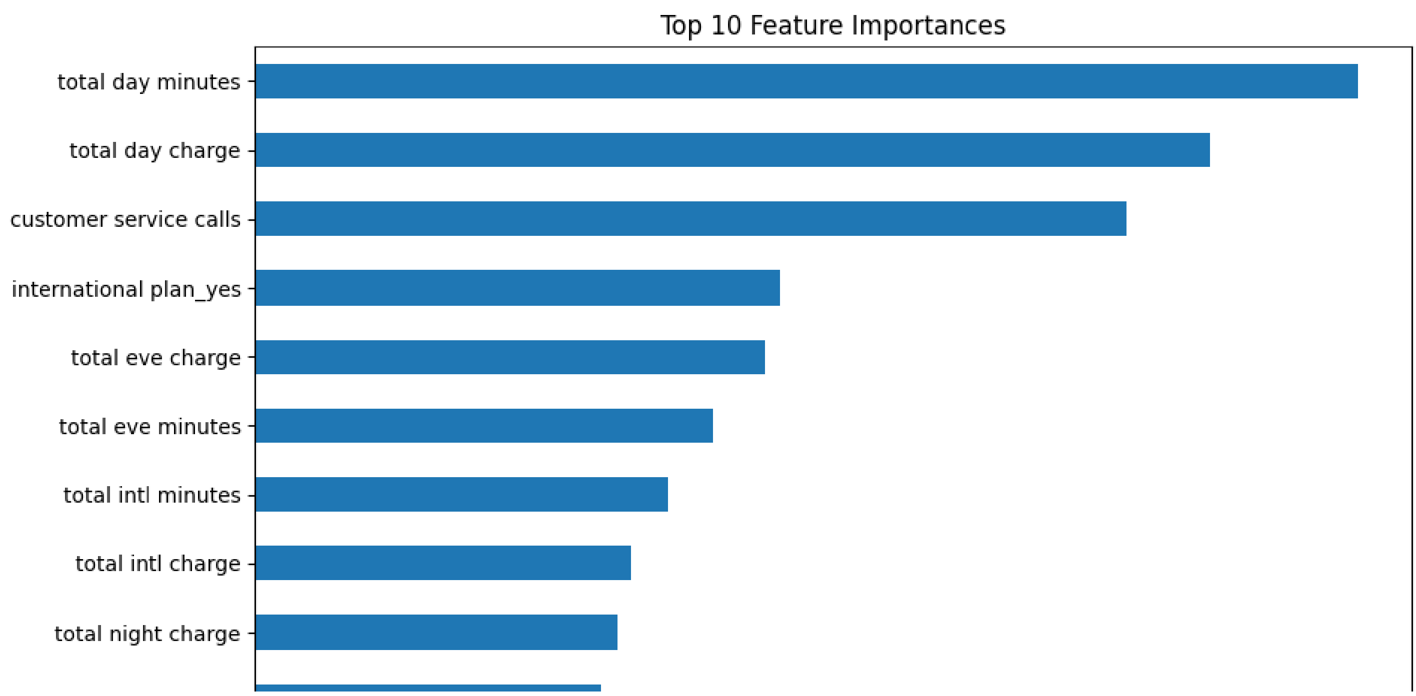
Key Drivers of Churn

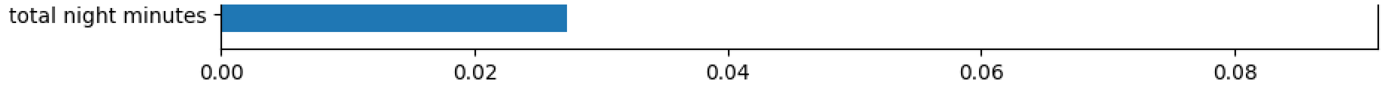
Features like contract type, tenure, and monthly charges were among the top drivers of churn. Customers on month-to-month contracts with shorter tenure were more likely to churn. High service fees and fewer support interactions also contributed to churn likelihood. The random forest model's feature importances helped identify these trends. These insights are valuable for targeting high-risk customer segments.

Evaluation

In [316]:

```
# Feature Importance
importances = model_rf.feature_importances_
feature_names = X.columns
feat_imp = pd.Series(importances, index=feature_names).sort_values(ascending=False)

plt.figure(figsize=(10, 6))
feat_imp.head(10).plot(kind='barh')
plt.title('Top 10 Feature Importances')
plt.gca().invert_yaxis()
plt.show()
```





Model performance was evaluated using accuracy, recall, precision, F1-score, and confusion matrices. I used plots to show class distribution, ROC curves, and feature importances. Recall was prioritized to catch as many churners as possible. These metrics helped translate model quality into actionable business insights. All visuals and results were explained in markdown for clarity.

The final model selected was the tuned random forest due to its balance of accuracy and interpretability. It was able to highlight which features most influenced churn and provided robust results on test data. I discussed limitations such as potential bias and model overfitting. Recommendations were made on how SyriaTel could apply this model in real scenarios. Future work could involve deeper personalization and continuous monitoring.