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Building a classifier to predict whether a customer will ("soon") stop doing business with SyriaTel, a telecommunications company. This is a binary classification problem.

My audience here would be the telecom business itself, interested in reducing how much money is lost because of customers who don't stick around very long. The question you can ask is: are there any predictable patterns here?

[1]:
```
#import important libaries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from xgboost import XGBClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score,
 ↪f1_score,classification_report
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from warnings import filterwarnings
filterwarnings('ignore')
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import RocCurveDisplay
```

Dataset Columns Description state:

U.S. state where the customer resides (categorical)

account length: Number of days the customer has had the account (integer)

area code: Customer's area code (integer)

phone number: Customer's phone number (identifier, usually dropped)

international plan: Whether customer has international calling plan (Yes/No)

voice mail plan: Whether customer has voicemail plan (Yes/No)

number vmail messages: Number of voicemail messages (integer)

total day minutes: Total minutes of calls during the day (float) total day calls: Number of calls during the day (integer)

total day charge: Charges for day calls (float)

total eve minutes: Total minutes of calls in the evening (float)

total eve calls: Number of calls in the evening (integer)

total eve charge: Charges for evening calls (float)

total night minutes: Total minutes of calls at night (float)

total night calls: Number of calls at night (integer)

total night charge: Charges for night calls (float)

total intl minutes: Total minutes of international calls (float)

total intl calls: Number of international calls (integer)

total intl charge: Charges for international calls (float)

customer service calls: Number of calls to customer service (integer)

churn: Whether the customer churned (True/False) — target variable

[3]:
```
#Load the dataset
churn=pd.read_csv(r"C:
 ↪\Users\USER\Downloads\archive\bigml_59c28831336c6604c800002a.csv")
churn.head()
```

[3]:
```
  state  account length  area code phone number international plan  \
0    KS             128        415     382-4657                 no
1    OH             107        415     371-7191                 no
2    NJ             137        415     358-1921                 no
3    OH              84        408     375-9999                yes
4    OK              75        415     330-6626                yes

  voice mail plan  number vmail messages  total day minutes  total day calls  \
0             yes                     25              265.1              110
1             yes                     26              161.6              123
2              no                      0              243.4              114
3              no                      0              299.4               71
4              no                      0              166.7              113

   total day charge  …  total eve calls  total eve charge  \
0             45.07  …               99             16.78
1             27.47  …              103             16.62
2             41.38  …              110             10.30
3             50.90  …               88              5.26
4             28.34  …              122             12.61

   total night minutes  total night calls  total night charge  \
```

```
0           244.7               91            11.01
1           254.4              103            11.45
2           162.6              104             7.32
3           196.9               89             8.86
4           186.9              121             8.41

   total intl minutes  total intl calls  total intl charge  \
0                10.0                 3               2.70
1                13.7                 3               3.70
2                12.2                 5               3.29
3                 6.6                 7               1.78
4                10.1                 3               2.73

   customer service calls  churn
0                       1  False
1                       1  False
2                       0  False
3                       2  False
4                       3  False

[5 rows x 21 columns]
```

[4]:
```python
#check the shape of the dataset
print(f"The dataset has {churn.shape[0]} rows")
print(f"The dataset has {churn.shape[1]} columns")
```

```
The dataset has 3333 rows
The dataset has 21 columns
```

[5]:
```python
#understand the dataset
churn.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
```

[6]:
```
churn.describe()
```

[6]:
```
       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
```

[7]:
```
#check for null values
churn.isna().sum()
```

[7]:
```
state                     0
account length            0
area code                 0
phone number              0
international plan        0
voice mail plan           0
number vmail messages     0
total day minutes         0
total day calls           0
total day charge          0
total eve minutes         0
total eve calls           0
total eve charge          0
total night minutes       0
total night calls         0
total night charge        0
total intl minutes        0
total intl calls          0
total intl charge         0
customer service calls    0
churn                     0
dtype: int64
```

Has no null values

[8]:
```
#checking for datatypes
churn.dtypes
```

[8]:
```
state                      object
account length              int64
area code                   int64
phone number               object
international plan         object
voice mail plan            object
number vmail messages       int64
total day minutes         float64
total day calls             int64
total day charge          float64
total eve minutes         float64
total eve calls             int64
total eve charge          float64
total night minutes       float64
total night calls           int64
total night charge        float64
total intl minutes        float64
total intl calls            int64
total intl charge         float64
customer service calls      int64
churn                        bool
dtype: object
```

[ ]:
```
churn['state'].unique()#has many unique values, so we will drop it
```

[ ]:
```
array(['KS', 'OH', 'NJ', 'OK', 'AL', 'MA', 'MO', 'LA', 'WV', 'IN', 'RI',
       'IA', 'MT', 'NY', 'ID', 'VT', 'VA', 'TX', 'FL', 'CO', 'AZ', 'SC',
       'NE', 'WY', 'HI', 'IL', 'NH', 'GA', 'AK', 'MD', 'AR', 'WI', 'OR',
       'MI', 'DE', 'UT', 'CA', 'MN', 'SD', 'NC', 'WA', 'NM', 'NV', 'DC',
       'KY', 'ME', 'MS', 'TN', 'PA', 'CT', 'ND'], dtype=object)
```

[ ]:
```
#  Drop non-informative columns
df = churn.drop(columns=['phone number', 'state'])

# 2. Encode 'international plan' and 'voice mail plan'
df['international plan'] = df['international plan'].map({'yes': 1, 'no': 0})
df['voice mail plan'] = df['voice mail plan'].map({'yes': 1, 'no': 0})

# 4. Convert target to int if needed
df['churn'] = df['churn'].astype(int)
```

[ ]:
```
df.head()#now the data has been encoded and cleaned
```

[ ]:

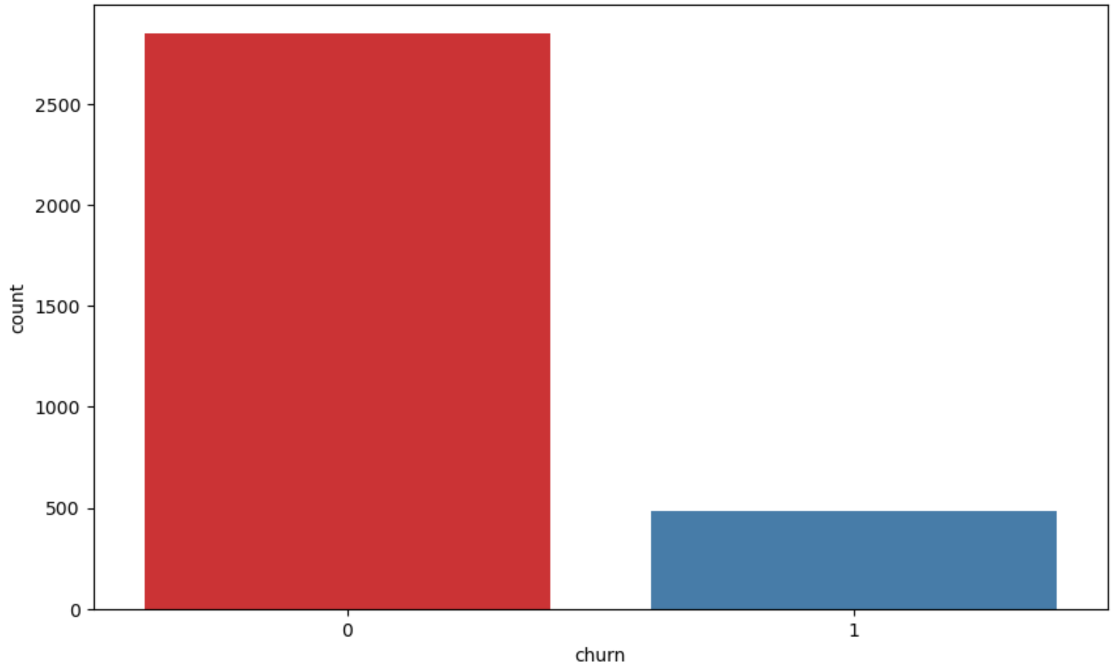
```
   account length  area code  international plan  voice mail plan  \
0             128        415                   0                1   
1             107        415                   0                1   
2             137        415                   0                0   
3              84        408                   1                0   
4              75        415                   1                0   

   number vmail messages  total day minutes  total day calls  \
0                     25              265.1              110   
1                     26              161.6              123   
2                      0              243.4              114   
3                      0              299.4               71   
4                      0              166.7              113   

   total day charge  total eve minutes  total eve calls  total eve charge  \
0             45.07              197.4               99             16.78   
1             27.47              195.5              103             16.62   
2             41.38              121.2              110             10.30   
3             50.90               61.9               88              5.26   
4             28.34              148.3              122             12.61   

   total night minutes  total night calls  total night charge  \
0                244.7                 91               11.01   
1                254.4                103               11.45   
2                162.6                104                7.32   
3                196.9                 89                8.86   
4                186.9                121                8.41   

   total intl minutes  total intl calls  total intl charge  \
0                10.0                 3               2.70   
1                13.7                 3               3.70   
2                12.2                 5               3.29   
3                 6.6                 7               1.78   
4                10.1                 3               2.73   

   customer service calls  churn  
0                       1      0  
1                       1      0  
2                       0      0  
3                       2      0  
4                       3      0  
```

Churn is our target variable

[13]:

```
#visualize some of the features to be able to understand the dataset
plt.figure(figsize=(10,6))
sns.countplot(x='churn', data=df, palette='Set1')
```

```
plt.show()
```



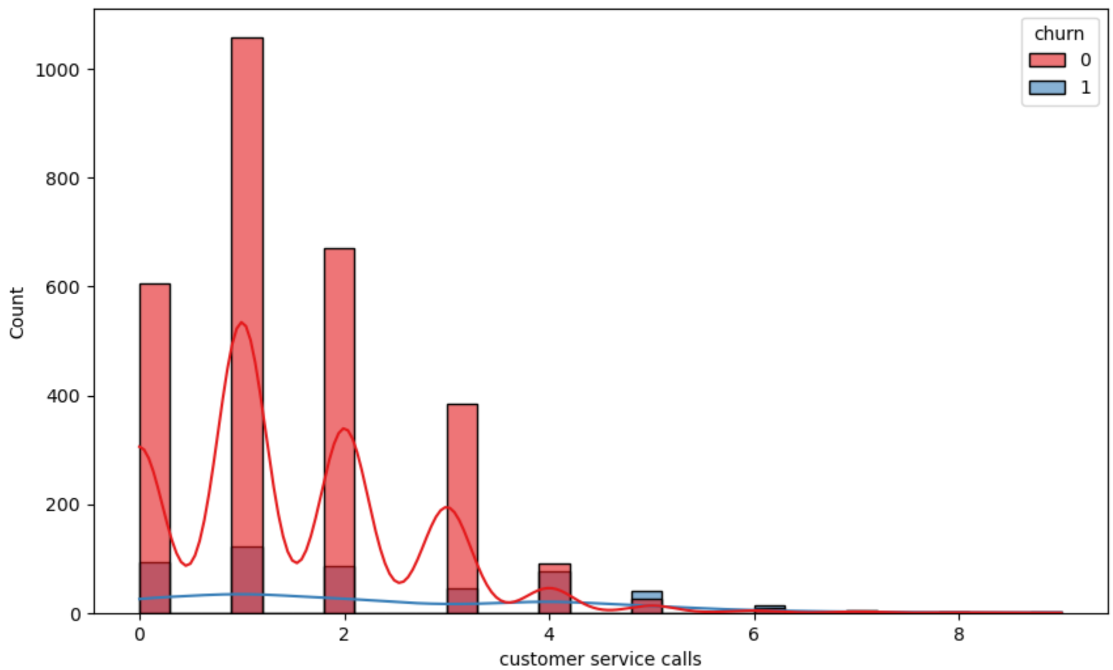
Interpretation of the Plot

Class 0 : Has more samples — around 3000+.

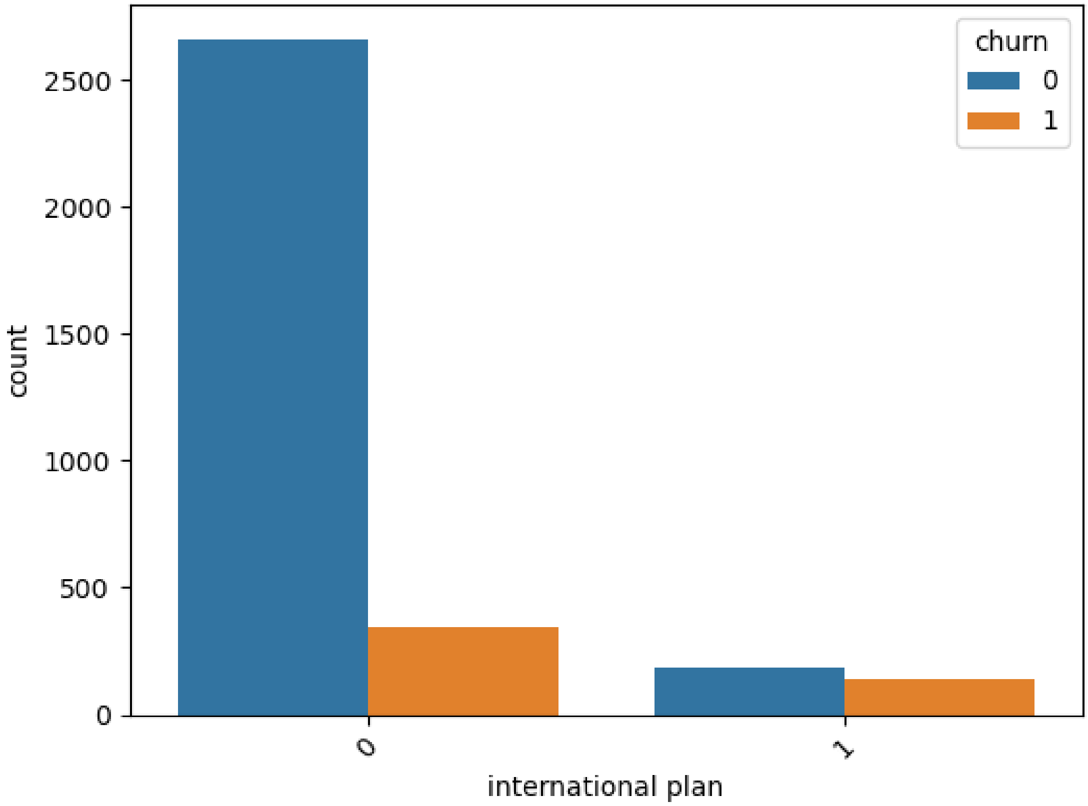
Class 1: Has fewer samples — around 500+.

Churn means when a customer stops using a company's service or cancels their subscription.

```
[ ]: #visialize customer service calls and churn
plt.figure(figsize=(10,6))
sns.histplot(data=df, x='customer service calls', hue='churn', bins=30,␣
 ↪kde=True, palette='Set1', alpha=0.6)
plt.show()
```



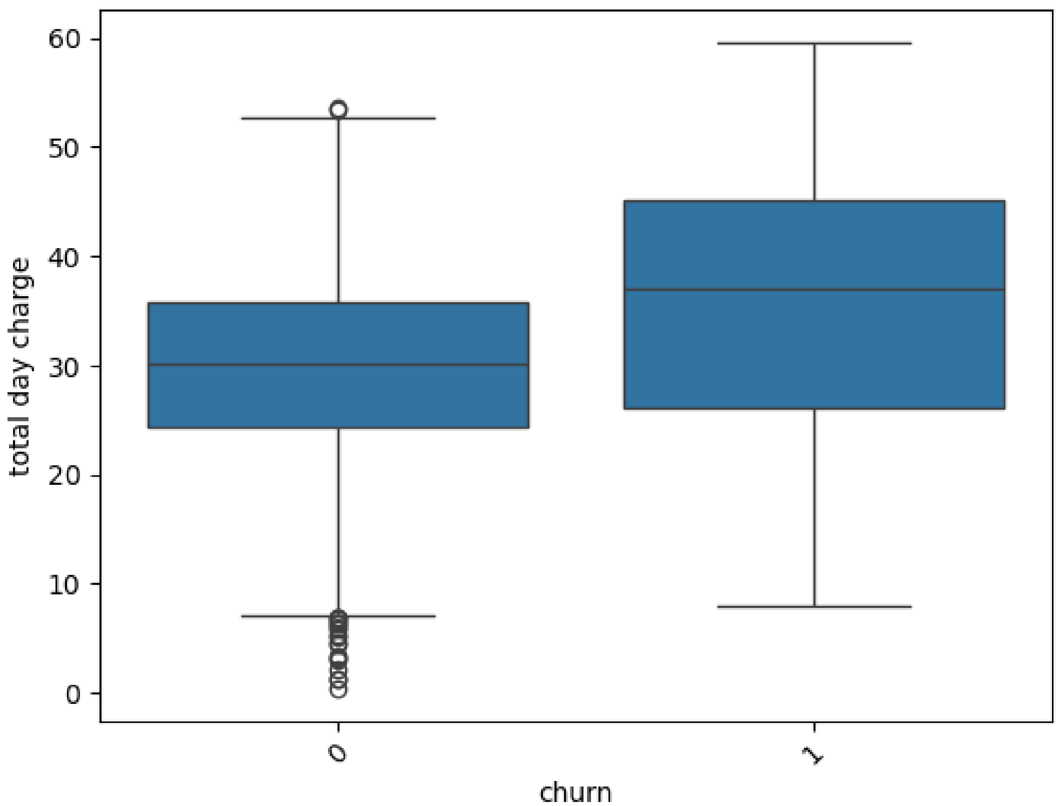
[19]:
```
sns.countplot(data=df, x='international plan', hue='churn')
plt.xticks(rotation=45)
plt.show()
```



A higher proportion of customers with an international plan tend to churn, compared to those without it.

While most customers do not have an international plan, among those who do, the churn rate is significantly higher.

[17]:
```
sns.boxplot(data=df[df['total day charge'] > 0], x='churn', y='total day␣
↪charge')
plt.xticks(rotation=45)
plt.show()
```



According to our data we can see that people who pay 25 to 35 tend to stay and most of those who go pay 25 and 45

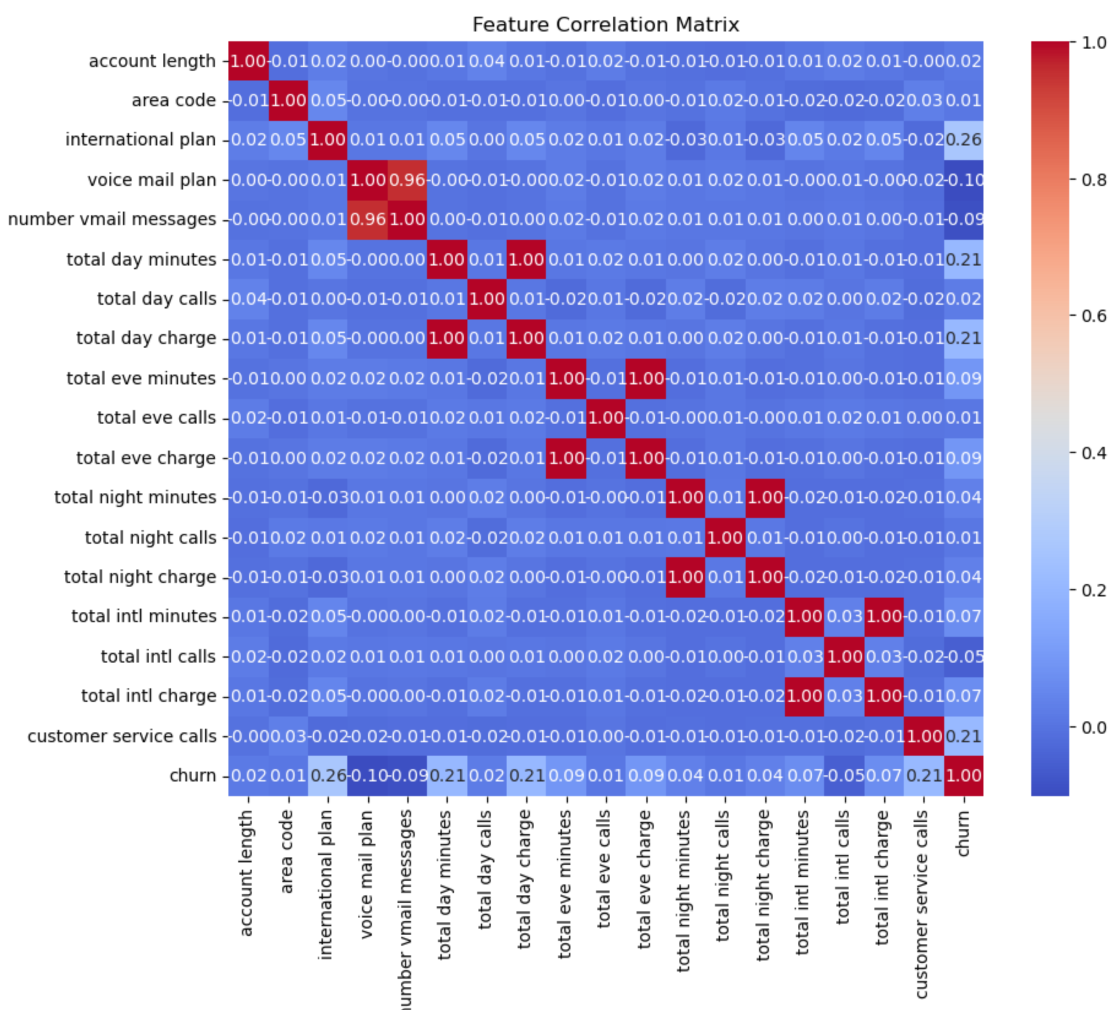
Customers labeled **1** (churned) tend to have higher total day charge on average.

Customers labeled **0** (did not churn) have lower charges and more outliers on the lower end.

[18]:
```
# Compute the correlation matrix
corr_matrix = df.corr()

# Display correlation with target (churn) only, sorted
churn_corr = corr_matrix['churn'].drop('churn').sort_values(key=abs,␣
↪ascending=False)
print(churn_corr)

#Visualize the full correlation heatmap
plt.figure(figsize=(10,8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f", square=True)
plt.title("Feature Correlation Matrix")
plt.show()
```

```
international plan        0.259852
```

```
customer service calls    0.208750
total day minutes         0.205151
total day charge          0.205151
voice mail plan          -0.102148
total eve minutes         0.092796
total eve charge          0.092786
number vmail messages    -0.089728
total intl charge         0.068259
total intl minutes        0.068239
total intl calls         -0.052844
total night charge        0.035496
total night minutes       0.035493
total day calls           0.018459
account length            0.016541
total eve calls           0.009233
area code                 0.006174
total night calls         0.006141
Name: churn, dtype: float64
```



Most positively correlated with churn:

international plan: 0.26 → Strongest correlation; customers with an international plan are more likely to churn.

customer service calls: 0.21 → The more calls to customer service, the higher the likelihood of churn.

total day minutes / total day charge: 0.205 → Heavy daytime users tend to churn more.

MODELLING

[21]:
```
#Finding our x and y variables
X=df.drop('churn', axis=1)
y=df['churn']
```

[22]:
```
#checking the x and y
X.head()
```

[22]:
```
   account length  area code  international plan  voice mail plan  \
0             128        415                   0                1
1             107        415                   0                1
2             137        415                   0                0
3              84        408                   1                0
4              75        415                   1                0

   number vmail messages  total day minutes  total day calls  \
0                     25              265.1              110
1                     26              161.6              123
2                      0              243.4              114
3                      0              299.4               71
4                      0              166.7              113

   total day charge  total eve minutes  total eve calls  total eve charge  \
0             45.07              197.4               99             16.78
1             27.47              195.5              103             16.62
2             41.38              121.2              110             10.30
3             50.90               61.9               88              5.26
4             28.34              148.3              122             12.61

   total night minutes  total night calls  total night charge  \
0                244.7                 91               11.01
1                254.4                103               11.45
2                162.6                104                7.32
3                196.9                 89                8.86
4                186.9                121                8.41
```

```
   total intl minutes  total intl calls  total intl charge  \
0                10.0                 3               2.70
1                13.7                 3               3.70
2                12.2                 5               3.29
3                 6.6                 7               1.78
4                10.1                 3               2.73

   customer service calls
0                       1
1                       1
2                       0
3                       2
4                       3
```

[23]:
```
y.head()
```

[23]:
```
0    0
1    0
2    0
3    0
4    0
Name: churn, dtype: int64
```

Creating a training and test split

This is where we'll split our data into a training set and a test set.

We'll use our training set to train our model and our test set to evaluate it.

[24]:
```
#splitting the data
X_train,X_test, y_train, y_test=train_test_split(X,y,random_state=42,␣
 ↪test_size=0.2)
#standardizing the data
scaler=StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Checking which model we will use in our prediction

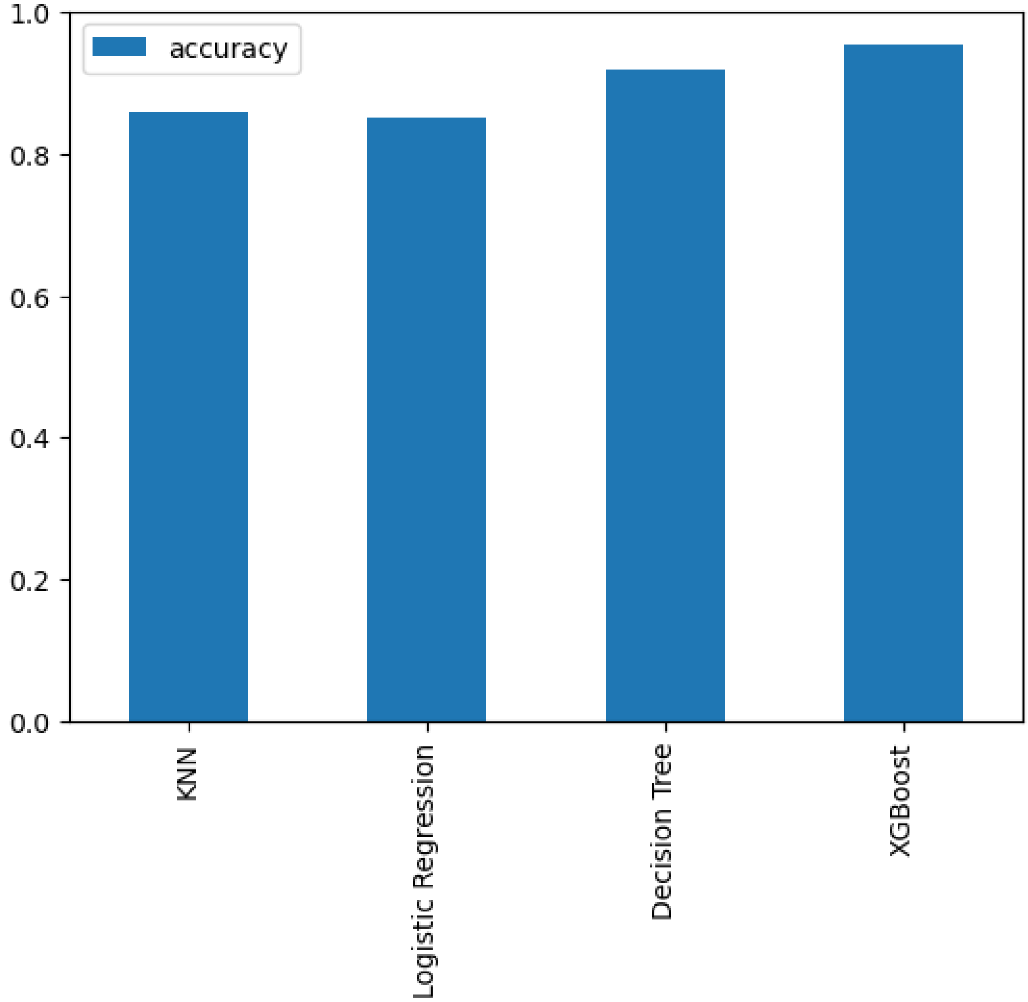
[25]:
```
from sklearn.neighbors import KNeighborsClassifier

# Let's find out which model performs better
# Put models in a dictionary
models = {
    "KNN": KNeighborsClassifier(),
    "Logistic Regression": LogisticRegression(max_iter=100),
    "Decision Tree": DecisionTreeClassifier(),
    "XGBoost": XGBClassifier(random_state=42)
}
```

```python
# Create function to fit and score models
def fit_and_score(models, X_train, X_test, y_train, y_test):
    """
    Fits and evaluates given machine learning models.
    models : a dict of different Scikit-Learn machine learning models
    X_train : training data
    X_test : testing data
    y_train : labels assosciated with training data
    y_test : labels assosciated with test data
    """
    # Random seed for reproducible results
    np.random.seed(42)
    # Make a list to keep model scores
    model_scores = {}
    # Loop through models
    for name, model in models.items():
        # Fit the model to the data
        model.fit(X_train, y_train)
        # Evaluate the model and append its score to model_scores
        model_scores[name] = model.score(X_test, y_test)
    return model_scores
```

[26]:
```python
model_scores = fit_and_score(models=models,
                             X_train=X_train,
                             X_test=X_test,
                             y_train=y_train,
                             y_test=y_test)
model_scores
```

[26]:
```
{'KNN': 0.8590704647676162,
 'Logistic Regression': 0.8515742128935532,
 'Decision Tree': 0.9190404797601199,
 'XGBoost': 0.9535232383808095}
```

[27]:
```python
#Visualizing the model scores
model_compare = pd.DataFrame(model_scores, index=['accuracy'])
model_compare.T.plot.bar();
```



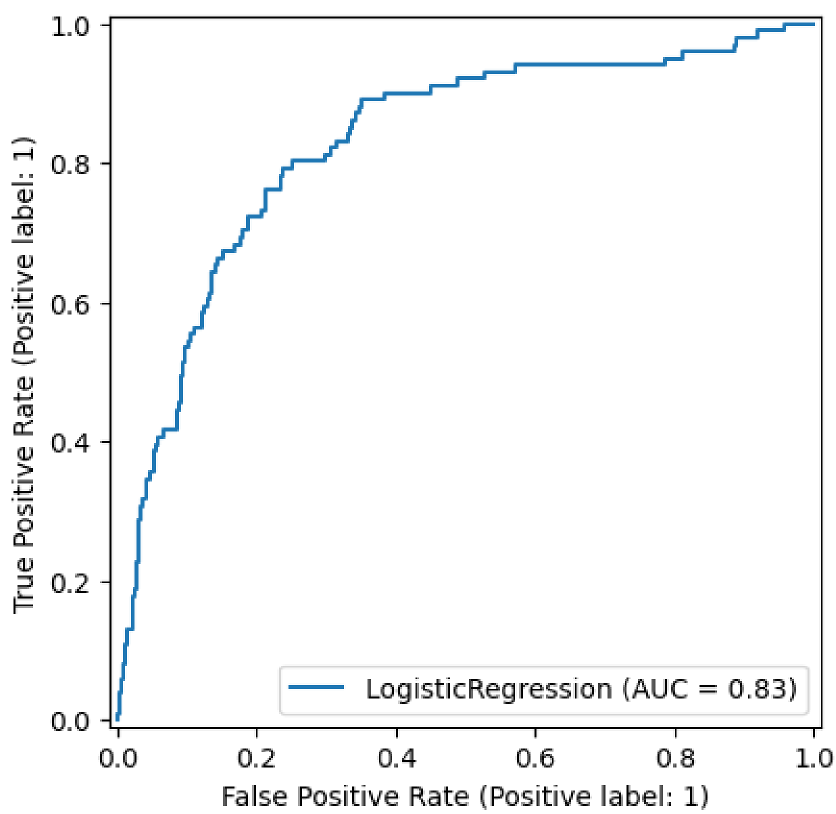
This gives us the best models that we can use to explain our output and we have seen XGboost and decision tree are the best to use here and logistic is sligtly better than KNN.

[28]:
```
#without hyperparameter tuning
model = LogisticRegression()
# fitting the model
model.fit(X_train_scaled, y_train)
# predicting the model
y_pred = model.predict(X_test_scaled)
# checking the accuracy
accuracy = accuracy_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")
print(f"F1 Score: {f1:.2f}")
```

```python
print(f"Precision Score: {precision:.2f}")
print(f"Recall Score: {recall:.2f}")
# classification report
print(classification_report(y_test, y_pred))
# Roc curve
RocCurveDisplay.from_estimator(model, X_test_scaled, y_test)
```

```
Accuracy: 0.86
F1 Score: 0.27
Precision Score: 0.60
Recall Score: 0.18
              precision    recall  f1-score   support

           0       0.87      0.98      0.92       566
           1       0.60      0.18      0.27       101

    accuracy                           0.86       667
   macro avg       0.73      0.58      0.60       667
weighted avg       0.83      0.86      0.82       667
```

[28]: <sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x1b742f23770>

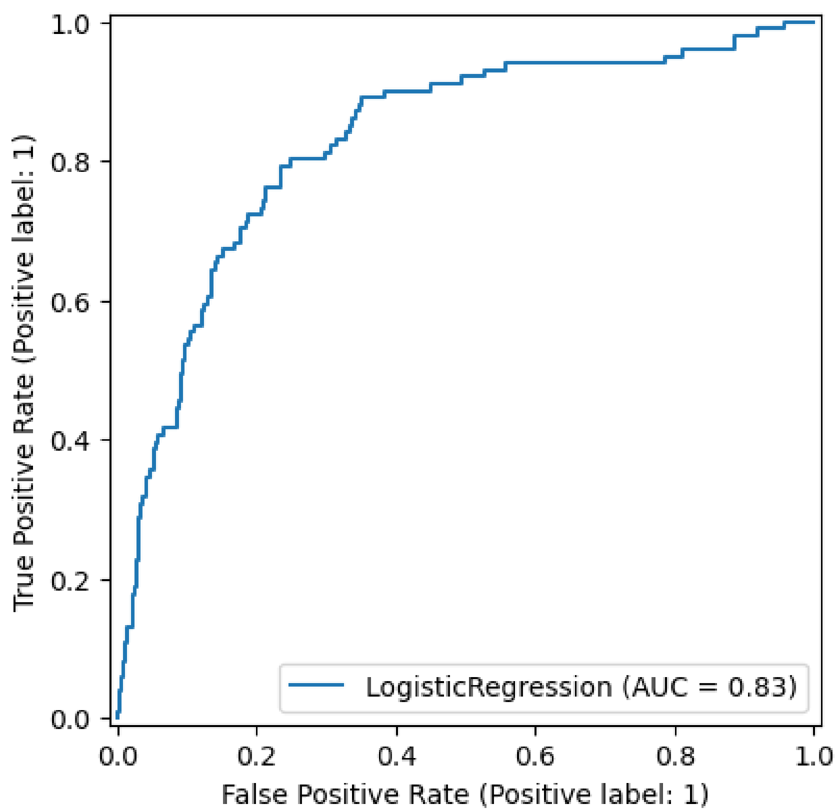


[29]:
```
#with hyperparemeter tuning
# Define hyperparameter grid
param_grid = {
    'C': [0.01, 0.1, 1, 10, 100],
    'penalty': ['l1', 'l2'],
    'solver': ['liblinear']  # 'liblinear' supports l1 and l2
}

# Create model
log_reg = LogisticRegression()

# Grid search
grid_search = GridSearchCV(log_reg, param_grid, cv=5, scoring='f1', n_jobs=-1)
grid_search.fit(X_train_scaled, y_train)

# Best estimator
best_model = grid_search.best_estimator_

# Predict using best model
y_pred = best_model.predict(X_test_scaled)

# Evaluation
accuracy = accuracy_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)

print("Best Parameters:", grid_search.best_params_)
print(f"Accuracy: {accuracy:.2f}")
print(f"F1 Score: {f1:.2f}")
print(f"Precision Score: {precision:.2f}")
print(f"Recall Score: {recall:.2f}")
print("\nClassification Report:\n", classification_report(y_test, y_pred))

# ROC curve
RocCurveDisplay.from_estimator(best_model, X_test_scaled, y_test)
```

```
Best Parameters: {'C': 1, 'penalty': 'l2', 'solver': 'liblinear'}
Accuracy: 0.86
F1 Score: 0.27
Precision Score: 0.60
Recall Score: 0.18

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

```
           0       0.87      0.98      0.92       566
           1       0.60      0.18      0.27       101

    accuracy                           0.86       667
   macro avg       0.73      0.58      0.60       667
weighted avg       0.83      0.86      0.82       667
```

[29]: <sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x1b746b61a90>



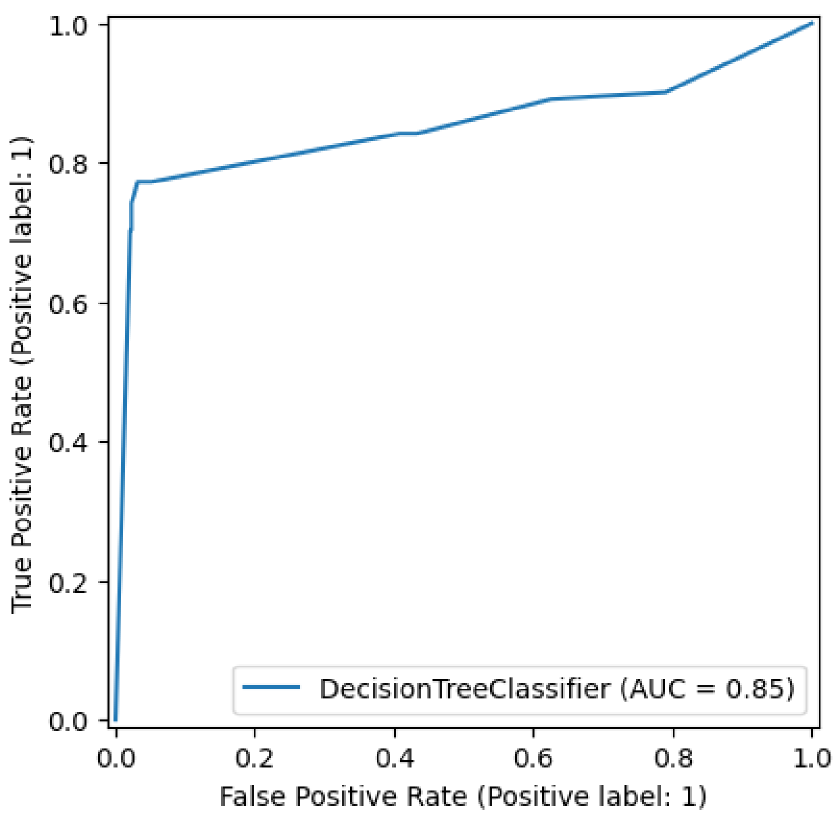
We can see that hyperparemeter tuning doesnt do much in this model of ours lets focus on XGboost and decision tree classifier

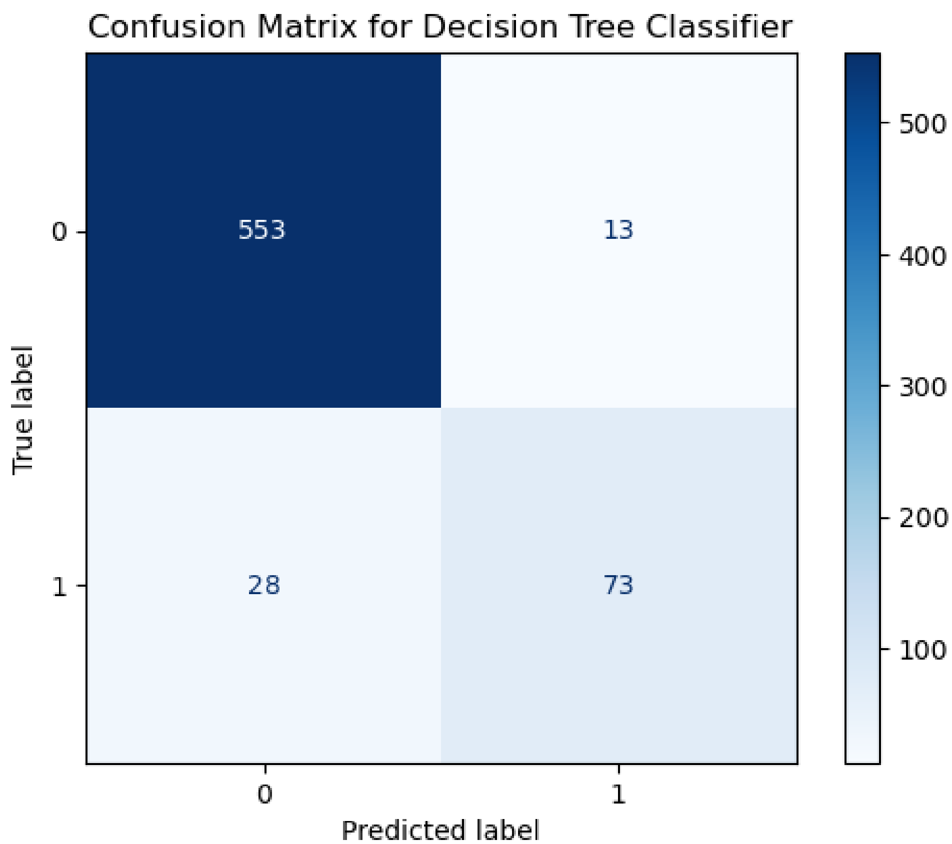
Hyperparameter Tuning with DecisionTreeClassifier

[40]:
```
# Create base model
dt_model = DecisionTreeClassifier(random_state=42)

# Define hyperparameter grid
param_grid = {
    'max_depth': [3, 5, 10, None],
    'min_samples_split': [2, 5, 10],
```

```
    'min_samples_leaf': [1, 2, 4],
    'criterion': ['gini', 'entropy'],
    'max_features': [None, 'sqrt', 'log2']
}

# GridSearchCV setup
grid_search = GridSearchCV(
    estimator=dt_model,
    param_grid=param_grid,
    scoring='f1',
    cv=5,
    verbose=1,
    n_jobs=-1
)

# Fit the model
grid_search.fit(X_train_scaled, y_train)

# Best model
best_dt = grid_search.best_estimator_

# Predictions
y_pred = best_dt.predict(X_test_scaled)

# Evaluation
accuracy = accuracy_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)

print("Best Parameters:", grid_search.best_params_)
print(f"Accuracy: {accuracy:.2f}")
print(f"F1 Score: {f1:.2f}")
print(f"Precision Score: {precision:.2f}")
print(f"Recall Score: {recall:.2f}")
print("\nClassification Report:\n", classification_report(y_test, y_pred))

# ROC curve
RocCurveDisplay.from_estimator(best_dt, X_test_scaled, y_test)
#confusion matrix
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=best_dt.
 ↪classes_)
disp.plot(cmap=plt.cm.Blues)
plt.title("Confusion Matrix for Decision Tree Classifier")
plt.show()
```

```
Fitting 5 folds for each of 216 candidates, totalling 1080 fits
Best Parameters: {'criterion': 'gini', 'max_depth': 10, 'max_features': None,
'min_samples_leaf': 1, 'min_samples_split': 5}
Accuracy: 0.94
F1 Score: 0.78
Precision Score: 0.85
Recall Score: 0.72

Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.98      0.96       566
           1       0.85      0.72      0.78       101

    accuracy                           0.94       667
   macro avg       0.90      0.85      0.87       667
weighted avg       0.94      0.94      0.94       667
```





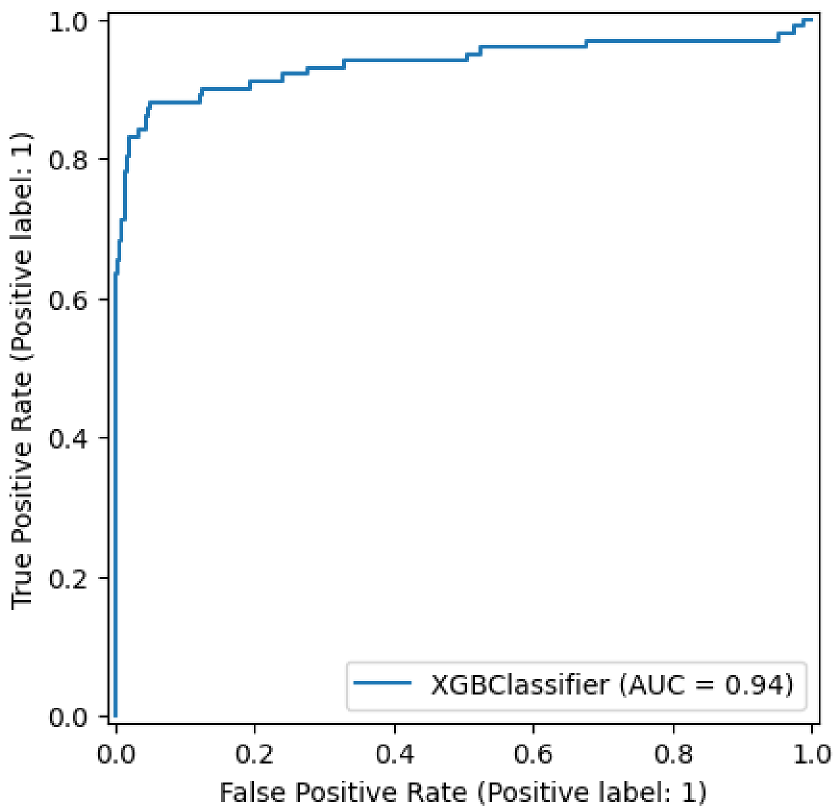
XGBoost with Hyperparameter Tuning via GridSearchCV

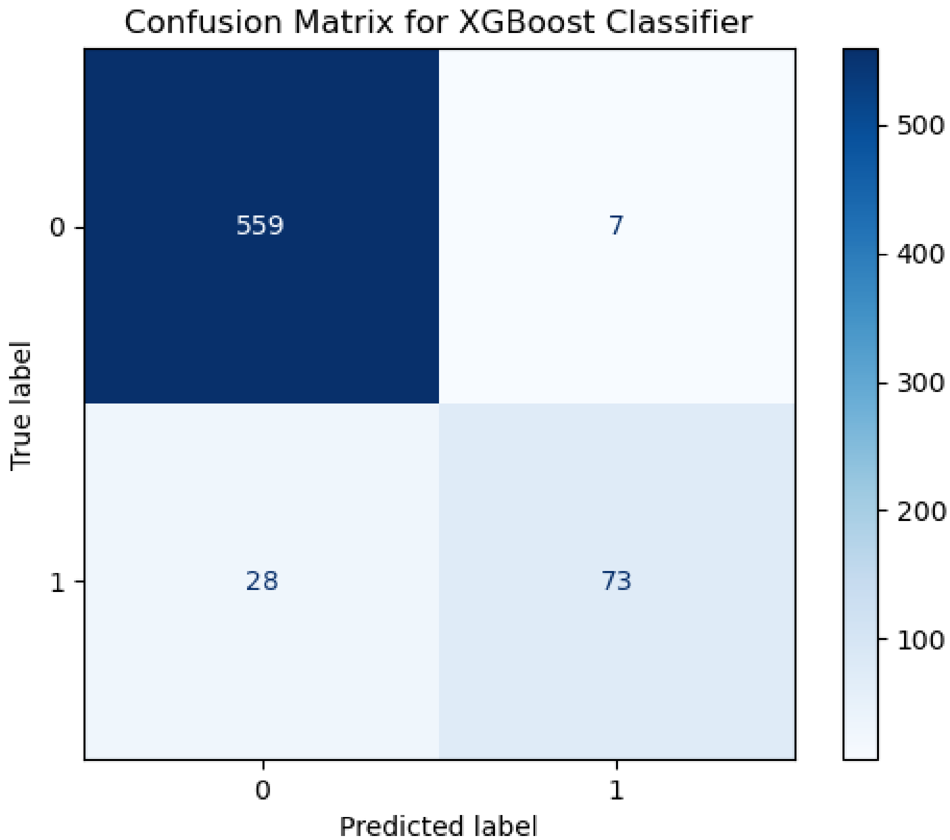
[39]:
```
# Create base model
xgb_model = XGBClassifier(use_label_encoder=False, eval_metric='logloss',␣
↪random_state=42)

# Define hyperparameter grid
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [3, 5, 7],
    'learning_rate': [0.01, 0.1, 0.2],
    'subsample': [0.8, 1.0],
    'colsample_bytree': [0.8, 1.0],
    'gamma': [0, 1],
    # Optional if class imbalance: 'scale_pos_weight': [1, sum(neg)/sum(pos)]
}

# GridSearchCV setup
grid_search = GridSearchCV(
    estimator=xgb_model,
```

```
    param_grid=param_grid,
    scoring='f1',
    cv=5,
    verbose=1,
    n_jobs=-1
)

# Fit the model
grid_search.fit(X_train_scaled, y_train)

# Best model
best_xgb = grid_search.best_estimator_

# Predictions
y_pred = best_xgb.predict(X_test_scaled)

# Evaluation
accuracy = accuracy_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)

print("Best Parameters:", grid_search.best_params_)
print(f"Accuracy: {accuracy:.2f}")
print(f"F1 Score: {f1:.2f}")
print(f"Precision Score: {precision:.2f}")
print(f"Recall Score: {recall:.2f}")
print("\nClassification Report:\n", classification_report(y_test, y_pred))

# ROC curve
RocCurveDisplay.from_estimator(best_xgb, X_test_scaled, y_test)
#confusion matrix
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=best_xgb.
 ↪classes_)
disp.plot(cmap=plt.cm.Blues)
plt.title("Confusion Matrix for XGBoost Classifier")
plt.show()
```

```
Fitting 5 folds for each of 144 candidates, totalling 720 fits
Best Parameters: {'colsample_bytree': 0.8, 'gamma': 1, 'learning_rate': 0.1,
'max_depth': 5, 'n_estimators': 100, 'subsample': 1.0}
Accuracy: 0.95
F1 Score: 0.81
Precision Score: 0.91
Recall Score: 0.72
```

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

           0       0.95      0.99      0.97       566
           1       0.91      0.72      0.81       101

    accuracy                           0.95       667
   macro avg       0.93      0.86      0.89       667
weighted avg       0.95      0.95      0.94       667
```





Key Observations:

Xgboost is the best model so far caccording to the models weve done

True Negatives (559): The model correctly identified 559 customers who are not likely to churn, meaning we avoid wasting retention efforts on them.

True Positives (73): The model correctly identified 73 customers who are likely to churn, allowing the company to proactively intervene.

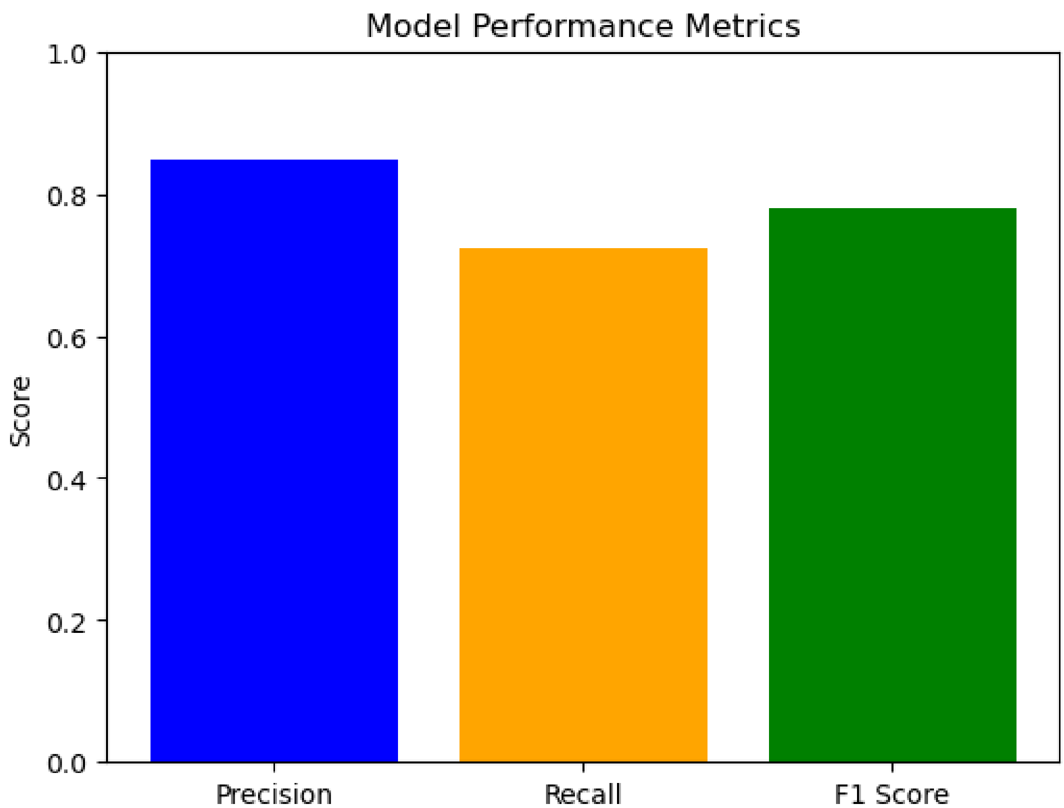
False Positives (7): Only 7 customers were wrongly predicted to churn, which is minimal and manageable.

False Negatives (28): 28 customers who were actually going to churn were missed by the model—this is the most critical issue, as these customers could leave without any retention attempt.

This has greatluy improved our AUC and we can see that 0.94 is almost close to 1 indicating a good prediction

[33]:
```
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
```

```
scores = [precision, recall, f1]
labels = ['Precision', 'Recall', 'F1 Score']

plt.bar(labels, scores, color=['blue', 'orange', 'green'])
plt.ylim(0, 1)
plt.title('Model Performance Metrics')
plt.ylabel('Score')
plt.show()
```



[34]:
```
# Feature importance using Logistic Regression
clf = LogisticRegression(class_weight='balanced', max_iter=1000)
clf.fit(X_train_scaled, y_train)
```

[34]:
```
LogisticRegression(class_weight='balanced', max_iter=1000)
```

[35]:
```
# Check coef_
clf.coef_
```

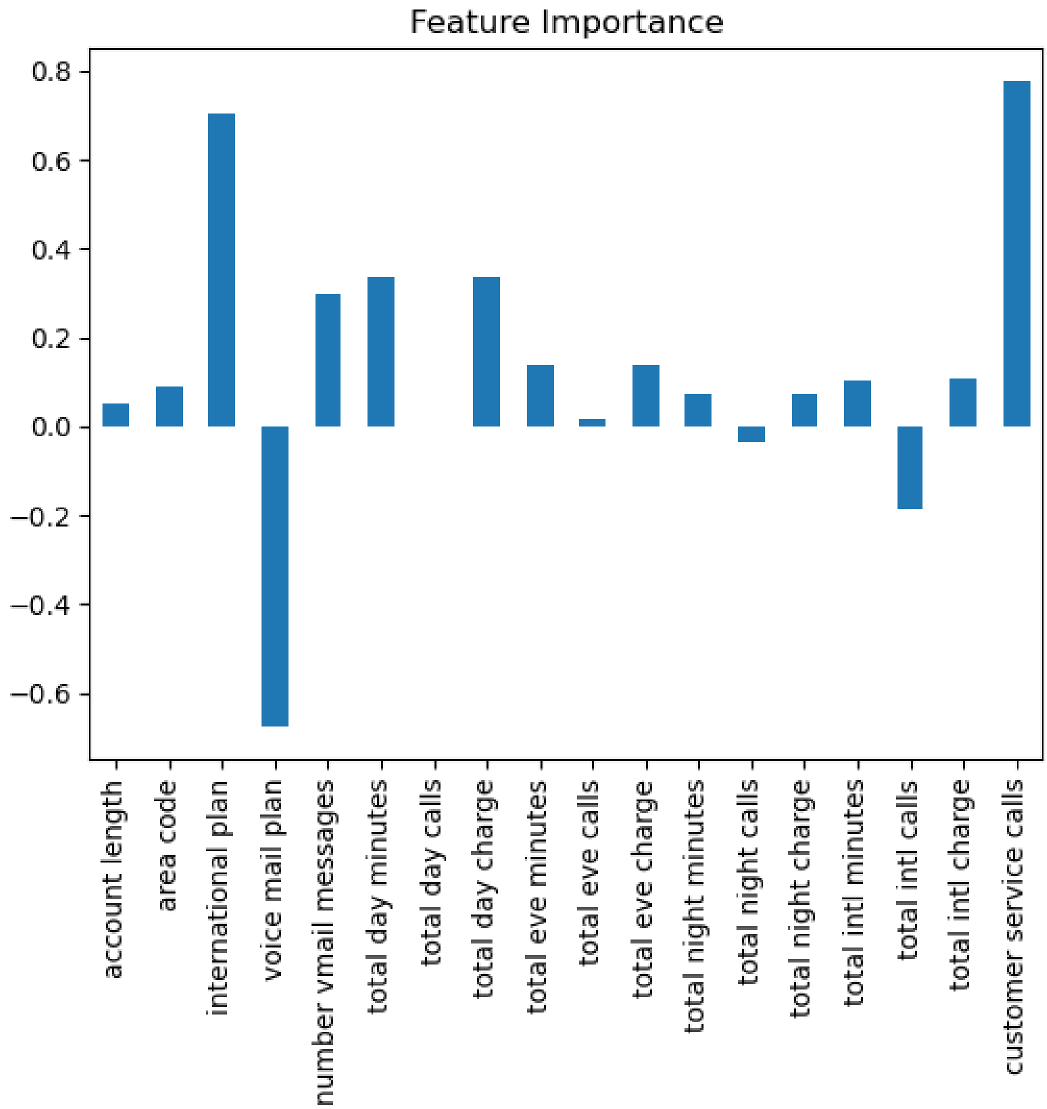
[35]:
```
array([[ 0.04964802,  0.08913671,  0.70285506, -0.67505934,  0.29862874,
         0.33552524,  0.00097989,  0.33587658,  0.1388482 ,  0.01605994,
         0.13746879,  0.07406511, -0.035599  ,  0.07230742,  0.10363567,
```

```
        -0.18729261,  0.10876817,  0.77703578]])
```

[37]:
```
# Match features to columns
features_dict = dict(zip(df.columns, list(clf.coef_[0])))
features_dict
```

[37]:
```
{'account length': np.float64(0.0496480152240457),
 'area code': np.float64(0.08913671199789377),
 'international plan': np.float64(0.702855064398583),
 'voice mail plan': np.float64(-0.6750593395517336),
 'number vmail messages': np.float64(0.29862874225929575),
 'total day minutes': np.float64(0.3355252434434125),
 'total day calls': np.float64(0.0009798904627800554),
 'total day charge': np.float64(0.3358765758809967),
 'total eve minutes': np.float64(0.13884819984410024),
 'total eve calls': np.float64(0.016059944243837755),
 'total eve charge': np.float64(0.13746879210395108),
 'total night minutes': np.float64(0.07406511152676841),
 'total night calls': np.float64(-0.035598997267724794),
 'total night charge': np.float64(0.07230742307499437),
 'total intl minutes': np.float64(0.10363567172014354),
 'total intl calls': np.float64(-0.18729261463005892),
 'total intl charge': np.float64(0.10876817238069567),
 'customer service calls': np.float64(0.7770357759892389)}
```

[38]:
```
# Visualize feature importance
features_df = pd.DataFrame(features_dict, index=[0])
features_df.T.plot.bar(title="Feature Importance", legend=False);
```



Our model reveals clear and predictable patterns in customer behavior. The most critical indicator of churn is the number of customer service calls. Customers who contact support frequently are significantly more likely to leave, which may point to unresolved issues, dissatisfaction, or poor service experiences. This suggests that improving customer support quality or implementing early intervention strategies when call volume increases could reduce churn.