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1.1.0 : Overview

The project aims to predict customer churn for SyriaTel, a telecommunications company, using historical customer data. The core goal is to build a robust machine learning classification model that can flag at-risk customers, enabling the company to implement effective retention strategies and reduce revenue loss.

1.1.1 : Working Libraries and Preliminaries

```
# Python Libraries
import pandas as pd
# sci-kit libraries
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.datasets import make_classification
from sklearn.metrics import accuracy_score, classification_report,
roc_curve, confusion_matrix, roc_auc_score
# SMOTE
from imblearn.over_sampling import SMOTE
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import LabelEncoder
# modelling and evaluation
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
# plotting
import matplotlib.pyplot as plt
```

1.1.2 : Importing the `dataset`:

```
# dataset location
file = "churn_in_telecoms_dataset.csv"

# creating a dataframe
df = pd.read_csv(file)

# shape of the dataset
```

```
print(df.shape)

# snapshot
df.head(3)
```

```
(3333, 21)

  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

  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

   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

   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

   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

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

[3 rows x 21 columns]
```

1.2.0 : Feature Engineering and Preprocessing

1.2.1 : Basic Exploratory Data Analysis

```
# General information of each column
# Including entry types
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

# drop the 'phone number' column
df = df.drop(columns='phone number')
# columns
print(df.columns)

Index(['state', 'account length', 'area code', 'international plan',
       'voice mail plan', 'number vmail messages', 'total day
minutes',
       'total day calls', 'total day charge', 'total eve minutes',
       'total eve calls', 'total eve charge', 'total night minutes',
       'total night calls', 'total night charge', 'total intl
minutes',
       'total intl calls', 'total intl charge', 'customer service
calls',
       'churn'],
      dtype='object')

# finding out entries of the 'churn' column
print(f"The Unique entries in the 'churn' column are:
{df.churn.unique()}")
# >>> array([False,  True])
```

```
df['churn'] = df['churn'].astype(int)
# Convert boolean values in the 'churn' column to integers: False → 0,
True → 1
print(f"After conversion, the new converted entries for ease of
classfication are: {df.churn.unique()}")
```

```
The Unique entries in the 'churn' column are: [False  True]
After conversion, the new converted entries for ease of classfication
are: [0 1]
```

```
# Column Description
df.describe()
```

```
       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        churn
count        3333.000000             3333.000000  3333.000000
mean            2.764581                1.562856     0.144914
std             0.753773                1.315491     0.352067
min             0.000000                0.000000     0.000000
25%             2.300000                1.000000     0.000000
50%             2.780000                1.000000     0.000000
75%             3.270000                2.000000     0.000000
max             5.400000                9.000000     1.000000
```

```python
# Categorical Columns
missing_columns = [col for col in df.columns if col not in
df.describe().columns]
print("Columns missing from df.describe():", missing_columns)
# printing them out
df[['state', 'international plan', 'voice mail plan']].head(3)
```

```
Columns missing from df.describe(): ['state', 'international plan',
'voice mail plan']
```

```
  state international plan voice mail plan
0    KS                 no             yes
1    OH                 no             yes
2    NJ                 no              no
```

```python
# Shape of the datset
print(f"The Shape of the dataset is: {df.shape}")
# 'Area Code' column
```

```
print(f"The 'area code has only 3 entries: {df['area
code'].unique()}") # 3
```

```
The Shape of the dataset is: (3333, 20)
The 'area code has only 3 entries: [415 408 510]
```

1.0 : Overview

1.1: Overview-Introduction: Customer Churn Prediction for SyriaTel

This project aims to predict customer churn for `SyriaTel`, a telecommunications company, using a sample of their historical customer data. By building a binary classification model since the customer either churns '1' or does not '0', we shall aim to identify patterns and factors that influence whether a customer will leave the company. The predictive model will assist the company in targeting at-risk customers with `retention strategies`, thereby reducing customer attrition and preserving revenue.

The overall project pipeline consists of:

1. **Business Understanding**: Understanding churn's impact on SyriaTel's business.
2. **Data Understanding and Preparation**: Exploring the structure and distribution of data. Cleaning, transforming, and encoding the dataset.
3. **Exploratory Data Analysis (EDA)**: Finding patterns and feature relationships with churn.
4. **Model Building**: Training and tuning classifiers such as Logistic Regression, Decision Trees or Random Forests.
5. **Evaluation**: Measuring performance using metrics like accuracy, precision, recall, F1-score, and AUC as well as ROC.
6. **Interpretation**: Identifying key drivers of churn.
7. **Recommendations and Actionable Insights**: Informing business interventions to reduce churn. Provide recommendations for customer retention based on analytical findings.

1.2: Project-Objectives

Here are the Objectives in this project:-

1. **Build a Predictive Model for Churn**

2. **Improve Churn Prediction Accuracy**

3. **Develop a Repeatable ML Pipeline**: Build a clean and modular workflow that can be reused with updated customer data in the future.
4. **Then Communicate Findings Clearly**: Present model insights

2.0 : Business and Data Understanding

2.1: Business Understanding

Customer churn is a critical business challenge for telco compianes such as SyriaTel. In a highly competitive and saturated market, retaining existing customers is often more cost-effective than acquiring new ones. Churn not only impacts immediate revenue but also affects long-term customer lifetime value, brand loyalty, and operational efficiency. Understanding why customers leave — and more importantly, identifying who is likely to leave — can empower SyriaTel to take timely, targeted actions. These may include `personalized marketing campaigns`, `service improvements`, or `tailored retention offers`.

The core business goal of this project is to reduce churn by building a predictive model that accurately flags at-risk customers. This enables SyriaTel to shift from reactive to proactive customer retention, thereby reducing revenue loss and enhancing customer satisfaction.

The project aligns with SyriaTel's strategic priorities:

1. `Preserving revenue` by minimizing customer loss.

2. `Improving customer loyalty` through better engagement.

3. `Increasing the return on investment (ROI)` of marketing and support efforts.

4. `Leveraging data` to drive smarter, faster business decisions.

Ultimately, this project supports SyriaTel’s mission to build lasting customer relationships in a competitive telecom landscape.

2.2: Data Understanding

The dataset provided by SyriaTel consists of over 3300 customer records and 21 features, each capturing various aspects of a customer's interaction with the company's service. The target variable is `churn`, which indicates whether a customer has discontinued service or not. Understanding the composition and behavior of these column-features is critical in helping us build an effective churn prediction model.

1. Several features describe customer demographics and account information, such as `state`, `area code`, and `account length`. While these may not directly cause churn, they can help identify regional trends or the effect of customer tenure on loyalty.

2. Other features capture service plans (`international plan`, `voice mail plan`), indicate whether a customer is subscribed to specific services. These features may influence customer satisfaction and costs, potentially affecting their decision to stay or leave.

3. A significant portion of the dataset focuses on usage behavior, including `call minutes`, `number of calls`, and `charges` during the day, evening, night, and for international calls. These metrics are split into separate fields for minutes, calls, and charges. This could allow an examinantion of customer engagement and how it relates to churn. However, since charges are typically derived from minutes, some of these columns may be redundant.

4. The dataset also includes features such as the number of `customer service calls`, which can be a strong indicator of dissatisfaction—customers who contact support frequently may be more likely to churn.

5. Importantly, the dataset is clean, with `no missing values`, and the data types are appropriate for analysis—numerical for continuous variables and object or boolean for categorical ones. However, some preprocessing will be necessary, including encoding categorical variables and dropping non-informative columns like phone number, as done previously, which acts only as an identifier.

Through a thorough EDA, we aim to understand the relationships between these features and the likelihood of churn. Identifying patterns, such as whether certain service plans correlate with higher churn, or whether customers with higher international usage are more likely to leave, will help us build a predictive model and generate actionable business insights.

3.1.0: EDA: Data Preparation

3.1.1 : Handle Categorical Variables

```
# Categories i.e. classify the values in the 'international plan' as
either 1 or 0
df['international plan'] = df['international plan'].map({'yes': 1,
'no': 0})
# Categories i.e. classify the values in the 'voice mail plan' as
either 1 or 0
df['voice mail plan'] = df['voice mail plan'].map({'yes': 1, 'no': 0})
# print feedback that it's done
print('Success: It is done!')
```

```
Success: It is done!
```

3.1.2 : Drop Irrelevant or Redundant Columns

As mentioned earlier in the overview and business understanding, features like `total day charge` might be redundant if `total day minutes` already provides similar information. You might choose to drop one.

- `note:` The feature `phone number` had been dropped already. This is because it only serves as a customer identifier.
- `note:` As noted earlier, there are no missing values. See section under `df.info()`.

```
# redundant columns
redundant_columns = ['total day charge', 'total eve charge', 'total night charge', 'total intl charge']
# dropping them
df.drop(redundant_columns, axis=1, inplace=True)

# Create a scaler object
scaler = StandardScaler()

# Choice of columns to standadise
cols_to_standardize = ['total day minutes', 'number vmail messages', 'total eve minutes']

# Apply standardization to relevant columns
df[cols_to_standardize] = scaler.fit_transform(df[cols_to_standardize])
```

3.1.4 : Feature Engineering

- Since the dataset is riddled with `minutes`, suppose we have `Total Call Usage` i.e the sum of `total day minutes`, `total eve minutes`, `total night minutes`, and `total intl minutes`.

- Also, we can have `Average Call Duration` i.e. for Average of `day`, `evening`, `night`, and `international minutes`.

```
# TOTAL CALL USAGE:
df['total minutes'] = df['total day minutes'] + df['total eve minutes'] + df['total night minutes'] + df['total intl minutes']
# AVERAGE CALL DURATION:
df['average call duration'] = df[['total day minutes', 'total eve minutes', 'total night minutes', 'total intl minutes']].mean(axis=1)
# print feedback that it's done
print('Success: It is done!')

Success: It is done!
```

3.1.5 : Choosing `Target` and `Feature` column(s)

It is obvious that the choice of our Target column is `churn` while the rest are automatically the `Features`.

Now, Splitting the Data into `Training` and `Test` dataSets

```
# Target Feature ## Dependent Feature
y = df.churn
# Other Features ## independent Features
X = df.drop('churn', axis=1)
# split-test-code
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.2, random_state = 42)
# print feedback that it's done
print('Success: It is done!')
```

```
Success: It is done!
```

3.1.6 : Check for Class Imbalance

Let's ensure that the model doesn't learn misleading patterns — especially because we have binary classification problem.

```
# first, let's check class distribution
print(f"The Value counts are: \n{df.churn.value_counts()}", end = '\n\
n')
# The proportions are:
print('Essentially, that is:-', end = '\n')
print(f"{df['churn'].value_counts(normalize=True)}", end = '\n')
# Inference and Conclusion
churn_perc = round(df['churn'].value_counts(normalize=True)[1] * 100,
2)
# print the result
print(' ')
print(f"INFERENCE: So, only {churn_perc}% of the customers churn —
this shows class imbalance.")
```

```
The Value counts are:
0    2850
1     483
Name: churn, dtype: int64

Essentially, that is:-
0    0.855086
1    0.144914
Name: churn, dtype: float64

INFERENCE: So, only 14.49% of the customers churn — this shows class
imbalance.
```

`Inference`:

This class imbalance refers to the fact that one class (non-churn) significantly outweighs the other `churning` group. This imbalance can affect the performance of machine learning model.

They may become biased toward predicting the majority class, the `non-churning`, which could result in misleading accuracy scores.

```
# RE_DONE
X_encoded = pd.get_dummies(X, drop_first=True)  # drop_first avoids
dummy trap

# Label encoder
le = LabelEncoder()
X['state'] = le.fit_transform(X['state'])

# Encode categorical variables
X_encoded = pd.get_dummies(X, drop_first=True)
```

Running the encoder

```
# Step 1: Encode categorical variables (e.g., 'State', 'Gender', etc.)
X_encoded = pd.get_dummies(X, drop_first=True)  # One-Hot Encoding

# Step 2: Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(
    X_encoded, y, stratify=y, test_size=0.2, random_state=42
)

# Step 3: Apply SMOTE to oversample the minority class in the training
data
smote = SMOTE(random_state=42)
X_train_res, y_train_res = smote.fit_resample(X_train, y_train)

# Step 4: Train a Random Forest Classifier with class weights to
handle class imbalance
clf = RandomForestClassifier(class_weight='balanced', random_state=42)
clf.fit(X_train_res, y_train_res)

# Step 5: Make predictions on the test set
y_pred = clf.predict(X_test)
y_proba = clf.predict_proba(X_test)[:, 1]

# Step 6: Evaluate the model performance
print("Classification Report:")
print(classification_report(y_test, y_pred))
print("ROC-AUC Score:", roc_auc_score(y_test, y_proba))

Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.92      0.93       570
           1       0.57      0.59      0.58        97

    accuracy                           0.88       667
```

```
   macro avg       0.75      0.76      0.75       667
weighted avg       0.88      0.88      0.88       667

ROC-AUC Score: 0.8444112859468258
```

4: Modeling and Evaluation

4.1 : Logistic Regression

Let us start with a `simple Logistic Regression` model, before we try others like Random Forest.

```
model = LogisticRegression(max_iter=1000, class_weight='balanced')  #
Use class_weight if you didn't use SMOTE
model.fit(X_train, y_train)
```

```
c:\Users\rurig\anaconda3\envs\learn-env\lib\site-packages\sklearn\
linear_model\_logistic.py:762: ConvergenceWarning: 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(
```

```
LogisticRegression(class_weight='balanced', max_iter=1000)
```

4.2 : Others

```
# One-hot encode categorical variables
X = pd.get_dummies(X, drop_first=True)

# Split into train/test
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42)

# Feature Scaling (optional, but needed for SVM, KNN)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

4.3 : Evaluation

```
# Define models
models = {
    "Logistic Regression": LogisticRegression(class_weight='balanced',
max_iter=10000),
    "Random Forest": RandomForestClassifier(class_weight='balanced',
random_state=42),
    # "XGBoost": XGBClassifier(scale_pos_weight=6,
use_label_encoder=False, eval_metric='logloss', random_state=42),
    # "SVM": SVC(class_weight='balanced', probability=True,
random_state=42),
    "KNN": KNeighborsClassifier()
}

# Train and evaluate each model
for name, model in models.items():

    print(f"\n----- {name} -----")

    if name in ["SVM", "KNN"]:
        model.fit(X_train_scaled, y_train)
        y_pred = model.predict(X_test_scaled)
        y_proba = model.predict_proba(X_test_scaled)[:, 1]
    else:
        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)
        y_proba = model.predict_proba(X_test)[:, 1]

    print(classification_report(y_test, y_pred))
    print("ROC AUC:", roc_auc_score(y_test, y_proba))
```

```
----- Logistic Regression -----
              precision    recall  f1-score   support

           0       0.95      0.76      0.85       570
           1       0.35      0.74      0.48        97

    accuracy                           0.76       667
   macro avg       0.65      0.75      0.66       667
weighted avg       0.86      0.76      0.79       667

ROC AUC: 0.8154277446192801

----- Random Forest -----
              precision    recall  f1-score   support

           0       0.93      0.99      0.96       570
           1       0.89      0.56      0.68        97
```

```
    accuracy                           0.93       667
   macro avg       0.91      0.77      0.82       667
weighted avg       0.92      0.93      0.92       667

ROC AUC: 0.9024507144149033

----- KNN -----
              precision    recall  f1-score   support

           0       0.89      0.98      0.93       570
           1       0.70      0.31      0.43        97

    accuracy                           0.88       667
   macro avg       0.80      0.64      0.68       667
weighted avg       0.86      0.88      0.86       667

ROC AUC: 0.7735756918068367
```

5.1.0 : Evaluation

5.1.1 : Logistical Regression

After training the model, it's important to evaluate its performance using:

1. `Accuracy`: The percentage of correct predictions.
2. `Confusion Matrix`:
   - Helps you understand the model's performance with respect to false positives, false negatives, true positives, and true negatives.
3. `Precision, Recall, F1-Score`:
   - Especially important for imbalanced datasets or when the costs of false positives/negatives differ.
4. `ROC-AUC Curve`: Evaluate the classifier's ability to distinguish between classes.

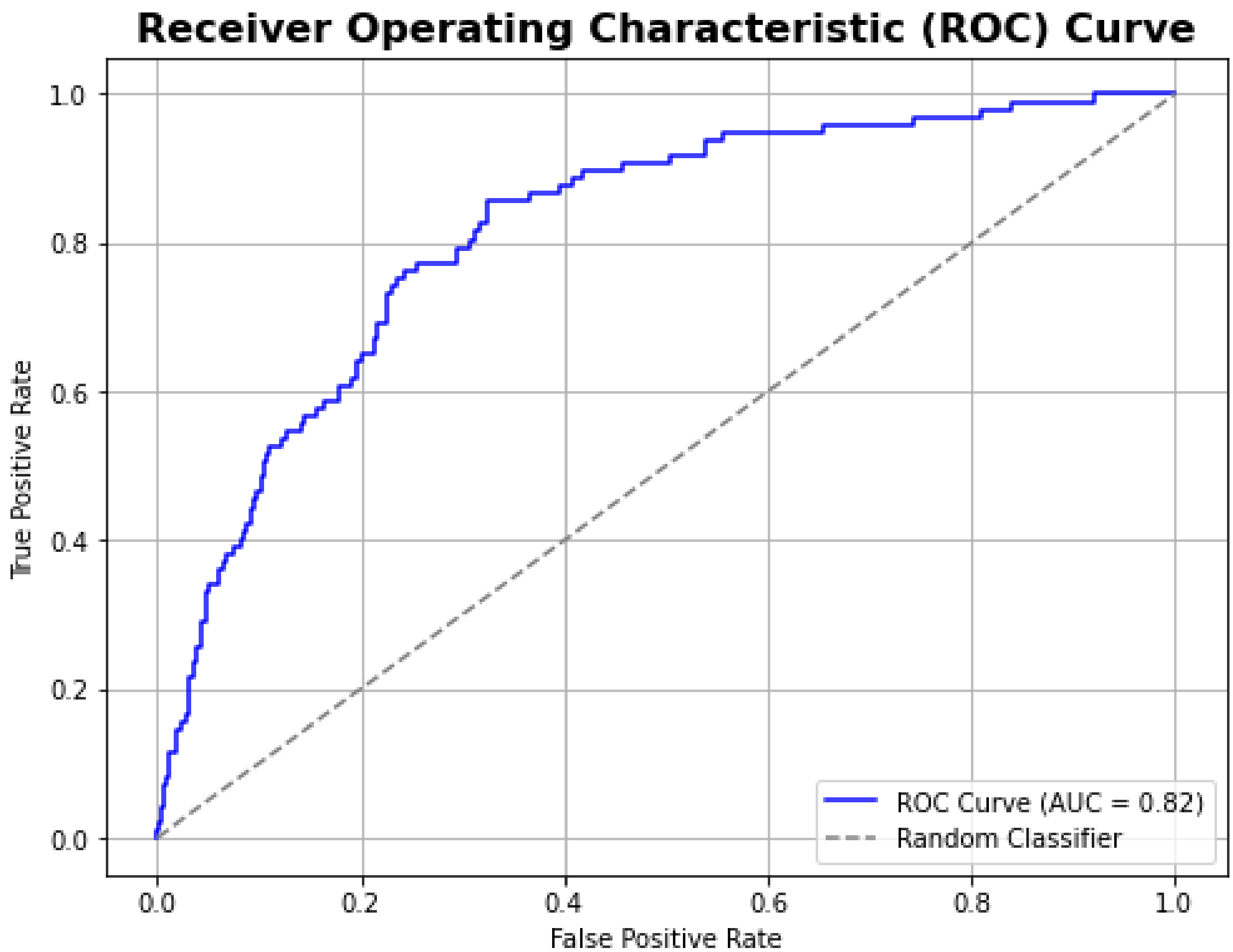
```
# Train the Model
# Fit a Logistic Regression model
Model = LogisticRegression()
Model.fit(X_train_scaled, y_train)

# Get prediction Probabilities
# Predict probability estimates for the positive class
y_probs = Model.predict_proba(X_test_scaled)[:, 1]
# y_probs

# Computing ROC Curve and AUC
# Compute False Positive Rate and True Positive Rate
```

```python
fpr, tpr, thresholds = roc_curve(y_test, y_probs)

# Calculate the AUC score
auc = roc_auc_score(y_test, y_probs)
auc
```

```
0.8164767589075782
```

5.1.2 : Plot the ROC Curve

```python
# Plot the ROC Curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', label=f'ROC Curve (AUC = {auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--', label='Random Classifier')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve',
          fontweight = 'bold', fontsize = 16)
plt.legend(loc = 4)
plt.grid(True)
plt.show()
```



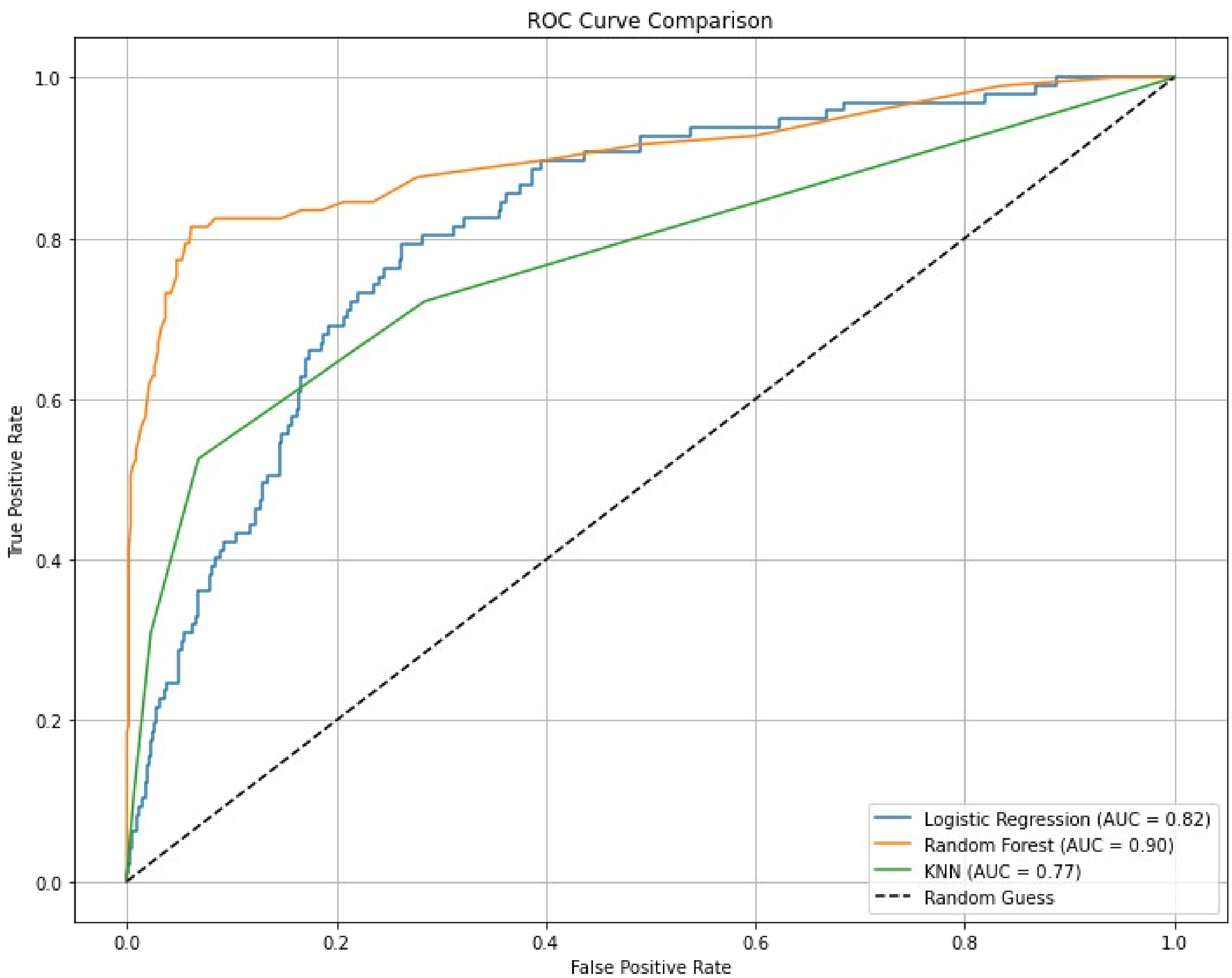
5.1.3 : Evaluate

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc

# Initialize a plot
plt.figure(figsize=(10, 8))

# Train and evaluate each model
for name, model in models.items():
    print(f"\n----- {name} -----")

    # Use scaled or unscaled data depending on the model
    if name in ["SVM", "KNN"]:
        model.fit(X_train_scaled, y_train)
        y_pred = model.predict(X_test_scaled)
        y_proba = model.predict_proba(X_test_scaled)[:, 1]
    else:
        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)
        y_proba = model.predict_proba(X_test)[:, 1]
```

```python
    # ROC curve values
    fpr, tpr, _ = roc_curve(y_test, y_proba)
    roc_auc = auc(fpr, tpr)

    # Plot ROC curve
    plt.plot(fpr, tpr, label=f'{name} (AUC = {roc_auc:.2f})')

    # Optionally print performance
    print(classification_report(y_test, y_pred))
    print("ROC AUC:", roc_auc)

# Plot reference line
plt.plot([0, 1], [0, 1], 'k--', label='Random Guess')

# Plot settings
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve Comparison')
plt.legend(loc='lower right')
plt.grid(True)
plt.tight_layout()
plt.show();
```

```
----- Logistic Regression -----
              precision    recall  f1-score   support

           0       0.95      0.76      0.85       570
           1       0.35      0.74      0.48        97

    accuracy                           0.76       667
   macro avg       0.65      0.75      0.66       667
weighted avg       0.86      0.76      0.79       667

ROC AUC: 0.8154277446192801

----- Random Forest -----
              precision    recall  f1-score   support

           0       0.93      0.99      0.96       570
           1       0.89      0.56      0.68        97

    accuracy                           0.93       667
   macro avg       0.91      0.77      0.82       667
weighted avg       0.92      0.93      0.92       667

ROC AUC: 0.9024507144149033

----- KNN -----
              precision    recall  f1-score   support
```

```
              0       0.89      0.98      0.93       570
              1       0.70      0.31      0.43        97

       accuracy                           0.88       667
      macro avg       0.80      0.64      0.68       667
   weighted avg       0.86      0.88      0.86       667

ROC AUC: 0.7735756918068367
```



6.0 : Conclusions and Recommendations

1. The ROC curve showing how your classifier performs across different thresholds.

2. The AUC value, 0.90 summarizing overall performance for the `Random Forest` points the best perfoming model. This means that it is the closest to perfect classification.

3. From this we infer and conclude that the `Random Forest Model` is the most accurate and reliable classifier among the three

4. Even though not as signicant as the inference above, it is worth noting that, All models outperform random guessing.