Customer Churn Prediction

August 22, 2023

1 Customer Churn Prediction for Telecommunications Company

Client Name: CommLink Telecom

Company Name: DataSense Solutions **Description:** CommLink Telecom, a telecommunications company, is facing high customer churn rates and wants to address the issue proactively. They have engaged DataSense Solutions to build a customer churn prediction model that can identify customers likely to churn in the near future. This will enable them to take targeted retention measures and improve customer retention rates.

Dataset:

CustomerID	Gender	Age	ServiceLength (months)	ContractType	MonthlyCharges (USD)	TotalCharges (USD)	Churn
1001	Male	42	24	Two-Year	85.00	2040.00	No
1002	Female	35	12	One-Year	79.50	942.50	Yes
1003	Male	62	48	Month-to-Month	94.20	4567.75	Yes
1004	Female	52	36	One-Year	78.25	2853.50	No
1005	Male	28	6	Month-to-Month	68.75	452.25	No
…	…	…	…	…	…	…	…

(Note: The dataset contains a total of 1000 customers with some churned (Yes) and others active (No).)

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

2 Generate Dataset

[2]:
```python
data_size = 1000
np.random.seed(42)

srv_length = np.random.randint(1, 50, data_size)
```

```python
monthly_charges = np.random.uniform(20, 100, size=1000)

# more realistic distribution of churn
churn_probabilities = [0.4, 0.6]
churn = np.random.choice(['Yes', 'No'], size=data_size, p=churn_probabilities)

data = {
    'CustomerID': list(range(1001, 2001)),
    'Gender': np.random.choice(['Male', 'Female'], size=data_size),
    'Age': np.random.randint(18, 70, data_size),
    'ServiceLength (months)': srv_length,
    'ContractType': np.random.choice(['Two-Year', 'One-Year',␣
 ↪'Month-to-Month'], size=data_size),
    'MonthlyCharges (USD)': monthly_charges,
    'TotalCharges (USD)': srv_length * monthly_charges * 0.9,
    'Churn': churn
}

df = pd.DataFrame(data)
```

[3]:
```python
df.head()
```

[3]:
```
   CustomerID  Gender  Age  ServiceLength (months)    ContractType  \
0        1001    Male   66                      39        Two-Year
1        1002  Female   27                      29  Month-to-Month
2        1003    Male   45                      15        Two-Year
3        1004    Male   38                      43        Two-Year
4        1005    Male   67                       8        Two-Year

   MonthlyCharges (USD)  TotalCharges (USD) Churn
0             75.756917         2659.067786   Yes
1             99.780443         2604.269557    No
2             91.728821         1238.339084   Yes
3             66.079873         2557.291102   Yes
4             93.391649          672.419873   Yes
```

[4]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 8 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   CustomerID              1000 non-null   int64
 1   Gender                  1000 non-null   object
 2   Age                     1000 non-null   int32
 3   ServiceLength (months)  1000 non-null   int32
 4   ContractType            1000 non-null   object
```

```
 5   MonthlyCharges (USD)    1000 non-null   float64
 6   TotalCharges (USD)      1000 non-null   float64
 7   Churn                   1000 non-null   object
dtypes: float64(2), int32(2), int64(1), object(3)
memory usage: 54.8+ KB
```

[5]:
```
df.describe()
```

[5]:
```
        CustomerID          Age  ServiceLength (months)  MonthlyCharges (USD)  \
count  1000.000000  1000.000000             1000.000000           1000.000000
mean   1500.500000    43.947000               25.379000             60.812403
std     288.819436    14.853984               14.122138             22.597415
min    1001.000000    18.000000                1.000000             20.019002
25%    1250.750000    32.000000               13.000000             41.524641
50%    1500.500000    44.000000               26.000000             62.128091
75%    1750.250000    57.000000               37.000000             79.855529
max    2000.000000    69.000000               49.000000             99.948280

       TotalCharges (USD)
count         1000.000000
mean          1374.978457
std            960.461013
min             18.074123
25%            564.412028
50%           1205.314557
75%           1944.868429
max           4295.379738
```

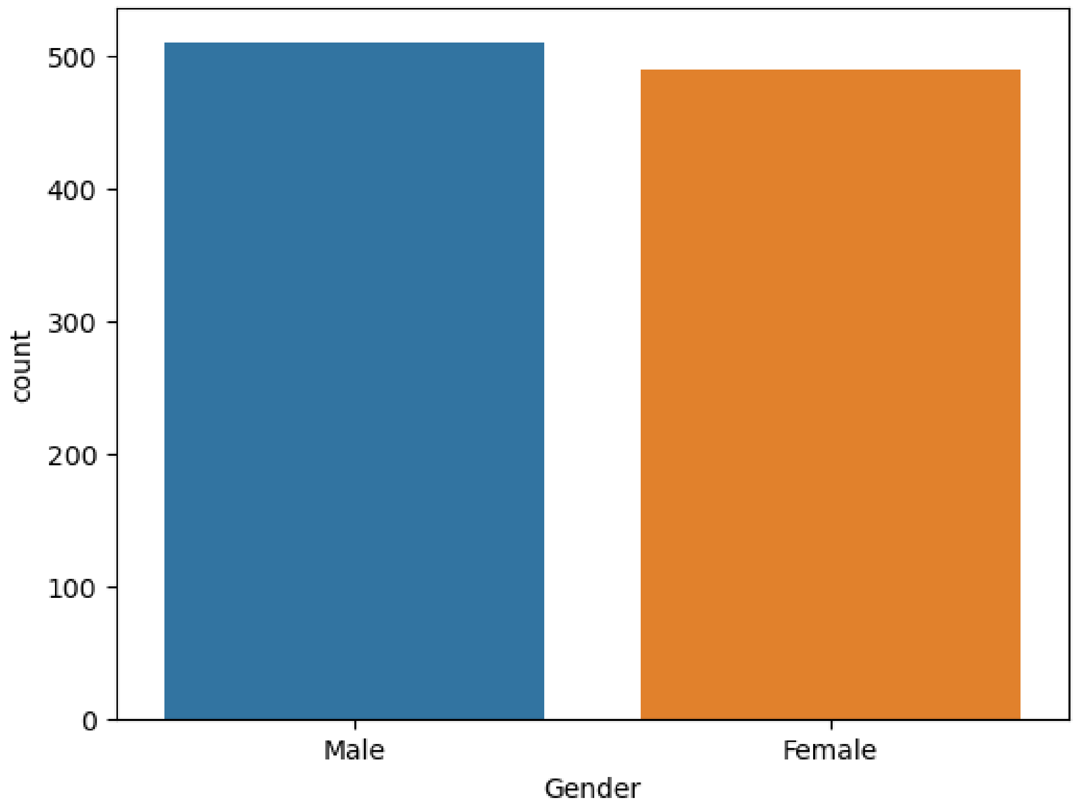
[6]:
```
df.isna().sum()
```

[6]:
```
CustomerID                0
Gender                    0
Age                       0
ServiceLength (months)    0
ContractType              0
MonthlyCharges (USD)      0
TotalCharges (USD)        0
Churn                     0
dtype: int64
```

3 Visualizationa

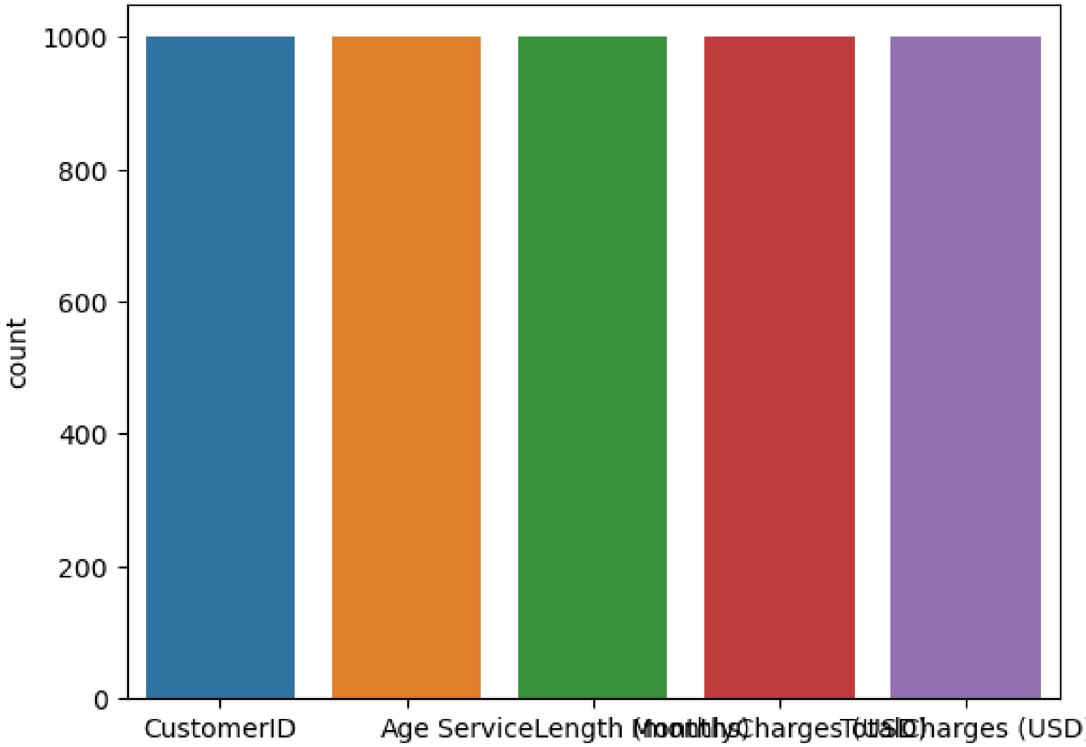
[7]:
```
sns.countplot(data=df, x='Gender')
```

[7]:
```
<Axes: xlabel='Gender', ylabel='count'>
```



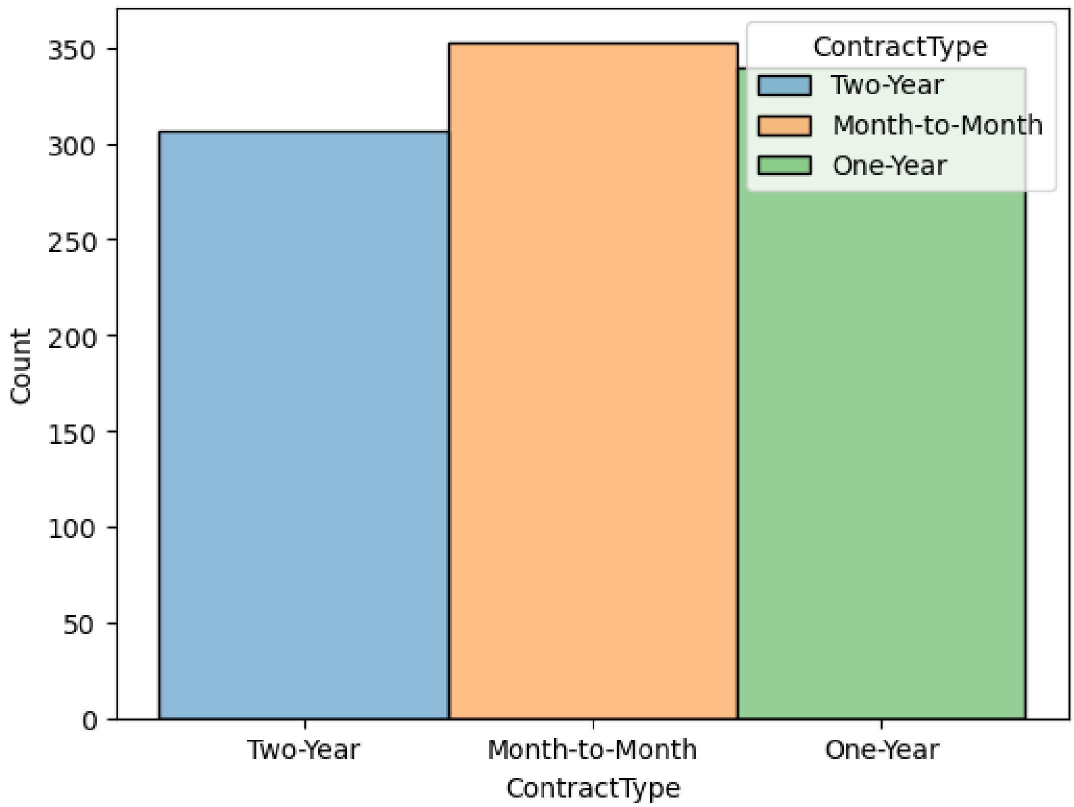
[8]:
```
sns.countplot(data=df)
```

[8]: <Axes: ylabel='count'>



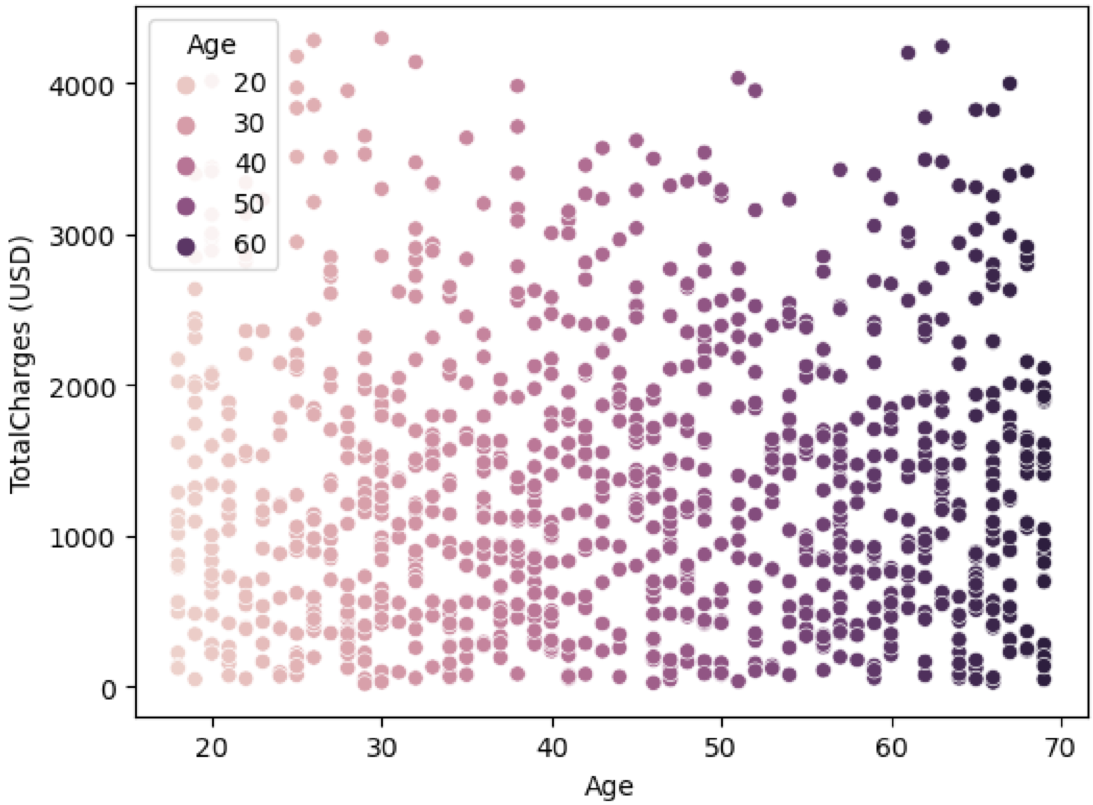
[9]:
```
sns.histplot(data=df, x='ContractType', hue='ContractType')
```

[9]: <Axes: xlabel='ContractType', ylabel='Count'>



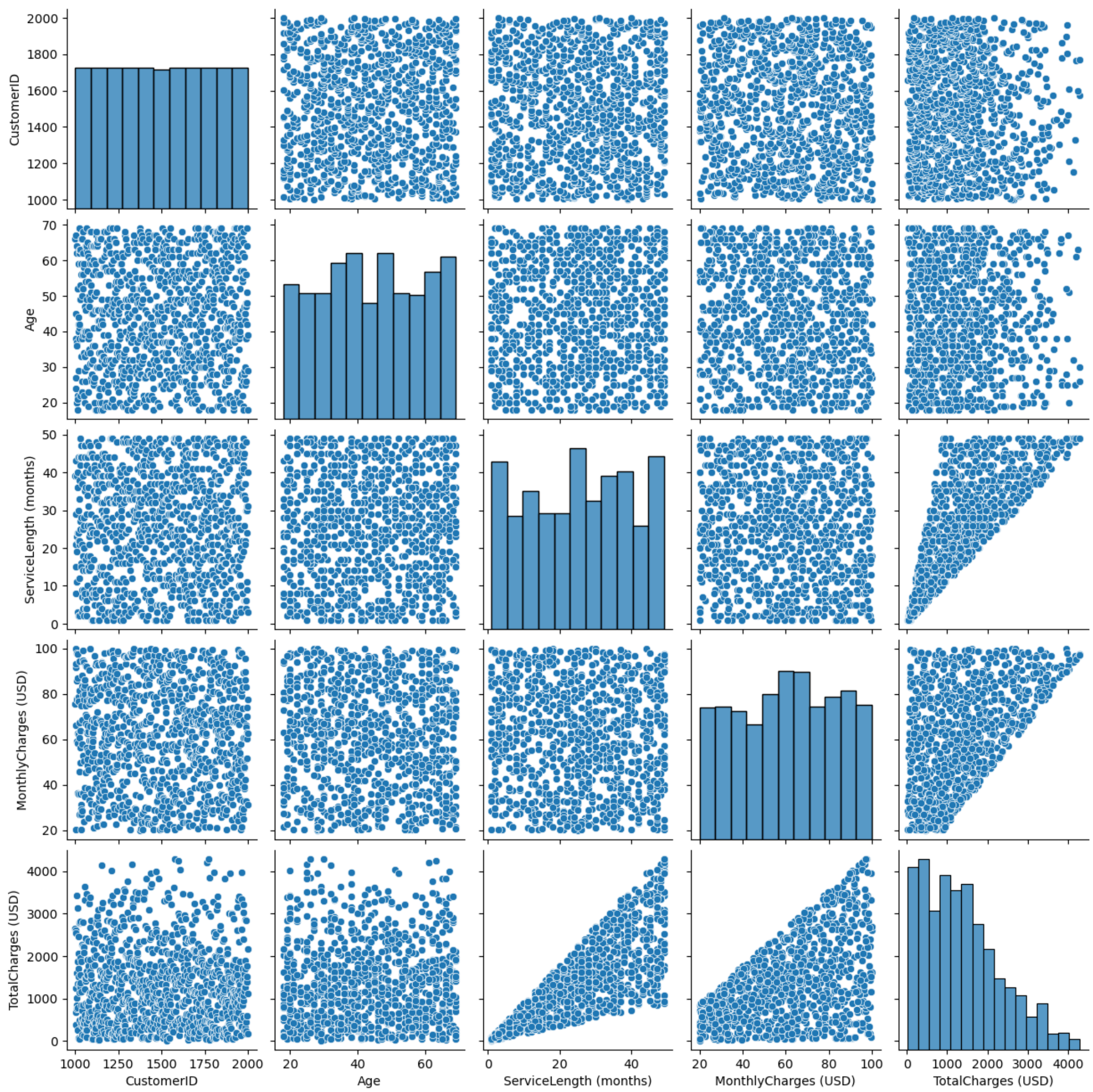
[10]:
```
sns.scatterplot(data=df, x='Age', y='TotalCharges (USD)', hue='Age')
```

[10]: <Axes: xlabel='Age', ylabel='TotalCharges (USD)'>



[11]:
```
sns.pairplot(df)
```

[11]: <seaborn.axisgrid.PairGrid at 0x12d4352f340>



4 Data Cleaning

[12]:
```
df
```

[12]:
```
     CustomerID  Gender  Age  ServiceLength (months)    ContractType  \
0          1001    Male   66                      39        Two-Year
1          1002  Female   27                      29  Month-to-Month
2          1003    Male   45                      15        Two-Year
3          1004    Male   38                      43        Two-Year
4          1005    Male   67                       8        Two-Year
..          …       …   …                       …             …
995        1996  Female   69                      24  Month-to-Month
```

```
996         1997    Male   42                      9         One-Year
997         1998  Female   29                      3         Two-Year
998         1999    Male   18                     31   Month-to-Month
999         2000    Male   39                     40         One-Year

     MonthlyCharges (USD)  TotalCharges (USD) Churn
0               75.756917         2659.067786   Yes
1               99.780443         2604.269557    No
2               91.728821         1238.339084   Yes
3               66.079873         2557.291102   Yes
4               93.391649          672.419873   Yes
..                    …                …    …
995             70.236004         1517.097691    No
996             73.944305          598.948867   Yes
997             62.598495          169.015938    No
998             77.713765         2168.214054    No
999             31.302244         1126.880782    No

[1000 rows x 8 columns]
```

[13]:
```python
# gender to numeric/reference numbers
gender = pd.get_dummies(data=df['Gender'], drop_first=True)

# contractType to numeric/reference numbers
contractType = pd.get_dummies(data=df['ContractType'])

# Churn to numeric/reference numbers
churn = pd.get_dummies(df['Churn'], drop_first=True)
churn.columns=['Churn_Status']
```

[14]:
```python
df = pd.concat([df, churn, gender, contractType], axis=1)
df.head()
```

[14]:
```
   CustomerID  Gender  Age  ServiceLength (months)    ContractType  \
0        1001    Male   66                      39        Two-Year
1        1002  Female   27                      29  Month-to-Month
2        1003    Male   45                      15        Two-Year
3        1004    Male   38                      43        Two-Year
4        1005    Male   67                       8        Two-Year

   MonthlyCharges (USD)  TotalCharges (USD) Churn  Churn_Status  Male  \
0             75.756917         2659.067786   Yes             1     1
1             99.780443         2604.269557    No             0     0
2             91.728821         1238.339084   Yes             1     1
3             66.079873         2557.291102   Yes             1     1
4             93.391649          672.419873   Yes             1     1
```

```
   Month-to-Month  One-Year  Two-Year
0               0         0         1
1               1         0         0
2               0         0         1
3               0         0         1
4               0         0         1
```

[15]:
```
# delete string/unnecessary columns as they are not needed
df.drop(columns=['CustomerID', 'Gender', 'ContractType', 'Churn'], inplace=True)
```

[16]:
```
df.head()
```

[16]:
```
   Age  ServiceLength (months)  MonthlyCharges (USD)  TotalCharges (USD)  \
0   66                      39             75.756917         2659.067786
1   27                      29             99.780443         2604.269557
2   45                      15             91.728821         1238.339084
3   38                      43             66.079873         2557.291102
4   67                       8             93.391649          672.419873

   Churn_Status  Male  Month-to-Month  One-Year  Two-Year
0             1     1               0         0         1
1             0     0               1         0         0
2             1     1               0         0         1
3             1     1               0         0         1
4             1     1               0         0         1
```

5 Data Splitting

[17]:
```
# INDEPENDENT/FEATURES and LABELS/DEPENDENT VARIABLES/COLS
X = df.drop('Churn_Status', axis=1)
y = df['Churn_Status']
```

[18]:
```
# SPLITTING DATA
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,
  ↪random_state=42)
```

6 Logistic Regression

[19]:
```
# CREATE MODEL AND TRAIN
from sklearn.linear_model import LogisticRegression

log_model = LogisticRegression()
log_model.fit(X_train, y_train)
```

[19]: LogisticRegression()

[20]:
```
# PREDICT
predictions = log_model.predict(X_test)
```

[21]:
```
# EVALUATION
from sklearn.metrics import classification_report, confusion_matrix

print(classification_report(y_test, predictions))
```

```
              precision    recall  f1-score   support

           0       0.61      0.99      0.76       153
           1       0.33      0.01      0.02        97

    accuracy                           0.61       250
   macro avg       0.47      0.50      0.39       250
weighted avg       0.50      0.61      0.47       250
```

[22]:
```
confusion_matrix(y_test, predictions)
```

[22]:
```
array([[151,   2],
       [ 96,   1]], dtype=int64)
```

7 Random Forest

[23]:
```
from sklearn.ensemble import RandomForestClassifier

rf_model = RandomForestClassifier()
rf_model.fit(X, y)
```

[23]: RandomForestClassifier()

[24]:
```
predictions = rf_model.predict(X_test)
```

[25]:
```
confusion_matrix(y_test, predictions)
```

[25]:
```
array([[153,   0],
       [  0,  97]], dtype=int64)
```

[26]:
```
print(classification_report(y_test, predictions))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       153
           1       1.00      1.00      1.00        97
```

```
    accuracy                           1.00       250
   macro avg       1.00      1.00      1.00       250
weighted avg       1.00      1.00      1.00       250
```

8 TESTING MODELS

[27]:
```
test_data = {
    'Age': 45,
    'ServiceLength (months)': 30,
    'MonthlyCharges (USD)': 60,
    'TotalCharges (USD)': 30 * 60,
    'Male': 0,
    'Month-to-Month': 0,
    'One-Year': 1,
    'Two-Year': 0
}

test_df = pd.DataFrame([test_data])
test_df
```

[27]:
```
   Age  ServiceLength (months)  MonthlyCharges (USD)  TotalCharges (USD)  \
0   45                      30                    60                1800

   Male  Month-to-Month  One-Year  Two-Year
0     0               0         1         0
```

[28]:
```
def check_churn_status(val):
    if val==0:
        return ("Customers is NOT expected to churn")
    elif val==1:
        return ("Customers is expected to churn")
```

[29]:
```
# LOGISTIC REGRESSION TEST
churn_prediction_lr_model = log_model.predict(test_df)

print("Logistic Model Result\n")
check_churn_status(churn_prediction_lr_model[0])
```

```
Logistic Model Result
```

[29]:
```
'Customers is NOT expected to churn'
```

[30]:
```
# RANDOM FOREST CALSSIFICATION TEST
churn_prediction_rf_model = rf_model.predict(test_df)

print("RANDOM FOREST CALSSIFICATION Model Result\n")
```

```
check_churn_status(churn_prediction_rf_model[0])
```

```
RANDOM FOREST CALSSIFICATION Model Result
```

[30]:

```
'Customers is NOT expected to churn'
```

9 FLASK API

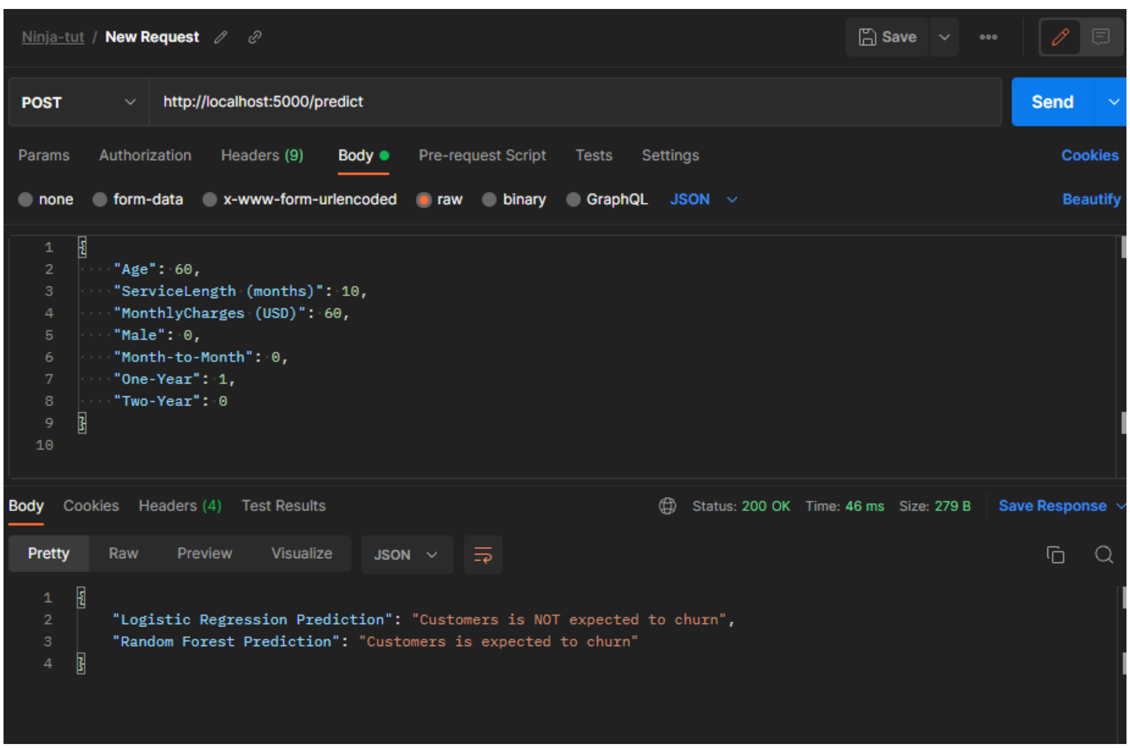
[31]:

```
from flask import Flask, request, jsonify

app = Flask(__name__)

@app.route('/')
def hello():
    return "Welcome to Churn Prediction API!"

@app.route('/predict', methods=['POST'])
def predict():
    try:

        test_data = {
            'Age': request.json['Age'],
            'ServiceLength (months)': request.json['ServiceLength (months)'],
            'MonthlyCharges (USD)': request.json['MonthlyCharges (USD)'],
            'TotalCharges (USD)': request.json['ServiceLength (months)'] *␣
↪request.json['MonthlyCharges (USD)'],
            'Male': request.json['Male'],
            'Month-to-Month': request.json['Month-to-Month'],
            'One-Year': request.json['One-Year'],
            'Two-Year': request.json['Two-Year']
        }

        test_df = pd.DataFrame([test_data])

        # Logistic Regression prediction
        churn_prediction_lr = log_model.predict(test_df)

        # Random Forest prediction
        churn_prediction_rf = rf_model.predict(test_df)

        return jsonify({
            "Logistic Regression Prediction":␣
↪check_churn_status(churn_prediction_lr[0]),
            "Random Forest Prediction":␣
↪check_churn_status(churn_prediction_rf[0])
        })
```

```
    except Exception as e:
        return jsonify({"error": str(e)})

if __name__ == '__main__':
    app.run(host='0.0.0.0', port=5000)
```

```
 * Serving Flask app "__main__" (lazy loading)
 * Environment: production
   WARNING: This is a development server. Do not use it in a production
deployment.
   Use a production WSGI server instead.
 * Debug mode: off
 * Running on all addresses.
   WARNING: This is a development server. Do not use it in a production
deployment.
 * Running on http://192.168.100.207:5000/ (Press CTRL+C to quit)
127.0.0.1 - - [22/Aug/2023 18:32:12] "POST /predict HTTP/1.1" 200 -
```

10 Postman Output




```
[ ]:
```