Customer_Churn_Prediction

September 22, 2025

Customer Churn Prediction Project

Author: Akshay Bhujbal
Project Type: AI / Machine Learning Portfolio Project

Project Overview

This project demonstrates a **Customer Churn Prediction system** using a **Random Forest Classifier**.

The app allows users to:

1. Enter customer details manually using the sidebar.

2. Predict whether a customer is likely to **churn (Yes)** or **not churn (No)**.

3. View the probability of churn for each customer.

The model was trained on the **IBM Telco Customer Churn dataset** with 19 features including demographic, subscription, and service usage information.
It predicts whether a customer will churn based on their profile, subscription type, and service usage patterns.

1 Import Libraries

We'll start by importing the required libraries.

Explanation:

- `pandas, numpy` → for data handling.
- `matplotlib, seaborn` → visualization.
- `LabelEncoder, StandardScaler` → handle categorical values and feature scaling.
- `RandomForestClassifier` → chosen algorithm (robust, works well with categorical + numerical mix).
- `metrics` → to evaluate performance.

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

```
# For preprocessing and model building
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix,␣
↪accuracy_score
```

2 Load Dataset

We'll load the IBM Telco Customer Churn dataset (from Kaggle).

- Load dataset from CSV.
- head() → quick view of data.
- shape → check number of rows and columns.

[3]:
```
#  Load dataset
df = pd.read_csv(r"C:
↪\Users\Lenovo\OneDrive\Desktop\Projects_Sorted\AI-Portfolio\Showcase-Projects\Customer-Chur
↪csv")

# Show first 5 rows
print(df.head())
print(df.shape)
```

```
   customerID  gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  7590-VHVEG  Female              0     Yes         No       1           No
1  5575-GNVDE    Male              0      No         No      34          Yes
2  3668-QPYBK    Male              0      No         No       2          Yes
3  7795-CFOCW    Male              0      No         No      45           No
4  9237-HQITU  Female              0      No         No       2          Yes

      MultipleLines InternetService OnlineSecurity  … DeviceProtection  \
0  No phone service             DSL             No  …               No
1                No             DSL            Yes  …              Yes
2                No             DSL            Yes  …               No
3  No phone service             DSL            Yes  …              Yes
4                No     Fiber optic             No  …               No

  TechSupport StreamingTV StreamingMovies        Contract PaperlessBilling  \
0          No          No              No  Month-to-month              Yes
1          No          No              No        One year               No
2          No          No              No  Month-to-month              Yes
3         Yes          No              No        One year               No
4          No          No              No  Month-to-month              Yes

              PaymentMethod MonthlyCharges  TotalCharges Churn
0          Electronic check          29.85         29.85    No
1              Mailed check          56.95        1889.5    No
```

```
2                Mailed check           53.85         108.15   Yes
3  Bank transfer (automatic)            42.30        1840.75    No
4            Electronic check           70.70         151.65   Yes

[5 rows x 21 columns]
(7043, 21)
```

3 Data Preprocessing

We'll clean the data, encode categorical variables, and scale features.

- `customerID` → unique identifier, drop it.
- `TotalCharges` → has empty strings, convert to numeric and fill missing values.
- Encode categorical columns (Yes/No, Male/Female, etc.).
- Scale numerical values so features are on similar scale.

[4]:
```python
# Check for missing values
print(df.isnull().sum())
```

```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

[5]:
```python
# Drop customerID column (not useful for prediction)
df = df.drop("customerID", axis=1)
```

[6]:
```python
# Replace empty strings in TotalCharges with NaN, then convert to float
df["TotalCharges"] = df["TotalCharges"].replace(" ", np.nan)
df["TotalCharges"] = df["TotalCharges"].astype(float)
```

```
df["TotalCharges"] = df["TotalCharges"].fillna(df["TotalCharges"].mean())
```

[7]:
```
# Encode categorical features
le = LabelEncoder()
for col in df.select_dtypes(include=["object"]).columns:
    df[col] = le.fit_transform(df[col])

# Scale numerical features
scaler = StandardScaler()
df[["tenure", "MonthlyCharges", "TotalCharges"]] = scaler.
 ↪fit_transform(df[["tenure", "MonthlyCharges", "TotalCharges"]])

print(df.head())
```

```
   gender  SeniorCitizen  Partner  Dependents    tenure  PhoneService  \
0       0              0        1           0 -1.277445             0
1       1              0        0           0  0.066327             1
2       1              0        0           0 -1.236724             1
3       1              0        0           0  0.514251             0
4       0              0        0           0 -1.236724             1

   MultipleLines  InternetService  OnlineSecurity  OnlineBackup  \
0              1                0               0             2
1              0                0               2             0
2              0                0               2             2
3              1                0               2             0
4              0                1               0             0

   DeviceProtection  TechSupport  StreamingTV  StreamingMovies  Contract  \
0                 0            0            0                0         0
1                 2            0            0                0         1
2                 0            0            0                0         0
3                 2            2            0                0         1
4                 0            0            0                0         0

   PaperlessBilling  PaymentMethod  MonthlyCharges  TotalCharges  Churn
0                 1              2       -1.160323     -0.994971      0
1                 0              3       -0.259629     -0.173876      0
2                 1              3       -0.362660     -0.960399      1
3                 0              0       -0.746535     -0.195400      0
4                 1              2        0.197365     -0.941193      1
```

4 Split Data

Separate features (`X`) and target (`y`) → churn.

- Target variable = `Churn`.
- Use `train_test_split` → 80% train, 20% test.

- `stratify=y` → ensures equal distribution of churn/no-churn in train/test.

[8]:
```python
#  Split into train & test
X = df.drop("Churn", axis=1)
y = df["Churn"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42, stratify=y)

print(X_train.shape, X_test.shape)
```

```
(5634, 19) (1409, 19)
```

5 Train Model

We'll use Random Forest Classifier.

- `RandomForestClassifier` → chosen ML algorithm.
- `n_estimators=200` → number of trees.
- `class_weight="balanced"` → handles class imbalance (more no-churn customers).
- Train on training data, then predict on test data.

[10]:
```python
#  Train Random Forest model
model = RandomForestClassifier(random_state=42, n_estimators=200,␣
 ↪class_weight="balanced")
model.fit(X_train, y_train)
```

[10]:
```
RandomForestClassifier(class_weight='balanced', n_estimators=200,
                       random_state=42)
```

[11]:
```python
# Predictions
y_pred = model.predict(X_test)
```

6 Evaluate Model

Check performance using classification metrics.

- `accuracy_score` → overall correct predictions.
- `confusion_matrix` → shows churn vs non-churn predictions.
- `classification_report` → precision, recall, F1-score (important for churn).

[12]:
```python
#  Evaluation
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.7856635911994322

Confusion Matrix:
```

```
 [[928 107]
 [195 179]]

Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.90      0.86      1035
           1       0.63      0.48      0.54       374

    accuracy                           0.79      1409
   macro avg       0.73      0.69      0.70      1409
weighted avg       0.77      0.79      0.78      1409
```

6.1 Accuracy: 0.7857

- This means the model correctly predicts **about 78.6% of all cases** (churn + no churn).
- Accuracy alone can be misleading because the dataset is **imbalanced**:
  - 0 → No churn (majority class)
  - 1 → Churn (minority class)
- The model predicts **no-churn customers better** than churners.

6.2 Precision, Recall, F1-Score

- **Class 0 (No churn)**
  - Precision = 0.83 → Out of all customers predicted as no-churn, 83% were actually no-churn
  - Recall = 0.90 → Out of all actual no-churn customers, 90% were correctly predicted
  - F1-score = 0.86 → Good balance for no-churn prediction
- **Class 1 (Churn)**
  - Precision = 0.63 → Out of all customers predicted as churn, 63% were actually churn
  - Recall = 0.48 → Out of all actual churn customers, only 48% were correctly detected
  - F1-score = 0.54 → Model struggles to detect churners reliably

Observation: Catching churners is harder, but more important for business decisions.

6.3 Next Steps to Improve

1. **Handle Class Imbalance:**
   - Use `class_weight='balanced'` in RandomForest (already applied)

- Or use **SMOTE** to oversample churn cases

2. **Feature Engineering:**
   - Create features like `AverageMonthlyCharges = TotalCharges / tenure` or `ServiceCount = sum of additional services`

3. **Tune Hyperparameters:**
   - Adjust `n_estimators`, `max_depth`, `min_samples_split` to improve churn detection (recall for class 1)

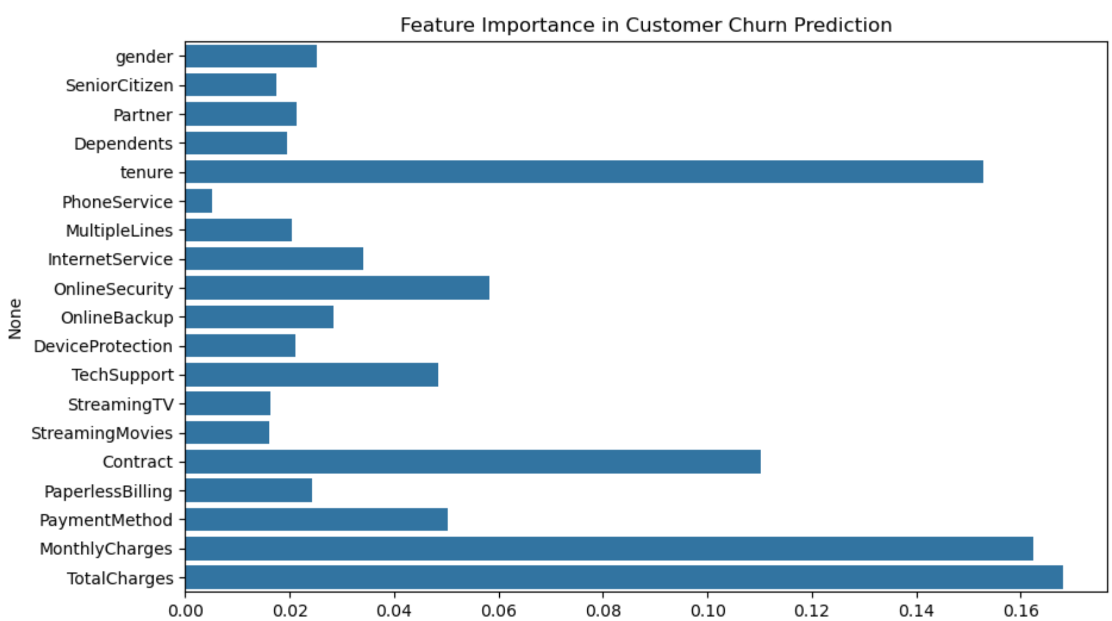
4. **Try Other Models:**
   - Gradient Boosting, XGBoost, LightGBM → often detect churners better in imbalanced datasets

7 Feature Importance

Find out which features are most important.

- Helps explain which features drive churn (e.g., tenure, contract type, monthly charges).

[13]:
```
# Feature Importance
importances = model.feature_importances_
features = X.columns

# Plot feature importance
plt.figure(figsize=(10,6))
sns.barplot(x=importances, y=features)
plt.title("Feature Importance in Customer Churn Prediction")
plt.show()
```



8 Save Model and Scaler

- Save trained model + scaler to use in Streamlit app without retraining

[16]:
```
import pickle
# Save model
pickle.dump(model, open("churn_model.pkl", "wb"))

# Save scaler
pickle.dump(scaler, open("scaler.pkl", "wb"))
```

9 Create Streamlit App (app.py)

- **Sidebar inputs** → users can enter feature values
- **Scaler** → scale inputs like during training
- **Predict** → model predicts churn probability and shows result

```
import streamlit as st
import pandas as pd
import numpy as np
import pickle

# --------------------------
# Load Model and Scaler
# --------------------------
model = pickle.load(open("churn_model.pkl", "rb"))
scaler = pickle.load(open("scaler.pkl", "rb"))

# Column names used in training
feature_columns = [
    'gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure', 'PhoneService',
    'MultipleLines', 'InternetService', 'OnlineSecurity', 'OnlineBackup',
    'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies',
    'Contract', 'PaperlessBilling', 'PaymentMethod', 'MonthlyCharges', 'TotalCharges'
]

# --------------------------
# Streamlit Page Config
# --------------------------
st.set_page_config(page_title="Customer Churn Prediction", layout="wide")
st.title("Customer Churn Prediction App")
st.write("Predict if a customer is likely to churn based on their details.")

# --------------------------
```

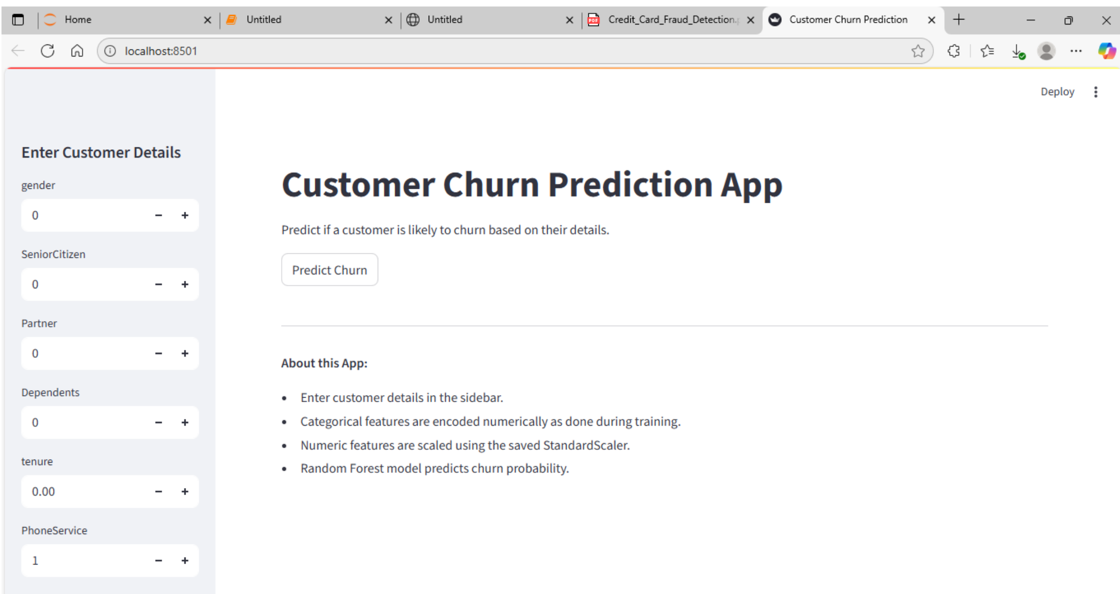
```python
# Sidebar Input
# --------------------------
st.sidebar.header("Enter Customer Details")

input_data = {}
# Default numeric values for example
default_values = {
    'gender': 0, 'SeniorCitizen': 0, 'Partner': 0, 'Dependents': 0, 'tenure': 0,
    'PhoneService': 1, 'MultipleLines': 0, 'InternetService': 0, 'OnlineSecurity': 0,
    'OnlineBackup': 0, 'DeviceProtection': 0, 'TechSupport': 0, 'StreamingTV': 0,
    'StreamingMovies': 0, 'Contract': 0, 'PaperlessBilling': 1, 'PaymentMethod': 0,
    'MonthlyCharges': 0.0, 'TotalCharges': 0.0
}

# Create inputs
for col in feature_columns:
    if col in ['tenure', 'MonthlyCharges', 'TotalCharges']:
        input_data[col] = st.sidebar.number_input(col, value=float(default_values[col]))
    else:
        input_data[col] = st.sidebar.number_input(col, value=int(default_values[col]))

# Convert to DataFrame
features = pd.DataFrame([input_data])

# --------------------------
# Scale numeric features
# --------------------------
numeric_cols = ['tenure', 'MonthlyCharges', 'TotalCharges']
features[numeric_cols] = scaler.transform(features[numeric_cols])

# --------------------------
# Prediction
# --------------------------
if st.button("Predict Churn"):
    pred = model.predict(features)
    pred_proba = model.predict_proba(features)[0][1]

    if pred[0] == 1:
        st.error(f"Customer is likely to CHURN! Probability: {pred_proba:.2f}")
    else:
        st.success(f"Customer is NOT likely to churn. Probability of churn: {pred_proba:.2f}")

# --------------------------
# Notes
# --------------------------
st.markdown("---")
st.markdown("""
**About this App:**
```

```
- Enter customer details in the sidebar.
- Categorical features are encoded numerically as done during training.
- Numeric features are scaled using the saved StandardScaler.
- Random Forest model predicts churn probability.
""")
```

10 App Overview

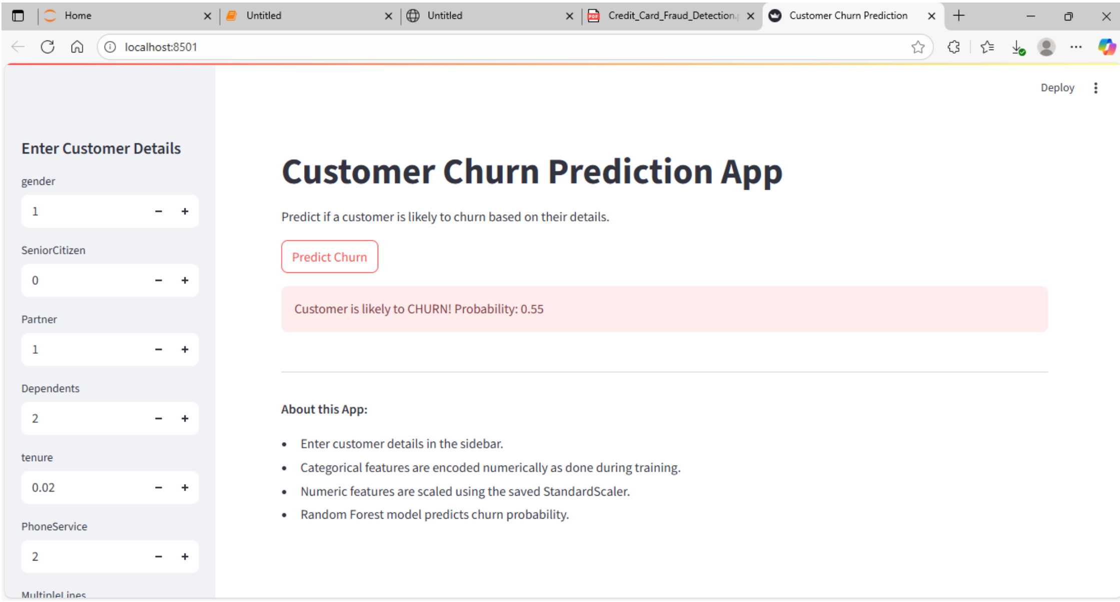
This Streamlit app predicts whether a customer will churn or not based on their details such as tenure, monthly charges, contract type, and services subscribed.

10.1 App_Overview



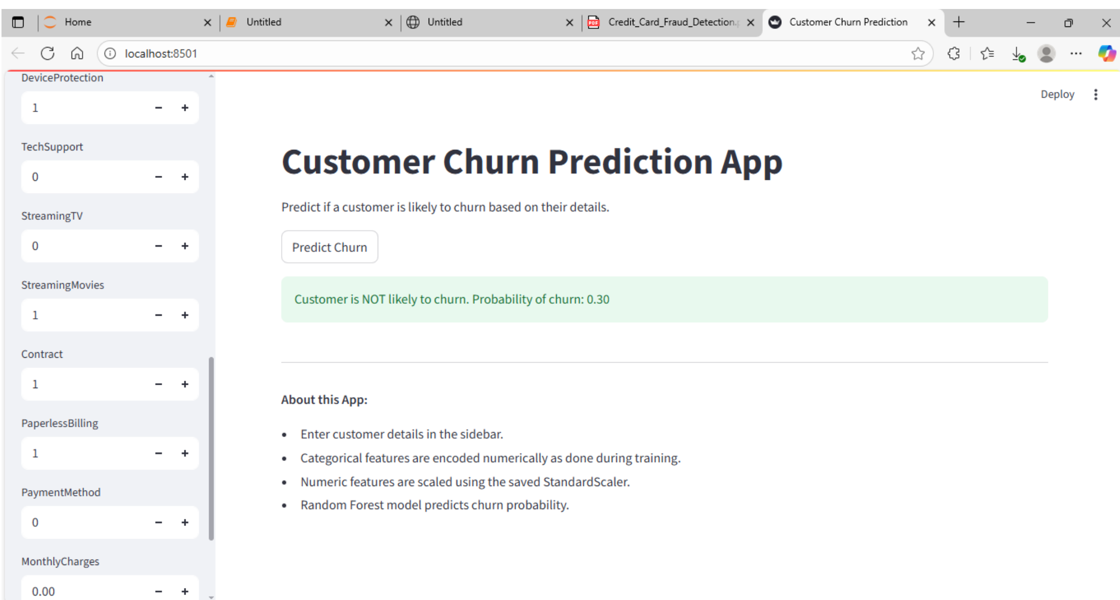
Main interface of the Customer Churn Prediction app showing input sidebar and prediction button.

10.2 Churn



Example of a customer predicted to CHURN. The app displays probability of churn and highlights risk.

10.3 Not_Churn



Example of a customer predicted NOT to churn. The app shows low probability of churn.

Classification Report:
- **Precision (Churn=1):** 0.63 → Out of all predicted churns, 63% were correct.
- **Recall (Churn=1):** 0.48 → Out of all actual churns, 48% were correctly detected.
- **F1-score (Churn=1):** 0.54 → Balance between precision and recall.

> Note: Accuracy is dominated by the majority class (non-churn). For churn prediction, **recall is critical** because missing a churned customer can be costly.

11 Conclusion & Next Steps

1. **Handle Class Imbalance:**
    - Use `class_weight='balanced'` in RandomForest (already applied)

    - Or use oversampling techniques like SMOTE.
2. **Feature Tuning:**
    - Evaluate feature importance and consider engineering new features (e.g., customer tenure $\times$ monthly charges).
3. **Try Other Models:**
    - XGBoost, LightGBM, or CatBoost may improve recall for the minority class.
4. **Deploy & Monitor:**
    - Streamlit app allows interactive predictions.

    - Collect real-world feedback and retrain periodically for better performance.