Assesment Report

on

"Classify Customer Churn:"

submitted as partial fulfillment for the award of

BACHELOR OF TECHNOLOGY DEGREE

SESSION 2024-25

in

Computer Science & Engineering (AI & ML)

By

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April, 2025

INTRODUCTION

Churn prediction is a crucial task for telecom companies to retain customers. Understanding the factors that lead to churn helps businesses take preventive actions and reduce customer loss.

This project uses a public dataset containing customer service records. We'll train a classification model using logistic regression to predict whether a customer will churn based on their service usage, contract type, monthly charges, etc.

METHODOLOGY

1. Data Upload & Cleaning:
   - The dataset is uploaded via Google Colab.
   - Missing values are detected and handled.
   - Non-numeric values in the TotalCharges column are converted and filled with median values.

2. Feature Engineering:
   - Non-numeric (categorical) variables are encoded using LabelEncoder.
   - Irrelevant columns (like customerID) are removed.

3. Model Building:
   - Features are scaled using StandardScaler.
   - Data is split into training and testing sets (80-20 split).
   - Logistic Regression is used as the classification algorithm.

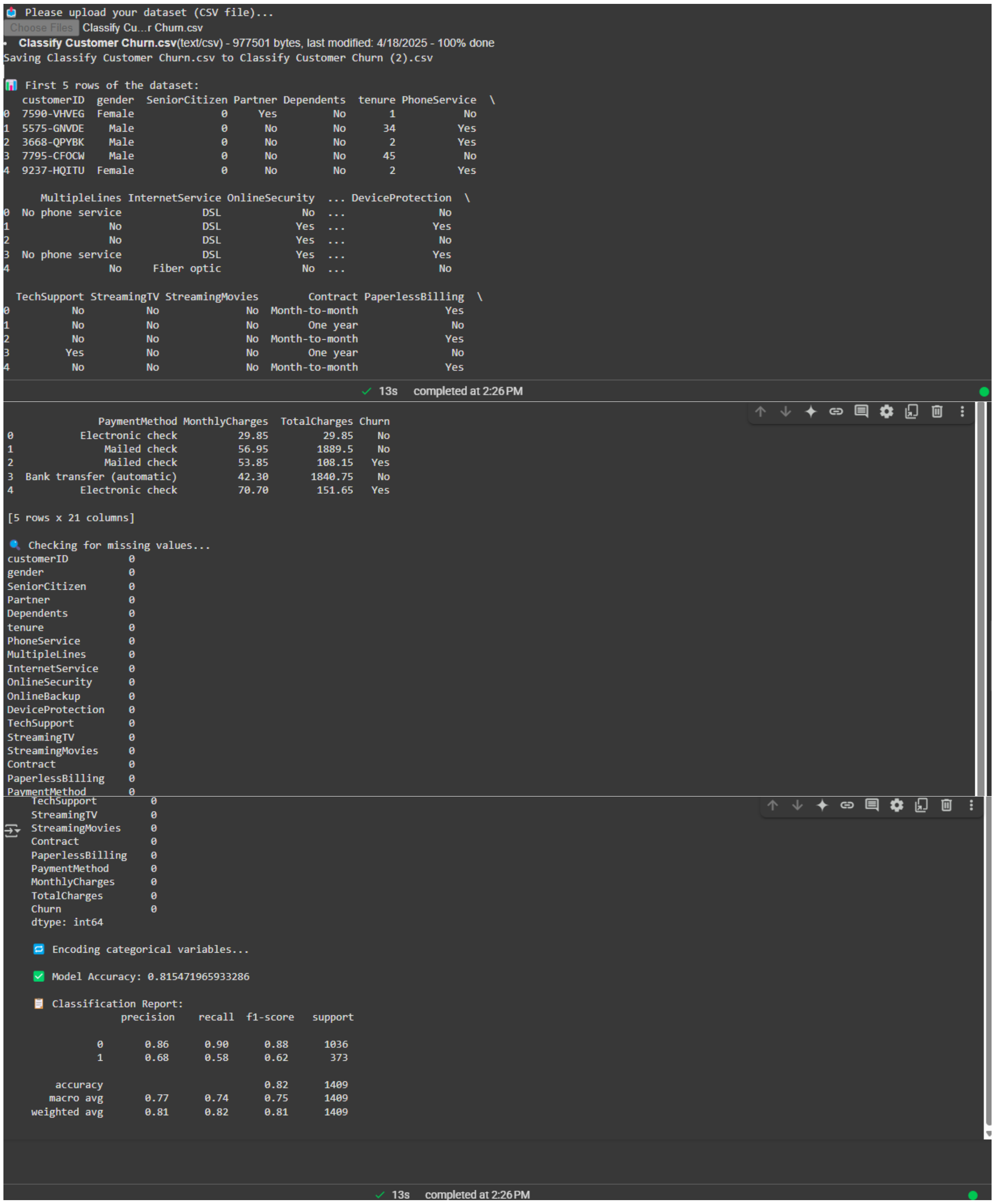
4. Evaluation:
   - Accuracy and a classification report are used to evaluate the model's performance.

CODE

```
# Customer Churn Classification in Google Colab (Improved Version)

# Step 1: Import necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score

from google.colab import files
from io import StringIO

# Step 2: Upload the dataset
print("📤 Please upload your dataset (CSV file)...")
uploaded = files.upload()

# Step 3: Load the dataset
file_name = list(uploaded.keys())[0]
df = pd.read_csv(StringIO(uploaded[file_name].decode('utf-8')))

# Step 4: Display the first few rows
print("\n📊 First 5 rows of the dataset:")
print(df.head())

# Step 5: Check for missing values
print("\n🔍 Checking for missing values...")
print(df.isnull().sum())

# Step 6: Drop unneeded columns (customerID is just an identifier)
if 'customerID' in df.columns:
   df.drop('customerID', axis=1, inplace=True)

# Step 7: Convert TotalCharges to numeric (some may be blanks or spaces)
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors='coerce')
df['TotalCharges'] = df['TotalCharges'].fillna(df['TotalCharges'].median())

# Step 8: Encode categorical variables
print("\n🔄 Encoding categorical variables...")
le = LabelEncoder()
```

```
for col in df.select_dtypes(include='object').columns:
    df[col] = le.fit_transform(df[col])

# Step 9: Define features and target
X = df.drop('Churn', axis=1)
y = df['Churn']

# Step 10: Scale features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Step 11: Split the data
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,
random_state=42)

# Step 12: Train Logistic Regression model
model = LogisticRegression(max_iter=500, solver='lbfgs')
model.fit(X_train, y_train)

# Step 13: Predict and evaluate
y_pred = model.predict(X_test)

print("\n✅ Model Accuracy:", accuracy_score(y_test, y_pred))
print("\n📋 Classification Report:\n", classification_report(y_test, y_pred))
```

OUTPUT / RESULT



```
📤 Please upload your dataset (CSV file)...
Choose Files  Classify Cu...r Churn.csv
• Classify Customer Churn.csv(text/csv) - 977501 bytes, last modified: 4/18/2025 - 100% done
Saving Classify Customer Churn.csv to Classify Customer Churn (2).csv

📊 First 5 rows of the dataset:
   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
```

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```
              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]

🔍 Checking for missing values...
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
```

```
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64

🔁 Encoding categorical variables...

✅ Model Accuracy: 0.815471965933286

📋 Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.90      0.88      1036
           1       0.68      0.58      0.62       373

    accuracy                           0.82      1409
   macro avg       0.77      0.74      0.75      1409
weighted avg       0.81      0.82      0.81      1409
```

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✅ Model Accuracy: 0.8133427963094393

References / Credits

- Dataset: https://www.kaggle.com/blastchar/telco-customer-churn
- Tools Used: Python, Google Colab, pandas, scikit-learn
- Libraries: pandas, numpy, seaborn, matplotlib, sklearn