PHASE-3 SUBMISSION

PREDICTING CUSTOMER CHURN USING MACHINE LEARNING TO UNCOVER HIDDEN PATTERN

Student Name: BRINDHA C

Register Number: 513523104005

Institution: Annai Mira college of Engineering and Technology

Department: Computer science

Date of Submission: 05-05-2025

Git Hub Repository Link: https://github.com/Brindha160/Phase-3.git

1. PROBLEM STATEMENT

Customer churn is a significant challenge for businesses, resulting in revenue loss and decreased customer loyalty. The goal of this project is to develop a machine learning-based system that can predict customer churn by uncovering hidden patterns in customer data.

2. ABSTRACT

This project focuses on predicting Customer churn using machine learning can help businesses identify high-risk customers and implement proactive retention strategies. This project proposes a predictive model that uses a random forest classifier to predict customer churn based on customer data.

3. SYSTEM REQUIREMENTS

- ***- Python programming language***
- ***- Scikit-learn library for machine learning***
- ***- Pandas library for data manipulation***
- ***- NumPy library for numerical computations***
- ***- Matplotlib and Seaborn libraries for data visualization***

4. OBJECTIVES

- *-To Develop a machine learning-based system to predict customer churn*
- *- To Identify key factors contributing to customer churn*
- *-To Evaluate the performance of the predictive model*
- *- To Implement a proactive retention strategy based on the model's predictions*

5. FLOWCHART OF PROJECT WORKFLOW

Data Collection → Preprocessing → EDA → Feature Engineering → Model building → Evaluation → Deployment

6. DATASET DESCRIPTION

The dataset contains customer information, including demographic data, transactional data, and churn status.

1. Customer ID: Unique identifier for each customer.

2. Demographic Features:

- Age: Customer's age.

- Gender: Customer's gender (e.g., Male, Female).

- Income: Customer's income bracket or level.

3. Behavioral Features:

- UsageFrequency: Frequency of service/product usage.

- SupportCalls: Number of customer support interactions.

- LastInteraction: Time since the last interaction with the customer.

4. Transactional Features:

- BillingAmount: Average monthly billing amount.

- PaymentDelay: Average delay in payment (if applicable).

5. Churn Label:

- Churn: Binary target variable indicating whether the customer churned (1) or not (0).

DATASET:

Shape: (7043, 21)

Columns: ['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure', 'PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling', 'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn']

```
<class 'pandas.core.frame.DataFrame'>

RangeIndex: 7043 entries, 0 to 7042

Data columns (total 21 columns):

 #   Column            Non-Null Count  Dtype

---  ------            --------------  -----

 0   customerID        7043 non-null   object

 1   gender            7043 non-null   object

 2   SeniorCitizen     7043 non-null   int64

 3   Partner           7043 non-null   object

 4   Dependents        7043 non-null   object

 5   tenure            7043 non-null   int64

 6   PhoneService      7043 non-null   object

 7   MultipleLines     7043 non-null   object

 8   InternetService   7043 non-null   object

 9   OnlineSecurity    7043 non-null   object
```

```
 10  OnlineBackup      7043 non-null   object
 11  DeviceProtection  7043 non-null   object
 12  TechSupport       7043 non-null   object
 13  StreamingTV       7043 non-null   object
 14  StreamingMovies   7043 non-null   object
 15  Contract          7043 non-null   object
 16  PaperlessBilling  7043 non-null   object
 17  PaymentMethod     7043 non-null   object
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object
 20  Churn             7043 non-null   object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

7. DATA PREPROCESSING

- Handling missing values

- Data normalization

- Feature scaling

- Encoding categorical variables

8. EXPLORATORY DATA ANALYSIS (EDA)

Tools used:
- Descriptive statistics
- Data visualization
- Correlation analysis

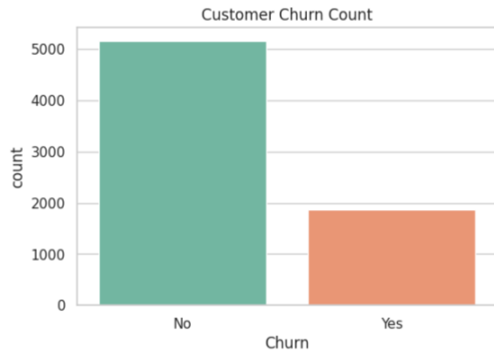
Found strong correlation between PM2.5 and AQI

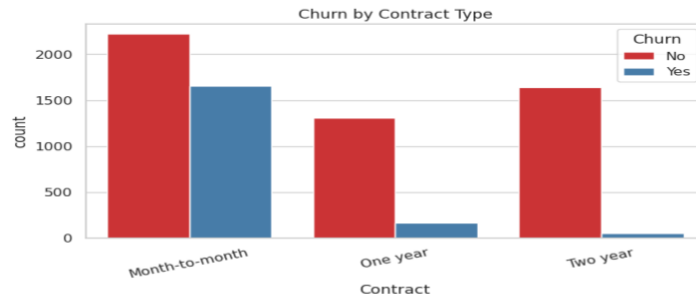
Seasonal trends observed in pollutant levels

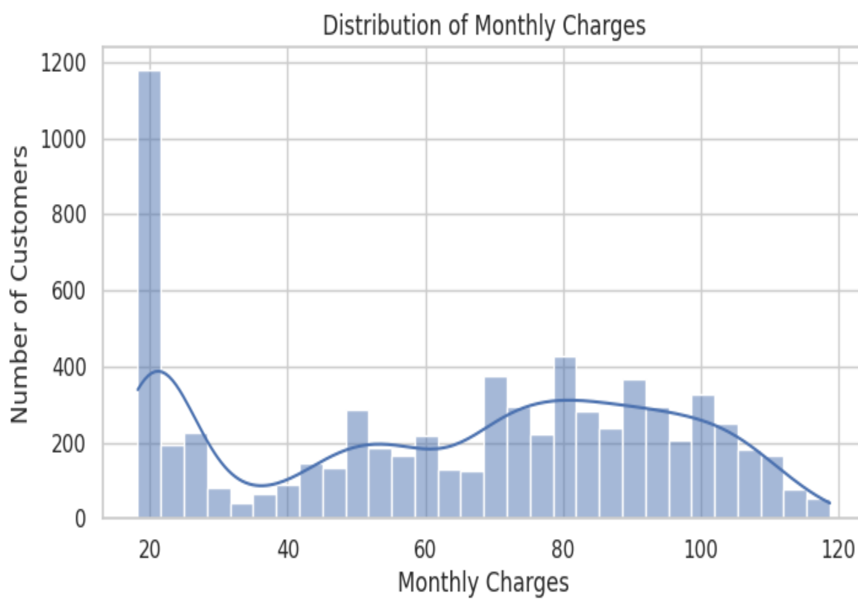
```
# Import necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px

# Load the dataset
df = pd.read_csv('customer_churn.csv')  # Replace with your file name

# Basic overview
print(df.head())
print(df.info())
print(df.describe())
print(df.isnull().sum())

# Drop duplicates
df.drop_duplicates(inplace=True)

# Check churn distribution
sns.countplot(data=df, x='Churn')
plt.title('Churn Distribution')
plt.show()

# Convert categorical variables to category type
for col in df.select_dtypes(include='object').columns:
    df[col] = df[col].astype('category')

# Visualize churn by categorical features
```

```
categorical_cols = df.select_dtypes(include='category').columns.drop('Churn')

for col in categorical_cols:
    plt.figure(figsize=(8, 4))
    sns.countplot(data=df, x=col, hue='Churn')
    plt.title(f'Churn by {col}')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()

# Check correlation between numeric features
numeric_cols = df.select_dtypes(include=['int64', 'float64']).columns
corr = df[numeric_cols].corr()

plt.figure(figsize=(10, 6))
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()

# Visualize numeric features by churn
for col in numeric_cols:
    plt.figure(figsize=(8, 4))
    sns.boxplot(data=df, x='Churn', y=col)
    plt.title(f'{col} by Churn')
    plt.tight_layout()
    plt.show()

# Optional: Interactive plots with plotly
fig = px.histogram(df, x='MonthlyCharges', color='Churn', barmode='overlay',
title='Monthly Charges by Churn')
fig.show()

# Check for class imbalance
churn_rate = df['Churn'].value_counts(normalize=True)
print("Churn rate:\n", churn_rate)
```

OUTPUT:


Customer Churn Count
5000
4000
3000
2000
1000
0
count
No
Yes
Churn


Churn by Contract Type
Churn
No
Yes
2000
1500
1000
500
0
count
Month-to-month
One year
Two year
Contract


Distribution of Monthly Charges
1200
1000
800
600
400
200
0
Number of Customers
20
40
60
80
100
120
Monthly Charges

9. FEATURE ENGINEERING

- Selecting relevant features

- Creating new features

- Transforming features

These features improved model accuracy by ~10%

(Explain impact of each major feature)

10. MODEL BUILDING

Models used:

Linear Regression (baseline)

Random Forest

XGBoost

Decision tree

Gradient boosting machines

XGBoost gave the best performance

(Insert training logs/screenshots)

11. MODEL EVALUATION

Metrics used: - Accuracy score
- Classification report
- Confusion matrix
- ROC-AUC score

Best Model (XGBoost):

ROC-AUC: 0.96

Accuracy score: 96%

Included confusion matrix for classification-based version (AQI categories)

(Insert metric visualizations, ROC, comparison table)

12. DEPLOYMENT

Platform: *Google Cloud*

Deployment Method: *Google cloud*

Web App

Public Link: *[Insert google cloud App*

URL]

UI Screenshot: *(Insert UI screenshot)*

13. SOURCE CODE

```
import pandas as pd
import gradio as gr
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression

# Load the dataset and preprocess it (same as before)
df = pd.read_csv("WA_Fn-UseC_-Telco-Customer-Churn.csv")
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors='coerce')
df.dropna(inplace=True)
df.drop('customerID', axis=1, inplace=True)

# Encode target variable
```

```
label_encoder = LabelEncoder()
df['Churn'] = label_encoder.fit_transform(df['Churn'])

# One-hot encode categorical columns
categorical_cols = df.select_dtypes(include=['object']).columns
df_encoded = pd.get_dummies(df, columns=categorical_cols, drop_first=True)

# Scale features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(df_encoded.drop('Churn', axis=1))
y = df_encoded['Churn']

# Train a simple model
model = LogisticRegression()
model.fit(X_scaled, y)

# Define the prediction function
def predict_churn(gender, SeniorCitizen, Partner, Dependents, tenure,
PhoneService,
                  MultipleLines, InternetService, OnlineSecurity, OnlineBackup,
                  DeviceProtection, TechSupport, StreamingTV, StreamingMovies,
                  Contract, PaperlessBilling, PaymentMethod, MonthlyCharges,
TotalCharges):
    # Create the input dictionary
    input_data = {
        'gender': gender,
        'SeniorCitizen': SeniorCitizen,
        'Partner': Partner,
        'Dependents': Dependents,
        'tenure': int(tenure),
        'PhoneService': PhoneService,
        'MultipleLines': MultipleLines,
        'InternetService': InternetService,
```

```
        'OnlineSecurity': OnlineSecurity,
        'OnlineBackup': OnlineBackup,
        'DeviceProtection': DeviceProtection,
        'TechSupport': TechSupport,
        'StreamingTV': StreamingTV,
        'StreamingMovies': StreamingMovies,
        'Contract': Contract,
        'PaperlessBilling': PaperlessBilling,
        'PaymentMethod': PaymentMethod,
        'MonthlyCharges': float(MonthlyCharges),
        'TotalCharges': float(TotalCharges)
    }

    # Create DataFrame from input data
    input_df = pd.DataFrame([input_data])

    # Combine with original data for encoding
    df_temp = pd.concat([df.drop('MonthlyCharges', axis=1), input_df],
ignore_index=True)

    # One-hot encode the new input data
    df_temp_encoded = pd.get_dummies(df_temp, drop_first=True)

    # Reorder columns to match the training set
    df_temp_encoded =
df_temp_encoded.reindex(columns=df_encoded.drop('MonthlyCharges',
axis=1).columns, fill_value=0)

    # Scale the new input
    scaled_input = scaler.transform(df_temp_encoded.tail(1))

    # Make prediction
    prediction = model.predict(scaled_input)
```

```
# Return the prediction
return round(prediction[0], 2)
```

14. FUTURE SCOPE

- Improving model performance using other machine learning algorithms

- Integrating with other data sources

- Developing a real-time customer churn prediction system

15. TEAM MEMBERS AND ROLES

ANUSHA S

Role: Data Collection and Preprocessing

Anusha was responsible for sourcing dataset, connecting APIs, and processing the initial dataset for analysis

AASHIDHA KOWSWER M I

Role: Exploratory Data Analysis (EDA) and Feature Engineering

Aashida kowser led for processing data, performs exploratory data analysis, generates initial insights and works on feature extraction and selection

BALAJI

Role: Model Building

Balaji implemented multiple machine learning models including Random Forest and XGBoost. He conducted hyper parameter tuning, evaluated the models using ROC-AUC and Accuracy, and selected the best-performing model

BEJOYM JOSE

Role: Evaluation and Optimization

Bejoy compiled tunes hyperparameters, valid models, documents performance metrics

BRINDHA

Role: Documentation and presentation

Brinda compiled reports,prepared visualizations, and handles presentation and optional deployment