Phase-2 Submission

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Institution: PPG Institute of Technology

Department: B.Tech Information Technology

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GitHub Repository Link: [Repo link]

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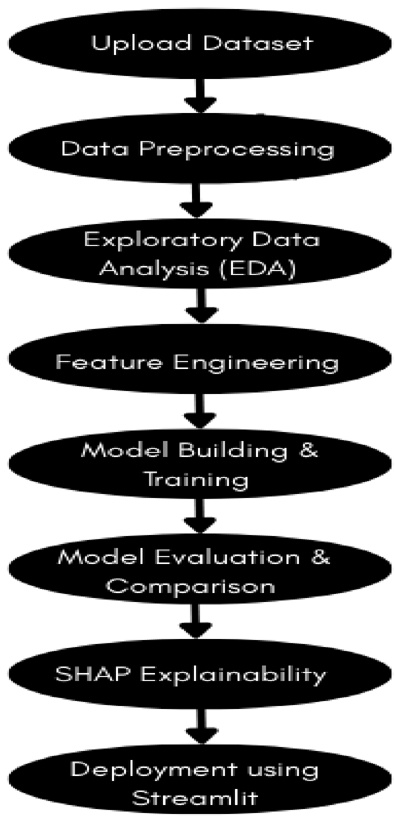
1. Problem Statement

- *Customer churn is a critical problem that affects long-term revenue and growth in industries like telecommute, banking, and subscription-based services. This project aims to solve a* ***binary classification*** *problem: predicting whether a customer will churn (i.e., leave the service) based on demographic and service usage features.*
- *Understanding churn behavior helps businesses reduce customer acquisition costs and improve retention strategies by proactively identifying high-risk customers.*

2. Project Objectives

- *Predict customer churn using machine learning classification models and important features that contribute to churn.*
- *Build interpret-able models that can be used for decision-making.*
- *Evaluate and compare different ML algorithms based on precision, recall, and F1 score.*
- *Deliver a functional model ready for integration with business dashboards.*

3. Flowchart of the Project Workflow



4. Data Description

- ***Data set Name and origin:*** *Telco Customer Churn and kaggle*
- *Dataset Link: https://www.kaggle.com/datasets/blastchar/telcocustomerchurn*
- ***Type:*** *Structured data*
- ***Records:*** *7043 (raw) → 7032 (preprocessed)*
- ***Features:*** *21 original features → 31 engineered features*
- ***Target Variable:*** *Churn (Yes/No)*
- ***Data set Type:*** *Static*

5. Data Preprocessing

- *Removed customer ID column as it does not influence churn.*
- *Handled missing/invalid entries in Total Charges by converting to numeric and removing invalid rows.*
- *Converted categorical variables using **one-hot encoding**.*
- *Normalized numeric fields (`TotalCharges`, `MonthlyCharges`) for better model learning.*
- *Ensured all features were numeric for compatibility with ML models.*

6. Exploratory Data Analysis (EDA)

Uni-variate Analysis:

- *tenure and Monthly-charges showed diverse distribution.*
- *Most customers have a month-to-month contract and electronic check payment.*

Bivariate/Multivariate Analysis:

- *High churn observed among customers with fiber optic internet and month-to-month contracts.*
- *Tenure is inversely related to churn likelihood.*

Insights Summary:

- *Contract type, payment method, internet service, and tenure are strong churn indicators.*

7. Feature Engineering

- *One-hot encoding of categorical variables.*
- *Removed multicellular columns and low-variance features.*
- *No PCA applied as models handled feature count well.*
- *No date features involved; no need for time-based extraction.*

8. Model Building

Models Used:*Logistic Regression*

- *Random Forest Classifier*
- *XGBoost Classifier*

Model Selection Justification:

- *All selected models are interpret able and suitable for binary classification.*
- *Random Forest and XG Boost help in identifying feature importance.*

Evaluation Metrics:

- *Accuracy, Precision, Recall, F1-Score, ROC - AUC*

Train-Test Split: *80/20 stratified split to maintain class balance.*

9. Visualization of Results & Model Insights

- ***Confusion Matrix****: Evaluated true positives and false negatives.*
- ***ROC-AUC Curve****: Compared model discriminative power.*
- ***Feature Importance****: Identified top predictors like Contract, tenure, and Internet Service.*
- ***SHAP Values*** *(optional): To interpret individual predictions.*

10. Tools and Technologies Used

- ***Programming Language: Python***
- ***IDE/Notebook: Google Colab, Jupyter Notebook***
- ***Libraries: pandas, numpy, matplotlib, seaborn, plotly, scikit-learn, xgboost***
- ***Visualization Tools: Sea born, Plot, SHAP***
- ***Optional Deployment: Streamlit (not yet deployed)***

11. Team Members and Contributions

NAME	*ROLE*
Thilshan S	*Data cleaning*
Dinesh D	*EDA*
Srimathi B	*Feature engineering*
Deeksha P	*Model development*
Tamilarasan B	*Documentation reporting*