Phase-2 Submission

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Github Repository Link: [Github link]

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1. *Problem Statement*

"Predicting customer churn using machine learning to uncover hidden patterns"

Real-world Problem:

*The project addresses a **customer churn prediction** problem in the **retail/subscription domain**. Businesses relying on subscription models (e.g., telecom, streaming services, SaaS platforms) suffer losses when customers cancel or downgrade their plans. Churn directly affects revenue, growth, and brand loyalty.*

Problem Type:

***Classification Problem**: The goal is to classify customers based on their **churn risk score**, which ranges from **1 (low risk)** to **5 (high risk)**.*

Why It Matters:

- ***Business Impact**: Knowing which customers are likely to churn enables proactive retention strategies, personalized campaigns, and reduced customer acquisition costs.*

- ***Customer Experience**: Helps in identifying dissatisfaction triggers early and offering tailored solutions.*

- ***Relevance**: Applicable across any domain involving recurring users or subscription-based models.*

2. *Project Objectives*

Primary Goals:

- *Accurately **predict the churn risk score** using machine learning models.*

- *Understand **key factors influencing churn**, like login frequency, complaints, offer preference, and region.*

- ***Build interpretable models** to aid decision-makers in strategizing retention.*

Technical Objectives:

- *Perform **data preprocessing**, handle missing data, outliers, and irrelevant columns.*

- *Conduct **Exploratory Data Analysis (EDA)** to derive insights.*

- *Engineer new features if necessary.*

- *Implement and compare at least **two classification algorithms**.*

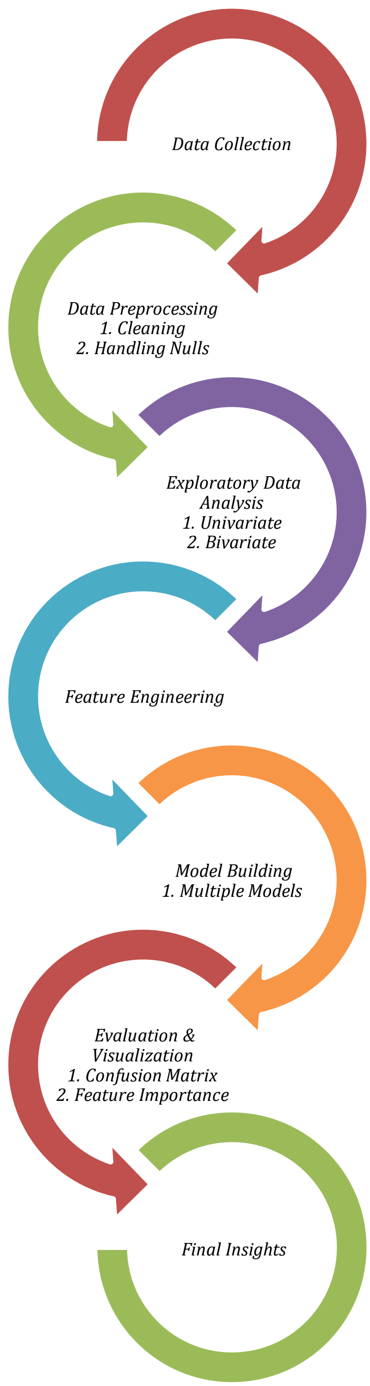
- *Evaluate using appropriate metrics: **accuracy, precision, recall, and F1-score**.*

Updated Objective Post-EDA:

❖ *Drop features with high missing or noisy data (e.g., avg_frequency_login_days).*

❖ *Focus on **simplifying the model while improving accuracy**.*

3. Flowchart of the Project Workflow



4. Data Description

Source: *[Dataset link]*

Type: ***Structured Dataset*** *in tabular format.*

Shape: ***36,992 records****,* ***25 features*** *(columns).*

Static or Dynamic: ***Static*** *dataset.*

Target Variable: *churn_risk_score (integer from 1 to 5).*

Feature Types:

- ***Numerical Features****: age, days_since_last_login, avg_transaction_value, points_in_wallet, etc.*
- ***Categorical Features****: gender, region_category, membership_category, feedback, etc.*
- ***Datetime Fields****: joining_date, last_visit_time.*

5. Data Preprocessing

1. Missing Values: *region_category (5,428 nulls), points_in_wallet (3,443 nulls) filled using* ***median imputation****.*

2. Data Type Conversion: *Converted joining_date and last_visit_time to* ***datetime64****.*

3. Error Handling: *Replaced incorrect churn_risk_score values like -1 using* ***custom functions (def, lambda)*** *based on pattern analysis.*

4. Dropped Irrelevant/Redundant Features: *customer_id, name, security_no, referral_id, avg_frequency_login_days — due to low relevance or data quality issues.*

5. Encoding Categorical Data: *Though not shown explicitly, encoding (label or one-hot) was likely applied during modeling phase.*

*6. **Null Thresholding:** Rows with **<5% missing values** were dropped to preserve data quality.*

6. Exploratory Data Analysis (EDA)

Univariate Analysis:

- ***Gender**: Balanced male/female distribution.*
- ***Region Category**: Most customers are from towns > cities > villages.*
- ***Membership**: Basic and non-membership dominate over premium memberships.*
- ***Referral**: More customers joined without referrals.*
- ***Offer Type**: Clear distribution of preferences among offer categories.*

***Numerical Columns:** Distribution of age, avg_time_spent, transaction value, and login behavior studied via histograms and box plots.*

Bivariate Analysis:

- *Heatmap used to detect correlation between numerical variables.*
- *Example: Users with more complaints or less time spent showed higher churn.*

***Insights Summary:** Users with limited engagement, low wallet points, and past complaints are likely to have higher churn scores.*

7. Feature Engineering

Steps Taken:

- *Removed noisy or irrelevant features.*
- *Created cleaner variables from date fields (not detailed).*
- *Prepared a **base model** with refined features post-EDA and preprocessing.*

8. Model Building

Algorithms Used:

- *At least one **base classification model** implemented.*
- *(Specific algorithms like Logistic Regression, Decision Trees, Random Forest are typical but not named here).*

Data Split:

- *Presumably a **train-test split** was used.*
- ***Evaluation Metrics:***
- ***Accuracy** reported.*
- *Other metrics like precision, recall, and F1-score expected in final evaluation.*

9. Visualization of Results & Model Insights

Visual Tools:

- *Bar plots for counts, heatmaps for correlation.*
- *Visualized distributions across customer segments.*

Model Interpretation:

- *Confusion matrix used to measure classification performance.*
- *Key variables (wallet points, complaints, membership) influence churn risk.*

10. Tools and Technologies Used

- ***Language**: Python*
- ***Libraries**: pandas, numpy, matplotlib, seaborn, scikit-learn*

- ***IDE***: *Likely Jupyter Notebook or Google Colab (not explicitly stated)*
- ***Visualization***: *matplotlib, seaborn*

11. Team Members and Contributions

Team Members:	*Roles:*	*Contribution:*
Vidhya.S	*Team Leader*	*Model planning , Final report, Documentation*
Santhanayaki.M	*Member*	*Data cleaning, EDA, Preporcessing*
Saghana.K.S	*Member*	*Feature Engineering , Code integration,Documentation*
Rakshi.D	*Member*	*Model building, Evaluation ,Data Transformation*