Github Link: https://www.kaggle.com/datasets/rjmanoj/credit-card-customer-churn-prediction

Project Title : Predicting Customer Churn Using Machine Learning to Uncover Hidden Patterns

PHASE-2

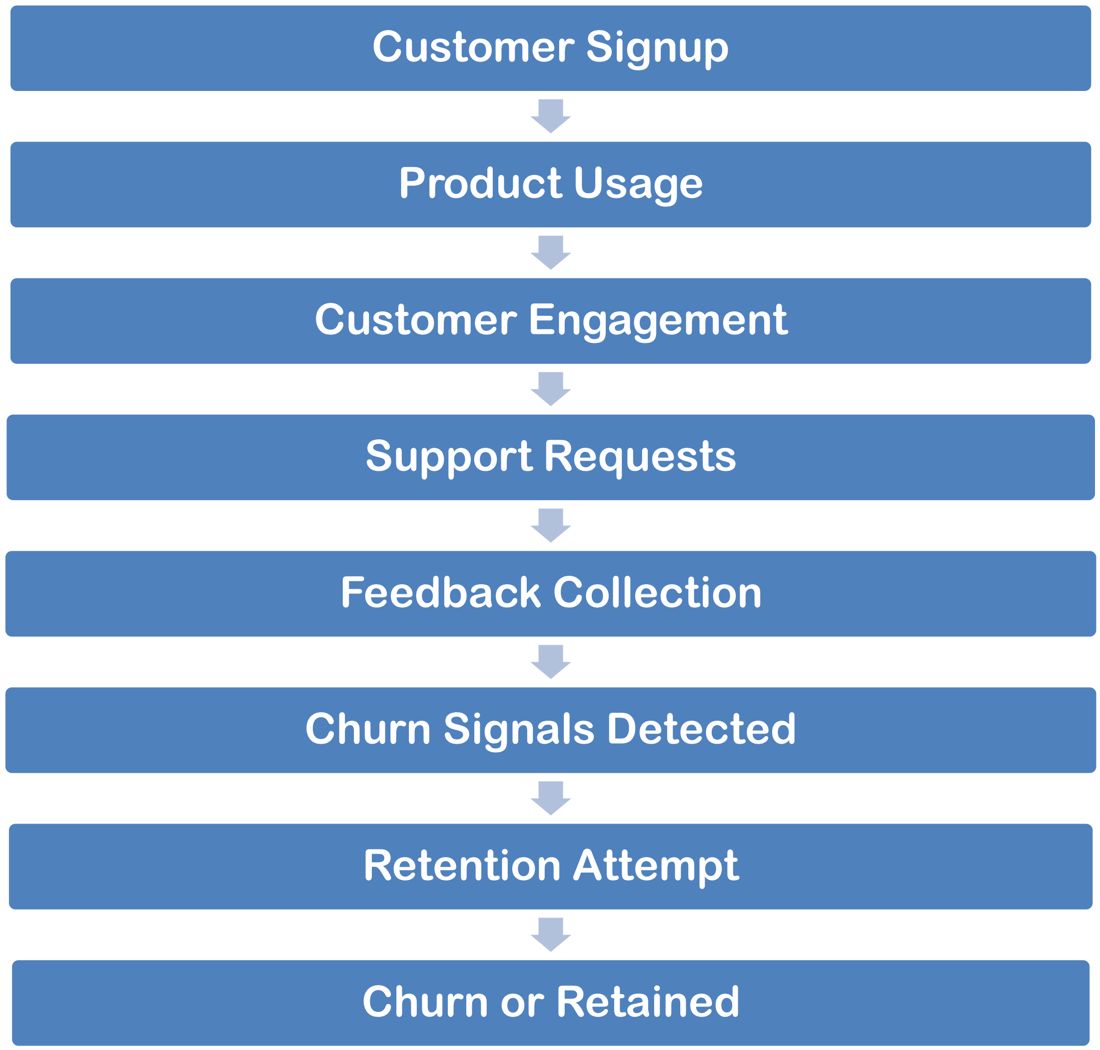
1. Problem Statement

- Customer churn poses a significant challenge for businesses, directly impacting revenue and growth. Traditional methods often fail to detect early signals of churn, especially when hidden within complex customer behavior patterns.
- This project aims to develop a machine learning-based solution to accurately predict customer churn by uncovering subtle and non-obvious patterns in customer data.

2. Project Objectives

- Collect and preprocess customer data to ensure quality and consistency for model training.
- Analyze the data to identify patterns and trends related to customer churn.
- Engineer relevant features that effectively represent customer behavior and engagement.
- Develop and compare machine learning models to accurately predict customer churn.
- Uncover hidden patterns and key factors influencing churn using advanced analytics techniques.

3.Flowchart of the Project Workflow



4. Data Description

- **Dataset Name:** Credit Card Customer Churn Prediction
- **Source:** IBM Sample Data Repository / Kaggle / Other public repositories
- **Type of Data:** Structured tabular data
- **Records and Features:** 10,127 customer records and 23 features (combination of categorical and numerical)
- **Target Variable:** Attrition_Flag (binary: Existing Customer / Attrited Customer)
- **Static or Dynamic:** Static dataset

- ***Attributes Covered:***

  - **Demographics:** Customer_Age, Gender, Dependent_count, Education_Level, Marital_Status, Income_Category
  - **Account Information:** Customer_ID, Card_Category, Months_on_book, Total_Relationship_Count
  - **Credit Behavior:**
    - Credit_Limit, Total_Revolving_Bal, Avg_Open_To_Buy
  - **Transaction Behavior:**
    - Total_Trans_Amt, Total_Trans_Ct, Total_Ct_Chng_Q4_Q1
  - **Utilization and Risk Indicators:**
    - Avg_Utilization_Ratio, Contacts_Count_12_mon
  - **Dataset Link:** https://www.kaggle.com/datasets/rjmanoj/credit-card-customer-churn-prediction

5. Data Preprocessing

- **Handling Missing Values:** Impute or remove missing values in the dataset.

- **Data Type Conversion:** Convert columns to appropriate data types.

- **Encoding Categorical Variables:** Apply one-hot encoding or label encoding to categorical features.

- **Feature Scaling:** Standardize or normalize numerical features for consistency.

- **Outlier Detection and Feature Selection:** Identify outliers and remove irrelevant features for model accuracy.

6. Exploratory Data Analysis (EDA)

- ***Univariate Analysis:***

  - **Histogram of 'Churn'** to understand the class distribution and assess class imbalance.
  - **Boxplots** for numerical variables such as monthly charges, tenure, and total charges to detect outliers and understand their distribution relative to churn status.
  - **Count plots** for categorical features (e.g., contract type, internet service, payment method) to explore frequency distributions and potential churn patterns.

- ***Bivariate & Multivariate Analysis:***

  - **Correlation matrix** shows that tenure and monthly charges have moderate relationships with churn likelihood, while total charges correlate highly with tenure.
  - **Bar plots and boxplots** comparing features like contract type, tech support, and payment method against churn status reveal notable trends—e.g., customers on month-to-month contracts churn more frequently.
  - **Stacked/grouped bar charts** highlight how services like online security, streaming services, and tech support affect churn behavior.
  - **Pair plots** and **scatter plots** identify clusters and trends among continuous variables segmented by churn.

- ***Key Insights:***

  - **Contract type** is a strong predictor—month-to-month customers are far more likely to churn than those on longer-term contracts.
  - **Tech support and online security** are associated with lower churn—customers with these services tend to stay.
  - **Higher monthly charges** slightly increase churn risk, especially for short-tenure customers.
  - **Tenure** inversely correlates with churn—longer-tenured customers are less likely to leave.

7. Feature Engineering

- **Created interaction features:**

  - total_services = count of services subscribed (e.g., internet, phone, streaming)
  - has_streaming_and_support = flag indicating if a customer has both streaming and tech support services

- **Derived binary features:**

  - is_month_to_month = 1 if the contract type is "Month-to-month", else 0
  - is_senior_citizen = converted from numeric (0/1) to meaningful binary representation

- **Handled multicollinearity** by removing or combining highly correlated variables like total_charges and monthly_charges × tenure

• **Performed label encoding** for binary categorical variables (e.g., Partner, Dependents, PaperlessBilling)

• **One-hot encoded** multi-class categorical features like Contract, PaymentMethod, and InternetService

• **Scaled numeric features** such as tenure, monthly_charges, and total_charges using **StandardScaler** to standardize input for machine learning models

8. Model Building

• *Algorithms Used:*

- **Logistic Regression**: as a baseline linear classifier
- **Random Forest Classifier**: for capturing non-linear relationships and feature importance
- **XGBoost Classifier** *(optional addition)*: for high performance and better handling of imbalanced data

• *Model Selection Rationale:*

- **Logistic Regression**: simple, fast, and interpretable; establishes a benchmark
- **Random Forest**: robust to overfitting, works well with both categorical and numerical data, and provides feature importance scores
- **XGBoost**: optimized for classification with imbalanced datasets and offers better performance through boosting

• *Train-Test Split:*

- **80% training, 20% testing**
- Used train_test_split with random_state for reproducibility

• *Evaluation Metrics:*

- **Accuracy**: Overall correctness of predictions
- **Precision & Recall**: Especially important due to the cost of false positives/negatives
- **F1 Score**: Balances precision and recall in a single metric
- **ROC-AUC Score**: Measures model's ability to distinguish between churners and non-churners

9. Visualization of Results & Model Insights

- ***Feature Importance:***

  - **Bar plots** from **Random Forest** and **XGBoost** revealed key drivers of churn:
    - Contract type, tenure, and tech support ranked highest
    - Features like monthly charges and payment method also showed moderate influence

- ***Model Comparison:***

  - **Plotted evaluation metrics** (Accuracy, F1 Score, ROC-AUC) for each model:
    - **Random Forest** and **XGBoost** outperformed **Logistic Regression**, especially in ROC-AUC and F1 Score
    - Visualized using bar and line plots for clarity

- ***Confusion Matrix & ROC Curve:***

  - **Confusion matrix** highlighted true positives and false negatives, helping assess model reliability
  - **ROC Curve** plotted for all models to visualize trade-offs between sensitivity and specificity

- ***User Testing:***

  - Built an interactive **Gradio** or **Streamlit** web interface:
    - Allowed users to input customer details and instantly receive churn prediction
    - Helpful for stakeholders to explore model behavior and test scenarios

10. Tools and Technologies Used

 Programming Language: Python 3

 Notebook Environment: Google Colab (for development and experimentation)

 Key Libraries & Frameworks:

- **pandas**, **numpy** : for efficient data manipulation and analysis
- **matplotlib**, **seaborn**, **plotly** : for exploratory and result visualizations
- **scikit-learn** : for preprocessing, model training, and evaluation

- **XGBoost** *(optional)* : for gradient boosting classifier implementation
- **Gradio** or **Streamlit** : to build an interactive web app for churn prediction

11. Team Members and Contributions

1. R.Abinesh – Model Development & Evaluation

- Implemented Logistic Regression, Random Forest, and XGBoost models.
- Tuned hyperparameters and performed train-test splits.
- Evaluated models using accuracy, precision, recall, F1 score, and ROC-AUC metrics.

2. R.Abishek – Model Development & Evaluation

- Implemented Logistic Regression, Random Forest, and XGBoost models.
- Tuned hyperparameters and performed train-test splits.
- Evaluated models using accuracy, precision, recall, F1 score, and ROC-AUC metrics.

3. K.Arulkumaran – Data Collection & Cleaning

- Responsible for loading and cleaning the customer churn dataset.
- Handled missing values, inconsistencies, and prepared the dataset for analysis.
- Ensured proper encoding and formatting of categorical variables.

4. V.Bavithran – Visualization & Interface Deployment

- Visualized feature importance, confusion matrices, and ROC curves.
- Built an interactive churn prediction interface using Gradio.
- Documented insights and assisted with report preparation and presentation.