Phase-2 Submission

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GitHub Repository Link:
https://github.com/Lohithravi69/NM_Lohith_DS.git

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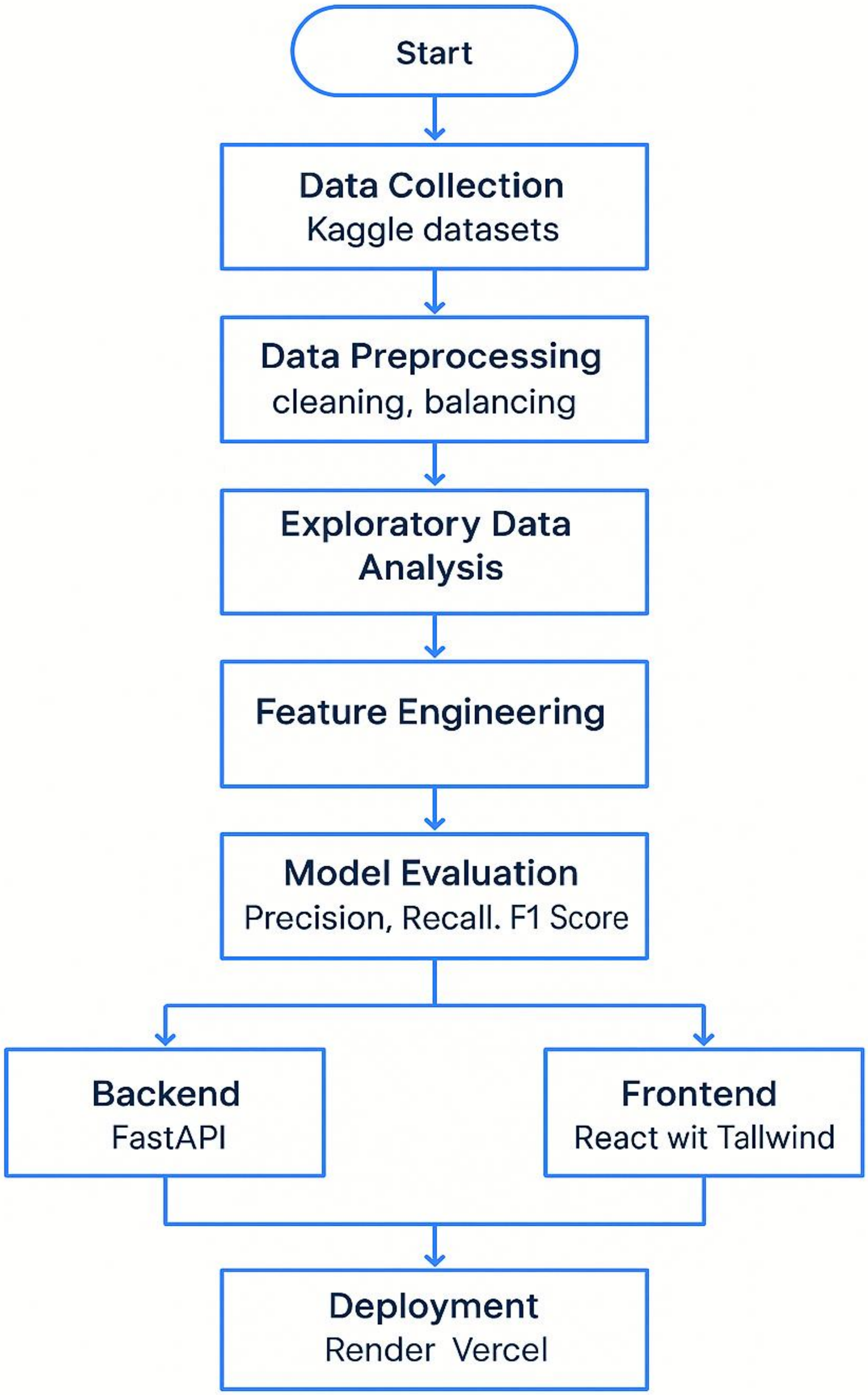
1. Problem Statement

Credit card fraud continues to cause massive financial losses globally, and traditional detection methods are not adaptive enough for modern fraud patterns. This project tackles a binary classification problem using machine learning to detect fraudulent transactions. Solving this helps improve financial security, prevent monetary loss, and protect customers in digital banking environments.

2. Project Objectives

- *Detect fraudulent transactions using classification models.*
- *Achieve high accuracy, recall, and F1-score.*
- *Build a real-time fraud detection API and frontend interface.*
- *Provide visual insights to explain prediction behavior.*
- *Objectives evolved after EDA: focus shifted to handling class imbalance and improving recall.*

3. Flowchart of the Project Workflow



4. Data Description

- ***Dataset:*** *Credit Card Fraud Detection (Kaggle)*
- ***Type:*** *Structured, tabular*
- ***Records:*** *284,807 rows, 31 features*
- *Static dataset*
- ***Target Variable:*** *Class (0 = Not Fraud, 1 = Fraud)*
- *Data Source Link:*https://www.kaggle.com/datasets/mlg-ulb/creditcardfraud?select=creditcard.csv

Transaction ID	Transaction Date	Amount	Merchant ID	Transaction Type	Location	Is Fraud
1	15:35.5	4189.27	688	refund	San Antonio	0
2	20:35.5	2659.71	109	refund	Dallas	0
3	08:35.5	784	394	purchase	New York	0
4	50:35.5	3514.4	944	purchase	Philadelphia	0

5. Data Preprocessing

- *No missing values found*
- *Duplicates checked and removed*
- *Outliers detected via boxplots and z-score*
- *Data is already scaled (PCA-transformed), so minimal normalization*
- *No categorical variables*
- *Final data checked for consistency and balanced using under sampling*

6. Exploratory Data Analysis (EDA)

- ***Univariate**: Countplot showed only 492 frauds (~0.17%).*
- ***Bivariate:** High correlation between some PCA components and Class.*
- ***Insights:** Feature V14 and V17 strongly impact prediction.*
- ***Target imbalance highlighted**: required use of stratified sampling.*

7. Feature Engineering

- *Created new binary feature: is_high_amount*
- *Added transaction time binning*
- *Removed low-variance features*
- *Feature selection with correlation and importance analysis*
- *PCA already applied in dataset, so dimensionality reduction was not repeated*

8. Model Building

- ***Models used**: Logistic Regression, Random Forest, XGBoost*
- ***Data split:** 80% train, 20% test (stratified)*
- *Random Forest and XGBoost showed best recall*
- ***Evaluation metrics:***
  - ***Accuracy**: ~99.9% (but not sufficient alone)*
  - ***Precision & Recall:** Focused on high recall due to fraud sensitivity*
  - ***F1-score:** Balanced evaluation used to compare models*

9. Visualization of Results & Model Insights

- ***Confusion matrix:** Showed low false negatives in XGBoost*
- ***ROC curve:** AUC > 0.98 for best models*
- ***Feature importance:** V14, V10, V17 were top predictors*
- ***Charts used:** bar plots, heatmaps, confusion matrix, ROC curve*

10. Tools and Technologies Used

- ***Programming Language:*** *Python*
- ***IDE:*** *Jupyter Notebook, VS Code*
- ***Libraries:*** *pandas, numpy, seaborn, matplotlib, scikit-learn, xgboost*
- ***Visualization Tools:*** *matplotlib, seaborn, plotly*
- ***Backend API:*** *FastAPI*
- ***Frontend:*** *React + Tailwind CSS*
- ***Deployment:*** *Render, Vercel*

11. Team Members and Contributions

NAME	***ROLE***	***WORK***
Jayaprakash K	*Frontend Developer*	*UI using React, styling with Tailwind*
Prajith R	*Backend Developer*	*FastAPI model integration*
Lohith R	*ML Engineer*	*Preprocessing, EDA, ML modeling*
Dinesh A	*Documentation and Presentation*	*Reports, PPT, flowcharts*
Prakadeeshwaran A	*Testing and Deployment*	*QA, Vercel + Render setup*