





Phase-2 Submission

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GitHub Repository Link:

https://github.com/Dineshkavitha2005/NM Dinesh DS.git

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

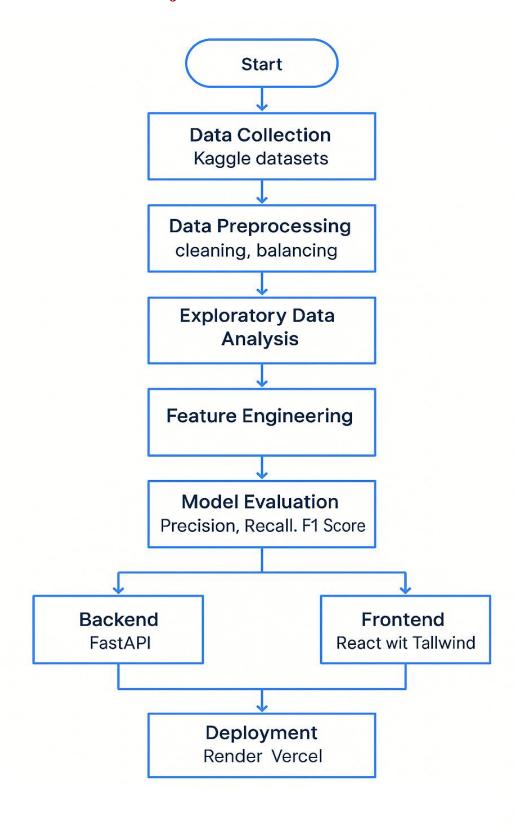
- Detect fraudulent transactions using classification models.
- Achieve high accuracy, recall, and F1-score.
- Build a real-time fraud detection API and frontend interface.
- Provide visual insights to explain prediction behavior.
- Objectives evolved after EDA: focus shifted to handling class imbalance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