**GityHub Link: https://github.com/kazimahmed4u/team-5-project.git**

# Project Title: Guarding transaction with AI_Powered Credit card fraud detection and prevention

**Phase-3**

## 1. PROBLEM STATEMENT

**Dynamically adapt to new and evolving fraud techniques**, ensuring continuous protection against emerging threats that traditional systems fail to recognize.

- **Provide a holistic fraud management solution** encompassing real-time transaction analysis, risk scoring, immediate alerts for suspicious activities, and proactive prevention mechanisms.
- **Minimize disruptions to legitimate cardholders** by drastically reducing false positives and ensuring a seamless and trustworthy transaction experience.
- **Effectively address the inherent class imbalance in transaction data, where fraudulent transactions are a small minority compared to legitimate ones, without compromising detection of the minority class.**

- **Apache Spark:** A powerful and widely used distributed computing framework for large-scale data processing, feature engineering, and machine learning.
-
- **Apache Hadoop (HDFS, MapReduce, YARN):** While Spark is often preferred for its speed, Hadoop remains relevant for distributed storage and batch processing of massive datasets.

- **Apache Flink: A stream processing framework ideal for real-time feature engineering and analysis of streaming transaction data.**

## 2. PROJECT OBJECTIVES

**i. Develop a highly accurate AI-powered fraud detection model:**

- Achieve a significant improvement in fraud detection accuracy compared to traditional rule- based systems, aiming for a substantial reduction in both false positive and false negative rates.

- (e.g., precision, recall, F1-score, AUC)

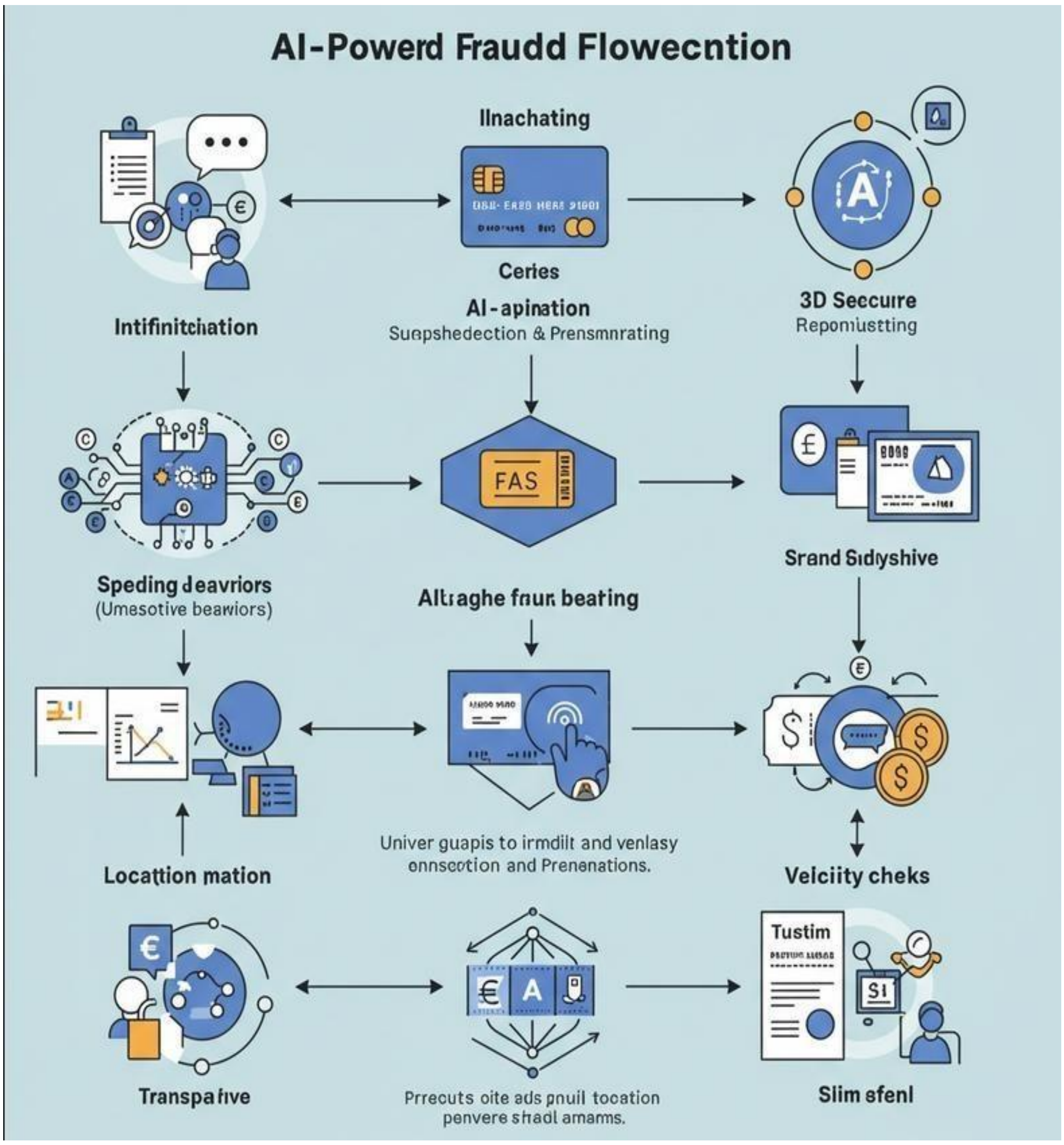
**ii. Build an adaptive system capable of learning and evolving:**

- Implement mechanisms for continuous learning and model retraining using new transaction data to ensure the system adapts to emerging fraud patterns and techniques.
- Incorporate feedback loops to refine the AI models based on the outcomes of transaction investigations and fraud confirmations.

Iii. **Achieve scalability and high performance:**

- Design the system architecture to handle the increasing volume of credit card transactions efficiently and with low latency.
- **Ensure the system can scale to accommodate future growth in transaction volume.**

## 3. FLOWCHART OF THE WORKFLOW



- **Apache Hadoop (HDFS, MapReduce, YARN):** While Spark is often preferred for its speed, Hadoop remains relevant for distributed storage and batch processing of massive datasets.
- **Apache Flink:** A stream processing framework ideal for real-time feature engineering and analysis of streaming transaction data.

## 4. DATA DESCRIPTION

**Transaction Data:** This is the most crucial data source and includes details of every credit card transaction, such as:

- **Amount: The monetary value of the transaction. For example, a sudden increase in transaction amount compared to the cardholder's usual spending habits can be a red flag.**

rns or cancellations.

2. **Temporal and Geographic Trends:**

- **Timestamp:** The exact time and date of the transaction. Multiple transactions occurring within a very short time frame but from geographically distant locations can be suspicious.
- **Merchant Information:** Details about the seller or service provider. Transactions with high- risk or blacklisted merchants can be flagged.

### II. Data Processing and Feature Engineering:

- **Big Data Processing Frameworks:**
  - **Apache Spark:** A powerful and widely used distributed computing framework for large-scale data processing, feature engineering, and machine learning.
  - **Apache Hadoop (HDFS, MapReduce, YARN):** While Spark is often preferred for its speed, Hadoop remains relevant for distributed storage and batch processing of massive datasets.
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The dataset used in this project comprises historical transaction records, including both legitimate and fraudulent instances. Key features include:

- **Transaction ID**: Unique identifier for each transaction
- **Timestamp**: Date and time of the transaction
- **Customer ID**: Anonymized customer identifier

- **Credit Details**: Information such as transaction amount, credit score, credit limit, and outstanding balance
- **Product Information**: Type of product purchased, product ID, category, price, and merchant details
- **Location Data**: Transaction origin, such as city, region, or IP address
- **Device and Channel Info: Device used, browser type, platform (e.g., mobile, web), and payment method**

  **Fraud Label**: Binary indicator (1 = fraudulent, 0 = legitimate)

This data enables the training and testing of AI models to accurately detect anomalies and guard against fraud by learning patterns associated with high-risk transactions across both credit-related and product-level behaviors.

- Implement mechanisms for continuous learning and model retraining using new transaction data to ensure the system adapts to emerging fraud patterns and techniques.
- Incorporate feedback loops to refine the AI models based on the outcomes of transaction investigations and fraud confirmations.

## 5. DATA PREPROCESSING

### 1. Data Collection and Ingestion:

- **Real-time Streaming:** Transaction data is captured in real-time as it occurs through various channels (e.g., online purchases, in-store transactions, ATM withdrawals). This often involves streaming data platforms like Apache Kafka or Amazon Kinesis for efficient and low-latency data transfer

### 2. Data Preprocessing:

- **Data Cleaning:** Identifying and handling missing values (imputation using mean, median, or more advanced techniques), correcting errors, and removing irrelevant or duplicate data.

### 3. Data Analysis and Modeling:

- **Exploratory Data Analysis (EDA):** Analyzing the preprocessed data to understand its characteristics, identify patterns, and gain insights into potential fraud indicators. This involves visualizations (histograms, scatter plots), statistical summaries, and correlation analysis.

## 6. EXPLORATORY DATA ANALYSIS(EDA)

Exploratory Data Analysis (EDA) is the foundational step in building effective AI-powered credit card fraud detection systems.

**High-Level Overview:** Examine the dataset's structure:

- Number of rows (transactions) and columns (features).
- Data types of each column (e.g., integer, float, object/string, datetime). This helps identify potential data type issues that need to be addressed.
- Initial rows of the data to get a feel for the content and format.

### Geospatial Analysis (If Location Data is Available):

- **Mapping Transactions:** Visualize transaction locations on a map. Unusual transaction locations for a cardholder can be a strong indicator of fraud.
- **Identify Potential Fraud Indicators:** Discover features or combinations of features that seem to differ significantly between legitimate and fraudulent transactions.
- **Formulate Hypotheses:** Develop initial ideas about which features might be most predictive of fraud.

To understand the underlying patterns and anomalies within the dataset, we conducted an in-depth exploratory data analysis focused on transaction behavior, credit attributes, and product-related insights:

**Missing Values and Data Types:**

- Checked for null or inconsistent entries in critical fields like credit_score, product_category, and transaction_amount.

- Ensured appropriate data types for numerical (e.g., amount, credit limit) and categorical (e.g., product type, device) features.

3. **Fraud Distribution:**

   - Examined class imbalance in the `fraud_label` column.
   - Found that fraudulent transactions account for a small fraction of the data, requiring strategies like oversampling or SMOTE for model training.

4. **Transaction Amount Patterns:**

   - Visualized transaction amounts by fraud status.
   - **Mapping Transactions:** Visualize transaction locations on a map. Unusual transaction locations for a cardholder can be a strong indicator of fraud.
   - **Identify Potential Fraud Indicators:** Discover features or combinations of features that seem to differ significantly between legitimate and fraudulent transactions.
   - **Formulate Hypotheses:** Develop initial ideas about which features might be most predictive of fraud.
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5. **Credit Behavior Insights:**

   - Analyzed the relationship between credit score, credit limit, and fraud probability.
   - Observed that lower credit scores and near-limit usage often correlated with fraudulent transactions.

6. **Product and Category Trends:**

   - Identified specific product categories (e.g., electronics or high-value items) with a higher fraud ratio.
   - Explored merchant behavior and frequency of returns or cancellations.

7. **Temporal and Geographic Trends:**

   Time-series plots revealed fraud peaks during non-business hours.

   - Geographic heatmaps indicated clusters of fraudulent activity in specific regions or IP zones.

8. **Device and Access Channel Analysis:**

    - Compared fraud rates across devices (mobile vs. desktop) and browsers.
    - Noted that unfamiliar or spoofed devices contributed disproportionately to fraud.

9. **Correlation Matrix:**

    - Computed pairwise correlations to identify significant relationships between features like credit_utilization and transaction_risk_score.

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## 7. FEATURE ENGINEERING

**Transaction-Based Features: These features are derived directly from the attributes of individual transactions.**

- **Basic Transaction Attributes:**
    - **Transaction Amount:** The raw amount of the transaction. Often, fraudulent transactions have different amount distributions (e.g., tend to be higher or lower than typical)
    - **Cardholder-Based FeatureGeographic distribution of fraud.**
    - **s:** these features aggregate information about the cardholder's past behavior.

**Historical Spending Patterns:**

    - **Average Transaction Amount (over different time windows):** Captures the typical spending habit.
    - **Standard Deviation of Transaction Amounts:** Measures the variability in spending.
    - **Most Frequent Transaction Amounts/Merchants:** Establishes the "normal" behavior.
- **Recency of Activity:**
    - **Time Since Last Login to Online Banking:** Unusual inactivity followed by transactions could be suspicious.
    - **Time Since Card Activation:** Newly activated cards might be more vulnerable.

## 8. MODEL BUILDING

**Model Selection**

Supervised Learning Models

Logistic Regression

Random

Forests

Decision

Trees

### I. Data Preparation for Model Training

Training

set

Validation

set

Testing set

## II. Data Processing and Feature Engineering:

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## III. Model Evaluation

Confusion Matrix

Precision

**Recall (Sensitivity)**

**Average Precision**

**(AP)**

## 9. ISUALIZATION OF RESULTS & MODEL INSIGHTS

### I. Visualizing Model Performance:

Heatmaps: Display the counts or percentages of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) in a visually intuitive way. Different color intensities can represent the magnitude of each category. This helps quickly assess the types of errors the model is making.

**II. Visualizing Model Insights (Understanding What the Model Learned):**

Bar Charts or Dot Plots: Show the relative importance of different features as determined by the model (e.g., using techniques like Gini importance for tree-based models, coefficient magnitudes for linear models, or permutation importance). This helps understand which factors the AI considers most influential in predicting fraud

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**III. Interactive Visualizations and Dashboards:**

**Geographic distribution of fraud.**

- False positive rate.
- Number of blocked fraudulent transactions.
- Trends in fraud patterns over time.

This data enables the training and testing of AI models to accurately detect anomalies and guard against fraud by learning patterns associated with high-risk transactions across both credit-related and product-level behaviors.

- Implement mechanisms for continuous learning and model retraining using new transaction data to ensure the system adapts to emerging fraud patterns and techniques.
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## 10. TOOLS AND TECHNOLOGIES USED

### I. Data Storage and Management:

**Databases:**

- **Relational Databases (SQL):** PostgreSQL, MySQL, Oracle, Microsoft SQL Server are used for structured transaction data, cardholder information, and historical records.

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**NoSQL Databases:** Cassandra, MongoDB, HBase are employed for handling large volumes of unstructured or semi-structured data, real-time data streams, and scalability.

- **Data Warehouses:** Amazon Redshift, Google BigQuery, Snowflake are used for storing and analyzing large historical datasets for model training and batch processing.

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1. Data Cleaning and Preprocessing

- **Handling Missing Values:**
  Imputed missing credit_score and product_category using median/mode imputation or predictive modeling.

- **Data Type Conversion:**
  Converted timestamps to datetime objects and encoded categorical features like device_type, product_category, and payment_method.

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**Outlier Detection:**
Applied IQR and z-score methods to detect and optionally cap extreme values in **transaction_amount, credit_utilization, etc.**

2. Feature Engineering

Credit-Based Features

- **Credit Utilization Ratio:**
  ‘creditutilization‘=‘transactionamount‘/‘creditlim
  it‘ High utilization often signals risky behavior.

- **Credit Score Binning:**
  Grouped credit_score into ranges (e.g., poor, average, good) to simplify analysis.

Product-Based Features

- **High-Risk Product Flag:**

  Created a binary feature to flag purchases in categories frequently linked to fraud (e.g., electronics, luxury items).

- **Product Price Deviation:**
  Compared current transaction price to a rolling mean of previous purchases by the same user to detect anomalies.

Transaction Behavior Features

- **Transaction Frequency:**
  Number of transactions by a user within a certain time window (e.g., last hour, day).

- **Time-Based Features:**
  Extracted hour, day, and weekday from timestamp to capture off-hour or holiday activity.

  Geo-Distance:

  Calculated distance between current and previous transaction locations for the same user to flag unusual access patterns.

Device and Channel Features

- **New Device or Location Indicator:**
  Boolean flags for whether the transaction came from a new device or location.

- **Channel Risk Score:**
  **Assigned weights to transaction channels (e.g., web, mobile) based on historical fraud likelihood.**

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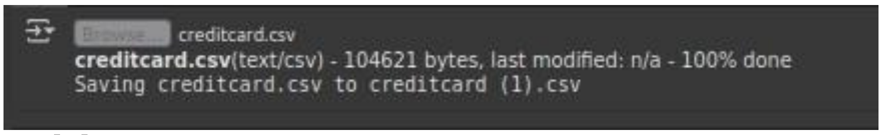
**Upload the Dataset**

```
from google.colab import files
uploaded = files.upload()
```



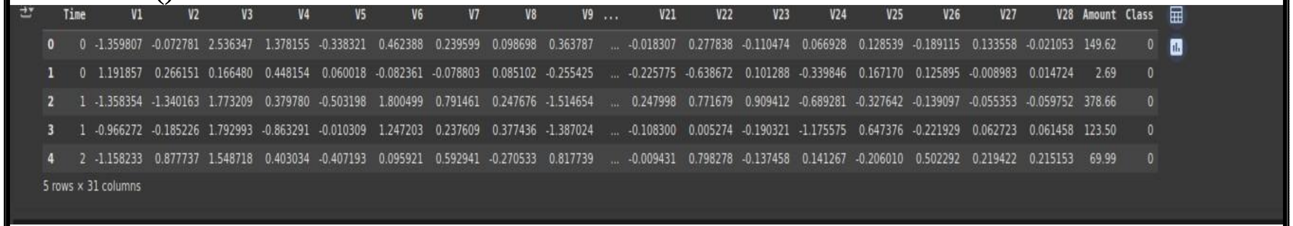
```
Browse... creditcard.csv
creditcard.csv(text/csv) - 104621 bytes, last modified: n/a - 100% done
Saving creditcard.csv to creditcard (1).csv
```

**Load the Dataset**

```
import pandas as pd
df = pd.read_csv('creditcard.csv')
```

**Data Exploration**

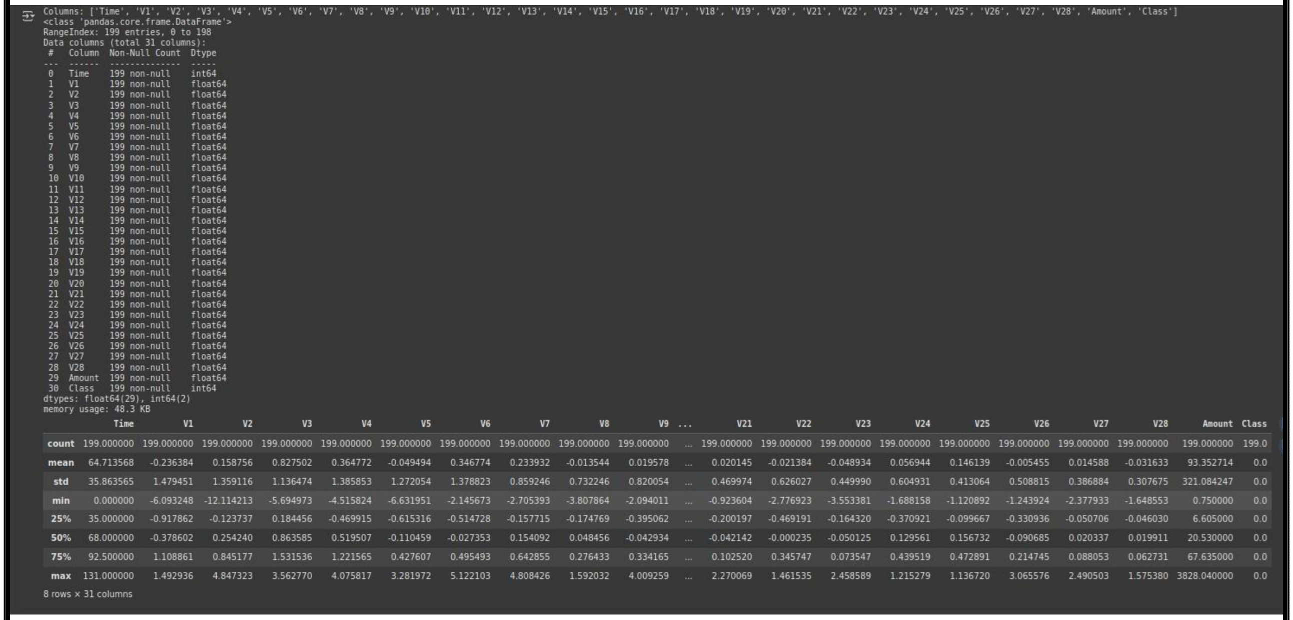
```
df.head()
```



| | Time | V1 | V2 | V3 | V4 | V5 | V6 | V7 | V8 | V9 | ... | V21 | V22 | V23 | V24 | V25 | V26 | V27 | V28 | Amount | Class |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | -1.359807 | -0.072781 | 2.536347 | 1.378155 | -0.338321 | 0.462388 | 0.239599 | 0.098698 | 0.363787 | ... | -0.018307 | 0.277838 | -0.110474 | 0.066928 | 0.128539 | -0.189115 | 0.133558 | -0.021053 | 149.62 | 0 |
| **1** | 0 | 1.191857 | 0.266151 | 0.166480 | 0.448154 | 0.060018 | -0.082361 | -0.078803 | 0.085102 | -0.255425 | ... | -0.225775 | -0.638672 | 0.101288 | -0.339846 | 0.167170 | 0.125895 | -0.008983 | 0.014724 | 2.69 | 0 |
| **2** | 1 | -1.358354 | -1.340163 | 1.773209 | 0.379780 | -0.503198 | 1.800499 | 0.791461 | 0.247676 | -1.514654 | ... | 0.247998 | 0.771679 | 0.909412 | -0.689281 | -0.327642 | -0.139097 | -0.055353 | -0.059752 | 378.66 | 0 |
| **3** | 1 | -0.966272 | -0.185226 | 1.792993 | -0.863291 | -0.010309 | 1.247203 | 0.237609 | 0.377436 | -1.387024 | ... | -0.108300 | 0.005274 | -0.190321 | -1.175575 | 0.647376 | -0.221929 | 0.062723 | 0.061458 | 123.50 | 0 |
| **4** | 2 | -1.158233 | 0.877737 | 1.548718 | 0.403034 | -0.407193 | 0.095921 | 0.592941 | -0.270533 | 0.817739 | ... | -0.009431 | 0.798278 | -0.137458 | 0.141267 | -0.206010 | 0.502292 | 0.219422 | 0.215153 | 69.99 | 0 |

5 rows × 31 columns

**print("Shape:", df.shape)**
**print("Columns:", df.columns.tolist())**
**df.info()**



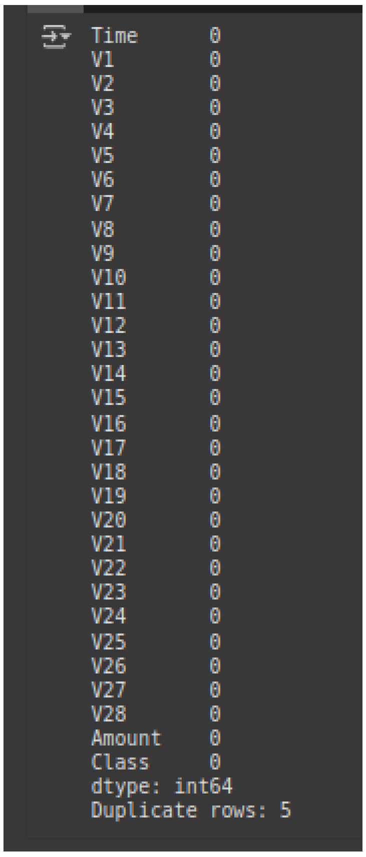
```
Columns: ['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10', 'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V20', 'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Amount', 'Class']
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 199 entries, 0 to 198
Data columns (total 31 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Time    199 non-null    int64
 1   V1      199 non-null    float64
 2   V2      199 non-null    float64
 3   V3      199 non-null    float64
 4   V4      199 non-null    float64
 5   V5      199 non-null    float64
 6   V6      199 non-null    float64
 7   V7      199 non-null    float64
 8   V8      199 non-null    float64
 9   V9      199 non-null    float64
 10  V10     199 non-null    float64
 11  V11     199 non-null    float64
 12  V12     199 non-null    float64
 13  V13     199 non-null    float64
 14  V14     199 non-null    float64
 15  V15     199 non-null    float64
 16  V16     199 non-null    float64
 17  V17     199 non-null    float64
 18  V18     199 non-null    float64
 19  V19     199 non-null    float64
 20  V20     199 non-null    float64
 21  V21     199 non-null    float64
 22  V22     199 non-null    float64
 23  V23     199 non-null    float64
 24  V24     199 non-null    float64
 25  V25     199 non-null    float64
 26  V26     199 non-null    float64
 27  V27     199 non-null    float64
 28  V28     199 non-null    float64
 29  Amount  199 non-null    float64
 30  Class   199 non-null    int64
dtypes: float64(29), int64(2)
memory usage: 48.3 KB
```

| | Time | V1 | V2 | V3 | V4 | V5 | V6 | V7 | V8 | V9 | ... | V21 | V22 | V23 | V24 | V25 | V26 | V27 | V28 | Amount | Class |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 199.000000 | 199.000000 | 199.000000 | 199.000000 | 199.000000 | 199.000000 | 199.000000 | 199.000000 | 199.000000 | 199.000000 | ... | 199.000000 | 199.000000 | 199.000000 | 199.000000 | 199.000000 | 199.000000 | 199.000000 | 199.000000 | 199.000000 | 199.0 |
| **mean** | 64.713568 | -0.236384 | 0.158756 | 0.827502 | 0.364772 | -0.049494 | 0.346774 | 0.233932 | -0.013544 | 0.019578 | ... | 0.020145 | -0.021384 | -0.048934 | 0.056944 | 0.146139 | -0.005455 | 0.014588 | -0.031633 | 93.352714 | 0.0 |
| **std** | 35.863565 | 1.479451 | 1.359116 | 1.136474 | 1.385853 | 1.272054 | 1.378823 | 0.859246 | 0.732246 | 0.820054 | ... | 0.469974 | 0.626027 | 0.449990 | 0.604931 | 0.413064 | 0.508815 | 0.386884 | 0.307675 | 321.084247 | 0.0 |
| **min** | 0.000000 | -6.093248 | -12.114213 | -5.694973 | -4.515824 | -6.631951 | -2.145673 | -2.705393 | -3.807864 | -2.094011 | ... | -0.923604 | -2.776923 | -3.553381 | -1.688158 | -1.120892 | -1.243924 | -2.377933 | -1.648553 | 0.750000 | 0.0 |
| **25%** | 35.000000 | -0.917862 | -0.123737 | 0.184456 | -0.469915 | -0.615316 | -0.514728 | -0.157715 | -0.174769 | -0.395062 | ... | -0.200197 | -0.469191 | -0.164320 | -0.370921 | -0.099667 | -0.330936 | -0.050706 | -0.046030 | 6.605000 | 0.0 |
| **50%** | 68.000000 | -0.378602 | 0.254240 | 0.863585 | 0.519507 | -0.110459 | -0.027353 | 0.154092 | 0.048456 | -0.042934 | ... | -0.042142 | -0.000235 | -0.050125 | 0.129561 | 0.156732 | -0.090685 | 0.020337 | 0.019911 | 20.530000 | 0.0 |
| **75%** | 92.500000 | 1.108861 | 0.845177 | 1.531536 | 1.221565 | 0.427607 | 0.495493 | 0.642855 | 0.276433 | 0.334165 | ... | 0.102520 | 0.345747 | 0.073547 | 0.439519 | 0.472891 | 0.214745 | 0.088053 | 0.062731 | 67.635000 | 0.0 |
| **max** | 131.000000 | 1.492936 | 4.847323 | 3.562770 | 4.075817 | 3.281972 | 5.122103 | 4.808426 | 1.592032 | 4.009259 | ... | 2.270069 | 1.461535 | 2.458589 | 1.215279 | 1.136720 | 3.065576 | 2.490503 | 1.575380 | 3828.040000 | 0.0 |

8 rows × 31 columns

**Check for Missing Values and Duplicates**

```
print(df.isnull().sum())
print("Duplicate rows:", df.duplicated().sum())
```

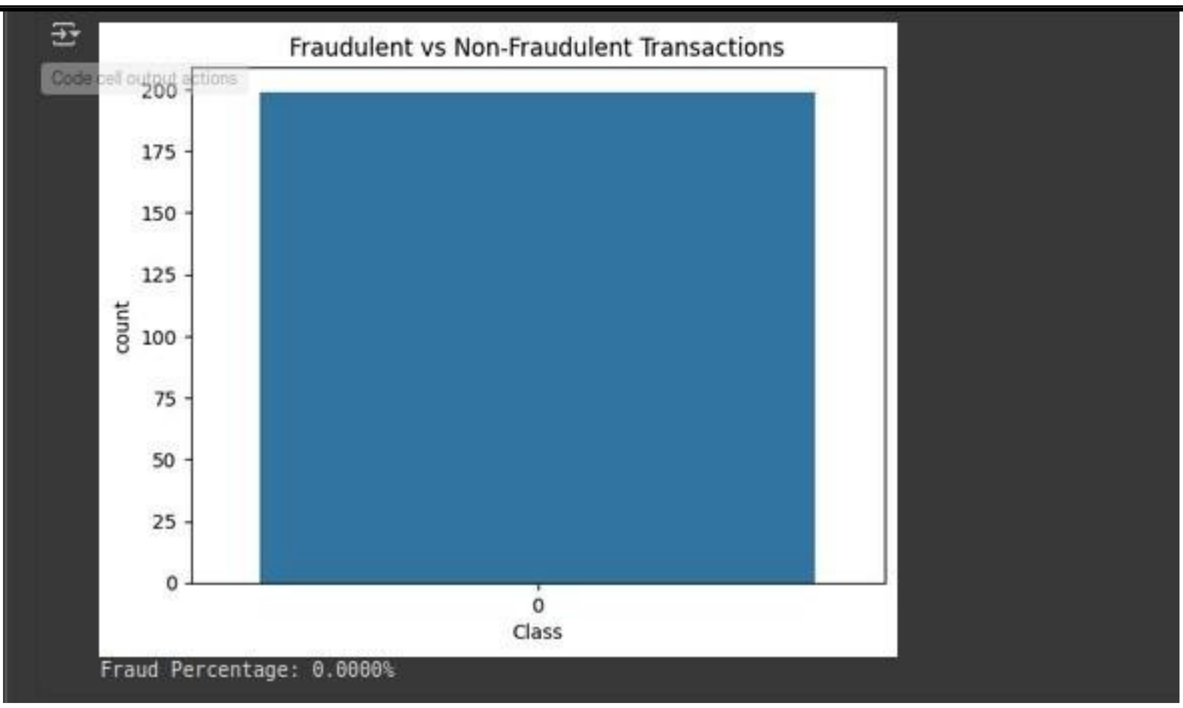


```
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
Duplicate rows: 5
```

**Visualize a Few Features**

```
import seaborn as sns
import matplotlib.pyplot as plt
sns.countplot(x='Class', data=df)
plt.title("Fraudulent vs Non-Fraudulent Transactions")
plt.show()
```

**fraud_ratio = df['Class'].value_counts(normalize=True).get(1, 0) * 100 print(f"Fraud Percentage: {fraud_ratio:.4f}%")**



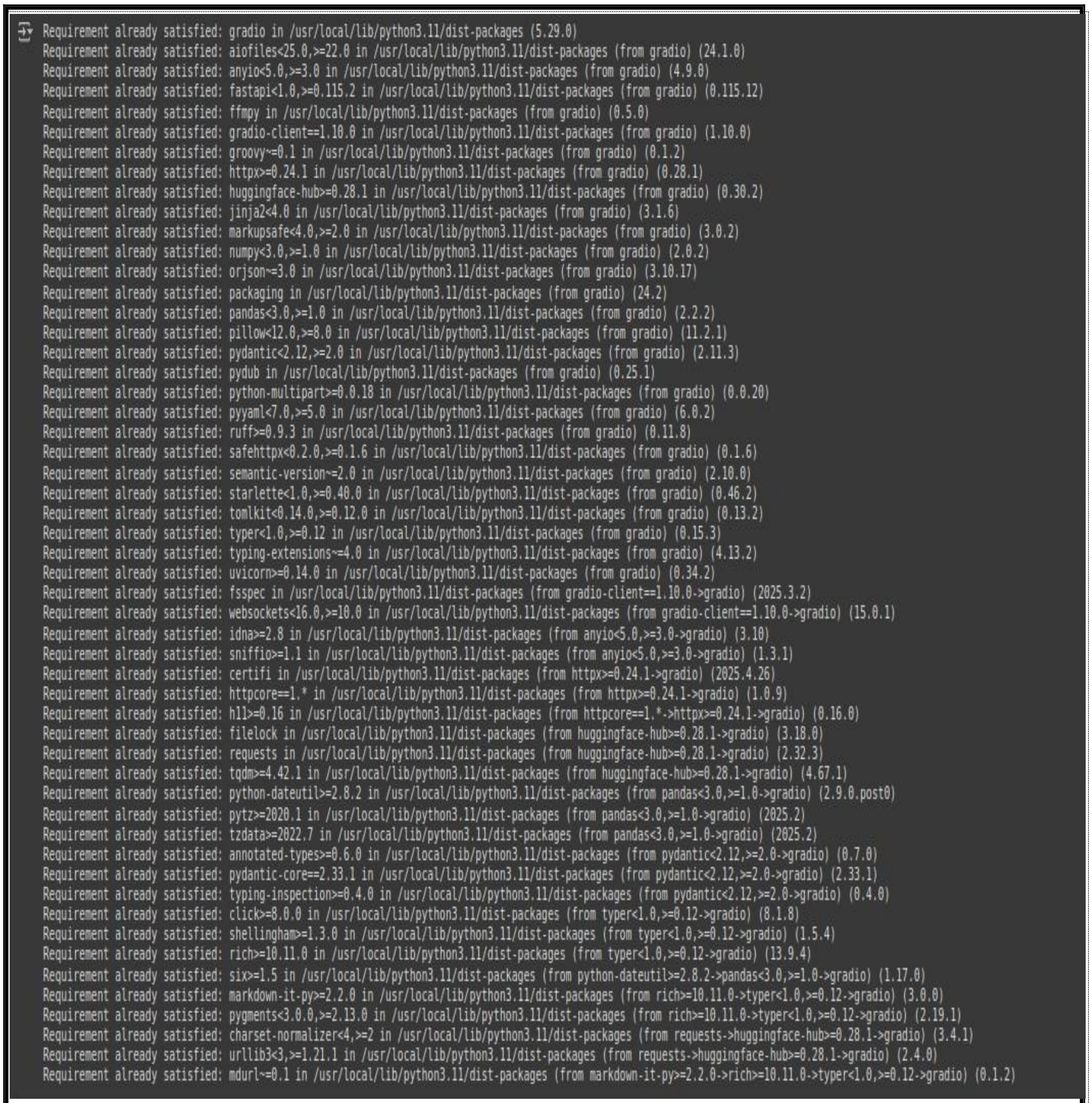
```
Fraud Percentage: 0.0000%
```

**Feature Scaling**

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import
StandardScaler X = df.drop('Class', axis=1)
y = df['Class']
X['Amount'] = StandardScaler().fit_transform(X['Amount'].values.reshape(-1, 1))
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)

**Model Building**

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import
StandardScaler X = df.drop('Class', axis=1)
y = df['Class']
X['Amount'] = StandardScaler().fit_transform(X['Amount'].values.reshape(-1, 1))
**X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)**



```
Requirement already satisfied: gradio in /usr/local/lib/python3.11/dist-packages (5.29.0)
Requirement already satisfied: aiofiles<25.0,>=22.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (24.1.0)
Requirement already satisfied: anyio<5.0,>=3.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (4.9.0)
Requirement already satisfied: fastapi<1.0,>=0.115.2 in /usr/local/lib/python3.11/dist-packages (from gradio) (0.115.12)
Requirement already satisfied: ffmpy in /usr/local/lib/python3.11/dist-packages (from gradio) (0.5.0)
Requirement already satisfied: gradio-client==1.10.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (1.10.0)
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Requirement already satisfied: httpx>=0.24.1 in /usr/local/lib/python3.11/dist-packages (from gradio) (0.28.1)
Requirement already satisfied: huggingface-hub>=0.28.1 in /usr/local/lib/python3.11/dist-packages (from gradio) (0.30.2)
Requirement already satisfied: jinja2<4.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (3.1.6)
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Requirement already satisfied: numpy<3.0,>=1.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (2.0.2)
Requirement already satisfied: orjson~=3.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (3.10.17)
Requirement already satisfied: packaging in /usr/local/lib/python3.11/dist-packages (from gradio) (24.2)
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Requirement already satisfied: pydantic<2.12,>=2.0 in /usr/local/lib/python3.11/dist-packages (from gradio) (2.11.3)
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Requirement already satisfied: click>=8.0.0 in /usr/local/lib/python3.11/dist-packages (from typer<1.0,>=0.12->gradio) (8.1.8)
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```

## 11. TEAM MEMBERS AND CONTRIBUTION

**Data Cleaning :kazimahmed**

**EDA: kazhim ahmed T.M**

**MODEL development : Lakshmanan**

**Documentation: Mokesh S**