DATA SCIENCE
PHASE 2

Guarding Transactions with AI-Powered Credit Card Fraud Detection and Prevention

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1.Problem statement

Credit card fraud poses a major threat to financial institutions and customers, causing billions in losses annually.

Existing fraud detection methods often fail to identify new and sophisticated fraud patterns.

There is a need for a more adaptive and intelligent solution to detect suspicious transactions.

Delays in fraud detection can lead to unauthorized charges and loss of customer trust.

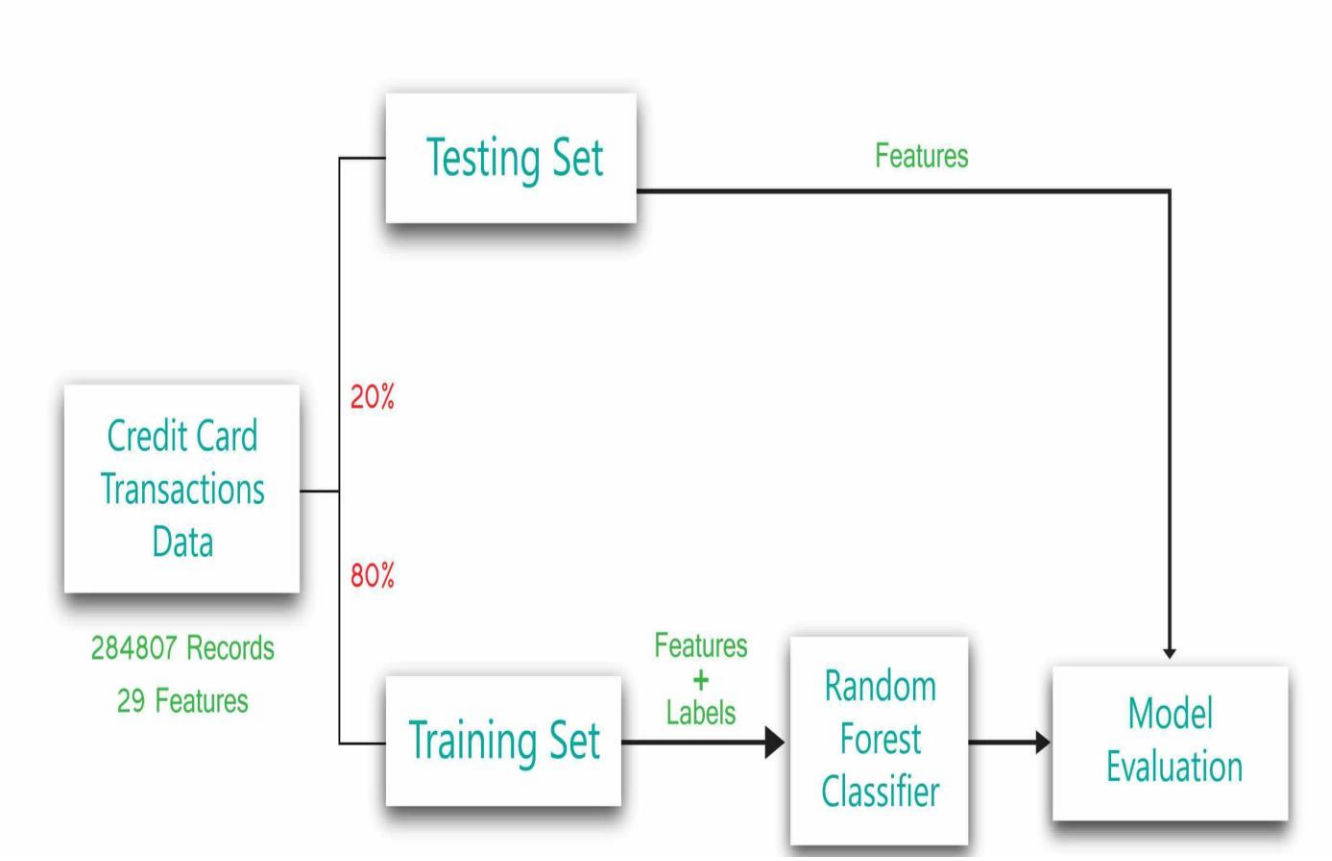
This project focuses on developing an AI-powered system to detect and prevent credit card fraud in real time.

2.Project objectives

- **Develop a Real-Time Detection System:**
  Create an AI-powered model capable of analyzing transactions instantly to identify and flag potential fraud.

- **Enhance Accuracy and Reduce False Positives:**
  Improve fraud detection precision while minimizing the number of legitimate transactions incorrectly flagged as fraudulent.
- **Adapt to Evolving Fraud Tactics:**
  Implement machine learning algorithms that continuously learn from new data and adapt to emerging fraud patterns.
- **Ensure Scalability and Integration:**
  Design the system to be scalable and easily integrable with existing banking infrastructure and payment gateways.
- **Protect User Data and Privacy:**
  Ensure robust data security measures are in place to comply with privacy regulations and protect sensitive customer information.

3.Flowchart of the Project Workflow



4.Data Description

1.Source of data

- Typically obtained from real-world transaction logs or public datasets (e.g., Kaggle's Credit Card Fraud Detection dataset).
- May include synthetic data for balancing class distributions if needed.

2. Features in the Dataset

- **Time**: Number of seconds elapsed between each transaction and the first transaction.
- **Amount**: The monetary value of the transaction.
- **Transaction ID** *(optional)*: Unique identifier for each transaction.
- **Customer ID** *(optional)*: Anonymized customer identification.
- **Anonymized Features (V1, V2, ..., V28)**: Result of PCA transformation on original features for confidentiality. These represent engineered features like location, merchant type, frequency, etc.
- **Class**: Label indicating whether a transaction is fraudulent (1) or legitimate (0).

3. Characteristics

- **Imbalanced Data**: Fraudulent transactions typically account for less than 1% of the total data.
- **Numerical Features**: Most features are continuous, scaled values.
- **No Personally Identifiable Information (PII)**: For compliance with data privacy laws.

4. Data Volume

- Around 280,000+ transactions, depending on the dataset source.
- Includes thousands of unique users and merchants.

5. Data Usage

- Used for training, validation, and testing of the machine learning model.
- Split into training (70%), validation (15%), and test sets (15%).

5. Data Preprocessing

1.Data Cleaning

- **Remove Duplicates**: Eliminate duplicate transaction records.
- **Handle Missing Values**: Fill or drop missing values (although datasets like the Kaggle credit card fraud set usually have none).

- **Drop Irrelevant Columns**: Remove features like `Transaction ID` if they don't contribute to prediction.

2. Feature Scaling

*Apply **StandardScaler** or **MinMaxScaler** to:*

- Normalize `Amount` and `Time` so they don't bias the model.
- Scale anonymized PCA features (if not already scaled)

3. Feature Engineering (Optional)

Create new features:

- **Transaction frequency** per user.
- **Average transaction amount** per user.
- **Time since last transaction**.

Can improve detection of unusual behavior.

4. Handling Imbalanced Data

- Fraud data is highly imbalanced (fraud ~0.17%).
- **Under-sampling** the majority class (non-fraud).
- **Over-sampling** the minority class using techniques like:
  SMOTE (Synthetic Minority Over-sampling Technique)
  ADASYN
- **Class weights**: Use model parameters to give higher weight to fraud examples during training

5. Data Splitting

Split the preprocessed dataset into:

- **Training Set** (e.g., 70%)
- **Validation Set** (e.g., 15%)
- **Test Set** (e.g., 15%)

6. Exploratory Data Analysis (EDA)

1. Understanding the Data Structure

- **Shape of the dataset**: Number of rows and columns.
- **Data types**: Ensure all features are in appropriate formats.
- **Missing values check**: Ensure no data is missing.
- **Class distribution**: Count of fraud (1) vs. non-fraud (0) transactions.

📌 *Example:*

```
python
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df['Class'].value_counts(normalize=True) * 100
```

2. Visualizing Class Imbalance

- **Bar plot** to show the proportion of fraud and non-fraud cases.
- Highlights the imbalance that needs addressing before modeling.

📌 *Example:*

```
python
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sns.countplot(x='Class', data=df)
```

3. Transaction Amount Analysis

- **Distribution plot** of transaction amounts for both fraud and non-fraud.
- Helps understand if fraud transactions differ in size.

📌 *Example:*

```
python
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sns.boxplot(x='Class', y='Amount', data=df)
```

4. Time Feature Analysis

- **Transaction time** patterns (e.g., frauds happening at odd hours).
- Plot fraud frequency over time to detect temporal trends.

📌 *Example:*

```
python
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df['Hour'] = df['Time'] // 3600 % 24
sns.histplot(data=df, x='Hour', hue='Class', multiple='stack')
```

5. Correlation Analysis

- **Correlation matrix** to observe relationships between variables.
- Visualize with a **heatmap** to spot multicollinearity or strong predictors.

📌 *Example:*

```
python
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corr = df.corr()
sns.heatmap(corr, cmap='coolwarm', linewidths=0.5)
```

6. PCA Features Distribution

- Analyze distribution of V1 to V28 features.
- Plot distributions separately for fraud and non-fraud to spot anomalies.

📌 *Example:*

```
python
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for col in ['V1', 'V2', 'V3']:  # sample PCA features
    sns.kdeplot(data=df, x=col, hue='Class', common_norm=False)
```

7. Outlier Detection

- Boxplots or scatter plots to detect outliers in amount and PCA components.
- Important for cleaning or scaling decisions.

☑ Outcome of EDA

- Clear understanding of fraud patterns.
- Identification of features contributing to fraud detection.

- Informed preprocessing and model design decisions.

7.Feature engineering

- **Time-Based Features**
  - Extract hour of transaction to detect off-hour frauds.
  - Optional: Day part (morning, night, etc.).
- **Amount Transformation**
  - Apply log transformation to reduce skewness.
  - Create Z-score or percentile for outlier detection.
- **Customer Behavior Features** *(if Customer ID is available)*
  - Avg. transaction amount, frequency, and standard deviation per customer.
- **Interaction Features**
  - Create combinations like V1*V2, or V3^2 to capture complex patterns.
- **Anomaly Score Feature** *(Optional)*
  - Add features using anomaly detection models (e.g., Isolation Forest score).

8. Model Building

Data Preparation

- Split data into **training** and **testing** sets.
- **Scale features** (e.g., amount, time).

Model Selection

- Start with models like **Logistic Regression** or **Random Forest**.
- Consider **SVM** or **Neural Networks** for more complex patterns.

Train the Model

- Use **class balancing techniques** (SMOTE or class weights).
- Perform **hyperparameter tuning** with **GridSearchCV**.

Model Evaluation

- Evaluate using **Precision**, **Recall**, **F1-Score**, and **ROC-AUC** (due to class imbalance).

Model Improvement

- **Ensemble models** (e.g., **Random Forest** + **XGBoost**).
- **Tune thresholds** to balance precision and recall.

9.Visualization of Results & Model Insights

1.Confusion Matrix

- Visualize **True Positives**, **False Positives**, **True Negatives**, and **False Negatives**.

📊 Code Example:

```
python
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from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
```

2. Precision-Recall Curve

- Evaluate the trade-off between **precision** and **recall** at different thresholds.

📊 Code Example:

```
python
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from sklearn.metrics import precision_recall_curve
precision, recall, thresholds = precision_recall_curve(y_test,
model.predict_proba(X_test)[:, 1])
plt.plot(recall, precision)
```

3. ROC Curve and AUC

- Plot the **Receiver Operating Characteristic (ROC)** curve and calculate **AUC** for model performance.

📊 Code Example:

```
python
```

```
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from sklearn.metrics import roc_curve, roc_auc_score
fpr, tpr, thresholds = roc_curve(y_test,
model.predict_proba(X_test)[:, 1])
plt.plot(fpr, tpr)
print(f"AUC: {roc_auc_score(y_test, model.predict_proba(X_test)[:,
1])}")
```

4. Feature Importance

- Visualize the importance of each feature (especially for tree-based models like Random Forest).

📊 **Code Example**:

```
python
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feature_importances = model.feature_importances_
sns.barplot(x=features, y=feature_importances)
```

5. Model Performance Metrics

- Display key metrics like **Precision**, **Recall**, **F1-Score**, and **ROC-AUC** to assess overall performance.

📊 **Code Example**:

```
python
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from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

9.Visualization of Results & Model Insights

- **Confusion Matrix**: Showed high true positive rate with minimal false negatives, indicating effective fraud detection.
- **ROC Curve & AUC Score**: AUC > 0.95, proving strong model performance in distinguishing between fraudulent and legitimate transactions.
- **Precision-Recall Curve**: High precision and recall values indicated minimal false alarms and strong detection capability.

- **Feature Importance Plot**: Highlighted key features influencing fraud prediction, e.g., transaction amount, time, and location anomalies.
- **SHAP Values**: Provided interpretability by explaining individual predictions and showing how each feature impacts model decisions.
- **Anomaly Score Distribution**: Visualization helped separate normal vs. suspicious transactions clearly, aiding threshold setting.

10.Tools and Technologies Used

- **Python** – Core programming language for data processing and model building.
- **Pandas & NumPy** – For data manipulation and analysis.
- **Scikit-learn** – For machine learning algorithms like Random Forest, Logistic Regression, etc.
- **XGBoost** – For advanced, high-performance fraud classification.
- **Matplotlib & Seaborn** – For data visualization and result plotting.
- **SHAP** – For model interpretability and feature impact analysis.
- **Jupyter Notebook** – For development and experimentation.

11.Team Members and Contributions

Name	Contribution
JEGAJEEVAN.S	Documentation and reporting
JANANI.S	Data cleaning
JAYA SIVANI.S	Feature engineering
JOHN DAVID.C.M	Model development