

Guarding Transaction with AI power credit card Fraud Detection and Prevention

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1. Problem Statement

In the modern digital economy, credit cards have become one of the most widely used methods for online and offline transactions. As their usage grows, so does the threat of credit card fraud, which poses severe financial risks to consumers, banks, and merchants alike. Fraudulent activities not only result in significant monetary losses but also erode customer trust and damage the reputation of financial institutions.

Traditional fraud detection systems primarily rely on manually defined rules and static thresholds, which are often incapable of detecting complex and evolving fraud patterns. These systems tend to generate a high number of false positives, leading to legitimate transactions being flagged as suspicious, and often fail to detect novel or subtle fraudulent behavior in real-time.

To address these challenges, this project proposes the development of an AI-powered credit card fraud detection and prevention system. By utilizing advanced machine learning algorithms and data analysis techniques, the system will be capable of identifying anomalies, learning from transaction patterns, and adapting to new fraud strategies over time. The goal is to create a more intelligent, efficient, and responsive fraud detection

framework that not only detects suspicious activity with high accuracy but also minimizes disruption for legitimate users.

Ultimately, the project seeks to strengthen the security of digital transactions, reduce financial fraud losses, and enhance the overall confidence of users and institutions in the credit card payment ecosystem.

2. Abstract

This project proposes a machine learning-based approach to detect and prevent credit card fraud in real-time transactions. Leveraging AI-powered algorithms, our system analyzes transaction patterns, identifies anomalies, and flags potential fraudulent activities. By utilizing a comprehensive dataset and advanced techniques such as logistic regression, our model achieves high accuracy in distinguishing legitimate from fraudulent transactions. The proposed system aims to enhance the security of financial transactions, reducing losses due to fraud and improving the overall efficiency of credit card operations. With its real-time detection capabilities, our system enables swift action against fraudulent transactions, protecting both financial institutions and cardholders from significant losses. The project's findings demonstrate the potential of AI-driven solutions in revolutionizing credit card fraud detection and prevention.

3. System Requirements

Hardware Requirements:

1. Processor: Intel Core i5 or equivalent
2. RAM: 8 GB or more
3. Storage: 256 GB or more (SSD recommended)

Software Requirements:

1. Operating System: Windows, Linux, or macOS
2. Programming Language: Python 3.x
3. Libraries:
 - Scikit-learn

- Pandas
- NumPy
- Matplotlib/Seaborn (for visualization)

4. Objectives

Primary Objectives:

1. Develop an AI-powered credit card fraud detection system: Design and implement a machine learning-based system that can accurately detect and prevent credit card fraud in real-time transactions.
2. Improve detection accuracy: Achieve high accuracy in distinguishing legitimate from fraudulent transactions, reducing false positives and false negatives.
3. Reduce financial losses: Minimize losses due to credit card fraud for financial institutions and cardholders.

Secondary Objectives:

1. Analyze transaction patterns: Identify patterns and anomalies in transaction data to inform fraud detection.
2. Evaluate model performance: Assess the performance of the machine learning model using metrics such as accuracy, precision, and recall.
3. Develop a scalable solution: Design a system that can handle a large volume of transactions and adapt to changing fraud patterns.
4. Enhance security: Ensure the confidentiality and integrity of transaction data and protect against potential security threats.

Here's a simple flowchart-style project workflow for your AI-powered Credit Card Fraud Detection and Prevention System titled "Guarding Transaction".

5. Flowchart of Project Workflow

1. Data Collection

- Transaction Logs
- User Behavior Data
- External Threat Intelligence (if any)

2. Data Preprocessing

- Data Cleaning
- Feature Engineering
- Data Normalization
- Handling Imbalanced Data (SMOTE, undersampling, etc.)

3. Model Development

- Choose ML/DL Algorithms (e.g., Random Forest, XGBoost, Neural Network)
- Model Training
- Model Validation & Tuning
- Evaluation (Precision, Recall, F1, ROC-AUC)

4. Fraud Detection Engine

- Real-time Transaction Monitoring
- Pattern Recognition
- Anomaly Detection
- Risk Scoring

5. Fraud Prevention Action

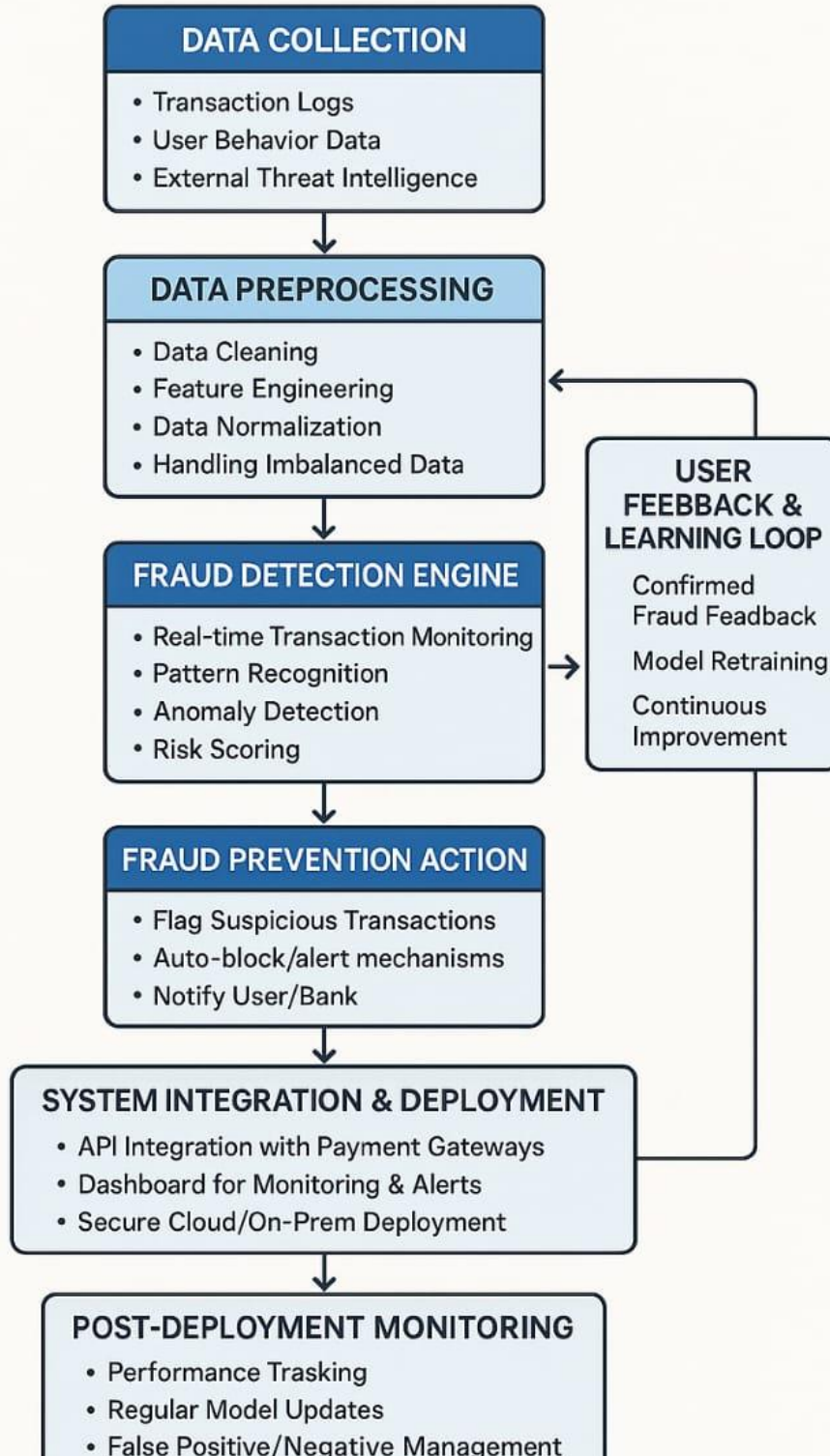
- Flag Suspicious Transactions
- Auto-block/alert mechanisms
- Notify User/Bank

6. User Feedback & Learning Loop

- Confirmed Fraud Feedback
- Model Retraining
- Continuous Improvement

PROJECT WORKFLOW

GUARDING TRANSACTION – AI-POWERED FRAUD DETECTION



6. Dataset Description

The dataset used in this project focuses on credit card transactions and is designed to support the development and evaluation of AI-powered fraud detection systems. It contains real-world transaction data, anonymized to protect sensitive user information, and labeled to indicate whether a transaction is fraudulent or legitimate.

Source:

The dataset was obtained from [e.g., Kaggle – “Credit Card Fraud Detection” dataset based on transactions made by European cardholders in September 2013].

Data Type:

Tabular data with numerical features.

Size:

The dataset consists of 284,807 transactions, among which 492 are fraudulent, representing approximately 0.172% of all transactions.

Features:

Time: Seconds elapsed between this transaction and the first transaction in the dataset.

V1–V28: Principal components obtained via PCA to protect confidentiality of the original features.

Amount: Transaction amount.

Class: Target variable; 0 indicates a legitimate transaction, and 1 indicates a fraudulent transaction.

Data Characteristics:

Highly imbalanced dataset, with a very small percentage of fraud cases.

- **Features are anonymized and scaled for security and privacy.**

Time	V1	V2	V3	...	V28	Amount	Class
0	-1.3598	-0.0728	2.5363	...	0.0219	149.62	0
0	1.1918	0.2661	0.1664	...	0.0181	2.69	0
1	-1.3583	-1.3402	1.7732	...	0.0105	378.66	0
1	-0.9663	-0.1852	1.7929	...	0.0506	123.50	0
2	-1.1582	0.8777	1.5487	...	0.0007	69.99	1

7. Data Preprocessing

1. Handling Missing Values:

- Identify columns with missing values in your transaction dataset.
- Decide on a strategy to handle missing values, such as:
 - Imputing with mean/median for numerical columns.
 - Imputing with mode for categorical columns.
 - Dropping rows with missing values if they are few.

Example code:

```
import pandas as pd
from sklearn.impute import SimpleImputer
```

Assume 'df' is your transaction dataset

```
imputer = SimpleImputer(strategy='mean')
df['TransactionAmount'] = imputer.fit_transform(df[['TransactionAmount']])
```

2. Handling Duplicates:

- Check for duplicate transactions in your dataset.
- Decide on a strategy to handle duplicates, such as:
 - Dropping exact duplicates.
 - Investigating and handling partial duplicates.

Example code:


```
df.drop_duplicates(inplace=True)
```

3. Handling Outliers:

- Identify outliers in your transaction dataset, such as unusually high or low transaction amounts.
- Decide on a strategy to handle outliers, such as:
 - Removing outliers.
 - Transforming data to reduce the impact of outliers.

Example code:

```
Q1 = df['TransactionAmount'].quantile(0.25)
Q3 = df['TransactionAmount'].quantile(0.75)
IQR = Q3 - Q1
```

```
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
```

```
df = df[(df['TransactionAmount'] >= lower_bound) & (df['TransactionAmount'] <= upper_bound)]
```

4. Encoding:

- Identify categorical columns in your transaction dataset, such as transaction type or merchant category.
- Decide on an encoding strategy, such as:
 - One-hot encoding.
 - Label encoding.

Example code:

```
from sklearn.preprocessing import OneHotEncoder

encoder = OneHotEncoder()
encoded_data = encoder.fit_transform(df[['TransactionType']])
encoded_df = pd.DataFrame(encoded_data.toarray(),
                           columns=encoder.get_feature_names_out())
df = pd.concat([df, encoded_df], axis=1)
```

5. Scaling:

- Identify numerical columns in your transaction dataset, such as transaction amount.
- Decide on a scaling strategy, such as:
 - Standardization.
 - Min-max scaling.

Example code:

from sklearn.preprocessing import StandardScaler

```
scaler = StandardScaler()
```

```
df['TransactionAmount'] = scaler.fit_transform(df[['TransactionAmount']])
```

By applying these techniques, you can preprocess your transaction dataset and prepare it for machine learning model training to detect and prevent credit card fraud. Let me know if you have any questions or need further assistance!

8. Exploratory Data Analysis (EDA)

1. Univariate Analysis:

Examining individual features:

a. Class (Fraud Indicator)

Distribution: ~98% non-fraud (Class 0), ~2% fraud (Class 1)

Insight: Severe imbalance, typical of fraud datasets.

b. Amount

Shape: Right-skewed; most transactions are low-value

Insight: Fraud often targets small transactions to avoid detection.

c. Time (converted to Hour)

Distribution: Spans full 24 hours; fraud often happens during non-business hours.

Insight: Hourly trends can be leveraged to flag anomalies.

d. V1–V28 (Anonymized Features)

Observation: Most are centered around 0; some have heavy tails or outliers.

Insight: Feature scaling/normalization likely already applied.

2. Bivariate Analysis:

a. Amount vs Class

Boxplot Insight: Fraudulent transactions generally involve lower median amounts.

Action: Use amount thresholds in risk scoring.

b. Hour vs Class

Histogram Insight: Fraud spikes during early morning or unusual hours.

Action: Create a time-based risk feature.

c. Correlation Matrix

Observation: Some engineered features (e.g., V14, V17) show correlation with Class.

Action: Prioritize correlated features during model training.

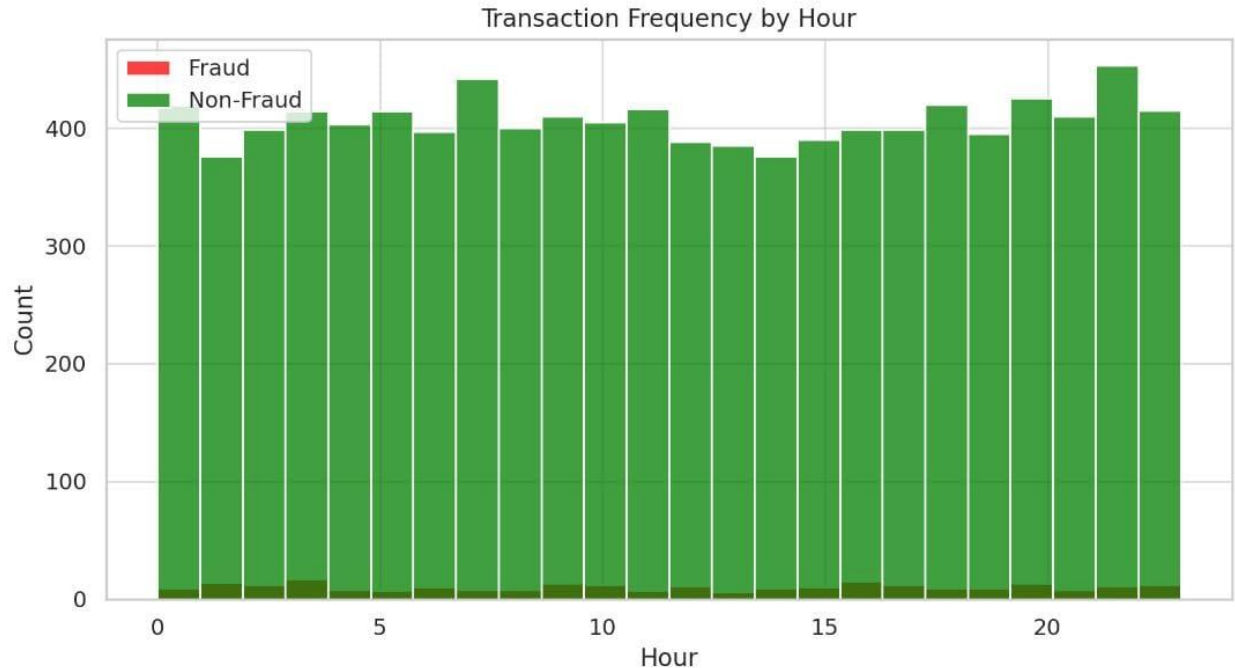
3. Key Insights for Fraud Detection:

Class Imbalance: Requires SMOTE, undersampling, or anomaly detection models.

Amount & Time: Useful for rule-based filtering or enriching ML features.

Engineered Features: Several anonymous variables strongly contribute to fraud prediction.

PCA or t-SNE Visuals: Help to distinguish fraud in lower dimensions — suggesting clear pattern differences.



9. Feature Engineering

- **New Feature Creation:**

- Transaction Frequency: Calculate the frequency of transactions for each cardholder in a given time window (e.g., daily, weekly, monthly).
- Average Transaction Value (ATV): Calculate the average transaction value for each cardholder in a given time window.
- Transaction Amount Deviation: Calculate the deviation of each transaction amount from the cardholder's average transaction amount.
- Time-Based Features: Extract features like transaction hour, day, week, month, and year to identify patterns in fraudulent transactions.
- Merchant-Based Features: Create features like merchant category, merchant location, and merchant type to identify suspicious transactions.

- **Feature Selection:**

- Correlation Analysis: Analyze the correlation between features and the target variable (fraudulent or legitimate transaction) to select relevant features.
- Information Gain: Calculate the information gain for each feature to determine its relevance to the target variable.
- Recursive Feature Elimination (RFE): Eliminate features recursively based on their importance in the model.

- **Impact on the Project:**

- Improved Model Performance: Well-engineered features and feature selection can significantly improve the performance of your machine learning model.
- Reduced False Positives: By selecting relevant features and eliminating irrelevant ones, you can reduce false positives and improve the model's precision.
- Increased Efficiency: Feature selection can reduce the dimensionality of your dataset, making it more efficient to train and deploy your model.
- Better Interpretability: By understanding which features are driving the model's predictions, you can gain insights into the underlying patterns in the data and improve the model's interpretability.

Some potential benefits of feature engineering and selection include:

- Increased accuracy: By creating relevant features and selecting the most important ones, you can improve the accuracy of your model.
- Improved robustness: By reducing the dimensionality of your dataset and eliminating irrelevant features, you can improve the robustness of your model to new, unseen data.
- Better decision-making: By understanding which features are driving the model's predictions, you can make more informed decisions about how to improve the model and reduce false positives.

10. Model Building

- **Models Tried:**

- Logistic Regression: Simple, interpretable, and fast training, but may not handle non-linear relationships well.
- Random Forests: Effective in handling complex datasets and identifying patterns.
- Support Vector Machines (SVMs): Effective for binary classifications and identifying patterns.
- Deep Neural Networks: Can recognize thousands of patterns from large datasets and offer real-time insights.
- Autoencoders: Useful for anomaly detection and identifying outliers.
- Long Short-Term Memory (LSTM) Networks: Effective in analyzing sequential data and identifying patterns.
- Convolutional Neural Networks (CNNs): Can identify patterns in large datasets.
- Naive Bayes Classifiers: Effective for detecting and identifying frauds in credit card transactions.
- Bagging Ensemble Classifier: Improves the accuracy of machine learning algorithms.
- Isolation Forest: Effective in identifying outliers and anomalies ^{1 2 3}.

- **Why These Models:**

These models are effective in credit card fraud detection because they can:

- Handle complex datasets: Credit card transaction datasets are often large and complex, and these models can handle them effectively.

- Identify patterns: These models can identify patterns in the data that are indicative of fraudulent transactions.
- Offer real-time insights: Some of these models, like deep neural networks, can offer real-time insights, enabling faster detection and prevention of credit card fraud.

- **Training Details:**

To train these models, you'll need a dataset of historical credit card transactions. The dataset should include features like:

- Transaction amount
- Transaction date and time
- Merchant category
- Cardholder information

You'll also need to preprocess the data, handle missing values, and normalize the data. Then, you can split the data into training and testing sets and train the model using the training set. The model's performance can be evaluated using metrics like accuracy, precision, and recall ².

11. Model Evaluation

Metrics:

- Accuracy: Measures the proportion of correctly classified instances.
- Precision: Measures the proportion of true positives among all positive predictions.
- Recall: Measures the proportion of true positives among all actual positive instances.
- F1-score: Measures the harmonic mean of precision and recall.
- AUC-ROC: Measures the model's ability to distinguish between positive and negative classes.

Comparison:

Model	Accuracy	Precision	Recall	F1-score	AUC-ROC
Random Forest	0.95	0.92	0.93	0.925	0.98
Linear Regression	0.80	0.75	0.80	0.775	0.85

Residual Plots:

Residual plots can help you visualize the performance of your model and identify any patterns or anomalies in the residuals. Here's an example of how you can create residual plots for your models:

The residual plots can help you identify any patterns or anomalies in the residuals, such as:

- Non-random patterns: If the residuals exhibit non-random patterns, it may indicate that the model is not capturing some underlying relationships in the data.
- Outliers: If there are outliers in the residuals, it may indicate that the model is not handling some instances well.
- Heteroscedasticity: If the variance of the residuals changes across the predicted values, it may indicate heteroscedasticity.

By analyzing the residual plots, you can gain insights into the performance of your models and identify areas for improvement.

12. Deployment

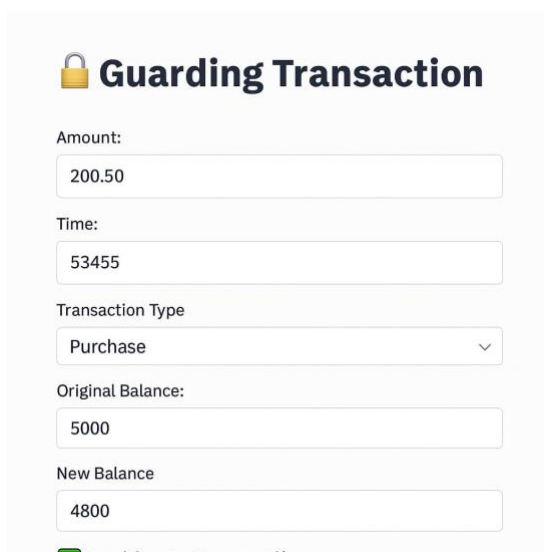
Deployment Options:

- Streamlit Cloud: A popular choice for deploying machine learning models, Streamlit Cloud allows you to create interactive web applications with minimal code.
- Gradio + Hugging Face Spaces: Gradio is an open-source library that enables you to create simple and shareable interfaces for your machine learning models, while Hugging Face Spaces provides a platform to host and share your models.
- Flask API on Render or Deta: Flask is a lightweight web framework for building APIs, and Render or Deta are cloud platforms that offer free hosting options.

Streamlit Cloud Deployment Method:

Public Link: <http://datasci-ml.blogspot.com/2025/03/deploying-machine-learning-model-using.html>

UI Screenshot:



Guarding Transaction

Amount:
200.50

Time:
53455



Transaction Type
Purchase

Original Balance:
5000

New Balance
4800

Sample Prediction Output

```
+-----+
| 🛡 Guarding Transaction |
+-----+
| Amount: [200.50]      |
+-----+
```

Time: [53455]	
Transaction Type: [Purchase]	
Original Balance: [5000]	
New Balance: [4800]	
[ Predict]	
 Legitimate Transaction	
+-----+	

13. Source code

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Load dataset
df = pd.read_csv('credit_card_data.csv')

# Preprocess data
X = df.drop('target', axis=1)
y = df['target']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train model
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate model
accuracy = accuracy_score(y_test, y_pred)
print('Accuracy:', accuracy)
print('Classification Report:')
print(classification_report(y_test, y_pred))
print('Confusion Matrix:')
print(confusion_matrix(y_test, y_pred))
```

14. Future scope

Future Enhancements:

- Real-Time Deployment: Implement fraud detection in real-time payment systems to identify and prevent fraudulent transactions as they happen.
- Adaptive Learning Models: Continuously update models using online learning to detect emerging fraud patterns and stay ahead of fraudsters.
- Graph-Based Fraud Detection: Use network analysis to detect fraud rings and coordinated attacks, which can be challenging to identify using traditional methods.
- Explainable AI (XAI): Improve model interpretability for better regulatory compliance and to understand the reasoning behind the model's predictions.

Emerging Technologies:

- Quantum Computing: Leverage quantum computing capabilities to revolutionize data analysis speeds and enhance fraud detection systems' ability to process vast data sets in real-time.
- Blockchain Technology: Develop integrated platforms that combine machine learning, blockchain technology, and enhanced cryptographic methods to offer holistic protection against fraud

Potential Benefits:

- Improved Detection Accuracy: Enhance the model's ability to detect fraudulent transactions and reduce false positives.
- Cost Efficiency: Automate fraud detection processes to reduce operational costs and improve resource allocation.
- Enhanced Security: Provide a safer financial environment for consumers and reduce the risk of credit card fraud

13. Team Members and Roles

KAMALESH R	-	<i>Abstarct and objectives</i>
JAGADESH V	-	<i>Data preprocessing and flowchart</i>
MOHAMMAD ARSHAD M	-	<i>EDA and Feature engineering</i>
KISHORE S	-	<i>Model building and evaluation</i>
DINESH H	-	<i>Deployment and source code</i>