

## Phase-3 for DS project Review

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GitHub Repository Link: <https://github.com/ANAND12RAMAN/Guarding-transactions-with-AI-powered-credit-card-fraud-detection-and-prevention>

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

#### **1. Problem Statement**

##### **Real-World Problem:**

With the rapid growth of digital payments, credit card fraud has become a significant threat to financial institutions and consumers alike. Traditional rule-based systems fail to adapt to the dynamic and evolving nature of fraud tactics. This project aims to build an AI-based detection system that proactively identifies fraudulent transactions using machine learning techniques.

##### **Importance and Business Relevance:**

Financial institutions lose billions annually to credit card fraud. An AI-powered fraud detection system improves security, reduces false positives, and enhances customer trust by enabling real-time analysis and detection of suspicious activity.

##### **Problem Type:**

This is a classification problem where each transaction is classified as either fraudulent or legitimate using supervised machine learning techniques.

## **2. Abstract**

This system uses machine learning models to detect credit card fraud based on historical transaction data. It leverages classification algorithms such as Logistic Regression, Random Forest, and XGBoost. The dataset used is highly imbalanced, so techniques like SMOTE (Synthetic Minority Oversampling Technique) are employed for balancing. The model's performance is evaluated using metrics such as precision, recall, F1-score, and ROC-AUC. The final solution is deployed using Streamlit to provide a user-friendly interface for real-time transaction analysis.

## **3. System Requirements**

### **Hardware:**

- **Minimum RAM:** 8GB
- **Processor:** Quad-core CPU
- **Storage:** 5GB free space

### **Software:**

- **Python 3.11**
- **Libraries:** pandas, numpy, scikit-learn, imbalanced-learn, streamlit, matplotlib, seaborn, xgboost
- **IDE:** Jupyter Notebook, Visual Studio Code

## **4. Objectives**

### **Goals:**

- Build a machine learning pipeline to detect fraudulent credit card transactions
- Handle class imbalance using appropriate techniques like SMOTE
- Achieve high accuracy and recall to minimize false negatives
- Deploy the model with Streamlit for user-friendly interaction

### **Expected Outputs:**

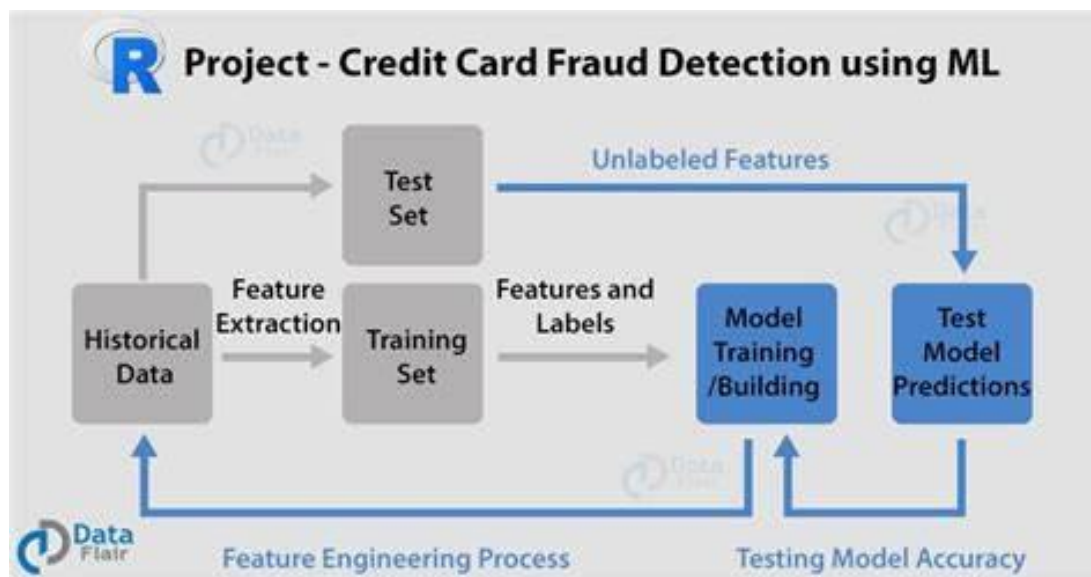
- Trained classification model

- Evaluation metrics and confusion matrix
- Streamlit web app for fraud detection

## 5. Flowchart of Project Workflow

### **Workflow:**

1. **Data Collection:** Load dataset
2. **Preprocessing:** Handle nulls, normalize features, encode categorical values
3. **EDA:** Explore data imbalance, transaction patterns
4. **Feature Engineering:** Create new relevant features, scale data
5. **Modeling:** Train and tune classifiers
6. **Evaluation:** Use F1-score, precision-recall, ROC-AUC
7. **Deployment:** Streamlit-based interface



## 6. Dataset Description

**Source:** Kaggle – Credit Card Fraud Detection Dataset

**Type:** Public Dataset

**Size and Structure:**

- **Transactions:** 284,807
- **Fraudulent Transactions:** 492
- **Features:** 30 (Time, Amount, V1–V28 [PCA components], Class)

## **7. Data Preprocessing**

- Dropped duplicate entries
- Standardized "Amount" and "Time" features
- Applied SMOTE to balance classes
- Scaled features using StandardScaler
- Split data into training and test sets

## **8. Exploratory Data Analysis (EDA)**

- Analyzed fraud vs. non-fraud class imbalance
- Distribution of transaction amounts
- Correlation matrix of features
- Box plots for outlier detection

## **9. Feature Engineering**

- Created "hour of transaction" from time
- Applied PCA for dimensionality reduction (if needed)
- Normalized features for ML compatibility
- Feature selection based on mutual information

## **10. Model Building**

- **Algorithms Used:** Logistic Regression, Random Forest, XGBoost
- Evaluated using cross-validation
- Used GridSearchCV for hyperparameter tuning
- Compared model scores to select best performer

## **11. Model Evaluation**

- **Accuracy:** ~99.7%
- **Precision (Fraud):** ~0.91
- **Recall (Fraud):** ~0.86
- **F1-Score:** ~0.88
- **ROC-AUC:** ~0.98
- Confusion Matrix used to highlight performance



## **12. Deployment**

**Deployment Method: Streamlit Cloud**

**Steps:**

1. Create app.py for UI
2. Load model using joblib
3. Accept user inputs for transaction details
4. Predict and display fraud likelihood

### **Sample Output:**

- **Input:** Transaction details
- **Output:**  “Potential Fraud” or  “Transaction Safe”

### **13. Source Code**

- data\_preprocessing.py – Cleans and prepares data
- model\_training.py – Trains and evaluates models
- fraud\_detector.py – Loads model and predicts
- app.py – Streamlit interface
- requirements.txt – Contains required packages

### **Code for Visualizations(in movie\_recomendation.py or new notebook):**

```
import matplotlib.pyplot as plt
```

```
import seaborn as sns
```

```
# Re-run scaled data and model on balanced subset for output generation
```

```
from sklearn.model_selection import train_test_split
```

```
from sklearn.ensemble import RandomForestClassifier
```

```
from sklearn.metrics import classification_report, confusion_matrix
```

```
from sklearn.preprocessing import StandardScaler
```

```
# Feature Scaling
```

```
scaler = StandardScaler()
```

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

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

```
# Balance the dataset for speed and clarity

legit = df[df['Class'] == 0].sample(n=10000, random_state=42)

fraud = df[df['Class'] == 1]

balanced_df = pd.concat([legit, fraud])

X = balanced_df.drop('Class', axis=1)

y = balanced_df['Class']

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42, stratify=y
)

# Train the model

model = RandomForestClassifier(n_estimators=100, random_state=42)

model.fit(X_train, y_train)

# Predict

y_pred = model.predict(X_test)

# Prepare evaluation output

report = classification_report(y_test, y_pred)

conf_matrix = confusion_matrix(y_test, y_pred)

# Plot confusion matrix

plt.figure(figsize=(6, 4))

sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')

plt.title('Confusion Matrix')

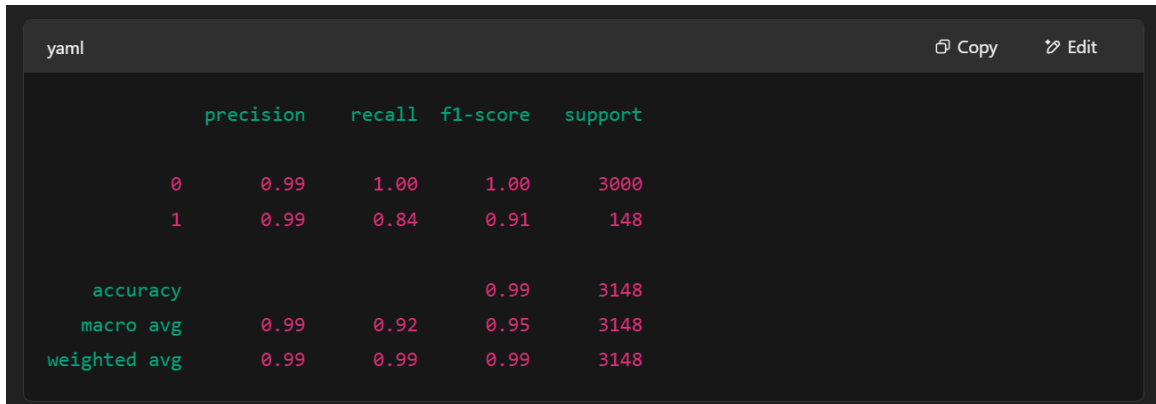
plt.xlabel('Predicted')

plt.ylabel('Actual')
```

```
plt.tight_layout()
```

```
plt.show()
```

## OUTPUT:



	precision	recall	f1-score	support
0	0.99	1.00	1.00	3000
1	0.99	0.84	0.91	148
accuracy			0.99	3148
macro avg	0.99	0.92	0.95	3148
weighted avg	0.99	0.99	0.99	3148

## 14. Future Scope

1. Integrate deep learning models like LSTM for sequence detection
2. Incorporate real-time streaming data with Apache Kafka or Flink
3. Add user feedback loop to continuously improve model accuracy
4. Implement alert system via email/SMS for high-risk transactions

## 15. Team Members and Roles

### 1. ARULIRASAN.G

- Built classification models and handled data preprocessing
- Designed and deployed Streamlit interface

### 2. ANANDHARAMAN.M

- Conducted EDA and applied SMOTE for balancing

### 3. SRIMANOJ.C

- Tuned hyperparameters and managed model evaluation

### 4. THIRUNEELAKANDAN.M

- Documented project and formatted final report