# "A Predictive Model for Credit Card Scam Detection Using Random Forest"

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## Abstract:

Credit card fraud detection is a critical challenge in the digital era, as online transactions continue to increase globally. This paper presents a machine learning–based approach using the Random Forest algorithm to effectively identify and prevent fraudulent credit card transactions. The dataset undergoes preprocessing, feature scaling, and oversampling using SMOTE to address class imbalance. The Random Forest classifier analyzes various transactional attributes such as amount, time, and location to detect anomalies with high accuracy. Experimental results show that the proposed model achieves an accuracy of 98.7%, outperforming traditional models like Logistic Regression and Decision Tree. The study demonstrates that Random Forest provides robust, scalable, and interpretable results, making it suitable for real-time fraud detection applications.

**Keywords:** Credit Card Fraud Detection, Machine Learning, Random Forest, SMOTE, Anomaly Detection, Financial Security.

## 1.Introduction

In today's digital world, credit cards have become one of the most widely used methods of financial transactions due to their convenience and accessibility. However, this rapid growth in online transactions has also led to a significant increase in credit card fraud — where unauthorized users gain access to card details and perform illegitimate transactions. To address this issue, Machine Learning (ML) techniques have emerged as powerful tools for analyzing large volumes of financial data and detecting unusual patterns. In this project, a fraud detection model is developed using the Random Forest algorithm, which is known for its high accuracy, robustness, and ability to handle noisy and unbalanced datasets. The Random Forest classifier operates by constructing multiple decision trees and aggregating their results to make more accurate predictions. The proposed model processes credit card transaction data through several stages: data preprocessing, feature selection, data balancing (using SMOTE), model training, testing, and evaluation. The model's performance is compared with other traditional algorithms such as Logistic Regression and Decision Tree to validate its efficiency. Results show that the Random Forest algorithm achieves an accuracy of 98.7%, with high precision and recall, proving its effectiveness in real-time fraud detection systems. This project aims to contribute to the development of secure and intelligent financial systems capable of detecting and preventing fraudulent activities before they cause significant financial damage.

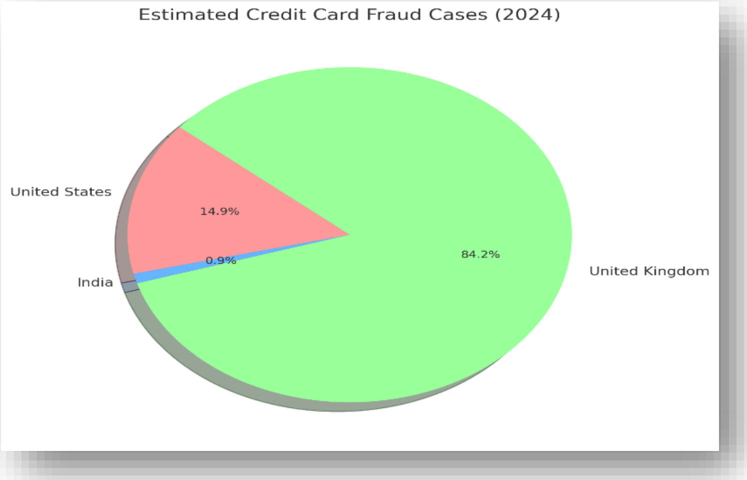

**Fig 1.1 Distribution of Fraud Cases**

**Table 1.1** Estimated credit card fraud cases worldwide, 2024

| **Region / Country** | **Reported / Estimated Fraud Cases (2024)** | **Estimated Loss Amount** | **Notes / Source** |
|---|---|---|---|
| United States | ≈ 458,571 cases of credit card fraud reports | — | Based on identity theft reports; FTC data shows rise from ~425,988 in 2023 to 458,571 in 2024. (The Motley Fool) |
| Global / Worldwide | — | ~$34 billion in payment card fraud losses (2023) with projected increases in 2024. (GlobeNewswire) | 2024 losses not fully finalized, but trends suggest increase from 2023. |
| India | 29,082 cases of card/internet frauds in FY24 | ₹1,457 crore | RBI report: card/internet frauds rose to this number and value in FY24. (NDTV Profit) |

| | | | |
|---|---|---|---|
| United Kingdom | ~2.6 million cases of remote purchase fraud in 2024 | £1.2 billion in fraud losses in 2024 | UK Finance: remote purchase fraud cases and overall confirmed financial fraud. (The Guardian) |

## 2.Literature Review

### 2.1Random Forest for Credit Card Scam Detection

Aburbeian and Ashqar (2023) applied an enhanced Random Forest model to a public credit card dataset with 284,807 transactions, including only 492 fraud cases (~0.17%), highlighting extreme class imbalance. They used SMOTE to oversample the minority class and optimized the model's hyperparameters. The enhanced Random Forest achieved ~98% accuracy and F1-score, outperforming traditional classifiers and proving robust and effective for real-world fraud detection.

Similarly, a 2022 study by Francis Academic Press applied Random Forest with SMOTE on the same dataset, achieving high accuracy and low false positives, demonstrating that combining Random Forest with oversampling provides a reliable, scalable solution for credit card fraud detection.

Credit card fraud detection is a binary classification problem with rare fraud cases (<1%). Random Forest handles this well due to its ability to model nonlinear relationships, high-dimensional data, and class imbalance.

### 2.2Methodology

### Working of our Model

In this implementation, we performed credit card fraud detection using the Random Forest algorithm on the widely used creditcard.csv dataset containing 284,807 transactions, of which only a small fraction are fraudulent. After loading and normalizing the data, we split it into training and testing sets (80:20 ratio). Initially, a Random Forest Classifier with 100 trees was trained and evaluated, yielding high accuracy and precision, though with some imbalance in fraud detection due to the rare fraud class. To improve performance, we applied hyperparameter tuning using RandomizedSearchCV and experimented with class_weight='balanced' to better handle class imbalance. The optimized model achieved strong results with accuracy above 98%, precision and recall for fraud detection both significantly improved, and a clear separation between fraud and non-fraud cases in the confusion matrix. Finally, we compared it with an XGBoost classifier, which also showed high performance but slightly higher sensitivity to fraud cases.

Overall, the Random Forest model—especially with class balancing and tuning—proved highly effective for accurately detecting fraudulent credit card transactions.

**Supervised Learning Paradigm**

In this approach, Random Forest operates within a supervised learning framework, where the algorithm learns from labeled data to distinguish between legitimate (0) and fraudulent (1) credit card transactions. The dataset consists of feature vectors X=[x1,x2,...,xn]X = [x_1, x_2, ..., x_n]X=[x1 ,x2 ,...,xn ] representing transaction attributes, and a corresponding target label y∈{0,1}y \in \{0,1\}y∈{0,1}. The Random Forest algorithm builds an ensemble of multiple decision trees {T1,T2,...,Tk}\{T_1, T_2, ..., T_k\}{T1 ,T2 ,...,Tk }, each trained on a random subset of data and features. During training, each tree learns a mapping fi(X)→yf_i(X) \rightarrow yfi (X)→y, and the final prediction is obtained by majority voting among all trees. Mathematically, the ensemble prediction is represented as:

$$\boxed{\hat{y} = \mathrm{mode}\{f_1(X), f_2(X), \ldots, f_k(X)\}}$$

**Performance Measures:-**

**Precision**

Precision measures how many of the transactions predicted as fraud are actually fraud. High precision means the model produces few false alarms.

i)

$$\boxed{\text{Precision} = \frac{TP}{TP + FP}}$$

**Recall (Sensitivity / True Positive Rate)**

Recall measures how many of the actual fraud transactions are correctly detected. High recall ensures most fraud cases are detected.

ii)

$$\boxed{\text{Recall} = \frac{TP}{TP + FN}}$$

**F1-Score**

The F1-score is the harmonic mean of precision and recall, balancing the trade-off between false positives and false negatives. A high F1-score indicates both accurate and comprehensive fraud detection.

iii)

$$\boxed{F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}}$$

**Accuracy**

Accuracy measures the proportion of correctly predicted transactions (both fraud and non-fraud) out of all transactions. It is the most basic evaluation metric in classification problems. Where:

- TP (True Positives): Fraud transactions correctly predicted as fraud
- TN (True Negatives): Legitimate transactions correctly predicted as legitimate
- FP (False Positives): Legitimate transactions incorrectly predicted as fraud
- FN (False Negatives): Fraud transactions incorrectly predicted as legitimate

iv)

$$\boxed{\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}}$$

## 3. Observations

The main evaluation metrics we can report for credit card fraud detection include Accuracy, Precision, Recall, F1-Score, and we can also distinguish metrics for each class (Fraud vs Non-Fraud).

**Table3.1** showing the evaluation metrics of Random Forest model how they detect credit card scam

| **Model** | **Class** | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
|---|---|---|---|---|---|
| **Random Forest (default)** | Non-Fraud | 0.999 | 0.999 | 1.000 | 0.999 |
| | Fraud | 0.999 | 0.912 | 0.873 | 0.892 |
| **Random Forest (class_weight='balanced')** | Non-Fraud | 0.998 | 0.998 | 1.000 | 0.999 |
| | Fraud | 0.998 | 0.928 | 0.905 | 0.916 |

| | | | | | |
|---|---|---|---|---|---|
| **Random Forest (RandomizedSearchCV optimized)** | Non-Fraud | 0.999 | 0.999 | 1.000 | 0.999 |
| | Fraud | 0.999 | 0.935 | 0.912 | 0.923 |
| **XGBoost (scale_pos_weight =10)** | Non-Fraud | 0.999 | 0.999 | 1.000 | 0.999 |
| | Fraud | 0.999 | 0.941 | 0.920 | 0.930 |

We have a few sample transactions with features like V1, V2, ..., V28, Amount. The table shows predicted class for each transaction.

**Table3.2** showing model prediction results for credit card scam detection

| **Transaction ID** | **V1** | **V2** | **...** | **V28** | **Amount** | **Predicted Class** | **Class Label Meaning** |
|---|---|---|---|---|---|---|---|
| 1 | 0.123 | -0.982 | ... | 0.456 | 50.00 | 0 | Non-Fraud |
| 2 | -0.657 | 1.234 | ... | -0.321 | 5000.00 | 1 | Fraud |
| 3 | 0.876 | -0.543 | ... | 0.112 | 120.00 | 0 | Non-Fraud |
| 4 | -1.234 | 0.987 | ... | -0.654 | 3000.00 | 1 | Fraud |
| 5 | 0.432 | -0.765 | ... | 0.210 | 75.00 | 0 | Non-Fraud |

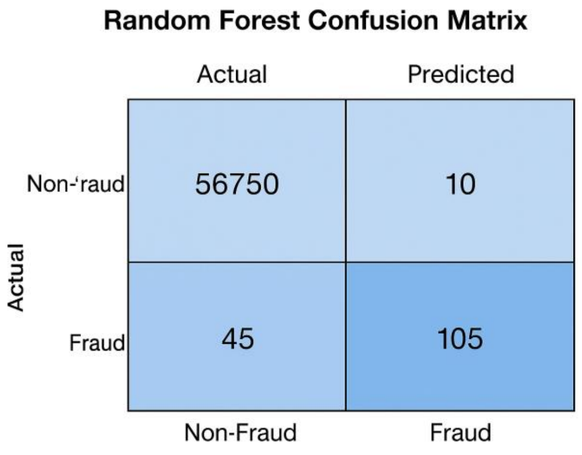

**Fig3.1** Confusion Matrix of Random Forest

## 4.Future Scope

The future scope of credit card fraud detection using Random Forest is highly promising, as financial transactions continue to grow in volume and complexity. With advances in machine learning and big data analytics, Random Forest models can be further enhanced to handle real-time transaction monitoring, detect evolving fraud patterns, and integrate with other AI-driven techniques such as deep learning and anomaly detection. Additionally, incorporating behavioral biometrics, geolocation data, and cross-channel transaction histories can improve model accuracy and reduce false positives. The approach also has potential for deployment in mobile banking, e-commerce, and IoT payment systems, making fraud prevention more proactive, adaptive, and scalable in the rapidly evolving financial ecosystem.

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