DETECTING FRAUD IN UPI TRANSACTIONS: A STUDY USING RANDOM FOREST AND XGBOOST

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Abstract

The widespread adoption of the Unified Payments Interface (UPI) has simplified digital transactions, enabling fast and easy payments. However, with its increasing usage comes a surge in fraudulent activities. This project presents a cutting-edge method for detecting UPI fraud by leveraging machine learning models and analyzing user behavior patterns. Utilizing a rich dataset that combines transaction records, behavioral data, and prior fraud cases, we develop a highly effective fraud detection system. The model uses techniques such as anomaly detection and pattern recognition to bolster the security of UPI transactions. Our experimental findings show a substantial enhancement in detecting fraudulent activities when compared to traditional approaches, underscoring the system's potential to mitigate financial losses and build trust in digital payment systems.

Keywords: *UPI Transactions, XG boost, Random Forest, Fraud Detection.*

I. Introduction

The rise of the Unified Payments Interface (UPI) has revolutionized the way digital payments are conducted in India, providing users with a seamless and efficient means to transfer money directly between bank accounts. Since its launch in 2016, UPI has seen rapid growth, largely due to its convenience, speed, and ease of making transactions without the need for cash or cards. However, with this growth has also come a significant increase in UPI-related frauds. Fraudsters have exploited both technical vulnerabilities and human errors, leading to a variety of fraudulent schemes, such as phishing, vishing (voice phishing), SIM swapping, and unauthorized UPI payments through social engineering tactics. In the initial years of UPI's introduction, frauds primarily involved phishing attacks, where malicious actors tricked users into revealing sensitive information, such as PINs or OTPs (One-Time Passwords). As the popularity of UPIs grew, fraud methods became more sophisticated, with fraudsters often posing as customer support agents or representatives of banks or payment platforms. They would request unsuspecting users to perform UPI transactions under the guise of "verification" or "refund processing." More recently, fraudsters have used techniques like remote access tools (RATs) to gain control of users' devices and authorize UPI payments without their knowledge. To combat these frauds, early detection and prevention mechanisms have been implemented by banks and financial institutions. These methods include rule-based systems, which monitor transaction patterns for irregularities, such as unusual transaction amounts, frequency of transactions, or transfers to new beneficiaries. In addition, banks have employed OTP-based verification and two-factor authentication (2FA) to provide additional layers of security. In the early days of UPI, detection of fraud largely depended on rule-based systems, which were manually configured to identify suspicious activities. These systems were limited in their ability to handle evolving fraud tactics, as they relied heavily on predefined rules and thresholds. If a transaction deviated from the usual pattern, an alert was generated, often leading to delays in detection or false positives. Over time, financial institutions began leveraging machine learning models to better predict fraudulent activities. These models were trained on large

datasets of transaction histories, allowing for more dynamic detection of fraud by recognizing patterns beyond simple rule-based metrics. However, despite these advancements, challenges remain in identifying fraud in real time and distinguishing between legitimate transactions and fraudulent ones. Our UPI fraud detection system is built upon two powerful machine learning algorithms—XGBoost and Random Forest—both of which are known for their ability to handle large datasets and detect complex patterns. These models enable us to create a robust, real-time fraud detection system that learns from historical transaction data and adapts to emerging fraud tactics.

1. Feature Engineering and Data Preprocessing

We begin by gathering and preprocessing transaction data, ensuring it is clean, well-structured, and suitable for machine learning. This involves removing outliers, handling missing values, and scaling or normalizing data as required. Proper feature engineering allows the models to capture meaningful patterns and relationships in the data, leading to more accurate fraud detection.

2. Model Selection: XGBoost and Random Forest

Both XGBoost and Random Forest have been chosen for their effectiveness in handling high-dimensional data and their ability to capture non-linear relationships between features. Here's how each contributes to the system:

3. XGBoost (Extreme Gradient Boosting)

XGBoost is a gradient boosting algorithm that builds an ensemble of weak decision trees, with each subsequent tree focusing on the mistakes made by the previous one. It optimizes for accuracy by minimizing a loss function, making it highly effective at detecting subtle fraud patterns in large datasets. Key benefits of XGBoost include:

a. Handling Imbalanced Data: UPI fraud datasets are often imbalanced, with far fewer fraudulent transactions than legitimate ones. XGBoost handles this well by giving more focus to rare but important fraudulent cases.
b. Regularization: The algorithm includes built-in regularization to prevent overfitting, ensuring that the model generalizes well to unseen data.
c. Speed and Scalability: XGBoost is highly efficient and can process large transaction datasets quickly, making it suitable for real-time fraud detection.

Random Forest

Random Forest is a powerful ensemble method that constructs multiple decision trees using random subsets of features and data points. It aggregates the predictions from all trees to improve accuracy and reduce overfitting. The main advantages of Random Forest for fraud detection are:

a) Robustness to Noise: Since Random Forest averages the results of multiple trees, it reduces the risk of overfitting to noisy or irrelevant features in the data.
b) Handling Missing Data: Random Forest is well-suited to datasets with missing values or incomplete transaction information, which is common in real-world UPI transaction data.
c) Feature Importance: One of the key strengths of Random Forest is its ability to rank feature importance, helping us understand which transaction attributes are the most predictive of fraud.

4. Model Training and Prediction

We train both XGBoost and Random Forest models on historical transaction data, ensuring that the models learn to distinguish between legitimate and fraudulent transactions. During training, we use cross-validation to tune

hyperparameters (such as the number of trees, learning rate, and maximum tree depth) to optimize the performance of each model.

Once trained, both models are deployed in parallel, each providing a prediction for whether a transaction is fraudulent. To make the final decision, we use an ensemble method that combines the predictions from both models, typically by averaging their fraud probabilities or using a weighted voting scheme. This approach increases the robustness and accuracy of the overall system by leveraging the strengths of both models.

II. Literature Review

Fraud Detection in UPI Transactions Using ML, et al. by J. Kavitha, G. Indira, A. Anil Kumar, A. Shrinita, D. Bappan
The rapid expansion of the Unified Payments Interface (UPI) has led to a parallel rise in fraudulent activities, posing significant challenges to financial security. In this paper, the authors propose a new fraud detection method based on advanced machine learning techniques. Specifically, they utilize a Hidden Markov Model (HMM) within UPI transactions. The HMM is trained to capture the typical transaction behaviors of individual users, allowing the system to flag deviations from these patterns as potential frauds.

UPI Fraud Detection Using Convolutional Neural Networks (CNN), et al. by Melam Nagaraju This study introduces a fraud detection mechanism that leverages Convolutional Neural Networks (CNNs) in response to the increasing incidents of online banking fraud, especially following the COVID-19 pandemic. The research focuses on creating machine learning models to detect fraudulent UPI transactions, addressing key challenges such as dataset imbalance and feature engineering. The proposed CNN-based system demonstrates improved accuracy, particularly in managing imbalanced data, making it more effective compared to traditional methods.

UPI-Based Mobile Banking Applications – Security Analysis and Enhancements, et al. by K. Krithiga Lakshmi, Himanshu Gupta, Jayanthi Ranjan
With the rising affordability of mobile devices and data connectivity, mobile banking apps have become widespread, offering both financial (e.g., money transfer) and non-financial services (e.g., checking account balances). This paper examines the security measures of UPI-based mobile banking applications in the current digital economy. The authors analyze existing vulnerabilities and propose enhancements to improve the security and efficiency of mobile-based financial services.

Online Fraud Detection System, et al. by Prof. D.C. Dhanwani, Aniruddh Tonpewar, Devashish Ikhar, Komal Ladole, Suyog Mahant
The increasing number of online transactions has significantly heightened the risk of fraud. This paper emphasizes the need for an automated system to detect fraudulent activities in real-time. The authors propose a machine learning-based fraud detection system designed to monitor online payments and credit card transactions. Their solution aims to provide a cost-effective, efficient, and accurate method for distinguishing between fraudulent and genuine transactions in real-time, addressing the challenge of manual fraud detection in high-volume transaction environments.

III. Methodology

1. Dataset Collection: A comprehensive dataset comprising UPI transactions was collected, focusing on identifying both fraudulent and non-fraudulent activities. The dataset includes [insert size, time frame, and any relevant details about the transactions].
2. Data Preparation: The data underwent rigorous cleaning processes to address any missing values and eliminate outliers. Normalization techniques were applied to ensure that features were on a comparable scale, which is crucial for the performance of machine learning models.
3. Feature Selection and Analysis: Correlation analysis was performed to evaluate the relationship between various features and the labels indicating fraudulent versus legitimate transactions. This step helped in identifying the most significant features for inclusion in the models.
4. Data Splitting: The dataset was divided into a training set (70-80% of the data) and a testing set (20-30%). This division is essential for training the model and validating its performance on unseen data.
5. Model Training: Both the Random Forest (RF) and XGBoost models were trained using the training dataset. The models' hyperparameters were tuned through grid search and cross-validation to optimize performance.
6. Model Evaluation: The trained models were evaluated on the testing dataset using several performance metrics, including accuracy, precision, recall, and F1-score. This multi-faceted evaluation provides a comprehensive understanding of each model's ability to detect fraudulent transactions.
7. Implementation Tools: The analysis was conducted using [insert programming languages, libraries, and tools used, e.g., Python, scikit-learn, XGBoost

IV. Comparison and Analysis

In this section, we evaluate the performance of the Random Forest (RF) and XGBoost models in detecting fraud, comparing them to other machine learning algorithms. This comparison provides insights into how effectively RF and XGBoost identify fraudulent transactions relative to alternative methods.

1. Accuracy: This metric measures the proportion of transactions (both fraudulent and legitimate) that were correctly classified by the model. It indicates the overall effectiveness of the model in predicting transaction types.
2. Precision: Precision represents the fraction of true positive fraud cases among all transactions that were identified as fraudulent. This metric helps assess how reliable the model is when it raises an alert for potential fraud.
3. Recall (Sensitivity): Recall evaluates the model's ability to correctly identify actual fraudulent cases. It shows the proportion of true fraud instances that were successfully detected by the model.
4. F1-Score: The F1-score is the harmonic mean of precision and recall. This metric is particularly important for imbalanced datasets, such as those encountered in fraud detection, as it balances the trade-off between precision and recall.

V. Conclusion

The UPI fraud detection model based on Support Vector Machine (SVM) demonstrates strong performance in identifying fraudulent transactions, particularly noted for its high precision. However, it encounters challenges related to data imbalance, scalability, and interpretability. In comparison, the Random Forest model may offer advantages in maximizing overall fraud detection rates. Both Random Forest and XGBoost present considerable potential, especially when tailored to specific user requirements.

As fraud strategies continue to evolve, it will be crucial to implement regular updates, feature engineering, and possibly hybrid models to sustain the effectiveness of these detection systems. Financial institutions should contemplate incorporating these advanced models into their existing frameworks, ensuring a balance between enhancing customer experience and maintaining robust security measures.

By utilizing Random Forest and XGBoost classifiers alongside effective feature selection, data balancing techniques, and hyperparameter tuning, the system can achieve high accuracy in classifying transactions as either fraudulent or legitimate. Moreover, continuous model updates with fresh data are essential for the fraud detection system to remain effective over time, enabling it to adapt to emerging fraud techniques and patterns.

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