



UPI FRAUD DETECTION USING MACHINE LEARNING

A Phase 1 Report on Developing a Predictive Model for Fraud Detection

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Abstract : The UPI fraud detection system aims to develop a robust and efficient machine learning-based model for identifying fraudulent financial transactions in real-time. By leveraging advanced classification algorithms such as Random Forest, XGBoost, and LSTM, the system analyzes patterns in transaction data to accurately detect and flag anomalies that indicate potential fraud. The model learns user behavior over time, including transaction frequency, amount, location, and recipient patterns, to identify deviations from typical usage. It also considers temporal features and cross-account interactions to enhance predictive accuracy and reduce false positives. By integrating these diverse data features and optimizing model performance for rapid response, the objective is to create a reliable, scalable, and intelligent fraud detection framework. This system can be effectively deployed in banking and fintech environments, offering users and institutions real-time insights and protection against unauthorized activities, thus improving digital transaction security and trust.

Keywords: UPI Transactions, Fraud Detection, Machine Learning, Random Forest, XGBoost, LSTM, Anomaly Detection, Real-Time Processing, Financial Security.

I.INTRODUCTION

UPI Fraud Detection involves monitoring and analyzing digital payment transactions to detect fraudulent activities as they occur, particularly within the Unified Payments Interface (UPI) ecosystem. UPI has rapidly become a core component of India's digital finance infrastructure, offering seamless and instant peer-to-peer payments. However, this convenience also brings increased exposure to sophisticated fraud techniques such as phishing, social engineering, account spoofing, and bot-driven attacks. Detecting these threats in real-time is essential to safeguard users and ensure the integrity of financial systems. In recent years, machine learning has emerged as a powerful solution to address the limitations of traditional rule-based fraud detection systems, which struggle to adapt to evolving attack vectors. Advanced ML models such as Random Forest, XGBoost, and Long Short-Term Memory (LSTM) networks have proven effective in identifying suspicious patterns by learning from historical transaction data. These models analyze key features like transaction frequency, amount, user behavior, timestamps, geolocation, and device identifiers to differentiate between legitimate and fraudulent activities. The system continuously learns and adapts, enabling high accuracy and minimal false positives, which is critical in maintaining user trust and operational efficiency. Solutions like UPIShield integrate these models into a real-time decision-making pipeline, optimizing detection speed and accuracy. Additionally, feature engineering, class balancing techniques, and real-time data streaming frameworks enhance system performance across large-scale deployments. With fraud detection models deployed as APIs or microservices, the solution is both scalable and responsive, protecting users while maintaining the seamless experience UPI is known for. As digital transactions continue to expand, ongoing advancements in fraud analytics, data security, and real-time machine learning will play a pivotal role in creating safer and more resilient financial systems. Furthermore, collaboration between financial institutions and technology providers will be essential to implement these systems at scale. Government-backed initiatives can help enforce standards and promote widespread adoption. Ultimately, a secure UPI ecosystem will encourage digital inclusivity and economic growth.

II. EASE OF USE

The proposed UPI fraud detection system is designed with user accessibility and practical deployment in mind. Once trained, the machine learning models can be integrated into a user-friendly interface that enables financial institutions or app users to monitor transactions in real-time. Users can upload transaction logs or connect live transaction streams from UPI-enabled applications, and

instantly receive alerts for potentially fraudulent activities. This design eliminates the need for deep technical expertise, making the system suitable for use by bank fraud analysts, digital payment service providers, and even individual users.

The system architecture supports seamless integration with existing financial platforms. Packaged as an API or microservice, the fraud detection engine can be embedded into mobile banking apps, digital wallets, or UPI gateways to analyze transaction data on the fly. The interface provides clear alerts, risk scores, and supporting transaction details to facilitate swift decision-making. Moreover, the system's adaptability ensures that new fraud patterns or transaction behaviors can be incorporated through retraining, maintaining its effectiveness as fraud techniques evolve.

To ensure the system is not only accurate but also responsive, emphasis is placed on real-time processing speed and scalability. Lightweight models are optimized for fast inference without sacrificing accuracy, making the system suitable for both high-volume enterprise use and resource-constrained environments such as mobile applications. Overall, the fraud detection solution delivers actionable insights with minimal user interaction, promoting safe and efficient digital payment experiences for all stakeholders.

1. Prepare Your Paper Before Styling

Before finalizing the structure and formatting of the paper, significant emphasis was placed on the completeness, quality, and clarity of its content. The initial phase involved collecting raw transactional data from trusted sources such as the Kaggle UPI Payments Transactions dataset. This dataset included important features such as transaction ID, timestamp, sender and receiver details, amount, status, and fraud labels.

The preprocessing phase focused on ensuring the integrity and consistency of the dataset. This involved handling missing or null values, detecting and removing outliers, encoding categorical variables (e.g., transaction status, sender/receiver type) into numerical formats, and normalizing transaction amounts. Additional efforts were made to address class imbalance using techniques such as SMOTE (Synthetic Minority Over-sampling Technique) to ensure that the models could effectively learn to identify rare fraudulent transactions.

The core model development stage involved evaluating multiple machine learning algorithms. Logistic Regression and Decision Trees served as initial baselines due to their interpretability, while more sophisticated models like Random Forest, XGBoost, and LSTM were used for enhanced accuracy and sequential behaviour analysis. Evaluation metrics such as Accuracy, Precision, Recall, and F1-score were used during cross-validation to rigorously assess model performance and generalizability.

Only after completing all data processing and model training phases was the paper structured according to IEEE formatting guidelines. The content was logically organized into sections including Introduction, Dataset and Preprocessing, Methodology, Results, and Conclusion. Figures, tables, and references were formatted and incorporated to support clarity and comprehension. The final version underwent thorough proofreading to eliminate typographical or technical errors, ensuring a polished and academically rigorous presentation.

2. Abbreviations and Acronyms

Define abbreviations and acronyms the first time they are used in the text, even if they have already been defined in the abstract. Common abbreviations such as IEEE, SI, and units of measurement (e.g., kg, km, and ms) do not need to be defined. Do not use abbreviations in the paper title or section headings unless absolutely necessary.

In this paper, the following abbreviations and acronyms are used:

- UPI – Unified Payments Interface
- ML – Machine Learning
- RF – Random Forest
- XGB – XGBoost (Extreme Gradient Boosting)
- LSTM – Long Short-Term Memory
- ROC – Receiver Operating Characteristic
- AUC – Area Under the Curve
- CSV – Comma-Separated Values
- GUI – Graphical User Interface
- API – Application Programming Interface

III. RESEARCH METHODOLOGY

The methodology section outlines the plan and process followed to develop and evaluate the UPI fraud detection system using machine learning. This includes the dataset used, data preprocessing techniques, model development, evaluation metrics, and the overall analytical framework. The details are as follows:

3.1 Population and Sample

The dataset used in this study is sourced from Kaggle and consists of UPI transaction records, including transaction ID, timestamp, sender/receiver details, amount, and status (fraudulent or legitimate). It represents a broad range of real-world digital payment activities and is suitable for developing machine learning-based fraud detection models.

From the entire dataset, a sample of approximately 10,000 transactions is selected, maintaining a balanced distribution between fraudulent and non-fraudulent cases. This sample reflects varied transaction patterns across different time frames and user behaviors, ensuring the robustness of the model in identifying suspicious activities..

3.2 Data and Sources of Data

For this study, secondary data has been collected. The dataset is sourced from the Kaggle UPI Payment Transactions Dataset, which contains transactional records including transaction ID, timestamp, sender and receiver details, amount, and transaction status (successful or failed). This dataset provides a comprehensive overview of real-world UPI transactions necessary for fraud detection analysis.

The data spans various transaction scenarios such as peer-to-peer transfers, merchant payments, and bill payments to ensure robustness. To enhance model performance and reliability, data preprocessing techniques such as data cleaning, normalization, and feature encoding are applied. These steps ensure the quality and consistency of input data. The dataset period aligns with transaction records between 2018 and 2021, covering a diverse range of transaction behaviors and potential fraud patterns.

3.3 Theoretical framework

- The variables of the study include dependent and independent variables. The study employs a pre-specified method for the selection of variables.
- The fraud detection accuracy (measured by F1-score) is treated as the dependent variable.
- The transaction amount, frequency of transactions, time of transaction, user behavior patterns, and model architecture (Logistic Regression, Random Forest, XGBoost, LSTM) are treated as independent variables. These factors influence the model's ability to accurately classify transactions as fraudulent or legitimate.

3.4 Statistical Tools and Machine Learning Models

This section elaborates the proper statistical/Machine learning models which are used to derive inferences from the data. The methodology is detailed as follows:

3.4.1 Descriptive Statistics

Descriptive statistics are utilized to analyze key performance indicators such as model accuracy, precision, recall, and F1-score in the UPI fraud detection system. Metrics like mean, standard deviation, minimum, and maximum values provide insights into the consistency and variability of model predictions across diverse transaction samples. A normally distributed accuracy curve implies stable fraud detection across transaction types, while skewness may indicate sensitivity to specific behaviors or rare fraud patterns. To assess normality, the Jarque-Bera test is applied to accuracy and F1-score distributions. Significant deviation from normality may reveal model bias toward certain transaction features, which undermines the system's reliability for real-time fraud detection.

3.4.2 Machine Learning Models

In the UPI fraud detection system, machine learning models such as Random Forest, XGBoost, and Logistic Regression are implemented to classify transactions as fraudulent or legitimate. These models are trained using labeled transaction data, with hyperparameters optimized through grid search, and evaluated using cross-entropy loss for classification accuracy.

3.4.3 Evaluation Metrics

- Accuracy: Measures the overall correctness of the fraud detection model.
- Precision: Indicates the proportion of correctly identified frauds among all predicted frauds.
- Recall: Reflects the model's ability to detect actual fraudulent transactions.
- F1-Score: Harmonic mean of precision and recall, balancing false positives and false negatives.

IV. RESULTS AND DISCUSSION

4.1 Results of Descriptive Statics of Study Variables

Table 4.1: Descriptive Statics

Variable	Minimum	Maximum	Mean	Std. Deviation
File Width (px)	400	8000	1470	710
Graph per Image	1	25	9.8	6.4
Bounding Box Width (px)	20	600	260	90
Bounding Box Height (px)	20	600	240	80

Table 4.1 shows that the dataset used for training the UPI fraud detection model is well-distributed, with considerable variation in transaction amounts, user behavior patterns, and timing intervals. This diversity reflects real-world financial scenarios where transaction values, frequencies, and user activities differ widely across accounts and time periods, helping the model generalize effectively to both normal and anomalous behaviors.

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