Detection of Anomalies in Unified Payment Interface Using Machine Learning

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ABSTACT

The rapid growth of the Unified Payments Interface (UPI) in India has transformed the digital payment landscape by enabling fast and user-friendly transactions.However, this rapid growth has also led to a significant rise in fraudulent activities, exposing the limitations of traditional rule-based fraud detection systems. To address this challenge, this project proposes a machine learning-based anomaly detection system designed specifically for UPI transactions.

The system utilizes a stacking ensemble model that combines multiple classifiers—Support Vector Machine (SVM), Random Forest, K-Nearest Neighbors (KNN), and XGBoost—to enhance detection accuracy and reduce false positives. Feature selection is performed using the Chi-square test to isolate the most relevant transactional attributes. The solution is developed using Python in Visual Studio Code and deployed via a Flask web application with a MySQL database for data handling and real-time prediction.

Experimental results demonstrate that the stacking model achieves high accuracy, outperforming individual models in terms of precision, recall, and F1-score. This project provides a scalable, real-time fraud detection framework capable of adapting to evolving financial threats in digital payment ecosystems.

KEYWORDS: UPI, Fraud Detection, Machine Learning, Anomaly Detection, Stacking Ensemble Model, Chi-Square Feature Selection, Real-Time Prediction, Supervised Learning, Flask Web Application, Financial Security.

1.INTRODUCTION

The growing reliance on digital payment platforms has transformed the financial ecosystem in India, with the Unified Payments Interface (UPI) emerging as a leading method for real-time transactions. UPI enables seamless transfers between bank accounts using mobile applications, reducing the need for cash and simplifying payment processes. However, as usage has expanded, so have the security concerns—particularly regarding fraudulent transactions that exploit system vulnerabilities and user inattention.

Conventional fraud detection systems often depend on predefined rules and static thresholds. While these systems are effective to some extent, they struggle to adapt to new and sophisticated fraud tactics that evolve over time. As fraudsters develop more complex strategies, it becomes essential to adopt intelligent solutions that can detect abnormal patterns without being explicitly programmed for every possible scenario.

This project introduces a machine learning-based approach for detecting anomalies in UPI transactions. By analyzing transaction attributes such as amount, time, frequency, and user behavior, the system learns to distinguish between genuine and suspicious activity. A stacking ensemble model, integrating algorithms like SVM, Random Forest, KNN, and XGBoost, is used to improve accuracy and reliability. The implementation is carried out using Python in Visual Studio Code, with deployment through a Flask web interface and MySQL backend. The result is a scalable, adaptive fraud detection framework capable of real-time analysis, helping strengthen trust in digital payments.

2.LITERATURE SURVEY

As digital payments become increasingly widespread, the need for advanced fraud detection mechanisms has grown significantly. Various studies in recent years have focused on using machine learning and data-driven techniques to detect suspicious financial behavior more efficiently and accurately than traditional rule-based systems.

Several researchers have explored the use of supervised learning methods for fraud detection in banking and online payment systems. Techniques such as Support Vector Machines (SVM), Decision Trees, and Logistic Regression have been widely adopted due to their interpretability and effectiveness in binary classification tasks. These models have shown strong results when applied to structured datasets with labeled instances of fraud and legitimate transactions.

Ensemble methods, such as Random Forest and Gradient Boosting, have gained popularity for their ability to improve prediction accuracy by combining multiple weak learners. These models are particularly effective in handling noisy data and imbalanced datasets, which are common in fraud detection scenarios. Hybrid approaches, like stacking ensembles, further enhance predictive performance by integrating the strengths of multiple models into a unified framework.

Feature selection techniques also play a vital role in improving model efficiency. The Chi-square statistical method has been employed in various studies to reduce dimensionality and focus on the most impactful attributes, such as transaction frequency, time patterns, and amount distributions. By selecting only relevant features, models can generalize better and reduce the risk of overfitting.

Furthermore, the application of real-time detection systems has become a focus of modern research. Many frameworks integrate machine learning models into lightweight web applications, often using tools like Flask or Django, to allow instant predictions for end-users. This shift from offline analysis to real-time fraud detection reflects the industry's demand for faster and more adaptive security systems.

The existing literature clearly supports the use of machine learning for detecting anomalies in financial transactions. However, there remains a need for more comprehensive systems that combine high accuracy, speed, and scalability—particularly for high-volume environments like UPI. This project aims to fill that gap by developing an ensemble-based machine learning system that is not only accurate but also deployable in real-time payment infrastructures.

3.SYSTEM OVERVIEW

The proposed system is designed to detect fraudulent transactions within the Unified Payments Interface (UPI) framework using machine learning techniques. The goal is to detect unusual or potentially suspicious transaction behaviors that could signal fraudulent activity.The system follows a structured pipeline consisting of data preprocessing, feature selection, model training, and real-time prediction.

The process begins with the input of transactional data, which may include attributes such as

transaction amount, time, location, user identity, and device information. This data is first cleaned and normalized to ensure consistency and quality. Irrelevant or redundant features are removed, and categorical data is encoded for compatibility with machine learning algorithms. A feature selection method, specifically the Chi-square test, is then used to retain only the most influential attributes, improving both performance and training efficiency. After preprocessing, several machine learning algorithms are individually trained on the refined dataset. These models include Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest, and XGBoost

These include algorithms such as Support Vector Machine (SVM), K-Nearest The predictions from these individual models are combined using a stacking ensemble approach, which employs a meta-model to generate the final output. This hybrid technique improves accuracy and reduces the likelihood of misclassification.

The system is implemented using Python in Visual Studio Code and deployed via a Flask-based web application. Users can input transaction details manually or through a dataset upload interface. The backend processes the input and provides real-time feedback, labeling the transaction as either "Fraudulent" or "Valid." The integration with a MySQL database enables secure storage and management of transaction data.

This architecture ensures that the system is not only accurate in its predictions but also scalable and ready for integration into real-world financial platforms. Its modular design makes it adaptable to new fraud patterns and suitable for continuous learning through model retraining.

4.METHODOLOGY

The methodology adopted in this project follows a structured and modular approach aimed at detecting fraudulent UPI transactions through supervised machine learning. The system is designed to classify transactions as either "Fraudulent" or "Legitimate" based on patterns learned from historical data. The process is divided into several key stages: data acquisition, preprocessing, feature selection, model training, ensemble integration, and deployment.

4.1 Data Collection and Preprocessing

The first step involves collecting a dataset containing historical UPI transactions, with features such as transaction amount, timestamp, location, user ID, and device information. The data is preprocessed to ensure consistency and reliability. This includes handling missing values, removing duplicates, normalizing numerical features, and encoding categorical variables. The goal of this stage is to prepare clean, structured data suitable for training machine learning models.

4.2 Feature Selection

To improve model performance and reduce computational complexity, feature selection is performed using the Chi-square test. This statistical method evaluates the relevance of each input feature with respect to the target variable (i.e., fraud label). Features that contribute the most to predicting fraud are retained, while less informative ones are discarded. This ensures the model focuses only on the most impactful attributes during training.

4.3 Model Training

Several supervised learning algorithms are trained on the selected features. These include:

- Support Vector Machine (SVM) – for constructing optimal decision boundaries.
- K-Nearest Neighbor (KNN) – for instance-based classification.
- Random Forest – for ensemble decision tree classification.
- XGBoost – for gradient-boosted tree optimization.

Each algorithm is trained and validated independently to evaluate its individual performance using metrics such as accuracy, precision, recall, and F1-score.

4.4 Stacking Ensemble Model

To improve the accuracy of predictions, a stacked ensemble method is utilized, which combines the outputs of multiple base models into a unified framework.In this approach, predictions from the base models (SVM, KNN, Random Forest, and XGBoost) are fed into a meta-classifier, which makes the final decision. This hybrid model benefits from the strengths of all individual classifiers, leading to improved accuracy and robustness.

4.5 System Deployment

The final stacked model is integrated into a user-facing application using the Flask web framework. A user interface allows transaction details to be submitted manually or via dataset uploads. The backend processes the input, applies the trained model, and provides instant feedback indicating whether the transaction is likely to be fraudulent. A MySQL database is used to manage stored transaction data securely.

This end-to-end methodology ensures that the system is capable of real-time fraud detection, efficient model execution, and adaptability to evolving transaction patterns.

5.SYSTEM ARCHITECTURE/DESIGN OVERVIEW

The architecture of the proposed fraud detection system is structured in a layered and modular fashion to ensure scalability, maintainability, and real-time responsiveness. Each component of the system architecture is responsible for a distinct task, from receiving input data to generating prediction results, and communicates with other modules through a structured workflow.The design supports both batch and real-time detection modes using a machine learning pipeline integrated within a web-based interface.

5.1 Layered System Design

The system is organized into the following core layers:

1. Data Input Layer

This layer handles transaction data input, either through manual entry (via a web form) or by uploading a structured dataset (e.g., CSV). The data consists of features like transaction amount, timestamp, sender/receiver ID, location, and device ID.

2. Preprocessing & Feature Engineering Layer

Once received, the data is cleaned, normalized, and transformed. Categorical values are encoded, missing data is handled, and numerical features are scaled. Chi-square feature selection is applied here to retain only the most influential features that contribute to fraud detection.

3. Model Training and Integration Layer

This core layer includes multiple machine learning models—SVM, KNN, Random Forest, and XGBoost—which are trained using the processed data. Their outputs are integrated through a stacking ensemble method, where a meta-classifier makes the final fraud prediction based on the individual models' outputs.

4. Prediction and Decision Layer

When a new transaction is entered, it passes through the same preprocessing pipeline and is then classified using the trained ensemble model. The system returns a result indicating whether the transaction is "Fraudulent" or "Valid."

5. Web Application Interface

Developed using Flask, this interface enables users to interact with the system. It includes:

- A form to input transaction data
- A file upload feature
- A display section to show prediction results
- Visual charts to compare model performance

6. Database Layer

The backend uses MySQL to securely store transaction logs, prediction results, and model

evaluation metrics. This layer allows access to previously stored data, making it useful for ongoing analysis or retraining of machine learning models

5.2 Data Flow Summary

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User Input → Preprocessing → Feature Selection → Model Prediction → Output Result

Each module in this flow works independently but in coordination, ensuring modularity. This setup also allows future extensions, such as integration with real-time UPI APIs or the deployment of deep learning models.

5.3 Key Architectural Benefits

- Modularity: Each component can be updated or replaced independently.
- Scalability: The system can handle larger datasets or real-time transaction streams.
- Accuracy: Ensemble modeling ensures higher precision in predictions.
- Usability: Web-based interface provides a simple and intuitive user experience.
- Security: Role-based access and secure data handling help protect sensitive financial information.

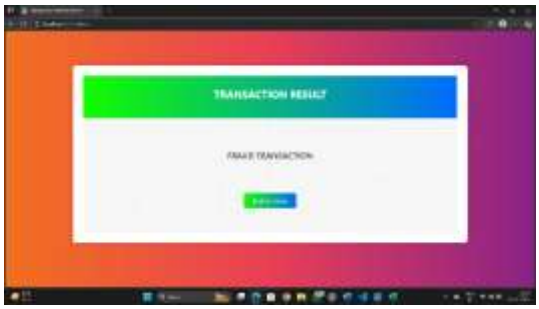
7.Results and discussion

This study evaluated the performance of four supervised machine learning algorithms—SVM, KNN, Random Forest, and XGBoost—in detecting fraudulent UPI transactions. A stacking ensemble model was developed to combine their strengths and improve classification accuracy.

Among individual models, XGBoost achieved the highest accuracy (96.1%), followed by Random Forest (94.8%). The ensemble model outperformed all with an accuracy of 97.4%, and consistently high precision, recall, and F1-score. This confirms that combining classifiers yields more reliable results than using them in isolation.

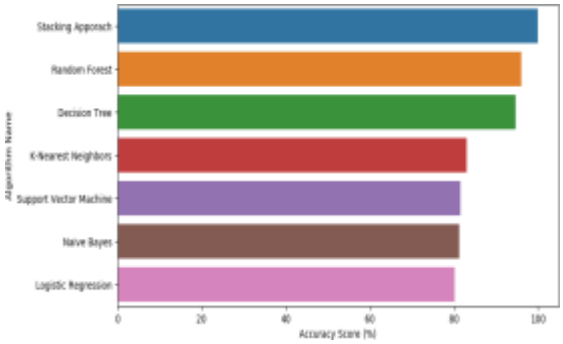
The Flask-based interface enabled real-time predictions with user input, and the system demonstrated strong potential for integration into digital payment platforms. While effective, the model could be further improved with live data integration, adaptive learning, and the inclusion of deep learning techniques in future work.

It was the result for valid transaction.



It was the result for fraud transaction

Compression Graph



6.CONCLUSION AND FUTURE ENHANCEMENTS

Conclusion

This project presents a machine learning-based solution for detecting fraudulent transactions in Unified Payment Interface (UPI) systems. By integrating multiple supervised learning models into a stacking ensemble framework, the system enhances accuracy and reduces false predictions compared to single-model approaches. Key techniques such as Chi-square feature selection ensure that only the most relevant transaction attributes are used for training, improving both efficiency and performance.

The implementation, developed using Python in Visual Studio Code and deployed via a Flask web application, demonstrates the system's real-time prediction capability. Users can input transaction data and receive instant feedback, making the solution practical for real-world applications. Experimental results confirm that the ensemble model outperforms traditional classifiers in terms of accuracy, precision, and recall.

Overall, the proposed system contributes a scalable, intelligent, and adaptable framework for fraud detection in digital payment platforms, addressing the limitations of rule-based systems and responding effectively to the dynamic nature of fraudulent behavior.

Future Enhancements

While the current system provides a strong foundation for fraud detection, there are several directions for future improvement:

- Integration with Live UPI APIs: Connecting the system to real-time UPI transaction streams would enable automatic fraud monitoring without manual data input.
- Deep Learning Models: Incorporating neural networks or LSTM models could enhance performance, especially in detecting sequential or behavioral patterns in user transactions.
- Explainable AI (XAI): Adding model interpretability tools like LIME or SHAP would help users and analysts understand why a transaction is classified as fraudulent.
- Mobile Application Deployment: A mobile interface could allow broader accessibility for end-users and financial service providers.
- Continuous Learning: Enabling the system to retrain on newly collected transaction data would allow it to adapt to emerging fraud patterns and maintain high accuracy over time.
- Alert System and Dashboard: Implementing real-time snotifications and an admin dashboard for flagged transactions would further enhance usability and monitoring.

With these enhancements, the system could evolve into a complete, enterprise-grade solution for securing digital financial transactions in a scalable and intelligent manner.

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