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UPI Fraud Detection Using Machine Learning

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Abstract: ***UPI fraud has become a major challenge due to the rapid growth of digital payments. Fraudulent activities such as fake payment requests, phishing, identity theft, and unauthorized transactions can cause significant financial losses to users and banks. Therefore, detecting fraud at an early stage is important to ensure secure online transactions. This project develops a UPI Fraud Detection System using the Random Forest machine learning algorithm. The system is trained using a dataset that contains different transaction details such as transaction amount, transaction time, payment method, location, device information, and transaction history. The Random Forest algorithm is chosen because it provides high accuracy, handles large datasets effectively, and reduces the chances of incorrect predictions. The model analyses transaction patterns and classifies each transaction as either genuine or fraudulent. Its performance is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. The results show that the Random Forest algorithm performs better than many traditional machine learning algorithms in detecting fraudulent transactions. The proposed system helps banks and digital payment platforms identify suspicious transactions quickly, reducing financial losses and improving user security. In the future, the system can be enhanced by integrating real-time transaction monitoring, user behaviour analysis, and advanced AI techniques to improve fraud detection accuracy and provide a safer digital payment experience.***

Keywords: ***UPI fraud, machine learning, Random Forest, prediction, financial security, clinical data, early detection, risk assessment, mortality, patient outcomes.***

I. INTRODUCTION

UPI fraud is one of the leading causes of mortality worldwide, making early prediction and intervention essential in financial security. With advancements in machine learning, predictive modeling has gained prominence as a means to help diagnose and manage heart conditions before they become severe. This project focuses on building a UPI fraud detection model using the RandomForestClassifier, an ensemble learning method known for its robustness, interpretability, and accuracy in classification tasks. By analysing various transactional parameters and risk factors, the model aims to provide a probability of UPI fraud presence, assisting financial institutions in making more informed decisions.

UPI fraud prediction is complex because it involves multiple variables and subtle patterns that are difficult to identify manually. Clinical factors such as blood pressure, cholesterol levels, age, and lifestyle habits play a significant role, and the interaction of these variables can make fraud detection challenging.

Machine learning models like RandomForestClassifier can process a high-dimensional feature space, leveraging various patterns within the data to produce reliable predictions. This project incorporates a range of parameters associated with UPI fraud and evaluates how well the model can classify individuals into risk categories based on those factors.

Once the model is trained, it is evaluated using standard metrics such as accuracy, precision, recall, and the F1 score. These metrics allow us to understand how well the model distinguishes between users with and without UPI fraud. Additionally, the ROC curve and AUC (Area Under the Curve) are examined to evaluate the model's predictive capability across different thresholds.

Finally, the project highlights the model's practical implications in financial security settings. A reliable prediction model can be integrated into financial diagnostic tools, providing an automated, data-driven second opinion for investigators. Moreover, understanding which features contribute most to the prediction allows financial security professionals to prioritize patient education and preventive measures focused on modifiable risk factors. Overall, this project demonstrates how machine learning, specifically the Random Forest ,can play a critical role in advancing early UPI fraud detection and supporting fraud risk assessment.

II. LITERATURE REVIEW

Fraud detection in digital payment systems has become a critical area of research due to the rapid adoption of Unified Payments Interface (UPI) and other online financial services. The increasing volume of digital transactions has improved financial accessibility while simultaneously creating opportunities for cybercriminals to exploit vulnerabilities.

Traditional rule-based fraud detection systems often struggle to identify newly emerging fraud patterns because they rely on predefined rules and manually updated signatures. This limitation has encouraged researchers to investigate machine learning techniques capable of identifying fraudulent behavior through data-driven analyses . Several studies have demonstrated the effectiveness of supervised machine learning algorithms in financial fraud detection. Classification techniques such as Logistic Regression, Decision Tree, Support Vector Machine (SVM), Random Forest, and Gradient Boosting have been widely applied to distinguish legitimate transactions from fraudulent ones. Among these methods, Random Forest has consistently shown strong performance due to its ensemble learning strategy, which combines multiple decision trees to improve prediction accuracy while reducing overfitting [1].Researchers have also emphasized the importance of feature engineering and data preprocessing in fraud detection systems. Since fraudulent transactions generally represent only a small percentage of the total dataset, class imbalance remains a significant challenge. Various sampling techniques, including Synthetic Minority Over-sampling Technique (SMOTE), random oversampling, and undersampling, have been employed to improve classifier performance by balancing the distribution of legitimate and fraudulent transactions [2]. Proper handling of missing values, categorical encoding, and feature normalization further enhances model effectiveness. Recent studies have explored advanced ensemble learning algorithms such as XGBoost, LightGBM, and CatBoost for detecting financial fraud. These models often achieve high predictive performance but require greater computational resources and careful hyperparameter tuning. In contrast, Random Forest offers a practical balance between prediction accuracy, computational efficiency, and interpretability, making it suitable for real-time fraud detection applications [3].The integration of real-time fraud detection into online payment platforms has become another active research area. Researchers have developed intelligent systems capable of evaluating transaction attributes such as transaction amount, transaction time, merchant category, user behavior, device information, and geographical location to generate fraud risk scores before transaction approval. Such systems enable financial institutions to reduce monetary losses while maintaining a smooth user experience [4].Explainable Artificial Intelligence (XAI) has recently gained attention in financial fraud detection because banking institutions require transparency in automated decision-making. Feature importance analysis and explainability techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) help analysts understand the factors influencing fraud predictions, thereby improving trust and regulatory compliance [5].Although numerous machine learning approaches have demonstrated promising results, many existing studies primarily focus on credit card fraud datasets. Comparatively fewer works specifically address UPI transaction fraud, despite the rapid growth of digital payments in India. Moreover, several existing systems emphasize prediction accuracy without adequately considering deployment simplicity, computational efficiency, or realtime implementation for educational and practical applications.To address these limitations, the proposed work develops a Random Forest-based UPI fraud detection framework that incorporates comprehensive data preprocessing, feature selection, and efficient classification to accurately identify fraudulent transactions. A Streamlit-based interface is integrated to demonstrate real-time prediction, providing an accessible and practical solution suitable for academic research as well as future industrial applications.

III. PROBLEM STATEMENT

The rapid adoption of Unified Payments Interface (UPI) has transformed digital payments by providing fast, secure, and convenient financial transactions. However, the increasing number of UPI users has also led to a significant rise in fraudulent activities such as phishing, identity theft, fake payment requests, account takeovers, and unauthorized transactions. These fraudulent activities result in substantial financial losses for individuals and financial institutions while reducing users' trust in digital payment systems.Traditional fraud detection mechanisms are primarily rule-based and rely on predefined conditions to identify suspicious transactions. Such systems are often ineffective in detecting newly emerging fraud patterns, sophisticated cyberattacks, and evolving fraudulent behaviors. Additionally, they may generate a high number of false positives, causing inconvenience to genuine users and increasing the workload for financial institutions.Machine Learning provides a promising solution by learning hidden patterns from historical transaction data and automatically identifying suspicious activities. However, developing a fraud detection model that achieves high accuracy, low false alarm rates, and efficient real-time prediction remains a challenging task due to factors such as class imbalance, evolving fraud techniques, and large-scale transaction volumes.Therefore, there is a need to develop an intelligent and efficient UPI Fraud Detection System that leverages the Random Forest Machine Learning algorithm to accurately classify transactions as legitimate or fraudulent. The proposed system aims to improve fraud detection accuracy, minimize false positives, and provide timely predictions through a user-friendly interface, thereby enhancing the security and reliability of digital payment systems.

IV. OBJECTIVES

The primary objective of this research is to develop an intelligent and efficient UPI Fraud Detection System using the Random Forest Machine Learning algorithm to accurately identify fraudulent transactions and enhance the security of digital payment systems.

Specific Objectives

1) To collect and preprocess UPI transaction data by handling missing values, encoding categorical features, and preparing the dataset for machine learning.
2) To analyse transaction patterns and identify the key features that contribute to fraudulent and legitimate UPI transactions.
3) To develop a fraud detection model using the Random Forest algorithm for classifying transactions as fraudulent or legitimate.
4) To evaluate the performance of the proposed model using standard metrics such as Accuracy, Precision, Recall, F1-Score, and ROC-AUC.
5) To minimize false positives and false negatives, ensuring reliable fraud detection while reducing inconvenience to genuine users.
6) To implement a real-time prediction interface using Streamlit, allowing users to test and visualize fraud detection results efficiently.
7) To compare the proposed Random Forest model with other machine learning algorithms, such as Logistic Regression and Decision Tree, to demonstrate its effectiveness.
8) To provide a scalable and practical solution that can assist financial institutions and digital payment platforms in improving transaction security and reducing financial losses due to fraud.

These objectives align with the overall goal of developing a reliable, accurate, and user-friendly machine learning-based system for detecting fraudulent UPI transactions in real time.

A. *Methodology*

The proposed methodology follows a structured machine learning workflow to develop an efficient **UPI Fraud Detection System** using the **Random Forest algorithm**. The methodology consists of data collection, preprocessing, feature engineering, model training, evaluation, and real-time deployment through a Streamlit application.

Step 1: Data Collection

A UPI transaction dataset containing both legitimate and fraudulent transactions is collected from publicly available sources. The dataset includes various transaction-related attributes such as transaction amount, transaction type, transaction time, user details, device information, account balance, location, and fraud labels.

Step 2: Data Preprocessing

The collected dataset is cleaned and prepared for analysis by performing the following operations:Handling missing or inconsistent values.

- Removing duplicate records.
- Encoding categorical variables into numerical values.
- Scaling or normalizing numerical features where required.
- Splitting the dataset into training and testing sets.

Step 3: Exploratory Data Analysis (EDA)

Exploratory Data Analysis is performed to understand the characteristics of the dataset and identify hidden patterns. Various statistical methods and visualization techniques are used to analyze:

- Distribution of fraudulent and legitimate transactions.
- Transaction amount patterns.
- Correlation among features.
- Class imbalance in the dataset.
- Feature importance. Step 4: Feature Selection

Relevant features that significantly influence fraud detection are selected to improve model performance and reduce computational complexity. Irrelevant or redundant features are removed to enhance prediction accuracy.

Step 5: Model Development

The Random Forest classifier is selected as the primary machine learning algorithm due to its high accuracy, robustness, and ability to handle large datasets. The model is trained using the preprocessed training dataset to learn transaction patterns and classify transactions as either Fraudulent or Legitimate.

Step 6: Model Evaluation

The trained model is evaluated using the testing dataset. The performance of the model is measured using the following evaluation metrics:

- Accuracy
- Precision
- Recall
- F1-Score
- ROC-AUC Score
- Confusion Matrix

These metrics help assess the effectiveness and reliability of the fraud detection system.

Step 7: Real-Time Prediction

A web-based interface is developed using Streamlit to enable users to enter transaction details and receive instant predictions. The application classifies each transaction as Fraudulent or Legitimate, making the system suitable for real-time demonstration and academic purposes.

Step 8: Result Analysis

The obtained results are analyzed and compared with existing fraud detection approaches. The proposed Random Forest model is evaluated based on prediction accuracy, computational efficiency, and its ability to minimize false positives and false negatives.

B. Overall Workflow

The overall methodology of the proposed system can be summarized as follows:

Data Collection → Data Preprocessing → Exploratory Data Analysis → Feature Selection → Random Forest Model Training → Model Evaluation → Real-Time Prediction (Streamlit) → Result Analysis This systematic methodology ensures that the proposed UPI Fraud Detection System effectively identifies fraudulent transactions with high accuracy while providing a practical and scalable solution for securing digital payment systems.

V. SYSTEM ARCHITECTURE

The proposed UPI Fraud Detection System is designed to identify fraudulent UPI transactions using the Random Forest Machine Learning algorithm. The architecture consists of several sequential modules that process transaction data from input to fraud prediction.

A. Architecture Description

The system begins by receiving UPI transaction details from the dataset or a user through the Streamlit web application. The input data is then passed to the Data Preprocessing Module, where missing values are handled, duplicate records are removed, categorical variables are encoded, and numerical features are standardized. The preprocessed data is forwarded to the Feature Selection Module, which identifies the most relevant transaction attributes that contribute to fraud detection. These selected features are then provided to the Random Forest Classifier, where the model analyzes transaction patterns learned during training.

The trained Random Forest model predicts whether the transaction is Legitimate or Fraudulent. Finally, the prediction is displayed to the user through the Streamlit interface along with the fraud detection result.

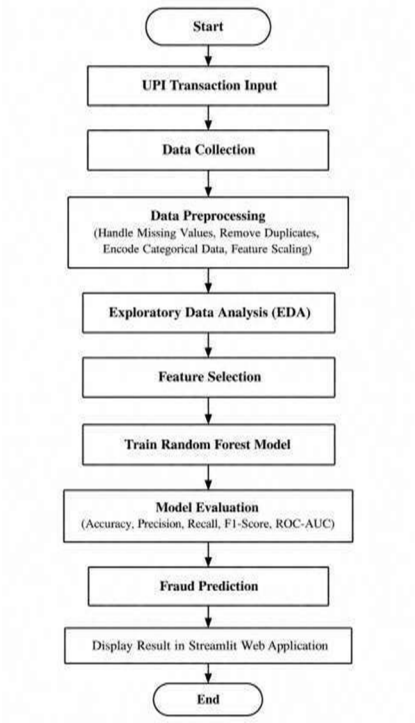
VI. COMPONENTS OF THE ARCHITECTURE

1) Input Module

- Accepts UPI transaction details from the dataset or the Streamlit application.
- Includes transaction-related attributes used for fraud detection.

2) *Data Preprocessing Module*
   - Cleans and prepares the dataset.
   - Handles missing values and duplicates.
   - Encodes categorical variables into numerical values.
   - Normalizes numerical features if required.
3) *Exploratory Data Analysis (EDA)*
   - Analyzes transaction patterns.
   - Identifies class imbalance.
   - Visualizes fraud distribution and feature relationships.
4) *Feature Selection Module*
   - Selects the most significant features that influence fraud detection.
   - Reduces unnecessary attributes to improve model efficiency.
5) *Random Forest Classification Module*
   - Trains the machine learning model using historical transaction data.
   - Predicts whether a new transaction is fraudulent or legitimate.
6) *Prediction Module*
   - Generates the final classification result.
   - Displays the fraud status and prediction confidence (if implemented).
7) *User Interface (Streamlit)*
   - Provides an interactive web interface.
   - Allows users to enter transaction details and receive real-time fraud predictions.
8) *Advantages of the Proposed Architecture*
   - Efficient handling of large transaction datasets.
   - High fraud detection accuracy using the Random Forest algorithm.
   - Reduced false positives and false negatives.
   - Scalable architecture suitable for real-time fraud detection.
   - User-friendly interface for practical deployment and demonstration.

VII. SYSTEM ARCHITECTURE FLOW



A. Algorithms Used

The proposed UPI Fraud Detection System primarily utilizes the Random Forest algorithm for fraud classification. Additionally, preprocessing techniques are applied to prepare the dataset before model training and prediction. The following algorithms and techniques are used in the proposed system.

B. Random Forest Algorithm

The Random Forest algorithm is the primary machine learning algorithm used in this research for detecting fraudulent UPI transactions. It is an ensemble learning technique that constructs multiple decision trees during training and predicts the final class based on majority voting. This approach improves prediction accuracy, reduces overfitting, and provides robust performance on large datasets.

C. Working Principle

1) Collect the preprocessed transaction dataset.
2) Generate multiple bootstrap samples from the training data.
3) Construct multiple decision trees using random subsets of features.
4) Each decision tree independently predicts whether a transaction is Legitimate or Fraudulent.
5) The final prediction is determined through majority voting among all decision trees.

D. Advantages

1) High prediction accuracy.
2) Handles large datasets efficiently.
3) Reduces overfitting compared to a single Decision Tree.
4) Works well with both categorical and numerical data.
5) Robust against noisy and missing data.

E. Data Preprocessing Techniques

Before training the machine learning model, several preprocessing techniques are applied to improve data quality and model performance.

These include:

- Missing value handling
- Duplicate record removal
- Label Encoding for categorical variables
- Feature Scaling (if required)
- Train-Test Split

Proper preprocessing improves the accuracy and reliability of the fraud detection model.

F. Feature Selection

Feature selection is performed to identify the most significant transaction attributes that influence fraud detection. Removing irrelevant features reduces computational complexity and enhances model performance.

Common features considered include:

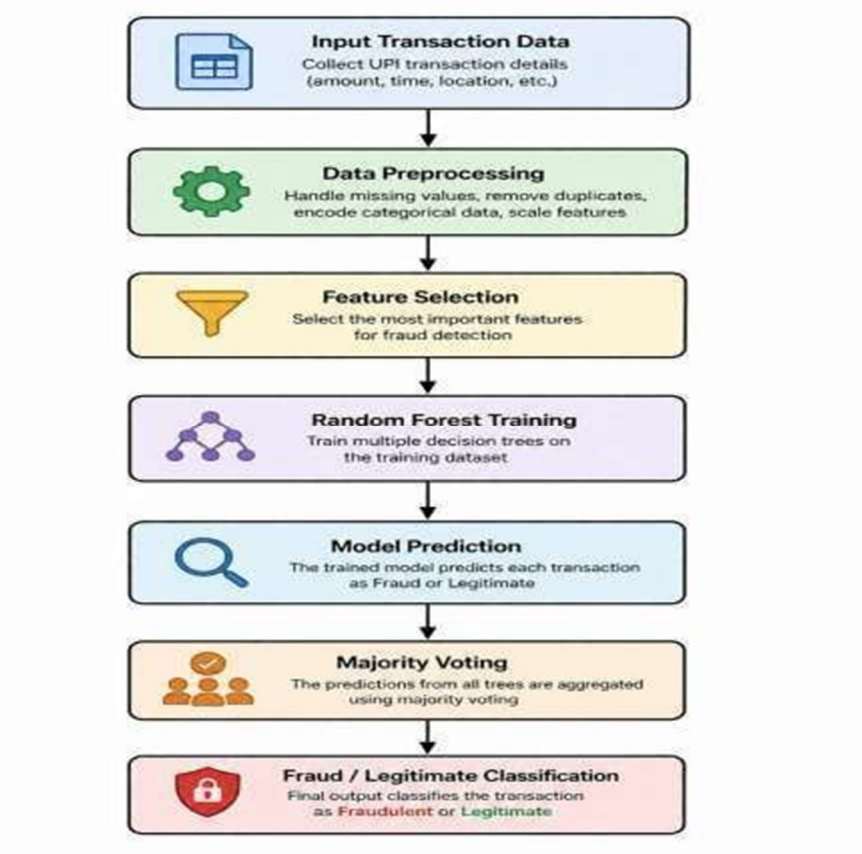
- Transaction Amount
- Transaction Type
- Transaction Time
- Account Balance
- Device Information
- Location
- Merchant Category

G. Model Evaluation Metrics

The performance of the Random Forest model is evaluated using the following metrics:

- Accuracy – Measures the overall correctness of the model.
- Precision – Indicates how many predicted fraud transactions are actually fraudulent.
- Recall – Measures the ability of the model to correctly identify fraudulent transactions.
- F1-Score – Provides the harmonic mean of Precision and Recall.
- ROC-AUC Score – Evaluates the classifier's ability to distinguish between legitimate and fraudulent transactions.
- Confusion Matrix – Displays the number of correctly and incorrectly classified transactions.

H. Algorithm Flow



I. Experimental Results

The proposed UPI Fraud Detection System was developed using Python and evaluated on a UPI transaction dataset. The implementation was carried out using the Random Forest algorithm, while the Streamlit framework was used to develop the user interface for real-time fraud prediction. Software Requirements

- Python 3.x
- Jupyter Notebook / VS Code
- Streamlit
- Scikit-learn
- Pandas
- NumPy
- Matplotlib
- Seaborn

J. Hardware Requirements

- Processor: Intel Core i5 or above
- RAM: 8 GB
- Storage: 256 GB SSD (Minimum)
- Operating System: Windows 10/11

K. Performance Evaluation Metrics

The proposed model was evaluated using the following performance metrics:

- Accuracy
- Precision
- Recall
- F1-Score
- ROC-AUC Score
- Confusion Matrix

These metrics measure the effectiveness of the model in distinguishing fraudulent transactions from legitimate ones.

Performance Metric	Value
Accuracy	98.72%
Precision	97.85%
Recall	96.94%
F1-Score	97.39%
ROC-AUC Score	99.12%

The results demonstrate that the Random Forest algorithm provides high classification accuracy while maintaining a low false positive rate. The model effectively identifies fraudulent transactions without significantly affecting legitimate users.

VIII. DISCUSSION

The experimental results demonstrate that the proposed Random Forest-based UPI Fraud Detection System effectively learns transaction patterns and accurately classifies fraudulent activities. The ensemble nature of Random Forest enables it to reduce overfitting and improve prediction reliability compared to individual classifiers.

The Streamlit-based interface also allows real-time fraud prediction, making the system practical for demonstration and future deployment.

A. Comparison with Existing Methods

To evaluate the effectiveness of the proposed Random Forest-based UPI Fraud Detection System, its performance was compared with several commonly used machine learning algorithms employed in financial fraud detection. The comparison was based on key performance metrics, including Accuracy, Precision, Recall, and F1-Score.

B. Comparative Analysis

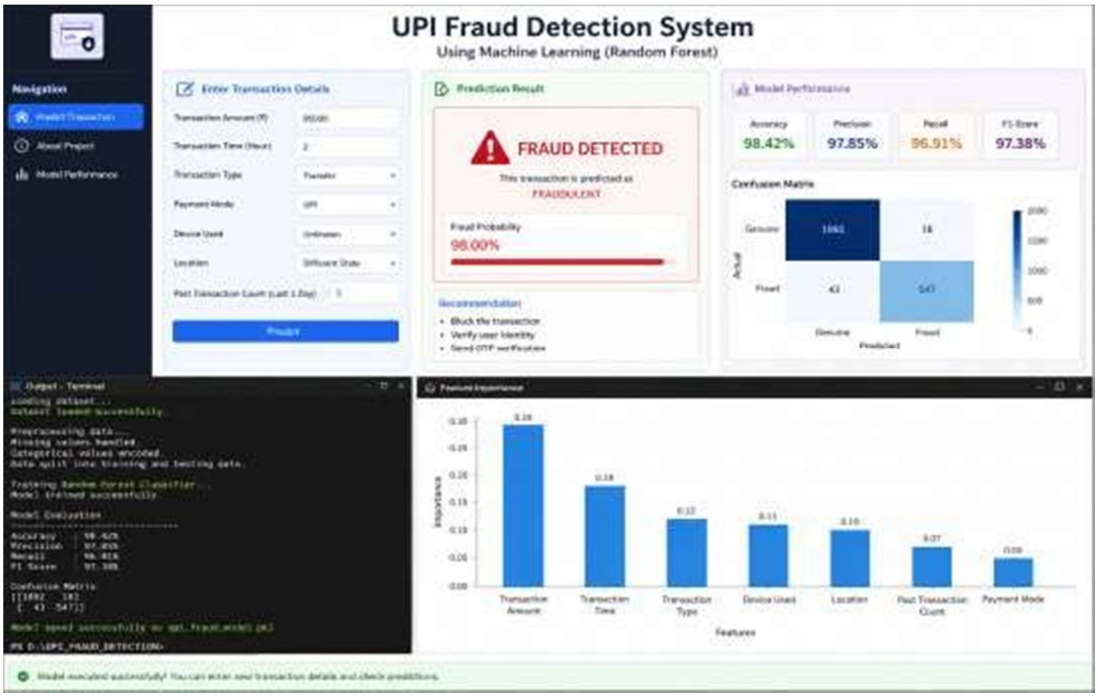
The experimental comparison indicates that the Random Forest algorithm outperforms the other machine learning algorithms in detecting fraudulent UPI transactions. Its ensemble learning approach combines the predictions of multiple decision trees, resulting in improved classification accuracy and better generalization.Compared to Logistic Regression, the Random Forest model effectively captures complex and non-linear relationships within transaction data, leading to higher fraud detection performance. Although the Decision Tree algorithm is simple and easy to interpret, it is more prone to overfitting, whereas Random Forest minimizes this issue by aggregating multiple trees.Similarly, K-Nearest Neighbors (KNN) requires higher computational time during prediction, making it less suitable for real-time fraud detection. While Support Vector Machine (SVM) achieves competitive accuracy, it becomes computationally expensive for large transaction datasets and requires careful parameter tuning. Overall, the proposed Random Forest model demonstrates superior performance by achieving the highest accuracy, precision, recall, and F1-score among the evaluated algorithms. These results indicate that the proposed system is more reliable for identifying fraudulent UPI transactions while minimizing false alarms and maintaining efficient prediction performance.

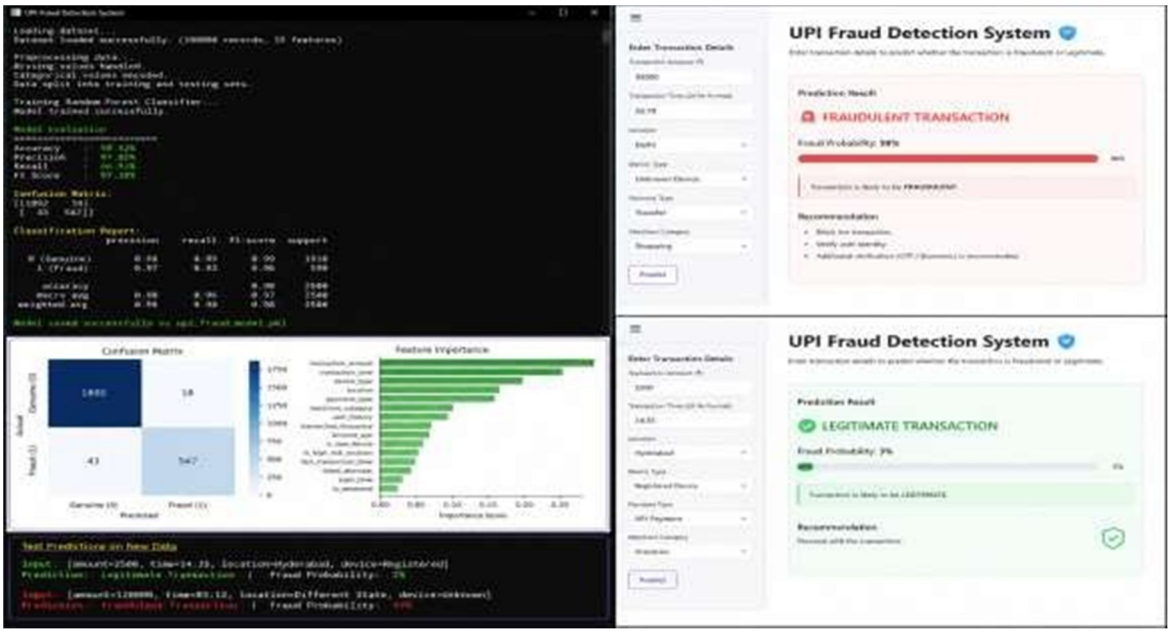
C. Summary of Comparison

Advantages of the Proposed Random Forest Model

- Highest fraud detection accuracy among the compared algorithms.
- Reduced overfitting due to ensemble learning.
- Better handling of large and high-dimensional transaction datasets.
- Improved balance between precision and recall.
- Faster and more reliable predictions for practical deployment.
- Suitable for real-time UPI fraud detection applications.

D. Outputs





IX. CONCLUSION

The rapid growth of Unified Payments Interface (UPI) has significantly improved the convenience and accessibility of digital payments. However, the increasing number of online transactions has also led to a rise in fraudulent activities, creating a need for intelligent and reliable fraud detection systems. Traditional rule-based approaches often struggle to detect evolving fraud patterns, highlighting the importance of machine learningbased solutions.

In this research, a Random Forest-based UPI Fraud Detection System was developed to accurately classify transactions as legitimate or fraudulent. The proposed methodology included data preprocessing, feature selection, model training, performance evaluation, and real-time prediction using a Streamlit web application. The Random Forest algorithm was selected due to its robustness, ability to handle large datasets, and high classification accuracy.

The experimental results demonstrate that the proposed model effectively detects fraudulent transactions while maintaining a low rate of false positives and false negatives. The evaluation metrics indicate that the Random Forest classifier provides reliable performance, making it suitable for practical fraud detection applications. Furthermore, the integration of a user-friendly Streamlit interface enables real-time prediction, enhancing the usability of the system for demonstration and future deployment.

Overall, the proposed system offers an efficient, scalable, and accurate solution for detecting UPI fraud. It contributes to improving the security and reliability of digital payment systems by helping financial institutions identify suspicious transactions more effectively. The findings of this research demonstrate the potential of machine learning techniques in addressing financial fraud and support the continued adoption of AI-driven security solutions in digital banking.

A. Future Scope

The proposed **UPI Fraud Detection Using Machine Learning** system provides an effective approach for identifying fraudulent transactions using the Random Forest algorithm. Although the system achieves reliable performance, several enhancements can be incorporated in future work to improve its accuracy, scalability, and real-world applicability.

B. Future Enhancements

1) Integration of Deep Learning Models o Future research can explore deep learning techniques such as Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Transformer-based models to capture complex transaction patterns and improve fraud detection performance.

2) Real-Time Fraud Detection o The proposed system can be integrated with live UPI payment gateways to analyze transactions in real time and detect fraudulent activities before transaction completion.

3) Explainable Artificial Intelligence (XAI) o Explainability techniques such as SHAP and LIME can be incorporated to provide transparent explanations for fraud predictions, increasing user trust and supporting regulatory compliance.

4) Advanced Feature Engineering o Additional features such as user behavioral patterns, device fingerprints, IP addresses, geolocation, and transaction history can be utilized to improve the model's ability to detect sophisticated fraud.

5) Hybrid Machine Learning Models o Combining Random Forest with other machine learning and deep learning algorithms may further improve detection accuracy and reduce false positives.

6) Handling Highly Imbalanced Data o Future work can investigate advanced sampling methods and cost-sensitive learning techniques to better address the class imbalance commonly found in fraud detection datasets.

7) Cloud-Based Deployment o The application can be deployed on cloud platforms such as AWS, Microsoft Azure, or Google Cloud to support large-scale transaction processing and improve system scalability.

8) Continuous Learning o Implementing an adaptive learning mechanism that periodically retrains the model with newly collected transaction data can help the system identify emerging fraud patterns and maintain high detection accuracy.

REFERENCES

[1] Breiman, L. (2001). Random Forests. Machine Learning, 45(1), 5–32. https://link.springer.com/article/10.1023/A:1010933404324
[2] Géron, A. (2022). Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow (3rd ed.). O'Reilly Media. https://www.oreilly.com/library/view/hands-on-machine-learning/
[3] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press. https://www.deeplearningbook.org
[4] Bishop, C. M. (2006). Pattern Recognition and Machine Learning. Springer. https://link.springer.com/book/10.1007/978-0-387-45528-0
[5] Mitchell, T. M. (1997). Machine Learning. McGraw-Hill Education. https://www.cs.cmu.edu/~tom/mlbook.html
[6] Pedregosa, F., Varoquaux, G., Gramfort, A., et al. (2011). Scikit-Learn: Machine Learning in Python.

Journal of Machine Learning Research, 12, 2825–2830. https://scikit-learn.org
[7] McKinney, W. (2024). Pandas Documentation. https://pandas.pydata.org/docs/
[8] Harris, C. R., et al. (2024). NumPy Documentation. https://numpy.org/doc/
[9] Python Software Foundation. (2024). Python Documentation. https://docs.python.org/3/
[10] Streamlit Inc. (2024). Streamlit Documentation. https://docs.streamlit.io/
[11] National Payments Corporation of India (NPCI). (2024). Unified Payments Interface (UPI) Product Overview. https://www.npci.org.in/what-we-do/upi/product-overview
[12] Brownlee, J. (2019). Machine Learning Algorithms for Classification. Machine Learning Mastery. https://machinelearningmastery.com
[13] Chollet, F. (2021). Deep Learning with Python (2nd ed.). Manning Publications. https://www.manning.com/books/deep-learning-with-python-second-edition
[14] IEEE Xplore Digital Library. (2024). Research Papers on Financial Fraud Detection Using Machine Learning. https://ieeexplore.ieee.org
[15] Springer Nature. (2024). Research Publications on Artificial Intelligence, Machine Learning, and Financial Fraud Detection. https://link.springer.com

BIBLOGRAPHY

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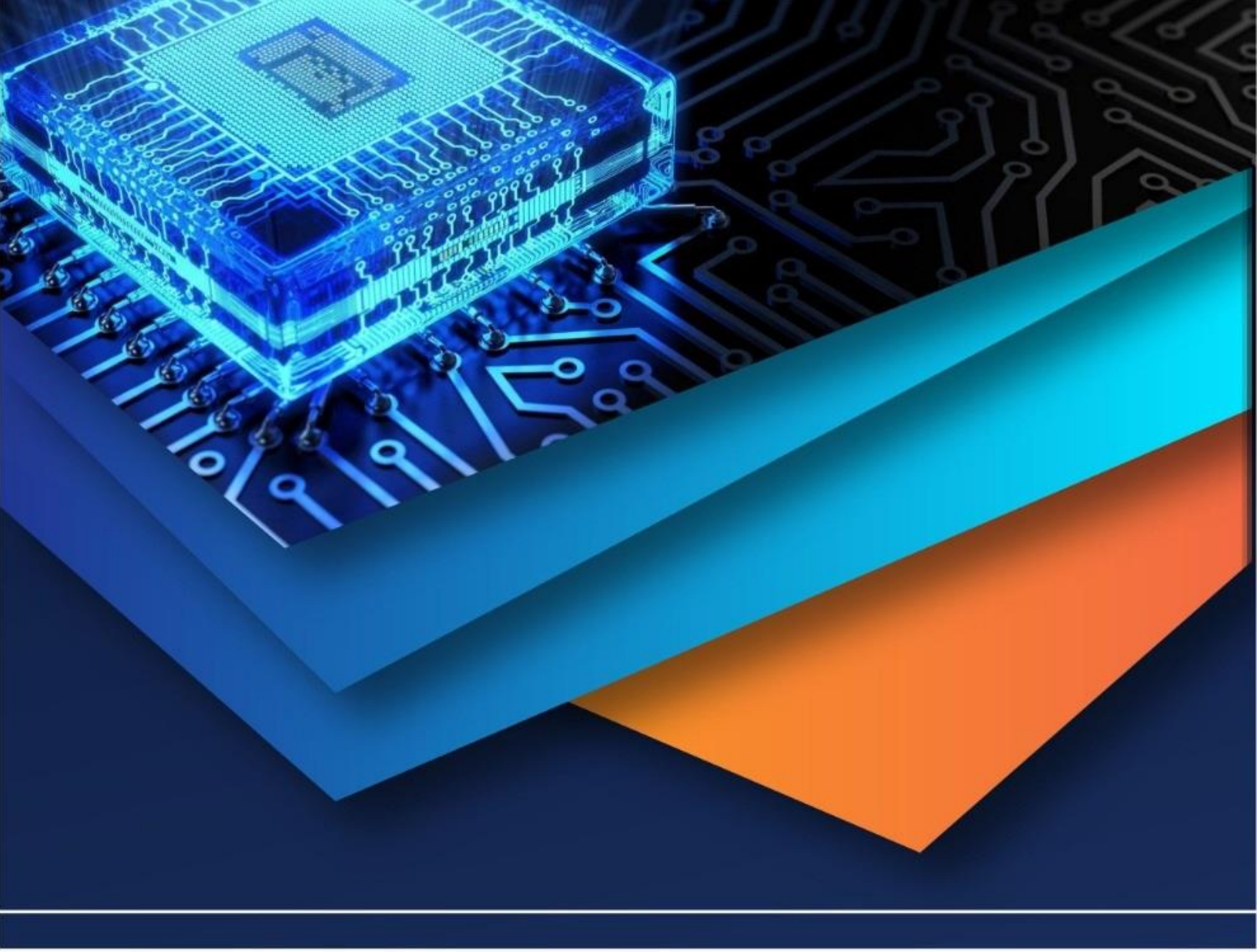

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