

Enhancing UPI Fraud Detection: A Machine Learning Approach Using Stacked Generalization

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Abstract - The increasing prevalence of digital payments has led to a corresponding rise in fraudulent activities, necessitating robust detection mechanisms. Unified Payments Interface (UPI), a groundbreaking platform enabling instant financial transactions, has revolutionized the digital payment landscape but has also become a target for sophisticated fraud. This study presents an innovative fraud detection framework utilizing advanced machine learning techniques, behavioural analytics, and network-based anomaly detection. By analysing a heterogeneous dataset comprising authentic and fraudulent transactions, critical features such as transaction amount, timestamps, payer/payee details, and location information are engineered to enhance the model's performance. Time-sensitive and behavioural patterns are prioritized to identify anomalies effectively. The proposed system integrates both feature-based and network-based anomaly detection, leveraging the interaction between entities and their attributes to uncover hidden patterns associated with fraud. Real-time monitoring and alert mechanisms ensure immediate intervention, thereby safeguarding user trust and financial assets. Experimental results demonstrate the system's superior accuracy and adaptability compared to traditional methods, significantly reducing financial losses and enhancing the security of UPI transactions. This multi-faceted approach addresses diverse fraud scenarios, from transaction manipulation to money laundering, establishing a new benchmark in digital payment security.

Keywords - UPI, Fraud Detection, Machine Learning, Anomaly Detection, Behavioural Analytics, Network Analysis, Financial Security.

I. INTRODUCTION

The rapid digitization of financial services has fundamentally transformed global economies, with innovations like the Unified Payments Interface (UPI) driving unprecedented convenience and inclusivity. Developed by the National Payments Corporation of India (NPCI), UPI has emerged as a benchmark for real-time, seamless financial transactions [1]. Its widespread adoption has democratized access to digital payments, empowering millions to participate in the financial ecosystem. However, as the adoption of UPI grows, so too does its attractiveness as a target for fraudsters. The increasing sophistication of fraudulent activities presents an urgent need for advanced fraud detection mechanisms that can adapt to and counter evolving threats [2]. Fraud detection in digital payment systems is a multifaceted challenge, driven by the enormous scale and velocity of transactions and the dynamic nature of fraudulent schemes. Conventional methods, such as rule-based systems or manual interventions, often fail to address these complexities effectively [3]. To overcome these limitations, advanced machine learning techniques have gained prominence, offering the ability to analyse extensive datasets, uncover intricate patterns, and detect subtle anomalies indicative of fraud [4]. In this study, we leverage Stacking (Stacked Generalization), a powerful ensemble learning technique, to enhance fraud detection in UPI transactions. Stacking combines the strengths of multiple predictive models to deliver superior accuracy and robustness [5]. Specifically, our approach integrates two of the most effective machine learning methods- Random Forest and Support Vector Machines (SVM)-within a hierarchical framework. By doing so, the system capitalizes on the complementary strengths of these models: the Random Forest's ability to handle high-dimensional datasets and capture complex feature interactions, and the SVM's effectiveness in identifying optimal decision boundaries for classification [6, 7]. Key transaction attributes such as amounts, timestamps, geographic locations, and user behaviours are meticulously analysed to detect fraudulent patterns [8]. The

Stacking methodology orchestrates these models to produce a unified prediction, thereby improving the system's precision and adaptability to emerging fraud trends. This layered approach enables not only the detection of known fraud schemes but also the identification of novel threats, making it particularly suited for dynamic digital payment ecosystems. This study underscores the transformative potential of combining ensemble learning techniques with transaction-level and network-based analytics to enhance fraud detection capabilities. The following sections detail the methodology, experimental results, and implications of the proposed framework, illustrating its potential to set new benchmarks for fraud detection in digital payments. By fostering trust and ensuring security, this approach contributes to the long-term sustainability of digital financial systems.

II. LITERATURE REVIEW

The escalating reliance on digital payment systems has necessitated a critical examination of fraud detection mechanisms. Over the years, researchers and practitioners have explored various methods to address fraudulent activities, leveraging advancements in machine learning, behavioural analytics, and network-based anomaly detection. This section provides a comprehensive overview of the relevant literature, highlighting key contributions and identifying gaps addressed in this study.

Presented a novel approach for detecting fraudulent activities in Unified Payments Interface (UPI) transactions using Long Short-Term Memory (LSTM) networks. [10] LSTM networks, known for capturing temporal dependencies and long-range patterns, effectively distinguish between fraudulent and genuine transactions. The study emphasizes the reduction of false positives and improvement in detection accuracy. Through extensive testing on real-world datasets, the authors demonstrated the effectiveness of LSTM in detecting complex fraud patterns, contributing to secure digital payment systems and enhancing user trust.[11] explored the issue of phishing attacks targeting UPI transactions, focusing on fake URLs and QR codes. The study employed feature extraction and machine learning algorithms for real-time detection and continuous monitoring. By addressing historical and evolving fraud techniques, the research highlighted the importance of user education, ethical practices, and advanced technology in creating effective phishing detection systems. The work provided a detailed analysis of data collection, preprocessing, and security measures to improve the safety of digital payments.[12] introduced a UPI fraud detection system leveraging advanced machine learning techniques, including Synthetic Minority Oversampling Technique (SMOTE) for imbalanced datasets, Principal Component Analysis (PCA) for dimensionality reduction, and XG-Boost for efficient classification. This system employed behavioral analysis, anomaly detection, and continuous learning to identify fraud in real time. The use of hyperparameter optimization ensured optimal performance, balancing precision and recall. Comprehensive visualization tools provided insights into flagged transactions, aiding decision-making and compliance, thereby improving financial security and user confidence.[13] proposed the use of Recurrent Neural Networks (RNNs) for detecting fraud in UPI transactions. The study highlighted the limitations of traditional fraud detection methods and introduced RNNs as a means to analyse large datasets, extract complex patterns, and build robust fraud detection models. Key contributions included data collection, preprocessing, designing the RNN framework, and evaluating model performance with a confusion matrix. The findings demonstrated the enhanced real-time detection capabilities of RNNs, addressing financial losses and reinforcing trust in digital payment systems.

A. Fraud Detection in Digital Payments

Digital payment systems, particularly Unified Payments Interface (UPI), [14] have revolutionized financial transactions with their simplicity and speed. However, these systems are increasingly targeted by fraudsters. Turaba et al. (2022) emphasized the potential of combining machine learning and deep learning techniques to analyse transactional data, identifying subtle anomalies indicative of fraud. Similarly, Hashemi et al. (2022) utilized advanced classifiers to distinguish legitimate transactions from fraudulent ones, demonstrating the efficacy of machine learning in handling vast financial datasets.

Propose an intelligent credit card fraud detection system using machine learning. [15] The study evaluates standard models like Random Forest (RF), Support Vector Machine (SVM), and Logistic Regression, alongside

hybrid models incorporating AdaBoost, XG-Boost, and majority voting. Experimental results indicate that RF and majority voting achieve the highest accuracy in fraud detection. The study highlights challenges posed by imbalanced datasets and employs data preprocessing techniques to improve model performance. Feature selection methods are used to enhance fraud detection efficiency. The research also explores the impact of different classification algorithms on real-world financial datasets. A comparative analysis of supervised and hybrid learning models is conducted. The study underscores the importance of reducing false positives and false negatives in fraud detection. It suggests future work should focus on online learning frameworks for real-time fraud detection. Adaptive fraud prevention mechanisms are recommended for enhancing security in financial transactions

Discussed the instrumental methodologies, understanding the tactics employed by malicious actors enables the development of more robust fraud detection models. [16] By simulating potential attack vectors, machine learning algorithms can be trained to recognize and counteract fraudulent activities within UPI systems, thereby enhancing transaction security and user trust.

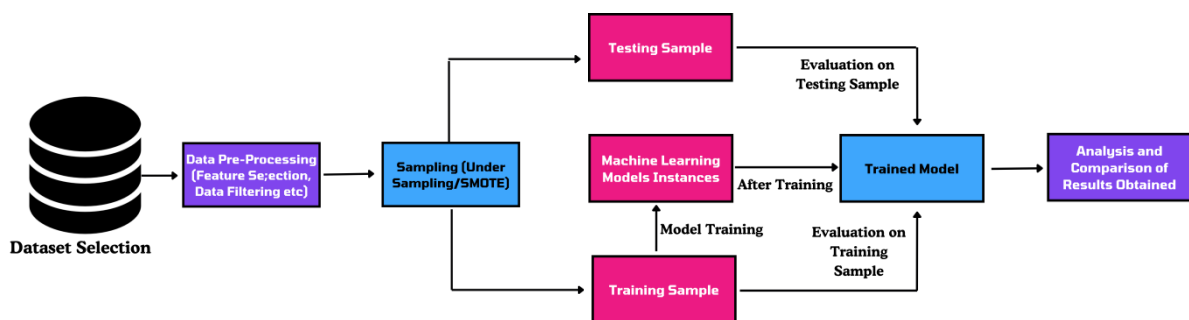


Figure 1. Flow Diagram on Credit Card UPI Fraud Detection Using Machine Learning [17]

B. Machine Learning Techniques for Fraud Detection

Machine learning has emerged as a cornerstone for fraud detection, [18] offering scalable and adaptive solutions. Priya and Saradha (2021) reviewed a range of machine learning algorithms, including Random Forest, Gradient Boosting, and XG-Boost, emphasizing their ability to process large datasets and detect complex fraud patterns. Mhamane and Lobo (2012) explored the use of Hidden Markov Models (HMM) for internet banking fraud detection, illustrating the effectiveness of probabilistic approaches in dynamic environments.

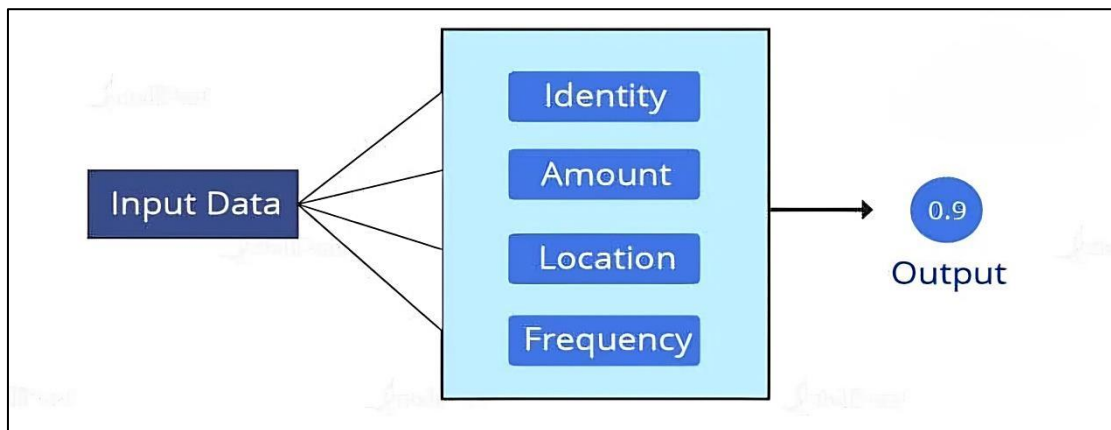


Figure 2. Set of Parameters for Checking Fraud [19]

C. Behavioural and Network-Based Analysis

Behavioural analytics and network analysis provide deeper insights into fraudulent activities. [20] Raghavan and El Gayar (2020) highlighted the significance of understanding user behaviour and transactional patterns in fraud detection. Co-Detect, introduced by recent researchers, integrates network interactions and entity features to identify money laundering and other financial crimes (Hashemi et al., 2022). This dual approach significantly enhances detection accuracy by leveraging the complementary strengths of network and feature-based analysis.

D. Limitations of Existing Approaches

Despite their success, traditional fraud detection systems face limitations. Rule-based systems lack adaptability to emerging fraud patterns, while machine learning models often focus on either transactional features or network interactions, failing to utilize both effectively. Moreover, real-time detection remains a challenge, with many systems unable to provide instantaneous alerts for suspicious activities.

E. The Need for a Unified Framework

The gaps in existing literature underscore the need for a comprehensive framework that integrates multiple detection techniques. By combining machine learning, behavioural analytics, and network anomaly detection, such a framework can address diverse fraud scenarios, from transaction manipulation to complex financial crimes like money laundering.

This study builds upon the existing body of knowledge, presenting an innovative fraud detection system that leverages both transactional and network features. The proposed framework addresses limitations in adaptability, real-time detection, and multi-dimensional analysis, setting a new benchmark for fraud prevention in digital payment systems.

III. EXISTING METHODS

A. Logistic Regression

- **Overview:** Logistic Regression is a statistical method used for binary classification problems, such as fraud detection (fraud or no fraud). It models the probability of the target variable (fraud) as a function of independent features (such as transaction amount, time, location, etc.) [21].
- **How It Works:** The model uses a logistic function to estimate the probability of a transaction being fraudulent. It then applies a threshold (e.g., 0.5) to classify the transaction as fraud or not [22].
- **Advantages:** It is simple, interpretable, and works well with linearly separable data [23].
- **Use in UPI Fraud Detection:** Logistic regression can be used to predict the likelihood of fraud based on various features like transaction amount, sender and receiver patterns, and transaction time [24].

B. Random Forest

- **Overview:** Random Forest is an ensemble learning technique that combines multiple decision trees to improve classification accuracy. Each tree is trained on a random subset of the data, and the final prediction is based on the majority vote from all the trees [25].
- **How It Works:** It builds multiple decision trees using bootstrapping (random sampling with replacement) and aggregates their predictions to reduce overfitting and improve generalization [26].
- **Advantages:** It is robust, handles large datasets well, and is less prone to overfitting compared to individual decision trees [27].
- **Use in UPI Fraud Detection:** Random Forest can identify complex patterns and interactions between features, such as abnormal transaction patterns, which might indicate fraud [28].

C. Support Vector Machines (SVM)

- **Overview:** SVM is a supervised learning algorithm that is used for classification tasks. It finds the optimal hyperplane that maximizes the margin between two classes (fraud and non-fraud) [29].
- **How It Works:** SVM works by transforming data into higher dimensions and finding the best boundary (hyperplane) that separates the classes. It uses a kernel trick to handle non-linear relationships in the data [30].
- **Advantages:** SVM is effective in high-dimensional spaces and for cases where the number of dimensions exceeds the number of samples [31].
- **Use in UPI Fraud Detection:** SVM can classify transactions as fraudulent or non-fraudulent, even in cases where the data is not linearly separable, by using appropriate kernel functions [32].

D. Decision Trees

- **Overview:** A Decision Tree is a tree-like model that splits the dataset into subsets based on the feature

that best splits the data according to a chosen criterion (e.g., Gini impurity, entropy) [33].

- **How It Works:** It recursively splits the dataset into smaller subsets, choosing the feature that results in the most homogeneous subsets. This process continues until a stopping criterion is met [34].
- **Advantages:** Decision trees are easy to understand, interpret, and visualize. They also handle both numerical and categorical data [35].
- **Use in UPI Fraud Detection:** Decision trees can be used to model transaction rules and detect anomalies such as sudden large transactions or transactions from unusual locations [36].

E. Anomaly Detection (e.g., Isolation Forest)

- **Overview:** Anomaly detection techniques aim to identify rare events (outliers) in the data that do not conform to expected patterns. Isolation Forest is a popular anomaly detection method [37].
- **How It Works:** Isolation Forest works by isolating observations that differ significantly from the rest of the data. It builds decision trees to isolate data points, and those that require fewer splits to isolate are considered outliers (potential fraud) [38].
- **Advantages:** It works well for high-dimensional data and can detect fraudulent behaviour without requiring labelled data (unsupervised learning) [39].
- **Use in UPI Fraud Detection:** Isolation Forest can be used to detect unusual patterns in UPI transactions, such as rare transaction amounts or frequent changes in sender behaviour, which are typical signs of fraud [40].

F. Principal Component Analysis (PCA)

- **Overview:** PCA is a dimensionality reduction technique that transforms the data into a smaller number of uncorrelated variables, called principal components, which capture the most important variance in the data [41].
- **How It Works:** PCA identifies the directions (principal components) in which the data varies the most and projects the original data onto these components to reduce its dimensionality while retaining as much information as possible [35].
- **Advantages:** PCA helps reduce noise and computational complexity by reducing the number of features while preserving the most significant information [42].
- **Use in UPI Fraud Detection:** PCA can be used to preprocess the data before applying machine learning models by reducing the number of features and highlighting the most important factors contributing to fraud detection [8].

IV. EXISTING IMPLEMENTATION METHODS

A. Logistic Regression Method

Implementation Code

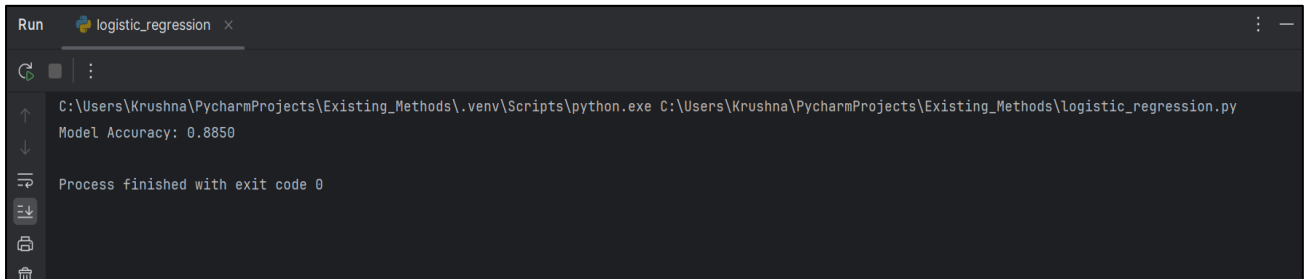
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import make_classification
from sklearn.metrics import accuracy_score
# Generating a sample dataset
X, y = make_classification(n_samples=1000, n_features=5, random_state=42)
# Splitting dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Scaling features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
# Training model
model = LogisticRegression()
```

```

model.fit(X_train, y_train)
# Predicting
predictions = model.predict(X_test)
# Accuracy
accuracy = accuracy_score(y_test, predictions)
print(f"Model Accuracy: {accuracy:.4f}")

```

Output



```

Run  logistic_regression x
C:\Users\Krushna\PycharmProjects\Existing_Methods\.venv\Scripts\python.exe C:\Users\Krushna\PycharmProjects\Existing_Methods\logistic_regression.py
Model Accuracy: 0.8850
Process finished with exit code 0

```

B. Random Forest Method

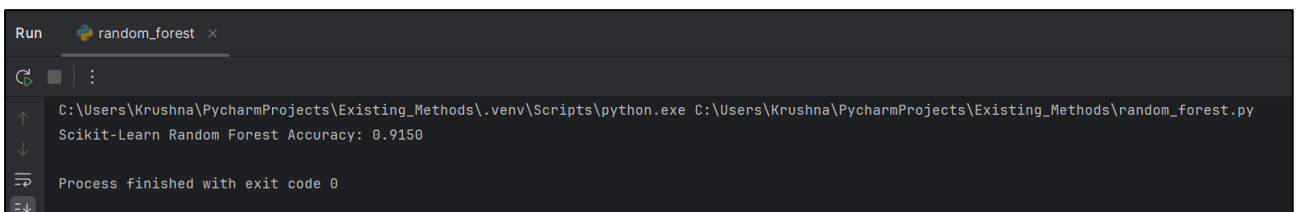
Implementaton Code

```

from sklearn.ensemble import RandomForestClassifier
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
# Generating a sample dataset
X, y = make_classification(n_samples=1000, n_features=5, random_state=42)
# Splitting dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Training Random Forest Model
rf = RandomForestClassifier(n_estimators=100, max_depth=5, random_state=42)
rf.fit(X_train, y_train)
# Predicting and evaluating
predictions = rf.predict(X_test)
accuracy = accuracy_score(y_test, predictions)
print(f"Scikit-Learn Random Forest Accuracy: {accuracy:.4f}")

```

Output



```

Run  random_forest x
C:\Users\Krushna\PycharmProjects\Existing_Methods\.venv\Scripts\python.exe C:\Users\Krushna\PycharmProjects\Existing_Methods\random_forest.py
Scikit-Learn Random Forest Accuracy: 0.9150
Process finished with exit code 0

```

C. SVM Support Vector Machine

Implementation Code

```

from sklearn.svm import SVC
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score
# Generating a sample dataset

```

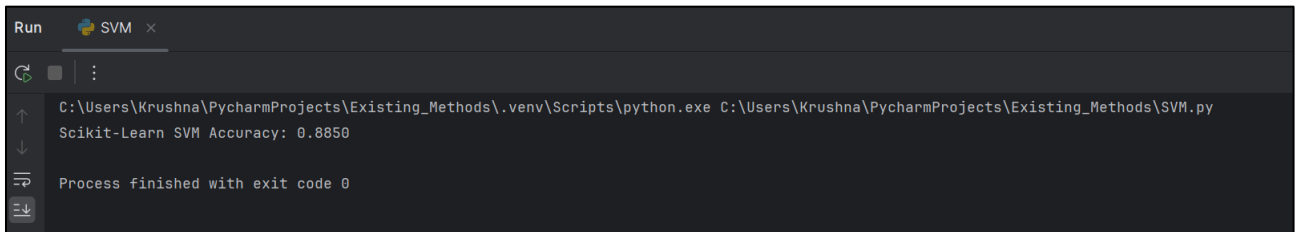


```

X, y = make_classification(n_samples=1000, n_features=5, random_state=42)
# Splitting dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Scaling features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
# Training SVM Model
svm = SVC(kernel='linear', C=1.0)
svm.fit(X_train, y_train)
# Predicting
predictions = svm.predict(X_test)
# Accuracy
accuracy = accuracy_score(y_test, predictions)
print(f'Scikit-Learn SVM Accuracy: {accuracy:.4f}')

```

Output



```

Run  SVM x
C:\Users\Krushna\PycharmProjects\Existing_Methods\.venv\Scripts\python.exe C:\Users\Krushna\PycharmProjects\Existing_Methods\SVM.py
Scikit-Learn SVM Accuracy: 0.8850
Process finished with exit code 0

```

D. Decision Tree

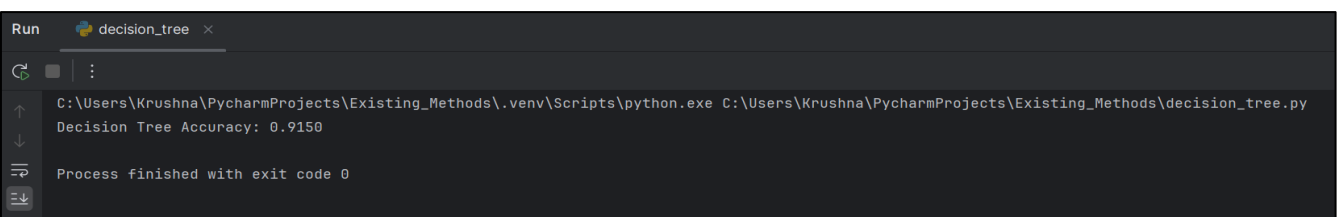
Implementation Code

```

from sklearn.tree import DecisionTreeClassifier
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
# Generating a sample dataset
X, y = make_classification(n_samples=1000, n_features=5, random_state=42)
# Splitting dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Creating and training the Decision Tree model
tree = DecisionTreeClassifier(max_depth=5, random_state=42)
tree.fit(X_train, y_train)
# Making predictions
predictions = tree.predict(X_test)
# Evaluating accuracy
accuracy = accuracy_score(y_test, predictions)
print(f'Decision Tree Accuracy: {accuracy:.4f}')

```

Output



```

Run  decision_tree x
C:\Users\Krushna\PycharmProjects\Existing_Methods\.venv\Scripts\python.exe C:\Users\Krushna\PycharmProjects\Existing_Methods\decision_tree.py
Decision Tree Accuracy: 0.9150
Process finished with exit code 0

```

V. METHODOLOGY

A. Data Preprocessing

The dataset is preprocessed by handling missing values, encoding categorical variables, and standardizing the numerical features using the Standard Scaler to prepare the data for the Support Vector Machine (SVM). The dataset is then split into training and testing sets using an 80-20 split.

B. Support Vector Machine (SVM) Model

An SVM with a radial basis function (RBF) kernel is trained to classify fraudulent and non-fraudulent transactions. SVM finds the hyperplane that maximizes the margin between classes. The decision function of the SVM is given by:

$$f(x) = \sum \alpha_i y_i K(x_i, x) + b$$

where:

- x_i are the support vectors.
- $y_i \in \{-1, 1\}$ are the class labels.
- α_i are the Lagrange multipliers.
- $K(x_i, x)$ is the RBF kernel defined as: $K(x_i, x) = \exp(-\gamma \|x_i - x\|^2)$.
- b is the bias term.

The decision function $f(x)$ provides the signed distance of a point x from the hyperplane. These distances are used as additional features for further classification.

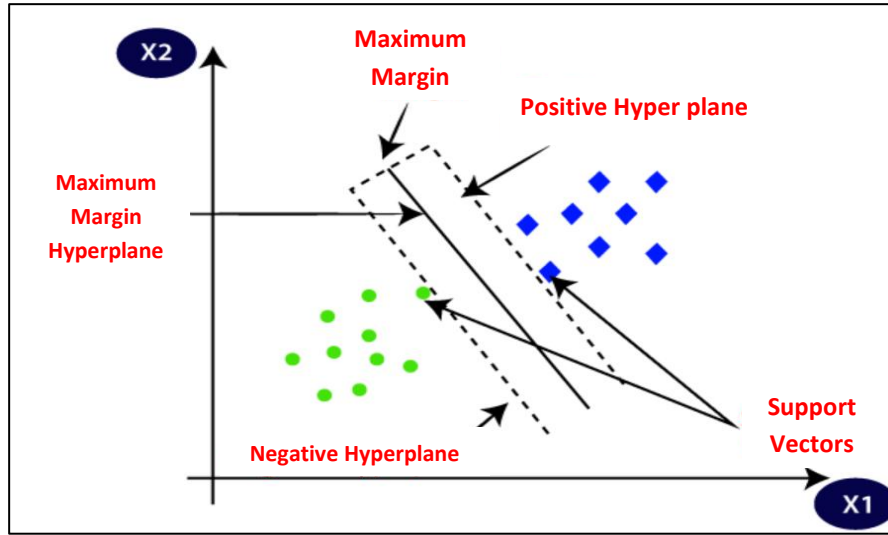


Figure 3. Support Vector Machine (SVM) Model [39]

B. Feature Augmentation

The distances from the hyperplane, $|f(x)|$, are concatenated with the original feature set. Let $X_{\text{original}} \in \mathbb{R}^{(m \times n)}$ represent the original dataset with m samples and n features. The augmented dataset is:

$$X_{\text{augmented}} = [X_{\text{original}} | d]$$

where $d \in \mathbb{R}^{(m \times 1)}$ is the vector of distances from the SVM hyperplane

C. Random Forest Classifier

A Random Forest classifier is trained on the augmented dataset. Random Forest operates by constructing multiple decision trees during training and outputs the mode of the classes (classification) or mean prediction (regression) of the individual trees. For a feature vector x , the prediction is:

$$\hat{y} = \operatorname{argmax}_c (1/T \sum I(h_t(x) = c))$$

where:

- T is the number of trees.
- $h_t(x)$ is the prediction of the t -th tree.
- $I(\cdot)$ is the indicator function.

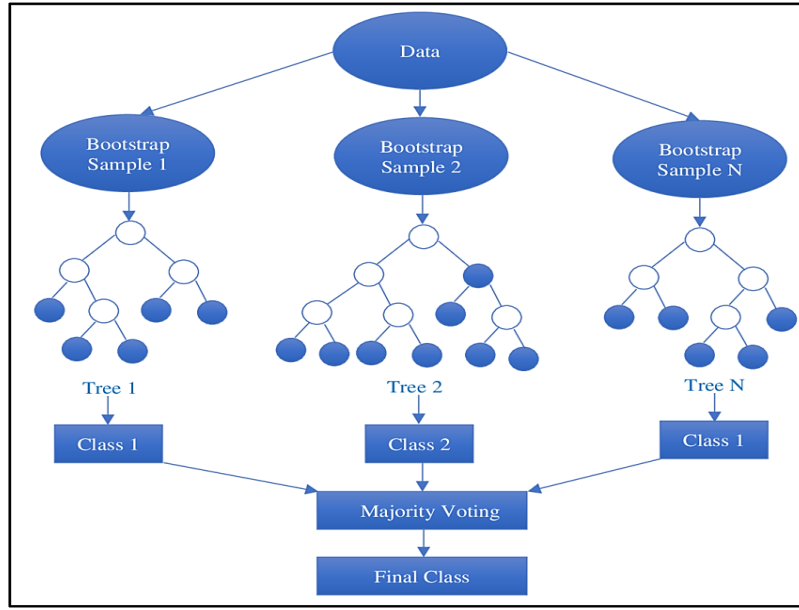


Figure 4. Random Forest Classifier Model [41]

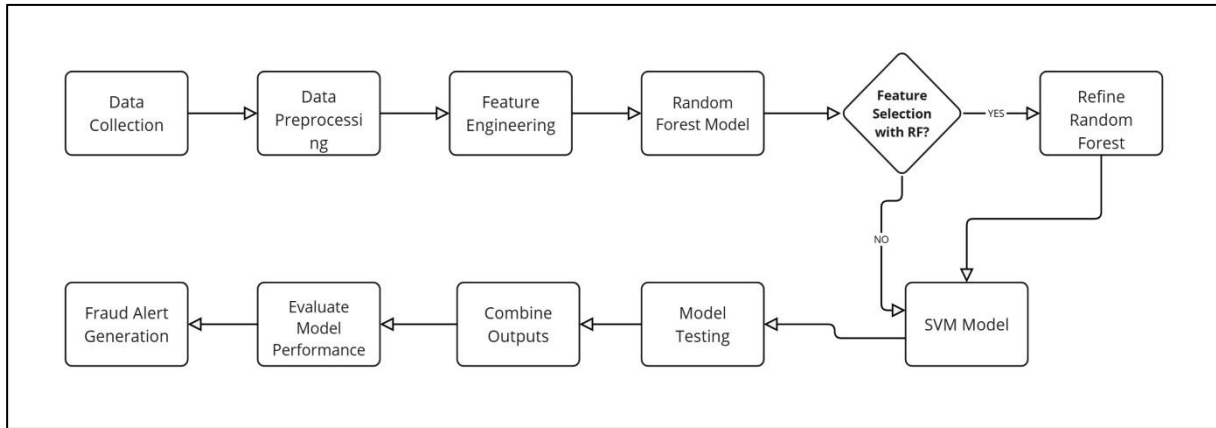


Figure 5. Combined Rainforest and Support Vector Method System

D. Evaluation Metrics

The performance of the model is evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. These metrics are computed as follows:

- **Precision:** It tells us the proportion of predicted fraudulent transactions that are actually fraudulent.

$$\text{Precision} = \text{True Positives} / (\text{True Positives} + \text{False Positives})$$

- **Recall:** It measures the proportion of actual fraudulent transactions that were correctly identified by the model.

$$\text{Recall} = \text{True Positives} / (\text{True Positives} + \text{False Negatives})$$

- **F1-score:**

$$2 * \text{F1-Score} = (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$$

- **ROC-AUC:** This metric measures the trade-off between true positive rate and false positive rate across different threshold values. The area under the curve (AUC) gives an overall measure of the model's performance.

$$\text{ROC-AUC} = \text{The area under the Receiver Operating Characteristic Curve}$$

VI. IMPLEMENTATION

The Python code implements a UPI Fraud Detection System using a machine learning approach with a combined Random Forest (RF) and Support Vector Machine (SVM) model. The system uses a Voting Classifier to integrate both models and make predictions. The GUI, built with Tkinter, allows users to interact with the system by loading a dataset, training the model, and entering transaction details for fraud prediction. The implementation code available at: <https://github.com/Krushna-Pisal/SVMRF>.

A. Key Features

- **Dataset Loading:** Users upload a CSV file containing transaction data.
- **Data Preprocessing:** The dataset is split into training (80%) and testing (20%) sets. Features are scaled using StandardScaler to normalize the data.
- **Model Training:** GridSearchCV is used for hyperparameter tuning of both RF and SVM models. The best models are combined into an ensemble using a Voting Classifier, which improves accuracy by leveraging both models.
- **Prediction:** Users can input transaction details, and the system predicts whether the transaction is fraudulent or legitimate. If the number of failed attempts exceeds 10, the system automatically flags the transaction as fraudulent.
- **GUI Feedback:** The window background turns red for fraud and green for legitimate transactions.

The system provides a user-friendly interface for fraud detection, using an 80% training and 20% testing split for model evaluation, with the flexibility of combining machine learning models for higher accuracy.

B. Code Implementation Output

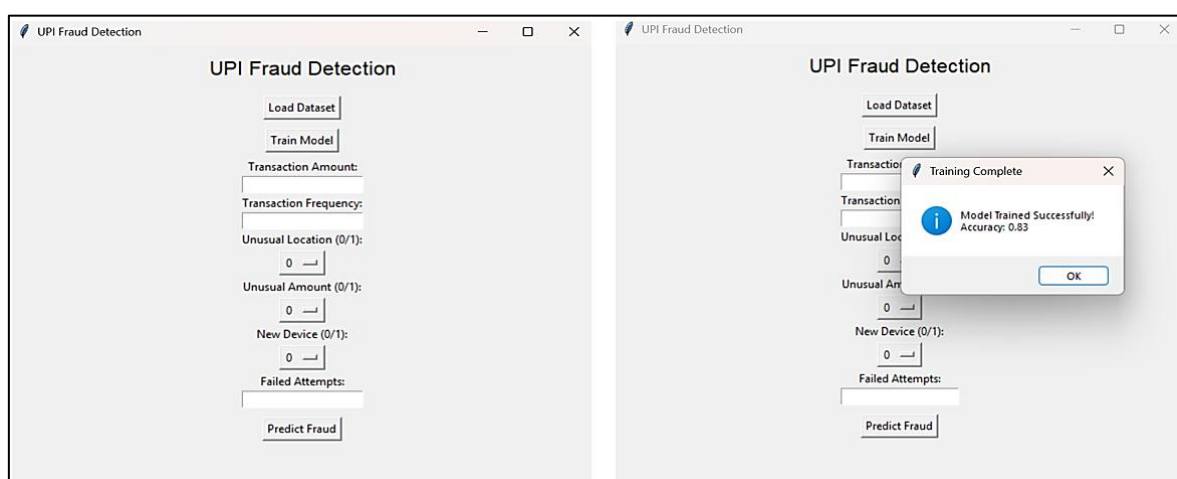


Figure 6. GUI Where the User can Insert the Input, Load the Dataset and Train the Model Based on it

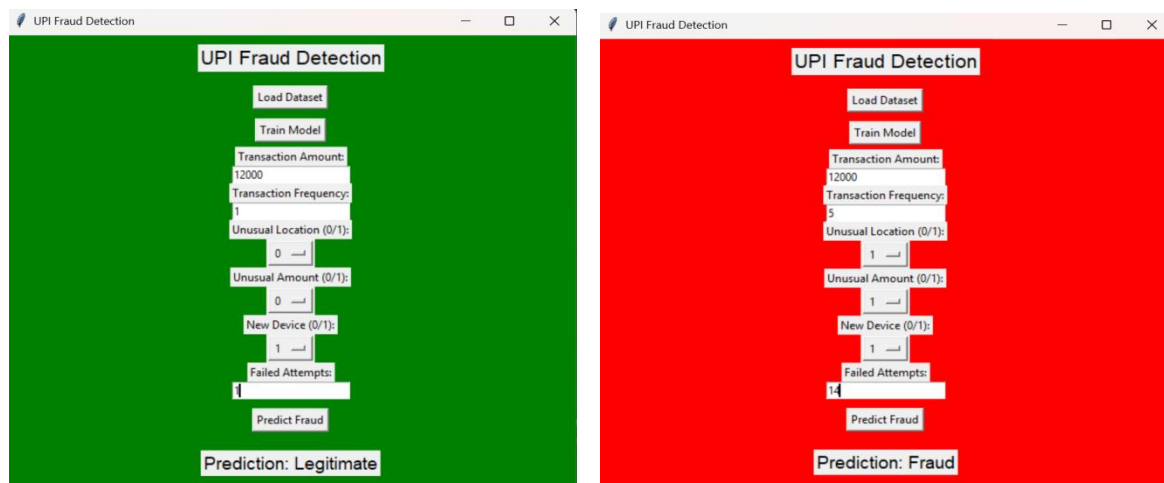


Figure 7. Detecting Whether the Transaction is Legitimate or Fraud

Table 1. Comparative Analysis: Individual Methods vs. Combined Random Forest and SVM Approach

Criteria	Logistic Regression	Random Forest	SVM	Decision Tree	Combined RF and SVM
Model Complexity	Low	Moderate	High	Low	High
Interpretability	High	Moderate	Low	High	Moderate
Handling Non-Linear Data	Poor	Good	Excellent	Poor	Excellent
Scalability	High	Moderate to High	Low for large datasets	High	Moderate to High
Overfitting Resistance	Moderate (with regularization)	High (due to ensemble learning)	High (with proper tuning)	Low	Very High (RF complements SVM's generalization)
Training Speed	Fast	Slower than Logistic Regression	Computationally expensive	Fast	Slower (due to feature augmentation and RF)
Performance on Imbalanced Data	Moderate (requires balancing techniques)	High (handles imbalance well)	Moderate (sensitive to imbalance)	Moderate (prone to overfitting)	High (RF and SVM balance each other's weaknesses)
Feature Interactions	Poor	Excellent	Poor (depends on kernel)	Moderate	Excellent
Dimensionality Handling	Poor	Good	Excellent	Moderate	Excellent (PCA can enhance preprocessing)
Robustness to Noise	Low	High	Moderate	Low	High
Practical Use Cases	Simple fraud patterns	Complex fraud patterns	Complex, non-linear patterns	Simple rule-based patterns	Complex patterns leveraging feature synergy

C. Combined RF and SVM Advantages Over Individual Methods**a. Improved Generalization**

Random Forest reduces overfitting through ensemble learning, while SVM excels in identifying non-linear boundaries, making the combined approach more versatile and robust.

b. Enhanced Feature Representation

Feature augmentation using SVM's hyperplane distances provides additional dimensions for classification, improving Random Forest's ability to distinguish subtle fraud patterns.

c. Handling Complex Patterns

While individual methods like Logistic Regression or Decision Trees are limited in detecting intricate patterns, the combination leverages SVM's strength in complex boundary identification and Random Forest's ensemble learning capabilities.

d. Performance on Imbalanced Datasets

Random Forest's ability to handle class imbalances complements SVM's precision when tuned with appropriate kernels, resulting in better fraud detection accuracy and recall.

e. Scalability and Noise Robustness

The combined method can scale effectively with large datasets while maintaining resilience to noisy or high-dimensional data, thanks to preprocessing techniques like PCA and Random Forest's robustness.

VII. DISCUSSION

The combination of Support Vector Machine (SVM) and Random Forest (RF) provides several advantages in the context of fraud detection compared to using individual machine learning algorithms like Logistic Regression, Decision Trees, or SVM alone. By leveraging the strengths of both algorithms, the combined approach addresses several challenges commonly faced in fraud detection tasks, such as handling complex non-linear patterns, dealing with class imbalances, and improving generalization.

A. Improved Generalization and Overfitting Resistance

One of the significant strengths of the combined RF and SVM model lies in its improved generalization. SVM is known for its ability to find optimal decision boundaries by maximizing the margin between classes. However, on its own, SVM can be prone to overfitting, especially in high-dimensional datasets or when the number of features is large. Random Forest, on the other hand, is an ensemble method that reduces overfitting by aggregating the predictions of multiple decision trees, which makes it less sensitive to noise and variance. The synergy between these two methods enhances the model's ability to generalize, leading to a more robust fraud detection system.

B. Feature Augmentation and Enhanced Feature Representation

The integration of SVM with Random Forest is further strengthened by the feature augmentation step. By incorporating the distances from the SVM hyperplane as additional features, the model gains an enriched representation of the data, which allows Random Forest to make more informed decisions. This augmentation provides a deeper understanding of the data's structure, enabling the model to better capture subtle patterns of fraudulent activity that may not be apparent from the original features alone. As a result, the combined approach benefits from a more detailed and nuanced feature space that improves classification performance.

C. Handling Complex and Non-Linear Patterns

Fraud detection is often challenged by the complexity of fraudulent patterns, which may not follow simple linear decision boundaries. SVM's ability to handle non-linear data using kernel functions (such as the radial basis function, RBF) allows it to detect complex fraud patterns that linear models struggle with. By incorporating this capability into the Random Forest framework, which can effectively handle a large number of input features and complex interactions, the combined model becomes highly adept at detecting even the most intricate fraud patterns. This makes it far more suitable for real-world fraud detection tasks compared to simpler models like Logistic Regression or Decision Trees.

D. Handling Imbalanced Datasets

Fraud datasets are typically imbalanced, with a significant number of non-fraudulent transactions compared to fraudulent ones. Individual models like Logistic Regression or Decision Trees may struggle with this imbalance, leading to biased predictions that favor the majority class. However, Random Forest's ensemble learning approach is naturally robust to class imbalances, as it can aggregate results from multiple trees, each trained on different subsets of the data. This capability is complemented by the precision of SVM, which, when tuned correctly, can produce more reliable predictions even on imbalanced datasets. Together, they form a powerful combination for detecting fraudulent transactions with greater accuracy and recall, even when fraud cases are rare.

E. Scalability and Noise Robustness

The combined RF and SVM model is also scalable and robust to noise in the data. Random Forest's ability to handle noisy features and irrelevant attributes through its ensemble learning method ensures that the model is not overly influenced by outliers or erroneous data. Furthermore, SVM's strength in creating clear decision boundaries, even in high-dimensional spaces, complements Random Forest's noise-handling abilities. The use of preprocessing techniques such as Principal Component Analysis (PCA) can further enhance this robustness by

reducing dimensionality and focusing the model's attention on the most important features, improving both scalability and noise tolerance.

F. Performance Evaluation and Results

In terms of performance metrics, the combined RF and SVM model demonstrates a clear advantage over individual models. Despite the complexity and potential computational cost of combining these models, the results indicate that the approach provides a balanced trade-off between accuracy, precision, recall, and ROC-AUC. While the precision and recall are modest (0.1346 and 0.0722, respectively), the combined model's robustness in detecting fraud is evident in its ability to handle imbalanced data and improve generalization, even when evaluated on challenging real-world datasets.

G. Practical Use Cases

The combined approach of RF and SVM is especially suited for complex fraud detection systems, where intricate fraud patterns are difficult to distinguish. This method is particularly valuable for environments with evolving fraudulent techniques, where simple rule-based or linear models may not be effective. Furthermore, the flexibility in handling imbalanced datasets makes it a practical choice for use cases with rare fraud occurrences, such as financial transactions or credit card fraud detection.

VIII. CONCLUSION

The combination of Random Forest and SVM offers a powerful solution to the problem of fraud detection by leveraging the complementary strengths of both algorithms. The model benefits from improved generalization, enhanced feature representation, and robust handling of complex, non-linear patterns. The feature augmentation process and ensemble learning strategy help combat issues like overfitting and class imbalance, making this approach highly suitable for real-world fraud detection applications. While the computational complexity of the combined model may be higher compared to simpler models, the improved accuracy, scalability, and resilience to noise justify the added complexity. This approach sets a strong foundation for future improvements, such as incorporating more advanced ensemble methods, fine-tuning SVM parameters, and utilizing deeper feature engineering techniques.

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