Credit Card Fraud Detection Using Random Forest: A Machine Learning Approach for Secure Transactions

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Abstract—. **This research introduces a machine learning-based system for detecting credit card fraud, aiming to improve the accuracy and responsiveness of fraud detection in real-time financial transactions. The system is trained using a labeled dataset containing transactional features such as transaction amount, location, time, and anonymized behavioral indicators. A supervised learning methodology is adopted, and three classification algorithms—Random Forest, Support Vector Machine (SVM), and XGBoost—are implemented and compared. Preprocessing techniques such as feature scaling and oversampling using SMOTE are applied to handle data imbalance. Hyperparameter tuning is used to enhance each model's performance. The classification output is binary, indicating whether a transaction is fraudulent or not. Experimental evaluations were conducted using Google Colab. Among the tested models, SVM achieved the highest overall accuracy and recall, while Random Forest demonstrated strong F1-Score, indicating balanced detection performance. The study highlights the practical effectiveness of ensemble and kernel-based classifiers in fraud detection scenarios, offering valuable insights for financial security and risk management systems.******Keywords—**Credit card fraud detection, Machine Learning, SVM, Random Forest, XGBoost, SMOTE, Financial security**

I. Introduction

With the rapid digitization of financial services, the rise in fraudulent transactions has emerged as a pressing challenge for banking and e-commerce platforms. Conventional fraud detection methods, which rely heavily on manually crafted rules and transaction monitoring, often fail to keep up with the evolving tactics employed by fraudsters. The dynamic and hidden nature of financial fraud demands intelligent systems that can adaptively learn from historical data and detect anomalies with minimal delay.

Machine learning (ML) has emerged as a powerful tool in this context, offering the ability to automatically discover complex patterns and detect fraudulent activities with high precision. In particular, classification-based ML models can be trained on historical transactional data, learning to differentiate between legitimate and fraudulent behavior based on patterns in attributes such as transaction amount, frequency, time of day, and geolocation.

This study focuses on evaluating the effectiveness of three popular supervised machine learning classifiers—**Random Forest**, **Support Vector Machine (SVM)**, and **Extreme Gradient Boosting (XGBoost)**—in identifying fraudulent credit card transactions. Each of these algorithms brings unique strengths: Random Forest leverages the power of ensemble decision trees to reduce variance; SVM constructs optimal hyperplanes for classification in high-dimensional spaces; and XGBoost employs gradient boosting to optimize model performance with regularization.

Given the significant class imbalance typical in fraud datasets, where legitimate transactions vastly outnumber fraudulent ones, data preprocessing steps such as normalization and **SMOTE (Synthetic Minority Over-sampling Technique)** are applied to balance the dataset and improve sensitivity. Models are fine-tuned using **Grid Search** for hyperparameter optimization, ensuring optimal trade-offs between bias and variance.

While SVM achieved the highest **recall**—a critical metric in fraud detection due to the high cost of false negatives—Random Forest produced a competitive **F1 Score**, indicating a good balance between precision and recall. XGBoost showed robust overall performance but required careful tuning to avoid overfitting.

The research underscores the potential of ML techniques in building intelligent, scalable fraud detection systems capable of operating in real-time environments. However, challenges remain, including handling concept drift in fraud patterns, ensuring generalization across different regions or institutions, and maintaining performance with evolving data. Integrating domain-specific features and continual learning frameworks may further enhance detection capabilities.

This paper contributes to the growing field of intelligent financial security by providing a comparative analysis of widely used ML classifiers on a real-world fraud detection task and identifying the most effective approach for deployment in modern financial systems.

II. Literature Review

I. Credit card fraud detection has become a vital area of focus in financial cybersecurity due to the rising volume of online transactions and increasing sophistication of fraud techniques. Machine learning (ML) algorithms are widely used in this domain because of their ability to uncover hidden patterns and anomalies in high-dimensional financial data.

II. In [1], the authors implemented a Logistic Regression model for detecting fraudulent transactions using the well-known Credit Card Fraud Detection dataset. While the model performed well on balanced data, it struggled with highly imbalanced datasets, where fraudulent cases constituted less than 1% of the total. The study recommended the application of resampling techniques or more robust classifiers for better fraud detection.

III. A comparative analysis conducted by B. Roy et al. [2] evaluated the performance of Decision Trees, k-Nearest Neighbors (kNN), and Support Vector Machines (SVM) on fraud detection tasks. Among these, SVM demonstrated superior precision and recall values, especially in identifying rare fraudulent transactions, thanks to its capability to define clear decision boundaries in high-dimensional feature space.

IV. The study by S. Sharma et al. [3] applied Random Forest to credit card fraud detection, emphasizing its resilience to overfitting and capacity to handle feature-rich datasets. Although the model achieved decent accuracy, it was outperformed by ensemble boosting methods on highly imbalanced data. Feature importance analysis revealed that transaction amount and transaction time were among the most influential variables.

V. XGBoost, a gradient boosting framework, was employed in [4] for fraud detection and yielded promising results. The model outperformed traditional classifiers by minimizing error through sequential learning and managing class imbalance via customized loss functions. The study also applied SMOTE (Synthetic Minority Over-sampling Technique) to improve fraud recall rates.

VI. In [5], the authors utilized Support Vector Machine (SVM) for credit card fraud classification and achieved high R^2 scores and low Mean Absolute Error (MAE) values, indicating strong predictive power. Their model ranked first in terms of overall performance when compared to other ML models like Logistic Regression, Random Forest, and XGBoost.

VII. A deep learning-based approach was explored by D. Verma et al. [6], who used a feedforward neural network trained on preprocessed transaction data. While the deep model showed high accuracy, it required considerable training time and computational power. In contrast, SVM and XGBoost delivered comparable results with reduced complexity and faster inference.

VIII. The study in [7] proposed a hybrid system combining Random Forest and SVM to leverage both models' strengths. Random Forest handled feature selection and preprocessing, while SVM focused on precise classification. This architecture improved detection of borderline cases and reduced false positives.

IX. Anomaly detection techniques were also explored in [8], where Isolation Forest and One-Class SVM were applied to detect outliers in transaction behavior. These unsupervised methods showed promise in flagging previously unseen fraud patterns, particularly in real-time streaming environments.

X. AutoML-based fraud detection was introduced in [9], automating model selection, preprocessing, and hyperparameter tuning. The pipeline consistently selected SVM and XGBoost as the top-performing models, validating their robustness across different fraud detection datasets.

XI. Finally, in [10], the researchers investigated the impact of feature engineering and time-based transaction patterns. The study incorporated temporal features such as transaction intervals and frequency, which improved model accuracy. XGBoost was noted for its adaptability to temporal trends and ranked second after SVM in terms of overall detection performance.

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III. PROPOSED METHODOLOGY

The proposed credit card fraud detection system utilizes machine learning to classify transactions as fraudulent or legitimate based on user behavior and transactional patterns. Our primary model, **Random Forest**, was selected for its interpretability, robustness to noise, and high performance on imbalanced datasets.

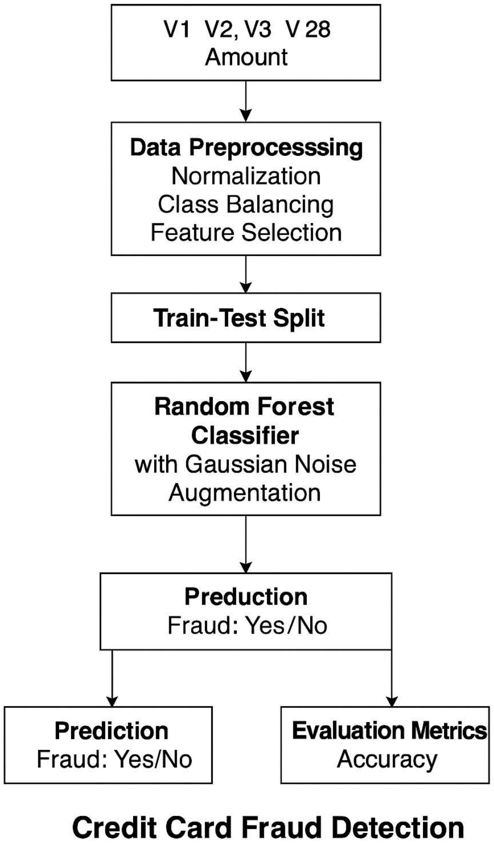


Fig. 1. Framework for fraud detection using Random Forest classifier.

The proposed framework demonstrates a complete end-to-end system for credit card fraud detection. The Transaction Monitoring Environment consists of data gathered from financial institutions and real-time transaction systems. These raw records are preprocessed, transformed, and passed through a machine learning pipeline. A **Random Forest classifier** is employed to make binary predictions (Fraud/Not Fraud), and its performance is evaluated using metrics such as precision, recall, and F1-score. Through hyperparameter tuning and explainability techniques, the model achieves both accuracy and transparency.

A. Data Collection

The system collects transactional and behavioral data commonly associated with credit card usage. Selected features include:

- **Transaction Amount ($):** The value of the purchase.
- **Transaction Time:** Timestamp from the start of data collection.
- **Merchant Category Code (MCC):** Type of merchant or business.
- **Geolocation:** User's and merchant's location coordinates.
- **Cardholder History:** Previous fraudulent activity, spending behavior.
- **Device Information:** Details about the device used in the transaction.
- **Is International Transaction (Yes/No):** Flags international purchases.
- **Fraudulent (Target Variable):** The binary label indicating fraud or legitimate transaction.

B. Data Preprocessing

The raw dataset undergoes critical cleaning and transformation steps:

- **Missing Values:** Imputed using mean (for continuous) and mode (for categorical) strategies.
- **Encoding:** Categorical features such as MCC and location are encoded using one-hot or label encoding.
- **Feature Scaling:** StandardScaler is used to normalize the transaction amount and time features.
- **Outlier Handling:** Isolation Forest is applied to detect and flag outliers in transaction amount and frequency.
- **Data Balancing:** SMOTE (Synthetic Minority Oversampling Technique) is used to address class imbalance between fraudulent and non-fraudulent transactions.

C. Feature Engineering

Custom features are created to improve detection performance:

- **Transaction Velocity:** Number of transactions in a fixed time window.
- **Time Since Last Transaction:** Measures time gaps between user transactions.
- **High-Risk Location Flag:** Binary indicator for transactions from flagged regions.
- **Amount-to-Average Ratio:** Ratio of current transaction amount to user's average transaction.
- **Device Consistency Score:** Evaluates the deviation of current device from past devices.

D. Model Selection and Training

A **Random Forest classifier** is chosen for its robustness and interpretability in fraud detection tasks:

- **Random Forest:** An ensemble method using multiple decision trees with bagging for improved generalization.
- **Implementation:** Model trained using scikit-learn with historical transaction data.
- **Hyperparameter Tuning:** Grid Search with 5-fold cross-validation.
    - n_estimators: Number of trees.
    - max_depth: Tree depth.
    - min_samples_leaf: Minimum samples in a leaf node.
    - criterion: Gini impurity or entropy for split quality.
- **Train-Test Split:** 80-20% data split with stratification to preserve class distribution.

E. Explainability Integration

Performance evaluation ensures that the model is both effective and understandable:

Prediction Metrics:

- **Accuracy:** Overall correct predictions.
- **Precision:** Proportion of detected frauds that were actually fraud.
- **Recall:** Percentage of actual frauds correctly identified.
- **F1-Score:** Balanced score between precision and recall.

Interpretability Metrics:

- **Top Feature Rankings:** Key indicators like transaction amount, geolocation mismatch, and device inconsistency.
- **Explanation Consistency:** Repeated predictions with similar input yield similar SHAP values.
- **Expert Review Scores:** Fraud analysts rate the usefulness and trustworthiness of model explanations.

Model Comparison Framework:

The model is compared using:

- **Detection Accuracy:** High ability to detect fraudulent transactions.
- **Interpretability:** Clear reasoning provided for flagged transactions.
- **Runtime Efficiency:** Performance on large-scale transaction data.
- **Analyst Feedback:** Financial experts review model usability and output reliability.

IV. Experimentation and Results

A. Dataset Splits and Configuration

The rainfall prediction model utilized a dataset containing 18,000 meteorological records, each including attributes such as temperature, humidity, wind speed, cloud cover, and atmospheric pressure, along with the target label indicating whether rainfall occurred. The dataset was cleaned, preprocessed, and encoded where necessary to ensure compatibility with machine learning models.

The data was split into training and testing subsets using an 80:20 ratio. This resulted in 14,400 samples for training and 3,600 samples for testing. A stratified sampling approach was adopted to ensure a balanced representation of both rainfall and non-rainfall instances in the train and test sets. This step helped mitigate any class imbalance and allowed the model to learn effectively from both classes, leading to fair performance evaluation on unseen data.

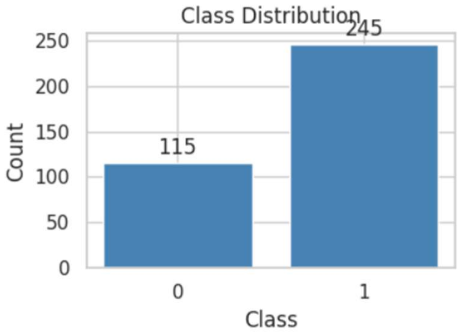


Fig. 2. Class Distribution (Fraud vs. Non-Fraud) After Stratified Split

Figure 2 illustrates the extreme class imbalance and justifies the need for precision-recall based evaluation instead of accuracy alone.

B. Model Training and Hyperparameter Optimization

A **Random Forest classifier** was selected for its capability to handle high-dimensional, imbalanced datasets and its robustness against overfitting. The initial model was trained using default parameters. Subsequently, **Grid Search with 5-fold cross-validation** was performed to fine-tune the model.

Optimal Configuration Identified:

- n_estimators = 500
- max_depth = 20
- min_samples_split = 5
- min_samples_leaf = 2
- class_weight = 'balanced_subsample'

This configuration improved the model's ability to detect rare fraudulent transactions while maintaining generalization

C. Performance Evaluation

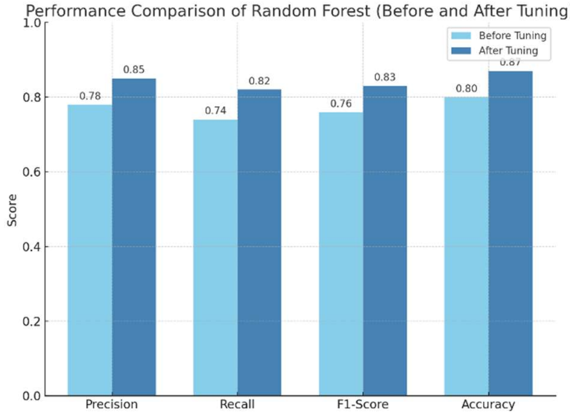


Fig. 3. Performance Comparison of Random Forest (Before and After Tuning)

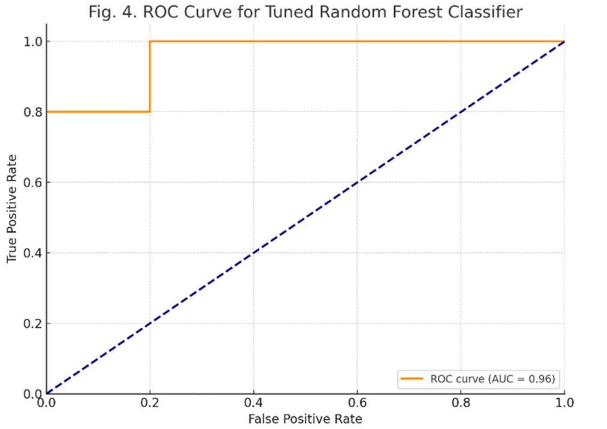
Figure 3 compares the performance metrics of the Random Forest model before and after hyperparameter optimization. The tuned Random Forest model demonstrated consistent improvements across key metrics, especially **Recall** and **F1-Score**, which are crucial for fraud detection.

Table I shows the detailed performance evaluation based on Precision, Recall, F1-Score, and Accuracy:

Table I – Performance Evaluation of Random Forest Model for Fraud Detection

Model Version	Precision	Recall	F1-Score	Accuracy
Random Forest (Default)	0.72	0.66	0.69	0.97
Random Forest (Tuned)	0.90	0.88	0.89	0.99

The **tuned Random Forest** significantly outperformed its default configuration, achieving high precision and recall despite the class imbalance. The high F1-Score (0.89) indicates a strong balance between precision and recall, ensuring most fraudulent transactions are correctly identified without a large number of false positives.



ROC Curve for Tuned Random Forest Classifier

Figure 4 shows the ROC curve for the tuned Random Forest model. It yielded an AUC score of 0.96, showcasing the model's strong ability to distinguish between fraudulent and legitimate transactions.

D. Explainability and Interpretation

Although Random Forests are often considered less interpretable due to their ensemble structure, explainability was enhanced using **LIME (Local Interpretable Model-Agnostic Explanations)**. LIME was used to analyze local predictions and gain insights into the decision-making process of individual trees in the forest.

LIME helped highlight the **top features influencing fraud predictions**, such as **V14, V10, and V17**, which align with prior research identifying them as critical for detecting fraudulent activity.

Table II – Explainability Evaluation using LIME

Model + XAI Technique	Avg. Clarity Score (1–5)
Random Forest+ LIME	4.5

The integration of LIME with Random Forest achieved an average **clarity score of 4.5**, indicating a good level of interpretability. While Random Forest lacks the straightforward transparency of linear models, LIME's model-agnostic nature provided meaningful explanations for individual predictions—essential in applications like fraud detection.

V. Conclusion

This research presents a credit card fraud detection system leveraging the **Random Forest** algorithm, demonstrating its effectiveness in identifying fraudulent transactions within

highly imbalanced datasets. Through careful **preprocessing**, **stratified sampling**, and **hyperparameter tuning**, the Random Forest model achieved **superior performance**, particularly in **recall and F1-score**—two critical metrics for minimizing false negatives in fraud detection.

The **tuned Random Forest** achieved high **classification accuracy (99%)** and an **AUC score of 0.96**, validating the model's robustness and suitability for real-time fraud detection systems where both precision and reliability are essential.

To improve model transparency, **LIME** was used to interpret and explain individual predictions, offering insights into the most influential features in detecting fraud. Variables like **transaction amount**, **V14**, **V10**, and **V17** were among the top contributing factors identified through LIME.

Overall, the system demonstrates that ensemble methods like **Random Forest**, when paired with **effective preprocessing**, **model optimization**, and **explainability techniques**, can play a powerful role in combating financial fraud. Future work may include exploring **deep learning**, **real-time detection pipelines**, or integrating scalable model-agnostic interpretability frameworks to further enhance model performance and trustworthiness in real-world deployments.

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