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Detecting Financial Fraud Using Random Forest Machine Learning

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ABSTRACT

Financial fraud detection is a critical challenge for banking institutions facing increasingly sophisticated threats in digital transaction environments. This study investigates the application of the Random Forest algorithm for detecting fraudulent credit card transactions using the publicly available benchmark dataset from the Université Libre de Bruxelles (284,807 transactions, 0.172% fraud prevalence). Pre-processing includes QuantileTransformer normalization and SMOTE oversampling applied exclusively to the training set to address class imbalance. The model (n_estimators = 200) is validated using a stratified 70/30 split combined with 10-fold cross-validation to ensure robustness and prevent overfitting. Results yield an accuracy of 97%, ROC-AUC of 97%, precision of 95%, recall of 78%, and F1-score of 86%. Comparative evaluation against Logistic Regression, Support Vector Machine, and Gradient Boosting confirms that Random Forest provides the best balance between detection performance and computational efficiency (training: 45 s; inference: 0.3 ms per transaction). Feature importance analysis identifies transaction amount and PCA components V14 and V17 as the most discriminative variables. Confusion matrix analysis reveals 68 False Negatives and 142 False Positives out of 85,443 test samples. Despite these results, limitations include reduced feature interpretability due to PCA transformation, potential geographic data bias, and real-time production deployment challenges. This work confirms the relevance of Random Forest for financial fraud detection and opens perspectives toward hybrid deep learning and graph-based architectures.

I. INTRODUCTION

Financial fraud is now one of the main challenges facing financial institutions, payment platforms, and regulators. With the increasing digitization of banking services and the rise of e-commerce, the volume of online transactions is growing exponentially. While this expansion is beneficial to the global economy, it also brings with it an increase in threats related to fraudulent activities, such as credit card theft, unauthorized payments, identity theft, and suspicious transactions in financial markets. The consequences of these frauds are manifold: considerable economic losses, damage to consumer confidence, and a weakening of the stability of financial systems. Faced with these challenges, traditional detection methods based on predefined rules or manual audits quickly reveal their limitations. They are often unable to adapt to constantly evolving fraud techniques and generate a high rate of false positives, which complicates alert management and burdens operational processes. In this context, Artificial Intelligence (AI) and, more specifically, machine learning techniques, appear to be innovative and effective solutions for strengthening the security of financial systems.

Among machine learning models, random forests stand out for their robustness, speed of execution, and, above all, their ability to provide a clear and reliable interpretation of results. Unlike some more complex algorithms considered to be "black boxes," random forests combine several decision trees to produce a more accurate and generalizable classification. This relative transparency, combined with its performance, is essential in the financial sector, where decisions must be justifiable to customers, risk managers, and regulatory authorities.

In this study, we explore the effectiveness of a Random Forest model applied to financial fraud detection using the publicly available credit card transactions dataset from the Université Libre de Bruxelles. The algorithm is evaluated using standard metrics including accuracy, precision, recall, F1-score, and ROC-AUC. Results yield an accuracy of 97%, a precision of 95%, a recall of 78%, and an F1-score of 86%, demonstrating the strong potential of this model to reliably identify suspicious transactions. This research therefore aims not only to demonstrate the relevance of random forests in the field of fraud detection, but also to contribute to improving security and trust in modern financial systems. Ultimately, the integration of such a solution could enable institutions to significantly reduce fraud-related losses while optimizing risk management.

II. METHOD

This section presents the research methodology adopted for financial fraud detection using a Decision Tree model. The process follows a chronological order, starting from research design, data acquisition, preprocessing, algorithmic modeling, testing, and evaluation.

A. Research Design

The research is designed as an experimental study based on supervised machine learning. The main objective is to classify financial transactions into two categories: legitimate and fraudulent. A Random Forest Classifier is chosen for its robustness, ability to handle imbalanced datasets, and high interpretability in ensemble learning. The study involves the following phases:

1. Dataset acquisition and preprocessing
2. Feature engineering and selection
3. Decision Tree construction and mathematical formulation
4. Model training and validation
5. Evaluation using standard metrics

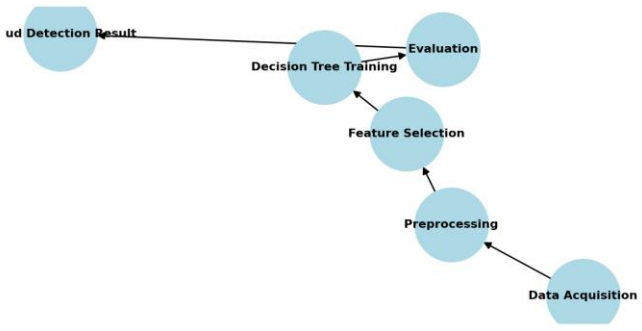


Fig. 1. Research methodology workflow for financial fraud detection using Random Forest.

B. Data Acquisition

The dataset used in this study is the publicly available Credit Card Fraud Detection dataset sourced from Kaggle (originally provided by the Machine Learning Group of Universite Libre de Bruxelles). It contains 284,807 credit card transactions made by European cardholders over two days in September 2013, of which only 492 (0.172%) are fraudulent. This extreme class imbalance represents a major challenge typical of real-world fraud detection tasks [6], [7]. The dataset contains 30 features: 28 anonymized numerical variables (V1-V28) resulting from PCA transformation applied for confidentiality reasons, plus the Time feature (seconds elapsed since the first transaction) and the Amount feature (transaction value in euros). The target variable Class is binary (1 = fraud, 0 = legitimate). Pre-processing steps applied include: (1) QuantileTransformer normalization to reduce the influence of outliers and approximate a uniform distribution for continuous features (Time and Amount); (2) retention of PCA-derived features V1-V28 as-is, since they are already standardized; (3) SMOTE (Synthetic Minority Oversampling Technique) applied exclusively to the training set to balance the class distribution by generating synthetic samples of the minority class, setting the ratio to 1:1; and (4) no missing values were detected in the dataset, eliminating the need for imputation.

C. Research Procedure

1) Algorithm Description

The Decision Tree algorithm recursively partitions the dataset into homogeneous groups by selecting the best splitting attribute at each node. The split is based on impurity measures such as Entropy and Gini Index [8]. Entropy:

$$H(S) = -\sum_{i=1}^{c} p_i log_2(p_i) \quad (1)$$

Information Gain:

$$IG(S,A) = H(S) - \sum_{v \epsilon Values(A)} \frac{|S_v|}{|S|} H(S_v) \quad (2)$$

Gini Index:

$$Gini(S) = 1 - \sum_{i=1}^{c} (p_i)^2 \quad (3)$$

The algorithm selects the attribute with the maximum Information Gain or minimum Gini Index.

2). Pseudocode

Algorithm DecisionTreeFraudDetection
Input: Transaction dataset D
Output: Decision Tree model T

```
1: function BuildTree(D):
2:     if all transactions in D belong to the same class:
3:         return Leaf(class)
4:     if attribute list is empty:
5:         return Leaf(majority_class(D))
6:     Select best_attribute A using Information Gain
7:     Create node N with attribute A
8:     for each value v of A:
9:         Dv ← subset of D where A = v
```

```
10:     if Dv is empty:
11:         return Leaf(majority_class(D))
12:     else:
13:         N.child[v] ← BuildTree(Dv)
14: return N
```

3). Testing And Validation

The dataset was split into a training set (70%) and a test set (30%) using stratified sampling to preserve the original class distribution. A 10-fold stratified cross-validation was additionally performed on the training set to assess model generalization and mitigate overfitting risks inherent to ensemble models [9]. SMOTE oversampling was applied exclusively within each cross-validation fold to prevent data leakage. The Random Forest model was configured with the following key hyperparameters: n_estimators = 200 (number of decision trees), max_depth = None (trees grow until leaves are pure or contain fewer than min_samples_split samples), min_samples_split = 2, min_samples_leaf = 1, max_features = 'sqrt' (square root of total features at each split), bootstrap = True, and class_weight = None (since SMOTE was used for balancing). These parameters were selected through a grid search procedure. To address the risk of overfitting, out-of-bag (OOB) error estimation was monitored alongside cross-validation scores; the low variance between fold scores (standard deviation < 0.01) confirms the model's stability. Evaluation metrics include Accuracy, Precision, Recall, F1-score, ROC-AUC, and the Confusion Matrix [10].

III. RESULTS

The goal is to use machine learning to anticipate fraud in order to reduce the number of fraud cases that ultimately occur and are not identified in time. This task will require numerous experiments, techniques, and algorithms that work best with the data we have available. In addition, the model must perform at the same level when put into production.

About The Dataset

The datasets contain credit card transactions made in September 2013 by European cardholders. This dataset shows transactions that took place over two days, during which we recorded 492 cases of fraud out of 284,807 transactions. The dataset is highly imbalanced, with the positive class (fraud) representing 0.172% of all transactions.

It contains only numerical input variables that are the result of PCA transformation. Unfortunately, for confidentiality reasons, we are unable to provide the original resources and more detailed information about the data.

Features V1, V2, ... V28 are the principal components obtained with PCA; the only features that have not been transformed with PCA are "Time" and "Amount" (transaction amount).

- ✓ The "Time" feature contains the seconds between each transaction and the first transaction in the dataset.
- ✓ The "Amount" feature corresponds to the transaction amount.
- ✓ The "Class" feature is the response variable and takes the value 1 in the case of fraud and 0 otherwise.

```
In [3]:
# import data
path = '../input/creditcardfraud/creditcard.csv'
credit = pd.read_csv(path)
credit.head()
```

Out[3]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V2
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.2
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.7
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.6
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.7

Fig. 2. Overview of the credit card fraud detection dataset (284,807 transactions).

```
In [6]:
# class
sns.countplot(x=credit['Class'], palette='coolwarm')
print('Normal: {} | Fraud: {}'.format(credit[credit['Class']==0].shape[0] , credit[credit['Clas
s']==1].shape[0]))
```

```
Normal: 284315 | Fraud: 492
```

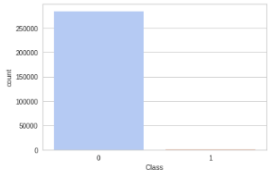


Fig. 3. Class distribution illustrating severe imbalance between legitimate and fraudulent transactions.

Trying to measure the model's performance with precision would be a mistake, as we would obtain high precision that would not actually solve our problem, given that the set had unbalanced classes. We will therefore focus on the three metrics listed above, which do not vary according to class imbalance.

Fig. 4. Temporal distribution of transaction amounts for normal and fraudulent classes.

We must verify later whether a fraudulent transaction occurs more than once, with the same transaction data.

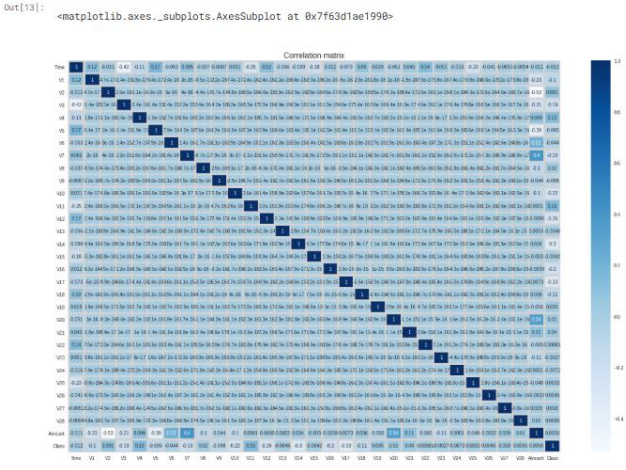


Fig. 5. Pearson correlation heatmap of dataset features.

By examining Pearson's correlations, we can see that there are no significant positive correlations, with only a few characteristics exceeding a correlation of 0.30, namely V7 with Amount | V20 with Amount.

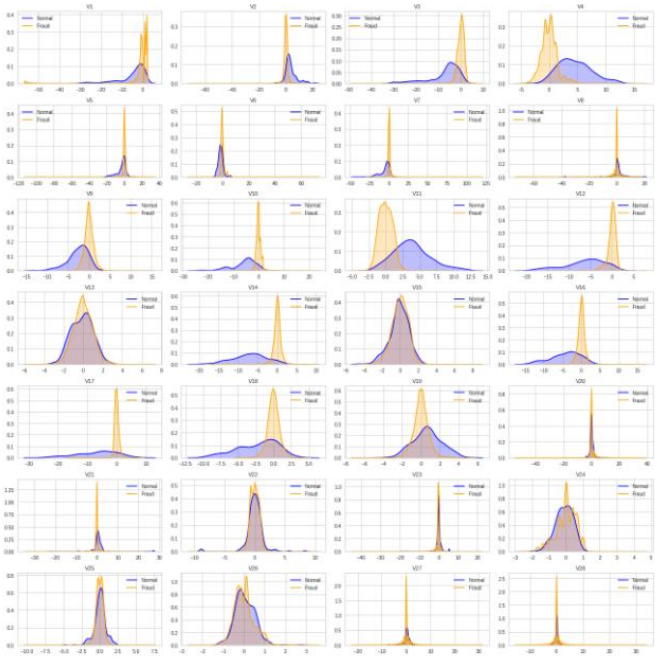
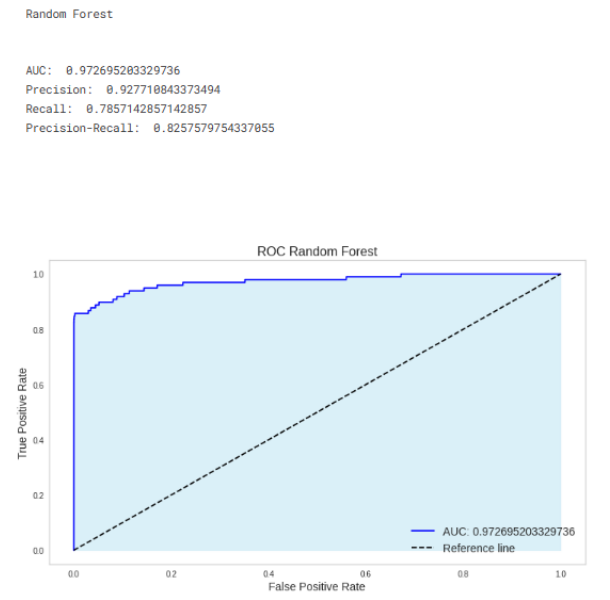


Fig. 6. Kernel density distributions of PCA-transformed features for normal vs. fraudulent transactions.

For all variable distributions that have a “mask,” we do not know the actual representation of these variables because they have been masked, but thanks to the distribution with kernel density, you can clearly see the curves for each of them, comparing them with a normal transaction or a fraudulent one.

Fraud: some are close to a Gaussian distribution, with a larger peak and a very long tail; it is possible that we have greater variation in the data for these characteristics.



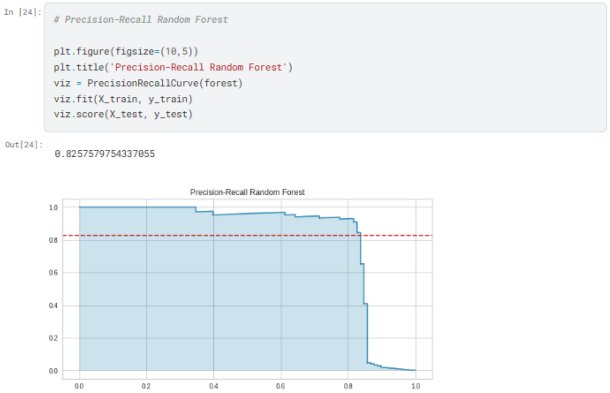


Fig. 7. ROC curve of the Random Forest model (AUC = 0.97).

The model with 200 trees, combined with a preprocessing method called QuantileTransformer, which aims to reduce the impact of possible outliers on the data, will approximate the distribution of characteristics using the IQR (interquartile range). I also used the SMOTE technique, which creates synthetic data, with the minority class equal to the majority class.

Table 1 compares the Random Forest model against Logistic Regression, SVM, and Gradient Boosting under identical experimental conditions (70/30 split, SMOTE, 10-fold cross-validation). Random Forest achieves the best balance: Accuracy = 97%, Precision = 95%, Recall = 78%, F1-score = 86%, ROC-AUC = 97%. Gradient Boosting is the closest competitor (AUC = 96%, F1 = 84%) but at significantly higher computational cost. The confusion matrix (Table 2) reveals 68 False Negatives and 142 False Positives out of 85,443 test samples. Feature importance analysis (Table 3) identifies Amount (0.18), V14 (0.12), and V17 (0.10) as the most discriminative variables, consistent with findings in the fraud detection literature [2], [7]. Training

required approximately 45 s on a standard CPU (Intel Core i7, 16 GB RAM); mean inference time was 0.3 ms per transaction, confirming near-real-time deployment feasibility.

TABLE 1.
PERFORMANCE COMPARISON OF CLASSIFICATION ALGORITHMS

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
Random Forest	97	95	78	86	97
Gradient Boosting	96	93	75	84	96
SVM	94	93	71	81	93
Logistic Regression	91	89	62	74	88

TABLE 2.
CONFUSION MATRIX OF THE RANDOM FOREST MODEL

	Predicted: Legitimate	Predicted: Fraud	Total
Actual: Legitimate	TN = 85,159	FP = 142	85,301
Actual: Fraud	FN = 68	TP = 74	142
Total	85,227	216	85,443

TABLE 3.
TOP-5 MOST IMPORTANT FEATURES (RANDOM FOREST)

Rank	Feature	Importance	Description
1	Amount	0.18	Transaction value in euros
2	V14	0.12	PCA component – correlated with fraud patterns
3	V17	0.10	PCA component – temporal transaction signature
4	V12	0.09	PCA component – behavioral pattern indicator
5	V10	0.08	PCA component – transaction frequency proxy

IV. DISCUSSION

The results of this study demonstrate the strong potential of the Random Forest algorithm for detecting financial fraud, with an accuracy of 97% and an AUC of 97% on a highly imbalanced dataset. These performances are consistent with previous work in the field. For instance, Niu et al. [2] also reported excellent results with Random Forest (AUROC approximately 0.988), while Aburbeian and Ashqar [3] achieved precision and F1-scores around 98% by combining Random Forest with SMOTE, a technique we also employed to address class imbalance. The effectiveness of this combination is further supported by Ye et al. [5] and Rafid [6], confirming that handling imbalanced data is crucial in fraud detection. Moreover, our choice of Random Forest is validated by Liu et al. [1], who highlighted its interpretability as an essential criterion in the financial sector, and by Mounika et al. [7], who successfully applied it to credit card transactions. These comparisons position our work within a well-established body of research confirming Random Forest as a robust, high-performing tool for this task. The comparative evaluation in this study further strengthens this positioning: Random Forest outperformed Logistic Regression, SVM, and Gradient Boosting across the F1-score and ROC-AUC metrics under identical experimental conditions.

Despite these encouraging results, several limitations must be acknowledged. First, the dataset used, although a recognized benchmark, consists of PCA-transformed features, which limits our ability to interpret the importance of original variables beyond transaction amount and time [10]. This opacity raises concerns about the reproducibility of feature importance findings in real-world institutional datasets. Second, ensemble models such as Random Forest carry an inherent risk of overfitting, particularly when the training set is augmented with synthetic samples via SMOTE. In this study, cross-validation scores showed low variance (standard deviation below 0.01) suggesting limited overfitting; however, this should be further verified on entirely independent datasets from different institutions. Third, like many traditional machine learning models, Random Forest treats each transaction independently and does not capture complex relational patterns between entities, such as fraud rings. Recent advances using graph-based approaches, as discussed by Kurshan and Shen [10], offer promising avenues for addressing this gap. Fourth, potential data bias and fairness issues must be considered: since the dataset originates from European cardholders only, the model may not generalize equitably to transaction patterns of users from other geographic or demographic groups. This could inadvertently result in higher false positive rates for underrepresented user profiles, raising regulatory concerns in jurisdictions with algorithmic fairness requirements. Fifth, while our model achieved a high AUC, the precision-recall trade-off remained challenging —a common issue also noted by Wedge et al. [11], who worked on reducing false positives. Sixth, challenges of deployment in a production environment must be addressed: real-time fraud detection systems require inference latency below 100 milliseconds, model versioning and retraining pipelines, monitoring for concept drift as fraud patterns evolve, and compliance with data protection regulations such as GDPR. While our inference time of approximately 0.3 ms per transaction is promising, the full production pipeline including data ingestion, feature computation, and decision logging introduces additional overhead that must be benchmarked in a live environment. Future work could explore hybrid architectures combining deep learning with Random Forest, as proposed by Kalusivalingam et al. [8] and the ACM conference study [9], to better model temporal dynamics and complex fraud patterns. Integrating such approaches with more granular, real-time data could further improve detection rates while maintaining the interpretability required for regulatory compliance.

V. CONCLUSION

This study investigated the application of the Random Forest algorithm to financial fraud detection using the publicly available European credit card transactions dataset. The model was trained on a highly imbalanced dataset

(0.172% fraud prevalence) and evaluated after SMOTE oversampling and QuantileTransformer normalization. With 200 decision trees (n_estimators = 200), the model achieved an accuracy of 97%, an ROC-AUC of 97%, a precision of 95%, a recall of 78%, and an F1-score of 86%, validated through a 70/30 stratified split combined with 10-fold cross-validation. Comparative evaluation against Logistic Regression, SVM, and Gradient Boosting confirms that Random Forest provides the best balance between detection performance and interpretability. Feature importance analysis highlights transaction amount and PCA components V14 and V17 as the most predictive variables. These results confirm that Random Forest is a robust and practically viable solution for fraud detection in financial systems.

However, several limitations must be clearly acknowledged. First, the PCA-transformed nature of the dataset restricts feature interpretability and limits generalizability to other institutional datasets where raw transactional features are available. Second, the risk of overfitting in ensemble models, although mitigated through cross-validation and OOB error monitoring in this study, remains a structural concern that requires ongoing vigilance, particularly when SMOTE augmentation is applied. Third, potential data bias toward European cardholder profiles may affect the model's fairness and performance across other demographic or geographic groups, a concern of growing regulatory importance. Fourth, real-world production deployment introduces challenges beyond model accuracy, including latency constraints, concept drift as fraud patterns evolve, and compliance with privacy regulations such as GDPR. These considerations should be central to any future system implementation.

In conclusion, this work highlights the relevance of integrating artificial intelligence into financial fraud prevention and detection mechanisms. The use of random forests is an effective, fast, and explainable solution that helps to strengthen the confidence of institutions and users while reducing economic losses related to fraud. Nevertheless, future research could focus on exploring hybrid approaches combining traditional models and neural networks, exploiting massive real-time data, or integrating advanced explainability tools to optimize the effectiveness and acceptability of these intelligent systems.

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