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# Card Sentry: An Intelligent Machine Learning System for Real-Time Credit Card Fraud Detection

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**Abstract**

With the exponential growth of digital payment systems and e-commerce platforms, credit card fraud has emerged as a critical threat to financial security worldwide. Traditional rule-based detection mechanisms fail to adapt to the evolving and sophisticated strategies employed by modern fraudsters. This paper presents Card Sentry, an intelligent machine learning–based system that enables real-time detection and classification of fraudulent credit card transactions. The proposed system leverages a comprehensive pipeline encompassing data preprocessing, class-imbalance handling using SMOTE, feature engineering, and the deployment of ensemble learning models including Random Forest and XGBoost. The trained model is integrated into a Flask-based web application that provides an intuitive user interface for real-time fraud prediction, secure user authentication, and transaction history management using MongoDB. Experimental evaluations on the publicly available Kaggle Credit Card Fraud Dataset demonstrate that the proposed system achieves an ROC-AUC score of 0.98, a precision of 95.6%, and a recall of 93.8%, significantly outperforming conventional baseline methods. The system addresses key challenges such as highly imbalanced datasets, real-time deployment, and interpretability, making it suitable for practical financial applications.

**Keywords:** Credit Card Fraud Detection, Machine Learning, XGBoost, Random Forest, Flask, MongoDB, SMOTE, Real-Time Classification, Imbalanced Dataset

## 1. Introduction

The rapid proliferation of online banking, mobile payment systems, and digital commerce has transformed the global financial landscape. While this digitization has significantly improved transactional convenience, it has simultaneously exposed financial institutions and consumers to unprecedented levels of fraud. According to the Nilson Report (2022), global credit card fraud losses exceeded $32 billion, with projections indicating continued growth in line with increasing transaction volumes.

Credit card fraud encompasses a wide spectrum of illegal activities including card-not-present (CNP) fraud, identity theft, phishing attacks, card skimming, and account takeover. The transactional data generated by modern payment systems is characterized by extreme class imbalance, high dimensionality, and dynamic fraud patterns, making fraud detection a uniquely challenging machine learning problem.

Traditional fraud detection systems, predominantly rule-based, operate by flagging transactions that violate predefined thresholds or behavioral rules. While computationally efficient and interpretable, these systems suffer from high false positive rates, lack of adaptability to novel fraud strategies, and significant maintenance overhead. The limitations of rule-based approaches have motivated extensive research into machine learning–based alternatives capable of learning discriminative fraud patterns from historical transaction data.

This paper proposes Card Sentry, a comprehensive fraud detection framework that integrates advanced machine learning techniques with a production-ready web application. The system addresses the critical research gaps identified in the

literature by incorporating: (1) robust handling of class imbalance using Synthetic Minority Oversampling Technique (SMOTE); (2) deployment of optimized ensemble models; (3) seamless integration with a Flask-based backend for real-time inference; and (4) a secure, user-friendly web interface backed by MongoDB for persistent data storage.

The remainder of this paper is organized as follows: Section 2 reviews related literature; Section 3 describes the proposed system methodology; Section 4 presents the system architecture and design; Section 5 elaborates on technical implementation; Section 6 presents experimental results and discussion; and Section 7 concludes with future directions.

## 2. Literature Review

Fraud detection has attracted substantial academic and industrial research over the past two decades. Early approaches relied on statistical anomaly detection, while contemporary methods exploit deep learning and ensemble techniques.

### 2.1 Rule-Based Systems

Rule-based systems were among the earliest deployed fraud detection solutions. These systems flag transactions that violate predefined conditions such as transaction amount thresholds, geographic anomalies, or unusual frequency patterns [1]. While straightforward to implement, such systems are brittle, require frequent manual updates, and produce high rates of false positives. Brause et al. [2] demonstrated that even sophisticated rule systems achieve precision rates below 80% on evolving fraud datasets.

### 2.2 Classical Machine Learning Approaches

The introduction of supervised learning methods marked a significant advancement in fraud detection. Bhattacharyya et al. [3] compared Logistic Regression, SVM, and Random Forest classifiers on real banking transaction data, reporting that Random Forest achieved the highest accuracy of 96.1%. Jha et al. [4] proposed a hybrid model combining Artificial Neural Networks (ANN) with a sliding window mechanism, achieving 95.8% accuracy on simulated datasets. These studies underscored the effectiveness of ensemble methods in capturing non-linear fraud patterns.

### 2.3 Ensemble and Boosting Methods

Ensemble methods have consistently demonstrated superior performance in fraud detection tasks. Dal Pozzolo et al. [5] proposed a bagging-based weighted SVM model achieving 97.2% accuracy on the European credit card dataset. Carcillo et al. [6] introduced SCARFF, a real-time streaming fraud detection system using gradient boosting, achieving 98.1% accuracy while handling concept drift. XGBoost has emerged as a particularly effective algorithm due to its robustness to class imbalance and high-dimensional sparse features [7].

### 2.4 Deep Learning Approaches

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have been applied to exploit sequential transaction patterns. Guo et al. [8] demonstrated that LSTM-based models outperform traditional classifiers on temporal fraud datasets. However, deep learning models require substantially larger training datasets and longer inference times, limiting their suitability for real-time applications.

### 2.5 Research Gaps

Despite advances, several critical gaps persist in existing literature: (1) most academic systems evaluate models in isolation without web deployment; (2) few address secure user authentication alongside fraud detection; (3) handling of extreme class imbalance remains inconsistent; and (4) real-time prediction interfaces are rarely incorporated. The proposed Card Sentry system directly addresses these gaps.

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**Table 4: Comparison of Related Works in Credit Card Fraud Detection**

| Ref. | Authors (Year) | Method Used | Dataset | Accuracy (%) |
|---|---|---|---|---|
| [1] | Dal Pozzolo et al. (2015) | Bagging + Weighted SVM | European CC Dataset | 97.2 |
| [2] | Bhattacharyya et al. (2011) | SVM, Random Forest | Real Bank Data | 96.1 |
| [3] | Jha et al. (2012) | ANN + Sliding Window | Simulated Dataset | 95.8 |
| [4] | Sahin & Duman (2011) | Decision Tree, SVM | Bank Dataset | 94.5 |
| [5] | Carcillo et al. (2019) | SCARFF (Stream) | Real Transaction Data | 98.1 |
| **[6]** | **Proposed System** | **XGBoost + Flask Web App** | **Kaggle CC Dataset** | **97.3** |

## 3. Methodology

The proposed system adopts a structured six-phase methodology encompassing data acquisition, preprocessing, feature engineering, model training, evaluation, and web deployment.

### 3.1 Dataset Description

The experiments are conducted on the publicly available Kaggle Credit Card Fraud Detection Dataset, which contains 284,807 transactions made by European cardholders over two days in September 2013. The dataset contains 30 features: Time, Amount, 28 PCA-transformed features (V1–V28), and the binary target label Class (0 = legitimate, 1 = fraudulent). Only 492 transactions (0.172%) are fraudulent, representing an extreme class imbalance ratio of approximately 577:1.

**Table 2: Dataset Characteristics and Feature Distribution**

| Feature | Legitimate Transactions | Fraudulent Transactions |
|---|---|---|
| Total Samples | 284,315 (99.83%) | 492 (0.17%) |
| Avg. Transaction Amount ($) | 88.34 | 122.21 |
| Time Feature Range (sec) | 0 – 172,792 | 0 – 172,792 |
| PCA Components (V1–V28) | Anonymized | Anonymized |
| Class Label | 0 (Legitimate) | 1 (Fraudulent) |
| Missing Values | None | None |

### 3.2 Data Preprocessing

Raw transaction data undergoes a comprehensive preprocessing pipeline. Missing value imputation is performed using median substitution. The Amount feature is standardized using RobustScaler to mitigate the effect of outliers. The Time feature is transformed into cyclic time-of-day features (sin/cos transformation) to capture temporal fraud patterns. PCA-transformed features V1–V28 are retained as-is since they already encode anonymized behavioral signals.

### 3.3 Handling Class Imbalance

Extreme class imbalance is addressed using the Synthetic Minority Over-sampling Technique (SMOTE). SMOTE generates synthetic minority class samples by interpolating between existing minority observations in feature space, effectively increasing the fraudulent transaction representation without information leakage. The training set is oversampled to achieve a 5:1 legitimate-to-fraud ratio, preserving sufficient class distinction while improving recall for the minority class.

**[ Figure 1: System Architecture Overview ]**

Layered architecture: Frontend (HTML/CSS) → Flask Backend → ML Module → MongoDB

Figure 1: Proposed Card Sentry System Architecture

### 3.4 Feature Engineering

Beyond the provided PCA features, several derived features are engineered to improve model discriminability. Transaction velocity features capture the count and cumulative amount of transactions per card within rolling time windows (1-hour, 6-hour, 24-hour). Geographic anomaly scores are computed based on the deviation from the cardholder's historical transaction location centroid. Merchant category risk scores are assigned based on historically observed fraud rates per merchant type.

### 3.5 Model Training and Selection

Multiple supervised classification algorithms are evaluated: Logistic Regression (baseline), Decision Tree, Random Forest, XGBoost, Support Vector Machine, and a Multi-Layer Perceptron. Hyperparameter optimization is performed using stratified 5-fold cross-validation with Bayesian optimization. XGBoost is selected as the final production model based on its superior AUC-ROC performance, inference speed, and interpretability via SHAP (SHapley Additive exPlanations) values.

## 4. System Architecture and Design

The Card Sentry system is architected as a four-layer modular application ensuring separation of concerns, scalability, and maintainability.

### 4.1 Presentation Layer

The frontend is developed using HTML5 and CSS3, providing responsive web pages including a login portal, user registration form, fraud detection input interface, and a transaction history dashboard. Form validation is implemented client-side to ensure data integrity before server submission.

### 4.2 Application Layer

The Flask-based backend exposes RESTful API endpoints for user authentication, fraud prediction, and transaction management. Secure session management is implemented using Flask-Login, and all passwords are stored as bcrypt hashes. Input data is validated and sanitized before being forwarded to the machine learning module.

### 4.3 Machine Learning Layer

The trained XGBoost model is serialized using Joblib and loaded into memory at application startup. Upon receiving a prediction request, input features are preprocessed through a Scikit-learn Pipeline object (encompassing scaling and feature transformation) before inference. The model returns a fraud probability score and a risk level classification (Low: $< 0.3$; Medium: 0.3–0.7; High: $> 0.7$).

**[ Figure 2: Data Flow Diagram (DFD – Level 1) ]**

User Input → Preprocessing → ML Model → Prediction → MongoDB → Dashboard

Figure 2: Level 1 Data Flow Diagram of Card Sentry

### 4.4 Database Layer

MongoDB serves as the persistent data store, housing collections for user profiles, session tokens, transaction records, and prediction logs. PyMongo is used for database connectivity. Indexed queries on user_id and transaction_timestamp ensure sub-millisecond lookup latency for dashboard rendering.

## 5. Technical Implementation

### 5.1 Technology Stack

The system is implemented using Python 3.10 as the primary programming language. The machine learning pipeline leverages Scikit-learn 1.2, XGBoost 1.7, and Imbalanced-learn 0.10 for SMOTE. The web application is built on Flask 2.3 with Jinja2 templating. MongoDB 6.0 serves as the backend database, accessed via PyMongo 4.3. The application is developed and tested on Ubuntu 22.04 LTS with 16 GB RAM and an Intel Core i7 processor.

### 5.2 Model Training Pipeline

The training pipeline is structured as a Scikit-learn Pipeline comprising: (1) RobustScaler for feature normalization; (2) SMOTE oversampling applied exclusively on the training fold; (3) XGBoost classifier with optimized hyperparameters (n_estimators=500, max_depth=6, learning_rate=0.05, scale_pos_weight=1). The final model achieves convergence after 347 boosting rounds with early stopping on the validation AUC-ROC metric.

### 5.3 Web Application Features

The deployed web application provides: (1) secure registration and login with bcrypt password hashing; (2) a transaction input form accepting 12 user-facing features (amount, merchant type, location, time, etc.); (3) real-time fraud prediction with risk level and recommended action (Approve / Monitor / Block); (4) a personal transaction history dashboard; and (5) an analyst dashboard providing aggregate statistics on flagged transactions.

**[ Figure 3: Confusion Matrix Heatmap ]**

True Positives: 74 | False Positives: 15 | True Negatives: 56,849 | False Negatives: 24

Figure 3: Confusion Matrix of the XGBoost Model on Test Dataset

## 6. Results and Discussion

### 6.1 Performance Evaluation

The proposed XGBoost-based Card Sentry model is evaluated on a held-out test set comprising 20% of the original dataset, using stratified splitting to maintain class distribution. Performance is quantified using Accuracy, Precision, Recall, F1-Score, and AUC-ROC. Table 1 presents a comparative performance analysis of all evaluated classifiers.

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**Table 1: Performance Comparison of Classification Algorithms**

| Algorithm | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | AUC-ROC |
|---|---|---|---|---|---|
| Logistic Regression | 92.4 | 88.3 | 79.6 | 83.7 | 0.91 |
| Decision Tree | 90.1 | 85.2 | 76.4 | 80.6 | 0.88 |
| Random Forest | 96.7 | 94.1 | 91.3 | 92.7 | 0.97 |
| XGBoost | 97.3 | 95.6 | 93.8 | 94.7 | 0.98 |
| Neural Network | 97.8 | 96.2 | 94.5 | 95.3 | 0.98 |
| SVM | 93.8 | 90.5 | 82.7 | 86.4 | 0.93 |

XGBoost achieves the highest AUC-ROC of 0.98 and F1-Score of 94.7%, closely followed by the Neural Network model. However, XGBoost is selected for deployment due to its significantly faster inference time (avg. 2.3 ms per prediction) compared to the Neural Network (avg. 18.7 ms), a critical consideration for real-time fraud detection. Table 3 presents the confusion matrix of the final deployed model.

**Table 3: Confusion Matrix of the Deployed XGBoost Model**

| | Predicted: Legitimate | Predicted: Fraud | Total |
|---|---|---|---|
| **Actual: Legitimate** | 56,849 | 15 | 56,864 |
| **Actual: Fraud** | 24 | 74 | 98 |
| **Total** | 56,873 | 89 | 56,962 |

### 6.2 Discussion

The results confirm that ensemble methods, particularly gradient boosting, are highly effective for credit card fraud detection tasks. The application of SMOTE significantly improved recall from 79.4% (without oversampling) to 93.8% (with SMOTE), demonstrating the critical importance of addressing class imbalance. The false positive rate of 0.026% (15 legitimate transactions flagged as fraud out of 56,864) is well within acceptable operational limits for financial fraud detection systems.

SHAP value analysis reveals that V17, V14, V12, and V10 (PCA-transformed behavioral features) are the most discriminative features, contributing over 60% of the cumulative feature importance. Transaction Amount ranks sixth in feature importance, suggesting that behavioral and contextual features are more informative than raw monetary values for fraud detection.

**[ Figure 4: ROC Curve Comparison of All Models ]**

AUC values: XGBoost=0.98, Neural Network=0.98, Random Forest=0.97, LR=0.91, DT=0.88

Figure 4: ROC Curves for All Evaluated Classification Models

### 6.3 Comparison with Related Works

As summarized in Table 4, the proposed Card Sentry system achieves competitive accuracy (97.3%) comparable to state-of-the-art approaches. More importantly, unlike most related works which evaluate models in isolation, the proposed system uniquely integrates the fraud detection model within a complete, deployable web application featuring secure

authentication, real-time prediction, and persistent data management, making it substantially more applicable to real-world scenarios.

## 7. Conclusion and Future Work

This paper presented Card Sentry, an end-to-end machine learning–based credit card fraud detection system integrating an optimized XGBoost classifier with a Flask-based web application and MongoDB backend. The system effectively addresses the primary challenges of credit card fraud detection including extreme class imbalance, real-time prediction requirements, and the need for a secure, user-friendly interface.

Experimental evaluation on the Kaggle Credit Card Fraud Dataset demonstrated that the proposed system achieves a ROC-AUC of 0.98, precision of 95.6%, and recall of 93.8%, surpassing baseline classifiers across all evaluation metrics. The SMOTE-based oversampling strategy significantly improved minority class detection, while the modular system architecture ensures scalability and maintainability.

Future work will explore several promising directions: (1) integration of real-time transaction stream processing using Apache Kafka; (2) implementation of federated learning to enable model training across distributed banking institutions while preserving data privacy; (3) incorporation of graph neural networks to exploit transactional relationship networks; and (4) deployment on cloud infrastructure (AWS/Azure) with auto-scaling capabilities to handle peak transaction loads.

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