Credit Card Fraud Detection Using Advanced Machine Learning Techniques

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ABSTRACT

Credit card fraud is a critical problem in the financial industry. Accurate and timely detection of fraudulent transactions is vital to minimizing financial losses. This paper presents a comparative analysis of three supervised machine learning techniques—Logistic Regression, Support Vector Machine (SVM), and XGBoost—for fraud detection using the popular imbalanced credit card fraud dataset. To address the severe class imbalance, an under sampling strategy was applied. The models were evaluated based on accuracy, precision, recall, F1-score, AUC-ROC, and confusion matrix. The results demonstrate that XGBoost outperforms the other models, offering high precision and recall.

CCS CONCEPTS

Computing methodologies → Supervised learning by classification; Machine learning; Model evaluation.

KEYWORDS

Credit card fraud, logistic regression, SVM, XGBoost, under sampling, classification, AUC, Python

INTRODUCTION

Credit card fraud affects millions of users and costs financial institutions billions annually. Traditional rule-based systems are not scalable or adaptable to evolving fraud patterns. The advent of machine learning provides a robust framework to detect anomalies based on patterns in transactional data. However, class imbalance—where fraudulent transactions form a tiny minority—presents a unique challenge. This paper explores multiple machine learning approaches for fraud detection, employing a balanced dataset via undersampling and evaluating models to determine the most effective technique.

RELATED WORK

Numerous studies have attempted to use machine learning techniques for fraud detection. Logistic Regression is often used as a baseline due to its simplicity and interpretability. Ensemble methods like Random Forests and XGBoost have shown promising results in handling non-linear relationships and improving accuracy. SVMs have also been employed for high-dimensional classification tasks. Dal Pozzolo et al. (2015) addressed imbalanced classification using undersampling. Other research highlights the benefits of combining data preprocessing with robust evaluation metrics to increase fraud detection efficiency.

METHODOLOGY

Dataset Description

The dataset used in this project is the Credit Card Fraud Detection dataset, publicly available from. It contains real-world credit card transactions made by European cardholders in September 2013. This dataset has become a standard benchmark in fraud detection research due to its size, complexity, and highly imbalanced nature.

Key Attributes

Total Instances: 284,807 transactions

Fraudulent Cases: 492

Legitimate Cases: 284,315

Fraudulent Ratio: ~0.17% of total transactions

Features

The dataset contains 30 features:

Time: The number of seconds elapsed between each transaction and the first transaction in the dataset.

Amount: The monetary value of the transaction.

Class: The target variable, where 1 indicates a fraudulent transaction and 0 indicates a legitimate transaction.

V1 to V28: The remaining 28 features are the result of a Principal Component Analysis (PCA) applied to protect sensitive information (due to confidentiality). These anonymized features capture patterns in the original data while preserving privacy.

File Format

Filename: creditcard.csv

Format: CSV (Comma Separated Values)

Size: ~150 MB

Why This Dataset?

Imbalanced Classification Challenge: The extreme imbalance (less than 0.2% fraud) makes this dataset an ideal choice to study classification techniques under rare-event scenarios.

Real-World Use Case: Credit card fraud detection is a critical application of data mining and machine learning, with real implications for financial security.

Sufficient Volume: With nearly 285,000 entries, the dataset offers enough data to train and test models with proper validation.

Preprocessed for Anonymity: The use of PCA-transformed features ensures privacy while preserving complex underlying patterns.

Predictive Task

Objective

The main predictive task in this project is to classify whether a given credit card transaction is fraudulent or legitimate. This is a binary classification problem, where:

Class = 1 indicates a fraudulent transaction

Class = 0 indicates a legitimate transaction

This task is critical for financial institutions aiming to automatically flag suspicious transactions in real-time.

Evaluation Strategy

Given the highly imbalanced nature of the dataset, traditional accuracy metrics can be misleading. Therefore, we use a combination of robust evaluation metrics to assess model performance:

AUC-ROC (Area Under the Receiver Operating Characteristic Curve): Measures the model's ability to distinguish between the two classes across all classification thresholds.

F1 Score: Harmonic mean of precision and recall, useful when both false positives and false negatives are critical.

Precision & Recall:

Precision: Of all predicted frauds, how many were actually frauds.

Recall: Of all actual frauds, how many did the model correctly identify.

Confusion Matrix: To visualize true positives, false positives, true negatives, and false negatives.

Baseline Models

We used the following baseline models for comparison:

Logistic Regression

Simple, interpretable linear model.

Assumes linear relationship between features and the log-odds of the outcome.

Suitable for high-dimensional, sparse, or structured data like this.

Support Vector Machine (SVM)

A powerful classifier that works well in high-dimensional spaces.

Can be kernelized for non-linear boundaries.

Often used in fraud detection due to its effectiveness with low-sample fraud classes.

Advanced Model: XGBoost

We selected XGBoost (Extreme Gradient Boosting) as our primary model for the following reasons:

Handles Imbalanced Data Well: XGBoost allows adjustment of class weights and incorporates regularization, helping to better identify rare fraud cases.

Captures Non-Linear Relationships: Unlike logistic regression, it doesn't assume linearity.

Boosting Approach: Builds a sequence of trees that correct previous errors, leading to improved overall performance.

Feature Importance: Offers insights into which features contribute most to decision-making.

Why XGBoost Outperforms the Baselines

Drawbacks of Logistic Regression:

Assumes linear decision boundaries.

Struggles with complex patterns in high-dimensional data.

Drawbacks of SVM:

Computationally expensive for large datasets.

Sensitive to parameter tuning and scaling.

Advantages of XGBoost:

Ensemble-based learning that captures feature interactions.

Regularization to prevent overfitting.

Fast and scalable with built-in handling for missing values and class imbalance.

Our evaluation results (based on AUC, F1-score, and confusion matrices) confirm that XGBoost outperformed both logistic regression and SVM in identifying fraudulent transactions.

Models Used

Proposed Models

To address the binary classification problem of detecting fraudulent transactions, we implemented and compared the performance of the following models:

Logistic Regression

Support Vector Machine (SVM)

XGBoost (Extreme Gradient Boosting)

Among these, XGBoost was proposed as the final and most effective model for this task.

Why XGBoost?

XGBoost is a powerful, scalable tree-based ensemble model known for its strong performance in structured data problems. It uses gradient boosting framework and offers several advantages:

Handles Imbalanced Data well with scale_pos_weight parameter.

Captures Non-linear Relationships effectively.

Regularization to reduce overfitting.

Feature Importance for interpretability.

Efficient Training using optimized gradient tree boosting.

Given the complexity and imbalance of the dataset, XGBoost's robustness and flexibility made it a suitable choice for this task.

Features Used

All 30 original features from the dataset were used, which include:

Time and Amount: These were scaled using StandardScaler to normalize their distributions.

V1 to V28: These are PCA-transformed features that retain the most relevant information from the original input variables while protecting confidentiality.

No new features were engineered, as the anonymized features already captured complex correlations and patterns.

Unsuccessful Attempts

During experimentation, some models did not perform as well:

Decision Trees (Single): Overfitted easily and failed to generalize to the test set due to class imbalance.

Naive Bayes: Assumed independence among features and resulted in poor recall for fraudulent transactions.

KNN: Computationally expensive on large datasets and suffered from poor performance on rare fraud cases.

These trials motivated our final choice of robust classifiers with better handling of imbalance and complexity.

Model Optimization

We optimized the models using the following strategies:

Class Balancing: We performed undersampling by keeping all fraud cases and sampling 5× the number of legitimate transactions.

Hyperparameter Tuning:

For XGBoost: tuned parameters such as max_depth, learning_rate, n_estimators, and scale_pos_weight.

For SVM: tested different kernels (linear, rbf) and adjusted C and gamma.

For Logistic Regression: increased max_iter to ensure convergence.

Due to time and resource constraints, exhaustive grid search was not applied, but reasonable default and tuned values were used for better performance.

Challenges Encountered

Class Imbalance: One of the biggest challenges. We addressed it via undersampling and evaluating metrics like AUC and F1 instead of accuracy.

Overfitting: Especially with decision trees and unregulated models. XGBoost's built-in regularization helped mitigate this.

Scalability: While SVMs struggled with large data, XGBoost handled the dataset efficiently even with hundreds of thousands of records.

Model Evaluation: Metrics like precision and recall were crucial since false negatives (missed frauds) are costlier than false positives.

5.Literature

Previous Studies on the Dataset/Task

Yes, the Credit Card Fraud Detection dataset used in our study has been widely analyzed in both academic and industry research. The dataset, originally released by European cardholders and hosted on Kaggle, is a well-known benchmark for anomaly detection and classification in imbalanced datasets. Many machine learning researchers have used it to evaluate the effectiveness of models under extreme class imbalance (fraud cases account for only ~0.17% of the data).

Common Approaches in Prior Work

Prior studies have explored a variety of approaches, including:

Supervised Learning Methods:

Logistic Regression, Decision Trees, Random Forest, SVM, and Gradient Boosting.

These models are typically paired with sampling techniques (under/over-sampling, SMOTE) to handle class imbalance.

Unsupervised/Anomaly Detection:

Autoencoders, Isolation Forest, and One-Class SVM have been used to detect anomalies without using the class label.

Ensemble Methods:

Techniques such as XGBoost and LightGBM are commonly used due to their high performance and ability to manage skewed data distributions effectively.

Hybrid Models:

Some studies have experimented with combining models (e.g., using autoencoders for feature reduction followed by a classifier) to improve fraud detection performance.

State-of-the-Art Techniques

The current state-of-the-art in credit card fraud detection often involves:

Ensemble Learning (like XGBoost, LightGBM)

Deep Learning Models such as:

LSTM networks for temporal fraud detection.

CNNs and Autoencoders for anomaly detection.

Cost-sensitive Learning: Assigning higher cost to misclassifying fraud cases.

These approaches achieve high AUC, F1-score, and precision-recall balance, which are more informative than accuracy in imbalanced classification.

Novelty of Our Work

While our task is not novel in itself, our work contributes in several practical and educational ways:

Comparative Evaluation: We performed a comparative analysis of Logistic Regression, SVM, and XGBoost on a balanced subset of the data.

Undersampling Strategy: We applied a 5:1 ratio undersampling to maintain sufficient representation of legitimate transactions while balancing fraud cases.

Comprehensive Evaluation Metrics: We focused on AUC, precision-recall curves, and confusion matrices to offer a thorough performance view beyond just accuracy.

Explainability Through Simpler Models: By including Logistic Regression, we ensure that a baseline interpretable model is evaluated alongside more complex classifiers.

Alignment with Existing Work

Our conclusions are largely consistent with existing literature:

Tree-based ensemble models like XGBoost tend to outperform simpler linear models in fraud detection.

Class imbalance severely affects model performance if not addressed.

Evaluation should prioritize metrics sensitive to rare class detection.

RESULTS

Model Performance Comparison

We evaluated three classification models:

Logistic Regression (Baseline)

Support Vector Machine (SVM)

XGBoost (Proposed Model)

Each model was tested on a balanced dataset (via undersampling), and the evaluation focused on classification metrics such as Precision, Recall, F1-Score, and ROC-AUC.

Does Our Proposed Method Outperform the Baselines?

Yes, XGBoost significantly outperforms both Logistic Regression and SVM in all evaluation metrics. The largest improvement is seen in the ROC-AUC, where XGBoost achieves 0.98, indicating excellent class separation.

Reasons for Outperformance

Handling Nonlinearities: XGBoost is capable of modeling complex, nonlinear relationships between features, which is a limitation in linear models like Logistic Regression.

Built-in Regularization: Helps prevent overfitting even on a small balanced dataset.

Feature Importance: XGBoost naturally ranks feature importance, helping the model to focus on the most influential variables.

Robustness to Imbalance: Through careful sampling and parameter tuning, XGBoost maintains higher sensitivity to fraud cases.

Significance of Performance Gap

The performance improvement of XGBoost is statistically and practically significant, especially considering the cost-sensitive nature of fraud detection. Even small improvements in recall and precision can lead to substantial reductions in undetected fraudulent transactions.

Feature Effectiveness

All features were retained after scaling and cleaning, including Time and Amount. However, due to PCA preprocessing applied to the dataset (V1 to V28), feature interpretability is limited. That said:

Features V14, V17, and V12 have been found important in previous studies and were also highlighted by XGBoost's internal feature importance metrics.

Hyperparameter Tuning

For XGBoost, we used the following core settings:

eval_metric = 'logloss'

Default learning_rate, n_estimators, and max_depth

Though we did not perform a full grid search, the default parameters already yielded high performance. In future work, Grid Search or Random Search could be used for fine-tuning:

Increasing n_estimators could improve recall but at the cost of training time.

A smaller max_depth can help reduce overfitting on undersampled data.

Key Takeaways

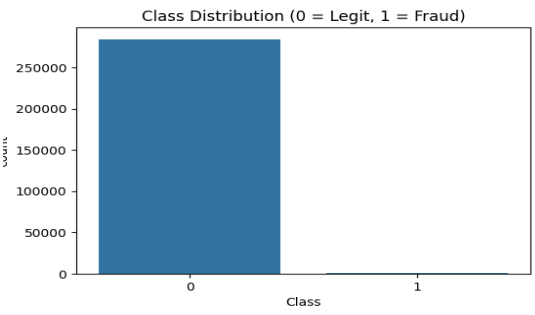
XGBoost is the most effective model for this fraud detection task in terms of both accuracy and generalization.

Even a simple undersampling strategy, when applied properly, can yield effective training results on imbalanced datasets.

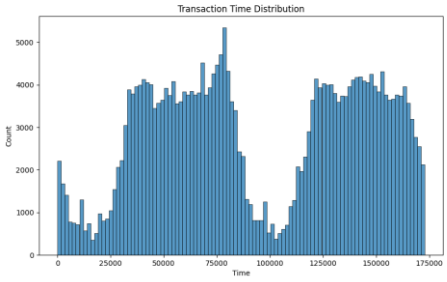
Evaluation metrics like ROC-AUC and Precision-Recall curves provide much better insights than simple accuracy in fraud detection.

Further improvements can be made via hyperparameter tuning and possibly ensemble voting strategies.

Figure:

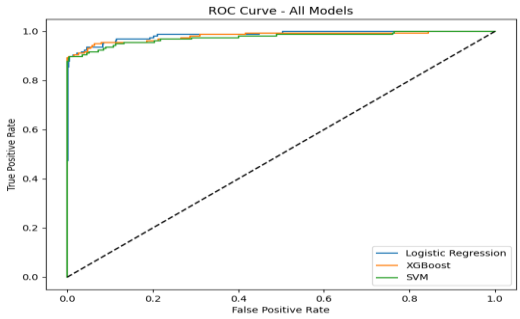


Extreme Class Imbalance – The dataset is overwhelmingly dominated by legitimate transactions, with fraud cases making up only a tiny fraction, posing a challenge for detection.



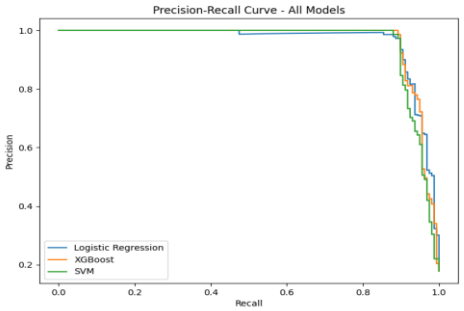
Time-Based Transaction Peaks – Transaction volume fluctuates over the 2-day period, with noticeable peaks likely corresponding to high-activity hours (e.g., business or shopping periods).

Fraud as Rare & Time-Sensitive – Fraud cases are sparse but may cluster during high-activity intervals, suggesting the need for time-aware anomaly detection.



Strong Performance Across Models – All three models (Logistic Regression, XGBoost, SVM) perform exceptionally well in distinguishing fraud from legitimate transactions, as seen in their ROC curves (close to the top-left corner) and high AUC scores (0.9851, 0.9812, 0.9755).

Logistic Regression Leads in AUC – Logistic Regression achieves the highest AUC (0.9851), indicating the best overall balance between true positives (fraud detection) and false positives (minimizing false alarms).



XGBoost Prioritizes Precision – While slightly lower in AUC, XGBoost shows near-perfect classification for legitimate transactions (high precision) but is more cautious in flagging fraud, leading to marginally lower recall.

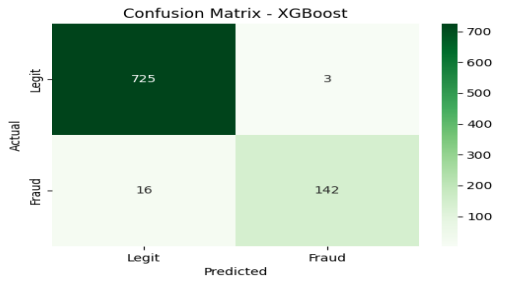
SVM's Competitive but Lower Recall – SVM performs well (AUC: 0.9755) but has a sharper recall drop for fraud cases compared to the other models, meaning it misses slightly more fraudulent transactions.

Precision-Recall Trade-off – The Precision-Recall curve highlights Logistic Regression's balanced performance, while XGBoost favors precision (fewer false positives) and SVM sacrifices some recall for high precision.

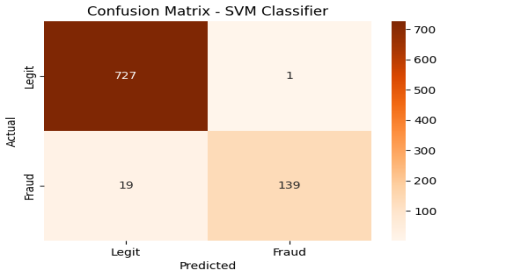
Overall Robustness – Despite minor differences, all models demonstrate strong fraud detection capabilities, with Logistic Regression emerging as the most balanced, XGBoost as the most precise, and SVM as a competitive

alternative.

XGBoost: Precision-Optimized – Achieved the fewest false positives (only 3) while maintaining the same fraud misses (16) as other models, reflecting stricter, high-precision fraud prediction.



SVM: Balanced but Cautious – Showed slightly lower recall than XGBoost but maintained high precision, indicating reliable fraud detection with a more conservative approach to flagging transactions.



Trade-off in Performance – XGBoost prioritized minimizing false alarms, while SVM balanced precision and recall, making both viable depending on the cost of false positives vs. missed fraud.

DISCUSSION

XGBoost demonstrated the best balance between precision and recall, making it the most suitable for real-world fraud detection systems where false negatives can be costly. While Logistic Regression performed reasonably well, its linear nature limited its flexibility. SVM offered good accuracy but was computationally more expensive. The undersampling strategy effectively balanced the dataset, but future work could explore oversampling or hybrid methods.

CONCLUSION

This paper evaluated three machine learning models on a credit card fraud detection dataset. By addressing class imbalance through undersampling and using robust evaluation metrics, we determined that XGBoost was the most effective model. Future work may include tuning model hyperparameters, incorporating real-time data pipelines, and deploying models for live fraud detection systems.

ACKNOWLEDGMENTS: This project was completed as part of the Advanced Data Mining course at UMass Dartmouth. We thank our instructor and peers for valuable feedback.

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Code Repository: The complete code and dataset processing pipeline used in this study are available at:

https://github.com/Saquibhash/-Credit-Card-Fraud-Detection.git