



## Development of an optimized real time financial fraud detection system using cluster computing, transaction data mining

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### Abstract

Financial fraud detection is a critical challenge in modern digital financial systems due to the increasing volume, velocity, and complexity of online transactions. This study develops and evaluates a real-time fraud detection framework that integrates distributed cluster computing (Apache Spark and Hadoop) with transaction data mining, combining Interquartile Range (IQR)-based anomaly detection, K-Means behavioural clustering, and four supervised classifiers, Random Forest, Support Vector Machine, Gradient Boosting, and a Neural Network, trained on a 284,807-record transaction dataset. Random Forest, SVM, and Gradient Boosting each achieved 0.98 accuracy, precision, recall, and F1-score, while the Neural Network achieved 0.97 across all metrics, the IQR/K-Means anomaly stage independently achieved 89% precision, 85% recall, and an 87% F1-score. The results demonstrate that combining cluster computing with transaction data mining yields a fraud detection framework that is both highly accurate and scalable for real-time deployment in modern digital financial ecosystems.

**Keywords:** Financial fraud detection, cluster computing, transaction data mining, Apache Spark, interquartile range (IQR), K-means clustering, machine learning

### Introduction

The rapid growth of digital banking, mobile payments, and point-of-sale technologies has driven a sharp rise in financial fraud. Global losses from financial fraud are estimated in the hundreds of billions of dollars annually, with the yearly cost to the U.S. economy alone exceeding \$600 billion (ACFE, 2024), and Interpol (2023) [24] notes that such proceeds frequently help finance organized crime and drug trafficking, giving the problem consequences beyond direct financial loss. In Nigeria, the Nigeria Inter-Bank Settlement System (NIBSS, 2024) [37] reported a 40% increase in fraud-related losses in the banking sector between 2022 and 2024 [7, 36], driven mainly by phishing, SIM-swap fraud, and social engineering; a notable case in March 2023 [1] saw cybercriminals exploit mobile banking vulnerabilities to divert over ₦1.3 billion across multiple banks, prompting regulatory intervention by the Central Bank of Nigeria.

Traditional detection approaches, manual audits and static rule-based systems, rely on post-transaction analysis that delays detection and increases financial exposure, and struggle to keep pace with both the volume of modern transaction streams and the evolving sophistication of fraud tactics (Pambudi *et al.*, 2019) [42]. Cluster computing, by distributing computational workloads across interconnected nodes, offers the scalability needed to analyze large-scale transaction data in parallel, substantially reducing the time required to identify potential fraud while allowing detection infrastructure to expand alongside growing data volumes (Nguyen *et al.*, 2022) [38]. When combined with transaction data mining, anomaly detection, clustering, and classification applied specifically to transactional data, this computational scalability enables systems capable of identifying suspicious activity as transactions occur rather than after the fact, narrowing the window of opportunity available to fraudsters (Patel & Kumar, 2023; Zhang *et al.*, 2022) [44, 60].

Despite the individual promise of both technologies, their integrated application remains underexplored, particularly within Nigeria's banking infrastructure, where limited data-sharing among institutions, inconsistent cybersecurity regulation, and underinvestment in modern detection infrastructure compound the challenge (Okoye & Obasi, 2023) [40]. This study addresses that gap by developing and evaluating a real-time financial fraud detection framework that integrates Apache Spark/Hadoop-based cluster computing with transaction data mining. The specific objectives are to: (i) develop a real-time financial fraud detection model using a clustering algorithm for data segmentation together with data mining techniques for pattern identification; (ii) implement the developed model within a distributed cluster computing environment; and (iii) evaluate the performance of the resulting system using accuracy, precision, recall, and F1-score.

### Related Work

Fraud detection has evolved from manual, auditor-led review through static rule-based systems and statistical models to machine learning and data mining techniques capable of uncovering complex, evolving fraud patterns (Phua *et al.*, 2010; Ngai *et al.*, 2011) [35, 45]. Rule-based systems remain valued for their interpretability and speed but are limited to known fraud patterns (Phua *et al.*, 2023) [46], while supervised methods, Random Forest, SVM, Gradient Boosting variants such as XGBoost and LightGBM, and deep neural networks, have consistently outperformed rule-based approaches by capturing complex, non-linear relationships in transaction data (Alwadain *et al.*, 2023; Zhang *et al.*, 2024; Rahman & Gupta, 2023) [3, 48, 62]. Unsupervised techniques such as K-Means clustering and Isolation Forest support anomaly detection where labelled fraud examples are scarce (Dhulipudi *et al.*, 2024; Han *et al.*, 2022) [13, 20], and recent work shows that cluster

computing can scale these techniques, particularly K-Means, to the volumes generated by modern financial systems (Huang *et al.*, 2024; Zhang *et al.*, 2018) <sup>[21, 59]</sup>.

The literature identifies several categories of real-time detection system beyond pure classification: hybrid systems combine machine learning-generated insight with rule-based validation to reduce false positives while retaining interpretability (Jiang *et al.*, 2018) <sup>[25]</sup>; real-time data stream processing platforms such as Apache Kafka and Apache Flink enable continuous ingestion and analysis of transaction streams (Gedik & Liu, 2018) <sup>[18]</sup>; and behavioural analytics techniques build detailed user profiles to flag deviations indicative of account takeover or identity theft. A recurring empirical theme across this work is the trade-off between detection accuracy and computational feasibility at scale: Menshchikov *et al.* (2022) <sup>[31]</sup> report high classification performance from a Multilayer Perceptron combined with boosting on Big Data architectures, but flag high training and prediction latency as a barrier to real-time deployment, a concern this study addresses directly through its distributed Spark-based architecture. Pambudi *et al.* (2019, 2022) <sup>[42, 43]</sup> improved SVM performance through data balancing and PCA-based dimensionality reduction respectively, but both studies note that class imbalance remains an ongoing challenge affecting model accuracy, directly motivating this study's use of IQR-based balancing prior to classification.

Within Nigeria specifically, fraud detection remains largely rule-based and reactive, constrained by limited data-sharing among institutions, inconsistent cybersecurity regulation, and underinvestment in modern infrastructure (Ayo *et al.*, 2021; Okoye & Obasi, 2023; Akinyemi & Uzoka, 2022) <sup>[2, 8, 40]</sup>, even as machine learning and distributed processing frameworks such as Spark and Kafka show clear promise for the country's high-volume mobile money environment (Obi *et al.*, 2023) <sup>[39]</sup>, with several local studies reporting over 90% classification accuracy using Random Forest, SVM, and decision trees (Nayak *et al.*, 2021; Husejinovic, 2020) <sup>[22, 34]</sup>. Despite these advances, the integrated application of cluster computing with transaction data mining for real-time detection remains insufficiently researched in the Nigerian context (Olowookere *et al.*, 2023) <sup>[23]</sup>, and more broadly, most fraud detection studies address either computational scalability or analytical accuracy in isolation rather than as a single, jointly evaluated framework, a gap this study is designed to address.

## Methodology

This study adopted a quantitative research approach, using a publicly available dataset of 284,807 anonymized transaction records, comprising transaction amount, timestamp, frequency, location indicators, and other behavioural features, containing no personally identifiable information, and partitioned 70:30 into training and testing subsets so that model performance could be assessed on data not seen during training. Preprocessing comprised missing-value imputation (mean/median substitution), Min-Max normalization of continuous features such as transaction

amount, One-Hot Encoding of categorical features such as transaction location, and removal of duplicate records, all carried out via Azure Data Factory (Microsoft, 2024) <sup>[32]</sup> to ensure consistent schema mapping and data quality ahead of model training.

Because financial transaction datasets are characteristically imbalanced, with legitimate transactions vastly outnumbering fraudulent ones, class balancing was performed using Apache Spark's MLlib in conjunction with the Interquartile Range (IQR) method, distributed across nodes for efficiency and scalability. The IQR is defined as the difference between the third and first quartiles of a distribution:

$$IQR = Q3 - Q1 \quad (1)$$

With outliers flagged using the bounds:

$$\text{Lower Bound} = Q1 - 1.5 \times IQR; \text{Upper Bound} = Q3 + 1.5 \times IQR \quad (2)$$

Any transaction falling outside these bounds was treated as a potential anomaly, a method chosen for its simplicity, robustness, and resistance to distortion by extreme values (Dhulipudi *et al.*, 2024) <sup>[13]</sup>. Following outlier treatment, K-Means clustering was applied within Spark MLlib to group transactions by behavioural similarity, minimizing the objective function

$$J = \sum_{i=1}^k \sum_{x \in C_i} \|x - \mu_i\|^2 \quad (3)$$

Where  $k$  is the number of clusters,  $C_i$  is cluster  $i$ , and  $\mu_i$  is the centroid of cluster  $i$  (Han *et al.*, 2022) <sup>[20]</sup>. Cluster identifiers and distance-to-centroid values produced by this stage were appended as additional input features, enriching the feature space presented to the downstream classifiers with behavioural context that raw transaction attributes alone would not capture.

The end-to-end pipeline combined cloud and distributed computing components as summarized in Table 1: raw data was version-controlled in GitHub, orchestrated via Azure Data Factory, stored in Azure Blob Storage and the Hadoop Distributed File System (HDFS), and transformed via Apache Spark on Databricks, whose in-memory computation reduced processing latency for normalization, feature selection, and IQR-based anomaly detection (Zaharia *et al.*, 2016, 2023) <sup>[57, 58]</sup>. The processed dataset was persisted in both CSV and columnar Parquet formats. Four supervised classifiers were then trained and evaluated within Spark MLlib on the preprocessed, cluster-augmented data: Random Forest, an ensemble of decision trees that reduces overfitting through bagging and random feature selection (Alwadain *et al.*, 2023) <sup>[3]</sup>; Support Vector Machine, which constructs an optimal separating hyperplane effective at detecting subtle anomalies in high-dimensional data (Singh & Rehman, 2023) <sup>[51]</sup>; Gradient Boosting, which builds models sequentially so that each new learner corrects the errors of its predecessors (Zhang *et al.*, 2024) <sup>[62]</sup>; and a feed-forward Neural Network, applied to capture non-linear, high-dimensional feature interactions (Rahman & Gupta, 2023) <sup>[48]</sup>.

**Table 1:** Data Pipeline and Infrastructure Components

| Component                | Role in the Pipeline                                                         |
|--------------------------|------------------------------------------------------------------------------|
| GitHub                   | Centralized, version-controlled repository for raw transaction datasets      |
| Azure Data Factory (ADF) | Orchestrates extraction, schema mapping, normalization, and scheduling (ETL) |

|                                              |                                                                                                                 |
|----------------------------------------------|-----------------------------------------------------------------------------------------------------------------|
| Azure Blob Storage                           | Primary data lake for raw and processed data, stored in CSV and Parquet formats                                 |
| Hadoop Distributed File System (HDFS)        | Distributed, fault-tolerant storage supporting the transformation and clustering phases                         |
| Apache Spark (on Databricks)                 | In-memory distributed processing: cleaning, IQR anomaly detection, K-Means clustering, model training via MLlib |
| Azure Machine Learning Pipelines / Endpoints | Automated, scalable deployment and real-time inference for trained models                                       |
| Flask web interface                          | User-facing application for submitting transactions and receiving classification results                        |

The trained models were deployed through Azure Machine Learning Pipelines and exposed via Azure Machine Learning Endpoints for continuous, near-real-time inference, with a Flask-based web interface allowing users to submit transaction details and receive an immediate classification. Performance was evaluated using accuracy, precision, recall, and F1-score, computed from the standard confusion-matrix quantities of true/false positives and negatives, since accuracy alone can be misleading on an imbalanced dataset such as this one.

## Results and Discussion

The Azure-based pipeline processed transaction batches at an average rate of 1.5 seconds and removed approximately 5.3% of noisy or redundant records during preprocessing, confirming the scalability of the distributed Spark/Hadoop architecture relative to single-node processing. The K-Means/IQR behavioural clustering and anomaly detection stage, evaluated independently, produced well-separated behavioural groups with distinct boundaries between normal and suspicious transaction patterns, achieving 89% precision, 85% recall, and an 87% F1-score in isolating anomalous transactions ahead of classification.

Table 2 summarizes the comparative performance of the four supervised classifiers on the held-out test set.

**Table 2:** Comparative Performance of Classification Models

| Model                  | Accuracy | Precision | Recall | F1-Score |
|------------------------|----------|-----------|--------|----------|
| Random Forest          | 0.98     | 0.98      | 0.98   | 0.98     |
| Support Vector Machine | 0.98     | 0.98      | 0.98   | 0.98     |
| Gradient Boosting      | 0.98     | 0.98      | 0.98   | 0.98     |
| Neural Network         | 0.97     | 0.97      | 0.97   | 0.97     |

Random Forest, Support Vector Machine, and Gradient Boosting each achieved 0.98 accuracy, precision, recall, and F1-score, reflecting their respective strengths in ensemble aggregation, margin-based separation, and sequential error correction, while the Neural Network achieved a marginally lower but still strong 0.97 across all metrics, a gap attributable to its greater sensitivity to hyperparameter tuning and dataset scale relative to the ensemble and margin-based methods (Alwadain *et al.*, 2023; Rahman & Gupta, 2023) [3, 48]. Random Forest's confusion matrix recorded 115 true negatives and 93 true positives against only 1 false positive and 3 false negatives; the Support Vector Machine showed an almost identical error profile, while Gradient Boosting recorded 114 true negatives and 93 true positives against 2 false positives and 3 false negatives. Across all four models, the close balance between precision and recall indicates that the framework minimizes both false positives, which erode customer trust and raise operational cost, and false negatives, which allow fraud to go undetected, a balance directly attributable to the IQR-based outlier removal, K-Means-derived behavioural features, and class balancing applied during preprocessing.

These results are consistent with prior comparative work showing ensemble and margin-based methods outperforming standalone Neural Networks on structured, tabular transaction data (Karthik *et al.*, 2021; Zhang *et al.*, 2023) [26, 61], while also improving on the latency limitations reported for boosting-based approaches deployed without a distributed architecture (Menshchikov *et al.*, 2022) [31]. Deployment through Azure Machine Learning Pipelines, together with a functioning Flask-based prediction interface, further demonstrated that the framework is not merely accurate in offline evaluation but practically deployable for real-time use, directly addressing a limitation, confinement to offline or small-scale prototypes, that recurs throughout the fraud detection literature reviewed above (Tran *et al.*, 2018; Sanwal & Soni, 2019) [50, 53]. Taken together, the combination of distributed preprocessing, IQR-based anomaly detection, K-Means behavioural clustering, and ensemble classification indicates that cluster computing and transaction data mining can be integrated into a single framework that is simultaneously accurate, scalable, and suitable for real-time deployment in high-volume, resource-constrained financial environments such as Nigeria's.

## Conclusion and Recommendations

This study developed and evaluated an optimized real-time financial fraud detection framework that integrates cluster computing (Apache Spark and Hadoop) with transaction data mining (IQR-based anomaly detection, K-Means behavioural clustering, and supervised classification), and the results, 0.98 accuracy, precision, recall, and F1-score for Random Forest, SVM, and Gradient Boosting, and 0.97 for the Neural Network, demonstrate that this integration provides a scalable, accurate, and practically deployable solution for real-time fraud detection in modern digital banking environments, including resource-constrained, high-transaction-volume contexts such as Nigeria's financial sector. Future work should incorporate additional contextual features such as user behavioural profiles, device identifiers, and geolocation data; apply systematic hyperparameter optimization to close the performance gap observed for the Neural Network; strengthen compliance with data protection regulations and encryption of sensitive transaction data; and implement a continuous feedback and retraining mechanism so the system adapts to evolving fraud patterns and detected false positives over time.

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