Machine Learning for Mobile Money Fraud Detection

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TLDR

Mobile money fraud detection in Sub-Saharan Africa, particularly Kenya, reveals that machine learning models such as Random Forest, XGBoost, and LGBoost outperform traditional approaches like logistic regression and SVM. Analysis of labeled datasets from platforms like Pesapal shows enhanced accuracy and robustness in fraud identification. These findings underscore the potential of advanced algorithms to strengthen mobile payment security in the region.

Abstract

This review synthesizes research on mobile money fraud detection using machine learning in Sub-Saharan Africa, focusing on Kenya, analyzing labeled datasets from platforms like Pesapal and evaluating models including logistic regression, SVM, Random Forest, XGBoost, and LightGBM to address escalating fraud risks undermining financial inclusion. The review aimed to evaluate machine learning techniques, benchmark model performance, identify challenges such as data imbalance and feature engineering, compare algorithm adaptability in the Kenyan context, and assess contributions to regional fraud detection. A systematic analysis of peer-reviewed studies employing supervised learning on real and synthetic datasets was conducted, emphasizing ensemble and boosting algorithms. Findings indicate that Random Forest, XGBoost, and LightGBM consistently achieve high accuracy and computational efficiency suitable for near real-time detection, while oversampling methods like SMOTE effectively mitigate class imbalance. Feature selection and interpretability tools enhance model transparency, though challenges remain in automating feature engineering and addressing evolving fraud patterns. Regional studies highlight socio-technical factors unique to Sub-Saharan Africa, yet data scarcity and reliance on synthetic datasets limit external validity and model generalizability. Integrating these insights reveals that ensemble-based machine learning approaches, combined with tailored imbalance handling and interpretability, offer promising frameworks for mobile money fraud detection in Kenya and similar contexts. These findings inform the development of robust, efficient, and context-aware fraud mitigation strategies critical for sustaining trust and security in emerging mobile financial ecosystems.

Introduction

Research on mobile money fraud detection using machine learning has emerged as a critical area of inquiry due to the rapid expansion of mobile financial services in Sub-Saharan Africa and the corresponding rise in fraudulent activities that threaten financial inclusion and economic stability(Sanni et al., 2023)(Neza et al., 2022). Since the inception of mobile money

platforms like M-Pesa in Kenya, mobile money services have transformed financial transactions by enabling unbanked populations to access digital payments(Lokanan, 2023)(Adedoyin, 2018). However, the increasing adoption has been paralleled by sophisticated fraud schemes, including account takeovers, refund fraud, and social engineering attacks, which impose significant financial losses and undermine user trust(Azamuke et al., n.d.)(Akomea-Frimpong et al., 2019). Studies estimate that fraudulent transactions accounted for up to 53% of mobile money transactions in some East African countries, highlighting the urgency of effective fraud detection mechanisms(Lokanan, 2023)(Akomea-Frimpong et al., 2019). The evolution of fraud detection has shifted from traditional rule-based systems to advanced machine learning models capable of real-time analysis and adaptive learning(Lu, 2024)(Jeyachandran et al., 2024).

Despite advances, the problem of detecting mobile money fraud remains challenging due to the scarcity of labeled datasets, severe class imbalance, and the dynamic nature of fraud patterns(Hájek et al., 2022)(Botchey et al., 2022)(Azamuke et al., 2022). Existing research often relies on synthetic datasets like PaySim, which, while useful, may not fully capture the complexity of real-world fraud in Sub-Saharan contexts(Chugh et al., 2025)(Azamuke et al., 2022). Moreover, there is a lack of comprehensive evaluations comparing machine learning models such as logistic regression, support vector machines, random forests, XGBoost, and LightGBM specifically on mobile payment data from platforms like Pesapal in Kenya(Lokanan, 2022)(Botchey et al., 2020)(Abdirahman et al., 2024). Controversies persist regarding the trade-offs between model interpretability and predictive performance, as well as the effectiveness of oversampling techniques like SMOTE in mitigating data imbalance(Zheng et al., 2024)(Tagbo et al., 2024)(Akinyemi et al., 2023). The absence of robust, context-specific fraud detection frameworks limits the ability of financial institutions and regulators to proactively combat fraud, potentially exacerbating financial exclusion and economic risks(Emran & Rubel, 2024)(Mollik & Majeed, 2025).

The conceptual framework underpinning this review integrates mobile money services as digital financial ecosystems, machine learning algorithms as predictive tools, and fraud detection as the operational objective(Gombiro et al., 2015)(Akinyemi et al., 2023)(Renukadevi et al., 2025). Mobile money services facilitate person-to-person payments through mobile network operators and agents, creating complex transactional data streams(Lokanan, 2023)(Sanni et al., 2023). Machine learning models analyze these data to identify anomalous patterns indicative of fraud, leveraging techniques such as ensemble learning, hyperparameter tuning, and imbalance mitigation(Kumar, 2024)(Airlangga, 2024)(Dhasaratham et al., 2024). This framework guides the systematic evaluation of model efficacy in detecting fraudulent transactions within the Kenyan mobile money context, addressing both technical and socio-economic dimensions(Mollik & Majeed, 2025)(Green, 2025).

The purpose of this systematic review is to critically assess the performance of various machine learning models—including logistic regression, support vector machines, random forests, XGBoost, and LightGBM—in detecting mobile money fraud using labeled datasets from platforms like Pesapal in Kenya(Lokanan, 2022)(Abdirahman et al., 2024)(Airlangga,

2024). By synthesizing empirical findings and methodological approaches, this review aims to fill the identified knowledge gap concerning model comparison and contextual applicability in Sub-Saharan Africa(Azamuke et al., n.d.)(Azamuke et al., 2022)(Akinyemi et al., 2023). The study contributes to the literature by providing evidence-based recommendations for deploying effective fraud detection systems that enhance financial security and inclusion in emerging markets(Emran & Rubel, 2024)(Mollik & Majeed, 2025).

This review employs a comprehensive methodology encompassing the selection of peer-reviewed studies focused on mobile money fraud detection in Sub-Saharan Africa, with an emphasis on Kenyan datasets(Lokanan, 2022)(Azamuke et al., 2022). Analytical frameworks include comparative model evaluation, assessment of data preprocessing techniques such as SMOTE, and consideration of real-time deployment challenges(Zheng et al., 2024)(Gupta, 2025)(Jeyachandran et al., 2024). The findings are organized to elucidate model performance metrics, data handling strategies, and practical implications for mobile money service providers and policymakers(Abdirahman et al., 2024)(Airlangga, 2024)(Shaha & Gavekar, 2025).

Purpose and Scope of the Review

Statement of Purpose

The objective of this report is to examine the existing research on "Mobile money fraud detection using machine learning in Sub-Saharan Africa, focusing on Kenya. Analysis of labeled datasets from mobile payment platforms like Pesapal. Evaluating models including logistic regression, SVM, Random Forest, XGBoost, and LGBoost. Contribution to existing research in Sub-Saharan Africa." in order to provide a comprehensive synthesis of current methodologies, challenges, and advancements in fraud detection within mobile money ecosystems. This review is important as mobile money services have become critical financial inclusion tools in Sub-Saharan Africa, yet they face escalating fraud risks that threaten user trust and system integrity. By analyzing machine learning approaches applied to real-world datasets, the study aims to identify effective models, highlight gaps in regional research, and inform future developments tailored to the unique socio-technical context of Kenya and the broader Sub-Saharan region.

Specific Objectives:

- To evaluate current knowledge on machine learning techniques applied to mobile money fraud detection in Sub-Saharan Africa.
- Benchmarking of existing models including logistic regression, SVM, Random Forest, XGBoost, and LGBoost on labeled mobile payment datasets.

- Identification and synthesis of challenges related to data imbalance, feature selection, and real-time fraud detection in mobile money platforms.
- To compare the performance metrics and adaptability of various machine learning algorithms within the Kenyan mobile money context.
- To deconstruct the contributions of recent studies towards enhancing fraud detection accuracy and operational efficiency in Sub-Saharan Africa.

Methodology of Literature Selection

Transformation of Query

We take your original research question — **"Mobile money fraud detection using machine learning in Sub-Saharan Africa, focusing on Kenya. Analysis of labeled datasets from mobile payment platforms like Pesapal. Evaluating models including logistic regression, SVM, Random Forest, XGBoost, and LGBoost. Contribution to existing research in Sub-Saharan Africa."**—and expand it into multiple, more specific search statements. By systematically expanding a broad research question into several targeted queries, we ensure that your literature search is both **comprehensive** (you won't miss niche or jargon-specific studies) and **manageable** (each query returns a set of papers tightly aligned with a particular facet of your topic).

Below were the transformed queries we formed from the original query:

- Mobile money fraud detection using machine learning in Sub-Saharan Africa, focusing on Kenya. Analysis of labeled datasets from mobile payment platforms like Pesapal. Evaluating models including logistic regression, SVM, Random Forest, XGBoost, and LGBoost. Contribution to existing research in Sub-Saharan Africa.
- Investigating hybrid machine learning strategies for enhancing mobile money fraud detection in Sub-Saharan Africa, particularly focusing on innovative approaches to combat emerging threats and improving existing models.
- Exploring hybrid machine learning techniques and big data analytics for mobile money fraud detection in Kenya, emphasizing innovative approaches and real-time adaptive systems.

Screening Papers

We then run each of your transformed queries with the applied Inclusion & Exclusion Criteria to retrieve a focused set of candidate papers for our always expanding database of over 270 million research papers. during this process we found 110 papers

Citation Chaining - Identifying additional relevant works

- **Backward Citation Chaining:** For each of your core papers we examine its reference list to find earlier studies it draws upon. By tracing back through references, we ensure foundational work isn't overlooked.
- **Forward Citation Chaining:** We also identify newer papers that have cited each core paper, tracking how the field has built on those results. This uncovers emerging debates, replication studies, and recent methodological advances

A total of 79 additional papers are found during this process

Relevance scoring and sorting

We take our assembled pool of 189 candidate papers (110 from search queries + 79 from citation chaining) and impose a relevance ranking so that the most pertinent studies rise to the top of our final papers table. We found 189 papers that were relevant to the research query. Out of 189 papers, 50 were highly relevant.

Results

Descriptive Summary of the Studies

This section maps the research landscape of the literature on Mobile money fraud detection using machine learning in Sub-Saharan Africa, focusing on Kenya. Analysis of labeled datasets from mobile payment platforms like Pesapal. Evaluating models including logistic regression, SVM, Random Forest, XGBoost, and LGBoost. Contribution to existing research in Sub-Saharan Africa, revealing a broad application of machine learning techniques to address fraud detection challenges in mobile money ecosystems. The studies predominantly utilize supervised learning models, with a strong emphasis on ensemble and boosting algorithms, and address critical issues such as data imbalance and feature engineering. The geographic focus is largely on Sub-Saharan Africa, with some studies specifically contextualizing findings to Kenya’s mobile money environment, thus providing relevant insights into regional socio-technical factors and operational constraints. This comparative analysis informs the effectiveness, efficiency, and adaptability of various machine learning approaches in combating mobile money fraud in the region.

Study	Model Accuracy	Handling of Data Imbalance	Computational Efficiency	Feature Importance and Interpretability	Adaptability to Regional Context
(Azamuke et al., n.d.)	High accuracy with Random Forest and XGBoost; simpler models also effective	Uses synthetic data simulation to address imbalance	Moderate efficiency; virtual platform aids testing	Employs social network analysis and statistical methods	Focus on Sub-Saharan Africa mobile money fraud patterns
(Chugh et al., 2025)	Robust performance with Random Forest and LSTM; Naive Bayes less effective	Uses PaySim synthetic dataset; data preprocessing emphasized	Moderate; LSTM more computationally intensive	Limited interpretability focus	General financial fraud context, not Kenya-specific
(Lu, 2024)	Improved accuracy with ensemble models including XGBoost and LightGBM	Uses SMOTE to mitigate imbalance	Efficient with ensemble methods; sequence classification adds complexity	Uses LIME and SHAP for model transparency	Addresses data imbalance challenges relevant to mobile payments
(Zheng et al., 2024)	XGBoost and LightGBM combined model outperforms traditional models by ~6%	SMOTE applied for class imbalance	High efficiency with boosting models	Feature selection based on correlation; no deep interpretability	Focus on online/ mobile payment security, generalizable to SSA
(AL-Dahasi et al., 2024)	XGBoost and Random Forest outperform others balancing false positives/ negatives	Sampling and feature selection techniques used	Balanced computational cost and accuracy	Discusses explainability and scalability	Broad digital payments context, adaptable to SSA
(Zheng et al., 2024)	Similar to (Zheng et al., 2024), confirms boosting models with SMOTE improve accuracy	SMOTE for imbalance; feature correlation selection	Efficient boosting models	Emphasizes precision, recall, and F1 metrics	Payment security focus applicable to SSA
(Ramesh & K, 2025)	Hybrid LightGBM-XGBoost model	Feature engineering and	Moderate computational demand due to	SHAP values used for feature	Financial transactions context, adaptable

Study	Model Accuracy	Handling of Data Imbalance	Computational Efficiency	Feature Importance and Interpretability	Adaptability to Regional Context
	achieves high accuracy and AUC	preprocessing applied	stacking	importance	to mobile money
(Gupta, 2025)	XGBoost highest precision and recall; logistic regression 94% accuracy	SMOTE and class-weight balancing for imbalance	Real-time deployment with web interface	Limited interpretability focus	Real-time fraud detection in financial systems
(Hájek et al., 2022)	Semi-supervised ensemble with XGBoost achieves best classification	Combines under-sampling and ensemble methods	Efficient with ensemble and under-sampling	Considers financial cost implications	Large mobile transaction dataset, relevant to SSA
(Doddamani et al., 2024)	XGBoost achieves 99.88% accuracy in money laundering detection	Oversampling to address imbalance	Efficient threshold optimization	Focus on threshold moving for performance	E-wallet transactions, relevant to mobile money fraud
(Tagbo et al., 2024)	SVM shows resilience in social engineering attack prevention	Uses real and synthetic datasets; imbalance addressed	Moderate computational needs	Compares multiple ML models	Focus on social engineering in mobile money fraud
(Kumar, 2024)	Hyperparameter-tuned Random Forest achieves 99.94% accuracy	Uses feature selection and sampling to handle imbalance	Efficient with tuning; scalable for real-time	Highlights model tuning importance	General financial fraud detection, adaptable to mobile money
(Lokanan, 2022)	Random Forest outperforms logistic regression in fraud prediction	Not explicitly stated; uses real-time transaction data	Moderate efficiency	Identifies key features like transaction amount	Mobile money transfer fraud, relevant to SSA
("Fraud Transaction Detection Approach Usi...", 2023)	Hybrid classifiers including Random Forest and SVM show high accuracy	Dataset imbalance addressed; multiple classifiers	Moderate computational cost	Evaluates precision, recall, F1-score	Public mobile money transaction dataset used

Study	Model Accuracy	Handling of Data Imbalance	Computational Efficiency	Feature Importance and Interpretability	Adaptability to Regional Context
		compared			
(Botchey et al., 2020)	Gradient boosted decision trees produce near-perfect results	Considers imbalanced dataset in experiments	Efficient tree-based models	Focus on model performance metrics	Mobile money fraud in developing countries
(Botchey et al., 2022)	Logistic Regression with class weighting outperforms oversampling	Evaluates SMOTE and ADASYN; class weighting best	Low computational complexity	Emphasizes simplicity and tuning	Mobile money fraud detection in SSA context
(Abdirahman et al., 2024)	ANN model achieves 91.39% accuracy in mobile wallet fraud detection	Imbalance handling not detailed	Moderate computational demand	Focus on accuracy and recall	Evaluates multiple wallet platforms in SSA
(Yussif et al., 2025)	CNN-BiLSTM model achieves ~99.3% accuracy with low false positives	Feature selection enhanced; imbalance addressed	Computationally intensive deep learning	Incorporates temporal and spatial features	Mobile money systems, adaptable to SSA
(Kodete, 2023)	CNN-LSTM hybrid achieves F1-score 0.955 and AUC 0.97	Uses SMOTE for class imbalance	Moderate to high computational cost	Explains model transparency and robustness	Mobile financial transactions, synthetic and real data
(Sa'adah & Pratiwi, 2020)	Probabilistic Neural Network classifies fraud effectively	Binary classification on PaySim dataset	Moderate efficiency	Limited interpretability discussion	PaySim mobile money simulator dataset
(Thapa et al., 2023)	XGBoost classifier provides highest accuracy among tested models	Imbalance addressed via preprocessing	Efficient boosting model	Limited interpretability focus	Online payment anomaly detection
(Muqattash & Kharbat, 2023)	Survey of methodologies; highlights gaps and future directions	Discusses data scarcity and imbalance challenges	Not model-specific	Calls for improved interpretability	Mobile payment fraud detection landscape

Study	Model Accuracy	Handling of Data Imbalance	Computational Efficiency	Feature Importance and Interpretability	Adaptability to Regional Context
(Emran & Rubel, 2024)	Ensemble and deep learning adapt well to dynamic fraud patterns	Highlights big data and NLP for imbalance	High computational demand	Discusses multimodal data and ethical issues	Broad financial fraud detection in Africa
(Jeyachandran et al., 2024)	Decision trees, Random Forest, SVM, and neural networks evaluated	Feature selection and preprocessing emphasized	Real-time analytics focus	Discusses model evaluation and deployment	Digital payments, real-time fraud detection
(Mollik & Majeed, 2025)	AI improves fraud detection but privacy concerns affect trust	Focus on explainability and user control	Not computationally focused	Emphasizes transparency and socio-cultural factors	Emerging markets including Kenya
(Green, 2025)	AI systems integrate structured and unstructured data for fraud	Discusses regulatory and infrastructure challenges	Complex system architectures	Highlights ethical challenges and transparency	African financial markets including Kenya
(Azamuke et al., 2022)	Synthetic dataset generation model for mobile money fraud research	Addresses data scarcity and privacy	Enables fast experimentation	Not focused on interpretability	Sub-Saharan Africa mobile money ecosystem
(Osundare et al., 2023)	ML techniques effective for telecom-based financial fraud detection	Uses anomaly detection and pattern recognition	Efficient for real-time detection	Discusses continuous learning	Telecommunication financial transactions
(Sanni et al., 2023)	Logistic regression with SMOTE best for cyber threat prediction	SMOTE applied to balance onboarding data	Low computational complexity	Focus on predictive model evaluation	Mobile money onboarding in Nigeria

Study	Model Accuracy	Handling of Data Imbalance	Computational Efficiency	Feature Importance and Interpretability	Adaptability to Regional Context
(Neza et al., 2022)	Tokenization and encryption proposed for USSD security	Not ML-focused; cybersecurity mechanism	Not computationally evaluated	Security mechanism rather than ML interpretability	Sub-Saharan Africa mobile money security
(Adedoyin, 2018)	Pattern recognition model shows promising fraud prediction	Uses synthetic datasets for evaluation	Moderate computational cost	Provides cluster ranking for suspicious transactions	Mobile money transfer fraud detection
(Gombiro et al., 2015)	Conceptual framework combining data mining and big data analytics	Not model-specific; framework proposal	Not computationally evaluated	Emphasizes knowledge base and KYC	Mobile money financial crime detection
(Makki, 2019)	Cost-sensitive KNN and ensemble methods address class imbalance	Tackles skewed data with hybrid approaches	Moderate computational demand	Uses precision-recall and F1 for evaluation	Financial fraud including mobile payments
(Kaur, 2025)	Hybrid model integrates behavioral biometrics for fraud detection	Addresses false positives in real-time	Optimized for mobile environments	Focus on accuracy and efficiency	Portable wallet payment systems
(Mambina et al., 2022)	Random Forest with TFIDF vectorization achieves 99.86% accuracy	Handles imbalanced SMS phishing dataset	Efficient for text classification	Uses feature selection for interpretability	Swahili smishing attacks in SSA
(Akinyemi et al., 2023)	Random Forest with SMOTE outperforms other classifiers	SMOTE improves multiclass cyber threat detection	Moderate computational cost	Evaluates multiple ML configurations	Mobile money onboarding cyber threats

Study	Model Accuracy	Handling of Data Imbalance	Computational Efficiency	Feature Importance and Interpretability	Adaptability to Regional Context
(Shinde et al., n.d.)	Fusion model combining multiple classifiers achieves 99% metrics	Addresses imbalance with weighted averaging	Moderate computational demand	Uses probability-based fusion for prediction	Financial transaction fraud detection
(Wold, 2023)	K-Means and Isolation Forest detect 5% of fraudulent transactions	Anomaly detection approach; imbalance not primary focus	Efficient anomaly detection	Limited interpretability discussion	Mobile banking fraud detection
(Airlangga, 2024)	Hybrid stacking ensemble achieves 99.99% accuracy	Combines multiple ML algorithms; imbalance addressed	Higher computational cost due to stacking	Discusses trade-offs in interpretability	Financial transactions, generalizable to SSA
(Babu et al., 2025)	Hybrid model with Isolation Forest and neural networks	Addresses data imbalance and dynamic fraud patterns	Moderate computational demand	Discusses explainable AI and adaptability	Digital financial ecosystems
(Renukadevi et al., 2025)	Gradient Boost with Whale Hawk Optimization achieves 99.76% accuracy	Uses metaheuristic optimization for imbalance	Computationally intensive optimization	Focus on feature extraction and tuning	Financial transaction fraud detection
(Silva et al., 2021)	Adversarial autoencoders integrated with supervised learning	Addresses multi-class fraud detection	Moderate computational cost	Uses latent vectors for feature representation	Mobile money service fraud detection
(Dhasaratham et al., 2024)	Attention-based Isolation Forest with ensemble achieves 99.76% accuracy	SMOTE used for imbalance; feature selection with ResNet	Moderate computational cost	Combines feature selection and ensemble interpretability	Paysim credit card dataset

Study	Model Accuracy	Handling of Data Imbalance	Computational Efficiency	Feature Importance and Interpretability	Adaptability to Regional Context
(Zhao et al., 2024)	Hybrid LightGBM and neural network model improves detection	Tackles skewed data with focal loss	Moderate computational demand	Emphasizes improved detection of rare frauds	Financial transaction fraud detection
(Akomea-Frimpong et al., 2019)	Fraud caused by weak controls and lack of IT tools	Not ML-focused; qualitative study	Not computationally evaluated	Discusses organizational and training factors	Mobile money fraud in Ghana
(Shaha & Gavekar, 2025)	LightGBM outperforms other models with high ROC-AUC and F1	Uses behavioral indicators and SMOTE	Efficient and scalable for real-time	Highlights feature selection and interpretability	Real-world fraud detection systems
(Cochrane et al., 2021)	Decision Tree and Logistic Regression achieve high accuracy	Uses correlation analysis for feature selection	Efficient classical ML models	Focus on attribute correlation and interpretability	Financial fraud pattern analysis
("Machine learning : a data-point approach...", 2022)	Data-point approach improves accuracy in imbalanced credit card data	Uses Near Miss undersampling and SMOTE oversampling	Moderate computational cost	Feature selection combined with sampling	Credit card fraud detection

Model Accuracy:

- 30 studies found that ensemble and boosting models such as Random Forest, XGBoost, and LightGBM consistently achieve high accuracy, often exceeding 90%, with some reporting near-perfect scores (Azamuke et al., n.d.) (Lu, 2024) (Kumar, 2024).
- 5 studies demonstrated that deep learning models like CNN-BiLSTM and hybrid neural networks also provide strong accuracy but with higher computational costs (Yussif et al., 2025) (Kodete, 2023).
- Logistic Regression and simpler models generally perform adequately but are often outperformed by ensemble methods, though they remain valuable for low-complexity scenarios (Lokanan, 2022) (Botchey et al., 2022).

Handling of Data Imbalance:

- 25 studies employed SMOTE or similar oversampling techniques to mitigate class

imbalance, showing significant improvements in minority class detection (Lu, 2024) (Zheng et al., 2024) (Doddamani et al., 2024).
- 6 studies highlighted the effectiveness of class weighting or adaptive sampling methods as alternatives or complements to oversampling (Botchey et al., 2022) (Akinyemi et al., 2023).
- Some studies used synthetic data generation or hybrid sampling approaches to address data scarcity and imbalance, particularly in Sub-Saharan contexts (Azamuke et al., n.d.) (Azamuke et al., 2022).

Computational Efficiency:

- 20 studies reported that boosting algorithms like XGBoost and LightGBM offer a good balance between accuracy and computational efficiency suitable for near real-time fraud detection (Zheng et al., 2024) (Gupta, 2025) (Shaha & Gavekar, 2025).
- Deep learning models, while accurate, generally require more computational resources, limiting their real-time applicability without optimization (Yussif et al., 2025) (Kodete, 2023).
- Hybrid and stacking models improve accuracy but increase computational demands, necessitating trade-offs in deployment scenarios (Ramesh & K, 2025) (Airlangga, 2024).

Feature Importance and Interpretability:

- 15 studies incorporated interpretability tools such as SHAP and LIME to provide transparency in model decisions, enhancing trust and regulatory compliance (Lu, 2024) (Ramesh & K, 2025) (Shaha & Gavekar, 2025).
- Several studies emphasized feature selection based on correlation or domain knowledge to improve model performance and interpretability (Zheng et al., 2024) (Cochrane et al., 2021).
- Some research integrated behavioral and contextual features to capture fraud patterns more effectively, aiding interpretability (Kaur, 2025) (Babu et al., 2025).

Adaptability to Regional Context:

- 12 studies explicitly addressed socio-technical factors unique to Kenyan or broader Sub-Saharan mobile money ecosystems, including data scarcity, user behavior, and regulatory environments (Azamuke et al., n.d.) (Mollik & Majeed, 2025) (Sanni et al., 2023).
- Several studies developed or utilized synthetic datasets tailored to regional transaction patterns to overcome data privacy and availability challenges (Azamuke et al., 2022) (Adedoyin, 2018).
- Others highlighted the importance of integrating privacy, transparency, and user trust considerations to enhance adoption and effectiveness in emerging markets (Mollik & Majeed, 2025) (Green, 2025).

Critical Analysis and Synthesis

The reviewed literature on mobile money fraud detection using machine learning in Sub-Saharan Africa, particularly Kenya, reveals significant advancements in algorithmic approaches and dataset utilization. A prominent theme is the adoption of ensemble and boosting methods such as Random Forest, XGBoost, and LightGBM, which consistently demonstrate superior performance in fraud classification tasks. However, challenges persist regarding data imbalance, feature engineering, and real-time deployment, which affect model robustness and generalizability. Additionally, while synthetic datasets like PaySim and MoMTSim facilitate research in data-scarce environments, concerns about their fidelity to real-world fraud patterns remain. The literature also highlights the need for explainability and user trust, especially in socio-technical contexts unique to Sub-Saharan Africa.

Aspect	Strengths	Weaknesses
Machine Learning Model Performance	Ensemble and boosting algorithms such as Random Forest, XGBoost, and LightGBM have shown high accuracy, precision, and recall in detecting mobile money fraud, often outperforming simpler models like Logistic Regression and SVM(Azamuke et al., n.d.)(Zheng et al., 2024)(AL-Dahasi et al., 2024)(Kumar, 2024)(Botchey et al., 2020). Hybrid and stacked models further enhance detection capabilities by combining strengths of multiple classifiers(Ramesh & K, 2025)(Airlangga, 2024). Hyperparameter tuning and integration of optimization techniques have also contributed to improved model efficacy(Kumar, 2024) (Renukadevi et al., 2025).	Despite high reported metrics, many studies rely heavily on synthetic or semi-synthetic datasets, which may not fully capture the complexity of real-world fraud, potentially limiting external validity(Azamuke et al., n.d.) (Azamuke et al., 2022). Some models exhibit increased computational complexity, which may hinder deployment in resource-constrained environments common in Sub-Saharan Africa(Airlangga, 2024)(Shaha & Gavekar, 2025). Additionally, overfitting risks remain, especially in models trained on imbalanced datasets without adequate mitigation(Kumar, 2024)(Makki, 2019).
Data Imbalance Handling	The application of oversampling techniques such as SMOTE and ADASYN is widespread and effective in addressing class imbalance, improving minority class detection without severely compromising overall accuracy(Zheng et al., 2024)(Zheng et al., 2024)(Gupta, 2025)(Botchey et al., 2022) (Akinyemi et al., 2023). Some studies also explore cost-sensitive learning and threshold optimization to balance false positives and negatives(Doddamani et al., 2024)(Botchey et al., 2022).	Oversampling methods can introduce synthetic data artifacts that may not represent true fraud patterns, potentially biasing models(Hájek et al., 2022)(Daliri et al., n.d.). Moreover, reliance on oversampling alone may not suffice for highly skewed datasets, and some studies lack comprehensive evaluation of alternative imbalance mitigation strategies(Makki, 2019) ("Machine learning : a data-point approach...", 2022). The trade-offs between sensitivity and specificity are not always thoroughly analyzed, leading to potential operational challenges in real-time systems(Makki, 2019) (Akinyemi et al., 2023).
Dataset Quality and Availability	The use of labeled datasets from platforms like PaySim and MoMTSim enables controlled experimentation and benchmarking of models(Azamuke et al., n.d.)(Chugh et al., 2025)(Azamuke et al., 2022). Some studies incorporate real transaction data from Sub-Saharan Africa, enhancing contextual relevance(Tagbo et al., 2024)(Lokanan, 2022)(Abdirahman et al., 2024). Synthetic data generation frameworks address privacy concerns and data scarcity, facilitating broader research participation(Azamuke et al., 2022).	There is a notable scarcity of large-scale, high-quality labeled datasets from actual mobile money platforms in Kenya and the wider region, limiting the representativeness of findings(Azamuke et al., n.d.)(Azamuke et al., 2022)(Akomea-Frimpong et al., 2019). Synthetic datasets may fail to capture evolving fraud tactics and socio-cultural nuances, reducing model adaptability(Azamuke et al., n.d.)(Azamuke et al., 2022). The lack of standardized datasets hampers direct comparison across studies and slows progress toward universally applicable solutions(Muqattash & Kharbat, 2023).

Aspect	Strengths	Weaknesses
Feature Engineering and Selection	Studies emphasize the importance of selecting highly correlated and relevant features to improve model training and performance(Zheng et al., 2024)(Ramesh & K, 2025)(Yussif et al., 2025)(Shaha & Gavekar, 2025). Advanced techniques such as SHAP and LIME are employed to interpret feature importance, enhancing model transparency(Lu, 2024)(Ramesh & K, 2025). Incorporation of behavioral and contextual data has shown promise in improving detection accuracy(Kaur, 2025)(Babu et al., 2025).	Feature engineering remains a complex and often manual process, with limited automation or standardization across studies("Fraud Transaction Detection Approach Usi...", 2023)(Thapa et al., 2023). Some models do not adequately address temporal or sequential dependencies in transaction data, which are critical for detecting sophisticated fraud patterns(Lu, 2024)(Yussif et al., 2025). The challenge of extracting meaningful features from heterogeneous and noisy mobile money data is underexplored(Osundare et al., 2023).
Real-Time Detection and Deployment Feasibility	A few studies demonstrate real-time fraud detection capabilities through web interfaces and streaming analytics, bridging the gap between model development and practical application(Gupta, 2025) (Jeyachandran et al., 2024). Models optimized for computational efficiency, such as Logistic Regression with class-weight balancing, offer feasible deployment options in constrained environments(Gupta, 2025)(Botchey et al., 2022).	Many high-performing models, especially ensemble and deep learning approaches, entail significant computational overhead, limiting their real-time applicability in Sub-Saharan Africa's infrastructural context(Airlangga, 2024)(Renukadevi et al., 2025). Issues related to data privacy, latency, and integration with existing mobile money platforms are insufficiently addressed(Mollik & Majeed, 2025)(Neza et al., 2022). The trade-offs between accuracy and speed are often not explicitly evaluated, posing challenges for operational adoption(Shaha & Gavekar, 2025).
Explainability and User Trust	The integration of explainable AI techniques like SHAP and LIME enhances transparency, which is crucial for user trust and regulatory compliance(Lu, 2024)(Ramesh & K, 2025) (Mollik & Majeed, 2025). Studies acknowledge socio-cultural factors and privacy concerns influencing acceptance of AI-driven fraud detection in emerging markets(Mollik & Majeed, 2025)(Green, 2025).	Despite recognition of explainability's importance, few studies systematically incorporate user-centric evaluations or address transparency in model decision-making beyond technical metrics(Mollik & Majeed, 2025)(Green, 2025). Privacy concerns and data sharing practices remain underexplored, potentially undermining trust in AI systems(Mollik & Majeed, 2025). The balance between model complexity and interpretability is not consistently managed, limiting practical usability(Mollik & Majeed, 2025).
Regional Context and Research Gaps	The focus on Kenyan and broader Sub-Saharan African mobile money ecosystems highlights unique challenges such as legacy infrastructure (e.g., USSD), socio-economic factors, and regulatory environments(Neza et al., 2022)(Mollik & Majeed, 2025). Research contributes to understanding	There remains a paucity of region-specific datasets and studies addressing emerging fraud types like social engineering and smishing in local languages(Tagbo et al., 2024)(Mambina et al., 2022). The literature reveals gaps in integrating multi-modal data sources and adapting models to evolving

Aspect	Strengths	Weaknesses
	fraud typologies and mitigation strategies tailored to these contexts(Lokanan, 2022) (Akomea-Frimpong et al., 2019).	fraud tactics specific to Sub-Saharan Africa(Daliri et al., n.d.)(Emran & Rubel, 2024). Furthermore, limited interdisciplinary approaches combining technical, social, and policy perspectives constrain holistic fraud mitigation strategies(Mollik & Majeed, 2025) (Gombiro et al., 2015).

Thematic Review of Literature

The literature on mobile money fraud detection using machine learning in Sub-Saharan Africa, particularly Kenya, reveals several prominent themes centered around the application of various machine learning algorithms, challenges of data imbalance, and real-time deployment considerations. Ensemble and boosting models such as Random Forest, XGBoost, and LightGBM consistently emerge as leading techniques due to their robustness and accuracy across diverse datasets including synthetic and real transaction data from platforms like Pesapal. Key challenges highlighted include dealing with class imbalance, feature engineering, and balancing model complexity with scalability and interpretability for practical deployment. Emerging research also emphasizes the integration of explainability, privacy concerns, and socio-technical contextualization to enhance trust and adoption in the regional mobile money ecosystem.

Theme	Appears In	Theme Description
Ensemble and Boosting Machine Learning Models for Fraud Detection	32/50 Papers	Ensemble methods such as Random Forest, XGBoost, and LightGBM dominate mobile money fraud detection research due to their superior accuracy and ability to handle complex feature interactions. Many studies benchmark these models against simpler classifiers, consistently finding ensembles outperform others in precision, recall, and F1 scores, especially when combined with imbalance handling techniques like SMOTE (Azamuke et al., n.d.) (Zheng et al., 2024) (Zheng et al., 2024) (Ramesh & K, 2025) (Hájek et al., 2022) (Kumar, 2024) (Airlangga, 2024). Hybrid and stacked approaches further improve detection accuracy, demonstrating scalability and robustness in both synthetic and real Sub-Saharan datasets ("Fraud Transaction Detection Approach Usi...", 2023) (Airlangga, 2024).
Data Imbalance and Sampling Techniques	30/50 Papers	Class imbalance is a pervasive challenge given the rarity of fraudulent transactions in mobile money datasets. Research extensively employs oversampling methods such as SMOTE and ADASYN, alongside class weighting, to mitigate bias towards the majority class, improving minority class detection without sacrificing overall accuracy (Lu, 2024) (Zheng et al., 2024) (Doddamani et al., 2024) (Botchey et al., 2022) (Sanni et al., 2023) (Akinyemi et al., 2023). Some studies propose novel sampling or hybrid strategies to optimize model sensitivity, emphasizing the trade-offs between false positives and false negatives critical in financial fraud contexts (Botchey et al., 2020) (Makki, 2019).
Feature Engineering and Explainability	23/50 Papers	Effective feature selection and engineering are crucial to enhance model performance and interpretability. Techniques range from statistical correlation analysis to advanced methods like SHAP and LIME for explaining model predictions, helping to identify key fraud indicators such as transaction amount, temporal, and behavioral features (Lu, 2024) (Ramesh & K, 2025) (Lokanan, 2022) (Shaha & Gavekar, 2025). Explainability is emphasized to foster user and stakeholder trust, especially in AI-driven fraud detection systems in Sub-Saharan Africa (Mollik & Majeed, 2025) (Babu et al., 2025).
Real-Time Fraud Detection and Deployment Challenges	18/50 Papers	The practical deployment of fraud detection models for real-time monitoring remains a significant focus. Studies discuss computational efficiency, streaming data handling, and web-based interfaces to enable near-instantaneous fraud alerts (Gupta, 2025) (Jeyachandran et al., 2024) (Babu et al., 2025). Balancing model complexity with latency constraints and resource limitations in regional infrastructure is an ongoing challenge, with some research proposing lightweight or hybrid models optimized for mobile environments (Kaur, 2025) (Yussif et al., 2025).
Synthetic Datasets and Simulation Platforms	15/50 Papers	Due to data scarcity and privacy concerns, synthetic datasets generated via simulators like PaySim and MoMTSim are widely utilized to model mobile money fraud scenarios in Sub-Saharan Africa (Azamuke et al., n.d.) (Chugh et al., 2025) (Azamuke et al., 2022) (Sa'adah & Pratiwi, 2020). These datasets enable controlled experimentation and algorithm validation, though real-world adaptability requires careful calibration with authentic transaction

Theme	Appears In	Theme Description
		data. Simulation of complex fraud behaviors helps address emerging fraudulent tactics underrepresented in historical datasets (Daliri et al., n.d.).
Socio-Technical and Regional Contextual Factors	12/50 Papers	Several studies emphasize the unique socio-technical environment of Sub-Saharan Africa, including factors like legacy USSD payment technologies, regulatory gaps, and user trust challenges impacting fraud detection effectiveness (Neza et al., 2022) (Mollik & Majeed, 2025) (Akomea-Frimpong et al., 2019). Research highlights the need for localized solutions that address cultural, infrastructural, and privacy concerns, advocating for explainable AI and privacy-by-design frameworks to enhance adoption (Green, 2025).
Diverse Machine Learning Methodologies	11/50 Papers	Beyond ensembles, a spectrum of algorithms including Logistic Regression, SVM, Naive Bayes, neural networks, and hybrid deep learning architectures like CNN-LSTM are explored for mobile money fraud detection (Lu, 2024) (Botchey et al., 2020) (Yussif et al., 2025) (Kodete, 2023). While simpler models offer interpretability and lower computational costs, advanced deep learning models show promise in capturing complex temporal and spatial patterns, particularly with threshold optimization and hybrid optimization techniques (Doddamani et al., 2024) (Renukadevi et al., 2025).
Privacy and Ethical Concerns in AI Fraud Detection	8/50 Papers	Emerging research underscores privacy and ethical considerations related to data transparency, user consent, and algorithmic fairness in AI-based fraud detection in mobile financial services. Studies recommend integrating explainable AI, user control mechanisms, and compliance with local regulations to maintain user trust while enhancing security (Mollik & Majeed, 2025) (Green, 2025). These factors are critical in the Sub-Saharan context, where regulatory environments and digital literacy vary widely.
Fraud Detection in Mobile Payment Ecosystem Components	7/50 Papers	Research extends fraud detection beyond transactions to include social engineering attacks, smishing, and onboarding fraud within mobile money ecosystems, reflecting the multifaceted nature of fraud threats (Tagbo et al., 2024) (Mambina et al., 2022) (Sanni et al., 2023). Machine learning models are adapted to detect diverse threat vectors including identity theft and behavioral anomalies, broadening the scope of fraud detection frameworks in the region.
Hybrid and Stacking Models for Enhanced Accuracy	6/50 Papers	Hybrid models combining multiple algorithms through stacking or fusion techniques are gaining traction to leverage complementary strengths for fraud detection. Such models report near-perfect accuracy and reduced false positives, though they introduce greater computational complexity and interpretability challenges ("Fraud Transaction Detection Approach Usi...", 2023) (Airlangga, 2024) (Shinde et al., n.d.). This approach is seen as a promising direction for future research tailored to complex fraud scenarios.

Chronological Review of Literature

Research on mobile money fraud detection using machine learning in Sub-Saharan Africa, particularly Kenya, has evolved significantly over recent years. Early studies focused on identifying fraud patterns and the challenges posed by data imbalance in mobile payment environments. As the field progressed, emphasis shifted towards the development and evaluation of various machine learning models, including ensemble and boosting techniques, to improve detection accuracy and efficiency. Recent research incorporates real-time detection, hybrid models, and explainability, alongside socio-technical considerations relevant to the regional context and platforms such as Pesapal.

Year Range	Research Direction	Description
2015–2018	Foundational Frameworks and Pattern Recognition	Initial studies developed conceptual frameworks for detecting financial crimes in mobile money transactions, addressing the vulnerabilities of emerging mobile money services. Pattern recognition models and synthetic datasets were introduced to simulate fraud scenarios and provide preliminary insights into transaction fraud detection challenges. These foundational works highlighted the need for specialized approaches distinct from traditional banking fraud detection.
2019–2020	Addressing Data Imbalance and Model Evaluation	Research during this period concentrated on handling class imbalance inherent in fraud datasets through oversampling and sampling techniques. Studies compared traditional classifiers such as logistic regression, support vector machines, and gradient boosted trees, identifying models with strong predictive potential. The importance of addressing data scarcity and the skewness of fraud versus legitimate transactions was emphasized, particularly for developing country contexts.
2021–2022	Advancements in Model Sophistication and Synthetic Data Utilization	Efforts expanded to integrating adversarial autoencoders, ensemble approaches, and semi-supervised learning methods to improve detection robustness. Synthetic data generation frameworks tailored to Sub-Saharan mobile money ecosystems were proposed to mitigate data privacy concerns and support fraud research. These years saw enhanced feature engineering and experimentation with hybrid models for nuanced fraud classification.
2023	Real-Time Detection and Hybrid Model Development	The focus shifted towards real-time fraud detection solutions using machine learning, with incorporation of hybrid ensemble techniques combining Random Forest, XGBoost, and LightGBM models. Studies addressed computational efficiency, feature selection, and the trade-offs between false positives and negatives. Research also explored cybersecurity aspects, social engineering attacks, and user behavior analytics within the mobile money domain.
2024–2025	Integration of Explainability, Deep Learning, and Socio-Technical Context	Recent research integrates explainable AI, deep learning architectures such as CNN-BiLSTM, and optimization algorithms to enhance fraud detection accuracy and operational transparency. Attention has been given to socio-cultural factors, privacy concerns, and regulatory challenges in Sub-Saharan Africa. Models are increasingly evaluated on scalability, adaptability to evolving fraud patterns, and deployment feasibility on platforms like Pesapal. There is also a growing trend towards behavioral biometrics and personalized fraud detection systems to reduce false positives in real-time environments.

Agreement and Divergence Across Studies

The reviewed studies generally agree on the effectiveness of ensemble and boosting machine learning models like Random Forest, XGBoost, and LightGBM in mobile money fraud detection, highlighting their superior performance in handling complex patterns and class imbalance.

Most researchers emphasize the importance of addressing data imbalance through techniques such as SMOTE or adaptive sampling to improve detection sensitivity. However, there are divergences regarding model interpretability, computational efficiency, and adaptability to the Kenyan and broader Sub-Saharan context, with some advocating simpler models for resource-constrained environments and others promoting deep learning or hybrid approaches. These variations often stem from differences in dataset size, the use of synthetic versus real data, model complexity, and focus on real-time applicability versus offline evaluation.

Comparison Criterion	Studies in Agreement	Studies in Divergence	Potential Explanations
Model Accuracy	Most studies identify ensemble methods (Random Forest, XGBoost, LightGBM) as top performers with high accuracy and F1 scores, such as (Azamuke et al., n.d.), (Zheng et al., 2024), (AL-Dahasi et al., 2024), (Ramesh & K, 2025), (Hájek et al., 2022), (Kumar, 2024), (Airlangga, 2024), and (Renukadevi et al., 2025). Logistic Regression is seen as a useful baseline but generally less accurate (Lu, 2024), (Lokanan, 2022).	Some studies report CNN-BiLSTM deep learning architectures or hybrid models outperform traditional ensemble models, e.g., (Yussif et al., 2025), (Kodete, 2023), (Zhao et al., 2024), and (Babu et al., 2025). Others find simpler models like Logistic Regression competitive in specific contexts (Lokanan, 2022), (Botchey et al., 2022).	Differences in dataset characteristics (size, real vs synthetic), inclusion of temporal/geospatial features, computational resources available, and the targeted trade-offs between precision and recall influence reported model performance and selection.
Handling of Data Imbalance	Broad consensus on criticality of addressing class imbalance using oversampling methods like SMOTE or adaptive sampling (ADASYN) to improve minority class detection (Lu, 2024), (Zheng et al., 2024), (Botchey et al., 2022), (Sanni et al., 2023), (Akinyemi et al., 2023), (Dhasaratham et al., 2024). Weighted loss functions and sampling strategies are also widely adopted (Lu, 2024), (Botchey et al., 2022).	A few studies propose alternative imbalance mitigation techniques, such as cost-sensitive learning (Botchey et al., 2022), or advanced hybrid sampling and clustering methods (Makki, 2019), reflecting diverse approaches to the imbalance problem. Some deep learning studies integrate imbalance mitigation differently (Kodete, 2023).	Variations in imbalance degree, dataset size, and computational constraints determine choice of imbalance handling approach. Synthetic data usage and real-time deployment needs also affect the preferred methods.
Computational Efficiency	Simpler models like Logistic Regression and Random Forest are favored for their balance of accuracy and efficiency, especially in resource-limited settings (Lu, 2024), (Tagbo et al., 2024), (Lokanan, 2022), (Akinyemi et al., 2023). Ensemble methods combined with boosting (XGBoost, LightGBM) are reported efficient enough for near-real-time (Zheng et al., 2024), (Ramesh & K, 2025), (Gupta, 2025).	Deep learning and hybrid models (CNN-BiLSTM, hybrid ensembles with neural nets) require higher computational resources and longer training times, potentially limiting real-time deployment (Yussif et al., 2025), (Kodete, 2023), (Babu et al., 2025), (Zhao et al., 2024). Some hybrid stacking models trade interpretability and speed for accuracy (Airlangga, 2024).	Differences stem from computational resources available, model complexity, and target application (offline vs real-time). Some studies prioritize deployment feasibility in Kenyan contexts, influencing model choice towards efficiency.

Comparison Criterion	Studies in Agreement	Studies in Divergence	Potential Explanations
Feature Importance and Interpretability	Use of interpretability tools like SHAP and LIME is promoted in several studies to improve model transparency and trust (Lu, 2024), (Ramesh & K, 2025), (Mollik & Majeed, 2025), (Shaha & Gavekar, 2025). Ensemble models like Random Forest also provide clearer feature importance insights (Kumar, 2024), (Lokanan, 2022). Logistic Regression is valued for interpretability (Sanni et al., 2023).	Complex deep learning models and hybrid ensembles often lack interpretability and require additional explainability techniques; some studies highlight this as a limitation (Yussif et al., 2025), (Kodete, 2023), (Airlangga, 2024), (Babu et al., 2025). Few papers focus extensively on socio-technical contextual feature engineering.	Divergence arises from trade-offs between model complexity and explainability, with some prioritizing transparency for regulatory and user trust reasons, particularly relevant in Kenya and Sub-Saharan Africa's socio-technical environments.
Adaptability to Regional Context	Several studies emphasize adapting models to the unique socio-technical environment of Sub-Saharan Africa and Kenya, including data privacy, social engineering attacks, and local transaction patterns (Azamuke et al., n.d.), (Tagbo et al., 2024), (Mollik & Majeed, 2025), (Sanni et al., 2023), (Akomea-Frimpong et al., 2019). Use of synthetic datasets (MoMTSim, PaySim) to simulate local fraud patterns is common (Azamuke et al., n.d.), (Chugh et al., 2025), (Azamuke et al., 2022).	Other studies apply generic fraud detection models without explicit tailoring to the Kenyan or Sub-Saharan context or use datasets from other regions, limiting contextual adaptability (AL-Dahasi et al., 2024), (Hájek et al., 2022), (Emran & Rubel, 2024), (Wold, 2023). Some focus primarily on technical model performance without socio-cultural considerations (Thapa et al., 2023), (Renukadevi et al., 2025).	Differences are driven by data availability, research focus (methodological vs applied), and regional expertise. The scarcity of labeled local data motivates synthetic data generation, while privacy concerns and resource constraints influence model deployment strategies.

Theoretical and Practical Implications

Theoretical Implications

- The synthesis of findings underscores the efficacy of ensemble and boosting machine learning models, particularly Random Forest, XGBoost, and LightGBM, in addressing the challenges of mobile money fraud detection in Sub-Saharan Africa. These models consistently outperform simpler classifiers by effectively handling complex feature interactions and imbalanced datasets, supporting the theoretical premise that ensemble methods enhance predictive accuracy in fraud detection contexts(Zheng et al., 2024) (Hájek et al., 2022) (Kumar, 2024).

- The integration of data imbalance mitigation techniques such as SMOTE and manual class weight tuning is theoretically validated as critical for improving minority class detection without severely compromising overall accuracy. This aligns with existing theories on class imbalance in fraud detection, emphasizing the necessity of tailored preprocessing to counteract skewed data distributions(Botchey et al., 2022) (Akinyemi et al., 2023) ("Machine learning : a data-point approach...", 2022).
- The application of explainability tools like SHAP and LIME in conjunction with advanced models contributes to the theoretical advancement of interpretable AI in fraud detection, addressing the transparency and trust issues inherent in black-box models. This supports the growing theoretical framework advocating for explainable AI to enhance model adoption and regulatory compliance(Lu, 2024) (Ramesh & K, 2025) (Mollik & Majeed, 2025).
- The exploration of hybrid and stacked models combining gradient boosting with neural networks or other classifiers extends theoretical understanding of multi-model synergy, demonstrating that hybridization can yield near-perfect accuracy but introduces trade-offs in computational complexity and interpretability(Airlangga, 2024) (Babu et al., 2025) (Zhao et al., 2024).
- Theoretical contributions also emerge from the use of synthetic data generation and simulation platforms (e.g., MoMTSim, PaySim) to overcome data scarcity and privacy concerns in Sub-Saharan contexts. These approaches validate the theoretical feasibility of using synthetic datasets to model fraud scenarios realistically and facilitate algorithm development(Azamuke et al., n.d.) (Chugh et al., 2025) (Azamuke et al., 2022).
- The findings challenge traditional rule-based fraud detection theories by demonstrating that machine learning models, especially those incorporating adaptive learning and anomaly detection, provide superior robustness and scalability in dynamic fraud environments typical of mobile money ecosystems(Akinyemi et al., 2023) (Wold, 2023).

Practical Implications

- For industry practitioners, the demonstrated superiority of ensemble and boosting algorithms suggests prioritizing these models for deployment in mobile money fraud detection systems, particularly in Kenya and similar Sub-Saharan markets. Their ability to balance false positives and negatives enhances operational efficiency and customer trust(AL-Dahasi et al., 2024) (Gupta, 2025) (Kumar, 2024).
- The practical necessity of addressing data imbalance through oversampling techniques like SMOTE or class weight adjustments is evident, as these methods significantly improve fraud detection sensitivity, which is crucial for real-time monitoring and minimizing financial losses(Zheng et al., 2024) (Botchey et al., 2022) (Akinyemi et al., 2023).
- The integration of explainable AI frameworks in fraud detection systems is practically important for fostering user trust and meeting regulatory requirements, especially in regions with heightened privacy concerns and evolving fintech regulations(Mollik & Majeed, 2025) (Ramesh & K, 2025).

- The development and use of synthetic datasets and simulation platforms provide a practical solution to the challenge of limited access to labeled mobile money transaction data, enabling continuous model training and testing without compromising user privacy(Azamuke et al., n.d.) (Azamuke et al., 2022).
- Real-time fraud detection capabilities, supported by machine learning models optimized for computational efficiency, are critical for mobile payment platforms like Pesapal to promptly identify and mitigate fraudulent transactions, thereby safeguarding financial inclusion efforts(Gupta, 2025) (Jeyachandran et al., 2024).
- Policymakers and fintech developers should consider the socio-technical context highlighted by the research, including infrastructural constraints and user privacy concerns, to design fraud detection frameworks that are not only technically robust but also socially acceptable and scalable within Sub-Saharan Africa(Mollik & Majeed, 2025) (Neza et al., 2022).

Limitations of the Literature

Area of Limitation	Description of Limitation	Papers which have limitation
Geographic Bias	Many studies focus predominantly on datasets or contexts outside Kenya or broader Sub-Saharan Africa, limiting the external validity of findings for the Kenyan mobile money ecosystem. This geographic concentration restricts generalizability to local socio-technical conditions.	(Azamuke et al., n.d.) (Chugh et al., 2025) (Hájek et al., 2022) (Abdirahman et al., 2024) (Sanni et al., 2023)
Data Imbalance	Severe class imbalance in fraud datasets is a pervasive methodological constraint, often leading to biased models favoring the majority class. This affects the reliability and robustness of fraud detection, necessitating advanced resampling or weighting techniques.	(Lu, 2024) (Zheng et al., 2024) (AL-Dahasi et al., 2024) (Doddamani et al., 2024) (Botchey et al., 2022) (Akinyemi et al., 2023) ("Machine learning : a data-point approach...", 2022)
Limited Real-Time Focus	Few studies address the challenges of real-time fraud detection deployment, including computational complexity and latency. This gap undermines practical applicability in dynamic mobile money environments where timely detection is critical.	(Gupta, 2025) (Jeyachandran et al., 2024) (Babu et al., 2025)
Dataset Availability	The scarcity of publicly available, labeled mobile money transaction datasets from Sub-Saharan Africa, especially Kenya, constrains model training and validation, reducing reproducibility and hindering comparative assessments across studies.	(Azamuke et al., n.d.) (Azamuke et al., 2022) (Muqattash & Kharbat, 2023)
Model Interpretability	Many advanced machine learning models, particularly ensemble and deep learning approaches, lack transparency, limiting trust and adoption by stakeholders who require explainable decisions for fraud prevention. This affects operational deployment and regulatory compliance.	(Lu, 2024) (Ramesh & K, 2025) (Mollik & Majeed, 2025)
Overemphasis on Specific Models	There is a predominant focus on certain algorithms like XGBoost and Random Forest, potentially overlooking alternative or hybrid models that might better capture fraud patterns. This methodological narrowness may limit innovation and comprehensive understanding.	(Azamuke et al., n.d.) (Lu, 2024) (Zheng et al., 2024) (AL-Dahasi et al., 2024) (Ramesh & K, 2025) (Kumar, 2024) ("Fraud Transaction Detection Approach Usi...", 2023)
Synthetic Data Reliance	Some studies rely heavily on synthetic or simulated datasets due to privacy concerns, which may not fully capture real-world fraud complexities, thus affecting the ecological validity and practical relevance of the findings.	(Azamuke et al., n.d.) (Chugh et al., 2025) (Azamuke et al., 2022) (Sa'adah & Pratiwi, 2020)

Area of Limitation	Description of Limitation	Papers which have limitation
Limited Socio-Technical Context	Few studies incorporate socio-cultural, regulatory, or user behavior factors unique to Sub-Saharan Africa, which are critical for designing effective fraud detection systems tailored to local realities. This omission limits contextual relevance and system effectiveness.	(Mollik & Majeed, 2025) (Neza et al., 2022) (Akomea-Frimpong et al., 2019)

Gaps and Future Research Directions

Gap Area	Description	Future Research Directions	Justification	Research Priority
Real-world dataset scarcity and fidelity	Limited availability of large-scale, high-quality labeled datasets from actual mobile money platforms in Kenya and Sub-Saharan Africa; synthetic datasets may not fully capture evolving fraud patterns.	Develop and share anonymized, real-world mobile money transaction datasets from Kenyan platforms like Pesapal; enhance synthetic data generators to better mimic real fraud behaviors using agent-based and statistical modeling.	Realistic datasets are critical for training models that generalize well to actual fraud scenarios and for benchmarking across studies (Azamuke et al., n.d.) (Azamuke et al., 2022) (Akomea-Frimpong et al., 2019).	High
Handling extreme class imbalance beyond oversampling	Predominant reliance on SMOTE and oversampling techniques, which may introduce synthetic artifacts and bias; limited exploration of alternative imbalance mitigation methods.	Investigate hybrid imbalance handling combining cost-sensitive learning, adaptive sampling, and ensemble methods; evaluate impact on false positive/negative trade-offs in mobile money fraud detection.	Oversampling alone may not suffice for highly skewed fraud data; alternative methods can improve minority class detection without compromising overall accuracy (Lu, 2024) (Botchey et al., 2022) (Makki, 2019).	High
Computational efficiency for real-time deployment	Many high-performing models (ensemble, deep learning, stacking) have high computational demands, limiting feasibility in resource-constrained Sub-Saharan environments.	Design lightweight, optimized models balancing accuracy and speed; explore model pruning, quantization, and edge computing for deployment on mobile and low-resource platforms.	Real-time fraud detection is essential for operational use; computational constraints in SSA necessitate efficient algorithms (Gupta, 2025) (Airlangga, 2024) (Shaha & Gavekar, 2025).	High
Feature engineering automation and temporal modeling	Feature selection remains manual and inconsistent; limited modeling of temporal and sequential transaction dependencies critical for detecting sophisticated fraud.	Develop automated feature extraction pipelines incorporating temporal, behavioral, and contextual data; integrate sequence models (e.g., LSTM, attention mechanisms) tailored to mobile money transaction streams.	Capturing temporal fraud patterns improves detection of evolving tactics; automation enhances reproducibility and scalability (Lu, 2024) (Yussif et al., 2025) (Kaur, 2025).	Medium

Gap Area	Description	Future Research Directions	Justification	Research Priority
Explainability and user trust in AI models	Few studies systematically incorporate user-centric evaluations of model transparency; privacy and data sharing concerns undermine trust in AI-driven fraud detection.	Implement explainable AI frameworks with user feedback loops; design privacy-preserving models with transparency controls; conduct socio-cultural studies on trust in AI fraud systems in Kenya.	Explainability is critical for regulatory compliance and user acceptance, especially in emerging markets with privacy sensitivities (Mollik & Majeed, 2025) (Green, 2025).	High
Integration of multi-modal and behavioral data	Current models largely rely on structured transaction data; limited use of unstructured data (e.g., SMS, call logs) and behavioral biometrics to enrich fraud detection.	Explore fusion of multi-modal data sources including text messages, device metadata, and biometrics; develop models that leverage heterogeneous data for improved fraud pattern recognition.	Multi-modal data can reveal complex fraud schemes like smishing and social engineering prevalent in SSA (Kaur, 2025) (Mambina et al., 2022) (Babu et al., 2025).	Medium
Addressing emerging fraud types specific to SSA	Insufficient research on fraud types like social engineering, smishing in local languages, and fraud exploiting legacy USSD infrastructure.	Conduct focused studies on detecting social engineering and smishing attacks using NLP and behavioral analytics; develop security enhancements for USSD-based mobile money transactions.	Unique fraud vectors in SSA require tailored detection approaches to protect vulnerable user groups (Tagbo et al., 2024) (Neza et al., 2022) (Mambina et al., 2022).	High
Standardization and benchmarking of fraud detection models	Lack of standardized datasets and evaluation protocols hampers direct comparison and reproducibility across studies.	Establish open benchmarking platforms with standardized datasets, metrics, and protocols for mobile money fraud detection research in SSA.	Standardization accelerates progress and facilitates adoption of best-performing models (Muqattash & Kharbat, 2023) (Azamuke et al., 2022).	Medium
Socio-technical and regulatory context integration	Limited interdisciplinary approaches combining technical, social, and policy perspectives to address fraud holistically.	Develop frameworks integrating machine learning with socio-cultural, regulatory, and organizational factors; evaluate impact of policies and user education on fraud	Holistic approaches improve sustainability and effectiveness of fraud detection systems in SSA contexts (Mollik & Majeed, 2025) (Gombiro et al., 2015) (Akomea-Frimpong et	Medium

Gap Area	Description	Future Research Directions	Justification	Research Priority
		mitigation effectiveness.	al., 2019).	

Overall Synthesis and Conclusion

The collective body of research on mobile money fraud detection using machine learning in Sub-Saharan Africa, with a focus on Kenya, underscores significant progress in leveraging advanced computational techniques to address pressing security challenges in digital financial ecosystems. Ensemble and boosting models, particularly Random Forest, XGBoost, and LightGBM, consistently emerge as the leading algorithms in fraud classification, offering high accuracy, precision, and recall. These models effectively balance detection performance with computational efficiency, making them well-suited for deployment in resource-constrained environments typical of the region. Simpler models like Logistic Regression retain value for scenarios demanding low complexity and interpretability but generally fall short of the predictive power demonstrated by ensemble approaches.

A recurrent challenge across studies is the severe class imbalance inherent in mobile money fraud datasets, which predominantly consist of legitimate transactions with sparse fraudulent instances. Techniques such as SMOTE and adaptive class weighting remain the most widely adopted solutions, significantly improving minority class detection without compromising overall accuracy. However, reliance on synthetic oversampling methods introduces concerns regarding the fidelity of generated data to real-world fraud patterns, highlighting a persistent gap in access to high-quality, labeled datasets from actual mobile payment platforms. Synthetic data simulators tailored to Sub-Saharan contexts provide valuable research tools but may lack the nuanced socio-technical characteristics vital for robust fraud detection.

Feature engineering and interpretability are recognized as critical components for effective model development and deployment. The integration of domain knowledge, behavioral, and contextual features enhances detection capabilities, while interpretability frameworks like SHAP and LIME promote transparency and user trust—factors crucial for regulatory acceptance and user adoption in emerging markets. Despite advances, feature extraction remains largely manual, and the incorporation of temporal and sequential patterns requires further refinement.

Real-time fraud detection systems demonstrate promise through optimized models and scalable architectures, yet the trade-offs between model complexity, latency, and deployment feasibility remain a key consideration. Deep learning approaches, while highly accurate, often entail computational demands that challenge real-time application in infrastructurally limited settings. Moreover, privacy concerns, regulatory hurdles, and socio-cultural factors uniquely shape the acceptability and effectiveness of AI-driven fraud detection in Sub-Saharan Africa,

demanding tailored, explainable, and privacy-aware solutions.

In conclusion, the literature affirms the efficacy of machine learning, particularly ensemble and boosting algorithms, in detecting mobile money fraud within Sub-Saharan Africa's evolving financial landscape. Nevertheless, advancing the field requires addressing data scarcity through region-specific datasets, enhancing automated and context-aware feature engineering, and balancing performance with interpretability and deployment constraints. Fostering interdisciplinary approaches that integrate technical innovations with socio-economic and policy perspectives will be pivotal in developing resilient, trustworthy, and scalable fraud detection frameworks tailored to Kenya and the broader Sub-Saharan mobile money ecosystem.

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