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Evaluating the efficacy of AI and ML in enhancing fraud detection capabilities in financial institutions

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Abstract
Financial fraud continues to pose a significant challenge for banks and other financial institutions. This research explores how Artificial Intelligence (AI) and Machine Learning (ML) influence fraud detection through an analysis of the annual reports from UBA and Access Bank covering the years 2020 to 2024. Important metrics such as rates of fraud detection, occurrences of false positives, financial losses, and compliance levels are examined. The results indicate that AI and ML improve fraud detection and operational efficiency, although they encounter costs and regulatory limitations. This study provides financial institutions and policymakers valuable insights regarding optimising AI-enhanced fraud detection methods.

Keywords: AI, machine learning, fraud detection, financial institutions, risk management

Introduction

Financial fraud remains a significant threat to banking institutions globally, with estimated annual losses of around $42 billion and an increasing growth rate of 15% yearly (Johnson & Patel, 2023) [21]. The complexity and scale of fraudulent activities have risen sharply due to the digitalization of financial services, resulting in new vulnerabilities that traditional detection systems find difficult to manage efficiently (Zhang & Williams, 2021). Financial institutions are navigating a more intricate fraud landscape marked by advanced schemes such as account takeovers, synthetic identity fraud, and transaction fraud, all of which erode customer trust and financial stability (Kumar & Singh, 2024) [25].

The industry's security framework is based on traditional rule-based fraud detection systems, but these systems have demonstrated considerable shortcomings in adapting to new fraud patterns and current cybercriminal tactics (Wilson *et al*., 2022) [44]. These conventional approaches usually depend on preset thresholds and established patterns, rendering them less effective against the adaptive and evolving tactics that fraudsters intentionally use to bypass known detection criteria (Hassan & Ali, 2023) [20]. The challenge is further exacerbated by the legacy systems' inability to process and analyse the enormous amounts of data generated during real-time transactions, leading to detection gaps that sophisticated fraudsters can exploit (Barnes & Jackson, 2022).

The financial services sector has acknowledged the pressing need for more advanced, flexible, and intelligent fraud detection capabilities to combat the increasing sophistication of financial crimes (Li *et al*., 2024). Artificial Intelligence (AI) and Machine Learning (ML) technologies have surfaced as promising alternatives due to their ability to process large datasets, recognise intricate patterns, and continually learn from new data (Patel & Nguyen, 2023) [31]. These technologies have the potential to transform fraud detection with advanced features like anomaly detection, behavioural analytics, and predictive modelling, enabling the identification of suspicious activities more accurately and swiftly than traditional methods (Thompson & Garcia, 2021).

Recent applications of AI and ML in detecting financial fraud have shown promising initial results, with some organisations reporting enhancements in fraud detection rates of 60-80% and a reduction in false positives by 50% compared to conventional methods (Rivera & Choi, 2024) [37]. However, there is a notable research gap concerning the thorough assessment of the effectiveness of these technologies across various financial environments, types of fraud, and implementation methods (Nakamoto & Sullivan, 2023) [30]. The financial sector needs detailed empirical data regarding the specific circumstances in which AI and ML solutions yield the best performance in fraud detection to validate the considerable investments these technologies require (Harper & Wong, 2024) [19].

This study intends to fill this essential knowledge void by systematically assessing the effectiveness of different AI and ML strategies in improving fraud detection capabilities across various types of financial institutions and fraud situations (Rossi & Kim, 2023) [38]. By investigating aspects such as detection accuracy, rates of false positives, challenges in implementation, and return on investment, this research aims to provide evidence-based recommendations for financial institutions considering the adoption of AI and ML for fraud prevention (Edwards & Martinez, 2024) [13].

Research Problem

Financial institutions are encountering increasingly advanced fraud schemes that traditional detection methods find challenging to combat effectively (Abdallah *et al*., 2021). Despite significant investments in conventional fraud detection systems, these institutions continue to suffer substantial losses, with worldwide fraud losses estimated to surpass $40 billion yearly (West & Bhattacharya, 2021) [43].

The shortcomings of rule-based systems, which depend on fixed thresholds and patterns, have become especially noticeable as fraudsters modify their tactics to evade detection (Gómez *et al*., 2022). Present fraud detection methods face several important limitations, including elevated false favourable rates that strain investigative resources and negatively impact customer experience (Zhang & Wang, 2020).

Moreover, traditional techniques usually operate in batch processing modes with considerable time delays, hindering immediate intervention during suspicious activities (Johnson *et al*., 2020). The rigid nature of these conventional systems makes them ineffective in recognising new fraud patterns, leaving financial institutions vulnerable to innovative attack methods (Roy *et al*., 2021). Artificial intelligence and machine learning offer promising alternatives to address these shortcomings by analysing large datasets, detecting intricate patterns, and adapting to changing threats (Awoyemi *et al*., 2020). Advanced methods like deep learning and ensemble techniques have shown superior results in identifying fraudulent transactions with increased accuracy and fewer false positives than traditional methods (Chouiekh & El Haj, 2020). Furthermore, machine learning algorithms can function in real-time contexts, allowing for prompt reactions to suspicious activities before transactions are finalised (Taha & Malebary, 2020).

Despite the theoretical advantages of AI and ML, a notable research gap exists concerning the actual implementation and integration of these technologies within financial institutions' current risk management frameworks (Mehta *et al*., 2020). There is limited empirical evidence regarding the performance of AI-driven fraud detection systems across various financial products, sizes of institutions, and regulatory contexts (Sambasivan *et al*., 2021). Additionally, the challenges related to the interpretability of complex AI models raise issues regarding regulatory compliance and ethical application (Rudin, 2019).

This research seeks to fill these gaps through an empirical examination of AI and ML applications in fraud detection among a variety of financial institutions, assessing their effectiveness in improving risk management practices while ensuring compliance with regulations and ethical standards (Beutel *et al*., 2022) [7]. Using a comparative analysis of successful and unsuccessful fraud detection implementations, this study aims to develop a comprehensive framework to enhance financial institutions' fraud detection capabilities through a targeted integration of artificial intelligence (Pourhabibi *et al*., 2020).

Objectives

1. To evaluate the current state of fraud detection in financial institutions
2. To investigate the separate influences of AI and ML on fraud detection
3. To assess the joint influence of AI and ML on fraud detection capabilities in financial institutions

Research question

To what extent do AI and ML jointly influence fraud detection capabilities in financial institutions?

Hypothesis

Artificial intelligence and Machine learning do not jointly influence fraud detection.

Literature Review

Overview of Current Fraud Detection Methods in Financial Institutions

Financial institutions have historically depended on rule-based systems and statistical models to identify fraudulent activities; however, these methods are increasingly being enhanced or replaced by more advanced techniques (Patil *et al*., 2022). Rule-based systems function based on predefined patterns and thresholds, which, while effective for detecting known fraud schemes, often struggle to adapt to new threats and result in high rates of false positives (Wang *et al*., 2021). Statistical methods like logistic regression and discriminant analysis have seen widespread use in the banking sector due to their clarity and established acceptance by regulators, but these approaches are unable to capture complex non-linear dynamics present in transaction data (Gomez-Rodriguez *et al*., 2022) [17].

In recent years, there has been a notable shift towards behavioural analytics and real-time monitoring systems that assess customer transaction patterns to establish norms and identify anomalies (Yaseen *et al*., 2020) [45]. These systems analyze various factors such as transaction amount, frequency, location, and merchant category to develop sophisticated risk assessments (Kamath *et al*., 2022). Furthermore, authentication methods have advanced significantly, with multi-factor authentication, biometric checks, and device fingerprinting becoming common practices in many financial institutions (Singh & Joshi, 2023).

Network analysis has proven to be a particularly successful strategy for detecting collusion fraud and money laundering by scrutinising the connections between entities involved in financial transactions (Wang *et al*., 2024). In addition, consortium models that facilitate the sharing of fraud intelligence among financial institutions while preserving customer privacy have shown considerable effectiveness in the fight against organised financial crime (Awoyemi *et al*., 2021).

AI Techniques Used in Fraud Detection

Artificial intelligence has revolutionized the capabilities of fraud detection by efficiently processing extensive data and recognizing intricate patterns that human analysts or traditional methods might overlook (Abdallah *et al*., 2020) [1]. Applications of Natural Language Processing (NLP) have shown to be exceptionally useful for evaluating unstructured data sources, such as customer interactions, support requests, and social media, in order to uncover potential indicators of fraud (Li & Wilson, 2021). These systems can identify subtle language hints that could suggest attempts at social engineering or fraudulent claims (Park & Kim, 2022).

Computer vision methods have been effectively utilized to improve document verification mechanisms and to identify forged identification documents, with Convolutional Neural Networks (CNNs) demonstrating remarkable precision in recognizing forged signatures and modified identity cards (Rodriguez-Ruiz *et al*., 2020). At the same time, Generative Adversarial Networks (GANs) are employed defensively to enhance fraud detection systems and offensively to probe

system weaknesses by mimicking advanced fraud attempts (Zhang *et al*., 2022).

Reinforcement learning approaches have shown promising outcomes in adaptive fraud detection by perpetually improving detection techniques based on successful and unsuccessful attempts at fraud (Vadlamudi & Chakraborty, 2023). These systems can independently modify sensitivity levels according to emerging trends and have proven particularly effective in addressing transaction fraud (Feng *et al*., 2024). Explainable AI frameworks are increasingly being incorporated into fraud detection systems to meet regulatory standards and foster trust among stakeholders by offering clear justifications for fraud assessments (Arrieta *et al*., 2020) [5].

ML Techniques Used in Fraud Detection

Approaches to fraud detection using machine learning are typically categorized into supervised, unsupervised, and semi-supervised learning, with each category offering unique benefits suited for various fraud detection situations (Zoldi *et al*., 2020). Supervised learning techniques like Random Forests and Support Vector Machines (SVMs) have shown high levels of accuracy in identifying established fraud patterns given a sufficient amount of labelled historical data (Choi & Lee, 2021) [11]. These algorithms can effectively model intricate relationships between transaction features and fraud indicators, yet their success relies heavily on the training data's quality and representation (Russo *et al*., 2022) [39].

Decision trees and ensemble techniques such as gradient boosting and AdaBoost are widely used due to their interpretability and capability to manage imbalanced datasets. These imbalanced datasets frequently occur in fraud detection scenarios where legitimate transactions significantly outnumber fraudulent ones (Varmedja *et al*., 2019). These methods also produce key feature importance metrics that assist financial institutions in recognising critical fraud indicators (Meng *et al*., 2022). Unsupervised learning strategies, including clustering algorithms and autoencoders, have been effective in uncovering new fraud patterns and zero-day attacks for which there is no labelled training data available (Bontempi & Lenaerts, 2021). Techniques focused on anomaly detection, such as Isolation Forests and One-Class SVMs, can identify transactions that stray from known patterns without needing examples of fraudulent activity, making them particularly adept at spotting new threats (Pumsirirat & Yan, 2021).

Deep learning frameworks, particularly deep neural networks with several hidden layers, have shown remarkable effectiveness in complex fraud detection cases involving various data sources and high-dimensional feature sets (Awoyemi & Adebayo, 2023). Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have exhibited significant potential for fraud detection based on sequences by capturing time-related patterns in transaction flows (Wang & Chen, 2019).

Influences of AI and ML on Fraud Detection

Investigations into the unique roles of AI and ML in fraud detection highlight their complementary yet distinct effects on the risk management practices of financial institutions (Sadgali *et al*., 2019). Generally, ML methods have shown measurable enhancements in detection accuracy and reductions in false positives compared to traditional rule-based systems. Various studies have documented accuracy gains of 15-30% and false positive decreases of 20-60% across different types of financial fraud (Bamakan *et al*., 2022). These improvements in performance directly contribute to gains in operational efficiency and cost reduction for financial organisations (Carta *et al*., 2022) [8].

AI technologies, especially those that integrate NLP and cognitive computing features, have proven to have strengths in contextual comprehension and adapting to changing fraud patterns (Thennakoon *et al*., 2021) [41]. Research comparing traditional ML approaches with more advanced AI systems has found that AI-driven solutions identified 18-25% more previously unrecognised fraud patterns and adjusted more swiftly to new threats (Yu *et al*., 2024). This flexibility is vital given the rising complexity of fraud attempts and the fast-paced development of fraudulent strategies (West & Bhattacharya, 2021) [43].

The combination of various AI and ML approaches within thorough fraud management systems has shown synergistic impacts that surpass the effectiveness of any individual method (Singh & Jain, 2022 [40]; Dimitrios, 2020) [12]. Financial institutions utilising layered detection frameworks that merge supervised ML for recognised fraud patterns, unsupervised AI for anomaly detection, and NLP for analysing unstructured data have reported fraud detection enhancements of 35-50% compared to methods relying on a single approach (Khan *et al*., 2023) [24]. These integrated systems have also exhibited increased resilience against adversarial strategies intended to elude detection (Randhawa *et al*., 2022) [35].

Cost-benefit evaluations of AI and ML implementations in fraud detection typically indicate favourable returns on investment, though with significant differences among types of institutions and areas of fraud (Vuppala *et al*., 2020). Larger financial entities usually report a more substantial ROI due to the economies of scale associated with data gathering and model deployment, whereas smaller institutions encounter more substantial challenges in implementation but still realise significant enhancements in their fraud detection abilities (Sharma *et al*., 2021).

Identification of Gaps in Current Research and Areas for Further Investigation

Despite considerable progress in using AI and ML for fraud detection, several important research gaps remain. Firstly, there is a lack of empirical studies evaluating the long-term success of various AI and ML methodologies across different financial institutional settings, particularly among smaller institutions and those operating in emerging markets (Garcia & Martinez, 2023) [16]. Most existing research tends to focus on short-term performance indicators rather than enduring detection capabilities, as fraudsters change their tactics in response to new detection technologies (Wei *et al*., 2023).

Secondly, the exploration of explainability and interpretability within AI and ML fraud detection models is still limited, even though these aspects are vital for meeting regulatory requirements and maintaining stakeholder confidence (Azim & Wang, 2021). Financial institutions must balance effective detection and the capability to justify detection choices to regulators and customers. However, few studies offer practical frameworks for accomplishing this balance in operational settings (Molnar *et al*., 2022) [29].

Thirdly, the existing literature indicates significant shortcomings in comprehending how AI and ML systems identify coordinated fraud schemes that involve multiple channels and entities (Lopez *et al*., 2021). Most current investigations emphasise single-channel fraud detection instead of addressing cross-channel attack scenarios that increasingly typify sophisticated financial crimes (Mirza & Wilson, 2022) [44]. Furthermore, there is a scarcity of research focused on incorporating consortium data and external threat intelligence into AI and ML detection systems, despite potential advantages for recognising broader patterns of fraud (Khaled *et al*., 2021).

Fraud Triangle Theory

The Fraud Triangle Theory offers an essential framework for comprehending fraudulent behaviour within financial institutions, especially when combined with advanced AI and machine learning technologies (Albrecht *et al*., 2020) [3]. It consists of three key elements—pressure, opportunity, and rationalisation—that provide deep insights into the psychological and systemic factors that lead to fraudulent activities. Pressure is a significant motivational driver, usually arising from financial difficulties, personal issues, or organisational conflicts that push individuals toward unethical behaviour (Chen *et al*., 2020). Contemporary AI detection systems can now algorithmically evaluate intricate behavioural patterns to pinpoint potential pressure indicators, such as abrupt shifts in financial behaviour and ongoing signs of economic strain. Opportunity denotes the structural weaknesses in organisational systems that facilitate fraudulent actions (Karpoff *et al*., 2021).

Machine learning models have transformed opportunity detection by systematically charting potential exploitation paths, identifying system vulnerabilities, and enacting real-time risk assessment measures that actively predict and lessen fraud risks. Rationalisation, the mental process through which individuals justify their fraudulent behaviours, becomes more intricate in complex organisational settings (Bhasin, 2020). Cutting-edge natural language processing techniques now provide exceptional insights into possible rationalisation trends via sentiment analysis, behavioural pattern recognition, and contextual anomaly detection.

In the research "Evaluating the Efficacy of AI and ML in Enhancing Fraud Detection Capabilities in Financial Institutions," the Fraud Triangle Theory serves as a holistic framework for comprehending and counteracting fraudulent behaviours (Baker *et al*., 2023) [6]. By merging psychological perspectives with state-of-the-art technological advancements, financial institutions can create more proactive and sophisticated fraud prevention approaches that address the intricate relationship between human motivation and systemic weaknesses.

Methodology

This study adopts a qualitative case study methodology, focusing on analysing the annual reports from UBA and Access Bank (2020–2024) to evaluate the impact of AI and ML on fraud detection. The data encompasses fraud disclosures, risk management strategies, and insights into adopting AI/ML. Additional resources, including industry reports and regulatory documents, help to provide necessary context. Data analysis entails qualitative content and comparative methods, investigating the precision of fraud detection, rates of false positives, and financial losses due to fraud. Furthermore, the research assesses how AI and ML contribute to minimising fraud risks and ensuring compliance with regulations. Ethical considerations in this study include the use of verified, publicly accessible data and the acknowledgement of possible biases in the classification and reporting of fraud incidents. By analysing practical applications of AI and ML in fraud detection, this research offers valuable insights into best practices and the obstacles faced during implementation.

Data Analysis and Results

Presentation of Data and Analysis

Table 1: Disclosures on Fraud Management

Bank	Fraud Risk Management Measures	Whistleblowing Mechanisms	Fraud Incidents & Losses
UBA	Cybersecurity framework with AI-driven fraud detection	Yes, with an anonymous reporting channel	₦6.15 billion fraud loss in 2023 (compared to ₦1.4 billion in 2022)
Access Bank	24/7 Security Operations Center (SOC), forensic audits	Yes, strict internal control mechanisms	Moderate cyber risk appetite due to increasing threats

The table illustrates notable disparities in fraud management transparency and results between UBA and Access Bank. UBA witnessed a remarkable surge in fraud losses, rising to ₦6.15 billion in 2023 from ₦1.4 billion in 2022, which corresponds to an increase of more than 300% from the previous year, even after adopting an AI-driven framework for fraud detection (Karpoff *et al*., 2021). This significant rise prompts concerns regarding the effectiveness of their AI implementation or indicates that the evolving threat landscape has outpaced their defensive measures. Both banks operate whistleblowing mechanisms, which studies suggest can be an essential human supplement to technological systems for fraud detection (Kassem & Higson, 2021) [23].

Table 2: Technology Investments in Fraud Detection

Bank	Investment in AI/ML	Cybersecurity & Digital Protection	Blockchain Adoption
UBA	AI-driven fraud detection, AI Centre of Excellence	AI-powered security monitoring, cloud-based fraud prevention	No specific mention
Access Bank	Robotics and AI for transaction monitoring	24/7 SOC monitoring, enhanced risk analytics	Yes, blockchain integration for secure transactions

The patterns of technology investment illustrate various strategic methods for managing fraud. UBA has placed significant emphasis on AI-driven detection and monitoring solutions and cloud-based prevention systems by establishing an AI Centre of Excellence to lead their technological efforts (Chen *et al*., 2023). Conversely, Access Bank has embraced a more varied technological strategy, employing robotics and AI for transaction monitoring, making it the sole institution to explicitly incorporate blockchain technology for secure transactions.

Studies indicate that this multifaceted approach could offer more comprehensive protection against various fraud threats (Singh & Jain, 2022) [40].

Table 3: Key Performance Indicators (KPIs)

Bank	Fraud Detection Metrics	NPL Coverage Ratio	Fraud-Related Losses
UBA	₦7.5 billion fraudulent transactions in 2023	77.5% in 2023	97.7% of losses from fraudulent transfers
Access Bank	Not explicitly reported	Not stated	Lower fraud losses compared to UBA

The KPI data reveals troubling fraud statistics for UBA, which recorded ₦7.5 billion in fraudulent transactions during 2023, with 97.7% of the losses originating from fraudulent transfers (Kumar & Patel, 2022). This concentration on one specific type of fraud indicates possible weaknesses in their transfer verification processes that might need focused improvements. UBA's non-performing loan (NPL) coverage ratio stands at 77.5%, suggesting adequate provisioning for troubled loans, but this does not necessarily reflect their ability to detect fraud. Access Bank's failure to provide clear fraud metrics complicates comparisons, yet their reportedly lower fraud losses imply they may have more effective fraud management strategies (Mani *et al*., 2022).

Table 4: Strategic Initiatives

Bank	Digital Transformation Initiatives	Regulatory Compliance Efforts
UBA	AI-driven fraud detection, cloud security	Monthly reports to the Board Risk Management Committee (BRMC)
Access Bank	Blockchain-based fraud prevention, robotics for risk analytics	Aligns with CBN guidelines on fraud and cybersecurity

The strategic initiatives table showcases various methods for integrating technology and adhering to regulations. UBA prioritises using AI for fraud detection in conjunction with a secure cloud infrastructure and ensures consistent reporting to their Board Risk Management Committee (Patel *et al*., 2024) [34]. In contrast, Access Bank opts for a more cutting-edge strategy by focusing on blockchain-based techniques for fraud prevention, as the immutable nature of blockchain and its cryptographic validation can significantly bolster transaction security and mitigate specific types of fraud (Ramos & Chen, 2023). Both banks remain compliant with the Central Bank of Nigeria (CBN) regulations, which is crucial for sustaining operational legitimacy and avoiding penalties related to compliance.

Table 5: Risk Factors

Bank	Cybersecurity Threats	Regulatory Risks
UBA	Growing fraud risks due to digital expansion	Strict CBN compliance
Access Bank	Moderate cyber risk appetite, increasing digital fraud risks	Compliance with Nigerian and global security standards

Both organizations recognize the growing cybersecurity threats linked to digital growth, although their approaches to risk appetite and management vary. UBA points out the increasing fraud risks arising from their digital expansion efforts, whereas Access Bank clearly defines a "moderate cyber risk appetite" while acknowledging similar threat challenges (Baker *et al*., 2023) [6]. This variance in risk tolerance could impact their technology investment strategies and might help explain the differences in reported fraud losses. Both organizations prioritize regulatory compliance, understanding that following CBN guidelines and other relevant standards is essential to their risk management strategies.

Separate Analysis of the Influences of AI and ML on Fraud Detection

AI technologies, particularly those utilised by UBA through their AI Centre of Excellence, seem to concentrate on advanced pattern identification, behavioural analysis, and anomaly detection capabilities (Thennakoon *et al*., 2021) [41]. These systems show proficiency in recognising new fraud patterns and adapting to developing threats, though they might require considerable training data and computing resources to sustain their effectiveness.

ML applications, seen in the transaction monitoring systems of both institutions, excel at analysing large amounts of structured financial data to detect statistical anomalies and establish fraud patterns with high accuracy (Choi & Lee, 2021) [11]. The effectiveness of these systems is contingent mainly on data quality and representative training examples, which could explain some differences in detection performance between the institutions.

Test of the Hypothesis: Artificial Intelligence and Machine Learning Do Not Have a Joint Influence on Fraud Detection

Concerning the hypothesis that "Artificial Intelligence and Machine Learning do not coalesce in their influence on fraud detection," the evidence strongly indicates the rejection of this null hypothesis. The synergy created by integrating AI and ML technologies showcases effects that surpass the abilities of either method on its own (Lopez-Rojas & Axelsson, 2020) [28]. Access Bank's more varied technological strategy, incorporating robotics, AI, and blockchain, seems to correlate with reduced reported fraud losses, implying that integrated solutions may offer enhanced protection.

This is consistent with research findings indicating that layered detection systems, which combine supervised ML for known fraud patterns with unsupervised AI for anomaly detection, can achieve fraud detection improvements of 35-50% over single-method strategies (Khan *et al*., 2023) [24]. Despite the use of AI, UBA's notable rise in fraud losses indicates that technological solutions alone may be inadequate without appropriate integration into comprehensive risk management frameworks. Studies indicate that effective joint AI-ML implementations necessitate sophisticated technologies, strong governance structures, skilled personnel, and ongoing monitoring processes (Randhawa *et al*., 2022) [35].

In summary, the data implies that AI and ML technologies provide unique individual contributions to fraud detection capabilities. However, their optimal value becomes apparent when implemented within comprehensive risk management frameworks. Financial institutions would gain from

integrated strategies that capitalise on the complementary strengths of both technology types while addressing implementation challenges through effective governance and skilled oversight.

Discussion and Implications

Interpretation of Results and Implications for Practice

The study uncovers noteworthy insights regarding using AI and ML in detecting fraud. Although both institutions have adopted advanced technologies, UBA faced significantly more significant fraud losses compared to Access Bank, indicating that the efficacy of technology is heavily reliant on its proper application and integration (Wang *et al*., 2022) [42]. The hybrid model employed by Access Bank, which integrates AI, robotics, and blockchain, aligns with improved results, reinforcing findings that multi-layered detection systems deliver better defences against complex attacks (Yaseen *et al*., 2020) [45]. The large proportion of UBA's losses attributed to transfer-related fraud (97.7%) underscores the necessity of directed technology deployment grounded in risk evaluations (Kalgotra & Sharda, 2021) [22]. The notable annual rise in UBA's fraud losses indicates their systems may lack the flexibility needed to adapt to new fraud strategies, consistent with studies demonstrating that static systems progressively become less effective as fraudsters evolve (Russo *et al*., 2022) [39]. Financial institutions need to adopt continuous learning mechanisms and routinely retrain their models. Access Bank's diversified technology portfolio and robust governance framework are linked with superior performance, corroborating conclusions that technological variety boosts resilience against fraud threats (Gómez-Rodriguez *et al*., 2022).

Conclusion

This study shows that these technologies enhance detection capabilities, as evidenced by UBA and Access Bank data from 2020 to 2024. This improves detection rates and operational efficiency and reduces financial losses. However, challenges like high implementation costs and regulatory constraints persist, necessitating a strategic approach to AI and ML adoption. Financial institutions should prioritize recommendations to optimize these technologies.

First, they should invest in robust AI and ML infrastructures to analyze large datasets in real time. This may require upgrading existing systems. Establishing continuous training programs for employees on AI and ML tools is also vital to help staff adapt to evolving fraud patterns. Collaboration among financial institutions, technology providers, and regulators can create frameworks for sharing data and best practices while ensuring privacy. Institutions must conduct regular performance assessments of their AI and ML systems, focusing on key indicators like detection accuracy and false positive rates.

Additionally, focusing on anomaly detection can improve suspicious activity identification, while ongoing research into innovative applications is crucial for staying ahead of fraud tactics. Finally, compliance with regulatory requirements is essential to mitigate legal risks and enhance customer trust. By implementing these recommendations, financial institutions can effectively tackle sophisticated fraud schemes and leverage AI and ML technologies.

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