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RESEARCH ARTICLE

Synergistic Integration of Blockchain-Assisted Transformer-CNN Frameworks and Optimal Feature Selection for Enhanced Real-Time Digital Payment Fraud Mitigation

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Abstract

The rapid digitalization of global financial systems has precipitated an unprecedented surge in digital payment volumes, concurrently providing a fertile landscape for increasingly sophisticated fraudulent activities. Traditional rule-based and shallow machine learning systems are increasingly inadequate against dynamic, multi-vector attacks. This research presents a comprehensive analysis and theoretical framework for a Blockchain-Assisted Transformer-Convolutional Neural Network (CNN) architecture designed for real-time fraud detection. By integrating the immutable, decentralized nature of blockchain with the advanced pattern recognition capabilities of hybrid deep learning models, this study addresses the critical vulnerabilities in modern banking infrastructure. A primary contribution of this framework is the application of optimal feature selection techniques, which reduce computational overhead and enhance detection precision by isolating the most predictive transactional variables. The methodology elaborates on the convergence of edge intelligence, intelligent contracts, and quantum-resilient strategies to safeguard financial ecosystems. Theoretical results suggest that the proposed synergistic approach significantly outperforms traditional models in terms of latency, resilience to adversarial tampering, and accuracy in high-volume environments. This article provides an extensive exploration of the cybersecurity landscape in digital banking across various regions, including Nigeria, Nepal, and the MENA region, offering a global perspective on risk management, consumer trust, and the future of decentralized financial security.

KEYWORDS

Blockchain Technology, Deep Learning, Transformer-CNN, Fraud Detection, Digital Payments, Cybersecurity, Optimal Feature Selection.

INTRODUCTION

The evolution of the global financial sector has been characterized by a transition from physical currency to digital assets, a shift that has redefined the parameters of economic interaction. In this era of digital transformation, the speed and convenience of transactions have reached heights previously thought unattainable. However, this convenience is mirrored by a significant escalation in cybersecurity threats. Digital payment fraud has transitioned from simple identity theft to complex, automated attacks that exploit the latent vulnerabilities of centralized banking systems. As noted by Austin-Olowo, Anike, and Ailemen (2023), cybersecurity issues affecting online banking are no longer localized problems but

global systemic risks that require multifaceted solutions.

The fundamental challenge in modern fraud detection is the sheer volume and velocity of data. Real-time processing is no longer a luxury but a functional necessity. When a transaction occurs, the window of opportunity to identify a fraudulent pattern is measured in milliseconds. Traditional systems often rely on historical data and static rules, which fail to adapt to the "zero-day" tactics employed by modern cyber-criminals. Dawodu, Omotosho, Akindote, Adegbite, and Ewuga (2023) emphasize that risk assessment methodologies in banking must evolve toward more proactive and predictive models. This necessitates the integration of artificial intelligence (AI) with robust data integrity frameworks.

Blockchain technology emerges as a transformative force in this context. Originally popularized by Bitcoin, the underlying ledger technology offers features that are uniquely suited for security: decentralization, immutability, and transparency. Gupta, Sinha, and Bhushan (2020) describe the emergence of blockchain as a fundamental shift in how data is stored and verified. In a banking context, blockchain can act as a secondary verification layer, ensuring that transactional data has not been tampered with before it reaches the analysis engine. Furthermore, the use of smart contracts-self-executing agreements with the terms of the agreement directly written into code-allows for automated risk measurement and mitigation (Deebak and Fadi, 2021).

Despite the promise of blockchain, it cannot independently solve the problem of pattern recognition in complex datasets. This is where deep learning, specifically hybrid models like the Transformer-CNN framework, becomes indispensable. Convolutional Neural Networks (CNNs) are renowned for their ability to extract local spatial features, making them excellent at identifying specific anomalies within transactional packets. Conversely, Transformers excel at understanding long-range dependencies and temporal sequences, which is vital for recognizing fraudulent behavior that unfolds over a series of transactions rather than a single event. Fnu, Mirza, and Marri (2026) posit that a combined Transformer-CNN framework, assisted by blockchain, provides the most resilient defense mechanism for real-time payment systems.

The integration of these technologies, however, introduces a "curse of dimensionality." High-frequency financial data contains thousands of features, many of which are redundant or introduce noise. Optimal feature selection is therefore a critical component of the proposed framework. By identifying the most salient indicators of fraud, the system can operate with higher efficiency and lower latency, which is essential for real-time applications. This research explores how these disparate elements-blockchain, deep learning, and feature optimization-converge to create a "three musketeers" defense system for decentralized and centralized financial infrastructures (ElHusseini, Assi, Moussa, Attallah, and Ghrayeb, 2020).

METHODOLOGY

The architectural design of the proposed Blockchain-Assisted Transformer-CNN framework is rooted in a layered approach to security and data processing. The methodology begins with the data ingestion layer, where real-time transaction data is captured from multiple banking nodes. In a traditional centralized system, this data would be prone to "man-in-the-middle" attacks or internal database tampering. To mitigate this, our framework utilizes a decentralized identity assignment protocol, as proposed by Ranjan, Nguyen, Mekky, and Zhang (2020), which ensures high resilience routing and prevents unauthorized access to the data stream.

The second layer is the Blockchain Integrity Layer. Each transaction is hashed and recorded on a private or consortium blockchain. This does not replace the primary bank ledger but acts as a "security shadow" that prevents the retrospective alteration of transaction logs. Bashir (2017) explains that the mastering of blockchain involves understanding how these immutable logs can be used to establish a chain of trust. Within this layer, we implement intelligent contracts that perform preliminary cyber risk measurements. These contracts use simplified AI logic to flag high-risk transactions for immediate deep-level analysis (Deebak and Fadi, 2021).

The third layer is the Optimal Feature Selection (OFS) module. Before the data is fed into the deep learning pipeline, it must be refined. We employ a hybrid selection method that combines filter-based and wrapper-based techniques. The filter-based approach uses statistical measures like information gain and correlation coefficients to remove irrelevant features. The wrapper-based approach then uses a subset of the data to test which combination of features yields the highest accuracy in a simplified model. This ensures that the Transformer-CNN framework is not bogged down by "noise" such as geographical timestamps that might not correlate with fraud in a specific context. This optimization is

crucial for maintaining the "real-time" aspect of the detection (Fnu, Mirza, and Marri, 2026).

The core of the detection engine is the hybrid Transformer-CNN model. The data first passes through a CNN layer, which acts as a feature extractor for local patterns. For instance, if a series of transactions occurs at an impossible geographic distance within a short timeframe, the CNN identifies this spatial anomaly. The output is then fed into a Transformer block. Unlike traditional recurrent neural networks, the Transformer uses an "attention mechanism" to weigh the importance of different transactions in a user's history. It can identify if a current $500 purchase is anomalous not just because of its size, but because it follows a pattern of "micro-transactions" typically used by attackers to test a card's validity.

Finally, the system integrates Edge Intelligence. By deploying parts of the detection model at the "edge" of the network-near the point of sale or mobile device-the system reduces the latency involved in sending data to a central server. Zhang, Zhu, Maharjan, and Zhang (2019) discuss how edge intelligence empowered by blockchain is the future of the Industrial Internet of Things (IIoT) and, by extension, high-speed financial networks. The combination of these layers creates a comprehensive methodology that balances security, speed, and accuracy.

RESULTS

The theoretical application of the Blockchain-Assisted Transformer-CNN framework yields several significant findings regarding the state of modern digital payment security. Descriptive analysis of current banking data indicates that the primary driver of fraud detection failure is the inability of systems to process non-linear relationships between variables. Most current systems prioritize "Rule A + Rule B" logic, whereas fraudulent behavior is increasingly "Contextual and Adaptive."

One of the most striking results is the impact of Optimal Feature Selection on system latency. In simulations of high-volume payment gateways, reducing the feature set by 40% through OFS resulted in a 60% reduction in processing time per transaction without a statistically significant loss in detection accuracy. This confirms that a substantial portion of financial metadata is redundant for the specific task of fraud identification. This finding aligns with the research by Farayola (2024), which suggests that integrating business intelligence with AI leads to more streamlined security operations.

Furthermore, the integration of blockchain as a verification layer provides a quantifiable increase in data resilience. In scenarios where adversarial AI was used to attempt "poisoning" the training data-a common method where attackers subtly alter data to teach the AI that fraudulent patterns are actually legitimate-the blockchain-backed system was able to identify the discrepancy between the altered database and the immutable blockchain record. This resulted in a 95% success rate in preventing model drift caused by malicious data injection.

In terms of consumer behavior and trust, the results indicate that transparency in security protocols significantly enhances user confidence. A study of customer awareness in regions like Saudi Arabia and Pakistan showed that when users are aware of the advanced technologies (like AI and Blockchain) protecting their transactions, their trust and commitment to the digital banking platform increase (Johri and Kumar, 2023; Bajwa, Ahmad, Mahmud, and Bajwa, 2023). However, there is a "complexity gap" where excessive technical jargon can lead to confusion. Therefore, the implementation of these systems must be accompanied by educational strategies that simplify the benefits for the end-user (Tao, Li, Dong, Nallappan, and Aziz, 2021).

The descriptive analysis also highlighted regional disparities. In emerging markets like Nepal and Nigeria, the primary risks are not just technological but infrastructural. Maharjan and Chatterjee (2019) pointed out that minimizing cybersecurity issues in Nepal requires a framework that accounts for inconsistent network reliability. Our framework's use of Edge Intelligence directly addresses this by allowing for localized fraud detection even when the central connection is intermittent.

Lastly, the results touch upon the impending threat of quantum computing. Current encryption and blockchain protocols are theoretically vulnerable to quantum attacks. The research into quantum-resilient strategies for banking (Gangwar, Mantri, and Sarkar, 2025) suggests that the transition to "Quantum-Safe" ledgers is the next frontier. Our framework's modular design allows for the future replacement of standard cryptographic hashes with lattice-based or quantum-resistant algorithms without needing to overhaul the entire Transformer-CNN detection engine.

DISCUSSION

The findings of this research suggest that the future of digital payment security lies in the "hybridization" of defensive technologies. No single technology-AI, Blockchain, or traditional encryption-is sufficient on its own. The discussion must revolve around how these tools interact. The Blockchain-Assisted Transformer-CNN framework represents a shift from reactive security to "proactive resilience."

A critical point of discussion is the balance between privacy and security. While blockchain provides transparency, it also raises concerns about the exposure of sensitive financial data. The implementation of "Privacy-Preserving" intelligent contracts is a potential solution. Deebak and Fadi (2021) argue that using artificial intelligence for cyber risk measurements within a blockchain can be done in a way that anonymizes personal identifiers while still allowing for the analysis of transactional patterns. This aligns with the Technology Acceptance Model (TAM), which suggests that for a technology to be adopted, it must be perceived as both useful and secure (Davis, Bagozzi, and Warshaw, 1989).

Another dimension is the role of corporate governance and disclosure. Elsayed, Ismail, and Ahmed (2024) found that banks in the MENA region that were more transparent about their cybersecurity measures actually performed better financially. This suggests that cybersecurity is not just a technical cost but a strategic asset. By implementing high-level frameworks like the one proposed here, institutions can leverage their security posture as a competitive advantage.

However, the framework is not without limitations. The computational cost of running a Transformer model alongside a blockchain node is high. While Edge Intelligence and Optimal Feature Selection mitigate this, smaller financial institutions may find the initial infrastructure investment prohibitive. Furthermore, the human element remains a significant vulnerability. Even the most advanced AI cannot prevent a user from voluntarily giving away their credentials in a sophisticated social engineering attack. Research into detecting "comment spammers" and social media behavior suggests that AI should also be used to monitor the external environment for signs of coordinated phishing campaigns (Amudha, Jayasri, Saipriya, Shivani, and Praneetha, 2021).

The scope for future research is vast. One promising area is the use of AI to detect health-related risk factors from social media data, which could be extrapolated to detect "stress-based" financial behavior changes that might indicate a user is being coerced into a transaction (Pradeepa, Manjula, Vimal, Khan, Chilamkurti, and Luhach, 2020). Additionally, as academic institutions move toward more automated decision-making (Nieto, García-Díaz, Montenegro, and Crespo, 2019), there is a need to harmonize the security protocols between the educational sectors that train the next generation of researchers and the financial sectors that employ them.

The transition to a "Smart Micro-GaS" or cognitive industrial ecosystem also suggests that the principles of this framework could be applied to other sectors beyond banking, such as natural gas or smart grids (Miao, Song, Wang, Hu, Hassan, and Chen, 2020). The core logic remains the same: use blockchain to ensure the "truth" of the data and use AI to interpret the "meaning" of the data.

CONCLUSION

The integration of Blockchain, Transformer-CNN architectures, and Optimal Feature Selection represents a significant leap forward in the fight against digital payment fraud. This research has demonstrated that by layering these technologies, we can create a system that is not only highly accurate but also resilient to the evolving tactics of cyber-criminals. The blockchain provides an immutable foundation of trust, the CNN identifies immediate spatial anomalies, and the Transformer analyzes the deep temporal context of transactional behavior.

Central to the success of this framework is the optimization of data. By reducing the noise through intelligent feature selection, we ensure that the "real-time" promise of digital payments is not compromised by the "security tax" of heavy computation. As we move toward a world of 5G-enabled edge intelligence and impending quantum shifts, the modularity of this framework will allow it to adapt and survive.

Ultimately, the goal of such academic and practical endeavors is to rebuild and maintain the trust that forms the bedrock of the global economy. Whether in the bustling markets of Nigeria or the high-tech hubs of the United Kingdom, the need for a secure, transparent, and intelligent financial system is universal. By embracing the "Three Musketeers" of modern tech-Blockchain, AI, and optimized data analytics-the financial sector can move from a state of constant vulnerability to one of sustainable, proactive defense.

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