Journal of Computer Science and Technology Studies
ISSN: 2709-104X
DOI: 10.32996/jcsts
Journal Homepage: www.al-kindipublisher.com/index.php/jcsts

JCSTS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

Evolution of Machine Learning: A Foundation for Intelligent Systems

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| ABSTRACT

Machine learning has transformed credit card fraud prevention by enabling more sophisticated detection capabilities compared to traditional rule-based systems. The evolution began with supervised learning algorithms like logistic regression, decision trees, and random forests, which classified transactions based on historical data patterns. Unsupervised learning techniques, including clustering algorithms and autoencoders, emerged as vital tools for detecting previously unknown fraud patterns without labeled data. Deep learning architectures such as Recurrent Neural Networks and Convolutional Neural Networks have further revolutionized transaction monitoring by processing sequential data and recognizing complex patterns across multiple dimensions. These advanced technologies can detect sophisticated fraud schemes that would remain invisible to conventional methods. Future directions include hybrid architectures combining multiple model types, federated learning for privacy-conscious collaborative training, and adversarial techniques to enhance resilience against emerging threats. Challenges persist in balancing detection accuracy with false positive rates, meeting regulatory requirements for transparency and fairness, and developing adaptive systems capable of responding to continuously evolving fraud tactics without complete redesign.

| KEYWORDS

Fraud detection, Machine learning, Supervised classification, Unsupervised anomaly detection, Deep learning architectures

| ARTICLE INFORMATION

ACCEPTED: 13 May 2025 **PUBLISHED:** 04 June 2025 **DOI:** 10.32996/jcsts.2025.7.5.74

1. Introduction: The Paradigm Shift in Fraud Prevention

The landscape of credit card fraud prevention has undergone a remarkable transformation over the past two decades, characterized by a decisive shift from traditional rule-based systems to sophisticated machine learning approaches. Throughout the 1990s and early 2000s, financial institutions primarily relied on static, manually-configured rule sets to identify potentially fraudulent transactions. These systems operated through a series of if-then conditions that flagged transactions based on predetermined thresholds, such as unusually large purchase amounts or transactions from high-risk geographical locations. While these rule-based frameworks demonstrated reasonable effectiveness against known fraud patterns, they proved increasingly inadequate as fraud tactics evolved in complexity and sophistication, requiring constant manual updates and reconfiguration to address new threats. As comparative research has demonstrated, these traditional methods struggled particularly with the detection of novel fraud strategies and suffered from high false positive rates that negatively impacted legitimate customers [1].

The need for more adaptive solutions became particularly urgent as credit card fraud emerged as one of the fastest-growing financial crimes globally. This escalation was driven by multiple factors, including the exponential growth of e-commerce platforms, the increasing sophistication of criminal organizations utilizing advanced technologies, and the proliferation of large-scale data breaches exposing sensitive payment information. Traditional detection methods faced fundamental limitations in this evolving threat landscape - they were inherently retrospective, could only detect previously identified patterns, and required significant human intervention to maintain effectiveness. Statistical analysis of fraud patterns during this period revealed that

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criminals were adapting their strategies faster than rule-based systems could be updated, creating a widening gap in detection capabilities that resulted in substantial financial losses across the banking sector [2].

Machine learning technologies emerged as a revolutionary force in addressing these challenges, offering capabilities fundamentally different from their rule-based predecessors. Unlike static systems, ML models could dynamically learn from patterns within vast quantities of transaction data, automatically adapting to new fraud strategies as they emerged. This adaptive quality represented a paradigm shift in the approach to fraud detection, moving from reactive to proactive prevention. The comparative analysis of various machine learning techniques has demonstrated that these approaches can significantly outperform traditional methods across multiple performance metrics, including reduced false positive rates, enhanced detection accuracy, and substantial decreases in fraud-related financial losses [1]. The integration of machine learning into fraud prevention systems has since become not merely advantageous but essential for maintaining financial security in an increasingly digital economy, with statistical evaluations confirming their superior ability to identify subtle patterns and anomalies that would remain undetectable to conventional rule-based approaches [2].

II. Supervised Learning Models in Fraud Detection

The evolution of supervised learning algorithms has fundamentally transformed the landscape of credit card fraud detection systems over the past decade. Initial implementations primarily leveraged logistic regression models due to their interpretability and computational efficiency. These models analyzed transaction characteristics to calculate fraud probability scores based on historical patterns, establishing the foundation for more advanced techniques. As computational capabilities advanced, decision trees gained prominence by partitioning transaction data into increasingly homogeneous subsets based on features like transaction amount, merchant category, and geographical location. This hierarchical approach allowed for more nuanced pattern recognition compared to earlier linear models, though it often suffered from overfitting when applied to complex fraud scenarios. The natural progression led to random forests, which addressed individual decision trees' limitations by aggregating predictions across multiple trees trained on different data subsets. This ensemble approach dramatically improved robustness against novel fraud patterns while maintaining reasonable computational requirements for real-time implementation. Comprehensive surveys of data mining approaches for fraud detection have consistently demonstrated that these classification algorithms represent a critical evolutionary pathway in the development of effective detection systems, with each generation building upon the insights and limitations of previous approaches while steadily advancing overall system capabilities in distinguishing fraudulent from legitimate transaction patterns [3].

Feature engineering emerged as a critical complementary discipline, focusing on the transformation of raw transaction data into meaningful inputs for machine learning models. This process includes temporal aggregations (analyzing transaction velocity over various time windows), derived ratios (comparing current behavior against historical patterns), and categorical encodings (transforming merchant categories and location data into model-compatible formats). Advanced feature engineering techniques incorporate behavioral profiling that establishes baseline patterns for individual cardholders, enabling the detection of subtle deviations that might indicate compromised accounts. The methodical development of these feature sets has proven instrumental in maximizing model performance, often contributing more significantly to detection improvements than algorithm selection alone. Research examining diverse fraud detection approaches across multiple financial domains has repeatedly emphasized that thoughtfully engineered features capturing the multidimensional aspects of transaction patterns substantially enhance detection performance regardless of the underlying algorithm employed, highlighting the foundational importance of this often understated aspect of fraud detection system development [3].

More recently, financial institutions have deployed increasingly sophisticated algorithms to address the evolving complexity of fraud tactics. Gradient boosting machines have gained particular traction due to their ability to iteratively improve upon weak predictive models by focusing subsequent iterations on previously misclassified instances. This approach has proven especially effective for fraud detection, where the imbalanced nature of the data (with legitimate transactions vastly outnumbering fraudulent ones) creates significant classification challenges that traditional methods struggle to address effectively. Deep neural networks represent the latest advancement in this domain, leveraging multiple processing layers to automatically discover hierarchical patterns within transaction data without extensive manual feature engineering. These architectures have demonstrated particular promise in identifying complex fraud patterns that evade detection by traditional methods. Experimental evaluations comparing bagging ensemble classifiers with traditional approaches across standardized financial datasets have demonstrated significant performance advantages for these advanced techniques, particularly in handling the class imbalance problems inherent in fraud detection applications. These studies emphasize that while individual algorithms show varying performance characteristics across different transaction environments, the overall trend clearly indicates that ensemble and advanced neural approaches consistently outperform single-classifier methods in practical fraud detection

scenarios, establishing them as the current state-of-the-art in supervised learning approaches for financial fraud mitigation [4].

Algorithm	Key Characteristics	Application in Fraud Detection
Logistic Regression	High interpretability, computational efficiency	Baseline probability scoring for transaction patterns
Decision Trees	Hierarchical partitioning, prone to overfitting	Feature-based transaction categorization
Random Forests	Ensemble of trees, reduced overfitting	Robust detection of novel fraud patterns
Gradient Boosting Machines	Iterative improvement, focus on misclassified cases	Handling imbalanced transaction datasets

Fig. 1: Evolution of Supervised Learning Models in Fraud Detection. [3, 4]

III. Unsupervised Learning for Novel Fraud Pattern Detection

Unsupervised learning techniques have emerged as critical components in modern fraud detection systems, particularly for identifying previously unknown fraud patterns that supervised approaches might miss. Unlike supervised methods that require labeled historical data, unsupervised techniques excel at detecting anomalies and outliers without prior knowledge of fraud signatures. Clustering algorithms represent the foundational approach within this domain, operating by grouping transactions based on inherent similarities across multiple dimensions including time, location, amount, and merchant type. These techniques partition the vast transaction space into distinct clusters that represent normal behavior patterns, thereby isolating outliers that deviate significantly from established norms. Distance-based methods calculate the proximity between transactions in a multidimensional feature space, while density-based approaches identify regions of varying transaction density to distinguish between common and unusual patterns. Research on distributed data mining frameworks for credit card fraud detection has demonstrated that these clustering approaches can effectively identify fraud patterns across decentralized transaction databases while maintaining data privacy requirements. By implementing agent-based learning architectures that combine local pattern detection with global knowledge integration, financial institutions can overcome the challenges associated with geographically distributed transaction processing systems while maintaining detection performance. Comparative analyses of these distributed clustering frameworks have shown that they maintain detection accuracy comparable to centralized approaches while significantly reducing computational overhead and enhancing scalability for high-volume transaction environments. These approaches have proven particularly valuable for financial institutions operating across multiple regions with varying fraud patterns and regulatory requirements [5].

K-means clustering has gained particular prominence in fraud detection applications due to its computational efficiency and conceptual simplicity. The algorithm partitions the transaction space into k distinct clusters, with each transaction assigned to the nearest centroid based on distance metrics such as Euclidean or Mahalanobis distance. In practical implementations, financial institutions typically apply domain-specific optimizations, including weighted distance calculations that prioritize fraud-indicative features and dynamic cluster number adjustments that respond to evolving transaction volumes. Beyond k-means, other grouping algorithms have demonstrated complementary strengths in fraud detection contexts. DBSCAN has proven particularly effective for identifying sparse outliers in transaction datasets, while spectral clustering techniques excel at detecting fraud patterns within transaction graphs that represent relationships between merchants, cardholders, and transactions. Self-organizing maps provide visual representations of transaction clusters that enable fraud analysts to intuitively identify emerging threat patterns. Meta-learning approaches that combine multiple classifiers have shown particular promise in credit card fraud detection scenarios, with empirical evaluations demonstrating that strategically combining clustering algorithms with cost-sensitive learning techniques can significantly improve detection accuracy compared to individual methods. These meta-learning frameworks adaptively weight the contributions of different clustering approaches based on their historical performance across various fraud types, creating integrated detection systems that leverage the complementary strengths of diverse algorithms while mitigating their individual weaknesses [5].

Autoencoder neural networks represent the cutting edge of unsupervised fraud detection, leveraging deep learning architectures to identify anomalies through reconstruction error. These networks compress transaction data through a bottleneck layer before attempting to reconstruct the original input, with the reconstruction error serving as an anomaly score. Unlike clustering approaches that rely primarily on distance metrics, autoencoders can capture complex non-linear relationships within transaction data, enabling the detection of sophisticated fraud patterns that linear methods might miss. Recent research has established that concept drift represents a significant challenge in fraud detection applications, as legitimate transaction patterns evolve over time due to changing consumer behaviors and seasonal variations. Traditional unsupervised methods often struggle to distinguish between natural pattern evolution and emerging fraud tactics, leading to increasing false positive rates over time. Advanced detection frameworks address this challenge through ensemble-based approaches that combine multiple detection models with drift adaptation mechanisms. By monitoring the statistical properties of transaction streams and implementing incremental learning techniques, these systems can continuously adapt to evolving patterns while maintaining detection sensitivity. Experimental evaluations of drift-adaptive detection methods across extensive real-world financial datasets have demonstrated significant improvements in long-term detection performance compared to static models. These adaptive approaches maintain high detection rates while substantially reducing false positives over extended operational periods, addressing one of the fundamental limitations of traditional unsupervised fraud detection methods in dynamic transaction environments [6].

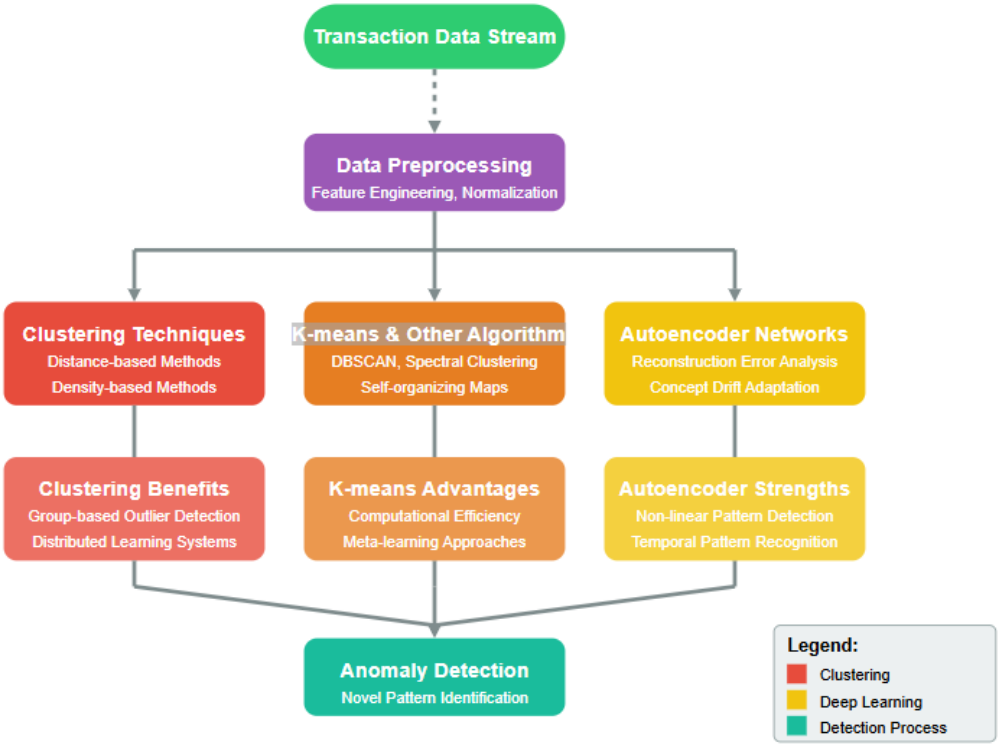

Fig. 2: Unsupervised Learning for Novel Fraud Pattern Detection. [5, 6]

IV. Deep Learning Applications in Transaction Monitoring

Deep learning architectures have revolutionized transaction monitoring by enabling financial institutions to analyze complex patterns that traditional methods often miss. Recurrent Neural Networks (RNNs) represent the cornerstone of sequential data analysis in fraud detection, offering unique capabilities for processing transaction streams as temporally-connected events rather than isolated occurrences. Unlike conventional models that evaluate each transaction independently, RNNs maintain internal memory states that capture dependencies across transaction sequences, allowing them to recognize suspicious patterns that manifest over time. Long Short-Term Memory (LSTM) networks, a specialized RNN variant, have demonstrated particular efficacy in this domain by addressing the vanishing gradient problem that limits standard RNNs when modeling long-term dependencies. These networks selectively remember or forget information through dedicated gate mechanisms, enabling them to maintain contextual awareness across extended transaction histories. Gated Recurrent Units (GRUs) offer a streamlined alternative that reduces computational requirements while maintaining comparable performance characteristics. Systematic literature reviews of deep learning applications in financial time series have documented the progressive adoption of these sequential models across fraud detection applications, with experimental evaluations consistently demonstrating their superior

performance for identifying complex fraud patterns compared to traditional methods. These reviews highlight that sequential models excel particularly in scenarios involving sophisticated card-not-present fraud tactics, where transactions may appear legitimate when viewed in isolation but reveal suspicious patterns when analyzed as sequences. The documented performance advantages extend across diverse financial domains and transaction types, establishing recurrent architectures as essential components in comprehensive fraud detection frameworks capable of addressing evolving threat landscapes [7].

Convolutional Neural Networks (CNNs), though initially developed for image recognition, have emerged as powerful tools for spatial pattern recognition in transaction data. These networks automatically extract hierarchical features through specialized convolutional layers that apply sliding filters across input data, identifying localized patterns regardless of their position within the data structure. In transaction monitoring applications, CNNs effectively recognize patterns across multiple dimensions simultaneously, including time, transaction amount, merchant category, and geographical location. One-dimensional CNNs analyze temporal patterns across transaction sequences, while two-dimensional variants can identify correlations between different transaction attributes. Hybrid architectures that combine convolutional layers for feature extraction with recurrent layers for temporal modeling have demonstrated particularly impressive performance in real-world implementations. These models first identify spatial patterns through convolutional processing before analyzing their temporal evolution through recurrent mechanisms, creating an integrated approach that captures both structural and sequential aspects of fraudulent behavior. Transfer learning techniques enable organizations to leverage pre-trained CNN components from related domains, reducing the data requirements for effective model training while accelerating implementation timelines. Comprehensive literature reviews examining the evolution of deep learning applications in financial forecasting have documented the growing adoption of convolutional architectures for fraud detection, with implementations progressively moving from experimental to production environments as their performance advantages have been validated across diverse transaction datasets. These reviews emphasize that convolutional approaches consistently outperform traditional feature engineering methods by automatically extracting relevant patterns from raw transaction data without requiring extensive domain-specific feature definition [7].

The integration of deep learning models into real-time transaction processing environments represents a significant technical achievement that has transformed fraud prevention capabilities. Modern implementations leverage specialized hardware accelerators, including Graphics Processing Units (GPUs) and Tensor Processing Units (TPUs), to execute complex neural network computations within millisecond timeframes required for authorization decisions. Distributed computing frameworks partition model execution across multiple processing nodes, enabling parallel computation that maintains performance even during peak transaction volumes. Edge computing deployments position model inference capabilities directly within transaction processing networks, minimizing latency while ensuring consistent performance across diverse geographical regions. Advanced implementations incorporate online learning mechanisms that continuously update model parameters as new transaction data becomes available, allowing systems to adapt to emerging fraud patterns without requiring complete retraining cycles. Streaming analytics frameworks process transaction data incrementally rather than in batches, ensuring that detection systems maintain current contextual awareness. Recent research examining fraud detection in symmetric crypto-asset transactions has established that optimized deep learning implementations can maintain real-time performance even in high-throughput blockchain environments where transaction volumes fluctuate dramatically. These studies highlight the critical importance of computational optimization techniques including model quantization, parallel processing, and efficient memory management in maintaining consistent performance across varying transaction loads. The documented implementations demonstrate that properly optimized neural network architectures can achieve decision latencies compatible with real-time processing requirements across diverse financial environments, from traditional payment networks to emerging cryptocurrency platforms [8].

Case studies across diverse financial institutions have provided compelling evidence of deep learning's transformative impact on fraud detection accuracy. Comprehensive evaluations in cryptocurrency transaction environments have demonstrated that specialized neural network architectures consistently outperform traditional approaches for identifying fraudulent patterns in blockchain data. These implementations leverage the transparent nature of blockchain transactions to create rich feature representations that capture transaction relationships and temporal patterns across the network. Multi-headed attention mechanisms enable these models to focus on relevant aspects of transaction history while ignoring irrelevant information, substantially improving detection precision compared to earlier approaches. Graph neural networks have shown particular promise in this domain by directly modeling transaction relationships as network structures rather than isolated events, enabling the identification of coordinated fraud activities across multiple accounts and transactions. Experimental evaluations across major cryptocurrency platforms have documented that these approaches successfully identify sophisticated fraud schemes including money laundering patterns, market manipulation attempts, and theft proceeds movement that conventional detection methods consistently miss. The performance advantages extend across multiple transaction types including exchange-based transactions, peer-to-peer transfers, and smart contract interactions. Importantly, these studies also highlight implementation challenges including computational requirements, model explainability limitations, and the need for specialized expertise in both blockchain technologies and deep learning architectures. Despite these challenges, the documented performance improvements

establish deep learning approaches as the current state-of-the-art in cryptocurrency transaction monitoring, with continued advancements expected as implementations mature and architectural innovations address current limitations [8].

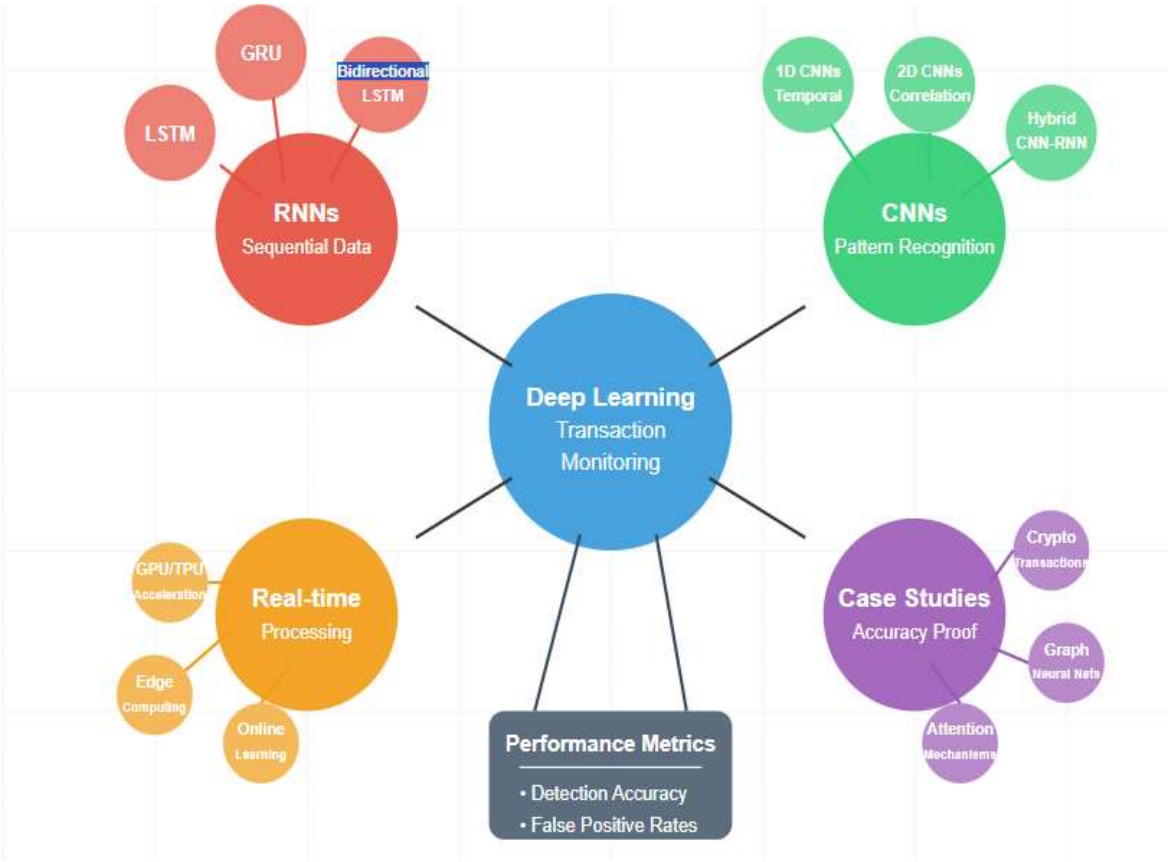

Fig. 3: Deep Learning Applications in Transaction Monitoring. [7, 8]

V. Future Directions and Challenges

The future landscape of machine learning in fraud detection is rapidly evolving toward hybrid architectures that combine multiple model types to address the inherent limitations of individual approaches. These ensemble frameworks integrate the complementary strengths of diverse algorithms, creating detection systems greater than the sum of their parts. Federated learning represents a particularly promising direction, enabling collaborative model training across multiple financial institutions without centralizing sensitive transaction data. This approach allows organizations to benefit from expanded training datasets while maintaining data privacy and regulatory compliance. Quantum machine learning algorithms, though still in their early stages, have demonstrated potential for dramatically accelerating pattern recognition in high-dimensional transaction data, potentially enabling real-time detection of previously unidentifiable fraud patterns. Zero-shot and few-shot learning techniques show promise for identifying novel fraud tactics with minimal historical examples, addressing the perpetual challenge of detecting emerging threats with limited training data. Comprehensive security evaluations of banking fraud analysis systems have demonstrated that hybrid approaches combining rule-based systems with machine learning models provide superior resilience against a diverse range of attack vectors. These evaluations employ systematic testing methodologies that assess detection capabilities across multiple fraud scenarios, including account takeover, identity theft, and transaction manipulation attacks. The findings highlight that integrated systems leveraging both static rules and adaptive learning components consistently outperform single-methodology approaches, particularly for sophisticated attack patterns that deliberately exploit the known limitations of conventional detection techniques. Financial institutions implementing these hybrid frameworks have reported substantial improvements in detection capabilities while maintaining acceptable false positive rates, establishing multi-faceted detection approaches as the emerging best practice for comprehensive fraud prevention in increasingly complex transaction environments [9].

The fundamental challenge of balancing detection accuracy with acceptable false positive rates continues to drive significant research and development efforts. False positive reduction remains critical as each incorrectly flagged transaction generates

costs through investigation resources, customer friction, and potential lost transaction revenue. Advanced cost-sensitive learning frameworks explicitly incorporate these asymmetric costs into model optimization, enabling more nuanced decision boundaries that reflect the operational realities of fraud management. Explainable AI techniques represent another critical direction, generating human-interpretable justifications for fraud alerts that enable analysts to rapidly evaluate detection accuracy while satisfying regulatory requirements for model transparency. These approaches range from attention mechanisms that highlight suspicious transaction features to counterfactual explanations that identify specific modifications that would change a transaction's classification. Security evaluations of banking fraud analysis systems have established that the optimal operational configuration typically involves multiple detection layers with distinct sensitivity levels. High-sensitivity components flag potentially suspicious transactions for additional scrutiny, while high-specificity components determine which subset of these transactions warrant immediate intervention. This multi-tiered approach effectively distributes computational resources according to risk levels, enabling intensive analysis of high-risk transactions while maintaining efficient processing for the vast majority of legitimate activity. Experimental evaluations across diverse financial datasets have confirmed that these strategically configured detection pipelines substantially outperform monolithic approaches in terms of both detection effectiveness and operational efficiency. The documented success of these implementations has driven growing industry adoption of architecturally sophisticated detection frameworks that dynamically adjust analytical depth based on preliminary risk assessments [9].

Regulatory considerations increasingly shape the evolution of machine learning in fraud detection, with growing requirements for model transparency, explainability, and fairness. Financial institutions must navigate complex regulatory frameworks including anti-money laundering requirements, data privacy regulations, and consumer protection mandates while implementing advanced detection capabilities. These requirements have accelerated research into inherently interpretable models and post-hoc explainability techniques that maintain compliance without sacrificing detection performance. Fairness-aware machine learning approaches address the critical challenge of ensuring that fraud detection systems do not disproportionately impact protected demographic groups or reinforce historical biases present in training data. Research examining online banking fraud detection has highlighted the importance of incorporating both local and global behavior patterns within regulatory-compliant frameworks. Local behavior analysis focuses on individual account activity, establishing personalized baselines for each customer's transaction patterns, while global analysis examines behavioral patterns across the entire customer base to identify coordinated fraud attacks targeting multiple accounts. This multi-level approach enables detection systems to identify anomalous behaviors relative to both individual history and population norms, substantially enhancing detection capabilities for sophisticated fraud schemes. Regulatory considerations have driven the development of configurable detection frameworks that can be adapted to address jurisdiction-specific requirements while maintaining core detection capabilities. These systems incorporate modular components for data anonymization, audit logging, and decision justification that can be configured to satisfy varying regulatory standards across different operating environments. The documented success of these compliance-oriented architectures demonstrates that regulatory requirements need not constrain detection capabilities when properly integrated into system design from the outset [10].

The continuously evolving nature of fraud tactics necessitates adaptive countermeasures capable of responding to emerging threats without requiring complete system redesign. Adversarial machine learning represents a promising approach, deliberately exposing detection systems to simulated fraud attacks during training to enhance resilience against novel tactics. These techniques proactively identify potential vulnerabilities by generating synthetic fraud patterns that would evade current detection mechanisms, enabling preemptive model improvements before actual fraud losses occur. Continuous learning architectures represent another critical direction, enabling models to incrementally adapt to emerging patterns without suffering catastrophic forgetting of previously learned fraud indicators. Research on online banking fraud detection based on local and global behavior patterns has established that multi-level analysis frameworks provide superior adaptability to evolving fraud tactics. These systems incorporate dynamic behavioral profiling at both individual and population levels, continuously updating baseline patterns to distinguish between legitimate behavioral evolution and potentially fraudulent anomalies. By maintaining separate behavioral models for different customer segments, transaction channels, and time periods, these approaches can rapidly identify emerging fraud patterns that target specific subpopulations while minimizing false positives across the broader customer base. Experimental evaluations of these adaptive frameworks have demonstrated their ability to maintain detection effectiveness during periods of significant pattern shifts, including seasonal variations, economic disruptions, and the introduction of new banking services. The documented resilience of these systems to both gradual and abrupt pattern changes has established them as the preferred approach for financial institutions operating in dynamic environments where both legitimate and fraudulent transaction patterns continuously evolve [10].

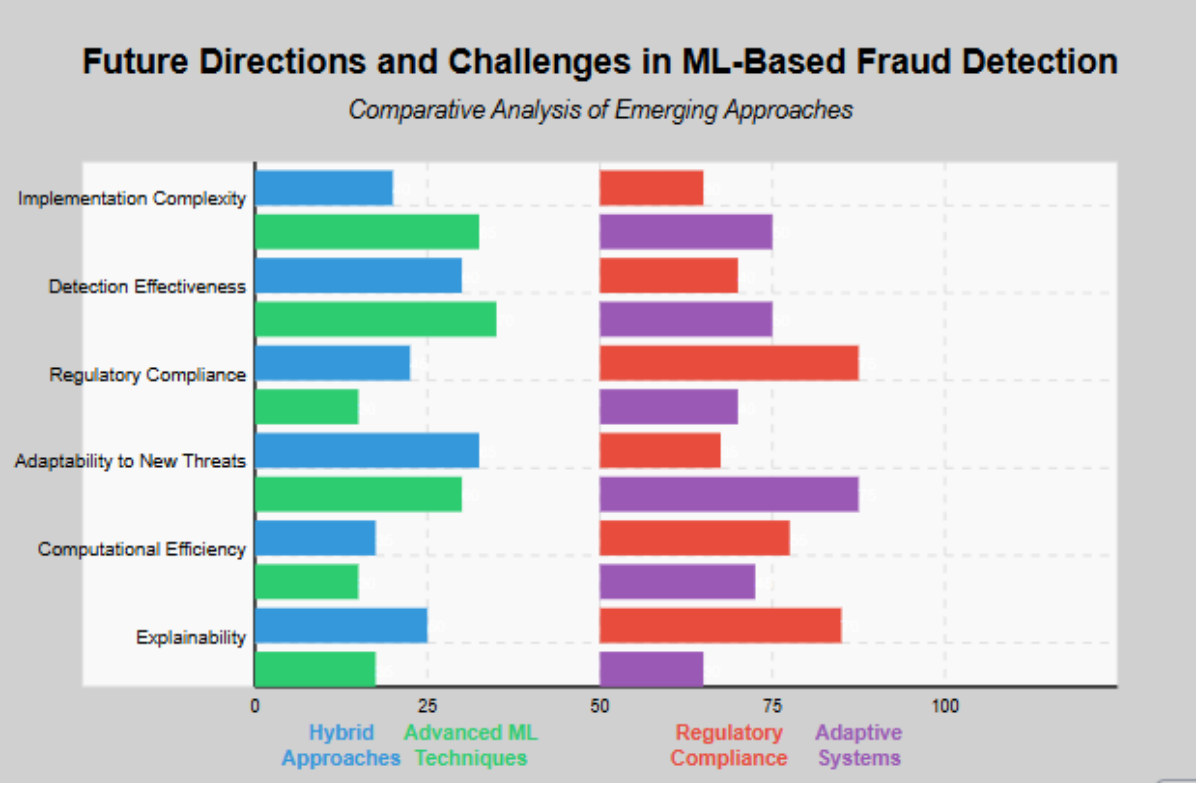

Fig. 4: Future Directions and Challenges in ML-Based Fraud Detection. [9, 10]

Conclusion

The evolution of machine learning in credit card fraud detection represents a paradigm shift from reactive to proactive prevention strategies. From basic supervised classification algorithms to sophisticated deep learning architectures, each advancement has enhanced the ability to identify increasingly complex fraud patterns while reducing false positives. Unsupervised learning techniques have proven essential for detecting novel fraud tactics without prior examples, while deep learning models excel at processing sequential transaction data and identifying subtle correlations across multiple dimensions. The future lies in hybrid approaches that combine complementary strengths of diverse algorithms, with federated learning enabling collaborative improvement while maintaining data privacy. As regulatory requirements for transparency and fairness continue to grow, explainable AI and fairness-aware techniques will become increasingly important. The most successful fraud prevention systems will incorporate multi-level analysis frameworks that adapt continuously to evolving tactics, balancing detection accuracy with operational efficiency. Through continued innovation in both algorithms and implementation strategies, machine learning will remain the foundation for effective defense against financial fraud in an increasingly digital economy.

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.
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References

[1] Andrea Dal Pozzolo et al., "Credit Card Fraud Detection: A Realistic Modeling and a Novel Learning Strategy," IEEE Transactions on Neural Networks and Learning Systems, 2017. https://ieeexplore.ieee.org/document/8038008
[2] Haichao Du et al., "AutoEncoder and LightGBM for Credit Card Fraud Detection Problems," Symmetry, 2023. https://www.mdpi.com/2073-8994/15/4/870
[3] Masoumeh Zareapoor, Pourya Shamsolmoali, "Application of Credit Card Fraud Detection: Based on Bagging Ensemble Classifier," Procedia Computer Science, 2015. https://www.sciencedirect.com/science/article/pii/S1877050915007103
[4] Michele Carminati et al., "Security Evaluation of a Banking Fraud Analysis System," ACM Transactions on Privacy and Security, 2018. https://dl.acm.org/doi/10.1145/3178370
[5] Omer Berat Sezer et al., "Financial time series forecasting with deep learning: A systematic literature review: 2005–2019," Applied Soft Computing, 2020. https://www.sciencedirect.com/science/article/abs/pii/S1568494620301216

[6] P.K. Chan et al., "Distributed data mining in credit card fraud detection," IEEE Intelligent Systems and their Applications, 2002. https://ieeexplore.ieee.org/document/809570
[7] Richard J. Bolton, David Hand, "Statistical Fraud Detection: A Review," Statistical Science, 2002. https://www.researchgate.net/publication/38326942_Statistical_Fraud_Detection_A_Review
[8] Shiguo Wang et al., "A Comprehensive Survey of Data Mining-Based Accounting-Fraud Detection Research," 2010 International Conference on Intelligent Computation Technology and Automation, 2010. https://ieeexplore.ieee.org/document/5522816
[9] Siddhartha Bhattacharyya, "Data mining for credit card fraud: A comparative study," Decision Support Systems, 2011. https://www.sciencedirect.com/science/article/abs/pii/S0167923610001326
[10] Stephan Kovach et al., "Online Banking Fraud Detection Based on Local and Global Behavior," ICDS 2011: International Conference on the Digital Society, 2011. https://www.semanticscholar.org/paper/Online-Banking-Fraud-Detection-Based-on-Local-and-Kovach-Ruggiero/f0f7bc77e59eefb7857a027d1851ea21b0d185af