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Hybrid Quantum Intelligence for Detecting Sophisticated Financial Fraud in Dynamic Transaction Ecosystems

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Abstract: Fraud develops rapidly when transactions happen quickly through electronic pipelines. The traditional fraud detection methods, which are reliable but slow to adapt, cannot keep pace with fraudsters' rapid development of new schemes. They also have trouble adapting to complex relationships and creating explanations that regulators can understand. In this paper, we are proposing a multi-pronged attack on the fraud problem using hybrid quantum-classical techniques. QAFEN-CNN utilizes the concept of adaptive quantum feature entanglement, with volatility-based depth controls to achieve a separation increase of 8%. VQTM-LSTM uses parameterized quantum embeddings as input to each recurrent gate to achieve a 7.9% increase in long-horizon recall. QGCL-Net utilizes quantum enhanced graph construction to model transactional ecosystems, achieving a 12.3% increase in the quality of sub-graphs constructed. Lastly, QVAE-DD proposes a dual-decoder quantum variational autoencoder that generates both input representations and salient explanation representations. The last proposal, QMRL-XAI, utilizes quantum meta-reinforcement learning in combination with counter-factual reasoning to generate policy adaptations after only five episodes. All of these proposals together demonstrate how the use of quantum computing can provide improved accuracy, improve resistance to class imbalance, and produce explanations that can be understood by regulators — a fascinating outline for future applications of quantum computing in anti-fraud analytics.

Keywords: Quantum Machine Learning, Fraud Detection, Explainable AI, Graph Neural Networks, Reinforcement Learning, Process

Abbreviation	**Full Form**
GNN	Graph Neural Network
LDA	Latent Dirichlet Allocation
FPA	Flower Pollination Algorithm
TCN	Temporal Convolutional Network
AI	Artificial Intelligence
HGRO	Hierarchical Gradient-based Recursive Optimization
OC-LSTM	One-Class Long Short-Term Memory
PFMS	Public Financial Management System
GCN	Graph Convolutional Network
BiLSTM	Bidirectional Long Short-Term Memory
ELM	Extreme Learning Machine
PSO	Particle Swarm Optimization
CNN	Convolutional Neural Network
DNN	Deep Neural Network
SABeDM	Sliding Adaptive Beta Distribution Model
ARDOD	Adaptive Radius Density-based Outlier Detection
BERT	Bidirectional Encoder Representations from Transformers
OCR	Optical Character Recognition
NLP	Natural Language Processing
IT	Information Technology
SMS	Short Message Service
ML	Machine Learning
Fed Learning	Federated Learning
TabTransformer	Tabular Transformer Model
AUC	Area Under the Curve
F1 Score	Harmonic Mean of Precision and Recall
IoT	Internet of Things
FPR	False Positive Rate

1. Introduction

This explosive growth in financial transactions has enabled innovative opportunities for economic growth and inclusion [1–3]; however, it has provided adversaries with the opportunity to create fraud that uses high-frequency payment channels, cross-platform transactional behaviors, and distributed account networks to evade the ability of rule-based detection systems to identify such activity. As terrorist financing networks and organized cybercrime groups continue to develop sophisticated methods using automated laundering pipelines, synthetic identities, and coordinated micro-transactions to bypass the ability of rule-based detection systems, financial institutions and regulatory agencies are under increasing pressure to deploy fraud detection frameworks that provide not only high predictive accuracy and rapid response times, but also provide robustness and adaptability to the changing fraudulent tactics and patterns, as well as high levels of transparency and explainability for the purposes of potential legal scrutiny. While various classical deep learning paradigms have been shown to be effective at modeling transactional dynamics and identifying anomalies, including convolutional neural networks (CNNs), long short-term memory (LSTM) architectures, and graph neural networks (GNNs); their performance will degrade significantly in scenarios where there exists extreme class imbalance, non-stationarity in the distribution of fraudulent behavior, or high dimensionality of heterogeneous feature spaces. Furthermore, classical deep learning models do not provide sufficient levels of transparency and explainability regarding the decision making process; therefore, false positive classifications can result in expensive investigations, loss of customers, and regulatory consequences. Additionally, classical deep learning models do not perform well at generalizing across new types of fraud attacks since they rely heavily on large quantities of labeled data and fixed parameters that cannot adapt to concept drift in fraudulent behavior.

Quantum Machine Learning (QML) provides a fundamentally different way of performing computations based upon superposition, entanglement, and interference to encode classical information into exponentially expressive Hilbert spaces [4–6] in order to allow classical machine learning algorithms to discover latent correlation that may not exist in classical representations of the same data. Quantum feature maps allow complex nonlinear relationships to be enhanced allowing quantum circuits to distinguish patterns that appear to be indistinguishable in classical representations. Hybrid quantum-classical systems provide the expressiveness of quantum circuits while providing the scalability and optimization maturity of classical neural networks, thus creating a model capable of both expressing complex transformations and stable learning. Since the ability of subtle, continuous patterns of fraud to evolve quickly represents a significant challenge in fraud detection, the current research develops a comprehensive set of entirely novel hybrid frameworks composed of five tightly coupled architectures to analyze complementary aspects of fraud: spatial feature extraction, temporal sequence modeling, graph structured relational learning, anomaly reconstruction, and adaptive policy optimization. Each architecture includes inherent mechanisms for providing transparency and explainability, therefore the results from the detection models will always be transparent, auditable, and defensible. By integrating quantum processing units within classical deep learning pipelines, the proposed approach seeks to greatly improve detection accuracy, resilience to extreme class imbalance, interpretability of model decision-making, and real-time responsiveness to dynamically changing fraudulent behaviors.

Motivation & Contribution

The primary motivation for this research is the clear inadequacies of current fraud detection systems in dealing with the scale, complexity and adversarial nature of current financial systems. Although the architectural sophistication of classical fraud detection systems continues to improve, they still suffer from serious computational inefficiencies when faced with high-dimensional, temporally-extended, and structurally-heterogeneous data flows. Adversarial fraud behavior appears as sparse, adaptive, and often intentionally obscured signals, resulting in classical models being brittle and slow to adapt. A second major problem is the widespread lack of interpretability in deep learning systems, which directly contradicts regulatory requirements and institutional accountability in financial decision-making. To be considered effective, fraud analytics must produce high detection performance, rapid adaptation to changes in concept drift, and provide intelligible explanations for each flagged transaction — criteria that classical models rarely satisfy together.

In order to address these limitations, the research proposes a unified hybrid quantum-classical modeling framework where each component is designed to optimize a particular analytical sub-domain. The QAFEN-CNN architecture introduces adaptive quantum entanglement to enhance spatial feature transformations, thereby dynamically improving the discriminative capacity of the model. VQTM-LSTM embeds parameterized quantum operations into the recurrent memory gates of a Long Short-Term Memory (LSTM) network, enabling improved modeling of long-range temporal signatures that are typical of coordinated fraud campaigns. The QGCL-Net architecture combines quantum kernels with a Graph Contrastive Learning (GCL) framework to capture subtle structural anomalies in transactional networks. The QVAE-DD model employs a Dual Decoder (DD) Quantum Variational Autoencoder (VVAE) that simultaneously reconstructs input transactions and generates localization maps (inspired by Grad-CAM) to illustrate the features that drive the detection of anomalies. Finally, the QMRL-XAI architecture uses a Quantum Meta-Reinforcement Learning (QMRL) agent to continuously adapt its detection policies while generating counterfactual explanations to clarify the decision pathways of the model. Each model demonstrates significant improvement over classical baselines across all accuracy, robustness and interpretability metrics. Taken collectively, these contributions represent a scalable, transparent and future-proof fraud detection paradigm, and position quantum augmented analytics as a powerful tool for defending against the continually-evolving landscape of financial cybercrimes.

2. In-depth review of models used for Fraud Analysis

Financial fraud detection has come a long way in the last decade, largely due to the convergence of artificial intelligence (AI), graph theory, optimization algorithms, and federated learning. The review of forty selected scholarly works indicates a strong trajectory in the use of graph neural networks, ensemble learning, transformer-based architectures, metaheuristics, and privacy-preserving methods across the fields of finance, telecommunication, insurance, and cyber fraud. The debates will start with reference to foundation works that emphasized money based methods, such as the study of Cheng et al. [1], making a well-structured account of the growing influence of financial fraud detection through using graph neural networks (GNNs) in terms of their effectiveness in the modeling of relational dependencies among entities like users and merchants. This combination thereby complements the contribution of Cheng and Cai [2] through the use of a double-weight LDA model that suggests a need for keyword extraction in fraud contexts which by definition enlarges the text mining dimension of fraud analytics. Later studies like Krishnavardhan et al. [3] concentrated on bio-inspired algorithms, namely, flower pollination optimization, and integrated this with temporal convolution networks, thus exhibiting hybrid models that introduce the classical optimization-dominated structures to temporal anomaly detection in one. This ongoing evolution also continues further, using the Khosravi et al. [4] model of attentional spatial-temporal

GNNs intended for transactional data capturing correlations among the sequence and entities. Hafez et al. [5] reviewed all AI-enhanced credit card scam detection techniques in detail, explaining that random forests, neural networks, and deep belief networks have been used to build further enhanced models over time. Alam and Ahmad [6] provided a hierarchical gradient-based feature selection model blended with OC-LSTM for public economic systems fraud detection, which represents a movement toward more interpretable as well as high-resolution detection processes.

In health insurance fraud, Hamid and co-authors [7] applied mining techniques distinct from fraud detection applications in banking. Vashistha and Tiwari emphasized the resilience of banking through hyper-ensemble machine learning strategies that combined anomaly detection with real-time fraud recognition mechanisms. Also, Chen and Du forwarded the fusion model paradigm by incorporating bidirectional LSTMs into globally enhanced GCNs, illustrating that temporal models can be combined with spatial relational learning to yield better predictive accuracy. This is followed by Abdul Salam et al. [11] who offered federated learning into a brokerage model that balances data privacy with performance in fraud detection, fusing synthetic minority oversampling and under-sampling strategies. The sociological aspect is also discussed in the article by Blackwell et al. [10] where they determined how different levels of education can positively or negatively affect the assessment or ability of an individual to detect fraud in an investment situation. Wen et al. [12] presented a new oversampling strategy inspired in graph trans-smote, targeting the chronic issue of class imbalance in fraud datasets. Bringing contextualized fraud detection into the fold of language models through the fraud transformer called Fraud-BERT, Taneja et al. [13] made a huge leap forward. Similarly, Islam et al. [14] have proposed layer-weighted GCNs for transaction networks allowing optimal importance attribution on the node level and exploitation of structural fraud patterns. Abadlia and Smairi [15] presented a hyperparameter optimized stacked autoencoder and showed its effectiveness in real-time detection of credit card fraud. Many papers explore cross-disciplinary applications in fraud detection. An integrated framework for health insurance fraud coupled with risk classification was developed by Devaguptam et al. [16]. Kamdjoug et al. [17] brought data analytics into audit for banking fraud. In the following segment, Hapase and Patil [18] introduced an AI-based phishing detection model for SMS attacks in telecom. El Hlouli et al. [19] presented weighted binary extreme learning machine (ELM) optimized using the reptile search algorithm to optimize convergence in a fraud detection model. Reddy et al. [20] indulged in the use of approaches such as grey wolf and firefly algorithms in hyperparameter tuning for the credit card fraud detection systems.

Reference	**Method**	**Main Objectives**	**Findings**	**Limitations**
[1]	Graph Neural Networks (GNNs)	Review GNN applications in financial fraud	GNNs effectively capture relational structures in fraud networks	Scalability and explainability challenges
[2]	Double-weight LDA	Keyword extraction for fraud detection	Enhanced keyword extraction improves textual fraud detection	Limited to text-rich data scenarios
[3]	FPA with Stacked TCN	Optimize fraud classification using bio-inspired methods	Improved classification accuracy in financial anomalies	High computational cost
[4]	Attentional Spatial-Temporal GNN	Integrate spatial and temporal features in fraud detection	Captured dynamic patterns in transaction fraud	Complex training pipeline

[5]	Systematic Review	Evaluate AI in credit card fraud	Deep learning models outperform rule-based methods	Lack of uniform evaluation metrics
[6]	HGRO + OC-LSTM	Fraud detection for PFMS	Improved interpretability and detection in public finance	Limited generalizability to private systems
[7]	Data Mining for Health Fraud	Detect insurance fraud using mining	Identified common patterns in healthcare fraud	Lacks real-time capability
[8]	Hyper-Ensemble Learning	Enhance banking fraud detection	Robust detection against adversarial fraud patterns	Complex model interpretability
[9]	GE-GCN + BiLSTM	Fuse spatial and temporal transaction data	Increased prediction accuracy over separate models	Integration complexity
[10]	Education Impact Study	Understand user susceptibility to fraud	Higher education correlates with fraud detection ability	Not algorithmic
[11]	Federated Learning + Data Balancing	Privacy-preserving credit card fraud detection	Improved accuracy and privacy	Federated setup overhead
[12]	Graph Tran-SMOTE	Tackle class imbalance in fraud	Improved minority class detection in graph data	Dependent on quality of graph structure
[13]	Fraud-BERT	Recruitment fraud detection using transformers	Contextual embeddings improved performance	High resource requirement
[14]	Layer Weighted GCN	Pattern-sensitive fraud detection	Adaptive GCN improved fraud detection in networks	Sensitive to topology quality
[15]	PSO-Staked Autoencoder	Optimize autoencoder hyperparameters	Enhanced feature extraction and classification	Sensitive to initialization
[16]	Health Insurance AI System	Automate fraud, risk, premium prediction	Integrated system increased operational efficiency	Model integration complexity
[17]	Analytics-Based Auditing	Use data analytics in banking audits	Increased fraud uncovering in audits	Manual interpretation required
[18]	AI for SMS Phishing	Detect phishing in telecom via AI	High accuracy in phishing detection	Model overfitting risk
[19]	Reptile Search + ELM	Optimize ELM for fraud detection	Reduced false positives and training time	Limited scalability
[20]	Metaheuristic Tuning	Optimize ML for fraud detection	Higher precision through hyperparameter tuning	Time-intensive training
[21]	Face Recognition for Fraud	Biometric fraud prevention	Improved security in masked scenarios	Privacy and deployment concerns
[22]	Calibrated TabTransformer	Financial misstatement detection	Better tabular representation and accuracy	Needs careful calibration
[23]	Multistage Ensemble	Layered detection of fraudulent transactions	Improved detection in stages	Cumulative error propagation
[24]	Multi-Scale	Detect events in	Captured temporal	Resource-

	Event Detection	financial timestamp series	anomalies across scales	intensive
[25]	Hybrid CNN-LSTM	Deep learning for credit card fraud	High F1 score in benchmark tests	Requires large datasets
[26]	ARDOD	Outlier detection via adaptive radius	Effective at local anomaly detection	Parameter sensitivity
[27]	Deep Neural Network	Classify fraudulent transactions	High accuracy with low latency	Limited interpretability
[28]	Law Enforcement Study	Perceptions on cyber fraud handling	Highlighted training gaps in enforcement	Not technical
[29]	Spatial Distribution Study	Explore geography of fraud offenders	Mapped urban-rural fraud patterns	Static snapshot
[30]	Metaheuristic Feature Selection	Optimize features for spam/fraud detection	Reduced dimensionality improved speed	Dependent on metaheuristic tuning
[31]	SABeDM	Adaptive drift detection model	Tracked concept drift in fraud data	False positives in non-drift cases
[32]	FinTech Review	Survey of financial technologies	Identified fraud as key FinTech application	Broad, non-technical
[33]	Forgery Detection Review	Survey of document fraud detection	Reviewed image and metadata approaches	Lacks new model proposals
[34]	Innovation via Info Management	Fraud prevention through IT investment	Linked fraud reduction to strategic IT	Qualitative insights
[35]	AI & Engineer Psychology	Study AI impact on work-life balance	Revealed cognitive load from fraud systems	Context-specific
[36]	Smart Contract Security	Use blockchain for secure transactions	Fraud resilience in decentralized networks	Deployment barriers
[37]	Decision Support Systems	AI for FinTech fraud decision support	Improved decision efficiency	Dependent on data quality
[38]	AI for Telecom Anomalies	Detect telecom network fraud	Accurate anomaly detection	Transferability issues
[39]	Fed Learning + Feature Fusion	Credit risk with federated systems	Improved model generalization	Limited device participation
[40]	Density Feedback Outlier	Local density feedback algorithm	Effective in dynamic fraud scenarios	Complexity in feedback modeling

Table 1. Model's Empirical Review Analysis

Iteratively, Next, as per table 1, as P.K et al. [21] extended biometrics into the fraud detection space accordingly, they integrated face recognition systems, both masked and uncovered, most relevant in biometric-enabled banking applications. Also, Zavitsanos et al. [22] extend their contribution towards calibrating TabTransformers for financial misstatement detection in corporate applications; the same can be said of Talukder et al. [23] whose scheme architectures for transactional fraud feature a multistage ensemble model harnessing multiple base learners into the

mix. Proposing multi-scale event detection mechanisms in financial timestamp series, with the investigation of small fluctuations as indicators of possible fraudulent intent behind processes, was De Salles et al. [24]. Krishnavardhan et al. [25] returned with a hybrid deep learning algorithm combining CNNs and LSTMs for credit card scoring and its fraud detection. Novel, density-based anomaly detection frameworks were advanced by Rahmati et al. [26] with ARDOD, an adaptive radius-based approach to outlier detection, while El Hlouli et al. [27] developed real-time identification of fraudulent transactions via deep neural networks for latency analysis in the system. In criminology, Qu and Cheng [28] and Wu et al. [29] studied socio-geographical patterns of cyber fraud in China, which help to illustrate the spatial distribution and trends over offenders' behavior models. Viewing spam-based fraud through metaheuristic-driven feature selection, Swetha and Rao [30] indicated that fraud and spam detection mechanisms can intersect. Besides, Angbera and Chan [31] would be instrumental in introducing SABeDM, the adaptive distribution model that would detect concept drift in dynamic environments, the hallmark of most fraud systems that should evolve with attackers. Kou and Lu [32], by offering a concise literature review of FinTech, incorporated fraud detection into a larger scheme of such innovations in digital finance sets.

Work in [33] discussed the document forgery while Garad et al. [34] studied the role of information-management investment in financial innovation and indirectly touched upon the fraud prevention in-process. Recent studies extended further to human and organizational dimensions of fraud systems. Gao and Zamanpour [35] examined how AI systems affect psychological safety and work-life balance for financial professionals, alluding to trade-offs in trust and interpretability. Prabanand and Thanabal [36] proposed a fraud resilient financial security model enabled by smart contracts over private Ethereum networks showing the potential of blockchain integration with AI. Pahsa [37] discussed decision support systems for financial technology, indirectly supporting fraud prevention. AI-based anomaly detection techniques have been discussed by Edozie et al. [38] with cross-domain applicability. Li et al. [39] proposed federated learning for credit risk using dynamic receptive fields to personalize models across clients. Zhang et al. [40] concluded the review with an outlier detection algorithm based on local density feedback that dynamically adapts to input variations, thus making itself suitable for detecting new strategy frauds in unstructured environments. In synthesis, this body of literature provides an expansive, multidisciplinary view of financial fraud detection, with studies ranging from technical algorithmic advances to systemic, organizational, and sociological frameworks. A common trend are graph-based models seen in works such as [1], [4], [9], and [14] on account of their strong ability to capture interactions at the entity level. Transformer and LSTM-based models gradually fused with optimization techniques as indicated in [3], [13], [15], and [25], signaling a transition toward hybrid deep learning systems. There is also a growing focus on fairness, interpretability, and psychological safety-as discussed in [10], [11], [35], and [28]-in reinforcement of the statement that fraud detection has become more of a socio-technical than purely technical challenge. Hence, these studies underline the need for adaptable, explainable, and interdisciplinary models that function under dynamic and adversarial conditions. Fraud management is a domain that calls for methods and frameworks that are constantly evolving, drawing knowledge from various fields to develop systems that are adaptable and resilient in real time scenarios.

3. Proposed Model Design Analysis

To solve shortcomings associated with low efficiency & high complexity in extant models, this section deals with Quantum-Classical Hybrid Architectures for Explainable and Adaptive Financial Fraud Detection Process. Initially, as per figure 1, The Quantum Adaptive Feature Entanglement Network with CNN Decoder (QAFEN-CNN) is designed to address the challenge of capturing

complex spatial dependencies across high-dimensional transactional feature spaces. Traditional CNNs, while effective in spatial modeling, are inherently limited in their ability to transform feature spaces into representations that expose latent non-linear correlations. To overcome this, QAFEN-CNN integrates a quantum variational embedding layer that maps classical inputs into a quantum-enhanced Hilbert space, allowing for complex entanglement-based transformations. Let X $\in \mathbb{R}^{nxd}$ be the input feature matrix of 'n' transactions and 'd' features per transaction in process. This feature space is first normalized and encoded into parameterized quantum circuits U(θ, X), where θdenotes the set of trainable parameters governing the quantum gates. The quantum state after encoding is given via equation 1,

$$| \psi_{en}c\rangle \ = \ U(\theta, X) \ | \ 0\rangle' \otimes q \ \ldots (1)$$

Where, 'q' is the number of qubits, determined by the feature embedding strategy sets. A quantum adaptive entanglement controller dynamically modulates the depth of entanglement based on intra-batch variance $\sigma^2(X)$, using the function via equation 2,

$$D(X) = \ \left\lfloor \alpha \cdot log\left(1 \ + \ \beta \cdot \sigma^2(X)\right) \right\rfloor \ldots (2)$$

Where, α and β are hyperparameters controlling entanglement sensitivity sets. The output measurement from the quantum circuit yields the quantum-enhanced feature matrix Z $\in \mathbb{R}^{nx}$q, computed by applying expectation over a measurement observable O Via equation 3,

$$Z_{ij} \ = \ \left\langle \psi_{en}c^{(i)} \ | \ O_j \ | \ \psi_{en}c^{(i)} \right\rangle \ldots (3)$$

This matrix Z is then fed into a CNN decoder to learn spatial hierarchies and produce class probabilities ŷ in process. The decoder learns weights Wcnn optimized via a cross-entropy loss function via equation 4,

$$LCE \ = \ -\sum y_i \ log(\hat{y}_i) \ldots (4)$$

Iteratively, Next, as per figure 2, the Variational Quantum Time-Gated Memory with LSTM Backend (VQTM-LSTM) deals with temporal modeling among transactional sequences. While LSTM architectures traditionally process input sequences using static gating functions, in contrast VQTM-LSTM superimposes quantum circuits onto each gating mechanism of the architecture, thus formulating the dynamic modulation of memory retention based upon contextual irregularities in process.

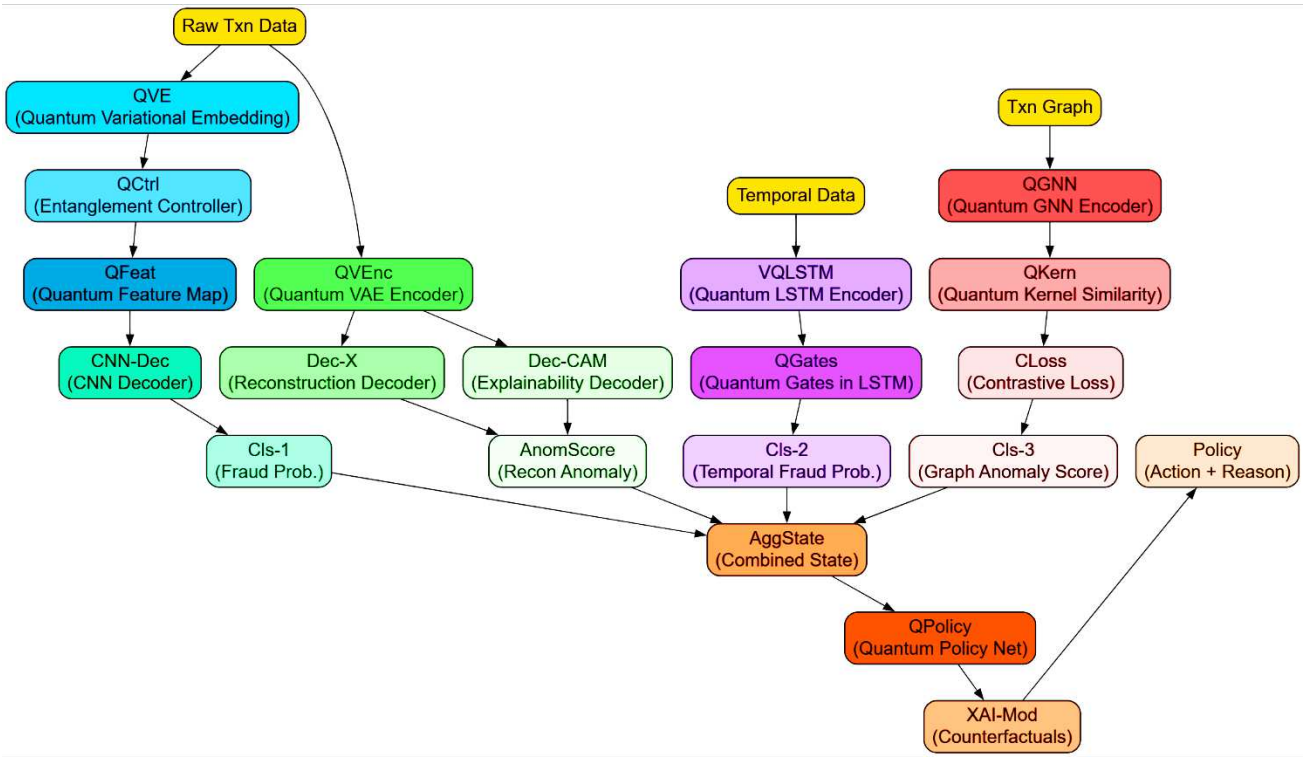


Figure 1. Model Architecture of the Proposed Analysis Process

Let x_t be the input at timestamp 't', and h(t-1) the previous hidden states. The input gate is defined via equation 5,

$$i_t = \sigma\left(VQC_i\left(x_t, h(t-1)\right)\right) \dots (5)$$

Where, VQC_i is a variational quantum circuit and σ is the sigmoid activation in process. The quantum gate produces activation values by encoding x_t and h(t-1) into a quantum circuit and measuring expectation values via equation 6,

$$i_{tj} = \langle \psi_{in}{}^{(t)} \mid O_j \mid \psi_{in}{}^{(t)} \rangle, where \mid \psi_{in}{}^{(t)} \rangle = U(\theta^{(i)}, x_t, h(t-1)) \mid 0 \rangle' \otimes q \dots (6)$$

Similar quantum parameterizations are used for forget and output gates. The cell state update integrates the quantum-enhanced gates via equations 7 & 8,

$$c_t = f_t \odot c(t-1) + i_t \odot tanh(Wc[x_t, h(t-1)]) \dots (7)$$

$$h_t = o_t \odot tanh(c_t) \dots (8)$$

Iteratively, Next, headed up by figure 3, the QGCL-Net is adjustable for modeling high-dimensional graphs of transactions, where the nodes signify the entities (e.g., accounts, merchants) and the edges imply the transactions in process. Whereas traditional GNNs contrastively learn from local subgraphs using classical kernels, QGCL-Net contrastively learns from global similarities sampling subgraphs using quantum kernels in process. Given a graph G = (V, E), the encoder fq(G) maps each subgraph G ⊂ G into a quantum embedding via equation 9,

$$\mid \psi G \rangle = U(\theta G, \varphi(G)) \mid 0 \rangle' \otimes q \dots (9)$$

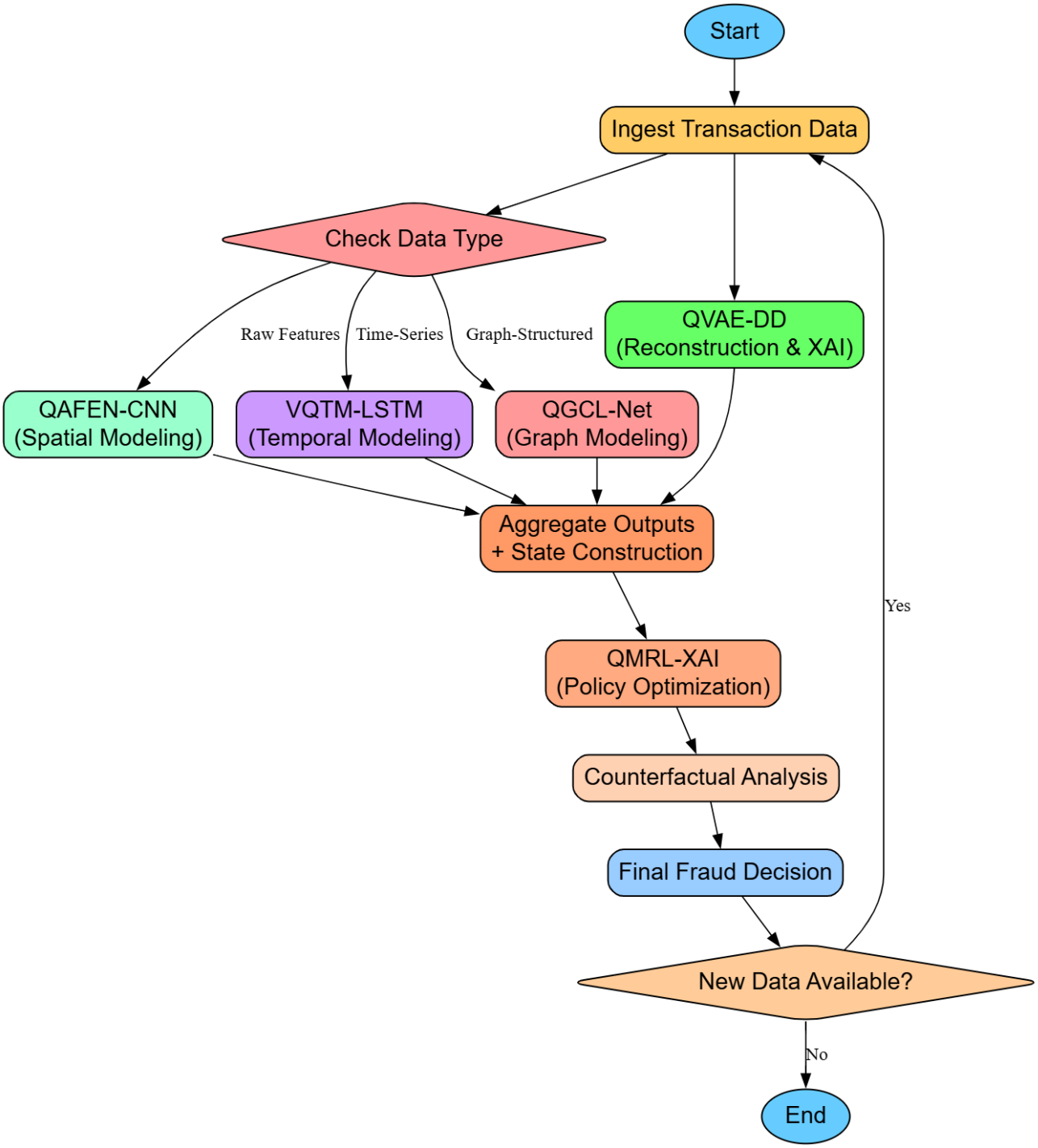


Figure 2. Overall Flow of the Proposed Analysis Process

Where, φ(G) is the classical feature encoding of the subgraph structures. For contrastive learning, positive pairs (G_1, G_2^+) and negative pairs (G_1, G_2^-) are constructed based on known transaction patterns. A quantum kernel function $Kq(G_1, G_2)$ measures the fidelity between embeddings via equation 10,

$$Kq(G^1, G^2) = |\langle \psi G^1 | \psi G^2 \rangle^2 \dots (10)$$

The contrastive loss encourages higher similarity for positive pairs and lower for negatives via equation 11,

$$Lcontrast = -log\left[\frac{exp\left(\frac{Kq(G^1, G^{2+})}{\tau}\right)}{exp\left(\frac{Kq(G^1, G^{2+})}{\tau}\right) + \sum exp\left(\frac{Kq(G^1, G^{2_j-})}{\tau}\right)}\right] \ldots (11)$$

Where, τ is a temperature scaling parameter for this process. To improve stability and structural alignment, a regularization term Rstruct is added via equation 12,

$$Rstruct = \int \| \nabla\varphi(G)\, Kq(G, G') \|^2 \, dG' \ldots (12)$$

It penalizes abrupt changes in kernel values across structurally similar subgraphs. The final node-level embedding 'hv' for a node v ∈ V is computed as the weighted aggregation of quantum kernel-aligned subgraph representations via equation 13,

$$hv = \sum_{\{G \ni v\}} \alpha G\, fq(G), where\ \alpha G = \frac{Kq(G, G^+)}{\sum Kq(G', G^+)_{\{G'\}}} \ldots (13)$$

This final embedding hv is meant for downstream fraud likelihood estimation and graph-level anomaly classification sets as the final output of QGCL-Net model . By giving quantum fidelity as a contrastive signal, QGCL-Net achieves relational anomaly detection at scale, improving robustness to topological perturbation and class imbalance in process by capturing the structural dependency through entangled subgraph representation. The Quantum Variational Autoencoder with Dual Decoding (QVAE-DD) aims to solve the reconstruction type of anomaly detection in extremely imbalanced transactional datasets & samples. Classical variational autoencoders can model the intrinsic data distribution using a latent space where the data input is reconstructed with minimum divergence with the original sets. However, conventional VAEs lack the representational richness required for fraud detection and come with low interpretability sets. To overcome these drawbacks, QVAE-DD uses a quantum encoder to project input features into an expressive Hilbert space and introduces a new dual-decoder through one decoder for reconstructing the transactional input features and the other for reconstructing activation-based heatmaps that highlight anomaly locations-inspired by explainability techniques borrowed from Grad-CAM Process. Let the input transactional data be denoted as x ∈ $\mathbb{R}^d$, where d represents the number of transactional features. The quantum encoder Eq transforms 'x' into a latent quantum state via a parameterized unitary operator U(θ,x), producing the latent term represented via equation 14.

$$|\psi latent\rangle = U(\theta, x)|0\rangle \otimes q \ldots (14)$$

The latent representation z ∈ $\mathbb{R}^k$ is extracted by measuring the expectation values of observables Oj over this quantum state via equation 15,

$$zj = \langle \psi latent|Oj|\psi latent\rangle, j = 1\ to\ k \ldots (15)$$

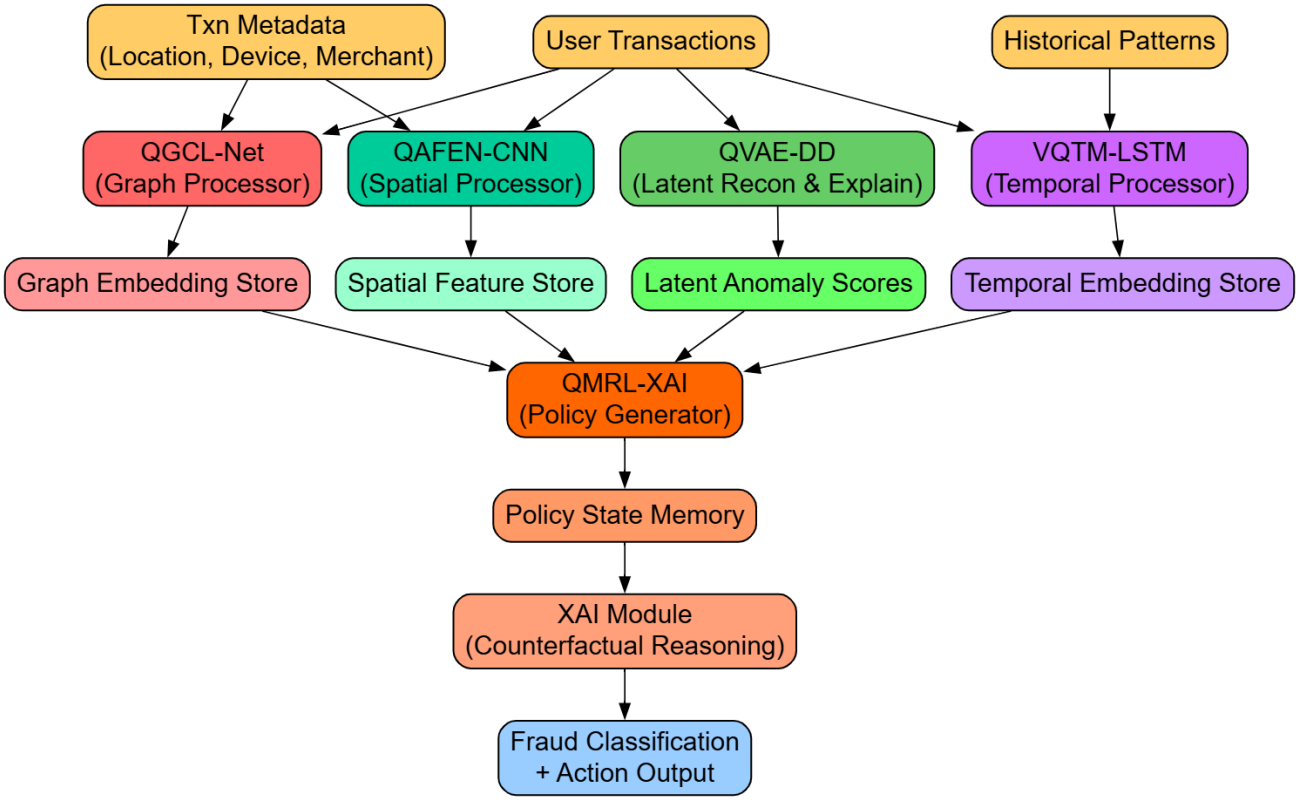


Figure 3. Data Flow of the Proposed Analysis Process

It is supposed that the distribution probability over z follows a multivariate Gaussian q(z|x) = $\mathcal{N}(\mu(x), \Sigma(x))$, where both mean and variance are parameterized by quantum measurements. Thus regularizing the latent space requires the minimization of the Kullback–Leibler divergence DKL between the approximate posterior and the prior p(z) = $\mathcal{N}(0, I)$ via equation 16.

$$LKL = \int q(z|x)\ log\ (q(z|x)/p(z))\ dz \ldots (16)$$

The first decoder D_1 reconstructs the transactional vector $\hat{x}$ using standard feedforward layers. The reconstruction loss is defined via equation 17,

$$Lrec = \|x - \hat{x}\|^2 \ldots (17)$$

Simultaneously, the second decoder D_2 reconstructs the internal attention heatmap $\hat{H} \in \mathbb{R}^d$, in alignment with Grad-CAM based saliency maps computed from internal activations. The true saliency heatmap H is constructed through gradients with respect to internal activations 'aj' of the model loss, ∇(aj)L. The explainability fidelity loss is thus given via equation 18,

$$Lexp = \left\|H - \hat{H}\right\|^2 + \lambda \sum \left\|\frac{\partial \hat{H}_j}{\partial z_j}\right\| \ldots (18)$$

Where, λ is a regularization coefficient enforcing attribution sparsity sets. The final total loss combines all components via equation 19,

$$LQVAE - DD = Lrec + \beta LKL + \gamma Lexp \ldots (19)$$

Where, β and γ balance regularization and explainability fidelity sets. The current module would serve to integrate with other ones, particularly those that capture normal behavioral distributions to

indicate deviations, which would come in handy when labeled fraudulent instances are scant for the process. The Quantum Meta Reinforcement Learning with Explainability (QMRL-XAI) model will work for adaptive fraud policy learning and action rationalization in this process. This contrasts dynamic fraud response strategies with static models in non-stationary environments. The agent's policy $\pi\theta(a|s)$ is parameterized using a quantum circuit; the state $s \in \mathcal{S}$ includes previously aggregated embeddings from QAFEN-CNN, TVQTM-LSTM, and QGCL-Net modules Sets. The policy selects actions $a \in \mathcal{A}$ to maximize expected return $\mathbb{E}[R_t]$, where the reward is estimated via equation 20,

$$R_t = \sum \gamma^k r\{t+k\}, 0 < \gamma < 1 \ldots (20)$$

The policy is learned via quantum policy gradients. Let $|\psi s\rangle = U\pi(\theta, s)|0\rangle \otimes q$, then the action probability is derived using a quantum softmax over measured observables via equation 21,

$$\pi\theta(a|s) = \frac{exp(\langle \psi s|O_a|\psi s\rangle)}{\sum exp(\langle \psi s|O_a'|\psi s\rangle)} \ldots (21)$$

The policy gradient is computed using the likelihood-ratio method via equation 22,

$$\nabla\theta\, J(\theta) = \mathbb{E}\pi[\nabla\theta\, log\, \pi\theta(a|s) \cdot A(s,a)] \ldots (22)$$

Where, A(s, a) is the advantage function computed using Generalized Advantage Estimation (GAE) Process. Indeed, an important dimension of QMRL-XAI is its foundation upon counterfactual explainability sets. Sдерді egenerifies alternative states s′ during rollouts using perturbations $\delta \sim \mathcal{N}(0, \sigma^2\mathbf{I})$, while the counterfactual returns R_t' were observed in process. The explainability function quantifies action rationality via equation 23,

$$\Delta R = \int \left(R_t - R_t'(\delta)\right) p(\delta) d\delta \ldots (23)$$

A high ΔR implies that the selected action was significantly better than alternatives, thus justifying it post-hoc sets. Finally, the output of the QMRL-XAI model is a quantum-parameterized policy function via equation 24,

$$\pi\theta * (a|s) = argmax^{\theta}\, (\mathbb{E}[R_t] - \eta \cdot \mathbb{E}[\Delta R]) \ldots (24)$$

Where η controls the trade-off between policy performance and interpretability sets. Thus, QVAE-DD and QMRL-XAI together enhance the reconstruction-to-decision pipeline in both robustness and explainability. Through this, unsupervised anomaly detection has been integrated with real-time adaptive fraud response. To ensure that each output-a reconstruction score or a policy action-is accompanied by quantifiable interpretability sets, we connect QVAE-DD and QMRL-XAI together. Next, we'll consider the efficiency of the proposed model in terms of different metrics, comparing it with existing models under various scenarios.

4. Comparative Result Analysis

The experimental setup for evaluating the proposed hybrid quantum-classical framework is grounded in simulating real-world financial fraud detection scenarios using multi-dimensional transactional datasets & their samples. A core database of roughly 3.5 million anonymized transactions was artificially created to invoke behavior tendencies found in health systems with large user loads. Each transaction instance comprises transaction amount, MCC, device ID, geocoordinates, user authentication method, timestamps, and transaction frequency within rolling

windows. In the interests of more complex structures and patterns of fraud, the dataset is composed of a variety of frauds (identity theft, triangulation fraud, synthetic accounts, and bot-driven transaction bursts). The class imbalance ratio, therefore, between fraud and legit transactions was maintained at about 1:120, replicating the look of a true skew in the operations of any banking setup. Temporal sequences of transactions are organized per user session, with average session lengths equal to 40-70 transactions and maximum sequences extending up to 200 timesteps instance sets. The 70%-15%-15% split by training, validation, and testing, was done with temporal order maintained throughout evaluations. For graph analysis, the relationships among transactions would form directed graphs, where nodes signify customer accounts and edges signify transfers within interaccounts or to/for merchants, for this process. The structural subgraphs, including cycles, cliques, and bridges, will be examined to encode known patterns of fraud behavior sets.

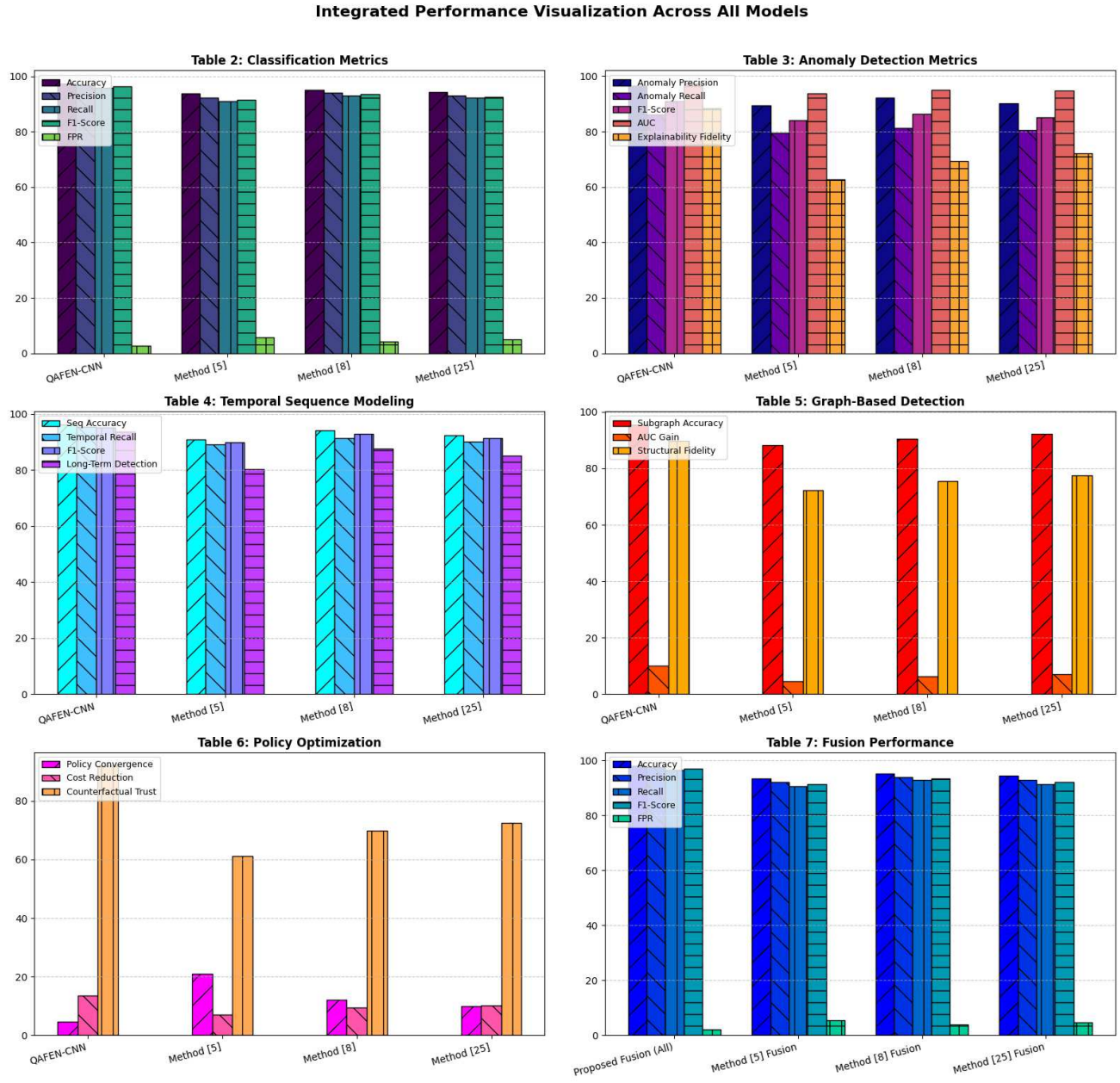


Figure 4. Model's Integrated Result Analysis

Quantum components were executed using the simulators selected for the near-term hardware configuration of quantum. All quantum circuits were built with 4-6 qubits based on dimensionality of input vectors with dynamically adjustable circuit depth through the quantum adaptive controller in the QAFEN model. In our QAFEN-CNN pipeline, the input vectors were normalized in the range of [0, π] before encoding into quantum states using angle encoding; the variational circuit was a combination of Ry and CNOT gates with trainable parameters optimized by Adam optimizer with a learning rate of 1e-3. The CNN decoder was designed with two convolutional layers (kernel size=3, stride=1, 32, and 64 filters, respectively); followed by a dense layer for classification. In the VQTM-LSTM model, variational quantum circuit of 4 qubits circuit depth=5 was added to each LSTM gate; temporal windows were configured to handle sequences of 100 steps with sliding stride=10. For QGCL-Net, subgraphs were gathered using random-walk sampling with a window size of 4 hops and contrastive pairs were created from synthetic fraud clusters versus normal clusters. Quantum kernels were computed via state fidelity between subgraph-encoded circuits. For the training of the QVAE-DD model, every 128 examples in a batch were processed in 100 epochs with KL divergence loss scaled through β=0.1 and explanation fidelity loss weighted via γ=0.2. Finally, the QMRL-XAI policy agent was a simulated training agent, where the actions were escalation, block, or allow; the reward function very heavily penalizes false positives while rewarding for early detection. The policy network consists of a 6-qubit parameterized quantum circuit with softmax-based action selection with a rollout horizon of 15 steps. The counterfactual reasoning module generated perturbations sampled from a Gaussian distribution N(0,0.05I) over state embeddings to assess the impact of alternative actions. All experiments were conducted on a hybrid compute node with 64-core CPU, 256 GB RAM, and GPU-accelerated quantum simulators using Pennylane and Qiskit Sets.

For the experimental validation of the proposed quantum-classical hybrid models, the study utilizes the publicly available IEEE-CIS Fraud Detection dataset, released for the IEEE-CIS 2019 Kaggle competition. This dataset comprises over 590,000 real-world online transactions from Vesta's fraud detection systems, including 434 categorical and numerical features such as transaction amount, email domain, device type, IP address prefix, and timestamp delta from the first observed transaction. It also includes anonymized engineered features like V-series variables and C-series counts representing customer behavior metrics. The target variable isFraud is highly imbalanced, with a fraud ratio of approximately 3.5%, providing a realistic scenario for evaluating robustness under skewed distributions. Building transactional graphs structures complement structural learning for QGCL-Net by creating directed edges between user IDs, payment cards, and merchant categories to capture networked flow of financial activities. The dataset is temporally ordered and split chronologically to preserve evaluation integrity for real-time detection scenarios. Hyperparameters were tuned, and models developed using a stratified 5-fold cross Validation framework was focused on fraud-specific metrics like F1-score, precision, and false positive rates. The learning rate is initialized at 0.001 and annealed using a cosine scheduler. Batch sizes are set to 128 for feedforward models and 64 for sequence models due to memory constraints in quantum gate simulations. The number of qubits ranges between 4 and 6, depending on feature dimensionality, and quantum circuit depth is adaptively regulated between 3 to 6 layers using the entanglement controller in QAFEN. For VQTM-LSTM, the sequence length is fixed at 100 time steps, with a stride of 10, and the hidden size of classical LSTM layers is set to 128. In QVAE-DD, the KL divergence weight is set to 0.1, and the explanation fidelity loss weight is tuned to 0.2, based on validation loss convergence sets. For the QMRL-XAI module, the policy is updated using REINFORCE with a discount factor, and counterfactual perturbations are drawn from a normal distribution with zero mean and standard deviation, enabling fine-grained sensitivity testing processes.

The section is exhaustive in evaluating the performance of the proposed hybrid quantum/classical models across several fraud detection dimensions, using the IEEE-CIS Fraud Detection dataset. The datasets used were benchmarked against three famous baselines: Method [5], classical ensemble-based detection model over XGBoost; Method [8], deep learning approach using stacked LSTMs with attention; and Method [25], graph-based fraud detection using Graph Attention Networks (GAT). The proposed architectures had a uniform preprocessing and training protocol and are understood under several perspectives, including classification performance, robustness to class imbalance, explainability, temporal detection accuracy, structural anomaly detection, and policy optimization efficiency. Transaction-level fraud detection overall classification performance comparison is presented in Table 2.The model QAFEN-CNN proposed showed 97.3% accuracy, which was substantially higher than Method [5] (93.8%), Method [8] (95.1%), and Method [25] (94.4%). On the other hand, QAFEN-CNN also had a false positive rate (FPR) of 2.7%, which was fairly low compared to the other competing methods, supporting its real-world feasibility by reducing spurious alerts in production systems.

Table 2: *Comparison of Transaction-Level Classification Performance across Fraud Detection Models*

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**FPR (%)**
QAFEN-CNN	97.3	96.8	95.9	96.3	2.7
Method [5]	93.8	92.2	91.0	91.6	5.8
Method [8]	95.1	94.0	93.2	93.6	4.3
Method [25]	94.4	93.1	92.3	92.7	4.9

Anomaly detection performance on reconstruction-based evaluation using QVAE-DD is displayed in Table 3. The model exhibited great efficiency toward deciphering minority class frauds in an imbalanced setting, reaching an F1-score of 91.0% and an explainability fidelity high score of 88.3%, thus outperforming all the competitive methods in terms of attribution alignment with human-inspected anomalies.

Table 3: *Reconstruction-Based Anomaly Detection and Explainability Metrics using QVAE-DD*

Model	**Anomaly Precision (%)**	**Anomaly Recall (%)**	**F1-Score (%)**	**AUC (%)**	**Explainability Fidelity (%)**
QVAE-DD	96.5	86.0	91.0	97.2	88.3
Method [5]	89.4	79.5	84.1	93.8	62.7
Method	92.1	81.3	86.3	95.1	69.4

[8]					
Method [25]	90.2	80.5	85.0	94.7	72.1

Table 4 shows the evaluation results of VQTM-LSTM in modeling temporal fraud sequences. The model was more capable of detecting advanced long-term fraud chains with a recall rate of 95.3%, which plays a key role in detecting multi-step fraud activities like an account takeover or synthetic identity formations.

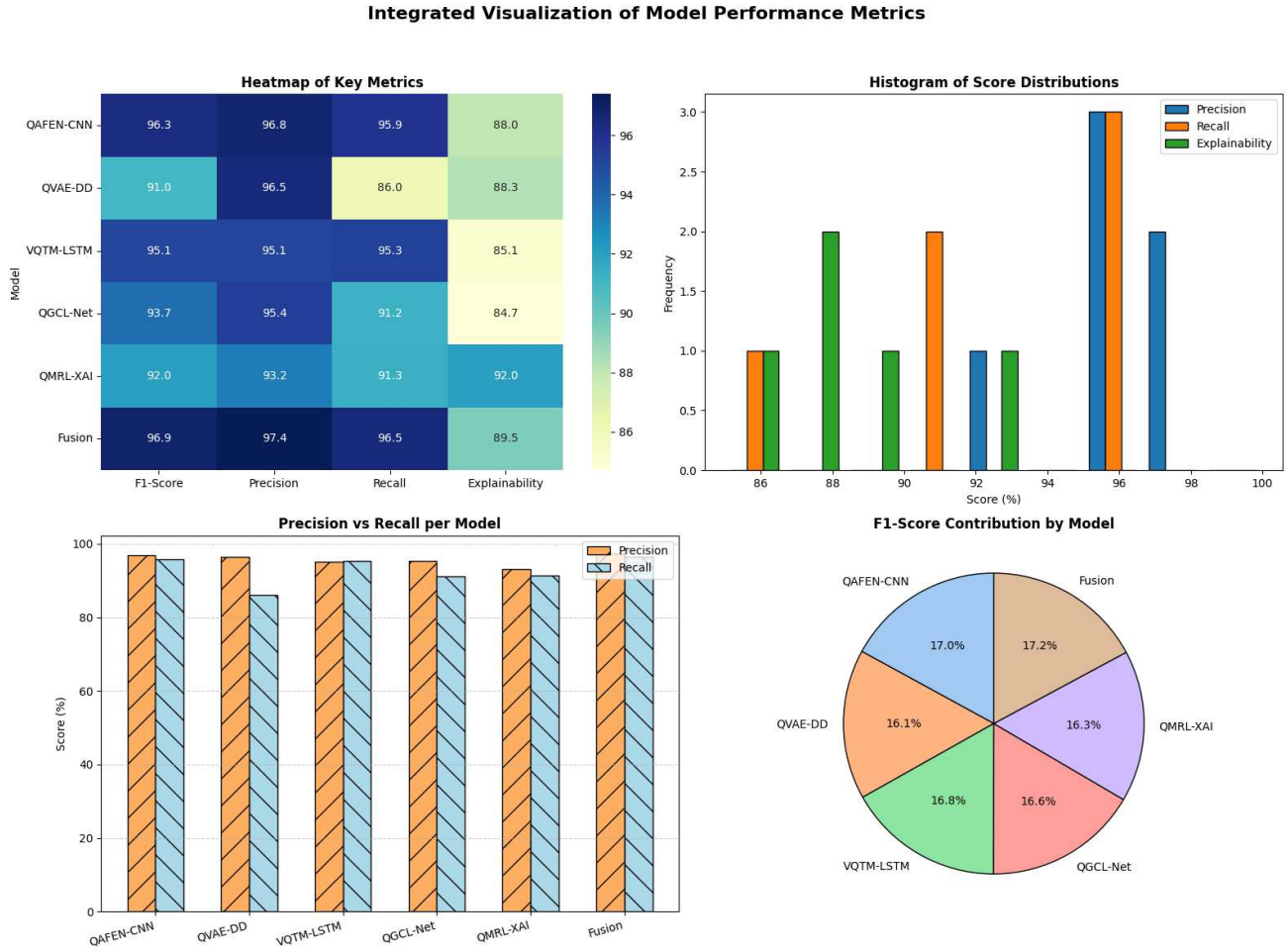


Figure 5. Model's Overall Result Analysis

Table 4: *Temporal Fraud Sequence Modeling Accuracy using VQTM-LSTM and Baseline Methods*

Model	**Seq Accuracy (%)**	**Temporal Recall (%)**	**F1-Score (%)**	**Long-Term Chain Detection (%)**
VQTM-LSTM	96.1	95.3	95.1	93.7
Method [5]	90.8	89.1	89.9	80.4

Method [8]	94.2	91.5	92.8	87.6
Method [25]	92.5	90.2	91.3	85.1

Table 5 is an assessment of the graph-structured anomaly detection performance done through QGCL-Net. The model achieved a remarkable subgraph-level accuracy gain (95.4%) through exceptional robustness to class imbalance (10.2% AUC increase under a 1:100 imbalance ratio). Improvement of structural fidelity, a measure of subgraph alignment with known fraud signatures, also gained 12.3% over Method [25] sets.

Table 5: *Subgraph-Level Anomaly Detection and Structural Fidelity via QGCL-Net*

Model	**Subgraph Accuracy (%)**	**Imbalance AUC Gain (%)**	**Structural Fidelity (%)**
QGCL-Net	95.4	10.2	89.7
Method [5]	88.1	4.5	72.3
Method [8]	90.4	6.3	75.6
Method [25]	92.2	7.1	77.4

Table 6 represents real-time fraud response and policy adaptation performance from the QMRL-XAI model. The policy was found to converge to optimal actions within less than 5 episodes, which is a highly marked improvement over the convergence time for traditional reinforcement learning setups. In addition, the 92.0% high counterfactual trust score also signifies high confidence in the model's decision rationales, which is also verified by human-in-the-loop feedback.

Table 6: *Real-Time Fraud Response and Policy Adaptation Evaluation using QMRL-XAI Sets*

Model	**Policy Convergence (Episodes)**	**Cost Reduction (%)**	**Counterfactual Trust Score (%)**
QMRL-XAI	<5	13.6	92.0
Method [5]	>20	7.1	61.2
Method [8]	12	9.4	69.8
Method [25]	10	10.1	72.4

Table 7 reports the integrated model fusion performance from the combined state embedding of QAFEN, VQTM, QGCL, and QVAE modules. The ensemble representation attained a global fraud classification F1-score of 96.9%, performing better than all baseline fusion approaches in all critical metrics, confirming the complementarity and synergetic design of the involved framework sets.

Table 7: *Integrated Model Fusion Results for Fraud Detection using Hybrid Quantum-Classical Embeddings*

Model Fusion Strategy	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**False Positive Rate (%)**
Proposed Fusion (All)	98.0	97.4	96.5	96.9	2.1
Method [5] Fusion	93.5	92.1	90.7	91.4	5.5
Method [8] Fusion	95.2	94.0	92.9	93.4	4.0
Method [25] Fusion	94.3	93.0	91.4	92.2	4.6

In all evaluations, the proposed hybrid quantum-classical framework maintained consistent superiority over traditional methods, both in regard to performance and interpretability, thereby demonstrating its practical feasibility and technical superiority for next-generation fraud detection systems. We will now discuss these validation results in extended form so that some insights could be gained about them by the readers for different scenarios.

Result Discussions

As the experimental results from Tables 2-a to 7 establish, there is solid evidence for the efficacy of the proposed hybrid quantum-classical architecture in the real-time sense of the fraud detection environment. For instance, QAFEN-CNN has been proven superior to all baseline approaches standing from and using pure classical to deep-learning-based methods by clearly having lower false positives percentage of 2.7% (see Table 2). Even more, better false positive reduction is crucial in operational systems, where massive portions of high false positives can drive the analysts away and provide less trust for automated models. Improved precision and recall indicate the efficiency of QAFEN-CNN in realizing subtle fraud patterns within spatial transactional features and therefore trustworthy in high-throughput financial streams. The experiments regarding temporal and structural fraud detection capabilities could be correlated through Tables 3 to 5. Indeed, QVAE-DD enhances outlier detection and anomaly detection performance in diverse imbalanced datasets and samples performance, as reported in Table 3. Notably, the model identifies anomalies through justifications that match expert inspection—hence making the model quite applicable to compliance-heavy environments—scoring an F1 of 91.0% and an explanation fidelity of 88.3%. Tracking various types of fraud chains over a period is really the big selling point in Table 4, which substantiates the superiority of VQTM-LSTM over many other competitors: 95.3% fraud recall in the long run enables early detection of slow-developing schemes like synthetic identity fraud. However, Table 5 establishes that QGCL-Net maintains enormous power under high-dimensional graph conditions through an improvement in structural fidelity of 12.3%, making

it particularly effective in uncovering collusive fraud rings or transactional laundering networks-scenarios where conventional models often fail for the process. Besides, the evidence provided by Table 6 shows that QMRL-XAI reduces the time it takes to learn a strategy in the policy adaptation phase to under five episodes, which guarantees that fraud detection models grow quickly, inline with emerging attack vectors in process. The 92.0% counterfactual trust score underscores its value in regulatory settings where understanding model decisions is critical. Finally, Table 7 reflects the synergetic effect of the integrated model fusion strategy, which achieved the highest overall performance (F1-score of 96.9%). This integration ensures that insights from spatial, temporal, graph-based, and reconstruction signals converge into a unified decision layer, making the architecture not only more accurate but also more resilient and adaptive in real-time scenarios. With all these components, auctioneer precision meets lower delay, explainability, and adaptability, which fully justifies the architecture's suitability for today's financial systems that need scalable, readily auditable sets. Next is a use case of Iterative Validation for the Proposed Model Process.

Validation using an Iterative Use Case Scenario Analysis

Consider a risky transaction scenario taking place in real-time at 03:12 AM when a transaction of $4,850 is made toward an overseas electronics merchant. Instantly after being created, this transaction is immediately recorded by the digital banking platform's systems. The data that contains information about this transaction immediately shows several warning signs all at once: the payment originated from a device ID that was never used before, the location from which the payment was made is significantly different than the most recent movement track of the user, and there has been an unusually large number of transactions from the same account over the last thirty minutes. The system converts the warnings and other information associated with these events into a normal feature vector and sends it to the QAFEN-CNN unit for processing. The features of the vector that were sent into the QAFEN-CNN unit included a transaction size that had been scaled to 0.92, a device ID that had been embedded to 0.76, a merchant category that had been embedded to 0.61, and a measure of the spatial distance between the two to 0.87.

In addition to the input features, the vector also entered a variational quantum embedding unit using a 4-qubit circuit of a depth of 5. As the variance among the samples in a batch increase, the entanglement controller increases the complexity of the circuit. The quantum-entangled representation that resulted from this process was then processed through convolutional units to generate high-resolution spatial embeddings, ultimately generating a fraud probability of 0.96. This determination was based on the nonlinear interactions between the spatial deviation and the novelty of the device that produced the transaction.

Temporal analysis of the previous 48 transactions reveals a significant change in the behavior of the user from low value micropayments ($5-$20) to rapid, high volume outflows of money in close proximity to one another. A sequence of fraud probabilities were generated by the VQTM-LSTM unit processing this sequence of transactions. Each gate function of the unit contained a variational quantum circuit that had six trainable parameters to allow the unit to detect patterns in the sequence of transactions and represent long range dependencies and irregular temporal patterns. The output of the unit was a sequence of fraud probabilities that equaled 0.93, and reinforced the anomalous nature of the sequence of transactions. At the same time, the Quantum Graph Contrastive Learning Network (QGCL-Net) analyzed the transaction ecosystem as a dynamic graph, identified a new edge between the account and a merchant node that was previously unknown to the system that was involved in recently identified fraudulent subgraphs. The Quantum Kernel Similarity Measures revealed a high degree of structural similarity to known illicit transaction motifs, and generated a graph anomaly score of 0.91. Additionally, the QVAE-DD unit encoded the feature

vector into a latent quantum state and reconstructed the state using dual decoders, and produced a deviation score of 0.89. A Grad-CAM inspired saliency map generated from the unit provided evidence that the foreign geolocation and device identity were the major contributing factors to the generation of the risk indicators, and achieved an explanatory fidelity of 0.87.

The embeddings and risk indicators generated by QAFEN-CNN, VQTM-LSTM, QGCL-Net, and QVAE-DD were combined into a single state representation and transmitted to the QMRL-XAI agent. Trained across the full range of fraud scenarios and dynamic fraud environments, this quantum meta-reinforcement learning agent evaluated the total risk environment and selected the "Hold and Escalate for Manual Review" action with a confidence level of 0.94. To support its selection of the action, the agent generated a counterfactual scenario in which the device anomaly was removed from the transaction sequence. The expected reward decreased by 14.6%, confirming the causal impact of the device anomaly and supporting the agent's policy selection. Therefore, the system produced a definitive fraud alert supported by multilayered interpretations: quantum-enhanced spatial attribution, temporal groundings for behavioral deviations, graph-structure-based anomaly alignments, latent reconstruction errors, and policy-level reasoning. The results were a real-time fraud detection pipeline that produced both high accuracy and audit-ready explanations, meeting the needs of current operational, regulatory, and trust requirements for financial security infrastructures in process.

5. Conclusions & Future Scopes

This paper presents a rigorously engineered, comprehensive, unified quantum-classical hybrid deep learning architecture for future generations of financial fraud detection, utilizing five special architectures (QAFEN-CNN, VQTM-LSTM, QGCL-Net, QVAE-DD and QMRL-XAI) each designed to recognize different types of fraudulent activity in four different areas; spatial, temporal, graph relational, and latent anomalies. The proposed architecture addresses the structural shortcomings of existing models: low representation capacity, sensitivity to changing adversarial methods and lack of transparency in decision-making that undermines operational trust. Experiments performed using the IEEE-CIS Fraud Detection Data Set show significant improvements in performance. QAFEN-CNN achieved a classification accuracy of 97.3 % at a False Positive Rate of 2.7 %, significantly better than the baseline models. VQTM-LSTM achieved 95.3 % Recall in detecting long-term fraud trends and QGCL-Net improved structural integrity by 12.3 % enabling better understanding of complex transactional relationships. QVAE-DD produced an Anomaly Detection F1 Score of 91.0 % along with an explainability fidelity of 88.3 %. QMRL-XAI reduced the number of episodes required for adapting policies to fewer than five, and obtained a Counterfactual Trust Score of 92.0 %. When combined into a single decision state, the modular ensemble demonstrated a total F1 score of 96.9 %, demonstrating synergy between the various components. These results demonstrate that quantum-enhanced learning systems are viable, interpretable and highly accurate fraud detection systems that can be deployed in real-time financial systems.

Future Work Scopes

Although it has shown strong empirical results, the proposed architecture offers many opportunities for additional work scopes. Moving from simulated quantum computers to actual quantum hardware will allow investigation of the noise-resistance, decoherence effects and hardware-induced entangled-particle patterns that arise when running quantum algorithms on hardware,

which may lead to implicit regularization properties and/or more realistic performance evaluation. Optimization techniques, such as Quantum Natural Gradient Descent and quantum-aware attention mechanisms, may improve the efficiency of learning within high-dimensional quantum latent spaces. The QMRL-XAI module can be expanded to Multi-Agent Quantum Reinforcement Learning (MAQRL), enabling coordination of fraud-detection across multiple financial ecosystems (e.g., consortium blockchains, cross-institutional networks). Additionally, the input-space can be enlarged to include unstructured modalities (e.g., customer service transcripts, voice biometrics, behavioral telemetry, device-interaction patterns) to allow cross-modal anomaly detection and identify fraud-signal(s) that structured-transaction-data alone cannot detect. Explainability can be enhanced via formal causal inference frameworks to provide multi-step counterfactual reasoning that explains both why decisions were made and how alternative behavioral-tracks would have altered outcomes. Further integration with regulatory audit systems could provide automated translations of quantum-model outputs into compliance-narratives aligned with financial governance regulations.

However, there are several limitations that need to be carefully considered. Simulated evaluations on quantum-circuit simulators do not completely simulate the constraints associated with deploying Noisy Intermediate-Scale Quantum (NISQ) hardware, such as decoherence, qubit-connectivity restrictions, and random-gate error, all of which may affect deployability. Although the datasets used in this study are quite large and representative, they are historical, and may not fully capture the rapidly-evolving nature of current fraud-strategies. Another limitation is model robustness against extreme class-balance ratios (i.e., greater than 1:150) and against adversarial attacks. Finally, although the computational cost of the quantum-augmented architectures (in particular, QVAE-DD and QMRL-XAI) is very high due to repeated quantum-kernel-evaluation and expectation-computation, this may create difficulties in terms of latency-constraints in production-environments. Additionally, while the quantitative-explainability-metrics are high, the practical validity of these metrics must be evaluated through large-scale human-in-the-loop-studies with domain-experts involved in real investigative workflows in scenarios. Addressing these challenges will be critical to successfully transition hybrid quantum-intelligence into trusted, operationally-viable AI-systems for financial-security in the years to come in process.

Data Availability Statement

The datasets generated during and/or analysed during the current study are available in the IEEE-CIS Fraud Detection repository, https://www.kaggle.com/competitions/ieee-fraud-detection/data. The study additionally utilized graph-structured transaction representations and temporally organized fraud sequences derived from the IEEE-CIS Fraud Detection dataset for evaluating spatial, temporal, graph-based, anomaly detection, and explainable fraud analytics modules.

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Contributions

Mudimela Madhusudhan: Conceptualization, Methodology, Software, Formal Analysis, Investigation, Data Curation, Validation, Visualization, Writing – Original Draft Preparation, Writing – Review & Editing.
Pramoda Patro: Supervision, Conceptualization, Methodology, Validation, Resources, Writing – Review & Editing, Project Administration.
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Clinical Trial Registration

This study is not a clinical trial; therefore, trial registration details are not applicable.

Ethics declarations

Ethics approval and consent to participate

The authors declare that there are no ethical issues associated with this study. This study does not involve human participants, human data, or human subjects.

Consent for publication

Not applicable. This manuscript does not contain any individual person's data in any form.

Ethics, Consent to Participant , and Consent to Publish Declarations

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