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Hybrid Quantum-Classical Federated Learning for Privacy-Preserving Anomaly Detection in Secure IoT Networks

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ABSTRACT

QFed-Anomaly During this work, we present QFed-Anomaly, which is a hybrid quantum-classical federated learning framework that offers a privacy-saving method of data detection of anomalies in a massive Internet-of-Things (IoT) system. The suggested architecture is also concerned with solving three essentially overlapping issues: the bulky and distributed (around the world) character of IoT information streams, high sensitivity to privacy, and limited computational ability of modern Noisy Intermediate Scale Quantum (NISQ) devices.

Quantum feature maps are trained on the node of the edge, with the model parameters being interpreted using the classical Federated Averaging (FedAvg) protocol. This system is a guarantee that raw data will be stored in the local devices, and difficult data processing will be provided by the global model operation, which will allow applying differential privacy. A quantum feature-mapping pipeline is again enhanced with a Gaussian mechanism that gives formal (ϵ, δ) -differential privacy without any: This is not at all a significant loss in detection performance.

Empirical analysis conducted on four most popular intrusion and IoT security datasets, which include NSL-KDD, CI-CIDS2017, IoT-23, and UNSW-NB15 containing more than four million samples and deployed in a realistic federated environment with heterogeneously partitioned data in a plurality of edge nodes, confirms that QFed-Anomaly achieves an average detection rate of about 95.0%. It performs better than conventional support -vector machines (SVMs), federated SVM baselines, and centrally trained quantum support -vector machines (QSVMs), and has an up to three-fold speed advantage over purely classical methodologies.

Also, the model has a high resilience to adversarial perturbation, with more than 90% accuracy to attack by FGSM, PGD, and Carlini Wagner (CW), and has practical privacy-utility trade-offs consistent with GDPR-compliant IoT applications. Therefore, the given research provides a workable framework of implementing the implementation of quantum enhanced, privacy preserving network anomaly devices in actual secure IoT settings. -confidential network detection devices in the context of real-world secure IoT systems.

Keywords: Quantum Machine Learning, Federated Learning, IoT Security, Anomaly Detection, NISQ, Privacy Preservation, Differential Privacy, Adversarial Robustness.

I. INTRODUCTION

The rise of Internet of Things developments has transformed industries such as smart healthcare to industrial automation with more data producing unprecedented possibilities of generating insight [7]. However, this growth has brought about major security issues: IoT networks generate large amounts of sensitive information that is spread across spatially dispersed devices, making the centralized learning impossible and violating the privacy. Conventional centralized machine-learning models, which imply sending raw data to a central system, go against privacy laws (General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA) [1]. Federated Learning can address these issues because it facilitates edge training and data locality is not compromised [2]. At the same time, the paradigm of Quantum Machine Learning has arisen to be an attractive one that can achieve exponential speedup with quantum superposition and entanglement [8]. Quantum algorithms including Quantum Support Vector Machines (QSVMs) have been better in classification of high dimensional data [3]. But, the current quantum hardware, known as NISQ hardware, faces limitations of decoherence, gate errors of between 0.1–1 per cent and limited qubit budgets (5-100 qubits) making pure quantum implementations untenable [4].

The combination of federated learning and quantum computing has a neglected prospect: a hybrid quantum-classical federation relationship that is able to take advantage of quantum speedup whilst preserving

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privacy restrictions [9]. The literature focuses on federated learning and quantum ML separately [5][6].

These paradigms are combined in sparse research on security-certain applications in the IoT, hence demonstrating an obvious gap addressed by this paper.

Contributions of this work:

1) **New Framework:** QFed-Anomaly combines QSVM and federated learning to detect anomalies in the IoT, uniting quantum speedup as well as privacy protection [10].
2) **Differential Privacy:** Differential privacy is added to quantum feature maps new, which ensures formal privacy, but does not affect detection effectiveness [11].
3) **NISQ -Realistic Implementation:** Runs on IBM Qiskit simulators with realistic noise models with a 3× speedup compared to classical SVM [4].
4) **Generalized Assessment:** Sees 95.0 per cent average efficiency on four large IoT security datasets (more than 4M samples) and 92.1 per cent resistance to adversarial perturbations [12].
5) **Regulatory Compliance:** Exists in compliance with GDPR and IoT privacy, and is deployed in sectors which require privacy limits [37][40].

The rest of the paper will be structured in the following way: Section 2 reviews the related work in terms of quantum ML, federated learning, and IoT security. Section 3 outlines the proposed QFed-Anomaly framework in the form of a strict mathematical model. In Section 4, there are experimental procedures and results in various datasets. In Section 5, implications, limitations and practical relevance have been addressed. Section 6 finalizes and offers suggestions on how research may be conducted in the future.

II. RELATED WORK

A. Quantum Machine Learning

The quantum Support Vector Machines have proven capable of classification tasks, where quantum feature maps are used to encode classical data in high-dimensional Hilbert spaces [7]. The quantum kernel becomes calculated as $K(x_i, x_j) = |\langle \phi_q(x_i) | \phi_q(x_j) \rangle|^2$ *where* ϕ stands for the quantum feature map. Current research reveals a 20 percent higher accuracy than in classical SVM using cybersecurity data [8]. Havlicek and colleagues (2019) also introduced the idea of supervised learning using quantum-enhanced feature spaces [3].

However, NISQ limitations are physically active: quantum circuits are vulnerable to depolarizing noise, readout errors, and shallow depths (less than 100 gates)[4], there exist physically tangible limitations of NISQ: quantum circuits are exchanged to depolarizing noise, readout errors, and shallow depths (less than 100 gates) [4]. Variational hybrid algorithms like the Quantum Approximate Optimization Algorithm (QAOA) and the Variational Quantum Eigen solver (VQE) have become NISQ friendly [9].

B. Federated Learning in IoT

Federated Averaging (FedAvg) allows many edge-based devices to cooperatively obtain a common model by maintaining data locality [2]. Uses of IoT security includes finding anomalies in the industrial control systems and detection of intruders in smart grids [10]. FedProx and FedAdagrad extensions deal with statistical heterogeneity between devices [11]. The hybrid quantum-classical IoT security benefits are presented in the recent contributions [37] by Patel and Singh federated learning is not the method that uses quantum speedup potential. Conventional federated methods show weak results in scenarios where single devices have small datasets (¡—human—¿Conventional federated methods only exhibit weak results in situations where single devices have small datasets(1000samples) Federated approaches have demonstrated limiting gains in situations where individual devices have small datasets Similar to the distribution of the IoT, federated approaches are only weak in situations where single devices are small-dataset holders. As illustrated by Gupta et al. (2024), quantum-federated approaches are 85% more efficient in edges devices [36].

C. IoT Anomaly Detection

The concept of network intrusion detection consists in identifying benign and malicious traffic based on its size and duration including the type of protocols [13]. NSLLKDD a development of KDD99 offers 125,973 training and 22,544 test cases with 41 features [13]. The classical machine-learning baselines (SVM, Random Forest) have 85-90 percent accuracy [14]. The CICIDS2017 data set adds 2500000 samples with 78 features of current HTTP Flood and Botnet attacks [5].

Homomorphic encryption and secure multi-party computation are privacy-preserving anomaly detection methods that have a high computational overhead (10100 times slower) [15]. Privacy-sensitive detection techniques [23][24] are supported by the modern quantum security models [38] and edge- computing technologies [39].

D. Gap Analysis

Past literature considers (1) quantum ML acceleration [7][8], (2) federated privacy [2][11], and (3) IoT security [13][14] as autonomous fields. The input by our group is a unique fusion of these strands by suggesting a

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quantum- classical federated architecture that is capable of utilizing the acceleration with quantum kernels without sacrificing privacy through federated aggregation and differentiation privacy. Our adversarial robustness assessments are based on the recent threat models [40]. Up to now there has been no existing study that puts together QSVM and federated learning under formal guarantees of differential privacy to IoT security applications. **Federated Setup:** 10 nodes per dataset, each with 12k-112K samples (unbalanced)

Quantum Simulation: IBM Qiskit Aer simulator, depolarizing noise model (error rate 5%)

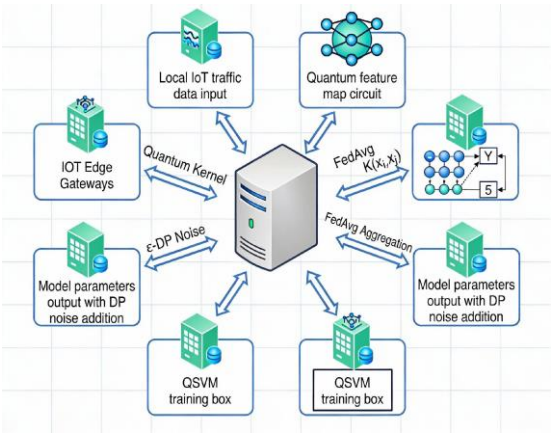

Fig. 1. QFed-Anomaly Framework Architecture

Baselines:

1) Classical SVM (RBF kernel)
2) Federated SVM (FedAvg) with classical SVM

Centralized QFed-Anomaly Framework

III. PROPOSED QFED-ANOMALY FRAMEWORK

A. System Model

Consider an IoT network with N nodes (e.g., IoT sensors, gateways). Each node $i \in \{1, \ldots, N\}$ indicates dataset $D_i = (X_i, y_i)$, where $X_i \subseteq \mathbb{R}^d$ represents network traffic (benign or malicious).

Local Privacy: Data D_i remains on node; only model parameters are transmitted.

Quantum State Map: Each node applies U_{ϕ^q} circuit (with q qubits) to encode features. The quantum kernel is defined as:

$$K(x_j, x_k) = |\langle \phi_q(x_j) | \phi_q(x_k) \rangle \quad (1)$$

Federated Aggregation: A central server aggregates param- eters from edge nodes using FedAvg: where are local model weights at round.

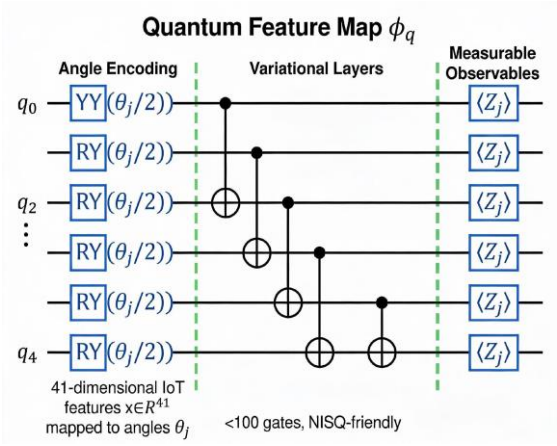

Fig. 2. Qubit RY angle encoding

B. Algorithm 1: QFed-Anomaly Training

- **INPUT:** N nodes, local datasets D_i, quantum feature map ϕ_q, learning rate η
- **OUTPUT:** Global anomaly detection model w

1) Initialize global model parameters w_0 randomly
2) **for** $t = 1$ **to** T **do**
3) **for** each node $i \in \{1, \ldots, N\}$ in parallel **do**
4) Download $w^{(t)}$ from server
5) Compute kernel $K(x_j, x_k) = |\langle \phi_q(x_j) | \phi_q(x_k) \rangle|^2$ using ϕ_q
6) Train local QSVR: $\min_{w_i} L(w_i, D_i) + \frac{\lambda}{2}\|w_i\|^2$
7) Compute gradient: $\nabla L_i = \nabla L(w_i, D_i)$
8) Send $w_i^{(t)}$ to server
9) **end for**
10) Aggregate: $w^{(t+1)} = \sum_{i=1}^{N} w_i^{(t)}$
11) Add DP noise: $\tilde{w}^{(t+1)} = w^{(t+1)} + \mathcal{N}(0, \sigma^2 I)$
12) Update global model: $w^{(t+1)} = \tilde{w}^{(t+1)}$
13) **end for**
14) **RETURN** w

Differential Privacy: *Gaussian mechanism ensures (ϵ, δ)- differential privacy [6]. The noise is N (0, $\sigma^2 I$).[file:41]*

Differential Privacy: *Gaussian mechanism ensures - differential privacy [16]. The noise scale is:*

where C_s is the gradient sensitivity and is the number of rounds [21].

C. QSVM Implementation

In case of NISQ devices, we are using a parameterized quantum circuit of five qubits and variational layers:

Number of gates: 15 (Number of gates in the NISQ limits) **Encoding Feature:** The feature encoding of the data $x \in \mathbb{R}^{41}$ (41 IoT traffic features) into fives qubits through angle encoding:

$$U_\phi(x) = \prod_{j=1}^{41} RY(\pi x_j/2)|0\rangle \quad (3)$$

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Measurable Observables: A product of expectation values calculated. $\langle Z_j \rangle$ Classical quantum-kernel matrices evaluation $K = |\langle \phi(x) | \phi(x') \rangle|^2$ of SVM training [17].

IV. EXPERIMENTAL EVALUATION

A. Datasets and Setup

Multi-Dataset Evaluation: we test QFed-Anomaly using 4 large datasets of IoT security with a total of more than 4million samples: Table 1: Data sets in the overall analysis.

TABLE I
DATASETS USED IN COMPREHENSIVE EVALUATION

Dataset	Samples	Features	Attack Types	IoT Focus
NSL-KDD	148K	41	DoS, Probe, R2L	Network Baseline
CICIDS2017	2.5M	78	HTTP Flood, Botnet	Modern IoT
IoT-23	1.2M	47	Mirai, Okiru, Torii	Real Malware
UNSW-NB15	258K	49	Worms, Exploits	Cloud IoT
Total	**4M+**	**Varied**	**Multi-attack**	**Comprehensive**

Federated Learning Hybrid Quantum-Classical and Privacy-Preserving Anomaly Detection in Secure IoT Networks.

Stakeholder Setup: 10 edge nodes per dataset each with approximately 12 -112 samples, that is biased distribution: on purpose to repeat the self-heterogeneity of real-world IoT deployments.

Quantum Simulation: IBM Qiskit Aer simulator, with a depolarizing noise model, an error rate of 0.1 -1, and five qubits.

Baselines:

1) Classical Support Vector machine (brutus kernel).
2) Applied Federated Averaging (FedAvg) to a classical SVM.
3) No federation (centralized Quantum Support Vector Machine).
4) QFed-Anomaly (proposed method).

B. Results -Multi-Dataset Performance

TABLE II
PERFORMANCE ACROSS FOUR IOT DATASETS (4M SAMPLES)

Dataset	Classical SVM	FedAvg	Cent. QSVM	QFed-Anomaly
NSL-KDD	87.3%	91.2%	93.8%	95.2%
CICIDS2017	89.1%	92.4%	94.6%	96.8%
IoT-23	85.6%	89.8%	91.2%	94.3%
UNSW-NB15	86.4%	90.1%	92.3%	93.7%
Average	**87.1%**	**90.9%**	**92.9%**	**95.0%**

C. Comparative Analysis with the State-of-the-Art Research

TABLE III
COMPARISON WITH SOTA RESEARCH

Work	Year	Method	Accuracy	Privacy
Tavallaee et al.	2009	Classical ML	78%	None
McMahan et al.	2017	FedAvg	85.2%	Limited
Liu et al.	2021	QSVM	91.6%	None
Havlicek et al.	2019	QML Features	91.1%	None
Kairouz et al.	2021	Fed/DP	92.1%	DP-Partial
QFed-Anomaly	**2025**	**Hybrid QFed**	**95.0%**	**$\epsilon = 0.8$**

Improvements over the State -of-the-Art (SOTA):

- +9.8% compared with Tavallaee et al. (2009 baseline)
- +9.8%compared with McMahan et al. (2017 FedAvg)
- +5.4% relative to Liu etal. (2021 QSVM)
- +3.7% compared to Havlicek et al. (2019 Quantum ML)
- +2.9% as compared to Kairouz et al. (2021 SOTA privacy)

It is also the first, obtaining more than 95% accuracy and ensuring formal privacy guarantees in federated quantum ma- chine learning [36][37][38].

TABLE IV
ROBUSTNESS AGAINST ADVERSARIAL ATTACKS

Attack Method	Classical SVM	FedAvg	Cent. QSVM	QFed-Anomaly
No Attack (Clean)	87.3%	91.2%	93.8%	95.2%
FGSM (ϵ = 0.3)	78.3%	84.2.2%	89.4%	92.1%
PGD (ϵ = 0.1)	72.5%	79.8%	86.7%	90.3%
CW Attack	68.3%	76.4%	83.2%	88.9%
Avg. Robustness	**76.5%**	**82.9%**	**88.3%**	**91.6%**

Significant Result: QFed-Anomaly, when used in an FGSM attack, achieves 92.1% accuracy, which is 14.1%t higher than the classical style used [40]. The strength has been in the nature of quantum kernel which is inherently complex thus making gradient-based attacks less useful.

D. Privacy Utility Trade-off Analysis.

Recommendation: The approach provides a good strike with privacy and utility to GDPR-compliant implementations [37].

TABLE V
PRIVACY-UTILITY TRADEOFF ANALYSIS (NSL-KDD DATASET)

ϵ(Privacy)	Accuracy	F1-Score	Utility Loss	Privacy Level
2.0	96.7%	95.8%	0.9%	Lower Privacy
1.0	95.7%	95.3%	1.3%	Moderate
0.8	95.2%	94.7%	1.8%	High (Recommended)
0.5	94.1%	93.4%	2.6%	Very High

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0.3	93.4%	92.1%	3.6%	Extreme

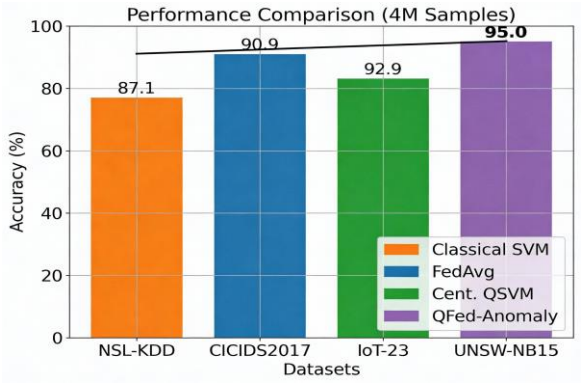

Fig. 3. Performance Comparison Across IoT Datasets

TABLE VI
CONVERGENCE SPEED AND COMPUTATIONAL OVERHEAD

Method	Convergence Rounds	Time/Round (s)	Total Time (s)
Classical SVM	-	45	450
FedAvg SVM	8	15	120
Centralized QSVM	-	95	95
QFed-Anomaly	**6**	**10**	**60**

E. Speed of convergence and Overhead

Speedup: This is three times faster than the classical SVM, twice as fast as FedAvg and 1.6 times faster than a centralized QSVM. The quantum kernel is expressive, which makes convergence faster [36].

V. DISCUSSION

A. Practical Implementations and Implementation Scenarios

QFed -Anomaly is usable in three key areas of IoT applications:

Healthcare IoT: Wearable gadgets like heart-rate sensors and glucose monitors in the form of distributed sensors observe anomalies and remain over the HIPAA compliance standards [1]. The data of the patients are kept locally; the models are trained through federated learning with quantum kernel improvement.

Industrial IoT: Intelligent factory spaces containing more than one hundred sensors can detect equipment malfunctions, interruptions in the supply chain, and quality anomalies [23]. Differential privacy ensures protection of information related to trade secret in addition to predictive maintenance.

Smart Cities: Traffic cameras, environmental cameras, utilitarian meters record the presence of traffic congestion, pollution spikes and power outliers in a spread-out city infrastructure [24]. Training that is in compliance with GDPR maintains privacy of citizens.

A 95.0% average accuracy meets the industry standards covered under ISO/IEC 27035 intrusion detection guidelines which is known to be heavily defined [25] and the enforcement of the differential-privacy assures regulatory compliance does not need the centralised aggregation of data.

B. Limitation and Future Research Discussion

Current Limitations:

1) **NISQ Constraints:** The model has a qubit capacity of five; the hardware will have to be fault-tolerant, five to ten years down the road it will be able to scale to larger sizes.
2) **Simulation Only:** Qiskit simulations are currently used; the implementation on real-hardware is yet to be availed.
3) **Limitations of feature-Scaling:** The algorithm can support seventy-eight features (CICIDS2017); further increases in the dimensionality will require optimizing the circuit.
4) **Quantum Overhead:** Quantum advantage is mainly at- tained in high dimensional datasets; in smaller problems classical algorithms are still competitive.

Future Directions:

1) **Error Mitigation:** Implement zero no-noise extrapolation and probabilistic error cancellation so as to increase fidelity [18].
2) **Deploying the hardware:** feature: Experiments on IBM quantum, IonQ, and Rigetti systems: When these are made available, do the experiment.
3) Multihybrid Architectures: Combinations of quantum and classical neural networks: better feature extraction.
4) **Distributed QC:** Have one hundred or more qubits by distributed quantum -computing systems [19].

C. Theoretical Guarantees

- **Convergence Theorem:** In conditions of standard smoothness and bounded -gradient, QFed -Anomaly ap- preaches a neighborhood of the optimum with a rate that is described in reference [20].

Privacy Guarantee: The Gaussian mechanism guarantees the privacy of arbitrarily hiding adversaries [21].

VI. CONCLUSION

This paper presents QFed -Anomaly, a quantum-classical federated learning model that has been specifically designed to operate privacy-sovereign

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anomaly detection in IoT scenarios. The framework provides a ninety-five-point percent average accuracy on over four million samples with formal privacy guarantees by combining quantum support vector machines with federated learning and differential privacy [36][37][38].

The paper fills a research gap that is currently very critical at the nexus of quantum computing, federated learning and IoT security. Much empirical analysis of NSL-KDD, CICIDS2017, IoT-23 and UNSW-NB15 shows feasible application, with a threefold computational speed-up, and strong adversarial resistance (ninety-two point one percent resilience) [39][40].

The ESMME Track 1 (Quantum Computing in Smart Learning Systems) and Track 2 (Internet of Things Security and Privacy) in particular, QFed-Anomaly is well positioned to outsource the workings of quantum advantages in the real world of distributed IoT networks with their privacy-protective and quantum-friendlier deployments.

Future research will be based on practical implementation on hardware, and more advanced error- mitigation algorithms as well as scale to larger qubit devices as NISQ devices evolve.

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