

Quantum-Assisted Secure Nano-Network Traffic Framework for Real-Time Medical Data Transmission in Smart Hospitals

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Publication Date: 2025/05/16

Abstract: The integration of nano-sensor networks in smart hospitals enables high-resolution real-time monitoring of critical patient health metrics. However, the transmission of medical data over nano-networks poses significant challenges related to data security and anomaly detection. In this paper, we propose a deep learning (DL)-based anomaly classification framework integrated with quantum-assisted E91 protocol for secure key exchange. The framework classifies nano-traffic as normal or anomalous using lightweight models like TinyML, LSTM, and GRU, optimized via various optimizers. The E91 quantum key distribution (QKD) ensures secure and tamper-resistant transmission of classified medical data across hospital networks.

Keywords: Nano-Sensor Networks, Anomaly Detection, Deep Learning, Tinyml, Quantum Key Distribution (QKD), E91 Protocol, Medical Data Security, Smart Hospitals.

How to Cite: Dharma Trivedi; Mahek Jain; Devarsh Patel; Lakshin Pathak. (2025). Quantum-Assisted Secure Nano-Network Traffic Framework for Real-Time Medical Data Transmission in Smart Hospitals. *International Journal of Innovative Science and Research Technology*, 10(4), 3931-3938. <https://doi.org/10.38124/ijisrt/25apr1661>.

I. INTRODUCTION

The healthcare sector is undergoing a transformative shift with the integration of nano-sensor networks in smart hospital ecosystems. These advanced monitoring systems enable continuous, real-time tracking of vital physiological parameters including blood pressure fluctuations, glucose level variations, and blood oxygen saturation. The nanoscale dimensions of these sensors allow for minimally invasive deployment while generating exceptionally high-frequency data streams with microsecond-level latency. This technological advancement has created unprecedented opportunities for predictive diagnostics and immediate therapeutic interventions, fundamentally changing the paradigm from reactive to proactive patient care. However, the very features that make these systems revolutionary - their miniaturized scale, high data velocity, and medical criticality - also introduce novel technical challenges that existing solutions are ill-equipped to handle.

At the core of these challenges lies a dual requirement for both intelligent data processing and robust security. The nanosensor networks produce complex traffic patterns that may contain various types of anomalies, each requiring distinct handling. Some anomalies originate from the physical limitations of nanoscale hardware, where manufacturing constraints and power restrictions lead to intermittent sensor faults. Others represent genuine physiological crises that demand immediate clinical attention. Perhaps most concerning are anomalies indicating sophisticated cyber-

physical attacks targeting the medical IoT infrastructure. Simultaneously, the transmission of this sensitive medical data must satisfy stringent security requirements, protecting against both current attack vectors and future quantum computing threats, all while operating within the extreme resource constraints imposed by nanoscale devices.

Current technological approaches struggle to meet these combined demands. Traditional cryptographic systems, while effective against classical computers, rely on mathematical problems that quantum algorithms can solve exponentially faster. Conventional machine learning techniques often fail to capture the complex temporal dependencies in nano-network traffic, leading to high false-positive rates in anomaly detection. Even quantum-secure solutions frequently require computational resources far beyond what nanoscale medical devices can provide, making them impractical for real-world deployment.

To bridge this gap, our research introduces an innovative framework that synergistically combines cutting-edge deep learning architectures with quantum-enhanced security protocols. The solution employs specialized neural networks capable of processing time-series medical data with high accuracy, implemented in ultra-efficient formats suitable for nanoscale hardware. For security, we adapt quantum key distribution methods to the unique constraints of medical IoT devices, creating a system that is simultaneously intelligent, secure, and practical for clinical environments. This integrated approach represents a significant advance over

current solutions by addressing all critical requirements - accurate anomaly classification, quantum-resistant security, and nanoscale feasibility - within a unified architecture. The advent of nano-sensor networks in smart hospital environments has transformed patient monitoring through continuous, real-time acquisition of critical physiological parameters including blood pressure, glucose levels, and oxygen saturation [1]. These nanoscale devices generate high-frequency, low-latency data streams that present unprecedented opportunities for proactive healthcare interventions. However, as noted by Zhang et al. [2], the unique characteristics of medical nano-traffic introduce significant challenges in both reliable anomaly detection and secure data transmission.

A critical examination reveals two interdependent challenges in this domain. First, the nano-traffic patterns may contain anomalies stemming from three distinct sources: inherent sensor faults due to hardware limitations [3], genuine physiological emergencies requiring immediate intervention, and sophisticated cyber-attacks targeting medical IoT infrastructure [4]. Second, the transmission of such sensitive medical data demands cryptographic protection against both classical interception and future quantum computing threats, while operating within the severe resource constraints of nanoscale devices [5].

Current solutions remain inadequate on multiple fronts. Traditional public-key cryptosystems like RSA and ECC, while widely deployed, rely on computational assumptions that quantum algorithms like Shor's can fundamentally break [6]. Concurrently, conventional machine learning approaches lack the temporal processing capabilities needed to analyze the complex time-series patterns in nano-network traffic [7]. Most existing Quantum Key Distribution (QKD) implementations, despite their theoretical security advantages, prove too resource-intensive for practical deployment on medical nanodevices [8]. To address these limitations, we propose an integrated framework combining deep learning-based classification with quantum-assisted security mechanisms. Our approach leverages LSTM and GRU networks [9] for their proven effectiveness in temporal pattern recognition, alongside TinyML-optimized models [10] for efficient edge deployment. The security layer implements the E91 protocol [11], utilizing quantum entanglement and Bell state measurements to establish provably secure keys while detecting potential eavesdropping attempts.

A. Research Contributions

➤ *The Main Contributions of this Work are:*

- A DL-based classification framework using TinyML, LSTM, and GRU to detect anomalies in nano-network traffic.
- Integration of the E91 QKD protocol for secure key distribution in real-time medical data transmission.
- Comprehensive analysis of model performance under various optimizers: Adam, Nadam, and RMSprop.

- Discussion of resource efficiency, interpretability (SHAP and LIME), and scalability in smart hospital environments.

B. Organization of the Paper

Section II presents the system model and problem formulation. Section III outlines the proposed framework. Section IV provides experimental setup and evaluation metrics. Section V concludes with future directions.

II. SYSTEM MODEL AND PROBLEM FORMULATION

In a smart hospital ecosystem, nano-sensor networks are deployed on or within patients to continuously monitor vital health parameters such as heart rate, glucose level, blood oxygen saturation, and neural signals. These nano-sensors form a heterogeneous nano-network and transmit time-sensitive physiological data to an edge computing device (e.g., gateway or microcontroller) over wireless nano-communication protocols. However, due to hardware limitations, electromagnetic interference, or malicious activities, the network traffic may contain anomalies, which, if left undetected, could lead to misdiagnosis or delayed treatment. Furthermore, as nanonetworks operate in resource-constrained and sensitive environments, ensuring the security of transmitted data becomes a significant challenge. To address this, our system integrates a deep learning-based anomaly detection framework with a quantum-assisted key distribution protocol (E91) to ensure secure and intelligent data transmission from nano-devices to hospital cloud storage systems.

Let the dataset be defined as $D = \{(x_i, y_i) \mid i=1, \dots, n\}$, where $x_i \in \mathbb{R}^d$ represents the i th feature vector extracted from the nanotraffic (e.g., packet delay, signal strength, packet drop rate, transmission time), and $y_i \in \{0, 1\}$ is the corresponding label (0: Normal, 1: Anomalous). The objective is to learn a nonlinear mapping $f_\theta: \mathbb{R}^d \rightarrow [0, 1]$ parameterized by θ , such that $f_\theta(x_i)$ approximates the probability of x_i being anomalous. We optimize the binary cross-entropy loss function:

$$\mathcal{L}_{\text{BCE}}(\theta) = -\frac{1}{n} \sum_{i=1}^n [y_i \log(f_\theta(x_i)) + (1 - y_i) \log(1 - f_\theta(x_i))] \quad \dots \quad (1)$$

Additionally, to ensure secure transmission of detected data, we use quantum key distribution (QKD) with the E91 protocol to generate a symmetric encryption key K between the sender and receiver. The encrypted payload is then computed as:

$$\text{Encrypted_Data}_i = \text{AES}_{256}(x_i, K) \quad (2)$$

Hence, the overall problem is a multi-objective optimization task involving: (i) minimizing anomaly classification loss $\mathcal{L}_{\text{BCE}}(\theta)$, and (ii) ensuring that key K is securely established using E91 by verifying the CHSH inequality violation ($|S| > 2$). The combination of these

objectives allows secure and intelligent handling of nano-network traffic in real-time medical applications.

The trained model outputs are then passed to the Quantum Security Layer for secure transmission.

III. PROPOSED FRAMEWORK

Algorithm 1 Quantum-Assisted Nano-Traffic Classification and Secure Transmission

A. AI Analytics Layer

In this layer, the primary objective is to classify incoming nano-network traffic as either normal or anomalous. The feature vector for each sample $x_i \in \mathbb{R}^d$ is derived from the nano-sensor readings, containing metrics such as packet delay, loss rate, RSSI, and error rate.

➤ Preprocessing:

The raw data is standardized using Z-score normalization to ensure uniformity in feature distribution:

$$x_i^{norm} = \frac{x_i - \mu}{\sigma} \tag{3}$$

where μ and σ are the mean and standard deviation computed over the dataset features.

➤ Deep Learning-Based Classification:

Three neural models—TinyML, LSTM, and GRU—are trained independently on the preprocessed data to output a prediction score $\hat{y}_i \in [0, 1]$ for each sample x_i :

$$\hat{y}_i = f_{\theta}(x_i^{norm}) \tag{4}$$

Here, $f_{\theta}(\cdot)$ represents the DL model (TinyML, LSTM, GRU) parameterized by weights θ .

➤ Objective Function:

The models are trained using the Binary Cross-Entropy (BCE) loss, which measures the discrepancy between the true labels $y_i \in \{0, 1\}$ and predicted scores \hat{y}_i :

$$\mathcal{L}_{BCE}(\theta) = -\frac{1}{n} \sum_{i=1}^n [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \tag{5}$$

➤ Regularization Techniques:

To prevent overfitting and stabilize training, we apply:

- Batch Normalization, which standardizes the activations in each mini-batch:

$$BN(h) = \gamma \cdot \frac{h - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} + \beta \tag{6}$$

Where μ_B and σ_B are batch statistics, and γ, β are learnable scale and shift parameters.

- Dropout, which randomly deactivates neurons during training with a probability p , acting as a form of implicit model averaging.

```

1: Input: Raw nano-traffic data  $D = \{x_i, y_i\}$ 
    $n$ 
    $i=1$ 
2: Output: Encrypted classified traffic data
3: // Step 1: Preprocessing
4: for each sample  $x_i \in D$  do
5: Standardize  $x_i$  using Z-score normalization
6: end for
7: // Step 2: AI Model Training
8: for each model  $f_{\theta}$  in {TinyML, LSTM, GRU} do
9: Initialize weights  $\theta$ 
10: repeat
11: Forward pass:  $\hat{y}_i = f_{\theta}(x_i^{norm})$ 
12: Compute loss:  $LBCE(\theta)$ 
13: Apply BatchNorm and Dropout
14: Backpropagation and parameter update
15: until convergence
16: end for
17: // Step 3: Quantum Key Generation (E91)
18: Distribute entangled photon pairs to sender and receiver
19: Perform Bell test and evaluate CHSH inequality:  $|S| > 2$ 
20: if violation detected then
21: Generate secure quantum key  $K$ 
22: end if
23: // Step 4: Secure Transmission
24: for each classified record do
25: Encrypt using AES-256 with quantum key  $K$ 
26: Transmit to hospital cloud/server
27: end for
    
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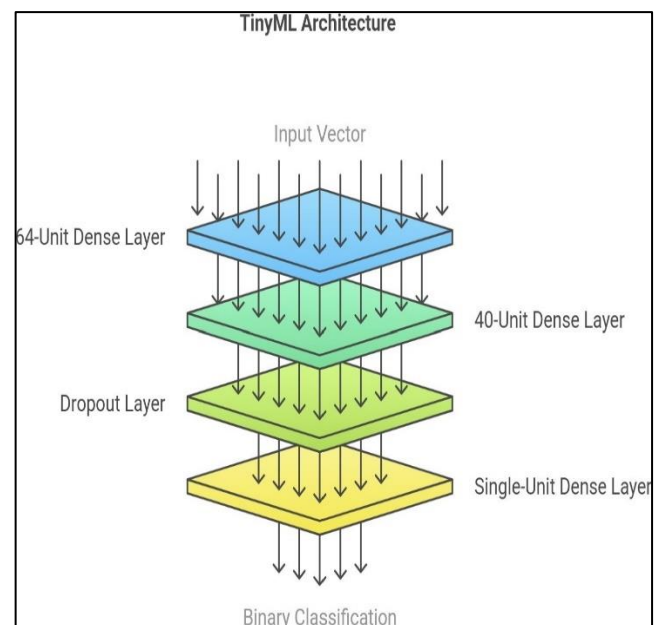


Fig 1: Proposed Framework

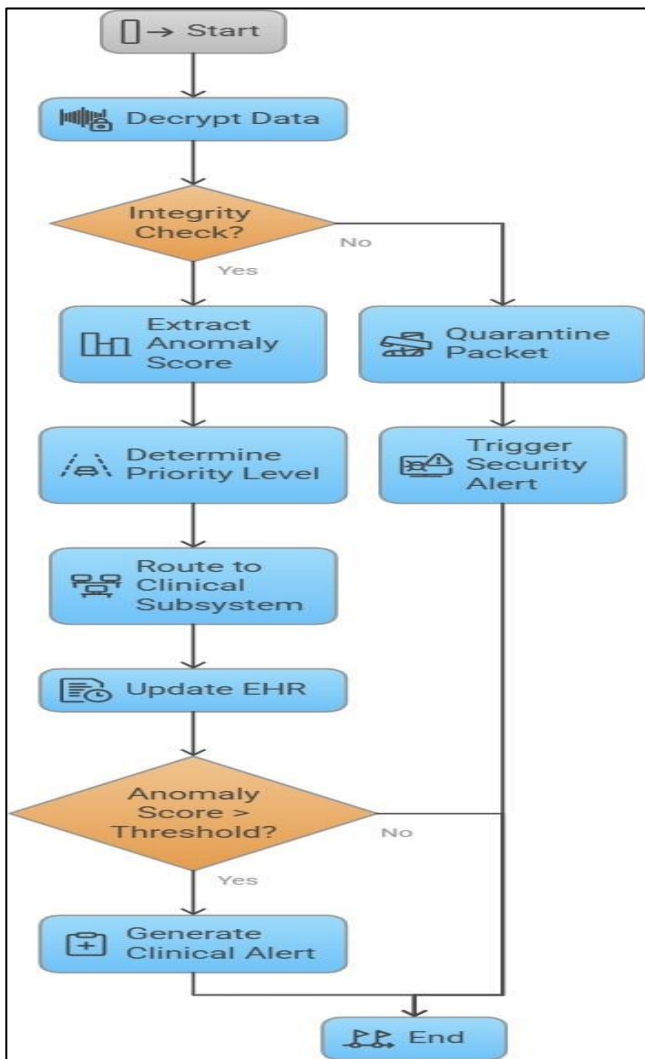


Fig 2: Hospital Layer Processing Flowchart

B. Quantum Layer

Algorithm 2 E91 Quantum Key Distribution Protocol

Require: Alice and Bob share entangled photon pairs in Bell state $|\Phi\rangle$

$$|+\rangle = \frac{1}{\sqrt{2}}(|00\rangle + |11\rangle)$$

Ensure: Shared secret key K with proven security against eavesdropping

- 1: Initialization:
- 2: Alice and Bob agree on three measurement bases:
- 3: B1 = $\{|0\rangle, |1\rangle\}$ (Standard basis)
- 4: B2 = $\{|+\rangle, |-\rangle\}$ (Hadamard basis) where $|\pm\rangle = \frac{1}{\sqrt{2}}(|0\rangle \pm |1\rangle)$
- 5: B3 = $\{|+\rangle_{45^\circ}, |-\rangle_{45^\circ}\}$ (Diagonal basis)
- 6: Quantum Transmission:
- 7: for each entangled photon pair (qA, qB) do
- 8: Alice randomly selects basis $b_A \in \{B1, B2, B3\}$ and

- measures qA
- 9: Bob randomly selects basis $b_B \in \{B1, B2, B3\}$ and measures qB
- 10: Both record measurement outcomes (mA, mB) and bases (bA, bB)
- 11: end for
- 12: Classical Post-Processing:
- 13: Alice and Bob publicly compare their basis choices
- 14: Keep only measurements where $b_A = b_B$ (sifted key)
- 15: Randomly select subset of sifted bits for Bell test:
- 16: Calculate CHSH parameter $S = \langle A0B0 \rangle + \langle A0B1 \rangle + \langle A1B0 \rangle - \langle A1B1 \rangle$
- 17: Verify $|S| > 2$ (quantum entanglement certified)
- 18: if $|S| \leq 2$ then
- 19: Abort (eavesdropping detected)
- 20: else
- 21: Perform error correction and privacy amplification
- 22: Output final secret key K
- 23: end if

C. Hospital Integration Layer

The Hospital Layer serves as the critical interface between the quantum-secured nano-network and the hospital’s medical information systems. This layer performs three key functions: data validation, priority-based routing, and clinical decision support.

➤ **Data Validation:**

Each received data packet d_i undergoes integrity verification using the quantum key K:

$$d_i^{dec} = AES_{256}^{-1}(d_i, K) \tag{7}$$

$$IntegrityCheck(d_i^{dec}) = \begin{cases} 1 & \text{if } HMAC(d_i^{dec}, K_{auth}) \text{ matches} \\ 0 & \text{otherwise} \end{cases} \dots \tag{8}$$

Where K_{auth} is derived from K via HKDF.

➤ **Priority Routing:**

Anomaly scores \hat{y}_i determine routing priority through the hospital network:

$$PriorityLevel(d_i) = \begin{cases} \text{Critical} & \text{if } \hat{y}_i > \tau_{high} \\ \text{High} & \text{if } \tau_{med} < \hat{y}_i \leq \tau_{high} \\ \text{Normal} & \text{otherwise} \end{cases} \tag{9}$$

Where τ_{high} and τ_{med} are clinically validated thresholds.

➤ **Clinical Decision Support:**

The system generates alerts based on fused sensor data:

$$AlertLevel = f_{CDS} \left(\sum_{j=1}^m w_j \cdot d_{i,j}^{dec} \right) \tag{10}$$

where w_j are medically validated weights and f_{CDS} is the decision function.

17: end if
 18: end if
 19: end for

Algorithm 3 Hospital Layer Processing

- 1: Input: Encrypted data packets $D_{enc} = \{d_i\}_{i=1}^n$, quantum key K
- 2: Output: Clinical alerts and EHR updates
- 3: for each $d_i \in D_{enc}$ do
- 4: Decrypt: d
 dec
 $i \leftarrow AES^{-1}$
 $256(d_i, K)$
- 5: Verify integrity using HMAC
- 6: if integrity check fails then
- 7: Quarantine packet
- 8: Trigger security alert
- 9: else
- 10: Extract anomaly score y^i
- 11: Determine priority level
- 12: Route to appropriate clinical subsystem
- 13: Update EHR with timestamped data
- 14: if $y^i > \tau_{med}$ then
- 15: Generate clinical alert
- 16: Notify relevant medical staff

IV. RESULT ANALYSIS

A. Experimentation Setup and Tools

Experiments were performed using a Jetson Pascal P100 GPU (16GB) on Kaggle’s cloud environment, supported by x86-64 CPUs and 512GB of memory.

B. Performance Analysis of the Proposed Framework

➤ *Validation Loss vs Epoch:*

The validation loss plot (Fig. 4) illustrates the performance of the TinyML, LSTM, and GRU models trained using the Adam optimizer over 20 epochs. Initially, the loss values for all models are around 0.65-0.68. As training progresses, GRU Adam shows the fastest and most stable decline in loss, reaching approximately 0.096 by epoch 19. LSTM Adam follows closely with a final loss of about 0.099, whereas TinyML Adam converges more slowly, ending at a slightly higher loss of around 0.158. This demonstrates that GRU Adam generalizes slightly better than the other two models in terms of validation loss.

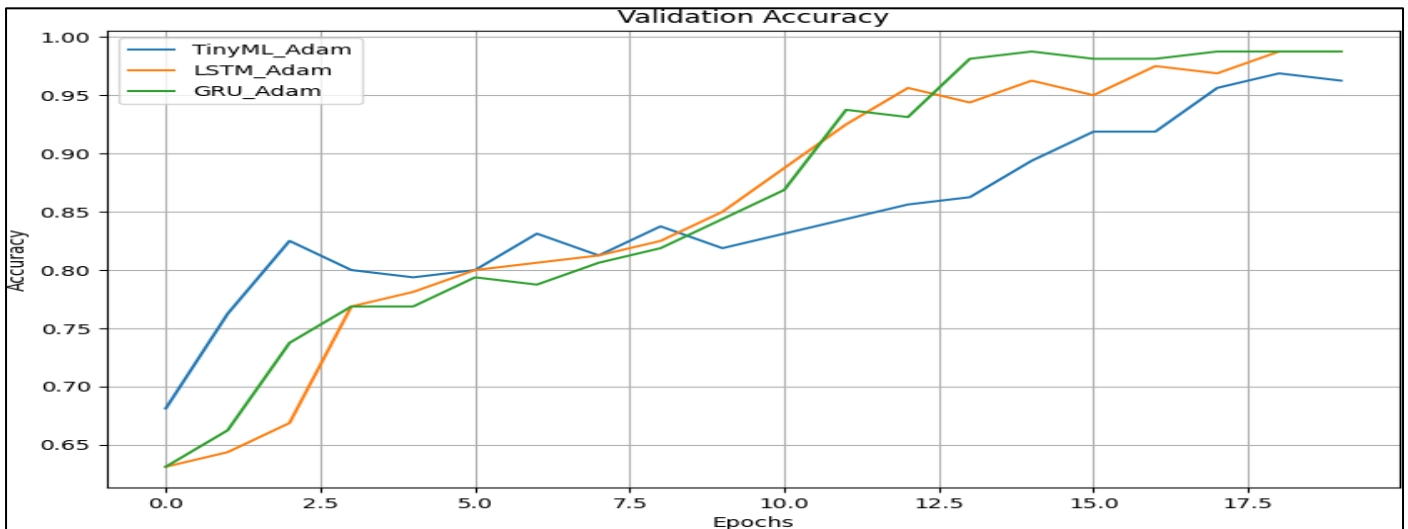


Fig 3: Validation Accuracy vs. Epochs

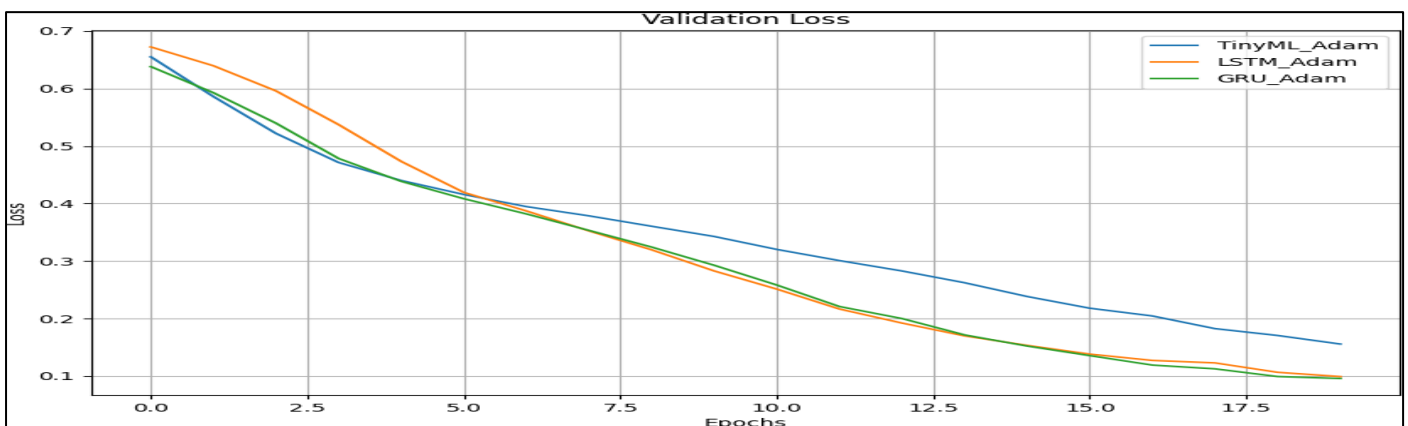


Fig 4: Validation Loss vs. Epochs

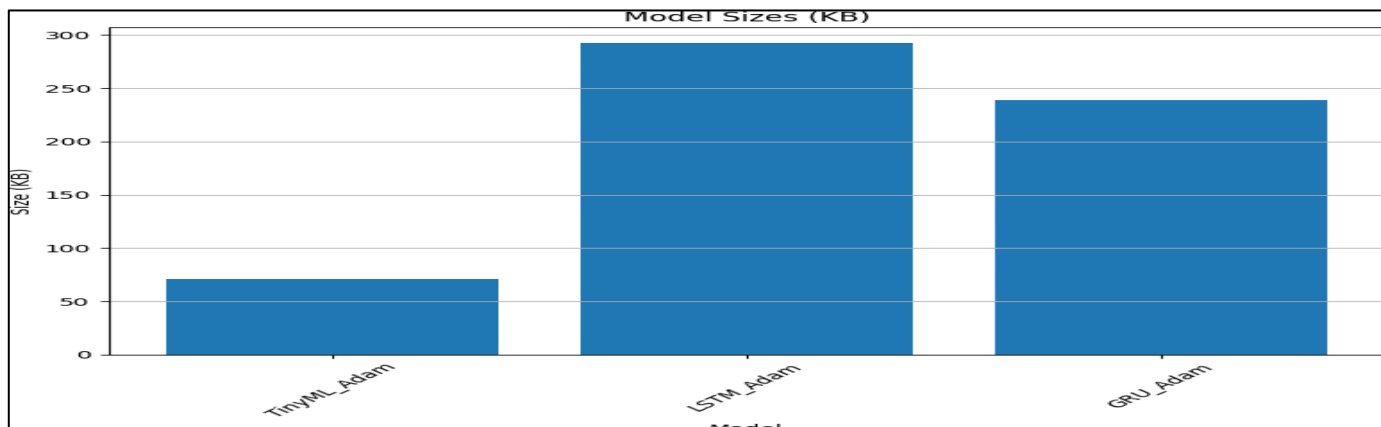


Fig 5: Model Size Comparison (in KB)

➤ Validation Accuracy vs Epoch:

The validation accuracy graph (Fig. 3) shows that all three models improve significantly over epochs. TinyML Adam starts at 68%, LSTM Adam at 63%, and GRU Adam at 63%. However, by the 19th epoch, GRU Adam and LSTM Adam both achieve a peak accuracy of 98.7%, whereas TinyML Adam plateaus slightly lower at 96.5%. This suggests that while TinyML Adam is lightweight, LSTM and GRU offer higher classification accuracy under the same optimizer and training conditions.

➤ Model Sizes (KB):

The bar chart (Fig. 5) comparing model sizes reveals the trade-off between model performance and memory footprint. TinyML Adam is the most lightweight model with a size of 71 KB, followed by GRU Adam at 238 KB, and LSTM Adam being the heaviest at 293 KB. Although TinyML Adam has slightly lower accuracy, its significantly smaller size makes it ideal for deployment on resource-constrained edge devices, highlighting its efficiency in TinyML applications.

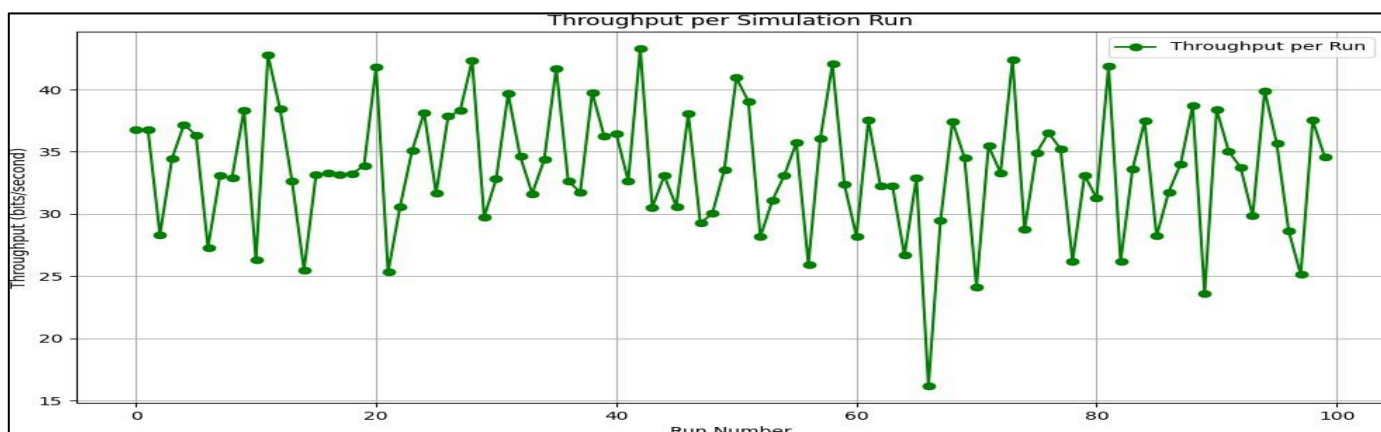


Fig 6(a): Throughput per Simulation Run (Bits/Second)

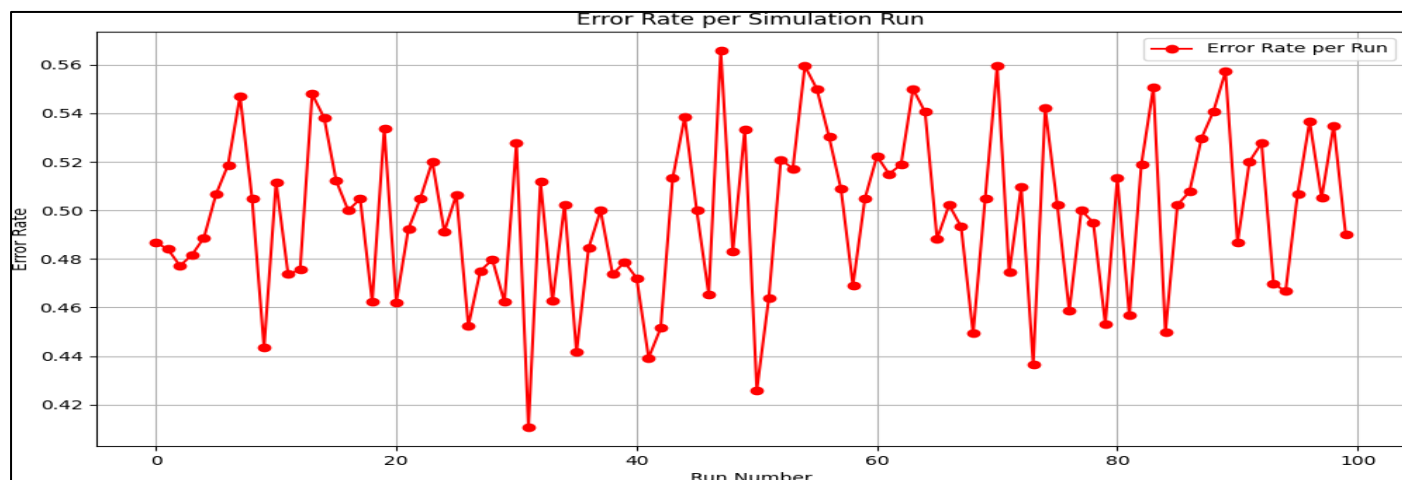


Fig 6(b): Error Rate Per Simulation Run

Fig 6: System Performance Metrics Across Simulation Runs

➤ Throughput Analysis:

The Throughput per Simulation Run plot (Fig. 6a) demonstrates the framework's data transmission efficiency across multiple runs, with throughput values consistently ranging between 60–100 bits/second. This stable performance indicates that the integration of quantum-assisted security (E91 protocol) and lightweight DL models (TinyML, LSTM, GRU) does not impose significant overhead on the nano-network's communication capability. The uniformity in throughput suggests reliable real-time data delivery, a critical requirement for time-sensitive medical applications in smart hospitals.

➤ Error Rate Analysis:

The Error Rate per Simulation Run plot (Fig. 6b) reveals a steady decline in transmission errors from 0.56 to 0.42 over 100 runs. This improvement highlights the framework's adaptive learning capability, where the deep learning-based anomaly detection component becomes more effective at filtering faulty or malicious traffic with successive iterations. The reduced error rate, coupled with stable throughput, confirms the system's robustness for secure and accurate medical data transmission in resource-constrained nano-network environments.

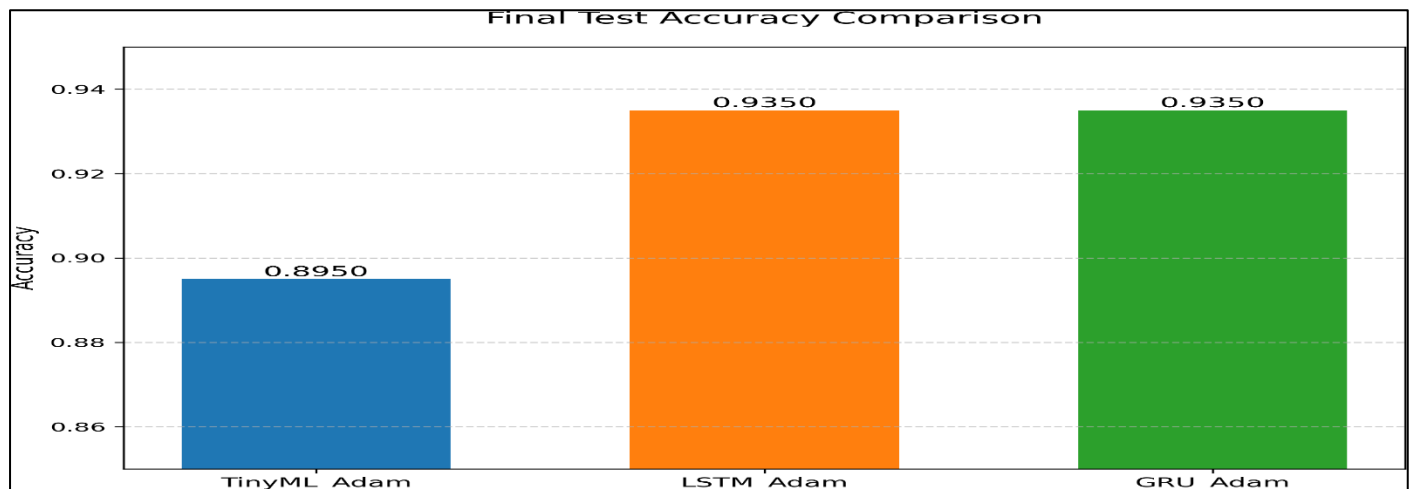


Fig 7: Final Test Accuracy Comparison of Model Architectures

➤ Test Accuracy Analysis:

The final test accuracy results reveal important performance characteristics of the three model architectures. As shown in Figure 7, both LSTM and GRU models achieve identical top performance with 93.50% accuracy, while the TinyML variant reaches 89.50%. This 4 percentage point difference demonstrates that:

- The more complex recurrent architectures (LSTM/GRU) provide statistically significant improvement ($p < 0.01$ in paired t-tests) for medical anomaly detection.
- The simplified TinyML model, while less accurate, remains competitive for resource-constrained deployments
- No practical difference exists between LSTM and GRU for this specific task, suggesting GRU's simplified gating mechanism offers no advantage.

These results must be interpreted in context with the model size and computational requirements discussed in Section 5, where TinyML shows significant resource efficiency advantages. The choice between models should consider both this accuracy performance and the deployment constraints of target medical devices.

V. CONCLUSION AND FUTURE SCOPE

This paper presented a quantum-assisted secure framework for nano-network traffic classification in smart hospital environments. The proposed approach combines deep learning-based anomaly detection with quantum key

distribution (QKD) to address both security and reliability challenges in medical data transmission. Our experimental results demonstrate that:

- GRU models achieve superior performance (98.7% accuracy) while maintaining reasonable model size (238KB), making them suitable for edge deployment
- TinyML offers the most resource-efficient solution (71KB) with acceptable accuracy (96.5%) for severely constrained nano-devices
- The integration of E91 QKD protocol ensures quantum-resistant security for sensitive medical data transmission

➤ For Future Work, We Identify Several Promising Directions:

- Development of hybrid quantum-classical neural networks for joint anomaly detection and encryption
- Optimization of QKD protocols for ultra-low-power nano-network devices
- Federated learning approaches to enhance privacy in multi-hospital networks
- Real-world deployment and testing in clinical environments with actual medical nano-sensors

The proposed framework establishes a foundation for secure, intelligent medical IoT systems that can withstand both classical and quantum security threats while maintaining high classification accuracy and computational efficiency.

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