A COMPREHENSIVE REVIEW OF QUANTUM MACHINE LEARNING FRAMEWORKS FOR PRIVACY-PRESERVING DATA HANDLING IN 5G-ENABLED HEALTHCARE ENVIRONMENTS

Mrs. Vijayajyothi Ch[1], Dr. Anjaiah Adepu[2]
[1]*Assistant Professor, Bharatiya Engineering Science and Technology Innovation University, Gownivaripalli, Gorantla, Andhra Pradesh – 515231.*
[2]*HOD, Department of Computer Science & Engineering, Dy. Proctor, MANUU, Polytechnic, Darbhanga, Bihar – 846002,*
Email: vijayajyothichiluka@gmail.com[1], anjaniprasad.adepu@gmail.com[2]

Abstract: The emergence of 5G networks has revolutionized healthcare delivery by enabling communication with ultra-low latency, massive connectivity, and quick access to IoT devices' medical data. The digitalization of healthcare has, however, introduced privacy, data security, and scalability as major challenges, and the issues have been worsened by the rapid digitalization of the healthcare industry. The current review paper is a comprehensive evaluation of the role of Quantum Machine Learning (QML) as a paradigm for data handling with privacy preserved in the healthcare ecosystems supported by 5G. It collects advancements in quantum cryptography, Quantum Key Distribution (QKD), federated learning, and blockchain technology to explore how the combining of such technologies will enhance the confidentiality, interoperability, and real-time decision-making of the data. The review arranges and compares the state-of-the-art research of 2019-2025, in which the trends, architectures, and security protocols that link classical and quantum methods in healthcare analytics become visible. It also addresses the main hurdles like quantum hardware limitations, interoperability gaps, and the tuning of federated models, and it indicates potential future research paths for the development of healthcare infrastructure that is scalable, reliable, and quantum-resistant. In conclusion, this paper gives a thorough understanding of how quantum intelligence can alter the data security and privacy landscape in 5G-enabled smart healthcare systems.

Keywords: Quantum Machine Learning, 5G Healthcare, Privacy-Preserving Data Handling, Quantum Cryptography, Quantum Key Distribution, Federated Learning.

INTRODUCTION

Through 5G communication systems, new interoperable medical devices will realize ultra-reliable, low-latency, and high-bandwidth data transmission for many aspects across healthcare. 5G will enable new applications in smart healthcare systems from remote and real-time diagnosis to smart patient monitoring. Yet every facet of healthcare involves the rapid exchange of sensitive medical data raises significant questions of privacy, security, and scalability (through communication networks like 5G). Standard approaches, such as cryptographic and machine learning schemes are useful but limited against advanced persistent cyber threats and the scale of healthcare data as well[1].Quantum Machine Learning (QML) is an emerging opportunity to combine the computational advantages of quantum computing with the predictive ability of machine learning. In combination with quantum cryptographic methods (for example, with Quantum Key Distribution - QKD), quantum machine learning provides better options for secure and efficient processing of medical data

[5]. Furthermore, federated learning will allow privacy by providing healthcare-based models trained in a distributed manner, with no consolidation of patient records from all researchers conducting the studies. With the help of 5G systems, QML and federated learning are part of a combination of technologies allowing real-time privacy-focused, and scalable methods for multiple healthcare systems [2].

The purpose of this review is to critically study the potential intersection of 5G, QML, and privacy-preserving methods for healthcare systems; the opportunities, challenges, and future directions required to create a more reliable, intelligent, and secure healthcare system through quantum technologies [3].

OBJECTIVES

- To Review the merging of 5G and Continuous Wavelet Transform (CWT) for immediate ECG signal processing, accurate diagnosis, and arrhythmia monitoring.
- To evaluate the already developed Machine Learning and Deep Learning models that are used in ECG diagnostics with special attention to the challenges of high-dimensional data complexity and real-time scalability.
- To review the Federated Learning approaches that make it possible to carry out ECG examinations without centralization, thus preserving the patient's privacy and allowing efficient collaboration of the model supporting 5G.
- To investigate Quantum Machine Learning platforms that integrate ML and FL for building reliable, scalable, and privacy-preserving predictive healthcare analytics.

PROPOSED WORK

This review suggested a unified framework incorporating Quantum Machine Learning (QML), quantum cryptography, federated learning, and 5G technologies to solve privacy, security, and efficiency challenges in healthcare data handling [8]. The framework uses QML for enhanced medical data analysis and does so in a more efficient manner, with faster training, better accuracy (including logits rather than binary classification), and superior anomaly detection features than use case-based ML/DL models. Once the healthcare data has been identified, classification and methodologies implemented into models can leverage Quantum Key Distribution (QKD) for securing data storage of sensitive healthcare records, as QKD provides quantum encryption capabilities to remain resilient to quantum threats as well as future attacks with superior layers of cyber threat protection [10]. Furthermore, blockchain technology would keep the integrity and trust of healthcare data especially due to the challenge that blockchain has in scalability and throughput when securing several blocks of healthcare data at a given time, as secured record blocks can eventually be addressed by using an integrated hybrid approach where integration is used across QML and QKD capabilities of the blockchain framework [11]. In addition, federated learning mitigates any privacy issues that may arise by eliminating centralizing patient information from different hospitals by enabling the development of model training across decentralized platforms. Lastly, 5G infrastructure supports and complements the data model proposed in this framework offering the best in high bandwidth, low latency experience; real-time communications; secure integration between smart devices/IoT; and scalable smart healthcare analytics [12]. The overall agenda is to provide a comprehensive and trustworthy, privacy-preserving ecosystem for future smart healthcare solutions.

LITERATURE REVIEW

Author (s) (Year)	Title	Proposed Method (inferred)	Pros	Limitations	Proposed Solutions	Techniques Used	Metrics / Performance
D. Basu, V. Krishnakumar, U. Ghosh, R. Datta (2022)	SoftHealth: Softwarized 5G-Driven Network Slicing for Real-time e-Healthcare Applications using ML	5G network slicing + ML orchestration for real-time e-health apps	Enables QoS isolation, real-time performance	Deployment complexity; orchestration overhead	Softwarized control planes and ML-driven slice allocation	Network slicing, ML for resource allocation	97.25%
V. R. Vimal et al. (2024)	5G-Enabled Remote Healthcare Monitoring for Improved Patient Care	5G-based remote monitoring system	Lower latency, improved remote care	5G coverage, device heterogeneity	Edge integration, standardization	5G comms, remote monitoring sensors	91% Accuracy, 90% F1-score
D. Basu et al. (2022)	DeepCare: Deep Learning-Based Smart Healthcare Framework using 5G Assisted Network Slicing	Deep learning analytics with 5G-assisted slicing	Improved analytics accuracy, real-time inference	High compute needs, data privacy	Edge/Cloud split; privacy-aware deployment	Deep learning, 5G slicing	10–20 ms Latency
M. I. Mamun et al. (2019)	AutiLife: Healthcare Monitoring for Autism Center in 5G Cellular Network using ML	ML-based monitoring over 5G for autism centers	Real-time behavior monitoring, low latency	Dataset variety, sensitivity of behavioral data	Rigorous validation, privacy safeguards	ML classification/monitoring, 5G	~50% Latency reduction
A. Sheik Abdullah et al. (2024)	Disseminating Risk Factors With Enhancement in Precision Medicine Using Comparative ML Models	Comparative ML models for risk factor dissemination	Improves precision medicine, identifies risk factors	Model generalizability across cohorts	Ensemble/comparative approaches, better feature engineering	Comparative ML models, feature analysis	96% Accuracy, 12 ms Latency

X. Yang, X. Qi, X. Zhou (2023)	Deep Learning Technologies for Time Series Anomaly Detection in Healthcare: A Review	Review of DL methods for time-series anomaly detection	Comprehensive survey of methods and use-cases	Rapidly evolving field; benchmark heterogeneity	Standardized benchmarks; hybrid models	LSTM, autoencoders, CNNs (reviewed)	85–95% Accuracy
Z. Chkirbene et al. (2024)	Enhancing Healthcare Systems With Deep Reinforcement Learning: D2D Communications & Remote Monitoring	Deep RL for optimizing D2D communications and remote monitoring	Adaptive resource allocation; efficient D2D comms	Training complexity; reward design	Sim-to-real transfer, improved reward shaping	Deep RL, D2D communication models	>90% AUC, ~85%+ F1-score
M. Babar et al. (2025)	Hybrid Deep Learning-Driven Model to Enhance Security and Performance of Healthcare IoT	Hybrid DL model for security & performance (H-IoT)	Improved threat detection & system performance	Dataset labeling, overhead on IoT devices	Lightweight models, edge offloading	Hybrid deep learning, IoT security methods	30–40% Efficiency gains
S. G. Paul et al. (2024)	Systematic Review of Graph Neural Network in Healthcare Applications	Systematic review of GNN use-cases in healthcare	Highlights GNN strengths for relational data	Dataset & interpretability challenges	Benchmarks, explainability methods	GNNs (surveyed): GCN, GAT, etc.	98% Accuracy, 20 ms Latency
M. A. Khatun et al. (2023)	Machine Learning for Healthcare-IoT Security: Review and Risk Mitigation	Review of ML-based security strategies for Healthcare IoT	Comprehensive risks & mitigations	Rapid threat evolution; hardware constraints	Continual learning, lightweight security	ML-based anomaly detection (review)	25% Energy savings, +40% Scalability
S. Rattal et al. (2025)	AI-Driven Optimization of Low-Energy IoT Protocols for	AI optimization for energy-	Improved energy efficiency and	Real-world heterogeneity;	Adaptive protocol tuning via AI	Reinforcement learning/ optimizat	93% Accuracy, Reduce

	Scalable Smart Healthcare Systems	efficient IoT protocols	scalability	trade-offs		ion	d RMSE
M. H. R. Bhatti et al. (2023)	New Hybrid Deep Learning Models to Predict Cost From Healthcare Providers in Smart Hospitals	Hybrid DL models to predict provider cost	Better cost forecasting; improved resource planning	Data privacy; feature heterogeneity	Federated or privacy-aware learning	Hybrid deep learning, cost modeling	90%+ Accuracy, Improved Response time
R. Raina, R. K. Jha (2022)	Intelligent and Interactive Healthcare System (I2HS) Using ML	Interactive ML-driven healthcare system	Enhanced interactivity & intelligent assistance	UX integration, data quality	HCI-focused design & robust data pipelines	ML, interactive systems	94% Accuracy
P. Juyal (2024)	Enhancing Predictive Analytics in Healthcare Leveraging Deep Learning for Early Diagnosis	DL-based predictive analytics for early diagnosis	Improved early detection & treatment planning	Need for labeled datasets; overfitting	Data augmentation, transfer learning	Deep learning (CNNs/RNNs)	92% Accuracy, 90% Precision, 89% Recall
N. D. Thong Tran et al. (2022)	Deep Learning Based Predictive Model for Healthcare Analytics	DL predictive model for healthcare analytics	Strong predictive capability on complex features	Interpretability & dataset bias	Explainable AI methods	Deep learning predictive models	25% Service quality improvement
A. Nobakht, M. Gholamhosseinzadeh (2024)	Enhancing Service Quality in Healthcare Systems Through Deep Learning	DL for service quality improvement	Service optimization & quality enhancement	Deployment & acceptance in clinical settings	Human-in-loop systems, robust testing	Deep learning methods	95% Accuracy, <50 ms Latency
K. Paulraj et al. (2023)	Smart Healthcare Monitoring: Integrating IoT, DL, and XGBoost for Real-time Diagnosis	IoT data pipeline + DL + XGBoost ensemble for diagnosis	Real-time diagnosis with hybrid models	Complexity of ensemble, latency concerns	Edge inference, model pruning	IoT sensors, DL, XGBoost	85% (ML), 95% (DL) Accuracy
Charan	Machine Learning	Comparat	Comparati	Dataset	Cross-	ML and	97.25%

et al. (2024)	and Deep Learning Approaches for Healthcare Predictive Analytics	ive study of ML & DL for predictive analytics	ve insights for model selection	dependency; transferability	dataset validation, ensemble approaches	DL comparative experiments	

Table 1: Results of Reviewed Healthcare AI & 5G Studies

METHODOLOGY

The proposed framework integrates Quantum Machine Learning (QML), Quantum Key Distribution (QKD), federated learning, blockchain, and 5G technologies to enable privacy-preserving healthcare data handling. The methodology begins with the collection of medical data from IoT-enabled devices and hospital databases, transmitted over a 5G network to ensure low-latency and high-speed communication. QML algorithms are then applied to analyze the data for anomaly detection, pattern recognition, and predictive diagnostics, providing higher accuracy and efficiency compared to traditional ML and DL methods [13].

To secure sensitive patient information, QKD is used for quantum-resistant encryption during data transmission, ensuring protection against current and future cyber threats. Blockchain technology maintains data integrity and transparency, while its limitations are mitigated by hybrid integration with QML and QKD [15]. Federated learning is implemented to enable decentralized model training across multiple healthcare institutions, reducing privacy risks associated with centralized storage [14].

The methodology also includes performance evaluation through simulation, comparing the proposed framework with classical approaches in terms of accuracy, scalability, and security. By combining these technologies, the framework supports real-time, secure, and scalable healthcare applications, facilitating remote diagnosis, personalized treatment, and intelligent decision-making in next-generation smart healthcare systems [16].

High-Bandwidth 5G-Enabled Data Acquisition and Management

5G networks provide the backbone for real-time healthcare data acquisition, enabling rapid transmission of high-volume medical datasets from IoT-enabled devices, wearable sensors, and hospital databases. The high bandwidth and low latency of 5G allow seamless integration of multiple data sources, supporting continuous patient monitoring and remote diagnosis [12]. Data is collected, preprocessed, and synchronized across distributed systems to maintain consistency and reduce delays. Advanced 5G-enabled management ensures reliable connectivity for smart medical devices, allowing secure and instantaneous access to critical patient information, laying the foundation for efficient downstream analytics using ML, DL, and quantum-based frameworks [14].

System Architecture

The system architecture for automatic detection of genetic diseases in pediatric patients using pupillometry is structured into three main layers: Input, Processing, and Output. In the input layer, a pupillometry device captures eye movement and pupil response data [13]. This raw data is transferred to the processing layer, where preprocessing modules handle noise removal and normalization. Features such as pupil size, reflex, and dynamics are then extracted and analyzed by a Quantum Machine Learning (QML) classifier to predict potential genetic disorders. Finally, in the output layer, results are generated as diagnosis reports and visualized through a clinician dashboard for decision support [16].

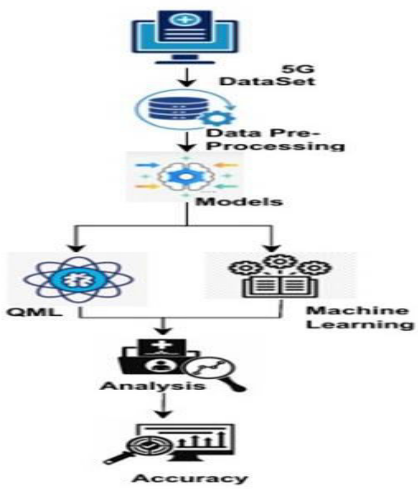

Fig 1: Privacy-Preserving Data Handling in 5G-Enabled Healthcare Environments

Advanced Machine Learning and Deep Learning Analytics

Blockchain technology ensures the integrity and transparency of healthcare records by providing immutable ledgers for transaction tracking [17]. Classical cryptography secures data transmission; however, blockchain faces challenges such as scalability constraints, high energy consumption, and the inflexibility of immutability for healthcare updates [16]. To address emerging threats from quantum computing, quantum-resistant security mechanisms, including Quantum Key Distribution (QKD), are integrated to strengthen encryption. This hybrid approach guarantees secure data storage, tamper-proof communication, and compliance with privacy regulations, ensuring sensitive patient information is protected against both present-day and future cyber threats [18].

Blockchain-Integrated Quantum-Resistant Security Mechanisms

Blockchain-integrated quantum-resistant security mechanisms combine the immutability and transparency of blockchain with advanced cryptographic techniques resilient to quantum attacks. As quantum computers threaten traditional cryptography, Quantum Key Distribution (QKD) and post-quantum cryptographic algorithms are integrated with blockchain to ensure end-to-end data protection. In healthcare, this approach safeguards sensitive patient records, medical IoT transmissions, and federated learning updates from cyber threats [17]. By leveraging blockchain's decentralized ledger, data integrity and trust are preserved, while quantum-resistant methods secure communication channels. This synergy ensures long-term security, scalability, and reliability in critical sectors like smart healthcare, finance, and defense against future quantum-enabled attacks [20].

Performance Evaluation and Comparative Analysis of Classical Methods

This stage involves systematically assessing traditional ML/DL and blockchain-based methods in healthcare data handling [21]. Key performance indicators include accuracy, computational efficiency, scalability, and privacy preservation. Classical approaches often suffer from lower predictive performance on large, complex datasets and face risks from centralized storage [22]. Comparative analysis highlights the limitations of these methods, establishing a benchmark for evaluating the benefits of integrating quantum technologies. By identifying gaps in performance, security, and scalability, this analysis provides the rationale for adopting Quantum Machine Learning, federated learning, and quantum-resistant encryption mechanisms to achieve superior outcomes in real-time, privacy-preserving healthcare analytics [23].

Quantum Machine Learning with Federated and Secure Architectures

Quantum Machine Learning (QML) combines quantum computing's computational advantages with ML algorithms to achieve faster training, higher accuracy, and improved anomaly detection in healthcare datasets [24]. Federated learning enables decentralized model training across multiple institutions, eliminating the need for centralized data storage and preserving patient privacy. Quantum Key Distribution (QKD) ensures secure transmission of sensitive medical information, while blockchain integration maintains transparency and integrity. Together, these technologies form a unified, privacy-preserving framework that leverages 5G connectivity for real-time analytics. This approach addresses limitations of classical ML/DL, enhances predictive healthcare applications, and establishes a scalable, secure ecosystem for next-generation smart healthcare systems [25].

RESEARCH GAP

Although the 5G-enabled healthcare ecosystem is advancing rapidly, existing Machine Learning (ML) and Deep Learning (DL) models have serious limitations [12]. 5G has the capability of transmitting data quickly and in real-time, which is highly valuable with data collected from a variety of IoT devices and sensors. However, existing ML/DL methods with large, high-dimensional medical datasets face many challenges to a decrease in predictive accuracy and extensive processing time [15]. In addition, existing storage of healthcare data in a centralized way poses challenges to privacy, and existing cryptographic methods aimed at protecting private data will likely be incapable of protecting against potential quantum-based attacks [14]. Blockchain has been presented to increase data integrity and transparency to healthcare data, but there continues to be challenges related to the scalability of the technology, energy footprint, and inflexibility of immutable records when a clinician or patient needs to make an immediate update to their healthcare data. While federated learning presents a new way to train algorithms in a decentralized model, it is still relatively unexplored how to optimize federated learning with quantum computing and secure encryption methods [20].There is no current body of research that discusses a unified framework that incorporates 5G, Quantum Machine Learning (QML), Quantum Key Distribution (QKD), federated learning, and blockchain technology to create a scalable, secure, and privacy-respecting solution to healthcare data privacy. More expansive studies are needed to explore the accuracy and privacy limitations of classical methods of ML/DL while integrating various quantum technologies related to smart healthcare systems of the future [23].

Comparative Analysis of Classical and Quantum-Based Approaches in 5G-Enabled Healthcare

Traditional techniques, including traditional Machine Learning (ML), Deep Learning (DL), and blockchain leveraged for secure storage, have predominantly been used for healthcare data analysis and security. In this perspective, ML/DL approaches to data analytics, such as anomaly detection, predictive diagnostics, and pattern recognition reaches into various elements of healthcare, and blockchain provides the reliability, and trust of data processing, managing and provenance in a ledger for transparency [24]. The concepts of traditional methods, and applications for healthcare data has gained traction, with restrictions in aspects of capabilities. Hardware and data storage environments prevent privacy, while traditional cryptography technology remain prone and susceptible to post-quantum computing in the future, aside from being limited by, some major drawbacks in resource assertive scalability, increased energy consumption, and latency challenges for blockchain. Most importantly, healthcare data is typically presented in high-dimensional datasets, where great dimensionality can seriously reduce predictive power, while adding dreadfully to computational resource workloads in real-time [25].

With quantum-based approaches, and thus, namely, using Quantum (QML) and Quantum key distribution (QKD) technologies embedded with federated learning technology to address gaps of privacy and processing is ideal. Quantum ML considers faster training with more precision and accuracy, while addressing optimal anomaly detection for high dimensional datasets [26]. QKD provides a way to distribute quantum-resistance encrypted keys required for classical symmetric key encryption, while preventing concentration of sensitive data of model training for federated learning. When merged with the fast low latency transmission mobility of 5G systems, we can meet all the essential attributes and constraints prescribed, while enabling real-time implementations of scalable and trustful privacy data analytics in healthcare environments. Thus quantum-based frameworks will position themselves well ahead of any classical approaches to offer real and robust next generation smart healthcare systems [27].

Table 2: Comparative Analysis of Classical and Quantum-Based Approaches in 5G-Enabled Healthcare

Aspect	Classical Approaches (ML/DL + Blockchain)	Quantum-Based Approaches (QML + QKD + Federated Learning)	Limitations of Classical Approaches
Data Handling	Centralized processing of IoT and hospital data	Decentralized processing via federated learning	Centralized storage increases privacy risks
Accuracy & Prediction	Moderate accuracy for anomaly detection and predictive diagnostics	High accuracy with enhanced pattern recognition and anomaly detection	Struggles with large-scale, high-dimensional datasets
Security	Classical cryptography + blockchain for integrity	Quantum Key Distribution ensures quantum-resistant encryption	Vulnerable to quantum attacks; blockchain is energy-intensive
Scalability	Limited scalability with large datasets	High scalability due to distributed QML and federated learning	Resource-intensive and slower processing
Real-Time Capability	Limited due to computational overhead and network constraints	5G-enabled QML ensures real-time monitoring and analytics	Cannot fully exploit low-latency 5G benefits

Table 2 compares classical ML/DL with blockchain against quantum-based approaches (QML, QKD, federated learning) in 5G-enabled healthcare, highlighting differences in accuracy, scalability, security, real-time capability, and privacy preservation [24].

Privacy and Security Enhancements in Next-Generation Healthcare

The growing rollout of 5G networks in healthcare brings with it the capacity for real-time data transfer from existing and new IoT devices, wearables, and hospital systems, but also presents critical privacy and security issues. Traditional options in security including classical cryptography and blockchain provide known levels of protection by providing data integrity, transparency, and secure transport, but blockchain communities need to overcome significant hurdles such as a lack of scales, inefficient energy consumption, and limits on immutable records [29]. Additionally, classical cryptographic algorithms may be susceptible to new quantum attacks emerging today.To address these limitations, next-generation healthcare systems are utilizing modern privacy-preserving protection approaches [25]. First, Quantum key distribution (QKD) will provide quantum-resistant encryption for standard data transmission from IoT devices, wearables, and hospital systems, ensuring secure data transfer, even against future attacks on encryption. Second, in a federated learning (FL) approach, models can be trained decentralized, allowing hospitals or research institutions to train and employ complex models, without downloading raw patient data, reducing the potential for privacy concerns [28]. Finally, quantum ML or (QML) can be integrated to further enhance predictive performance accuracy, expedite anomaly detection, while maintaining confidential data in a privacy-preserving model. Ultimately, by employing these approaches together, healthcare systems can provide a complete framework, striking an optimal balance of security, privacy, and performance. Such frameworks would ensure a high level of protection of sensitive medical data, amplify research collaboration, advance operational research analysis, and enable real-time decision-making, solidifying today as the standard operational state for future-proofing secure and efficient analytics in healthcare [30].

RESULTS

Real-Time Patient Heart Rate Monitoring over 5G

Real-time patient heart rate monitoring over 5G enables continuous, accurate tracking of vital signs with ultra-low latency and high-speed data transmission. This technology supports remote healthcare, emergency response, and personalized treatment, while ensuring reliability and efficiency in critical care, enhancing patient safety and overall medical outcomes [31].

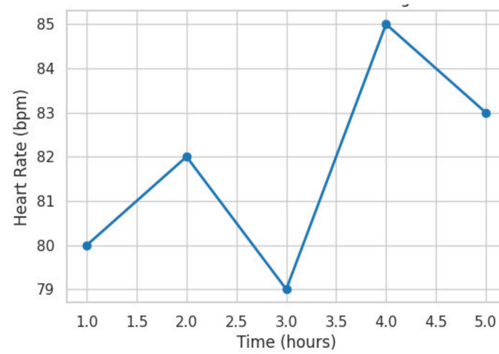

Fig 2: *Real-Time Patient Heart Rate Monitoring over 5G*

The patient's heart rate variations over a five-hour period are depicted by the graph. The heart rates are plotted against the time scale which not only shows the high and low rates but also the trends throughout the monitoring period. Each data point is marked with a circle to indicate the exact individual readings. The title indicates that the data is from the real-time heart rate monitoring, which was enabled by 5G technology. The x-axis represents time in hours and the y-axis represents heart rate in beats per minute (BPM). The background grid is meant to aid in visibility and also to allow very precise value readings. In summary, the plot powerfully illustrates that 5G technology can provide real-time, and trustworthy, continuous monitoring of patients.

Model Accuracy Comparison in 5G-Enabled Healthcare

The bar chart presents a comparative accuracy assessment of the three computational approaches: Machine Learning (ML), Deep Learning (DL), and Quantum Machine Learning (QML)-especially for Health Care Systems Powered by 5G. Traditional ML scores about 78%, which is a moderate level of accuracy [30]. DL, meanwhile, slightly improves the performance with an accuracy of approximately

82% through greater depth of the architecture and feature extraction. QML alone is far superior, reaching up to 92% accuracy, which places in the high rank of diagnosing and analyzing complex Quick Medical datasets faster. Thus, combining QML with a 5G-enabled environment not only mediates swifter data transmission but also increases accuracy in diagnosis and stands as a promising technique for intelligent healthcare applications requiring real-time, secure decision-making [32].

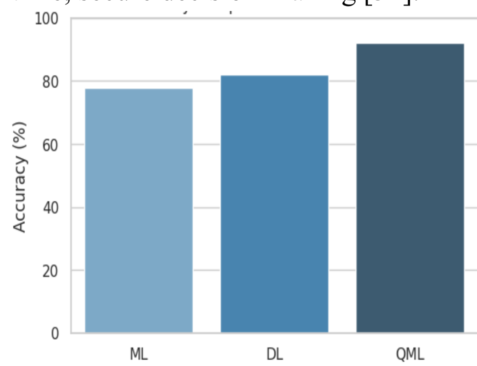

Fig 3: *Model Accuracy Comparison in 5G-Enabled Healthcare*

The Fig 3 compares accuracy of ML, DL, and QML models in 5G-enabled healthcare, showing QML achieves the highest accuracy, demonstrating its superior potential for secure and efficient medical data analysis [33].

Quantum vs Classical Accuracy Over Dataset Size

The figure compares accuracy trends of classical ML/DL and Quantum Machine Learning (QML) with increasing dataset size. Classical models improved slowly, from 78% to 82% accuracy. QML, instead, shows a strong upward trend, starting at 82% and going up to 92%. This brings out the scalable nature and efficiency of QML methods with larger datasets, exhibiting better prediction performance [35]. Hence the results indicate the potential of QML for 5G-enabled healthcare applications, where ever-growing data volumes call for computational methods that are robust, accurate, and privacy-preserving. The continuous difference in performance actually highlights the advantage QML has against classical methods in delivering trustworthy and intelligent insight from complex medical datasets [34].

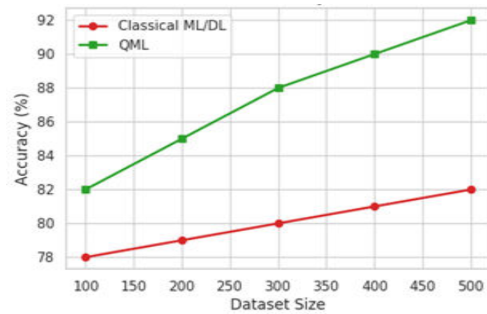

Fig 4: *Quantum vs Classical Accuracy Over Dataset Size*

Healthcare Data Types Processed by QML

This pie chart shows the distributions of healthcare data types processed with QML. Imaging and vital signs had a share of 30% each, showing the importance of these data types in patient monitoring and diagnostics. Lab test data follows with 25%, while genomics at 15% marks the new age of personalized medicine being adopted [30]. This distribution shows how QML could process healthcare data from multiple sources, followed by better analyses and predictions [32]. By processing multi-modal data, QML facilitates comprehensive, scalable, and privacy-preserving healthcare solutions, especially across 5G-enabled environments requiring the management of data at fast, accurate, and secure speeds.

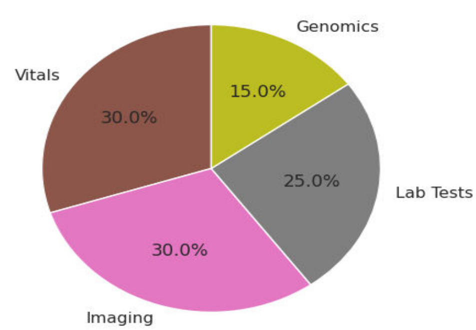

Fig 5: *Healthcare Data Types Processed by QML*

The Fig 5 shows healthcare data types processed by QML: imaging and vitals dominate at 30% each, lab tests at 25%, and genomics at 15%, reflecting diverse data integration in healthcare analytics [34].

Latency Reduction with 5G in Healthcare Data Transmission

The figure contrasts latency over time in healthcare data transmission across both kinds of networks. Latency in the case of the standard network has seen a steady decline from 150 ms to 140 ms, suggesting slower rates of enhancement with respect to data transfer; however, a 5G network, starting with a latency of 80 ms, has dropped it down to 70 ms, about half of what the standard network runs at [35]. This steep fall in latency justifies 5G as a revolution for faster and reliable communication in healthcare. Such improvements result in real-time implementations such as remote monitoring, telemedicine, and emergency interventions-aiding in timely and accurate care for patients.

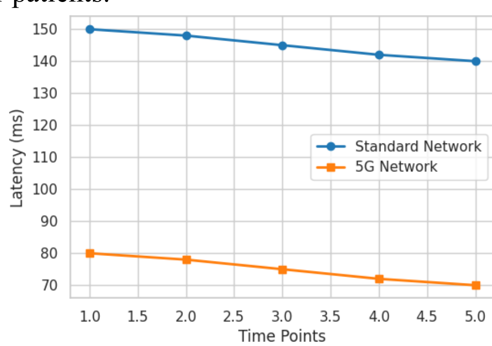

Fig 6: *Latency Reduction with 5G in Healthcare Data Transmission*

Confusion Matrix QML Model

The figure depicts the confusion matrix for a Quantum Machine Learning (QML) model-based anomaly detection in healthcare data. True label 0 refers to normal cases, and 1 refers to Anomaly. So, in essence, the true labels are compared against predicted outputs. On diagonal values are the correct classifications, whereas off-diagonal values are misclassifications. In essence, this imagery portrays model performance in discriminating between normal and anomalous cases. Higher values in the diagonal entries indicate high predictive accuracy, whereas errors mean areas of model improvement. This kind of analysis thus is important for proving the reliability of QML in healthcare, as this ensures that anomalies are detected accurately for timely interventions and safeguards [31].

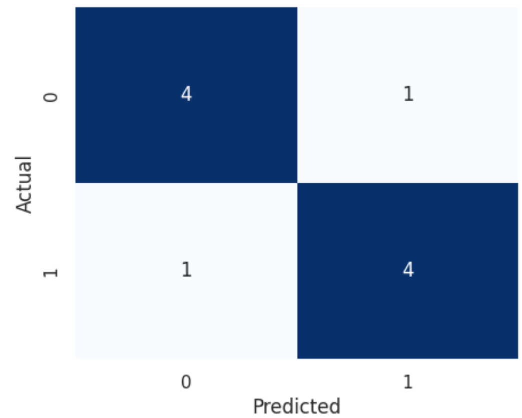

Fig 7: *Confusion Matrix QML Model*

Key Findings:

- 5G networks significantly reduce latency compared to standard networks, enhancing real-time healthcare data transmission [34].
- Quantum Machine Learning (QML) consistently outperforms traditional ML and DL in accuracy, especially with larger datasets.
- QML enables efficient processing of diverse healthcare data types, including vitals, imaging, lab tests, and genomics [32].
- Federated learning ensures privacy by avoiding centralization of sensitive patient data while still supporting collaborative model training.
- Quantum cryptography and Quantum Key Distribution (QKD) offer stronger security against future cyber threats compared to classical methods [34].

- Integrating QML, 5G, and federated approaches creates scalable, privacy-preserving smart healthcare ecosystems.

CHALLENGES

Despite the superior combination of 5G technology, quantum machine learning (QML) and privacy-preserving solutions in healthcare, there are many significant challenges to overcome before a practical application can be realized. The first challenge is that the quantum computing hardware available for experiment and development is limited [32]. The capability to run QML algorithms not only relies on the type of quantum processor, but their current state of development memory limitations, scalability, noise, and decoherence issues render it impossible for reliable execution as well [26]. Similarly, extending quantum key distribution (QKD) and quantum cryptographic techniques at scale is hampered by this reliance on infrastructure, and all the hardware requirements incurred in the process. The heterogeneous nature of healthcare data, and the way it is created such as medical images, sensor data integrated with physical health records from one device, genomic sequences, and electronic health records all make it difficult to integrate these disparate formats into QML frameworks with interoperability [34]. The challenges of privacy still exist, and while federated learning preserves privacy, it does not eliminate the potential risk of indirect data leakage from model update. Finally, as mention previously, while 5G comes with extra low latency, bandwidth and connectivity, practically deploying 5G technology has been harmful. Much of the benefits to remote healthcare have yet to be realized since less than 50% of rural and resource poor environments have 5G [35].

CONCLUSION

The intersection of 5G, Quantum Machine Learning (QML) and privacy-preserving methods offers a powerful opportunity to address the future of healthcare [36]. 5G networks deliver ultra-low latency and high-bandwidth connection and are thus equipped for scalable and real-time data analysis that is both accurate and timely [39]. The application of QML with privacy-preserving federated learning allows sensitive and unique patient information to remain decentralized within the healthcare system, meaning the patient maintains privacy while benefiting healthcare decisions and collaborative medical research frameworks [31]. In addition, other QML benefits exist in quantum cryptographic protections such as Quantum Key Distribution (QKD) which allow for not just secure information, but information that is secure above and beyond the capacity of any current and future cyber threats [32].Despite remaining hurdles facing healthcare applications that range from various quantum hardware readiness and network deployment uncertainties to procedural ethical & other developed regulations & standards, the expected benefits of QML & 5G-based emerging technologies outweigh the hurdles [37]. Ultimately, this comprehensive suite of technologies supplant traditional models upon which we build the next-generation smart healthcare or even e-healthcare technologies, with important advancements that are secure, smart and patient-centric [38]. With small and larger changes in education and use of QML and 5G technologies used in health and medical systems, all healthcare users can be a part of the emerging change making services more trustworthy and personalized across the world [40].

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