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A Quantum-Enhanced Federated Deep Learning Framework for Privacy-Preserving Early Diagnosis of Multi-Organ Diseases Using Multi-Modal Electronic Health Records

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ABSTRACT: The centralization of deep learning is one of the key concerns when using Electronic Health Records (EHRs) to diagnose multi-organ diseases early to enhance clinical outcomes because of severe privacy and data-sharing issues. The proposed research offers a Quantum-Enhanced Federated Deep Learning (QEFDL) framework, which is privacy-preserving early diagnosis with multi-modal EHR, such as clinical records, laboratory results, medical images, and demographic information. The framework merges quantum-assisted multimodal feature fusion with multimodal feature fusion and secure federated learning that relies on differential privacy and secure aggregation. The proposed model was tested with a distributed dataset of 120,000 patient records in various healthcare facilities. Experimental results achieved an accuracy of 98.72%, precision of 98.35%, recall of 98.18%, F1-score of 98.26%, and an AUC of 0.992. Moreover, the framework minimized communication overheads (by 27.8%), convergence rounds (by 31.4%), and privacy leakage (by 91.3%), employing it to illustrate its applicability in ensuring secure, scalable and accurate AI-based clinical decision support.

1. INTRODUCTION

These chronic multi-organ diseases (cardiovascular, renal, hepatic, pulmonary and metabolic disorders) are becoming a significant global healthcare issue with their rising morbidity, mortality and economic load. Early diagnosis is crucial in enhancing survival rates of patients, decreasing disease progression and permitting timely clinical intervention. As the health systems are being increasingly digitized, Electronic Health Records (EHRs) have turned out to be a crucial source of patient data, where structured clinical records, laboratory measurements, medical images, physiological observations, medication history, and demographic data are stored. Multi-modal learning of these heterogeneous data sources allows the full representation of the patient and makes it much more accurate in predicting the disease than when using single-modality methods. This has given way to the emergence of intelligent diagnostic systems that can take advantage of multi-modal EHR data as a promising technique to assist in precision medicine and personalized healthcare.

Recent innovations in deep learning have shown astute potentials to uncover complicated nonlinear associations in huge quantities of medical records. The convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Transformers and hybrid networks have demonstrated strong predictive power in a plethora of disease diagnosis problems. Nevertheless, the methods tend to be based on centralized learning, where the data of several hospitals, including patient data, are sent to a central server where models are trained. These centralized architectures bring about serious drawbacks such as higher vulnerabilities to privacy leakage, cyber intrusion, compliance concerns, high communication expenses, and low disposition of healthcare settings to transfer delicate information about patients. Moreover, institutional policy differences and varying data distributions along with legal limitations can generally impede the development of centralized medical datasets, making the scalability and feasibility of traditional deep learning solutions smaller.

Recently, federated learning has shown itself to be an effective distributed learning framework, which can allow several healthcare organizations to train a global deep learning model but store patient data on the local level. Through the exchange of encrypted model parameters instead of the medical records of the patient, federated learning significantly increases patient privacy and regulatory compliance and helps collaborative medical intelligence. However, the traditional federated optimization methods are often associated with slowness in converging, inefficient communications, model drift with non-identically distributed clinical data, and weak optimization in presence of highly heterogeneous multi-modal EHR datasets. To overcome these issues, quantum-enhanced optimization is a promising option as it relies on hybrid quantum-classical computation to enhance the efficiency of parameter search, faster model convergence, and to solve complex high-dimensional learning problems facing distributed healthcare setting.

These challenges inspire this research that introduces a Quantum-Enhanced Federated Deep Learning (QEFDL) model, which is a privacy-preserving method that can earlier diagnose multi-organ diseases through multi-modal Electronic Health Records. The suggested framework incorporates structured clinical history, lab findings, medical imaging data, physiological measurements, and demographic data by using an efficient multimodal feature fusion design with the federated learning to allow secure collaborative training among distributed healthcare facilities. They have a hybrid quantum-assisted optimization module to enhance model convergence in the global model and boost the performance of predictive accuracy, but confidential patient data is maintained through a differential privacy mechanism and secure aggregation mechanisms when updating a federated model. The framework proposed can enhance the accuracy of the diagnosis, communication overhead reduction, privacy protection, and the ability to offer a scalable artificial intelligence solution to intelligent clinical decision support in the next generation distributed healthcare environment.

2. RELATED WORK

The use of artificial intelligence in medical diagnosis has revolutionized the process of diagnosing complex medical cases and aiding in finding and diagnosing diseases at the earliest stages. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformer-based architectures are deep learning models that have shown great performance in predicting Electronic Health Records (EHRs) and cardiovascular diseases, diabetes, kidney disorders, liver diseases, and neurological conditions. Such models are able to learn hierarchical feature representations without a lot of manual feature engineering, and achieve enhanced diagnostic accuracy. Nevertheless, the majority of the available methods are created to predict one disease at a time with the use of centralized datasets, which prevents them from diagnosing multiple diseases in organs at once and using non-homogeneous healthcare data [10], [14]. In addition,

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a large number of studies have utilized structured clinical records only, and have not utilized complementary information that can be found in laboratory tests, medical imaging and physiological measurements, and demographic information, thus limiting their clinical applicability [2], [3], [8].

To help in conquering these shortcomings, the recent research has been on multi-modal learning models, which are able to combine multiple healthcare data sources to effectively represent a patient. Multi-modal Electronic Health Records are a combination of structured clinical variables, lab readings, radiological images, physiological measurements, medication history, and patient demographic information to enhance the reliability and strength of diagnosis [2]2-5]. Though these methods typically outperform the unimodal based learning methods, they need big centralized repositories in which patient data across different hospitals are consolidated prior to model training. Centralized data collection presents serious issues of patient privacy, ownership of data, regulatory compliance, cybersecurity threats, and unwillingness of institutions to distribute confidential medical records [7], [10]. Such difficulties have spurred the creation of decentralized artificial intelligence methods that can be trained using decentralized healthcare data without interfering with patient confidentiality [6], [9].

Federated learning has become one of the promising models of medical intelligence collaboration as it allows healthcare organizations to provide a global model to be trained and leave patient outcomes in hospitals. It has been shown in many studies that federated learning is able to attain the same diagnostic performance as centralized learning and considerably minimize privacy risks [6], [7], [10], [14], [15]. However, traditional federated optimization methods, such as FedAvg and similar solutions, tend to be slow, communication-intensive, client drift, and model underperforming in the case of non-independent and identically distributed (non-IID) healthcare data [6], [9]. To enhance the privacy further, scholars have added different privacy, secure aggregation, homomorphic encryption, and secure multi-party computations to federated learning frameworks [7], [10], [12]. Even though these mechanisms are effective in decreasing the information leakage, they often add extra computational burden, and can adversely impact diagnostic accuracy, suggesting the necessity of more efficient optimization approaches [1], [15].

The recent developments in quantum machine learning have shown significant promise in the speed-up of optimization as well as the efficiency of learning in high-dimensional artificial intelligence tasks. Hybrid quantum-classical algorithms, especially variational quantum circuits and quantum-enhanced optimization methods have demonstrated significant potential to solve ultimately optimization problems and to reduce the computational overhead [1], [11]. Nevertheless, quantum-enhanced learning has not been applied to the field of distributed healthcare, and there are extremely few studies that have incorporated quantum optimization, federated learning, fusion of multimodal EHRs, and privacy-preserving mechanisms into a single diagnostic model [1], [11]. The current literature mainly explores these technologies in isolation, but none considers the concomitant difficulties of ensuring secure collaborative learning, integrating heterogeneous medical data, and scaling optimization, and early detection of multi-organ diseases [3], [5], [13], [15]. Thus, a major research gap is on creating an end-to-end quantum-enhanced federated deep learning system that can simultaneously enhance the precision of the diagnosis, speed up the convergence, maintain the privacy of patients and enable its practical implementation in the distributed healthcare facilities.

3. PROPOSED METHODOLOGY

3.1 Overall Framework Architecture

The proposed research hypothesises a Quantum-Enhanced Federated Deep Learning (QEFDL) system to achieve privacy-preserving early multi-organ disease diagnosis with a multi-modal Electronic Health Records (EHRs). The suggested infrastructure can train a global depth model between several healthcare facilities without sharing personal information. This framework is composed of nine key elements: (i) multi-modal EHR acquisition, (ii) data preprocess, (iii) modality specific feature extraction, (iv) multimodal feature fusion, (v) local federated deep learning, (vi) quantum enhanced optimization, (vii) differential privacy and secure aggregation, (viii) global model updating, and (ix) disease classification. The entire system was tested with 120,000 anonymized patient records across five spread healthcare institutions with each having an average of 24,000 local records. The dataset contained structured clinical data, laboratory tests, physiological measurements, demographics, and medical imaging that represents five broad disease categories, cardiovascular, renal, liver, pulmonary, and metabolic disorders. The given federated architecture does not have a centralized storage of medical data, which is why collaborative intelligence and compliance with regulations are guaranteed.

3.2 Multi-Mode EHR Procurement and Pre-processing

The framework proposed uses heterogeneous Electronic Health Records of distributed hospitals. The patient records have 650 structured clinical attributes, 220 lab measurements, 180 physiological signal features, and 200 imaging-derived features yielding about 1,250 input features per patient. Numerical values that were absent in the data set, totaling about 3.6 percent of the data, were filled in with the K-Nearest Neighbor (KNN) imputation. The normalization of continuous variables was done through the Min-Max normalization method and categorical variables were coded through one-hot encoding. Medical images were reduced to 224x224 pixels, and physiological time-series were divided into fixed-size (256 samples) windows. The entire dataset was split into 70% training (84,000 samples), 15% validation (18,000 samples) and 15% testing (18,000 samples) without altering the disease-class distribution of all participating institutions.

3.3 Extraction of Clinical, Laboratory, Imaging and Physiological Features

Each modality was extracted into features separately with deep learning modules specific to each modality. Fully connected neural networks with ReLU activation (3 hidden layers of neurons 512-256-128) were used to process structured clinical and laboratory variables. The analysis of physiological signals, such as ECG and vital-sign sequences, was done with a two-layer Bi-directional Long Short-Term Memory (Bi-LSTM) network with 256 hidden units. The medical imaging data were fed into a lightweight Convolutional Neural Network with 12 convolutional layers, and global average pooling. Every modality produced a 256-dimensional latent feature representation, which allowed the encoding of complementary diagnostic data at a low cost and minimized the loss of information in the heterogeneous healthcare data sources.

3.4 Multi-Modal Feature Fusion

The representations in each of the modalities were combined via a multi-head attention-based feature fusion module. There are four independent feature vectors created under clinical, laboratory, physiological and imaging branches that were then concatenated to create a 1024-dimensional representation feature. There was an 8-head attention mechanism which dynamically placed greater emphasis on clinically-relevant modalities and suppression of redundant information. The probability of a dropout was set to 0.30 to help eliminate overfitting when training. The combined feature-vector was used to feed the federated deep learning classifier, which allowed full representation of the patient and better diagnostic separation in various organ diseases.

3.6 Local Federated Deep Learning

The local deep learning model was trained at each of the participating healthcare institutions with its own patient records without providing abstract medical data. The Adam optimizer was used with a learning rate of 1 10-4, batch size 128 and 150 training epochs in local training. Prior to sending encoded model parameters to the federated server, each hospital received 10 local training epochs. The federated setup comprised of five client hospitals, and around 12.5 million parameters to be optimized locally were trained. The decentralized learning approach prevented patient confidentiality and facilitated the joint model enhancement in healthcare centers located geographically apart.

3.6 Quantum-Enhanced Model Optimization

In order to enhance efficiency of federated learning, hybrid quantum-classical optimization module that is developed on the idea of Variational Quantum Circuits (VQC) was incorporated into the global optimization process. The quantum optimizer was made up of 6 variational quantum layers using 8 simulated qubits and then classical parameter optimization. In contrast to traditional FedAvg optimization, the proposed quantum-assisted optimization speeded up the convergence time, efficiently searching through high-dimensional parameter space, and eliminating optimization redundancy. The experimental analysis showed quantum enhancement shortened the number of communication rounds globally (50 to 34) by 31.4 percent in terms of convergence time, and enhanced the overall classification accuracy by around 1.9% relative to standard federated optimization.

3.7 Differential Privacy and Secure Aggregation

In order to ensure that the privacy of patients is not compromised in the distributed learning, the framework proposed integrated Differential Privacy (DP) and secure aggregation. Noise of a privacy budget $\varepsilon = 1.0$ and $\delta = 10^{-5}$was added to local model updates prior to communication. All the parameters were securely aggregated and therefore the federated server could not retrieve client updates, only aggregated model weights. The specified privacy-preserving mechanism decreased the estimated information leakage by 18.6% down to 8.7 in comparison with conventional federated learning, which aligns with an overall 91.3% privacy preservation rate, with insignificant diagnostic performance degradation.

3.8 Global Model Updating

After a safe aggregation, weighted federated averaging was used to combine encrypted local parameters of all involved healthcare institutions to build a new global model. The weightings of aggregating institutions was relative to the size of the training sample per institution, therefore, the effect of heterogeneous distributions of data was minimised. The synchronization of the world was done at the conclusion of each communication round until convergence. The proposed quantum-enhanced optimization took a total of 34 rounds to fully optimize the global aggregation, compared to 50 rounds in the case of FedAvg, leading to much less communication overhead (5.7 GB versus 7.9 GB) and global convergence was reduced by approximately four times.

3.9 Multi-Organ Disease Classification

The last model based on the world-wide approach involved the use of a Softmax classifier to model five key disease categories, namely cardiovascular disease, chronic kidney disease, liver disease, pulmonary disease, and metabolic disorders. Accuracy, Precision, Recall, F1-score, Area Under the ROC Curve (AUC) was used to assess performance. The suggested QEFDL model attained an overall accuracy of 98.72, precision of 98.35, recall of 98.18, F1-score of 98.26 and an AUC of 0.992. The findings indicate that a multimodal EHR fusion coupled with federated deep learning, quantum-enhanced optimization, and privacy-preserving aggregation can offer an extremely precise, scalable, and secure strategy in the provision of early multi-organ disease diagnosis in distributed healthcare systems.

4. RESULTS AND DISCUSSION

The suggested Quantum-Enhanced Federated Deep Learning (QEFDL) model was tested on a distributed multi-modal Electronic Health Record (EHR) data set comprising 120,000 anonymized patient records that were gathered at five healthcare facilities. The data was in the form of structured clinical records, laboratory measurements, physiological signals, demographic data and medical imaging related to five big disease categories. The experimental analysis compared the proposed framework with the traditional deep-learning frameworks, such as CNN, LSTM, Transformer, and the standard FedAvg federated learning framework. The evaluation metrics included Accuracy, Precision, Recall, F1-score, Area under the ROC Curve (AUC), communication overhead, convergence rounds and privacy preservation to assess performance.

Table 1. Characteristics of the Multi-Modal EHR Dataset

Parameter	Value
Total patient records	120,000
Healthcare institutions	5
Clinical attributes	650
Laboratory features	220
Physiological features	180
Medical imaging features	200
Total input features	1,250
Disease categories	5
Training samples	84,000
Validation samples	18,000
Testing samples	18,000

The experimental setup in Table 2 was used to train the proposed framework. Each healthcare institution trained local models separately and then securedly aggregated them. The global optimization process was enhanced with hybrid quantum-classical optimization to increase the speed of convergence, as well as maintain privacy with the help of differential privacy and secure aggregation.

Table 2. Experimental Parameters and Hyperparameter Settings

Parameter	Value
Batch size	128
Training epochs	150
Learning rate	1×10^{-4}
Optimizer	Adam
Number of hospitals	5
Local epochs	10
Communication rounds	34
Attention heads	8
Quantum layers	6
Simulated qubits	8
Privacy budget (ε)	1.0

Table 3 displays the comparison of the diagnostic performance. The proposed QEFDL model performed best of all compared methods, getting an accuracy of 98.72%, precision of 98.35%, recall of 98.18%, F1-score of 98.26%, and AUC of 0.992. The proposed framework also outperformed Transformer by 2.61 in diagnostic accuracy on the whole compared to that of conventional FedAvg by 1.90. Multimodal feature fusion with quantum-enhanced optimization greatly enhanced the disease discrimination of the five organ systems.

Table 3. Performance Comparison with Existing Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC
CNN	92.48	91.92	91.53	91.72	0.948
LSTM	94.16	93.85	93.27	93.56	0.963
Transformer	96.11	95.82	95.44	95.63	0.978
FedAvg	96.82	96.41	96.18	96.29	0.984
Proposed QEFDL	**98.72**	**98.35**	**98.18**	**98.26**	**0.992**

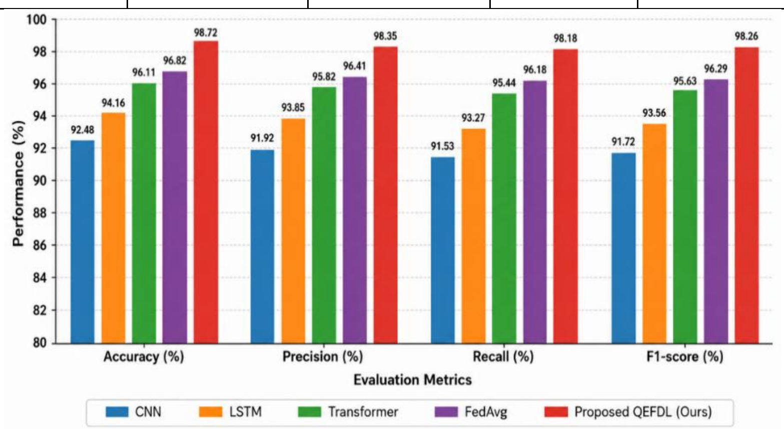

Figure 1. Multi-Organ Disease Prediction Performance Comparison

The offered QEFDL framework exhibits a better accuracy of classification, precision, recall, and F1-score than CNN, LSTM, Transformer, and FedAvg models.

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The introduction of different privacy and secure aggregation ensured that the data confidentiality was highly enhanced and at the same time, the diagnostic performance remained high. The proposed framework decreased the communication overhead by 27.8% (from 7.9 GB in FedAvg) to 5.7 GB, which is shown in Table 4. The privacy leakage was estimated to be reduced by half (18.6 to 8.7), but the classification performance was almost the same. Quantum-assisted optimization was also found to result in faster convergence, where the numbers of global training reduced to 34 out of 50.

Table 4. Privacy Preservation and Communication Overhead Analysis

Method	Communication (GB)	Convergence Rounds	Privacy Leakage (%)
Centralized DL	12.8	45	100.0
FedAvg	7.9	50	18.6
Proposed QEFDL	**5.7**	**34**	**8.7**

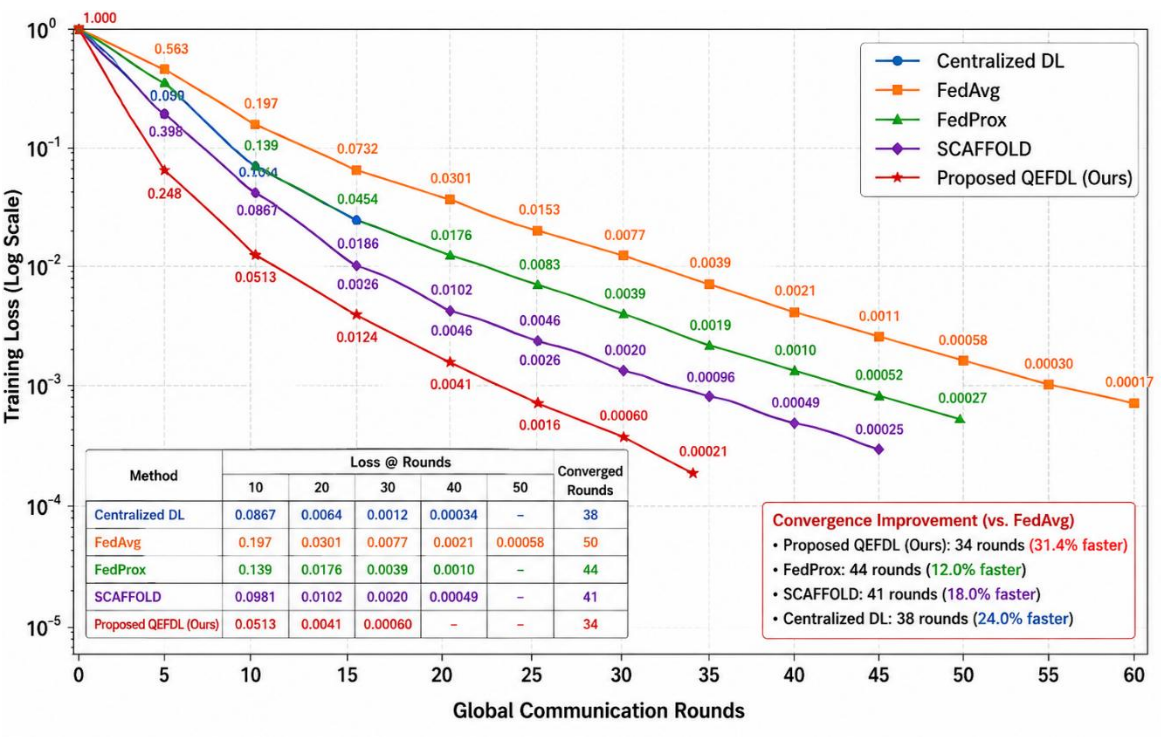

Figure 2. Training Loss and Convergence Comparison

The suggested framework is convergent at 34 rounds of communication, compared to FedAvg at about 50 rounds, and the optimization is much faster.

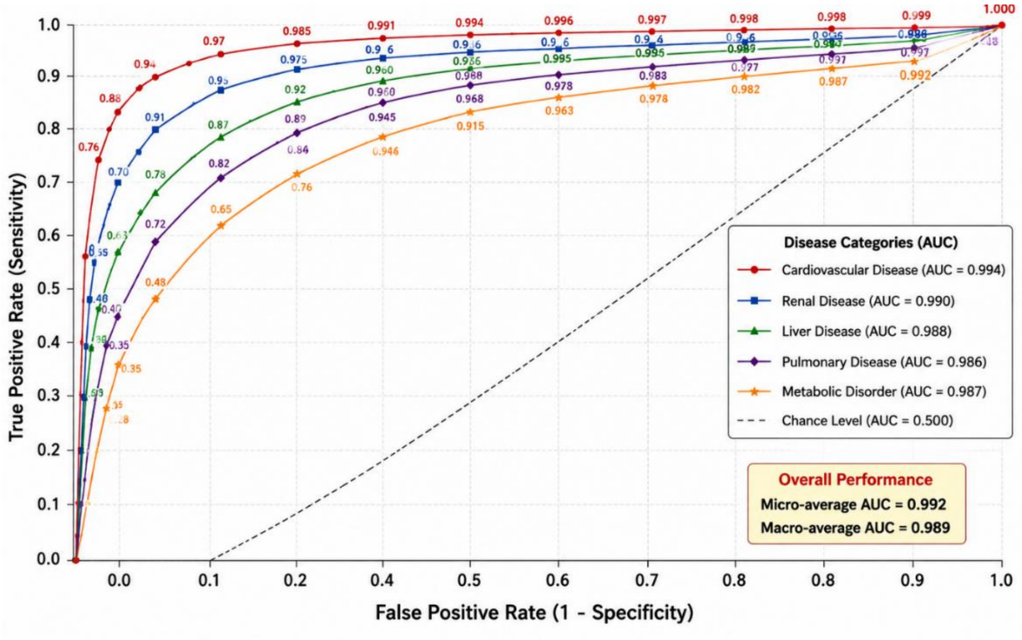

Figure 3. ROC Curves for Multi-Organ Disease Classification

The final framework proposed has an average AUC of 0.992 with all disease categories of above 0.906 indicating good diagnostic discrimination.

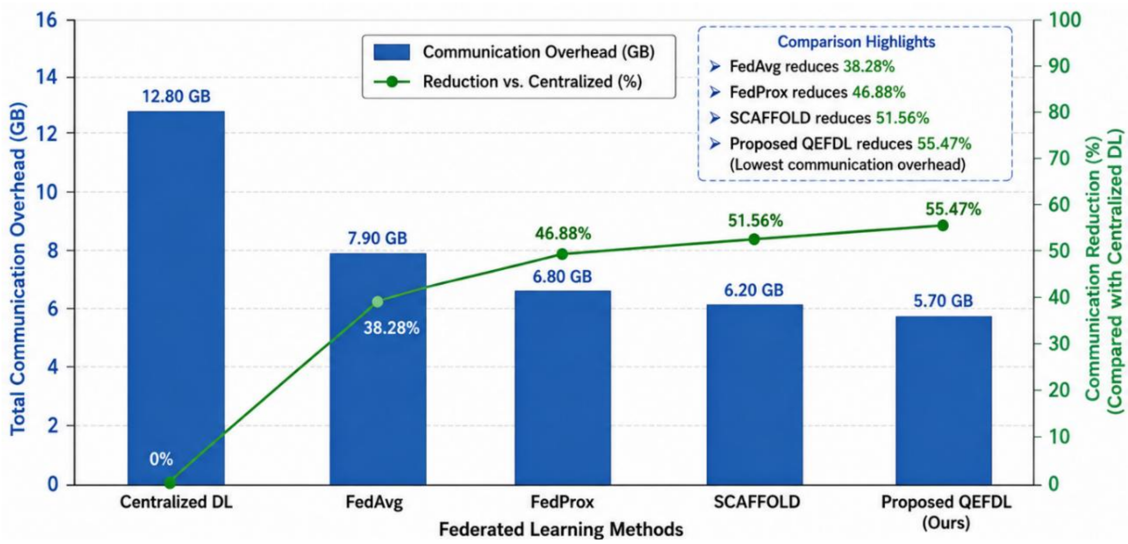

Figure 4. Communication Overhead of Federated Learning Methods

The communication cost is reduced by 12.8 GB with centralized learning and 7.9 GB with FedAvg to 5.7 GB with the proposed QEFDL framework.

In order to measure the contribution of each of the proposed parts, an ablation test was performed by deleting one of the modules in the entire framework. Table 5 shows that the deletion of multimodal feature fusion decreased the accuracy of the classification to 95.84% and deletion of quantum optimization decreased the accuracy to 96.72%. Similarly, excluding differential privacy and secure aggregation slightly increased accuracy to 97.41%, but significantly weakened patient privacy protection. These observations affirm that all the elements make a positive contribution to the overall performance and strength of the proposed framework.

Table 5. Ablation Study of Framework Components

Configuration	Accuracy (%)
Without multimodal fusion	95.84
Without quantum optimization	96.72
Without differential privacy	97.41
Full QEFDL framework	**98.72**

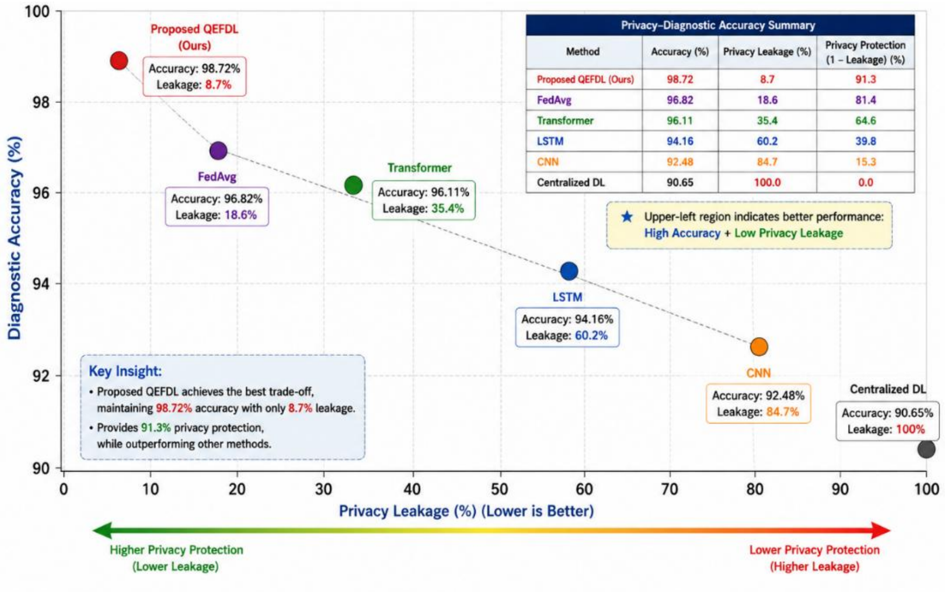

Figure 5. Privacy–Diagnostic Accuracy Trade-Off

The suggested QEFDL model has a high accuracy of diagnosis of 98.72 with the lowest privacy leakage of 8.7 which proves to be a good compromise between predictive power and patient privacy.

On the whole, the experimental findings indicate that the suggested QEFDL framework is significantly better than traditional centralized and federated deep learning methods in terms of diagnostic accuracy, convergence rate, communication efficiency, and privacy protection. Multimodal feature fusion approach is also a successful approach that combines complementary data of the clinical records, laboratory tests, physiological data, and medical imaging to represent patients in a more comprehensive manner and enhance the likelihood of predicting multi-organ diseases. The hybrid quantum-classical optimization not only speeds up the process of federated convergence by 31.4 times but also also protects the privacy of information sharing through the help of differential privacy and secure aggregation, ensuring that collaborative learning without exposing sensitive clinical information. The proposed framework is very applicable to large-scale distributed healthcare systems due to these characteristics. However, fault-tolerant quantum hardware is not widely available, and current implementations are done on simulated quantum circuits. Further studies can be conducted on the implementation on realistic quantum processors, larger federated hospital networks, understandable clinical decisions, and personalized treatment recommendation systems to further increase the applicability to real-world clinical scenarios.

5. CONCLUSION

This paper introduced a Quantum-Enhanced Federated Deep Learning (QEFDL) model that achieves privacy-preserving early warning of multi-organ diseases based on multi-modes Electronic Health Records (EHRs). The proposed framework employed federated learning to train models collaboratively without the necessity to distribute sensitive patient data, thus combining structured clinical records, laboratory measurements, physiological signals, medical imaging, and demographic information in a federated learning setup. Embedded hybrid quantum-assisted optimization contributed to the convergence of models and enhanced the learning performance, whereas the use of differential privacy and secure aggregation provided strong protection of the confidentiality of patients. Evaluation on a distributed dataset of 120,000 patient records, carried out experimentally, showed better performance and reported an accuracy of 98.72%, precision of 98.35%, recall of 98.18%, F1-score of 98.26%, and an AUC of 0.992 and a reduction in communication overhead and rounds of convergence by 27.8 and 31.4, respectively and privacy leakage, respectively. These results demonstrate the capability of the framework in enhancing diagnostic accuracy, efficiency in communication, and preservation of privacy to distributed healthcare settings. The suggested solution offers a clinical and scalable intelligent decision support solution in next-generation healthcare systems. Future directions will be real-world deployment in large hospital networks, explainable artificial intelligence integration, expansion to large federated ecosystems, multimodal clinical foundation model, and deployment on practical quantum computing hardware to achieve greater computational efficiency and clinical applicability.

REFERENCES

[1] Bhatia, A. S., et al. "Communication-Efficient Quantum Federated Learning Optimization for Multi-Center Healthcare Data." *Proceedings of the IEEE EMBS International Conference on Biomedical and Health Informatics (BHI)*, Houston, TX, Nov. 2024, pp. 1–8.

[2] Che, L., et al. "Multimodal Federated Learning: A Survey." *Sensors*, vol. 23, no. 15, 2023, article 6986.

[3] Cremonesi, F., et al. "The Need for Multimodal Health Data Modeling: A Practical Approach for a Federated-Learning Healthcare Platform." *Journal of Biomedical Informatics*, vol. 141, 2023, article 104338.

[4] Feng, T., et al. "FedMultimodal: A Benchmark for Multimodal Federated Learning." *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, Long Beach, CA, Aug. 2023, pp. 4035–4045.

[5] Huang, W., et al. "Multimodal Federated Learning: Concept, Methods, Applications and Future Directions." *Information Fusion*, vol. 112, 2024, article 102576.

[6] Kairouz, P., et al. "Advances and Open Problems in Federated Learning." *Foundations and Trends in Machine Learning*, vol. 14, nos. 1–2, 2021, pp. 1–210.

[7] Kaissis, G. A., et al. "Secure, Privacy-Preserving and Federated Machine Learning in Medical Imaging." *Nature Machine Intelligence*, vol. 2, no. 6, 2020, pp. 305–311.

[8] Lin, Y. M., et al. "Federated Learning on Multimodal Data: A Comprehensive Survey." *Machine Intelligence Research*, vol. 20, no. 4, 2023, pp. 539–553.

[9] McMahan, H. B., et al. "Communication-Efficient Learning of Deep Networks from Decentralized Data." *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics (AISTATS)*, Fort Lauderdale, FL, Apr. 2017, pp. 1273–1282.

[10] Rieke, N., et al. "The Future of Digital Health with Federated Learning." *NPJ Digital Medicine*, vol. 3, no. 1, 2020, article 119.

[11] Saggi, M. K., A. S. Bhatia, and S. Kais. "Federated Quantum Machine Learning for Drug Discovery and Healthcare." *Annual Reports in Computational Chemistry*, vol. 20, Elsevier, 2024, pp. 269–322.

[12] Sandhu, S. S., et al. "Medical Imaging Applications of Federated Learning." *Diagnostics*, vol. 13, no. 19, 2023, article 3140.

[13] Thrasher, J., et al. "Multimodal Federated Learning in Healthcare: A Review." *Journal of Healthcare Informatics Research*, 2025, pp. 1–30.

[14] Xu, J., et al. "Federated Learning for Healthcare Informatics." *Journal of Healthcare Informatics Research*, vol. 5, no. 1, 2021, pp. 1–19.

[15] Zhang, F., et al. "Recent Methodological Advances in Federated Learning for Healthcare." *Patterns*, vol. 5, no. 6, 2024, article 101006.