Advanced Cardiovascular Health in a Quantum AI-driven Healthcare Framework

Sarvapriya M Tripathi[1], Himanshu Upadhyay[1], and Jayesh Soni[1]

[1]Electrical and Computer Engineering, Florida International University Miami

April 02, 2024

Advanced Cardiovascular Health in a Quantum AI-driven Healthcare Framework

Sarvapriya M Tripathi
Electrical and Computer Engineering
Florida International University
Miami, USA
stripath@fiu.edu

Himanshu Upadhyay
Electrical and Computer Engineering
Florida International University
Miami, USA
upadhyay@fiu.edu

Jayesh Soni
Electrical and Computer Engineering
Florida International University
Miami, USA
jsoni@fiu.edu

***Abstract*—With the advent of Healthcare 4.0, there is increased interest from researchers the world over in the application of modern, cutting-edge Artificial Intelligence (AI) and Quantum Artificial Intelligence (QAI) algorithms in solving healthcare challenges. The era of Quantum Computing (QC) promises to bring significant advancements in several areas of healthcare such that it may be sensible to give this hybrid Quantum/Classical paradigm its own name – Healthcare4Q. The potential of QC will extend the reach of Healthcare4Q with the help of diverse technologies such as quantum-enabled wearables, quantum-secure transfer and storage of data, and quantum computing at edge, fog, and cloud. All of these technologies promise to catapult Healthcare4Q to become the most capable healthcare framework in the advancement of medical innovations and improvement of patient care.**

An integral part of a person's health lies in cardiovascular health, and thus prioritizing and optimizing cardiovascular health remains vital to the broader goals of public health and healthcare sustainability. In this study, under the paradigm of Healthcare4Q, we propose a framework called the Quantum AI-driven Heart Health Framework (QAIHHF) that can provide advanced predictive intelligence to healthcare providers by utilizing historical and real-time data and processing capabilities proposed in Healthcare4Q. We show that when applied to various diagnostics and health indicators such as ECG data, the Quantum AI provides accuracy at a level equal to or higher as compared to the classical methods thus proving itself to be the critical component that will herald the era of Healthcare4Q.

Keywords— Healthcare 4.0, Healthcare4Q, Heart Failure, Quantum AI Heart Health Framework, Machine Learning, Deep Learning, Quantum Machine Learning, Random Forest, Long Short-Term Memory (LSTM), Quantum Neural Networks (QNN), Quantum LSTM

I. INTRODUCTION

Modern healthcare is currently poised for a revolution in the form of Healthcare 4.0 [1], [2], [3], [4], which represents a transformative approach to advancing medical innovations, and thus patient care, by leveraging the latest advances in information processing systems. This approach promises to deliver real-time personalized healthcare to patients, physicians, and caregivers by shifting from hospital-centric to a patient-centered model. As we will show below, adding Quantum technologies to healthcare gives a significant potential boost to the effectiveness and capability of healthcare. We call this paradigm Healthcare4Q.

To achieve the central tenet of providing enhanced patient experience and increased satisfaction, the medical field will have to rely very heavily on advancements in technologies and updates in methods and procedures [5], [6], [7], [8]. The current and future advancements in data acquisition, secure transmission and storage, and advanced data processing using Machine Learning (ML) and Artificial Intelligence (AI) promise to deliver the envisioned benefits [9], [10], [11]. This would require the development, deployment, and management of new solutions and infrastructure to enable flexible and effective access to information from any location. The systems will also have to traverse the diverse and challenging privacy and security landscape while ensuring effective data management [12], [13]. And while concerns have been raised regarding the successful implementation of all of these aspects, the potential to revolutionize healthcare for modern society can be realized with a sustained and disciplined approach along with further research and innovation using AI/ML. AI/ML has already proven the potential to handle massive and diverse amounts of data generated by healthcare systems [14], [15], [16]. Noteworthy achievements using AI/ML include the interpretation of medical images [17], [18] and assisted robotic surgeries [19], [20].

In addition to the classical computing advances, there is a new and potentially far superior technology on the horizon in the form of quantum computing (QC) [21]. QC promises to provide processing speedups as compared to classical computation [22], [23]. This capability is particularly valuable to healthcare research where simulations, modeling, and data analysis can all benefit from the speedup promise of QC. Data Analysis can see the benefits of Quantum Machine Learning (QML) algorithms [24], [25], [26] that can efficiently analyze large and complex datasets which will lead to more accurate and rapid analysis of patient data such as biotelemetry, medical imagery and scans, and genomic data to improve diagnostics and medical planning. QC and QML algorithms also hold a promise to bring speed and accuracy in medical image analysis leading to better detection of subtle anomalies [27], [28], [29]. Drug discovery research can also benefit tremendously from QC with the superior molecular interaction modeling capabilities to aid in predicting potential drug candidates [30], [31] thus greatly accelerating the development of new medications and treatments. This research can be further aided by the capability provided by QC to simulate biological systems at a level of detail that classical computers struggle to achieve [32], [33]. This capability is crucial for understanding intricate biological processes and designing targeted interventions in areas such as personalized medicine. Quantum technology research has also seen advancements in cryptography, which can provide enhanced security for sensitive healthcare data. Quantum Key Distribution (QKD) can provide substantially improved Encryption and Security capabilities to create secure communication channels thereby protecting patient information during transit and in storage [34], [35], [36]. Lastly, QC can also prove critical in optimizing the logistics of healthcare [37], [38] by improving resource allocation, scheduling, and supply chain management etc., leading to efficiency and cost-effectiveness of healthcare delivery.

In this paper, we study the proposed Healthcare4Q paradigm by demonstrating the effectiveness of the combination of Quantum and Classical ML algorithms in detecting cardiovascular health. As a leading cause of mortality in modern Western society, cardiovascular health remains a top concern and priority in healthcare research. There have been important algorithmic studies and advances in this area using classical AI and ML [39], [40] with varying degrees of accuracy. They have, for a large part, utilized ECG data and applied various classification algorithms such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Decision Trees, Naïve Bayes, etc. [41], [42].

There is also existing research using QML methods such as QSVM [43] where they study the QSVM algorithm and find the accuracy to be superior to classical SVM. Munshi et al. [44] study the problem using Quantum Support Vector Classifier (QSVC) and Variational Quantum Classifier (VQC) methods where they have shown the QML algorithms to be equally or more accurate than the equivalent classical methods.

In our study, we investigated the MIT Electrocardiogram (ECG) dataset, which consists of the ECG shapes of heartbeats of healthy human subjects as well as those suffering from arrhythmia and myocardial infarctions. The relative effectiveness of various classical and quantum machine learning and deep learning algorithms on the ECG data were studied, and the results were used to propose a novel health prediction score called Quantum AI-driven Heart Health Framework Score (QAIHHF Score). This study also proposed a larger framework involving utilizing this score with modern wearable technologies with real-time acquisition and analysis of the heartbeat data. This framework, along with technical details for Healthcare4Q are discussed in section II.

The rest of the paper is organized as follows: Section II provides greater details on Healthcare4Q and Quantum AI-Driven Heart Health Framework. Section III provides background information on the Quantum and Classical ML methods and algorithms. Section IV describes the experimental setup and the results obtained. Finally, in Section V we talk about the conclusions drawn from this study and future work.

II. Healthcare4Q Technical Stack and Quantum AI-Driven Heart Health Framework (QAIHHF)

In this work, we propose two new frameworks, Healthcare4Q and QAIHHF. Healthcare4Q looks at the future of healthcare in light of the upcoming technological upheaval expected in the next two decades. QAIHHF lays down a framework for scoring cardiovascular health using the technologies and capabilities made available by Healthcare4Q.

A. Healthcare4Q Technical Stack

The technological framework for Healthcare4Q (Fig. 1) relies very heavily on current and upcoming quantum technologies. Providing the foundational structure for Healthcare4Q will be Quantum cloud infrastructure and will include compute and store capabilities in the cloud that may get extended to fog and edge computing as well. Built on top of the cloud is the Quantum Privacy and Security framework, bringing in and relying on revolutionary capabilities such as quantum communication and encryption, to ensure the safety and security of sensitive data such as patient medical history. Quantum blockchains ensure that the information is secure, decentralized, and tamper-free. This data is extended to Quantum IoTs such as wearables, which can use and enhance this data. Additionally, the use of Quantum ML, Quantum DL, and Quantum Generative AI brings in enhanced decision-making capabilities to fulfill the vision of Healthcare4Q (Fig. 2).

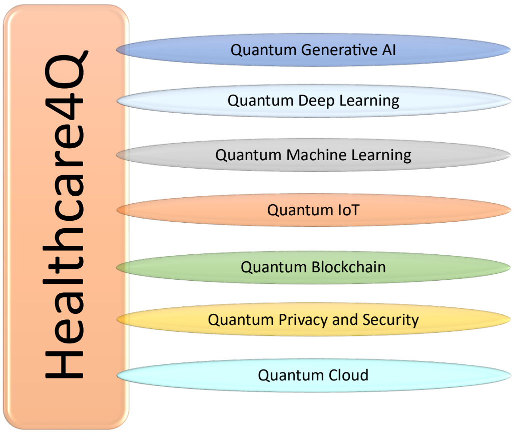

Fig. 1. Healthcare4Q Technology Framework

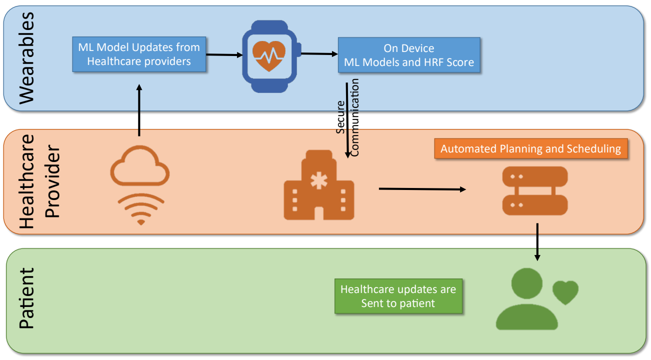

Fig. 2. Quantum-AI Driven Heart Health Framework

B. Quantum AI-driven Heart Health Framework (QAIHHF)

As part of this study, we are introducing a new framework called Quantum AI-driven Heart Health Framework (QAIHHF). The framework, and score as shown in Fig. 3, focus on three major categories of factors that influence cardiovascular health:

Genetic and Familial Factor: This category scores the ethnic, genetic, environmental, and hereditary risk factors, all of which have a significant influence on an individual's susceptibility to various heart-related conditions.

Historical Factors: Past medical history can provide significant clues to the current and future heart health. Conditions like diabetes, hypertension, and high cholesterol can be excellent predictors of risks to cardiovascular health. And so too can some other chronic conditions like kidney disease or rheumatoid arthritis. This category measures that risk and is a crucial component of the QAIHHF score.

Current Health Bio-Markers and Lifestyle Factors: A person’s lifestyle choices impart a profound impact on cardiovascular health. Factors such as Nutrition, Physical Activity, Smoking and Drinking, Stress and Sleep, etc. can prove to be important data points for the QAIHHF score. This is further supplemented by data points obtained from common tests and measurements such as Blood Pressure, Weight and BMI, Blood Cholesterol and Glucose levels, ECG and Cardiac Imaging, etc. This category is the most important component of the score.

Full detailed description and study of the proposed QAIHHF score are planned for a future study.

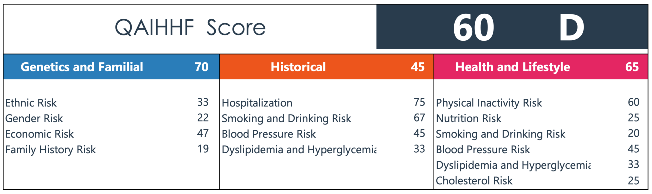

Fig. 3. QAIHHF Scorecard

III. Background And Related Work

In this section, we will provide a brief overview of the quantum technologies and algorithms that will be crucial in enabling Healthcare4Q. Specifically, we will discuss Quantum Machine Learning. Details on the other quantum technologies will be part of our future work.

A. *Quantum Computing and Quantum Circuits*

The fundamental unit of information in Quantum Computing, a qubit, can be described in Dirac notations as $|\Psi\rangle = \alpha|0\rangle + \beta|1\rangle$, where $|\Psi\rangle$ is a vector in Hilbert space with $|0\rangle = \binom{1}{0}$ and $|1\rangle = \binom{0}{1}$. A qubit allows several quantum mechanical operations, which can be grouped together to act like logic gates, much similar to what exists in classical computing. Physics of the quantum mechanical systems also allows the qubits to be entangled to form a composite system of n qubits that can describe 2^n states together. Additionally, the property of superposition allows a qubit to represent a state out of infinitely many states (unlike a classical bit which can only represent one of two states), and only upon measurement does it collapse to give one of the two states as defined by the physics of the quantum system. Qubits and quantum gates can be combined to form what is called a quantum circuit. Fig. 4 shows an example of a quantum circuit [45].

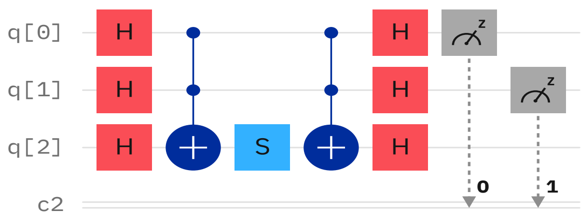

Fig. 4. An example of a quantum circuit.

Using quantum circuits, it is possible to design complex algorithms in a hybrid manner. Fig. 5 shows one such environment where encoded input data is fed into the quantum layer, and the output of the quantum layer is measured and used for cost function calculation and optimization.

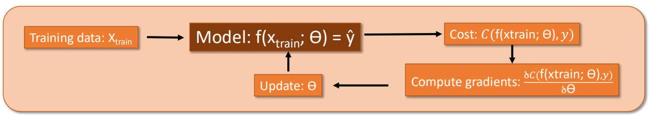

Fig. 5. Hybrid ML environment.

In their work [46], Schuld et al. discuss the thought process of designing a classification algorithm based on quantum circuits, a sample of which is shown in Fig. 6. The work proved the feasibility of quantum-ready design on near-term intermediate-scale quantum devices. Around the same time, several other research works [47], [48], [49], [50], [51] have investigated quantum algorithms to solve classification problems using linear algebra. Fig. 7 shows a schematic of the aforementioned quantum layer, commonly called a parameterized quantum circuit (PQC) or Variational Quantum Circuit (VQC)) [52].

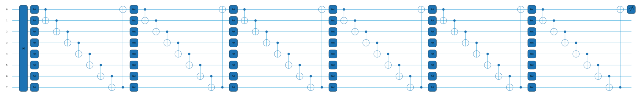

Fig. 6. A six-layer quantum circuit

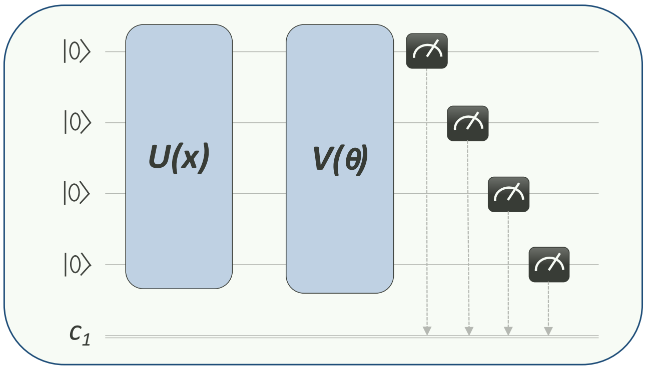

Fig. 7. Generic VQC Design. U(x) is the encoding layer for the input data x, while the V(θ) is the quantum layer acting on tunable parameters θ.

B. *Classification using Quantum and Classical ML*

For a typical supervised learning task, the goal is to train the model $f : x \rightarrow y$ so that the model can accurately recognize (whether via regression or classification) previously unseen data. The simplest of these, the binary linear classifier, can be depicted in the form of a threshold function:

$$y = f(x \mid \theta) = sign(x^T w + b) \quad (1)$$

where $x \in \mathbb{R}^N$ are the trainable inputs, θ are the parameters {w, b} with weight $w \in \mathbb{R}^N$ and bias $b \in \mathbb{R}$.

In QML, the above classification process reduces to linear algebraic computations using quantum perceptron [53] which implements the binary linear classifier described in (1). The calculation of $\varphi = x^T w$ is done with appropriate feature engineering, which in this context involves data encoding of the features as normalized inputs mapping $x \in \mathbb{R}^N$ to the 2^n dimensional amplitude vector $|\varphi\rangle$. The output of the circuit provides the classification of the normal and abnormal conditions as the binary outputs, thereby accurately implementing a binary linear classifier as a quantum circuit Fig. 8.

The data encoding strategy used for quantum algorithms, in general, depends on the problem domain, and can generally be described as $\varphi : \mathbb{R}^N \rightarrow C^{2^n}$ where N features are encoded into n qubits. The input vector $x \in \mathbb{R}^N$ is first pre-processed into a normalized state of unit length. If N is not a direct power of 2, the data is padded with an appropriate number of zero-length features such that the new feature space can all be accommodated in the 2^n amplitudes of the n-qubit system. Not every problem domain yields itself to this way of pre-processing and some datasets might get distorted due to this normalization. A possible solution for this [46] may exist in padding the feature space before the normalization with non-zero padding terms such that the data is transformed from the original feature space to a higher-dimensional space.

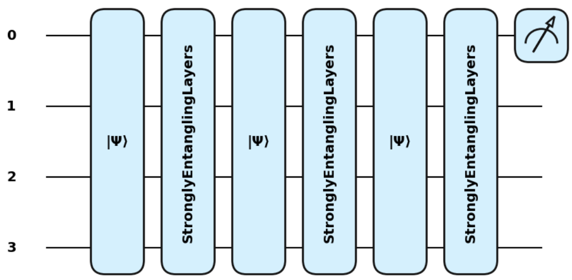

Fig. 8. A Quantum Circuit with Amplitude Embedding and Strongly Entangling Layers used for Classification.

The results from the Quantum binary linear classifier can then be compared with classical classification algorithms such as Support Vector Machines (SVM), Decision Trees (DT), Random Forest (RF), and XG Boost.

C. *Classification using Quantum and Classical Long Short-Term Memory (LSTM)*

LSTM (and by extension Quantum LSTM) is a form of Recurrent Neural Networks (RNN) that can learn long dependencies. This allows them to retain information for a longer time. LSTM was first introduced by Hochreiter & Schmidhuber [54], and implements a 4-layer network, each with its unique function, acting on consecutive time steps. Quantum LSTM implementation follows very similarly to LSTM (as depicted in Fig. 9) [52], [55], [56]. Implementation of QLSTM also utilizes a VQC layer with tunable parameters (as depicted in Fig. 7 and Fig. 10).

The QLSTM model can be described by equations that are quite similar to LSTM as follows [55]:

$$f_t = \sigma\left(VQC_f[h_{t-1}, x_t]\right) \quad (2a)$$

$$C_t = f_t \otimes C_{t-1} + i_t \otimes \tilde{C}_t \quad (2b)$$

$$\tilde{C}_t = tanh(VQC_c.[h_{t-1}, x_t]) \quad (2c)$$

$$i_t = \sigma(VQC_i.[h_{t-1}, x_t]) \quad (2d)$$

$$o_t = \sigma(VQC_o.[h_{t-1}, x_t]) \quad (2e)$$

$$h_t = o_t \otimes \tanh(C_t) \quad (2f)$$

Here σ is the sigmoid function and *tanh* is the hyperbolic tangent function.

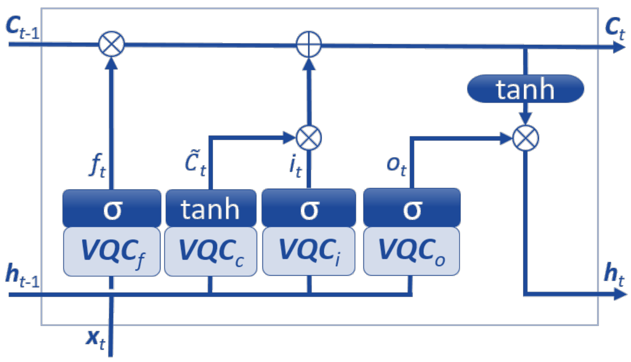

Fig.9. A QLSTM cell

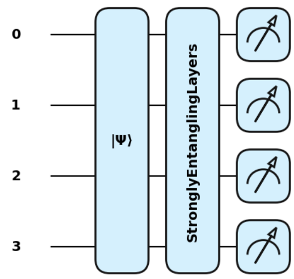

Fig. 10. A Variational Quantum Circuit (VQC)

IV. EXPERIMENT SETUP AND RESULTS

The following libraries are used to train ML, DL, and QML algorithms.

Traditional Machine Learning: We have utilized the widely recognized Python library called Scikit-learn (sklearn) which presents a diverse array of tools for carrying out various machine learning tasks.

Deep Learning: We use the well-known pairing of TensorFlow and Keras. TensorFlow, which was created by Google, is a versatile and widely utilized framework for deep learning. It offers robust assistance in constructing and training neural networks. Meanwhile, Keras has been seamlessly integrated into TensorFlow as a high-level API.

Quantum Machine Learning: We make use of PennyLane [57] with PyTorch for our QML. PennyLane is a freely available library for Quantum Machine Learning that seamlessly integrates with PyTorch. This combination allows us the ability to construct and train QNN and QLSTM models, all while taking advantage of the automatic differentiation capabilities offered by PyTorch (Fig. 11).

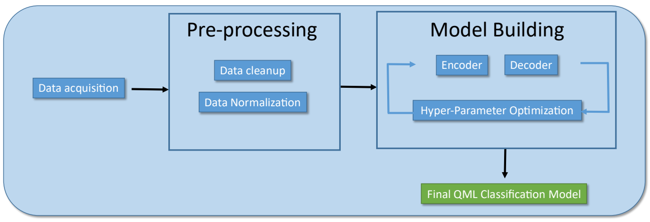

Fig. 11. QML Framework

A. *Data and the Evaluated Metrics*

Data used in this study is the MIT ECG data (in two datasets referred to in this work as PTB and Arrhythmia datasets respectively) consisting of the ECG shapes of heartbeats of healthy human subjects as well as those suffering from arrhythmia and myocardial infarctions (Fig. 12). The data was normalized before processing, and the training set was ensured to have equal weightage across categories.

In our study, we use the *accuracy*, *precision*, *recall*, and *F1–score* metrics to evaluate the trained models. The *accuracy* score indicates how often the model correctly predicted the category of the test data. The *precision* score allows us to measure how well our models predict the positive outcomes, while the *recall* metric indicates how well our models identify the true positives. And finally, the *F1–score* combines precision and recall indicating the 'robustness' of the models.

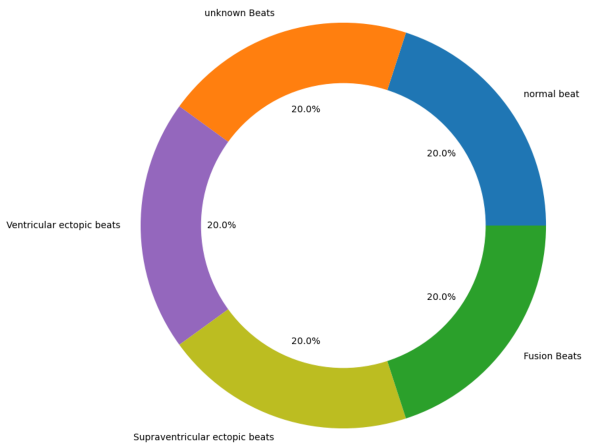

Fig. 12. ECG Training Data categories

B. Experimental Results

The following are the hyper-parameters used and results achieved from traditional ML, conventional DL, and Quantum ML algorithms on both datasets :

1) Classical Machine Learning Algorithms:

Support Vector Machine (SVM) Optimization: The parameter *C* controls the trade-off between minimizing the classification error and maximizing the margin. We explored a range of values, including 0.001 and 0.0001. On the other hand, *Gamma* is a kernel coefficient parameter, and we experimented with various values, including 1, 10, and 100.

Decision Tree (DT) Optimization: We explored both 'gini' and 'entropy' for *Criterion*, used to measure the quality of a split at each node in the tree. In the case of *Max Depth*, which represents the maximum depth of the tree, we tested different depths including 50, 100, and 150.

Random Forest (RF) Optimization: The *n_estimators* parameter represents the number of decision trees in the ensemble, and we explored different values, including 50, 100, and 150. The *max_depth* parameter, which denotes the maximum depth of each decision tree in the ensemble, was experimented with depths of 50, 100, and 200.

XGBoost Optimization: The parameter *learning_rate* controls the step size at each iteration while moving toward a minimum of the loss function and was explored with the values of 0.01 and 0.10. The parameter *max_depth*, like DT and RF optimization above, specifies the maximum depth of each decision tree in the ensemble. We experimented with depths of 50, 100, and 150.

TABLE I. ALGORITHMS WITH THE OPTIMAL PARAMETERS FOR PTB DATASET

Algorithm	Best Parameters
SVM	Gamma:1 ; C: 0.0001
DT	Criterion: Gini ; Max_Depth: 150
RF	N_estimators: 50 ; Max_Depth: 200
XGBoost	Learning Rate: 0.01 ; Max_Depth: 150

TABLE II. EVALUATED METRICS ON TRAINING SET ON BEST ALGORITHM FOR PTB DATASET

Algorithm	Accuracy	Precision	Recall	F1-Score
SVM	0.71	0.66	0.71	0.66
DT	1.00	1.00	1.00	1.00
RF	1.00	1.00	1.00	1.00
XGBoost	1.00	1.00	1.00	1.00

TABLE III. EVALUATED METRICS ON TESTING SET ON BEST ALGORITHM FOR PTB DATASET

Algorithm	Accuracy	Precision	Recall	F1-Score
SVM	0.72	0.65	0.70	0.67
DT	0.92	0.92	0.92	0.92
RF	0.97	0.97	0.97	0.97
XGBoost	0.98	0.98	0.98	0.98

As we can see from Tables I – III, both DT, RF, and XGBoost have managed to achieve high scores for accuracy, precision, recall, and F1-score, suggesting they possess a certain level of robustness when it comes to extrapolating their learning to novel data instances. Furthermore, both RF and XGBoost also showcase strong performances with impressive scores. Based on these findings, it can be inferred that DT, RF, and XGBoost are all good contenders for these datasets. On the other hand, the SVM model obtained lower scores, suggesting SVM may require some additional fine-tuning to match the performance levels of the other algorithms on this specific dataset.

TABLE IV. ALGORITHMS WITH THE BEST PARAMETERS FOR ARRHYTHMIA DATASET

Algorithm	Best Parameters
SVM	Gamma:100 ; C: 0.0001
DT	Criterion: Entropy ; Max_Depth: 150
RF	N_estimators: 50 ; Max_Depth: 200
XGBoost	Learning Rate: 0.01 ; Max_Depth: 150

TABLE V. EVALUATED METRICS ON TRAINING SET ON BEST ALGORITHM FOR ARRHYTHMIA DATASET

Algorithm	Accuracy	Precision	Recall	F1-Score
SVM	0.28	0.33	0.28	0.28
DT	1.00	1.00	1.00	1.00
RF	1.00	1.00	1.00	1.00
XGBoost	1.00	1.00	1.00	1.00

TABLE VI. EVALUATED METRICS ON TESTING SET ON BEST ALGORITHM FOR ARRHYTHMIA DATASET

Algorithm	Accuracy	Precision	Recall	F1-Score
SVM	0.23	0.30	0.23	0.24
DT	0.92	0.94	0.92	0.93
RF	0.96	0.98	0.96	0.97
XGBoost	0.96	0.98	0.96	0.97

Tables IV-VI give the evaluation metrics and results for the Arrhythmia dataset, and we see results similar to the PTB dataset. The DT and RF models achieved high values in terms of accuracy, precision, recall, and F1 score, although it is important to interpret these results in the context of model complexity; DT and RF models can easily overfit, meaning they may be tuned too closely to the specific nuances of the training data. SVM, on the other hand, has lower values across all metrics, indicating its challenges in capturing the complexity of the arrhythmia dataset during training, indicating that it may not be the most suitable choice for this particular dataset.

2) Deep Learning Algorithms:

Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM): Our optimization focused on three key hyperparameters. *Batch Size* determines the number of data samples used in each iteration during training. We explored a range of batch sizes, including 32, 64, 128, 256, and 512, allowing us to optimize between convergence speed and generalization. *Learning Rate*, which plays a pivotal role in controlling the step size during the gradient descent optimization process. Here we experimented with three different learning rates, 0.01, 0.001, and 0.0001. Adjusting the learning rate allowed us to fine-tune the training process and strike a balance between rapid convergence and avoiding overshooting the minimum. Finally, the *Number of Layers* influences a neural network's capacity to capture complex patterns. We looked at network architectures with 2, 4, 6, 8, and 10 layers. Varying the number of layers helped us determine the optimal network depth for the given dataset.

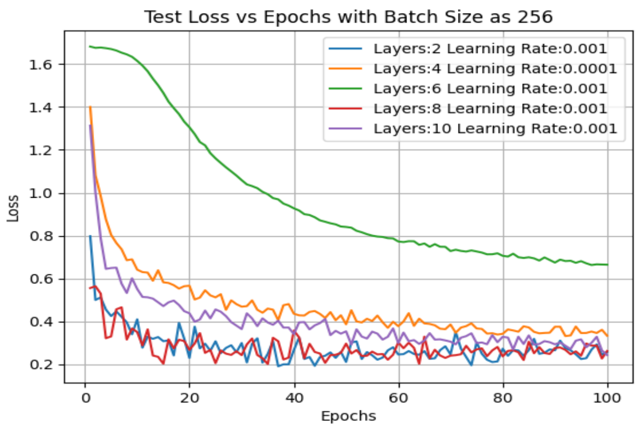

Fig. 13. ANN Test Loss for Arrhythmia dataset

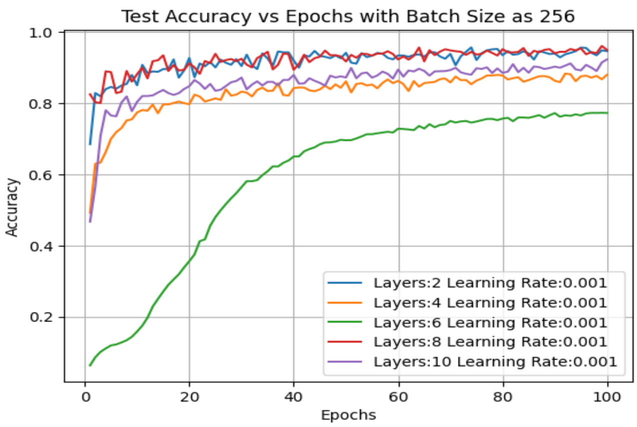

Fig. 14. ANN Test Accuracy for Arrhythmia dataset

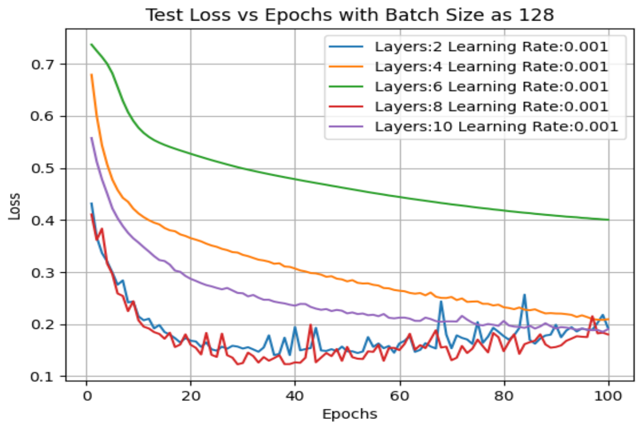

Fig. 15. ANN Test Loss for PTB dataset

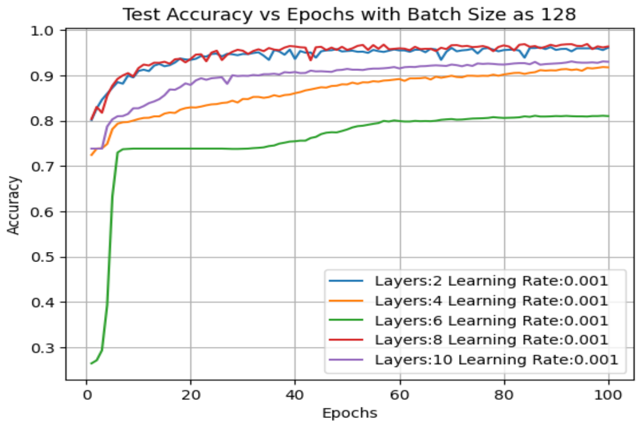

Fig. 16. ANN Test Accuracy for PTB dataset

Studies on ANN performance using two datasets offer significant results. This is because for both datasets, as the batch size increases, we see a fluctuating pattern in test accuracy along with a clear general trend towards an increase in minimum test loss. The smaller batch sizes (32 and 64) always yield a high level of accuracy and low loss, which means that one of the most important aspects of model optimization is the size of batches. The ECG-MIT dataset delivers its best results with the lowest batch size; however, the ECG-PTB dataset shows an inclination in this direction.

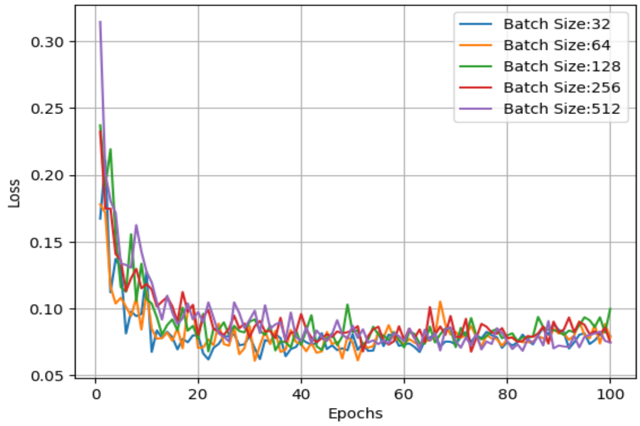

Fig. 17. LSTM Test Loss for Arrhythmia dataset

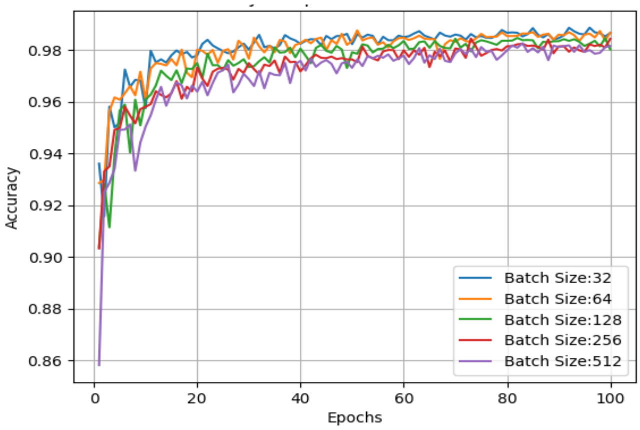

Fig. 18. LSTM Test Accuracy for Arrhythmia dataset

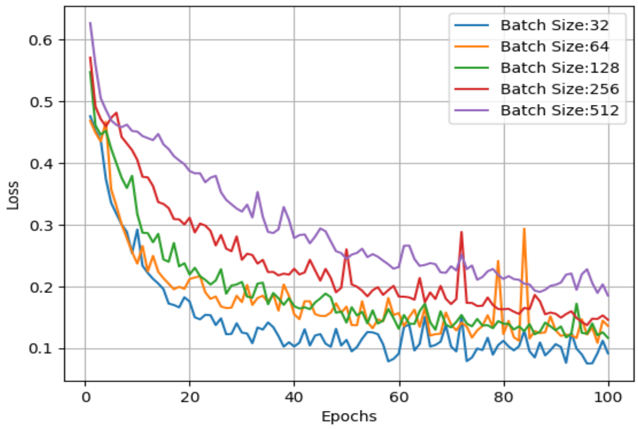

Fig. 19. LSTM Test Loss for PTB dataset

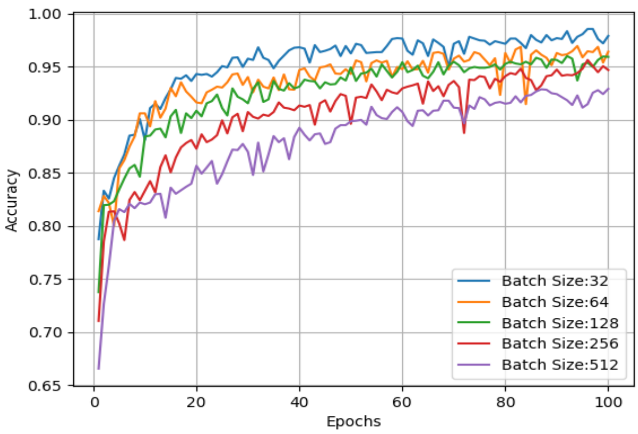

Fig. 20. LSTM Test Accuracy for PTB dataset

The performances of LSTM on the two datasets demonstrate a relationship between batch size, loss, and accuracy. We found that for the PTB dataset when the batch size is 32, the model can achieve the highest accuracy and lowest loss, which means it would be best to train on smaller batch sizes for this dataset. In the case of other datasets, as the batch size increases, both loss and accuracy decrease, indicating that larger batch sizes are less efficient in the learning process. Another example of this tendency was found in the Arrhythmia dataset, where smaller batch sizes led to better performance of the model, with the loss being minimal and accuracy at its maximum among 256 (loss) and 32 (accuracy). These findings emphasize that neural network training effectiveness and model accuracy are both strongly influenced by batch size, which should be chosen thoughtfully for optimizing diagnostic capabilities.

3) Quantum Machine Learning Algorithms:

Quantum Long Short-Term Memory (LSTM): The QLSTM model is implemented using 8 Qubits in strong entanglement with data encoded using amplitude encoding. We evaluated the model with varying batch size values including 32, 64, 128, 256, and 512. Below are the experimental results for both datasets.

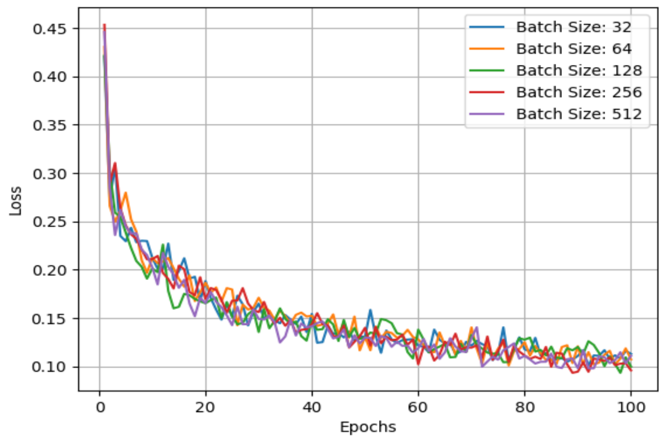

Fig. 21. QLSTM Test Loss for Arrhythmia dataset

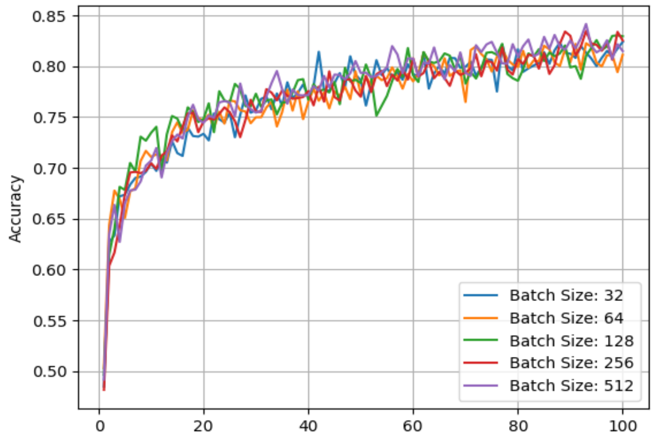

Fig. 22. QLSTM Test Accuracy for Arrhythmia dataset

TABLE VII. EVALUATED METRICS ON TESTING SET FOR ARRHYTHMIA DATASET FROM QLSTM

Batch Size	Accuracy	Precision	Recall	F1 Score
32	0.8105	0.8219	0.8105	0.8128
64	0.8075	0.8241	0.8075	0.8078
128	0.8070	0.8312	0.8070	0.8104
256	0.8095	0.8312	0.8095	0.8140
512	0.8155	0.8337	0.8155	0.8193

Figures 21 and 22 show the test loss and test accuracy respectively of the QLSTM network on the Arrhythmia dataset. Table VII presents a more detailed summary of the metrics calculated by this model. It can be concluded that among the different batch sizes, with high consistency, the network's precision did not fall below 82%, accuracy was mostly within the range from 80.70% to 81.55%, and the F1 score oscillated around 80.78% to 81.93%. We also noted that the best result in terms of accuracy and F1 score could be obtained for a batch size equal to 512 as increased batch size tended to make a slight improvement in performance.

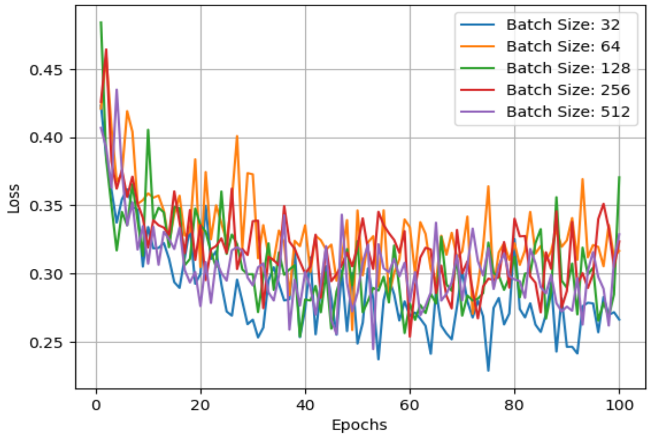

Fig. 23. QLSTM Test Loss for PTB dataset

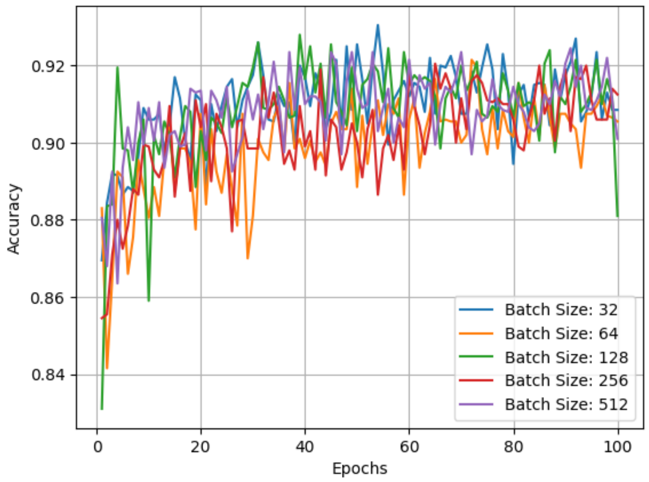

Fig. 24. QLSTM Test Accuracy for PTB dataset

TABLE VIII. EVALUATED METRICS ON TESTING SET FOR PTB DATASET FROM QLSTM

Batch Size	Accuracy	Precision	Recall	F1 Score
32	0.9125	0.9135	0.9125	0.9125
64	0.9035	0.9038	0.9035	0.9035
128	0.9055	0.9060	0.9055	0.9055
256	0.9125	0.9125	0.9125	0.9125
512	0.9065	0.9081	0.9065	0.9066

Figures 23 and 24 depict the test accuracy and test loss respectively from the PTB dataset. Table VIII presents the performance measures based on batch sizes. A significantly higher accuracy was found compared to the Arrhythmia dataset, which rose to 91.25% with batch sizes of 32 and 256. Again, a stable range between 90.35% and 91.25% across all batch sizes for the F1 score signifies a balanced performance.

QLSTM network performed well on both the data sets and its performance was particularly better with an increased size of the batch, though it was most visible in the case of the Arrhythmia dataset. The stability seen from different metrics across various analyses suggests that QLSTM can be used to deal with the complexities of ECG signal classification. In this light, the PTB dataset with higher scores on different metrics is an indication that QLSTM is very effective in classifying biomedical signals.

V. CONCLUSION AND FUTURE WORK

In this work, we set out to explore the capabilities and advantages of the proposed Healthcare4Q paradigm. The potential architectural and computational superiority offered by quantum computing will prove to be the turning point in the privacy and security needs of the future of healthcare. Quantum technologies of the future will also extend to IoT, wearables, and other edge devices thereby providing end-to-end coverage, from data generation to processing workflow and decision-making to actionable intelligence.

We further proposed and studied a heart health framework called QAIHHF. We also created a score based on this framework indicating the state of the health of a person's heart. We listed various factors and contributors to this score, and we are currently working on creating the full model of that score that we plan to present in the near future.

Working towards creating the QAIHHF score, we investigated several classical and quantum machine learning algorithms to study the efficiency and accuracy of quantum methods. We saw that the quantum algorithms were equally accurate when training with the ECG data and that these methods can indeed be used for the QAIHHF framework.

This work was done using PennyLane's default quantum simulation environment. The quantum simulation environment, owing to the single-threaded nature of the runtime, runs slower when compared to classical methods. We hope to improve upon the speed of model training in our subsequent work by optimizing code and utilizing GPU-enabled environments. We will also explore the model training and related statistics in the quantum computing environments provided by IBM Quantum [58].

REFERENCES

[1] J. Al-Jaroodi, N. Mohamed, and E. Abukhousa, "Health 4.0: On the Way to Realizing the Healthcare of the Future," *IEEE Access*, vol. 8, pp. 211189–211210, 2020, doi: 10.1109/ACCESS.2020.3038858.

[2] S. Abbate, P. Centobelli, R. Cerchione, E. Oropallo, and E. Riccio, "Investigating Healthcare 4.0 Transition Through a Knowledge Management Perspective," *IEEE Trans. Eng. Manage.*, vol. 70, no. 9, pp. 3297–3310, Sep. 2023, doi: 10.1109/TEM.2022.3200889.

[3] J. Al-Jaroodi, N. Mohamed, N. Kesserwan, and I. Jawhar, "Healthcare 4.0 – Managing a Holistic Transformation," in *2022 IEEE International Systems Conference (SysCon)*, Montreal, QC, Canada: IEEE, Apr. 2022, pp. 1–8. doi: 10.1109/SysCon53536.2022.9773863.

[4] A. Gupta and A. Singh, "Healthcare 4.0: recent advancements and futuristic research directions," *Wireless Pers Commun*, vol. 129, no. 2, pp. 933–952, Mar. 2023, doi: 10.1007/s11277-022-10164-8.

[5] H. Qiu, M. Qiu, M. Liu, and G. Memmi, "Secure Health Data Sharing for Medical Cyber-Physical Systems for the Healthcare 4.0," *IEEE J. Biomed. Health Inform.*, vol. 24, no. 9, pp. 2499–2505, Sep. 2020, doi: 10.1109/JBHI.2020.2973467.

[6] R. Ranchal *et al.*, "Disrupting Healthcare Silos: Addressing Data Volume, Velocity and Variety With a Cloud-Native Healthcare Data Ingestion Service," *IEEE*

J. Biomed. Health Inform., vol. 24, no. 11, pp. 3182–3188, Nov. 2020, doi: 10.1109/JBHI.2020.3001518.

[7] S. Wehner, D. Elkouss, and R. Hanson, "Quantum internet: A vision for the road ahead," *Science*, vol. 362, no. 6412, p. eaam9288, Oct. 2018, doi: 10.1126/science.aam9288.

[8] K. Azuma *et al.*, "Quantum repeaters: From quantum networks to the quantum internet," *Rev. Mod. Phys.*, vol. 95, no. 4, p. 045006, Dec. 2023, doi: 10.1103/RevModPhys.95.045006.

[9] M. Ali, F. Naeem, M. Tariq, and G. Kaddoum, "Federated Learning for Privacy Preservation in Smart Healthcare Systems: A Comprehensive Survey," *IEEE J. Biomed. Health Inform.*, vol. 27, no. 2, pp. 778–789, Feb. 2023, doi: 10.1109/JBHI.2022.3181823.

[10] M. Akter, N. Moustafa, T. Lynar, and I. Razzak, "Edge Intelligence: Federated Learning-Based Privacy Protection Framework for Smart Healthcare Systems," *IEEE J. Biomed. Health Inform.*, vol. 26, no. 12, pp. 5805–5816, Dec. 2022, doi: 10.1109/JBHI.2022.3192648.

[11] X. Yu, D. Zhan, L. Liu, H. Lv, L. Xu, and J. Du, "A Privacy-Preserving Cross-Domain Healthcare Wearables Recommendation Algorithm Based on Domain-Dependent and Domain-Independent Feature Fusion," *IEEE J. Biomed. Health Inform.*, vol. 26, no. 5, pp. 1928–1936, May 2022, doi: 10.1109/JBHI.2021.3069629.

[12] M. J. Hossain Faruk, S. Tahora, M. Tasnim, H. Shahriar, and N. Sakib, "A Review of Quantum Cybersecurity: Threats, Risks and Opportunities," in *2022 1st International Conference on AI in Cybersecurity (ICAIC)*, Victoria, TX, USA: IEEE, May 2022, pp. 1–8. doi: 10.1109/ICAIC53980.2022.9896970.

[13] A. Kuznetsov, A. Kiian, V. Babenko, I. Perevozova, I. Chepurko, and O. Smirnov, "New Approach to the Implementation of Post-Quantum Digital Signature Scheme," in *2020 IEEE 11th International Conference on Dependable Systems, Services and Technologies (DESSERT)*, Kyiv, Ukraine: IEEE, May 2020, pp. 166–171. doi: 10.1109/DESSERT50317.2020.9125053.

[14] A. Qayyum, J. Qadir, M. Bilal, and A. Al-Fuqaha, "Secure and Robust Machine Learning for Healthcare: A Survey," *IEEE Rev. Biomed. Eng.*, vol. 14, pp. 156–180, 2021, doi: 10.1109/RBME.2020.3013489.

[15] J. Wiens and E. S. Shenoy, "Machine Learning for Healthcare: On the Verge of a Major Shift in Healthcare Epidemiology," *Clinical Infectious Diseases*, vol. 66, no. 1, pp. 149–153, Jan. 2018, doi: 10.1093/cid/cix731.

[16] N. Jahan, I. B. Rashid, O. Al Numan, A. S. M. T. Hasan, and N. Begum, "Collaborative AI in Smart Healthcare System," in *2021 International Conference on Automation, Control and Mechatronics for Industry 4.0 (ACMI)*, Rajshahi, Bangladesh: IEEE, Jul. 2021, pp. 1–5. doi: 10.1109/ACMI53878.2021.9528125.

[17] B. J. Erickson, P. Korfiatis, Z. Akkus, and T. L. Kline, "Machine Learning for Medical Imaging," *RadioGraphics*, vol. 37, no. 2, pp. 505–515, Mar. 2017, doi: 10.1148/rg.2017160130.

[18] N. Dey, A. S. Ashour, and S. Borra, Eds., *Classification in BioApps: Automation of Decision Making*, vol. 26. in Lecture Notes in Computational Vision and Biomechanics, vol. 26. Cham: Springer International Publishing, 2018. doi: 10.1007/978-3-319-65981-7.

[19] Y. Kassahun *et al.*, "Surgical robotics beyond enhanced dexterity instrumentation: a survey of machine learning techniques and their role in intelligent and autonomous surgical actions," *Int J CARS*, vol. 11, no. 4, pp. 553–568, Apr. 2016, doi: 10.1007/s11548-015-1305-z.

[20] A. Moglia, K. Georgiou, E. Georgiou, R. M. Satava, and A. Cuschieri, "A systematic review on artificial intelligence in robot-assisted surgery," *International Journal of Surgery*, vol. 95, p. 106151, Nov. 2021, doi: 10.1016/j.ijsu.2021.106151.

[21] A. Abbas, D. Sutter, C. Zoufal, A. Lucchi, A. Figalli, and S. Woerner, "The power of quantum neural networks," *Nature Computational Science*, vol. 1, no. 6, pp. 403–409, Jun. 2021, doi: 10.1038/s43588-021-00084-1.

[22] J. Preskill, "Quantum computing in the NISQ era and beyond," *Quantum*, vol. 2, Aug. 2018, doi: 10.22331/q-2018-08-06-79.

[23] H.-Y. Huang, R. Kueng, and J. Preskill, "Information-Theoretic Bounds on Quantum Advantage in Machine Learning," *Phys. Rev. Lett.*, vol. 126, no. 19, p. 190505, May 2021, doi: 10.1103/PhysRevLett.126.190505.

[24] M. Schuld and F. Petruccione, *Machine Learning with Quantum Computers*, 2nd ed. in Quantum Science and Technology. Springer Cham.

[25] J. Biamonte, P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd, "Quantum machine learning," *Nature*, vol. 549, no. 7671, pp. 195–202, Sep. 2017, doi: 10.1038/nature23474.

[26] M. Cerezo, G. Verdon, H.-Y. Huang, L. Cincio, and P. J. Coles, "Challenges and opportunities in quantum machine learning," *Nat Comput Sci*, vol. 2, no. 9, pp. 567–576, Sep. 2022, doi: 10.1038/s43588-022-00311-3.

[27] N. Mathur *et al.*, "Medical image classification via quantum neural networks," Sep. 2021, [Online]. Available: http://arxiv.org/abs/2109.01831

[28] U. Ullah and B. Garcia-Zapirain, "Quantum Machine Learning Revolution in Healthcare: A Systematic Review of Emerging Perspectives and Applications," *IEEE Access*, vol. 12, pp. 11423–11450, 2024, doi: 10.1109/ACCESS.2024.3353461.

[29] S. Suneel, R. Krishnamoorthy, A. Gopatoti, L. P. Maguluri, P. Kuncha, and G. Sunil, "Enhanced image diagnosing approach in medicine using quantum adaptive machine learning techniques," *Opt Quant Electron*, vol. 56, no. 4, p. 534, Jan. 2024, doi: 10.1007/s11082-023-06203-8.

[30] K. Atz, C. Isert, M. N. A. Böcker, J. Jiménez-Luna, and G. Schneider, "Δ-Quantum machine-learning for medicinal chemistry," *Phys. Chem. Chem. Phys.*, vol. 24, no. 18, pp. 10775–10783, 2022, doi: 10.1039/D2CP00834C.

[31] Y. Cao, J. Romero, and A. Aspuru-Guzik, "Potential of quantum computing for drug discovery," *IBM J. Res. & Dev.*, vol. 62, no. 6, p. 6:1-6:20, Nov. 2018, doi: 10.1147/JRD.2018.2888987.

[32] R. Y. Li, R. Di Felice, R. Rohs, and D. A. Lidar, "Quantum annealing versus classical machine learning applied to a simplified computational biology problem," *npj Quantum Inf*, vol. 4, no. 1, p. 14, Feb. 2018, doi: 10.1038/s41534-018-0060-8.

[33] C. Outeiral, M. Strahm, J. Shi, G. M. Morris, S. C. Benjamin, and C. M. Deane, “The prospects of quantum computing in computational molecular biology,” *Wiley Interdisciplinary Reviews: Computational Molecular Science*, vol. 11, no. 1, Jan. 2021, doi: 10.1002/wcms.1481.

[34] S. R. Hasan, M. Z. Chowdhury, Md. Saiam, and Y. M. Jang, “Quantum Communication Systems: Vision, Protocols, Applications, and Challenges,” *IEEE Access*, vol. 11, pp. 15855–15877, 2023, doi: 10.1109/ACCESS.2023.3244395.

[35] J. S. Sidhu *et al.*, “Advances in space quantum communications,” *IET Quantum Communication*, vol. 2, no. 4, pp. 182–217, Dec. 2021, doi: 10.1049/qtc2.12015.

[36] T. M. Fernandez-Carames and P. Fraga-Lamas, “Towards Post-Quantum Blockchain: A Review on Blockchain Cryptography Resistant to Quantum Computing Attacks,” *IEEE Access*, vol. 8, pp. 21091–21116, 2020, doi: 10.1109/ACCESS.2020.2968985.

[37] R. Correll, S. J. Weinberg, F. Sanches, T. Ide, and T. Suzuki, “Quantum Neural Networks for a Supply Chain Logistics Application,” *Adv Quantum Tech*, vol. 6, no. 7, p. 2200183, Jul. 2023, doi: 10.1002/qute.202200183.

[38] S. J. Weinberg, F. Sanches, T. Ide, K. Kamiya, and R. Correll, “Supply chain logistics with quantum and classical annealing algorithms,” *Sci Rep*, vol. 13, no. 1, p. 4770, Mar. 2023, doi: 10.1038/s41598-023-31765-8.

[39] F. I. Alarsan and M. Younes, “Analysis and classification of heart diseases using heartbeat features and machine learning algorithms,” *J Big Data*, vol. 6, no. 1, p. 81, Dec. 2019, doi: 10.1186/s40537-019-0244-x.

[40] H. Lee *et al.*, “Real-time machine learning model to predict in-hospital cardiac arrest using heart rate variability in ICU,” *npj Digit. Med.*, vol. 6, no. 1, p. 215, Nov. 2023, doi: 10.1038/s41746-023-00960-2.

[41] A. Jasinska-Piadlo, R. Bond, P. Biglarbeigi, R. Brisk, P. Campbell, and D. McEneaneny, “What can machines learn about heart failure? A systematic literature review,” *Int J Data Sci Anal*, vol. 13, no. 3, pp. 163–183, Apr. 2022, doi: 10.1007/s41060-021-00300-1.

[42] S. Aziz, S. Ahmed, and M.-S. Alouini, “ECG-based machine-learning algorithms for heartbeat classification,” *Sci Rep*, vol. 11, no. 1, p. 18738, Sep. 2021, doi: 10.1038/s41598-021-97118-5.

[43] Z. Ozpolat and M. Karabatak, “Performance Evaluation of Quantum-Based Machine Learning Algorithms for Cardiac Arrhythmia Classification,” *Diagnostics*, vol. 13, no. 6, p. 1099, Mar. 2023, doi: 10.3390/diagnostics13061099.

[44] M. Munshi *et al.*, “Quantum machine learning-based framework to detect heart failures in Healthcare 4.0,” *Softw Pract Exp*, vol. 54, no. 2, pp. 168–185, Feb. 2024, doi: 10.1002/spe.3264.

[45] IBM, “IBM Quantum Learning Tutorials,” *IBM Quantum Learning Tutorials*. [Online]. Available: https://learning.quantum.ibm.com/tutorial/repeat-until-success

[46] M. Schuld, A. Bocharov, K. Svore, and N. Wiebe, “Circuit-centric quantum classifiers,” Apr. 2018, doi: 10.1103/PhysRevA.101.032308.

[47] B. D. Clader, B. C. Jacobs, and C. R. Sprouse, “Preconditioned quantum linear system algorithm,” *Phys. Rev. Lett.*, vol. 110, no. 25, p. 250504, Jun. 2013, doi: 10.1103/PhysRevLett.110.250504.

[48] H.-Y. Huang, K. Bharti, and P. Rebentrost, “Near-term quantum algorithms for linear systems of equations.” arXiv, Dec. 16, 2019. Accessed: Oct. 08, 2023. [Online]. Available: http://arxiv.org/abs/1909.07344

[49] Y. Subasi, R. D. Somma, and D. Orsucci, “Quantum algorithms for systems of linear equations inspired by adiabatic quantum computing,” *Phys. Rev. Lett.*, vol. 122, no. 6, p. 060504, Feb. 2019, doi: 10.1103/PhysRevLett.122.060504.

[50] C. Bravo-Prieto, R. LaRose, M. Cerezo, Y. Subasi, L. Cincio, and P. J. Coles, “Variational Quantum Linear Solver.” arXiv, Jun. 02, 2020. Accessed: Oct. 08, 2023. [Online]. Available: http://arxiv.org/abs/1909.05820

[51] Y. Lee, J. Joo, and S. Lee, “Hybrid quantum linear equation algorithm and its experimental test on IBM Quantum Experience,” *Sci Rep*, vol. 9, no. 1, p. 4778, Mar. 2019, doi: 10.1038/s41598-019-41324-9.

[52] R. D. Sipio, J.-H. Huang, S. Y.-C. Chen, S. Mangini, and M. Worring, “THE DAWN OF QUANTUM NATURAL LANGUAGE PROCESSING”.

[53] M. Schuld, I. Sinayskiy, and F. Petruccione, “Simulating a perceptron on a quantum computer,” *Physics Letters A*, vol. 379, no. 7, pp. 660–663, Mar. 2015, doi: 10.1016/j.physleta.2014.11.061.

[54] S. Hochreiter and J. ¨ Urgen Schmidhuber, “Long Short-Term Memory.”

[55] S. Yen-Chi Chen, S. Yoo, and Y.-L. L. Fang, “QUANTUM LONG SHORT-TERM MEMORY”.

[56] J. Bausch, “Recurrent Quantum Neural Networks,” Jun. 2020, [Online]. Available: http://arxiv.org/abs/2006.14619

[57] Pennylane, “Pennylane (https://pennylane.ai/),” https://pennylane.ai/.

[58] IBM, “IBM Q (https://quantum-computing.ibm.com/),” https://quantum-computing.ibm.com/.