European Journal of Computer Science and Information Technology,13(11),1-16, 2025
Print ISSN: 2054-0957 (Print)
Online ISSN: 2054-0965 (Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

Testing Healthcare AI Algorithms with Quantum Computing: Enhancing Validation and Accuracy

Mani Joga Rao Cheekaramelli
chmanijogarao@gmail.com

doi: https://doi.org/10.37745/ejcsit.2013/vol13n11116 Published May 03, 2025

Citation: Cheekaramelli M.J..R. (2025) Testing Healthcare AI Algorithms with Quantum Computing: Enhancing Validation and Accuracy, *European Journal of Computer Science and Information Technology*,13(11),1-16

Abstract: *Due to its capacity to handle information in fundamentally new ways, leading to computational powers that were previously unreachable, the multidisciplinary subject of quantum computing has recently grown and attracted significant interest from both academia and industry. Quantum computing has great promise, but how exactly it will change healthcare is still largely unknown. The potential of quantum computing to transform compute-intensive healthcare tasks like drug discovery, personalized medicine, DNA sequencing, medical imaging, and operational optimization is the primary focus of this survey paper, which offers the first comprehensive analysis of quantum computing's diverse capabilities in improving healthcare systems. A new era in healthcare is on the horizon, thanks to quantum computing and AI coming together to transform complicated biological simulations, the processing of genetic data, and advances in drug development. Biological data may be extremely large and complicated, making it difficult for traditional computing tools to handle. This slows down and impairs the accuracy of medical discoveries. Combining the predictive power of AI with the exponential processing speed of quantum computers presents a game-changing opportunity to speed up biological research and clinical applications. The function of quantum machine learning in improving drug discovery molecular dynamics simulations powered by artificial intelligence is discussed in this article. Quickly modeling chemical interactions, analyzing drug-receptor binding affinities, and predicting pharmacokinetics with extraordinary precision are all possible with quantum-enhanced algorithms. To further improve disease progression prediction and therapeutic target identification, we also investigate quantum-assisted deep learning models for understanding complex biological processes like protein folding, epigenetic changes, and connections between metabolic pathways.*

Keywords*:* AI, healthcare, quantum computing, reinforcement learning, CNN

INTRODUCTION

Due to the ever-increasing data volumes produced by clinical and research settings, as well as the growing complexity of biological systems, healthcare technology has been rapidly expanding. Even though they are strong, traditional computational techniques frequently fail to meet the magnitude and complexity of contemporary healthcare problems, especially in fields like drug development, genomic sequencing, and molecular dynamics. By allowing for quicker and more accurate simulations and analyses, the paradigm shift toward quantum computing—which is based on the principles of quantum mechanics—could revolutionize healthcare [1].

There will be revolutionary changes to illness diagnosis, treatment, and management made possible by quantum computing and artificial intelligence (AI) in the healthcare system [2, 3]. The fundamental difference between classical binary computing and quantum computing is the use of quantum bits, or qubits, which, by virtue of entanglement and superposition, are able to represent and store information in a myriad of states. Since quantum computers can analyze massive volumes of data produced by healthcare at rates that conventional supercomputers can't match, they might prove to be an important tool in this field.

Quantum computing has the potential to greatly improve AI's capabilities when used to healthcare [4,5, 6]. Machine learning and deep learning, two subfields of artificial intelligence, rely substantially on data for pattern recognition, prediction, and outcome learning algorithm training. Quantum computing has the potential to drastically cut down on processing times, opening the door to healthcare settings where data analysis and decision-making may take place in real-time. By working together constructively, we can improve diagnostic accuracy and speed, allowing us to detect illnesses using genetic data or medical imaging much more quickly than is now achievable.

Quantum computing may also open up new avenues for individualized healthcare. Medical professionals might improve the efficacy and safety of therapy by taking into account each patient's individual genetic composition, lifestyle choices, and environmental circumstances. AI with quantum enhancements has the potential to model intricate biological processes and foretell the interactions between various medicines and each patient's unique biological systems, opening the door to highly individualized medical care.

It is believed that quantum computing has the potential to completely alter the medication research and discovery processes. To better understand how to create medications to interact with certain biological processes, scientists would benefit from the capacity to model molecular interactions at a quantum level. By improving the accuracy of predictions regarding the medications' efficiency and possible adverse effects, this might hasten drug development and boost the success rate of new treatments. Issues in AI-assisted Healthcare Systems [7], [8]:

Although AI shows great promise in healthcare analysis, it does have several limits. These include worries about data privacy, the possibility of algorithmic bias, the requirement for human oversight, and the difficulties in assuring accountability and ethical considerations.

Data Quality

When it comes to AI-powered personalized healthcare, data quality is a major consideration. It is the quality of the training data that determines how accurate and dependable AI models will be. The reason behind this is that AI models are built to analyze data, find patterns, and then make predictions. Artificial intelligence (AI) models are vulnerable to performance degradation due to biased, inadequate, or incorrect training data. The AI algorithm may produce inaccurate forecasts or suggestions due to biased data. For instance, it's possible for an AI model to underperform when applied to different ethnic or socioeconomic groups if it's trained on data that mostly represents one of those groups. Healthcare results might become more unequal as a result of this. The efficacy of AI models is also jeopardized by missing or inaccurate data. Insufficient data could prevent the AI model from making reliable predictions. When crucial information like a patient's family medical history is absent from an AI model meant to forecast the probability of a patient having a specific ailment, the accuracy of the model's projections is called into question. Lastly, AI model performance might be affected by erroneous data. It is possible for the AI model to make erroneous predictions if the data utilized to train it is inaccurate or inconsistent. As an example, if the data used to train an AI model includes inaccurate values for a certain measurement, like blood pressure, the algorithm might end up making inaccurate predictions.

Privacy Concerns

There are legitimate privacy issues with using AI in healthcare, as there are with any technology that processes personally identifiable information. Patients have valid concerns over the handling of their personal health information, including its collection, storage, and usage. Patients face substantial dangers from data breaches, data abuse, and illegal access, all of which can have devastating effects. The risk of unauthorised access to or use of

European Journal of Computer Science and Information Technology,13(11),1-16, 2025
Print ISSN: 2054-0957 (Print)
Online ISSN: 2054-0965 (Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

patient data is a major privacy concern with artificial intelligence (AI) in healthcare. Patients may be wary of entrusting AI systems with their private health information if they have doubts about the security of such data. Another possible source of anxiety for patients is the possibility that their data may be utilized for reasons unrelated to healthcare, such research or marketing.

Complexity of Healthcare Data

Using XAI methods presents significant problems because to the complexity of healthcare data. Data in healthcare may be characterized by its volume, velocity, variability, and heterogeneity. This data comes from a variety of sources, including medical imaging, genetic data, wearable devices, EHRs, and patient-related outcomes.

Temporal Dynamics

Temporal dependencies and longitudinal trends can be seen in the data, which illustrates how a patient's health status changes over time. Accurate and interpretable predictions over different time points should be provided by XAI models that account for changes in time, detect temporal relations, and make use of time-series data.

Interactions and Contextual Factors

Medical decision-making is impacted by numerous factors, including patient demographics, treatment procedures, environmental exposures, clinical history, and more. For AI predictions to be understandable, it is necessary to understand the intricate interplay between the many variables and components that go into making such predictions.

Missing and Noisy Data:

A number of issues can impact the accuracy of healthcare data models, including missing outliers, measurement errors, noise, and values. The robustness and reliability of AI-driven insights should be preserved using XAI strategies that deal with missing data imputation, data preparation, and outlier identification.

Difficulty in Error Detection and Diagnosis:

Overfitting bias and model drifting are two reasons why blackbox algorithms could produce erroneous predictions. In addition, because the inner workings of a blackbox system are not visible to the naked eye, it is very difficult to diagnose and fix flaws in such systems. Both patient safety and the effectiveness of clinical parameters are at risk when there is a lack of genuine and open communication on the nature of the problem and the steps taken to resolve it.

Consistency and Reliability:

Reliability and consistency are key components in building confidence in XAI. Artificial intelligence systems are anticipated to consistently provide explanations and predictions in same contexts. Trust in the system increases when AI-driven results are trustworthy and match expectations. On the other hand, if XAI is inaccurate, it might undermine the trust and confidence that has been built up.

Feedback and Clarity of Uncertainty:

Users generally like the XAI systems' input on the degree of uncertainty in forecasts. Users may better evaluate the quality and dependability of AI ideas with clear and transparent information, which in turn helps them make better judgments in unforeseen situations. Honesty and humility in AI's skills may be demonstrated by accepting the unknown characteristic and building trust in it.

By facilitating more efficient and rapid data processing, solving complicated problems, and the creation of new algorithms that surpass the capabilities of classical computers, quantum computing has the potential to improve AI algorithms, ultimately resulting in AI systems that are more powerful and intelligent [9], [10].

Improved Learning and Performance:

Compared to conventional computers, quantum computers are light years ahead when it comes to processing massive datasets and the intricate interactions within them. This bodes well for artificial intelligence algorithms. Quantum algorithms can improve AI performance in areas such as scheduling, planning, and resource allocation by solving complicated optimization problems that classical computers are unable to handle.

Revolutionizing Algorithms:

With the advent of quantum computing, new algorithms and models in artificial intelligence (AI), including quantum machine learning (QML), may be created, taking use of the distinct properties of quantum systems.

The ability of quantum computers to do several calculations concurrently via entanglement and superposition is known as quantum parallelism. This enables them to rapidly explore a large solution space and arrive at optimum solutions.

Enhanced Accuracy

QML models are able to analyze more data and more intricate relationships within datasets, resulting in more accurate predictions.

The ability of quantum computers to mimic chemical interactions and speed up the development of new drugs is only one of many scientific uses for quantum simulations.

Cybersecurity:

By facilitating quicker and more complicated computations, quantum computing has the ability to improve AI-driven cybersecurity. This might result in the creation of unbreakable encryption methods and the quick identification of threats.

Quantum Natural Language Processing:

AI's comprehension and generation of human language might be improved with the help of quantum algorithms.

RELATED WORKS

With healthcare 5.0 and quantum neural network breakthroughs, the healthcare analytics workplace is changing. We not only examine a large body of case studies, but also survey the literature on smart healthcare analytics and quantum deep neural networks, with an emphasis on their potential applications in quantum computing. The current research gaps concerning the implications of quantum neural networks in healthcare analytics are the target of this study. We contend that new research and exploration opportunities are opening up in the healthcare business as it moves away from automation and towards true cooperation with quantum networks. The goal of this research is to assess how well Healthcare 5.0 works, a system that incorporates several quantum neural network and machine learning algorithms. With an emphasis on the incorporation of quantum neural networks, this research delves into a variety of possible obstacles and future paths for Healthcare 5.0. [11].

The accuracy of quantum support vector machine (QSVM) classifications is greatly affected by the data encoding circuits utilized by the kernels. Nevertheless, there are substantial performance and time constraints associated with manually building these circuits. We solve this by selecting gate sequences in QSVM kernel circuits using the GASP (Genetic Algorithm for State Preparation) architecture. We investigate the effect of supervised and unsupervised kernel loss functions on the optimization of encoding circuits and test them on various datasets supporting binary and multiple-class problems. When compared to classical and quantum kernels, GA-generated circuits perform as well as, or even better than, the industry standard. We study the association between test accuracy and quantum kernel entropy and find it positive. Applications in the fields of materials science, healthcare, and finance may all benefit from our automated framework's reduced reliance on trial and error and enhanced QSVM-based machine learning performance [12].

The ability to associate memories with inputs is known as associative memory, and it aims to fix broken patterns. In traditional physical systems, such as neural networks, where attractor dynamics finds stable solutions, it has been studied extensively. There are a number of newly reported expansions of the quantum realm that exhibit distinct characteristics. Using open quantum system dynamics as a basis, we provide a general framework for a quantum associative memory that we can use to evaluate current models, find the theoretical conditions for associative memory tasks, and extend in many ways. We derive the map that, compared to classical systems, increases the number of stored patterns exponentially. We prove that dissipation and symmetry play an essential part in how quantum associative memory works. We show that it is possible to handle classical and quantum patterns, memories that are orthogonal and those that are not, operating regimes that are stationary and those that are metastable, and outputs produced by measurements. Last but not least, this paves the way for novel real-world uses of quantum computing and ML, such quantum memory and quantum error correction [13].

New possibilities for machine learning algorithms to aid the healthcare sector in identifying complicated health issues, such heart disease, have emerged as a result of recent advances in quantum technology. We review the efficacy of QuEML in predicting cardiac events in this paper. The Kaggle heart disease dataset, which includes 1190 samples with 53% and 47% positive and negative labels, was used to compare QuEML's performance to that of more conventional machine learning techniques. When compared to more conventional machine learning algorithms, QuEML fared better in terms of recall, accuracy, precision, specifcity, F1 score, and training time. According to the results of the experiments, conventional machine learning methods were able to forecast about 49.58% of positive samples as positive and 44.31% of negative samples as negative, whereas the suggested quantum methods were able to forecast about 50.03% of positive samples as positive and an average of 44.65% of negative samples as negative. In addition, it was found that QuEML's computational complexity was 670 µs on average during training, while typical machine learning techniques might use an average of 862.5 µs. So, compared to typical machine learning methods, QuEL showed promise in predicting heart disease, with a 0.6% better accuracy rate and a training time that was 192.5 µs quicker [14].

When it comes to modeling sequential data, Hidden Quantum Markov Models (HQMMs) are like quantum probabilistic graphical models. We add three things to the prior work on HQMMs: First, we demonstrate the feasibility of simulating conventional hidden Markov models (HMMs) on a quantum circuit. Second, we rethink HQMMs by easing the requirements for quantum circuit modeling of HMMs. Lastly, we introduce a learning technique that can estimate the parameters of an HQMM using data. Although there is room for improvement in our approach when it comes to handling larger datasets, we have successfully evaluated it on many synthetic datasets. In contrast to HMMs trained using the Baum-Welch approach, which necessitate more states to achieve the same predictive accuracy as real HQMMs, our algorithm is able to learn HQMMs using HQMM-generated data with the same amount of hidden states and predictive accuracy [15].

This paper proposes a new model for fast COVID-19 identification using CT scans that is based on deep learning. A pre-trained convolutional neural network (CNN), in this case VGG16, and the power of quantum computing come together in a model known as a pre-trained quantum convolutional neural network (QCNN). The proposed model is significant compared to both classical and quantum-based models in previous works because it improves feature extraction and classification accuracy by combining the robust feature learning of classical models with the complex data handling of quantum computing. The combination of QCNN and the pre-trained VGG16 model achieves this [16].

EVALUATION OF HEALTHCARE AI ALGORITHMS

Background of Quantum Computing (QC)

Based on quantum theory, quantum computing uses qubits rather than bits, which is a major departure from classical computing. The superposition of these qubits allows them to be in two or more states at once, greatly increasing the computing capability. Another quantum phenomenon, entanglement, connects qubits so that their states are instantly influenced by each other, distance being irrelevant. Crucial to quantum computing, this quality allows for interconnection and parallelism that are impossible in classical systems.

As shown in Figure 1, QC has several uses in medicine and has the ability to improve computing power and efficiency, which might lead to a revolution in areas including radiation, drug creation, genomics, medical diagnostics, and AI-enhanced healthcare. Medical research and clinical practice stand to benefit greatly from the increased speed and accuracy that QC is able to bring to each of its subfields.

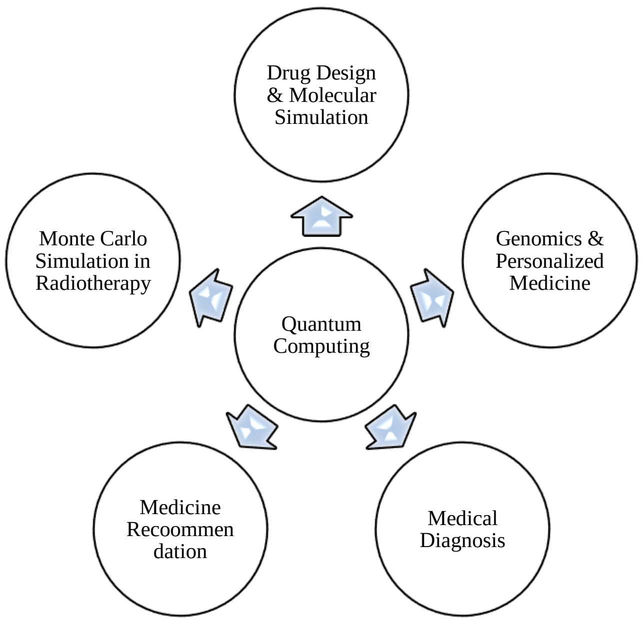


Fig.1 QC-in Medical Data Analysis

Quantum Mechanics:

To conduct computations, quantum computers make use of superposition and entanglement, two properties of quantum bits that allow them to exist in multiple states at once.

Qubits

In contrast to traditional bits, which can only hold the values 0 or 1, qubits may hold any combination of the two, opening the door to parallel processing and, maybe, quicker answers.

Quantum Algorithm

To solve particular problems efficiently, algorithms can take advantage of qubits' quantum nature; these algorithms are known as quantum algorithms.

Quantum Application

Key to the development of quantum computers is the specialized hardware, such superconducting circuits or trapped ions, that is required to construct and operate qubits. Possible uses of quantum computing extend to many domains, such as AI, medicine development, materials research, and finance.

Working Procedure:

- The fact that a qubit may be in both the 0 and 1 states at the same time opens up a world of possibilities for parallel processing and simultaneous exploration.
- When two or more qubits get entangled, they are bound together in a way that makes their fates identical, no matter how far apart they are.
- The status of both entangled qubits may be inferred from measurements taken of only one of them.
- Advancements in Quantum Algorithms: The goal of these algorithms is to outperform traditional algorithms in a particular computation by taking use of superposition and entanglement.

AQC-AI Algorithms in Healthcare

There are two quantum algorithms that have made huge strides in artificial intelligence:

Grover's Algorithm

Information retrieval and decision-making are two examples of AI-based activities that rely on scanning unstructured databases; Grover's Algorithm offers a quadratic speedup in this area.

Better Pattern Recognition: Grover's Algorithm improves artificial intelligence's pattern recognition capabilities by swiftly sorting through massive datasets. This is especially important in fields where pattern identification is crucial, such healthcare diagnostic imaging and financial fraud detection.

Quantum Fourier Transform (QFT)

Applications of artificial intelligence (AI) in areas such as market trend analysis, weather forecasting, and speech recognition rely heavily on time-series data processing, and QFT plays a crucial role in this process.

Feature extraction is an important preprocessing step in machine learning, and it has to be robust. Improved input quality for machine learning algorithms and more accurate AI models are the results of QFT's ability to evaluate complicated datasets and extract significant characteristics.

Quantum Neural Networks (QNNs):

Neural networks that run on quantum computers, which might be useful for some jobs. The quantum perceptron, which is similar to the conventional perceptron but operates on a quantum scale, is the fundamental unit of a quantum neural network. The quantum perceptron, as we define it in our proposal, is a unitary operator that can take m input qubits and n output qubits. With ð2mþnÐ 2 1 parameters, our perceptron is just an arbitrary unitary applied to the m + n input and output qubits. It is easy to expand this approach to qubits; the input qubits are initialized in a mixed state ρin, which may or may not be known, and the output qubits in a fiducial product state j i 0 0 out. Here, we simplify things by assuming that our perceptrons are (m + 1)-qubit unitaries, meaning that they process data using m input qubits and a single output qubit. Our quantum neural network design may now be described by a quantum neuron. Based on practical considerations and analogies to the classical case, we suggest that a QNN is a quantum circuit with L hidden layers of qubits that acts on the input qubits' initial state ρin and produces an output qubits' mixed state ρout.,

$$P^{out} = tr_{in.hid}\left(U\left(p^{in} \otimes \left|0 \ldots . 0\right\rangle_{hid,out} \langle 0 \ldots 0|\right) U^{t}\right)$$

Ut layers comprise the quantum circuit in this case. The significance of the sequence of operations is highlighted by the fact that our perceptrons, being arbitrary unitary operators, do not typically commute. Even with two-input one-output qubit perceptrons, our QNNs are able to perform universal quantum computing due to their quantum-circuit architecture (Fig. 2). Even more astounding is the finding that a QNN can still perform universal quantum computation to take advantage of noncommuting perceptrons on qubits, even if it is composed of quantum perceptrons working on 4-level qudits that commute within each layer. Actually, any quantum channel can be applied to the input qudits by our most general form of quantum perceptrons.

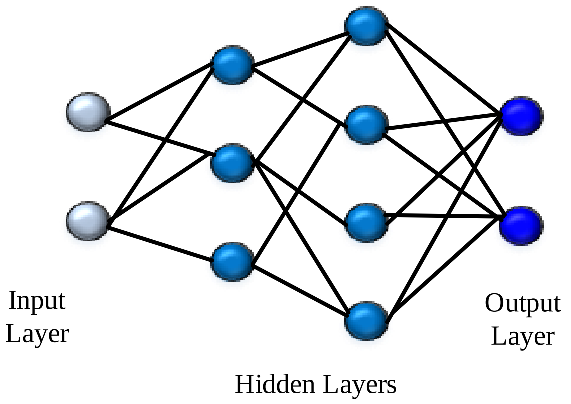


Fig.2 QNN Model

Quantum Support Vector Machines (QSVMs)

A quantum-enhanced support vector machine (SVM) algorithm for classification and regression. The SVM is tasked with sorting m training data points into two categories, where yk can be either 1 or -1, depending on the class that xk belongs to. The data points are in the form of {(xk, yk) : xk ∈ Rn, yk = ±1}k=1,...,m. After optimizing the Lagrangian, the issue may be expressed as a linear equation in LS-SVM.:

$$F\begin{pmatrix} b \\ \alpha \end{pmatrix} = \begin{pmatrix} 0 & 1^T \\ 1 & K + \gamma^{-1} I_m \end{pmatrix} \begin{pmatrix} b \\ \alpha \end{pmatrix} = \begin{pmatrix} 0 \\ y \end{pmatrix}$$

This sentence describes the following: I_m is the m×m density matrix with dimensions 1=(1,…,1)^T, γ is a hyperparameter that describes the ratio of the Lagrangian's components, α is the Lagrange multiplier, y is the label of the training set, b is the offset of the hyperplane, and K is a m×m kernel matrix. The following function can be used to calculate the classifier using query data x∈R^n, as per Eq. (1):

Print ISSN: 2054-0957 (Print)
Online ISSN: 2054-0965 (Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

$$f(x) = \operatorname{sign}\left(\sum_{k=1}^{m} \alpha_k \boldsymbol{x}_k^{\mathrm{T}} \boldsymbol{x} + b\right)$$

Rewriting Eq. (1) as F|b,α⟩=|0,y⟩ is a compact representation in the quantum case. The quantum state |b,α⟩=F^(-1) |0,y⟩ is generated using the HHL technique [49] when the matrix F is well-conditioned and possesses polylogarithmic sparsity in the dimension. Here are the parameters for the LS-QSVM that you want:

$$|b, \boldsymbol{\alpha}\rangle = \frac{1}{\sqrt{C}}\left(b|0\rangle + \sum_{i=1}^{M} \alpha_k |k\rangle\right)$$

where $C = b^2 + \sum_{k=1}^{M} \alpha_k^2$.

For a classification task, the training data oracle is constructed as follows:

$$|\tilde{\boldsymbol{\mu}}\rangle = \frac{1}{\sqrt{N_{\tilde{\mu}}}}\left(b|0\rangle|0\rangle + \sum_{k=1}^{m} \alpha_k |\boldsymbol{x}_k||k\rangle|\boldsymbol{x}_k\rangle\right)$$

Quantum Boltzmann Machines

Boltzmann machines, typically employed in generative modeling, have a quantum counterpart. To fit in with the quantum computing paradigm, BMs naturally evolve into QBMs, or quantum Boltzmann machines. Quantum black holes (QBMs) construct their underlying networks using a parameterized Hamiltonian operator, as opposed to an energy function where nodes are represented by binary spin values:

$$H_\theta = \sum_{i=0}^{p-1} \theta_i h_i$$

where σj,i is an element of {I, X, Y, Z} and acts on the j th qubit, and θ is a member of Rp. The Pauli matrices σj,i are used to describe the nodes in the network. The quantum Gibbs state is related to this Hamiltonian, which is ρGibbs = e−Hθ /(kBT) /Z, where kB and T are the Boltzmann constant and the system temperature, respectively, and Z = Tre−HŸ /(kBT). Note that visible qubits are those that decide the model output, whereas hidden qubits are those that function as latent variables. A target system can be represented by the resultant Gibbs state if the model is successful in learning the Hamiltonian parameters. This framework, in contrast to BMs, permits the utilization of quantum structures that may be unavailable conventionally. Exactly like the classical model, QBMs may be used for both discriminative and generative learning with θ ∈ Rp and hi = n−1 j=0 σj,i, where σj,i is an element of {I, X, Y, Z} that acts on the j th qubit. The Pauli matrices σj,i are used to describe the nodes in the network. The quantum Gibbs state is related to this Hamiltonian, which is ρGibbs = e−Hθ /(kBT) /Z, where kB and T are the Boltzmann constant and the system temperature, respectively, and Z = Tre−HŸ /(kBT). Note that visible qubits are those that decide the model output, whereas hidden qubits are those that function as latent variables. A target system can be represented by the resultant Gibbs state if the model is successful in learning the Hamiltonian parameters. This framework, in contrast to BMs, permits the utilization of quantum structures that may be unavailable conventionally. With QBMs, you get the same flexibility in discriminative and generative learning as with the classical model.

Quantum Associative Memories

Computer programs that use quantum mechanics to store and retrieve data. This leads us to the following description of the QuAM's operation. Repetition of a sequence of patterns is just,

$$|\varphi\rangle = P'|\bar{0}\rangle$$

A quantum superposition of basis states, one for each pattern, is represented as ├ |φ⟩. So, let's say we want to remember a pattern but only know n-1 bits of it. If there are no patterns that vary just in the final bit, we may remember the pattern using Grover's technique, where τ is the target pattern,

$$|\varphi'\rangle = G'I'|\varphi\rangle$$

repeated π times with an N-th iteration. Therefore, the QuAM can store up to N=2n patterns in O(mn) steps and recall a pattern in O(N) time using 2n+1 neurons (qubits).

Quantum-Enhanced Reinforcement Learning

Making use of quantum computers to enhance or expedite methods for reinforcement learning. It is possible to examine the reward function and the map that indicates the next percept that the environment will display independently, given any task environment. This map is often a stochastic function fE■H → S, which maps elapsed histories onto the next percept. The second one is defined as the relation Λ■H × S → S, which is dependent on the past and enhances the percept by determining its reward status. Despite being turn-based, interactions in basic, strictly epochal settings may be represented as sequences of M-step maps (where each step resets the environment and there is only ever one reward):

$$|a_1, \dots, a_M\rangle \to |s_1 \dots., s_M\rangle$$

where sM's "bar" indicates that it has a reward status. Furthermore, in deterministic settings, when the perceptual responses are fixed, the maps fE and Λ are directly influenced by the agent's actions. It is much easier to develop a suitable oracle for such basic, predictable, purely epochal situations. Every M-step block can have its actions returned to the agent since each block is independent of the previous one.

Hidden Quantum Markov Models

Hidden Markov Models modified for the quantum realm. A collection of CP linear mappings {Kˆi} that do not increase the trace is the quantum counterpart of observable operators. A density operator can be mapped to another density operator using trace-preserving Kraus operators PN i Kˆ † i Kˆi = I. Operations on a smaller portion of a quantum system, denoted as trace-decreasing Kraus operators PN i Kˆ † i Kˆi < I, might let probability to 'leak' to other states that are not being taken into account. In this work, we will define issues in a way that guarantees all sets of Kraus operators preserve trace. Uˆ is considered a unitary matrix when there is a single operator in the set, i.e., Uˆ such that Uˆ …U} = I. The development of the 'whole' system, which might be high-dimensional, is often modeled using unitary operators. However, Kraus operators can be employed if the primary concern is monitoring the development of a smaller sub-system that could interact with its surroundings. When working with a density matrix, the simplest basic quantum operation is,

$$P' = \frac{\sum_i^M K_i' p K_i}{tr\left(\sum_i^M p' K_i\right)}$$

From a mathematical perspective, this is the same as tracing across ⇓ˆYt while applying a projection operator to the joint state. This means that the forward algorithm that explicitly models a hidden Markov model on a quantum circuit is expressed as:

$$p' \propto tr_{pY_t}\left(P_y' U_2' \left(tr_{pt-1}(U_1'(p_{t-1}' \otimes p' x_t) U_1') \otimes p_1'\right) U_2' p_2'\right)$$

It is possible to streamline this circuit by applying Kraus operators to the ⇓ˆXt lower-dimensional state space. We only need to worry about representing the evolution of the particle Xt since we always prepare Yt in the same state. Therefore, the operation Uˆ2 on the joint state of Xt and Yt, followed by the application of the projection operator Pˆy, can be more concisely expressed as a Kraus operator on Xt alone. It is necessary to build a set of Kraus operators {Kˆy} for any observable output y, with the condition that P y(Kˆy)†(Kˆy) = I.

We may describe a classical HMM using the set of Kraus operators {Kˆwy,y} that is obtained by post-multiplying each operator in {Kˆw} with each operator in {Kˆy},

$$p'_t = \frac{\sum_w K'_{w,y_t} p'_{t-1} K'_{w,y_t}}{tr\left(\sum_w K'_{w,y_t} p'_{t-1} K'_{w,y_t}\right)}$$

Quantum Convolutional Neural Network

Convolutional Neural Network in a quantum form. When it comes to classification tasks like image identification, convolutional neural networks (CNNs) offer an effective machine learning architecture1,22,23. It is common practice for convolutional neural networks (CNNs) to include many interconnected image processing layers, with each layer building upon the one before it to create a feature map, an intermediate 2D array of pixels (Figure 1a)24. The weights wa,b create a w × w matrix, and the convolution layers calculate new pixel values x (') ij by linearly combining close ones in the previous map x (') i,j = Pw a,b=1 wa,bx ('−1) i+a,j+b. Applying a nonlinear (activation) function after a pooling layer reduces the size of the feature map (by, for example, picking the maximum value from a small number of nearby pixels). The final output is calculated using a function that depends on all the remaining pixels (completely linked layer) after the feature map size is small enough. Training on massive datasets optimizes the fully connected function and the weights. On the other hand, for a given CNN1, hyperparameters like the size of the weight matrices (w) and the amount of convolution and pooling layers are hardcoded. Thus, CNN's most salient features are its hierarchical structure, sequential data size reduction, and translationally invariant convolution and pooling layers, which have a fixed set of parameters regardless of system size.

As a result, a QCNN with O(log(N)) parameters can categorize N-qubit input states. In comparison to a general classifier based on quantum circuits, this permits efficient learning and implementation, and it corresponds to a reduction that is twice as exponential. As an illustration, the mean-squared error might be calculated using the following training data: {(|ψαi, yα) : α = 1,..., M}, where |ψαi represent the input states and yα = 0 or 1 represent the associated binary classification outputs,

$$MSE = \frac{1}{2M}\sum_{\alpha=1}^{M}\left(y_i - f\{u_i, v_j, F\}(|\psi_\alpha\rangle)\right)^2$$

The predicted QCNN output value for input |ψαi is represented by f{Ui,Vj,F }(|ψαi). Then, learning means setting all unitaries to zero and then optimizing them one by one until they converge, for instance via gradient descent.

VALIDATION OF QC-AI ALGORITHMS

Data Collection

Dataset 1: All experimental public datasets pertaining to the mortality rate of heart, lung, and renal disorders, as well as other symptoms, were retrieved from healthdata.gov for this investigation. On the other hand, COVID-19 symptoms led to hospitalization for individuals with certain medical histories, including smoking and asthma. We may find the sample experimental dataset at Google Drive.

European Journal of Computer Science and Information Technology,13(11),1-16, 2025
Print ISSN: 2054-0957 (Print)
Online ISSN: 2054-0965 (Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

Dataset 2: Datset from UCI repository. Two sources were utilized to get the patient records pertaining to diabetes: an automated electronic recording system and paper records. Unlike the paper records, which only offered "logical time" slots (breakfast, lunch, supper, bedtime), the automated gadget featured an internal clock to date occurrences. Bedtime (22:00), lunch (12:00), supper (18:00), and morning (08:00) were all given set hours for paper records.

Comparative Analysis

Confusion matrices were used to display the classification results of all methods. A confusion matrix compares the classifier's actual classifications to the original data set and displays the number of accurate and wrong predictions. In the confusion matrix, n represents the number of classes in the output variable, and the matrix is two-dimensional and n by n. There were just two categories in this study: healthy and asthmatic. In this matrix, the actual classifications are shown by each row, and the predictions are shown by each column as shown in table.1 and table.2.

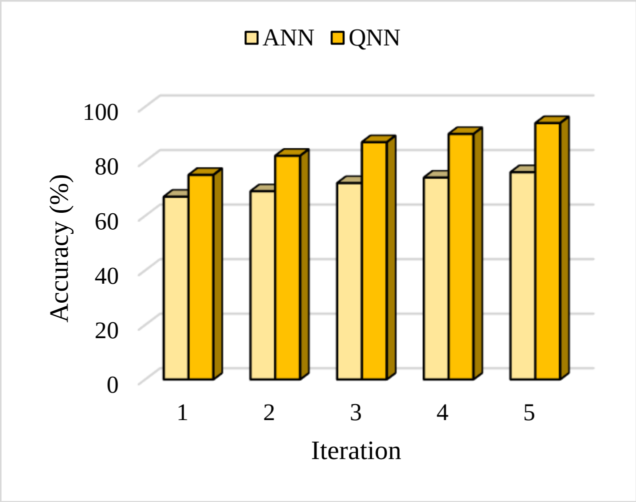
Table.1 Confusion Matrix (Covid-19)

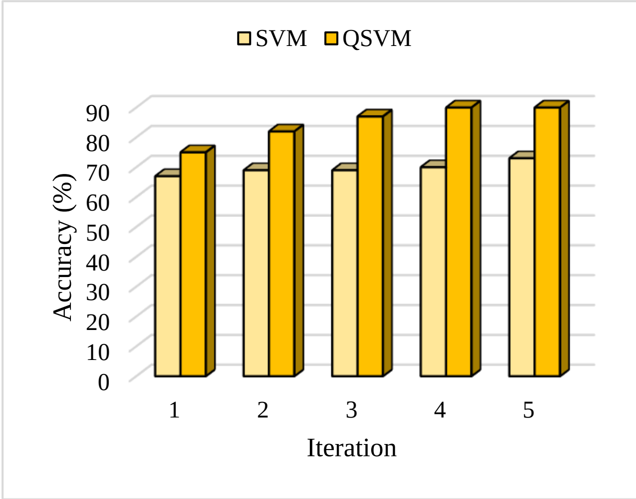
		Prediction	
		Healthy	Covid-19
Actual	Healthy	1340	1
	Covid-19	2	765

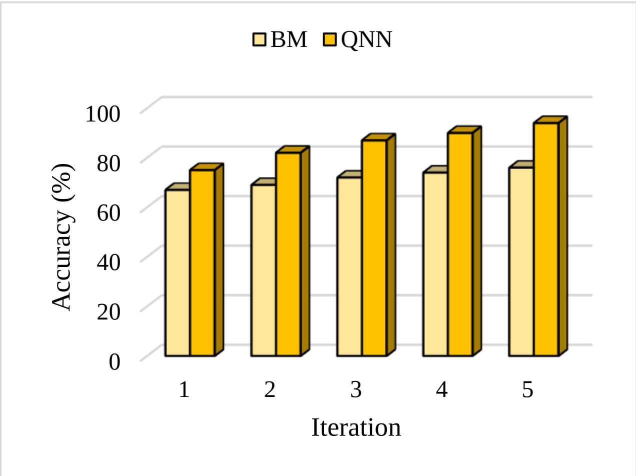
Table.2 Confusion Matrix (Diabetics)

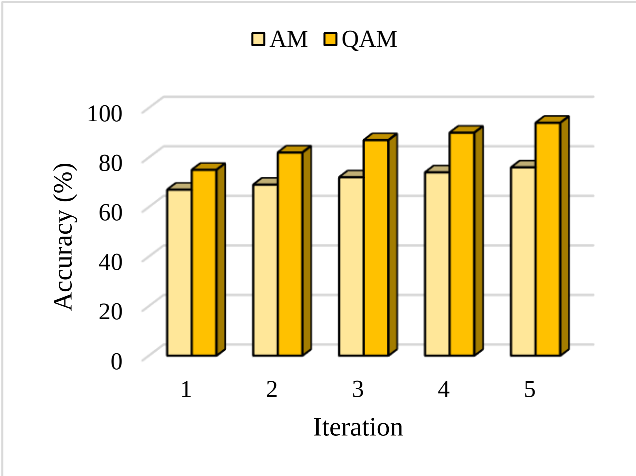
		Prediction	
		Healthy	Covid-19
Actual	Healthy	1340	1
	Covid-19	2	765

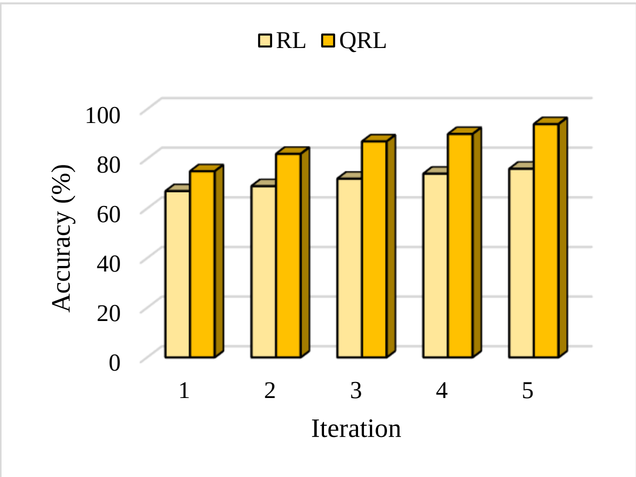
The confusion matrix is a useful tool for determining if a prediction model is biased towards one class over another or if it is mislabeling classes. Fig.3 & 4 exhibit the comparative analysis that reveal the outcomes of the ANN, QNN, and QCNN classification algorithms, correspondingly. The confusion matrix shows that two normal case were mistakenly identified as having Covid-19 illness (i.e., a false positive) and two recordings with Covid-19 disease were mistakenly identified as having normal sound (i.e., a false negative). In order to assess a classifier's efficacy, we calculated the following statistical parameters: Precision: The fraction of all healthy-subject recordings that were accurately labeled as such divided by the total number of healthy-subject recordings.

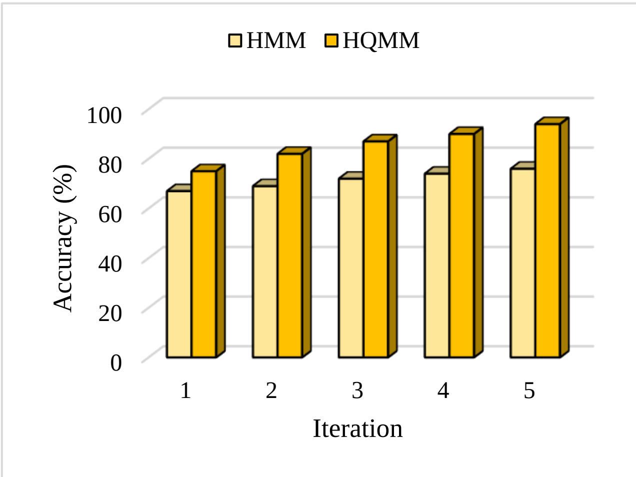

ANN QNN
Accuracy (%)
0 20 40 60 80 100
1 2 3 4 5
Iteration


SVM QSVM
Accuracy (%)
0 10 20 30 40 50 60 70 80 90
1 2 3 4 5
Iteration


BM QNN
Accuracy (%)
0 20 40 60 80 100
1 2 3 4 5
Iteration


AM QAM
Accuracy (%)
0 20 40 60 80 100
1 2 3 4 5
Iteration


RL QRL
Accuracy (%)
0 20 40 60 80 100
1 2 3 4 5
Iteration


HMM HQMM
Accuracy (%)
0 20 40 60 80 100
1 2 3 4 5
Iteration

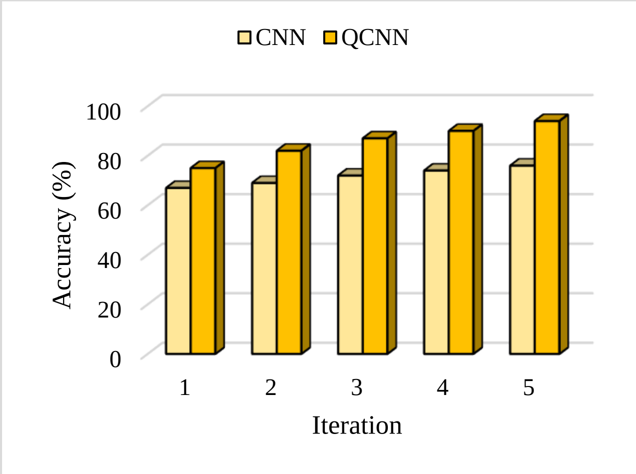
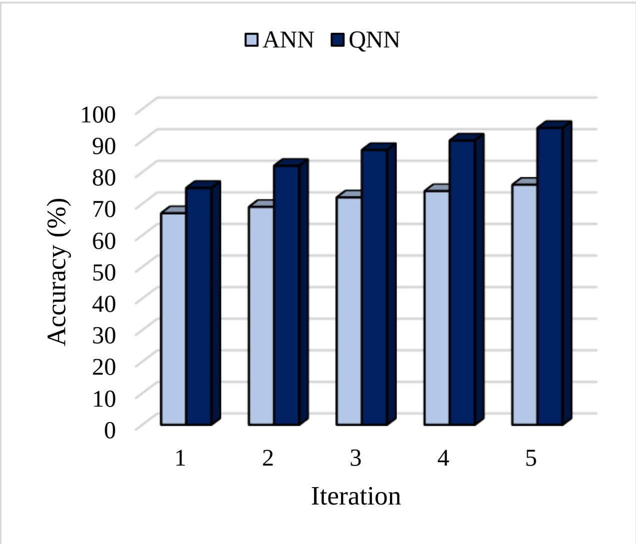
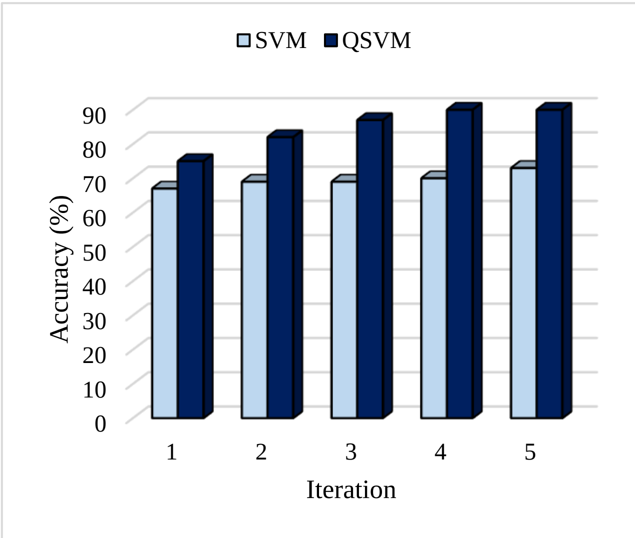
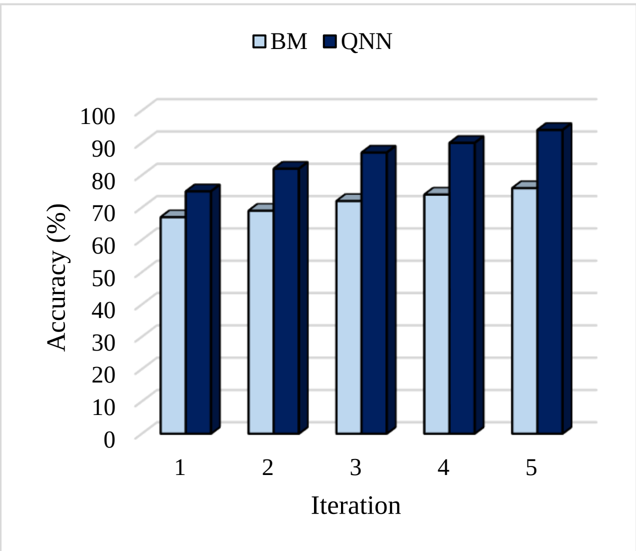
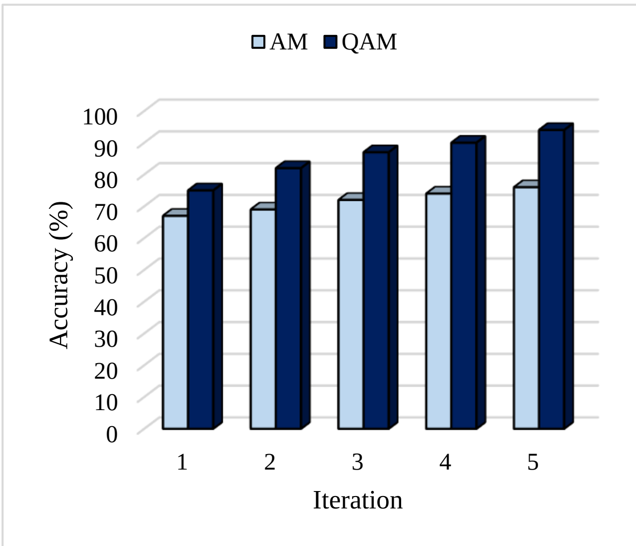


Fig.3 Validated results (Dataset 1: Covid-19)









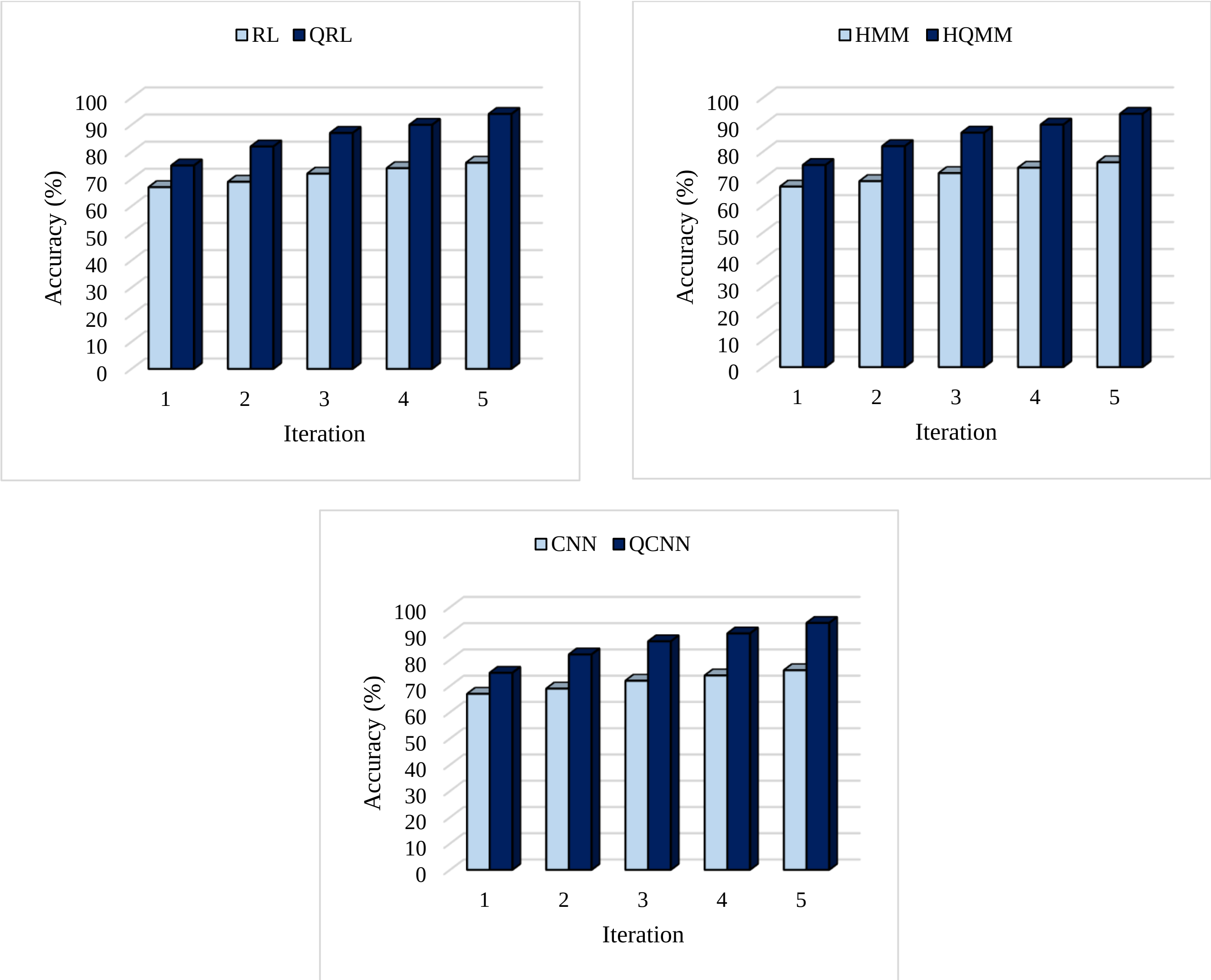


Fig.4 Validated results (Dataset 2: Diabetics)

The sensitivity of an Covid-19 model is defined as the ratio of the number of properly identified recordings from Covid-19tic participants to the total number of recordings from Covid-19tic subjects, Measured as a percentage of the total recordings, accuracy is the proportion of well-classified recordings. These statistical performance metrics include values for all of the classification algorithms. When combined, ANN and QNN achieved a 90% overall classification accuracy. We determined that there are 5 variables to split on at each node, denoted as n. With this setting, the out-of-bounds error rate was minimized. Thirty iterations were selected as the maximum for the QNN algorithm. We built a 15-node network with a single hidden layer to use with the QCNN algorithm. We used a learning rate of 0.3 and a momentum of 0.2 during training.

CONCLUSION

Academic and business communities have lately shown a great deal of interest in the rapidly expanding field of quantum computing, which has the potential to revolutionize the way we process data and unlock computational capabilities that were previously out of reach. Although quantum computing has a lot of potential, the precise way it will impact healthcare is yet unclear. This survey paper provides the first comprehensive analysis of quantum computing's diverse capabilities in improving healthcare systems. Its primary focus is on the potential of quantum computing to transform compute-intensive healthcare tasks such as drug discovery, personalized medicine, DNA sequencing, medical imaging, and operational optimization. When quantum computing and artificial intelligence unite to revolutionize genetic data processing, complex biological simulations, and medication creation, a new age in healthcare will dawn. Because of its potential size and complexity, biological data presents unique challenges for conventional computing methods. Medical discoveries are hindered in speed and precision as a result of this. A revolutionary possibility to accelerate biological research and therapeutic applications exists when the predictive capacity of AI is combined with the exponential processing speed of quantum computers. Learn how quantum machine learning can enhance AI-powered molecular dynamics simulations for drug development in this article. Algorithms enabled by quantum technology allow for the rapid modeling of chemical interactions, the analysis of drug-receptor binding affinities, and the prediction of pharmacokinetics with unprecedented precision. Additionally, we explore quantum-assisted deep learning models to better comprehend intricate biological processes such as protein folding, epigenetic alterations, and metabolic pathway linkages; these can in turn enhance disease progression prediction and therapeutic target discovery.

REFERENCES

1. Ossa, Laura Arbelaez et al. “AI Through Ethical Lenses: A Discourse Analysis of Guidelines for AI in Healthcare.” Science and Engineering Ethics 30 (2024): n. pag.
2. Gani, Raiyan et al. “Impact of AI in Healthcare Services: Analysis Using Medical Synthetic Data.” 2024 International Conference on Advances in Computing, Communication, Electrical, and Smart Systems (iCACCESS) (2024): 01-06.
3. Ali, Hassan. “Quantum computing and AI in healthcare: Accelerating complex biological simulations, genomic data processing, and drug discovery innovations.” World Journal of Advanced Research and Reviews (2023): n. pag.
4. Mallesham, Devasane. “Enhancing Data Compatibility Through Quantum Computing and AI: A Hybridized Strategy.” INTERANTIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT (2025): n. pag.
5. Xu, Xusheng et al. “MindSpore Quantum: A User-Friendly, High-Performance, and AI-Compatible Quantum Computing Framework.” (2024).
6. Atadoga, Akoh et al. “THE INTERSECTION OF AI AND QUANTUM COMPUTING IN FINANCIAL MARKETS: A CRITICAL REVIEW.” Computer Science & IT Research Journal (2024): n. pag.
7. Saeed, Mariwan Hama and Jihad Ibrahim Hama. “Cardiac disease prediction using AI algorithms with SelectKBest.” Medical & Biological Engineering & Computing 61 (2023): 3397-3408.
8. Chen, Zhenghua et al. “Survey on AI Sustainability: Emerging Trends on Learning Algorithms and Research Challenges [Review Article].” IEEE Computational Intelligence Magazine 18 (2023): 60-77.
9. Chiang, Hung-Li et al. “How Fault-Tolerant Quantum Computing Benefits from Cryo-CMOS Technology.” 2023 IEEE Symposium on VLSI Technology and Circuits (VLSI Technology and Circuits) (2023): 1-2.
10. Deb, Arighna et al. “Exploring the Potential Benefits of Alternative Quantum Computing Architectures.” IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems 40 (2021): 1825-1835.
11. Chakraborty, Sanjay. “A Study on Quantum Neural Networks in Healthcare 5.0.” ArXiv abs/2412.06818 (2024): n. pag.
12. Creevey, Floyd M. et al. “Kernel Alignment for Quantum Support Vector Machines Using Genetic Algorithms.” (2023).
13. Labay-Mora, Adrià et al. “Theoretical framework for quantum associative memories.” (2024).
14. Babu, S Venkatesh et al. “Revolutionizing heart disease prediction with quantum-enhanced machine learning.” Scientific Reports 14 (2024): n. pag.
15. Srinivasan, Siddarth et al. “Learning Hidden Quantum Markov Models.” International Conference on Artificial Intelligence and Statistics (2017).
16. Asadoorian, Nazeh et al. “Pre-trained quantum convolutional neural network for COVID-19 disease classification using computed tomography images.” PeerJ Computer Science 10 (2024): n. pag.