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Research Article

Quantum Computer Architecture: A Quantum Circuit-Based Approach Towards Quantum Neural Network

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Abstract: According to recent research on the brain and cognition, the microtubule level activities in the brain are in accordance with the quantum mechanical concepts. Consciousness is the emergent phenomenon of the brain's subsystems and the quantum neural correlates. Based on the global work-space theory and traditional neural networks, investigations in machine consciousness and machine intelligence are reporting new techniques. In this study, a novel approach using circuit-based quantum neural network is proposed and simulated. This approach satisfies all the criteria of quantum computing and is tested for the exclusive OR (XOR) gate's nonlinear learning. As a result of the use of quantum gates, various quantum circuits, such as quantum adders and subtractors, are also created and included in the designing and simulation of circuit of the quantum neural networks. Moreover, it is also argued that the proposed circuit of quantum neural network may also be tested and implemented on real quantum computer hardware. The present study also stresses the applicability of techniques of machine learning algorithms such as quantum and classical neural networks to various challenges of High Energy Physics.

Keywords: High Energy Physics, Artificial Neural Network, Quantum Computing, Quantum Circuits, Quantum Neural Network.

1. INTRODUCTION

To recreate the characteristics of human intellect in computers, different theories of consciousness such as Global Workspace Theory [1–5] and Neural Correlate Theory have proposed different models in the recent years [6–18]. In machine intelligence, neurological correlates of consciousness are employed by artificial neural networks (ANNs) [18–21] which consist of layers (input, hidden and output) of neurons [21–23]. Real values are used as the ANNs' inputs, weights (connection strengths), and outputs [22, 23]. The artificial neural networks are being simulated to learn and recognize using the typically available computer architecture, which represents information with "0" or "1". By claiming that information at the microtubule level in human brain follows the laws of quantum physics [9], Roger Penrose and Hameroff's Orch-OR model [13, 21] was used to describe the capabilities of the brain at the microtubule level. This model further contended that higher-level characteristics of the brain, such as consciousness and unconsciousness, may be explained by general relativity and quantum physics principles [6-7, 13, 21]. Quantum physics may more effectively describe nature, including energy and matter at the microscopic level [24]. Quantum computing based upon its marvelous features such as superposition and entanglement is promising to provide answers to those higher dimensional issues that conventional computing has not yet been able to resolve [25]. The amazing properties of interference, entanglement, and superposition in quantum computing also offer a genuine parallel architecture [21, 24-27].

The typical concepts about Quantum Circuits, Quantum Neural Networks (QNNs) and Machine Learning in High-Energy Physics are as follows. As far as the Quantum Circuits are concerned, the quantum counterpart of classical information, known as a qubit, is denoted by the Dirac notations which are Ket (column) and Bra (row) vectors. Qubits may be a superposition of these states [24–25, 27] even if they are in the state of "|0>" or "|1>." The arithmetic and logical units, registers,

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and memory are only a few examples of the several classical gates utilized in classical computers. Quantum computing also consists of Hermitian matrices/operators named as single-qubit and multiqubit gates (H, X, Y, Z, CNOT, Toffoli, Fradklin etc.) to process information in quantum circuits required to build quantum computer architecture. The Toffoli gate, which can be seen in Figures 1, 2, and 3, is used to transform classical gates and circuits therefore named as the universal gate of quantum computing. As a result, Toffoli gate is used to form quantum circuits for the corresponding classical circuits (as seen in Figures 4, 5, 6, and 7).

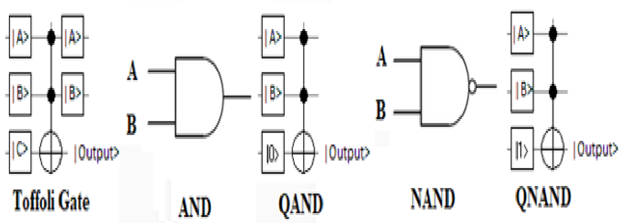

Fig. 1. By fixing the Toffoli gate's third qubit to |0> or |1>, the classical AND and NAND gates are transformed into Quantum AND and Quantum NAND gates respectively. Where inputs (|A⟩, |B⟩ and |C⟩ are named as Qubits (quantum states) with A and B being classical bits (0 or 1) [28-30].

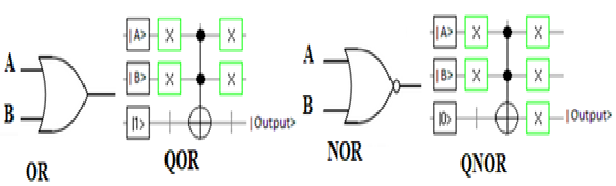

Fig. 2. By fixing third qubit of Toffoli gate to be |1> or |0>, the classical OR and NOR gates are transformed into QOR and QNOR gates respectively. Where, inputs (|**A**⟩, |**B**⟩ and |**C**⟩ are named as Qubits (quantum states) and A and B are classical bits (0 or 1) [28-30].

The Quantum Neural Networks (QNNs) are neural networks that use quantum mechanical concepts. Similar to artificial neuron, the quantum neurons are arranged in different layers of neuron such as input, hidden, and output. In contrast to conventional neural networks, quantum neural networks (QNNs) use complex column vectors for input and output, and complex Hermitian matrices or quantum operators for connection weights. Quantum neural networks are more effective than

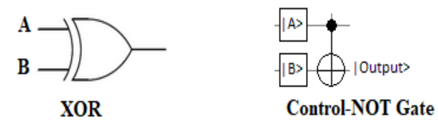

Fig. 3. CNOT gate of quantum computing is equivalent of Classical XOR gate. Where, inputs (|**A**⟩, |**B**⟩ and |**C**⟩ are named as Qubits (quantum states) and A and B are classical bits (0 or 1) [28-30].

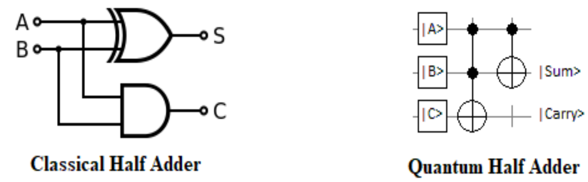

Fig. 4. Classical half adder is transformed into quantum half adder by applying Toffoli gate on the three qubits followed by CNOT gate applied to the first two qubits. Where, inputs (|**A**⟩, |**B**⟩ and |**C**⟩ are named as Qubits (quantum states), and A, B, S (Sum), and C (Carry) are classical bits (0 or 1) [28-30].

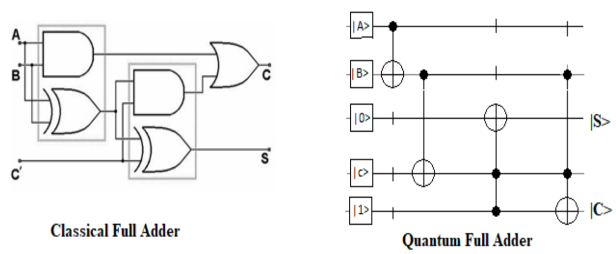

Fig. 5. Classical full adder is transformed into quantum full adder with CNOT gate and three Toffoli gates acting on different qubits. Where, inputs (|**A**⟩, |**B**⟩ and |**C**⟩are named as Qubits (quantum states) and A, B, S (Sum), and C (Carry) being classical bits (0 or 1) [28-30].

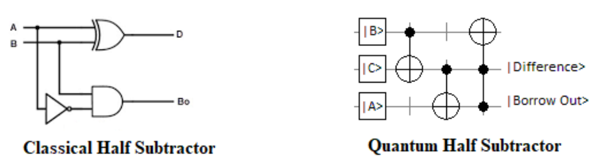

Fig. 6. Classical Half Subtractor is transformed into quantum Half Subtractor with two CNOT gates and one Toffoli gate acting on different qubits. Where, inputs (|**A**⟩, |**B**⟩ and |**C**⟩ are named as Qubits (quantum states), A and B are classical bits (0 or 1), D (Difference) and B (borrowed) are classical outputs (0 or 1) [28-30].

conventional neural networks, as shown by earlier research in this field [22–23]. Li Fei [22] argued that one quantum neuron outperforms a network of six conventional neurons for the different input

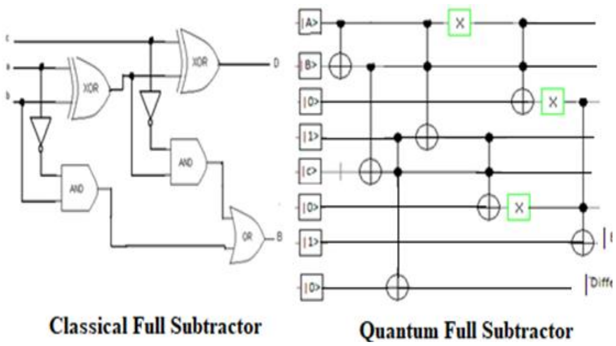

Fig. 7. Classical Half Subtractor is transformed into quantum Half Subtractor with three X gates, 6 Toffoli gates, and one CNOT gate acting on different qubits. Where, (|**A**⟩, |**B**⟩ and |**C**⟩ , |Difference⟩ and |Borrow⟩ are Qubits (quantum states) and A, B, D (Difference) and B (Borrow) are classical bits (0 or 1) [28-30].

patterns of the XOR gate's nonlinear learning. The concepts of Machine Learning in High-Energy Physics are also quite important. The high energy physicists (HEP) conduct experiments employing accelerator and detector technology as well as the Standard Model of particle physics to study the fundamental properties of the cosmos. Gravitational, strong, electromagnetic, and weak interactions are the basic forces that control how particles behave towards one another. The Standard Model, which was created in the 1970s, has proven very effective in describing physical processes involving basic interactions (apart from gravity), becoming the most thoroughly tested theory of physics, and accurately predicting the results in a broad range of events [31-33]. To optimize high-energy physics processes, several issues are being resolved using artificial neural networks [34–39]. Artificial neural networks are used in experimental high energy physics for classification of events [43–44], reconstruction of objects [45–46], triggering process [47–48], and track finding [49–50], while they are used in theoretical high energy physics to solve the Schrodinger wave equation and calculate the mass spectra of particles [40–42]. In addition, ordinary and partial differential equations of various domains [52-54] as well as quantum many-body problems are being resolved using artificial neural networks [51]. Quantum neural networks have also been emphasized recently by developments in high-energy physics and machine learning [55–58]. This research will be expanded in the future to address the issues in the aforementioned fields.

During the last ten years, a lot of research has been done on quantum neural networks [18-20, 22-23, 58-75]. Alexander's research on "quantum neural networks" basically presents explanation of the paradigm of shifting from classical computing to quantum computing. There was also discussion of the advantages of quantum computing (using quantum neural networks) over conventional computing (using conventional neural networks) [23]. These advantages included high performance, Exponential memory, faster learning, processing speed, compact size, great stability, and reliability. By duplicating certain characteristics of the conventional neural network into a quantum counterpart, many algorithms have been developed for quantum neural networks, however, they are missing other qualities and limitations imposed by quantum computing.

QNNs are created by solely altering the input, output, and weights of artificial neural network into their quantum counterparts, by having overall architecture and methodology to be the same [19-20, 22-23, 57-58, 69-73]. However, Gradient Descent-based Algorithms are used for the majority of ANN implementation [22]. The present architecture of conventional and quantum neural networks is shown in Figure 8, and it has the following three shortcomings:

(a) Cloning in Quantum Circuits: In conventional computers, it is simple to make a duplicate of the information, but according to the quantum theory of nature, because information is the

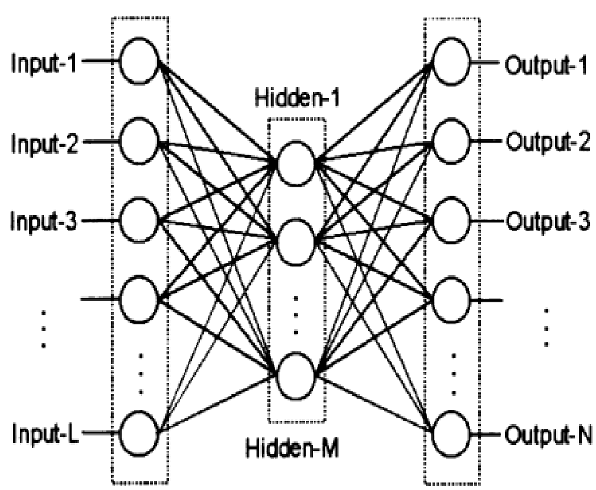

Fig. 8. Currently existing Classical or Quantum Neural Network Structure [30]

representational state of a physical system, like electrons or photons, it cannot be directly copied. In quantum computing, information may be copied from one location to another via the fan-out operator or circuit of teleportation [76]. Therefore, without teleportation or the use of the fan-out operator, it is not feasible to transmit copies of the quantum information to the other neurons.

(b) Reversibility in Quantum Computing: In quantum computing, information is processed by using quantum gates which are Hermitian matrices which make quantum circuits and quantum processes to be reversible. Because classical weight signals are not Hermitian matrices, therefore, a straight modification from classical to quantum is irretrievable.

(c) Loss of Information: In classical circuits, number of inputs varies from number outputs resulting into loss of information in the form of heat and direct conversion of classical neural network into quantum neural network in which inputs are qubits which represent of the physical system and this variation of input and output results into loss of information.

The main objectives of the present studies are as follows: (i) To highlight the drawbacks of the architecture of the existing conversion of classical neural networks to quantum neural networks, (ii) To address these drawbacks through a proposed quantum circuit-based approach and to simulate for the non-linear learning of XOR Gate, (iii) To process the proposed algorithm for each pattern of the truth table of the XOR Gate.

2. MATERIALS AND METHODS

The rules of quantum computing are not satisfied when a conventional neural network circuit or design is replicated into a quantum counterpart, therefore, it is essential to create a circuit or architecture for quantum neural networks that complies with all conceivable principles and computing/quantum mechanics limitations. Since traditional gates/circuits and neural networks have only one output and two input lines, respectively. Moreover, they are irreversible and lost their information as heat. However, one cannot claim that limitations exist in quantum computing, such as information loss, irreversibility, and the no-cloning theorem, since the number of input and output lines in quantum circuits is identical. The current research in quantum neural networks continues in accordance with the classical hierarchy rather than the principles of quantum mechanics/computing. The present work argues that every transformation of the classical circuit into its quantum counterpart must satisfy all limitations or principle(s) of quantum computing. Therefore, it is argued that present practice of QNNs may not be used for the quantum mechanical way of implementation of higher-level feature of mind and brain into machines to accomplish intelligence. Because of the above-mentioned flaws, it is difficult to say that existing QNNs are capable of quantum learning. The presented quantum neuron has four inputs and four outputs, as shown in Figure 9. The connection weights are quantum operators with complex entities, whereas the inputs and outputs are complex column vectors.

The suggested quantum neurons (Figure. 9) may be used to build quantum neural networks

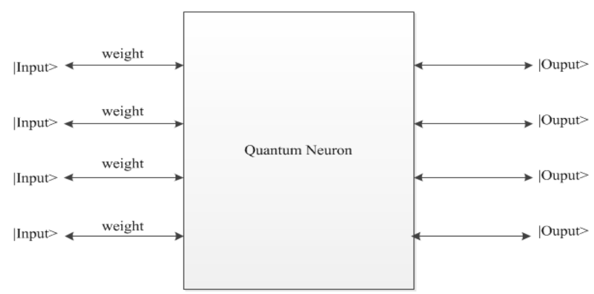

Fig. 9. Circuit Diagram of Quantum Neuron

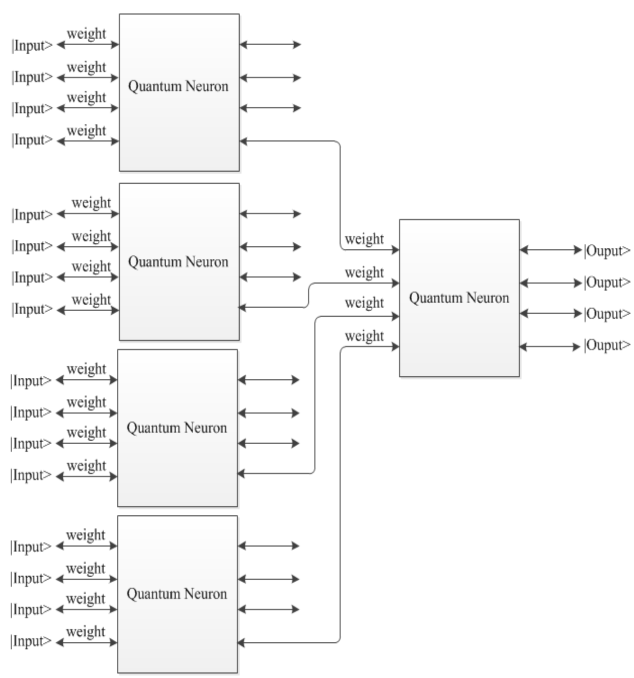

Fig. 10. Suggested model of Quantum Neural Network

(Figure. 10). The circuit lines that are not used by the next quantum neuron, may be passed on to other brain cells to accomplish additional functions. The suggested design prevents information loss by having an equal number of input and output lines, avoiding copying of quantum information, and having a reversible neural network. Quantum neuron layers may also be added to aid in the understanding of complicated events.

The suggested quantum neural network in this research complies with all restrictions and quantum computing principles. The identification and recovery of data about the suggested circuit/ hierarchy of quantum neural networks is thus said to be beneficial for the employment of quantum learning, and it may also be advantageous to title it for the quantum-oriented involvement of the complicated processes in the brain and mind.

For quantum circuit-based simulation of the non-linear learning of XOR Gate, it is necessary to initially define the input and output patterns of the Quantum XOR gate. Table 1 shows the Truth table with the corresponding input and output patterns of the Quantum XOR gate.

Subsequently, the following quantum circuit-based algorithm/approach or steps are proposed for the simulation of non-linear learning of XOR Gate.

Step 1: Set up the quantum neuron's initial parameters, such as count=0, the connection weights as quantum operators, the learning rate (eta), the acceptable minimal error as Emin, and $\emptyset, \gamma, \delta$ *and* θ with random values for each various weight.

Table 1. Truth table with corresponding input and output patterns of Quantum XOR gate.

Input Pattern #	$\vert\mathbf{A}\rangle$	$\vert\mathbf{B}\rangle$	$\vert\mathbf{t}\rangle$
1	$\vert 0\rangle$	$\vert 0\rangle$	$\vert 0\rangle$
2	$\vert 0\rangle$	$\vert 1\rangle$	$\vert 1\rangle$
3	$\vert 1\rangle$	$\vert 0\rangle$	$\vert 1\rangle$
4	$\vert 1\rangle$	$\vert 1\rangle$	$\vert 0\rangle$

Where $|\mathbf{0}\rangle = \begin{bmatrix}\mathbf{1}\\ \mathbf{0}\end{bmatrix}$, $|\mathbf{1}\rangle = \begin{bmatrix}\mathbf{0}\\ \mathbf{1}\end{bmatrix}$ and mixed or superposition state $|\mathbf{\Psi}\rangle = \begin{bmatrix}\mathbf{a}\\ \mathbf{b}\end{bmatrix} = \mathbf{a}|\mathbf{0}\rangle + \mathbf{b}|\mathbf{1}\rangle$ (here $\boldsymbol{a}$ and $\boldsymbol{b}$ are probability amplitudes).

Step 2: Compute Wa and Wb by using undermentioned function for further calculation of corresponding output for different patterns of XOR gate.

$$W(\emptyset, \gamma, \delta, \theta) = e^{i\emptyset}\begin{pmatrix} \cos\delta e^{i\gamma} & \sin\delta e^{i\theta} \\ -\sin\delta e^{-i\theta} & \cos\delta e^{-i\gamma} \end{pmatrix}$$

|Out>=W*|In>

e.g. |Ao> = Wa*|A>, |Bo> = Wb*|B>

Note: A tensor product of weights may be used to match the desired input order.

Step 3: Quantum neuron's final output is calculated by applying the quantum adder upon |Ao> and |Bo>.

Step 4: Obtain a transfer function to use on the estimated |Out> that is comparable to the one mentioned by Li Fei [22]. The following is the transfer function:

$$FT = \frac{1}{\sqrt{2}}\begin{bmatrix} 0 & 1 \\ 1 & -1 \end{bmatrix}\begin{bmatrix} \sin(\bullet) & 0 \\ 0 & \sin(\bullet) \end{bmatrix}$$

Step 5: Use the transfer function: |Yo> =FT*|Out> i.e

$$|Yo\rangle = \frac{1}{\sqrt{2}}\begin{bmatrix} 0 & 1 \\ 1 & -1 \end{bmatrix}\begin{bmatrix} \sin(\bullet) & 0 \\ 0 & \sin(\bullet) \end{bmatrix}|Out\rangle$$

Here $|Out\rangle$ may be a mixed state:

$$|Out\rangle = \begin{bmatrix} \pm a \\ \pm b \end{bmatrix}$$

$$|Yo\rangle = \frac{1}{\sqrt{2}}\begin{bmatrix} 0 & 1 \\ 1 & -1 \end{bmatrix}\begin{bmatrix} \sin(\bullet) & 0 \\ 0 & \sin(\bullet) \end{bmatrix}\begin{bmatrix} \pm a \\ \pm b \end{bmatrix}$$

$$= \frac{1}{\sqrt{2}}\begin{bmatrix} 0 & 1 \\ 1 & -1 \end{bmatrix}\begin{bmatrix} \sin(\pm a) \\ \sin(\pm b) \end{bmatrix} = \frac{1}{\sqrt{2}}\begin{bmatrix} 0 & 1 \\ 1 & -1 \end{bmatrix}\begin{bmatrix} +a \\ +b \end{bmatrix}$$

$$|Yo\rangle = \frac{1}{\sqrt{2}}\begin{bmatrix} b \\ a - b \end{bmatrix}$$

Step 6: Calculate error for the current patterns using |Er> = QSub(|t>, |Yo>)

Step 7: Determine error by taking the inner product with itself error = <Er|Er>

Step 8: compare this error with the Emin If error is less than Emin then increases the value of count++.

Step 9: If the patterns of XOR gate is fourth and the value of count equal to 4 then proceed to step 11 otherwise update the weight parameters in step 10 and then choose first pattern again as input/output, set the value of counter equal to 0 and goto step2.

Step 10: Update the following parameters.

$\emptyset=\emptyset+$ eta*<In| QSub (|t>,|Yo>)

$\gamma=\gamma+$ eta*< In | QSub (|t>,| Yo >)

$\delta=\delta+$ eta*< In | QSub (|t>,| Yo >)

$\theta=\theta+$ eta*< In | QSub (|t>,| Yo >)

<In| = <A| and <In| = <B| for Wa and Wb respectively.

Step 11: Break

3. RESULTS AND DISCUSSIONS

The suggested approach is simulated using the Open Quantum Computing Framework (OpenQCF), which was created in Python and C#. It uses the QRegister (|xxxx>), which is made up of various XOR Gate patterns, as the inputs and outputs (target output) to the quantum neuron. The Hermitian matrices are used as connection weights. Through the tensor product, many qubits are merged to create a QRegister, for example. $|AB\rangle = |A\rangle \otimes |B\rangle$

$$\text{Let } |A\rangle = |0\rangle = \begin{bmatrix}1\\0\end{bmatrix} \text{ and } |B\rangle = |1\rangle = \begin{bmatrix}0\\1\end{bmatrix}$$

$$|01\rangle = |0\rangle \otimes |1\rangle = \begin{bmatrix}1\\0\end{bmatrix} \otimes \begin{bmatrix}0\\1\end{bmatrix} = \begin{bmatrix}0\\1\\0\\0\end{bmatrix}$$

Figures 11 and 12 show the mean squared error convergence rate with respect to number of iterations for minimum errors 0.000000005 and 0.000000005 corresponding to learning rates 0.035 and 0.0135, respectively.

From the truth table of XOR gate (Table 1) choose first pattern as input |A> = $|0\rangle = \begin{bmatrix}1\\0\end{bmatrix}$, |B> = $|0\rangle = \begin{bmatrix}1\\0\end{bmatrix}$. Initialize the Wa weight and corresponding output by using the following:

$$W(\emptyset,\gamma,\delta,\theta) = e^{i\emptyset}\begin{pmatrix}\cos\delta e^{i\gamma} & \sin\delta e^{i\theta}\\ -\sin\delta e^{-i\theta} & \cos\delta e^{-i\gamma}\end{pmatrix},$$

|Out>=W*|In>

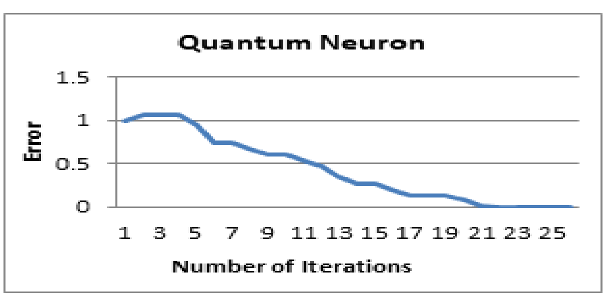

Fig. 11. Convergence of mean squared error of Quantum learning with learning rate=0.035 and MinError=0.000000005

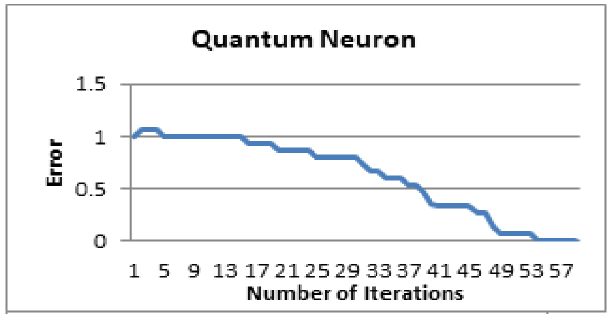

Fig. 12. Convergence of mean squared error of Quantum learning with learning rate=0. 0135 and MinError=0.000000005

To explain the algorithm in simpler way, suppose following weight matrices are initialed based upon the random values of $\emptyset, \gamma, \delta$ *and* θ.

$$\text{Wa} = \frac{1}{\sqrt{2}}\begin{bmatrix}1 & 1\\1 & -1\end{bmatrix}, \quad \text{Wb} = \frac{1}{\sqrt{2}}\begin{bmatrix}1 & 1\\1 & -1\end{bmatrix}$$

then

$$|Ao> = Wa*|A> = \frac{1}{\sqrt{2}}\begin{bmatrix}1 & 1\\1 & -1\end{bmatrix}\begin{bmatrix}1\\0\end{bmatrix} = \frac{1}{\sqrt{2}}\begin{bmatrix}1\\1\end{bmatrix} = \begin{bmatrix}\frac{1}{\sqrt{2}}\\\frac{1}{\sqrt{2}}\end{bmatrix}$$

$$|Bo> = Wb*|B> = \frac{1}{\sqrt{2}}\begin{bmatrix}1 & 1\\1 & -1\end{bmatrix}\begin{bmatrix}1\\0\end{bmatrix} = \frac{1}{\sqrt{2}}\begin{bmatrix}1\\1\end{bmatrix} = \begin{bmatrix}\frac{1}{\sqrt{2}}\\\frac{1}{\sqrt{2}}\end{bmatrix}$$

Quantum adder is applied on |Ao> and |Bo> to calculate the quantum neuron's final |Out>.

|Out> = QAdd (|Ao> and |Bo>) = $\begin{bmatrix}\sqrt{2}\\\sqrt{2}\end{bmatrix}$ (assume QAdd provides this output)

Apply the following transfer function upon the calculated |Out> which is considered by Li Fei [22].

$$FT = \frac{1}{\sqrt{2}}\begin{bmatrix}0 & 1\\1 & -1\end{bmatrix}\begin{bmatrix}\sin(\bullet) & 0\\0 & \sin(\bullet)\end{bmatrix}$$

Final output is calculated as |Yo> =FT*|Out>

$$|Yo> = \frac{1}{\sqrt{2}}\begin{bmatrix}0 & 1\\1 & -1\end{bmatrix}\begin{bmatrix}\sin(\bullet) & 0\\0 & \sin(\bullet)\end{bmatrix}|Out\rangle$$

Here we may get $|Out\rangle$ aa a mixed quantum state $|Out\rangle = \begin{bmatrix}\pm a\\\pm b\end{bmatrix}$

$$= \frac{1}{\sqrt{2}}\begin{bmatrix}0 & 1\\1 & -1\end{bmatrix}\begin{bmatrix}\sin(\bullet) & 0\\0 & \sin(\bullet)\end{bmatrix}\begin{bmatrix}\sqrt{2}\\\sqrt{2}\end{bmatrix}$$

$$= \frac{1}{\sqrt{2}}\begin{bmatrix}0 & 1\\1 & -1\end{bmatrix}\begin{bmatrix}\sin(\sqrt{2})\\\sin(\sqrt{2})\end{bmatrix} = \frac{1}{\sqrt{2}}\begin{bmatrix}0 & 1\\1 & -1\end{bmatrix}\begin{bmatrix}\sqrt{2}\\\sqrt{2}\end{bmatrix}$$

$$|\text{Yo}>= \frac{1}{\sqrt{2}}\begin{bmatrix}\sqrt{2}\\0\end{bmatrix} = \begin{bmatrix}1\\0\end{bmatrix} = |0>$$

As |t> = |0>, |Yo> = |0> calculate

|Er> = QSub(|t>,|Yo>)

to Estimate error= $\|\text{QSubt}(|\text{t}>, |\text{Yo}>)\|^2$=0.

Based upon this error weights parameter will be updated by following formulas.

For Wa, $|\text{In}> = |\text{A}> = |0>$

$\emptyset$=$\emptyset$+ eta*<In| (QSub (|t>,|Yo>)>

$\emptyset$=$\emptyset$+ eta*<A| Er>

$\gamma = \gamma$ + eta*<In| (QSub (|t>,|Yo>)>

$\delta = \delta$ + eta*<In| (QSub (|t>,|Yo>)>

$\theta = \theta$ + eta*<In| (QSub (|t>,|Yo>)>

$$\text{Wa} = \text{W}(\emptyset,\gamma,\delta,\theta) = e^{i\emptyset}\begin{pmatrix}\cos\delta e^{i\gamma} & \sin\delta e^{i\theta}\\ -\sin\delta e^{-i\theta} & \cos\delta e^{-i\gamma}\end{pmatrix}$$

For Wb, $|\text{In}>$ is $|\text{B}> = |0>$ and the factors α, ψ, φ and χ will be revised to evaluate Wb consequently. For the current pattern weights will not be updated because error=0, therefore, XOR gate's second pattern will be processed which is |A> = $|0\rangle = \begin{bmatrix}1\\0\end{bmatrix}$, |B> = $|1\rangle = \begin{bmatrix}0\\1\end{bmatrix}$

Wa = $\frac{1}{\sqrt{2}}\begin{bmatrix}1 & 1\\1 & -1\end{bmatrix}$, Wb = $\frac{1}{\sqrt{2}}\begin{bmatrix}1 & 1\\1 & -1\end{bmatrix}$, Then

$$|\text{Ao}> = \text{Wa}*|\text{A}> = \frac{1}{\sqrt{2}}\begin{bmatrix}1 & 1\\1 & -1\end{bmatrix}\begin{bmatrix}1\\0\end{bmatrix} = \frac{1}{\sqrt{2}}\begin{bmatrix}1\\1\end{bmatrix} = \begin{bmatrix}\frac{1}{\sqrt{2}}\\\frac{1}{\sqrt{2}}\end{bmatrix}$$

$$|\text{Bo}> = \text{Wb}*|\text{B}> = \frac{1}{\sqrt{2}}\begin{bmatrix}1 & 1\\1 & -1\end{bmatrix}\begin{bmatrix}0\\1\end{bmatrix} = \frac{1}{\sqrt{2}}\begin{bmatrix}1\\-1\end{bmatrix} = \begin{bmatrix}\frac{1}{\sqrt{2}}\\-\frac{1}{\sqrt{2}}\end{bmatrix}$$

Quantum adder is applied on |Ao> and |Bo> to calculate the quantum neuron's final |Out>.

$$|\text{Out}> = \text{QAdd}\ (|\text{Ao}> \text{ and } |\text{Bo}>) = \begin{bmatrix}\sqrt{2}\\0\end{bmatrix}$$

(Assume QAdd provides this output)

Apply the following transfer function upon the calculated |Out> which is considered by Li Fei [22]

$$\text{FT} = \frac{1}{\sqrt{2}}\begin{bmatrix}0 & 1\\1 & -1\end{bmatrix}\begin{bmatrix}\sin(\bullet) & 0\\0 & \sin(\bullet)\end{bmatrix}$$

Final output is calculated as |Yo> =FT*|Out>

$$|\text{Yo}> = \frac{1}{\sqrt{2}}\begin{bmatrix}0 & 1\\1 & -1\end{bmatrix}\begin{bmatrix}\sin(\bullet) & 0\\0 & \sin(\bullet)\end{bmatrix}|\text{Out}\rangle$$

Here we may get $|\text{Out}\rangle$ aa a mixed quantum state $|\text{Out}\rangle = \begin{bmatrix}\pm a\\\pm b\end{bmatrix}$

$$|\text{Yo}> = \frac{1}{\sqrt{2}}\begin{bmatrix}0 & 1\\1 & -1\end{bmatrix}\begin{bmatrix}\sin(\bullet) & 0\\0 & \sin(\bullet)\end{bmatrix}\begin{bmatrix}\sqrt{2}\\0\end{bmatrix}$$

$$= \frac{1}{\sqrt{2}}\begin{bmatrix}0 & 1\\1 & -1\end{bmatrix}\begin{bmatrix}\sin(\sqrt{2})\\\sin(0)\end{bmatrix} = \frac{1}{\sqrt{2}}\begin{bmatrix}0 & 1\\1 & -1\end{bmatrix}\begin{bmatrix}\sqrt{2}\\0\end{bmatrix}$$

$$|\text{Yo}>= \frac{1}{\sqrt{2}}\begin{bmatrix}0\\\sqrt{2}\end{bmatrix} = \begin{bmatrix}0\\1\end{bmatrix} = |1>$$

As |t> = |1>, |Yo> = |1> calculate

|Er> = QSub(|t>,|Yo>)

to Estimate error= $\|\text{QSub}(|\text{t}>, |\text{Yo}>)\|^2$=0.

For this pattern weights will not again be updated because error=0. In the same way, next input will be processed i.e. (|B> = $|0\rangle = \begin{bmatrix}1\\0\end{bmatrix}$, |A> = $|1\rangle = \begin{bmatrix}0\\1\end{bmatrix}$) and the fourth pattern (|A> = $|1\rangle = \begin{bmatrix}0\\1\end{bmatrix}$, |B> = $|1\rangle = \begin{bmatrix}0\\1\end{bmatrix}$) for XOR Gate. If four patterns yield no error, the processing will be stopped; if not, it will resume with first pattern of truth table by using updated weights and will continue until acceptable error is obtained.

There is no information loss or copying since the circuit for quantum neurons or neural networks has an equal number of input and output lines. Therefore, the suggested approach qualifies all limitations of quantum computing by considering the architecture's processing power, which is used to run the proposed algorithm's simulation. The findings and execution of the suggested method make it evident that the limitations discussed in this study are resolved. The suggested quantum neuron's corresponding circuit and algorithm satisfy all the fundamental laws and theorems of quantum computing. The simulation findings also demonstrate that it can learn many phenomena. Therefore, the proposed quantum circuit and algorithm is it is suggested, for the solution of Partial differential equations (PDEs) and Ordinary Differential Equations (ODEs), to implement quantum neural correlates of consciousness into machines, to calculate mass spectroscopy, and in high energy physics instead of using existing quantum or classical artificial neural networks. The related detail can be seen in author's PhD thesis [30] for further information.

A prominent work on the non-linear learning of XOR gate through quantum neural network is by Li Fei [22]. The algorithm used by Li Fei [22] violates the quantum computing principles such as no-loss of information, reversibility, and no-cloning theorem etc. The algorithm explained in the present study is free of such drawbacks and ensures that principles of quantum computing are fully satisfied.

4. CONCLUSION

The present study proposes and implements a novel paradigm of quantum neural networks for the XOR gate's nonlinear learning. It is demonstrated that the proposed method follows all quantum computing constraints. Therefore, it is recommended to utilize the suggested QNNs circuit and corresponding algorithm for the modelling and employment of higher-level characteristics in conscious robots if the brain functions are in accordance with the principle of quantum mechanics. Additionally, the suggested quantum neural network and its associated circuits and algorithms may be employed to address certain high-energy physics issues.

5. CONFLICT OF INTEREST

Authors declare no conflict of interest.

6. DATA AND CODE AVAILABILITY

On reasonable request, the corresponding author will provide the code along with data sets created and used in the present work.

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