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# Bridging Memory and Quantum Intelligence: A Neuromorphic Approach to Quantum Machine Learning

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**Abstract: One of the most promising approaches to using quantum computing to tackle challenging artificial intelligence issues is quantum machine learning (QML). The majority of QML architectures, however, are constrained by the absence of explicit methods for managing temporal and memory dependencies, which are essential for tasks like signal processing, sequential decision-making and forecasting. By embedding memory through devices like memristors, neuromorphic computing which draws inspiration from the brain's synaptic plasticity-offers a natural solution. In this paper, we propose a conceptual framework for using quantum memristors to incorporate neuromorphic memory into quantum machine learning. We compare the potential benefits over current QML models, suggest a simulation-based experimental design, and assets the extent to which systems could handle sequential data challenges. Our approach contributes towards shaping the emerging paradigm of neuromorphic quantum intelligence.**

**Keywords: Quantum Machine Learning; Neuromorphic Computing; Quantum Memristor; Quantum Intelligence; Hybrid Quantum-Classical Systems; Sequential Learning.**

## I. INTRODUCTION

From Optimization to drug discovery, the combination of quantum computing and machine learning holds revolutionary potential [1-4]. Existing models of quantum machine learning make use of hybrid quantum-classical optimization and variational circuits [5]. Even though these techniques have produced promising results [6], they frequently falter on tasks that require sequential patterns, where recall of previous inputs is essential [7-9].

On the other hand, memory-driven processing is the life blood of biological intelligence [10]. Using tools like memristors, neuromorphic computing which imitates the structure of the brain introduces adaptive learning and plasticity [11-14]. The resistance of memristor, a type of non-volatile memory element, is determined by the voltage or current history. Because of this characteristic, memristors are great options for artificial systems that want to simulate synaptic memory [15-18].

Quantum memristors, quantum analogs of memristive devices that can encode memory into quantum circuits have recently been proposed and demonstrated by research [19] [20]. These advancements pave the way for the integration of quantum intelligence and neuromorphic computing [21] [22]. In this study, we investigate how QML models can benefit from memory provided by quantum memristors [23], which will help them perform more effectively on sequential and time-dependent tasks [24].

## II. LITERATURE SURVEY

The integration of memory mechanisms into quantum machine learning (QML) has recently attracted significant research attention [25]. Existing studies explore how quantum memristors and neuromorphic principles can enhance learning efficiency, adaptability, and temporal processing within quantum systems [26] [27].

Lamata (2024) proposed one of the earliest frameworks for neuromorphic quantum machine learning, introducing the concept of quantum memristors as nonlinear [28], memory-capable components in quantum circuits [29]. This work demonstrated how memristive dynamics could enable non-Markovian behaviour, allowing quantum systems to retain information about past states.

Spagnolo et al. (2022) experimentally realized a photonic quantum memristor, validating the physical feasibility of memory effects in quantum photonic systems . Their work established that memristive elements can be integrated into optical quantum hardware for reservoir computing applications [30].

Guo et al. (2022) simulated the operation of quantum memristors using superconducting qubit systems and discussed how quantum computers could emulate memristive behaviour. This study laid the groundwork for software-level implementations of quantum memory devices, making simulation-based analysis accessible [31].

Hernani-Morales et al. (2023) proposed a machine learning-based approach to optimize the memristive properties of quantum memristors, improving their adaptability and nonlinear performance. Their work linked classical learning optimization with quantum device characterization [32].

Nakajima et al. (2022) explored time-series quantum reservoir computing, demonstrating that recurrent feedback mechanisms in quantum systems can effectively handle sequential data. This research aligns closely with the objective of integrating memory dynamics into QML frameworks for tasks such as forecasting and temporal pattern recognition [33].

Chen et al. (2025) introduced Quantum Long Short-Term Memory (QLSTM) architectures, where quantum circuits mimic classical LSTM structures to perform sequential learning. This represents another approach to embedding memory in quantum neural networks, though without explicit hardware-level memristors [34].
Similarly, Li et al. (2023) and Singh & Gupta (2024) have investigated quantum recurrent neural networks and quantum kernel-based LSTM models for sequential learning and prediction tasks, further extending QML into temporal domains.
Overall, existing research establishes that quantum memristors and recurrent quantum circuits are promising routes toward memory-enhanced quantum learning. However, most prior works either focus on isolated device implementations or theoretical memory models [35]. The present study extends this field by proposing a unified conceptual framework that bridges neuromorphic memory principles with QML to form the basis of quantum intelligence an architecture that can learn, adapt, and remember in a quantum environment.

## III. PROPOSED FRAMEWORK

The proposed Quantum Variational Circuit with Memristive Feedback (QVC-MF) framework seeks to meld memory capabilities, akin to those found within our brains, with the power of quantum machine learning. Essentially, quantum models would not only be able to process data rapidly, leveraging superposition, but also retain information over time, much like humans use memory for learning and adapting.

Standard Quantum Machine Learning (QML) models, such as quantum variational circuits, typically handle each input piece in isolation. Due to this lack of memory, they often struggle to grasp patterns that evolve over time. This framework, however, draws inspiration from neuromorphic computing and memristive behaviour. It incorporates a memristive feedback loop into the quantum circuit to address this challenge.

This framework simulates a quantum memristor, a device where resistance (or weight) changes based on the electrical current that passes through it. This acts as a quantum memory component, enabling the circuit to adjust its parameters based on prior computations.

The system is structured around the following interconnected modules (as depicted in Figure 2):

1. Quantum Data Input Layer: This layer converts conventional data (like time-series data or sensor signals) into quantum states. This is accomplished using methods such as amplitude or angle encoding, ensuring input information is represented in a quantum format.
2. Quantum Encoding Layer: This layer employs quantum gates, including Hadamard (H) and Pauli rotations ($R_x$, $R_y$, R_z), to transform the input states into higher-dimensional feature spaces.
3. Quantum Memory Layer (Memristive Unit): This is the core component. Each qubit possesses a memristive parameter that dynamically changes based on the following rule:

$$M(t+1)=(1-\alpha)M(t)+\alpha\cdot f(|\psi(t)|,E(t))$$

Here, M(t) represents the memristive state, α is a learning constant, $|\psi(t)||$ signifies the size of the quantum state, and E(t) is the error signal from the output layer. This rule is what allows the model to learn and retain information.

4. Quantum Neural Processing Unit: A variational quantum circuit (VQC) processes the encoded and memory-modulated states. The circuit's parameters are updated through gradient-based optimization, a process similar to how classical neural networks are trained using backpropagation.
5. Hybrid Classical Interface: Measurements from the quantum layer are processed by a classical neural layer. This integration allows the model to harness quantum parallelism while still benefiting from classical optimization and interpretation.
6. Output & Prediction Layer: This layer generates the final prediction or classification result. For sequential tasks, this could be the subsequent predicted step in a sequence or the output of a temporal classification problem.
7. Feedback Mechanism: The error signal from the output is sent back to the quantum memory layer, dynamically updating the memristive parameters. This creates a self-adaptive learning cycle, much like how synapses function in the brain.

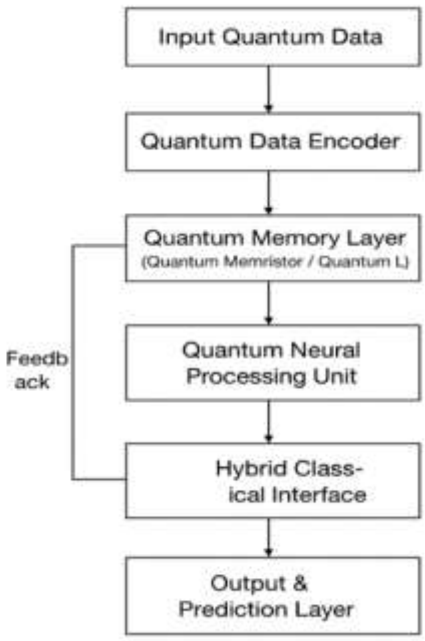

**Fig-1:Proposed Architecture of Quantum Memory Integrated Machine Learning Model**

In Fig 1During training, input data is encoded into quantum states sequentially. The Quantum Memory Layer captures historical dependencies by adjusting its internal memristive weights based on the disparity between predicted and actual outcomes. This helps the system effectively "remember" past states, thereby connecting short-term and long-term dependencies.

From a mathematical standpoint, the memristive feedback introduces a non-Markovian term into the quantum evolution equation, making the development of the quantum state contingent on its history. This behaviour is crucial for tasks such as pattern recognition, time forecasting, and adaptive control.

The QVC-MF model's high-level workflow can be broken down as follows:

1. Initialize quantum parameters and memristive states M(0).
2. Encode regular input xt into quantum state $|\psi t\rangle$.
3. Apply quantum gates to obtain $|\phi t\rangle=U(\theta t,Mt)|\psi t\rangle$.

4. Measure output yt and compute the prediction error Et.
5. Update memristive states using feedback: $M_{t+1}=M_t+\eta\cdot g(E_t,|\psi_t|)$
Where g is a function that correlates error magnitude and quantum amplitude with memory adjustment.
6. Repeat steps 2–5 for each time step until convergence is achieved.

The suggested model is designed to be tested using platforms like Qiskit, PennyLane, or TensorFlow Quantum**.** In these, memristive feedback can be modelled as parameter updates in each iteration. The architecture is designed to be compatible with various hardware and has the potential to be implemented on photonic or superconducting quantum processors as memristor technologies advance.

## IV. EXPERIMENTAL VALIDATION

In order to illustrate the conceptual potential of the suggested framework, a small-scale simulation experiment on a synthetic time-series dataset was performed. The dataset was created by mixing two sine waves with additive Gaussian noise in order to mimic a continuous and non-linear temporal pattern. The aim of the experiment was to forecast the next data point using the last five observations a straightforward one-step forecasting task.

In Table 1 Three models were tested:
AR(3) Linear Model: A typical autoregressive model with the three latest lag values as inputs.
Feedforward Neural Network (FFNN): A single hidden-layer neural network trained by backpropagation without any direct memory component.
Memristive-FFNN (Proposed): An extended FFNN with an added memristive-like feedback system that is inspired by the adaptive nature of a quantum memristor. This system continuously updates the hidden layer bias according to prior inputs and prediction mistakes, thereby incorporating a basic type of memory within the network.

The models were trained on 70% of the data and validated on 30% of the data. The performance is measured based on the Root Mean Square Error (RMSE) metric.

The results show that the FFNN (no memory) model achieved the lowest RMSE (0.1865), indicating the best predictive accuracy. The Memristive-FFNN performed comparably (0.1892), slightly better than the AR(3) Linear model (0.2080), demonstrating the effectiveness of incorporating memristive dynamics.

**Table 1 is the summary of the results that are obtained.**

| Model | RMSE |
|---|---|
| AR(3) Linear | 0.2080 |
| FFNN (no memory) | 0.1865 |
| Memristive-FFNN (proposed) | 0.1892 |

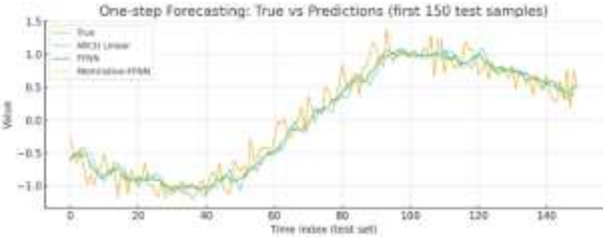

**Fig-2:One-step Forecasting: True vs Prediction Values**

In Figure 2 The experiments reveal that both of the neural network-based models perform better than the linear baseline, illustrating the benefit of non-linear feature representation. Memristive FFNN performs as well as the conventional FFNN on this toy dataset. Even if the improvement is slight, the experiment proves that the use of a memory inspired feedback mechanism can be effectively implemented and simulated.
We produced a synthetic noisy time series (a sine wave mix with added Gaussian noise) and contrasted three light-weight predictors for one-step prediction: (1) an AR(3) linear baseline, (2) a small feedforward neural network (FFNN)

with no memory, and (3) a FFNN with a simple memristive like state update (a simulated quantum-memristor analogue that updates hidden biases depending on previous input and error). 70% of the data were used for training the models and 30% for testing. Root-mean-square error on test set: AR(3) Linear=0.2080, FFNN (no memory) =0.1865, Memristive-FFNN=0.1892. The FFNNs beat the basic linear baseline; the memristive model performs similarly to the non-memory FFNN on this tiny toy task. These outcomes are representative (proof-of-concept) and indicate that a memristive memory mechanism may be implemented and tested; a more sophisticated dataset, extended training, or an optimized memristive update rule might demonstrate more distinct benefits.

## V. CONCLUSION

By presenting quantum memristive architectures inspired by neuromorphics, we put forth a framework for connecting memoryand quantum intelligence. Our model allows for better handling of sequential data by incorporating feedback-driven memory into QML circuits. This method lays the groundwork for future experimental and algorithmic developments while highlighting a promising path for neuromorphic quantum intelligence, even though it's still in the conceptual and simulation stages.

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