# A Quantum Leaky Integrate-and-Fire Spiking Neuron and Network

Dean Brand[1,*] and Francesco Petruccione[1,2]

[1]*School of Data Science and Computational Thinking and Department of Physics, Stellenbosch University, Stellenbosch 7602, South Africa*

[2]*National Institute for Theoretical and Computational Sciences (NITheCS), South Africa*

Quantum machine learning is in a period of rapid development and discovery, however it still lacks the resources and diversity of computational models of its classical complement. With the growing difficulties of classical models requiring extreme hardware and power solutions, and quantum models being limited by noisy intermediate-scale quantum (NISQ) hardware, there is a growing niche of solving both problems at once. The field of quantum neuromorphic computing has shown a lot of conceptual potential, but mostly in the form of hardware developments. In this work we introduce a new software model of quantum neuromorphic computing — a quantum leaky integrate-and-fire (QLIF) neuron.

This new quantum neuron takes inspiration from a well-studied classical spiking neuron, the Leaky Integrate-and-Fire neuron, which is a simple and more bio-plausible model than current artificial neurons. While the classical model processes spikes of input current to vary a membrane potential within an RC-circuit, the quantum model utilises simple state population measurements, varied by basic rotation gates. The leak of the classical model is either manually calculated or, in the case of neuromorphic hardware, a feature of the circuit dynamics, in the quantum model the leak is due to the natural presence of excited state relaxation through the $T_1$ decay process.

This elegant design allows for a quantum machine learning model that not only utilises the noisy environment of NISQ devices, but is also not at the mercy of noise as in other deep-circuit quantum models. This QLIF model takes the form of a recurrent circuit. It only uses $R_X$ gates to record the influence of an input spike, and a simple time-delay gate ($\Delta(t)$) instructing the circuit to do nothing and let noise decrease excited state population. In noise-less simulations this effect of exponential decay can also be implemented with a single rotation gate. As a spiking model the input spike and firing threshold decision boundary needs to be accounted for in every step, which is done simply in this model by reinstating the previous excited state population with a rotation gate. All of this leads to a recurrent single-qubit model that only utilises two gates and a measurement, shown in Figure 1a. This leads to benefits through linear scaling and thereby simulation of thousands of qubits being used in a network.

This model has been used as the foundation of a quantum spiking neural network (QSNN) as the first of its kind. Additionally, due to architectural compatibility, the model has also been used in the construction of the first quantum spiking convolutional neural network (QSCNN). Both models have been applied to the MNIST, Fashion MNIST, and Kuzushiji-MNIST image classification problems, with findings that the noise resilience and scaling potential lead to high accuracy and fast classification of images. The models perform very similarly to the classical spiking counterpart, and much faster than the variational quantum classifier and Quanvolutional neural network methods which attain comparable levels of accuracy, as seen in Figure 1b. These performances are further improved when the network architectures are optimised, and not kept at a benchmark standard. The models are all trained on 60 000 images and tested on 10 000 images, kept at a simple architecture using the same loss function and optimiser. For these results all quantum models have been simulated without noise, which provides more advantage for the non-spiking circuits. This model is being extended in capability to neuromorphic-specific datasets, as well as other machine learning models to be applied to problems such as time-series anomaly detection.

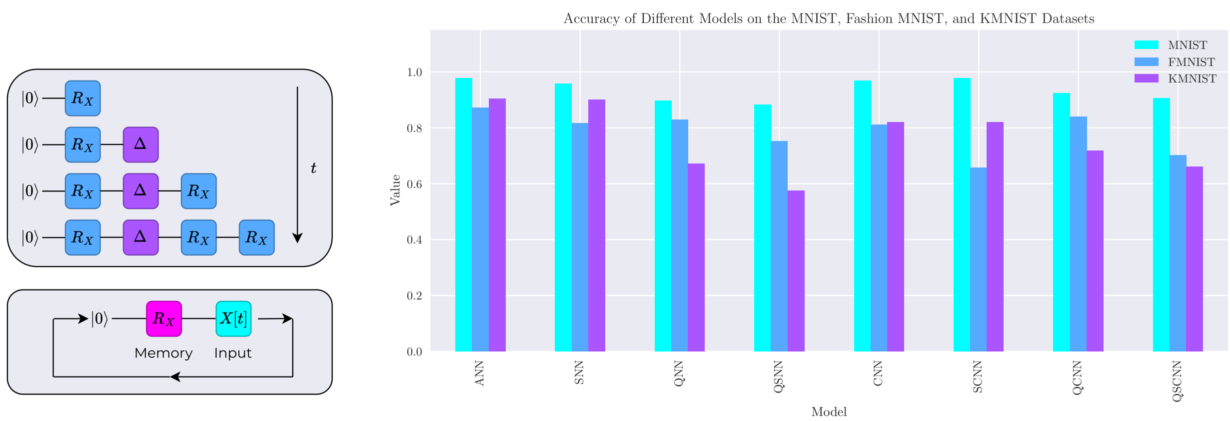


FIG. 1: a) Recurrent QLIF quantum circuit model. b) Accuracy comparison of neural network models on MNIST, Fashion MNIST, and Kuzushiji-MNIST datasets.

*Electronic address: deanbrand@proton.me