MINOR PROJECT PRESENTATION

High Fidelity Brain Tumor Detection and Compartmentalization using Quantum Convolutional Neural Networks

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Key points to be covered in this presentation

- Task- Brain Tumor Segmentation and Classification
- What is Quantum Computing?
- Quantum Computing basics- Qbits, Superposition, Schrödinger's Thought Experiment
- Why Quantum Computing?
- Classical Convolutional Neural Network for Image Classification
- Quantum Convolutional Neural Network for Image Classification

Task- Brain Tumor Segmentation and Classification

INPUT A set of Labelled Images brain MRI

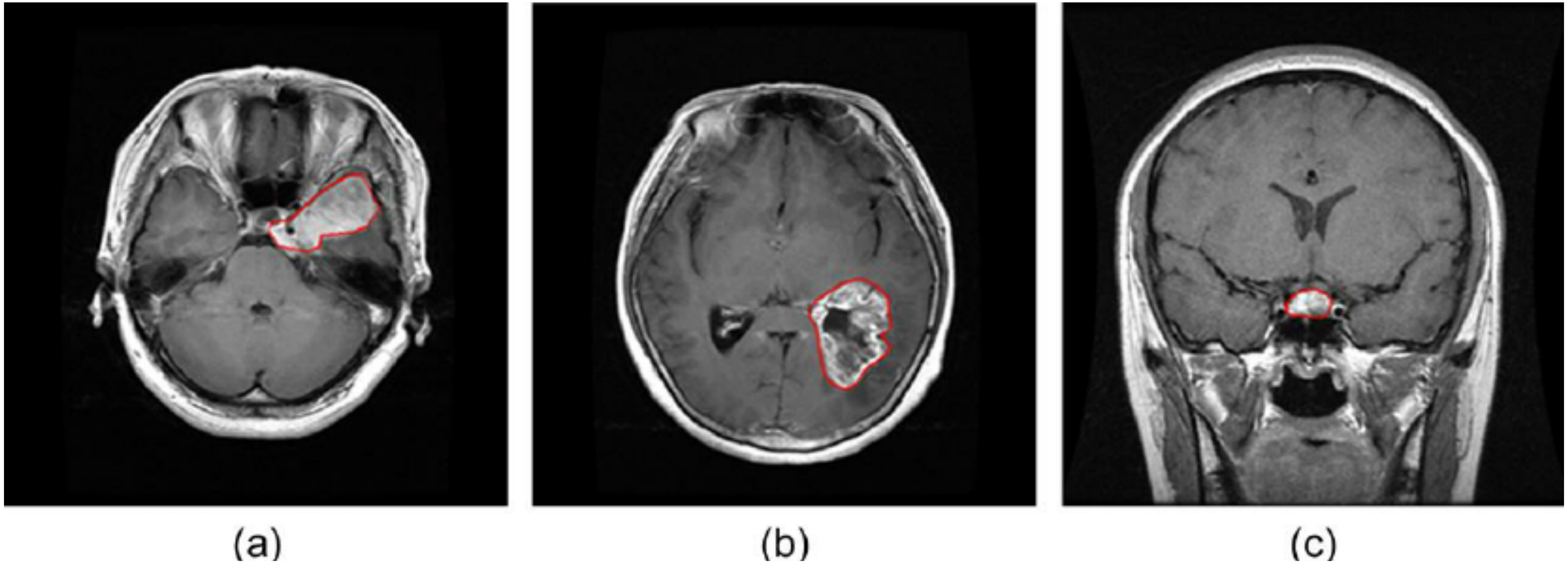


Fig 1. Labelled brain MRI scans from Kaggle [6]. (a) Glioma (b) Meningioma & (c) Pituitary Tumor

OUTPUT Classification of Images

What is Quantum Computing?

- Quantum computing focuses on developing computer technology based on the principles of **QUANTUM THEORY**, which explains the behavior of energy and material on the atomic and subatomic levels.
- Three quantum mechanical phenomenons —

  A. Superposition

  B. Entanglement

  C. Interference

  are used in quantum computing to manipulate the state of a **qubit**.

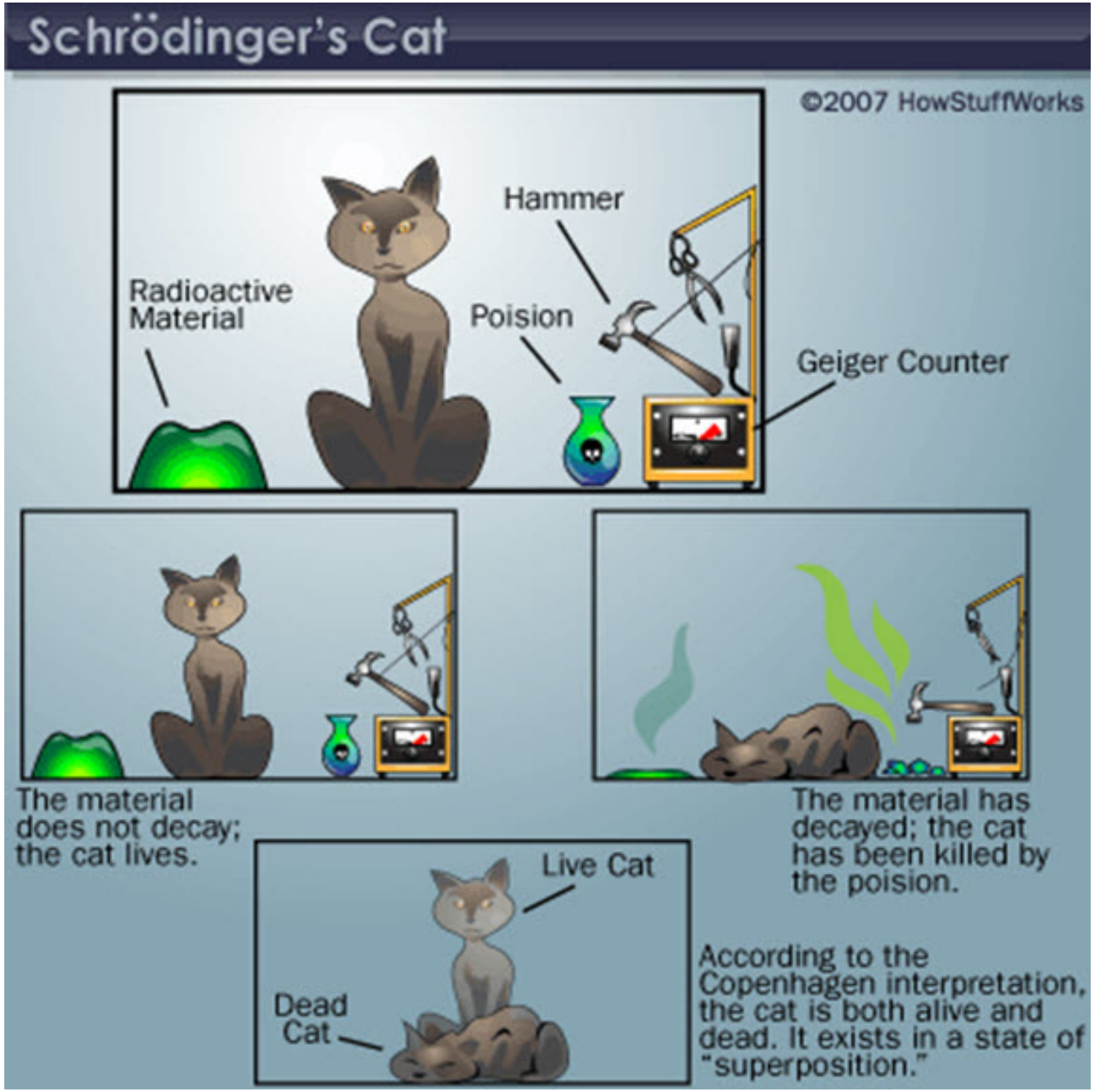


Fig 2. Schrödinger's Thought Experiment in detail

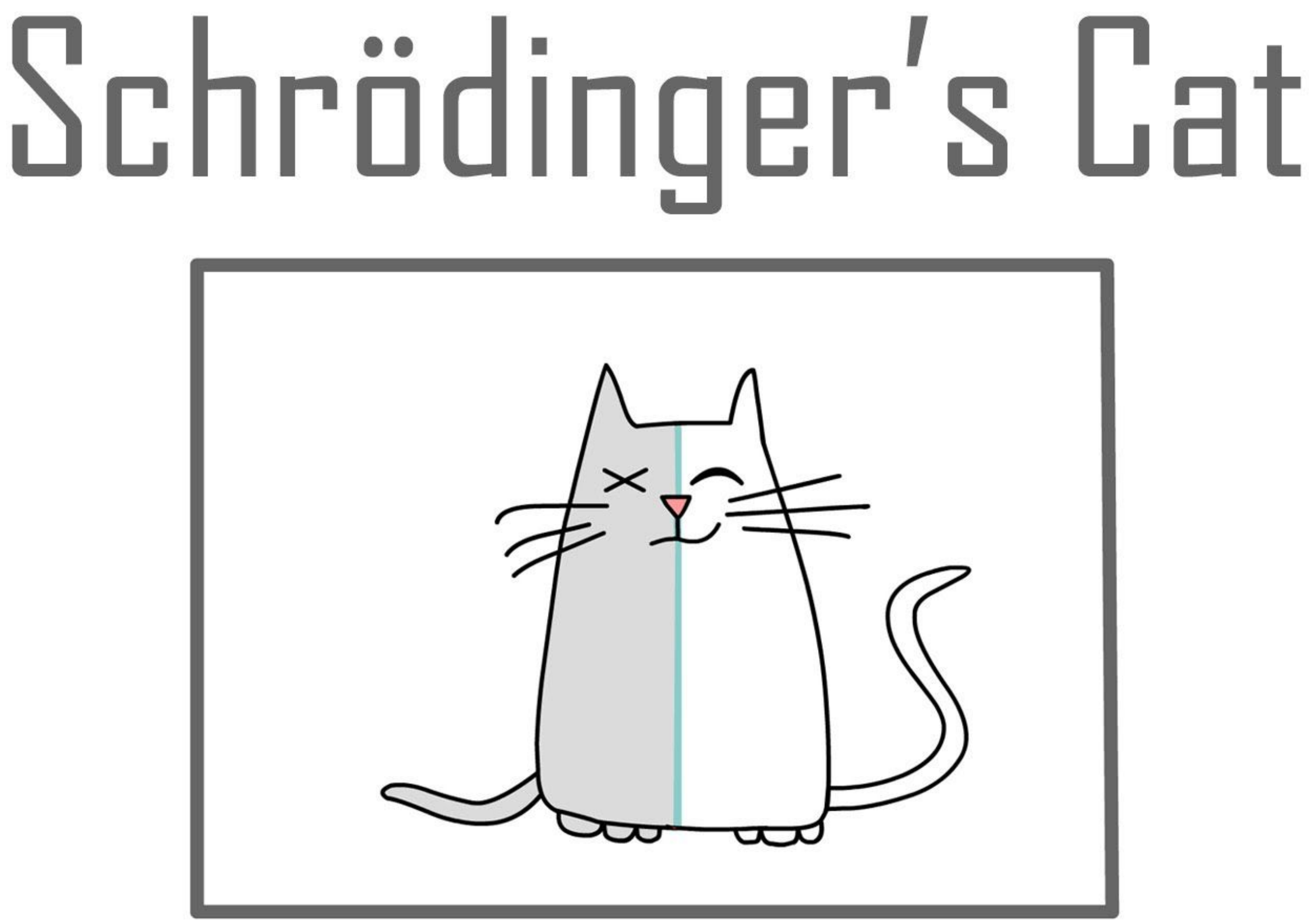


Fig 3. Schrödinger's Cat

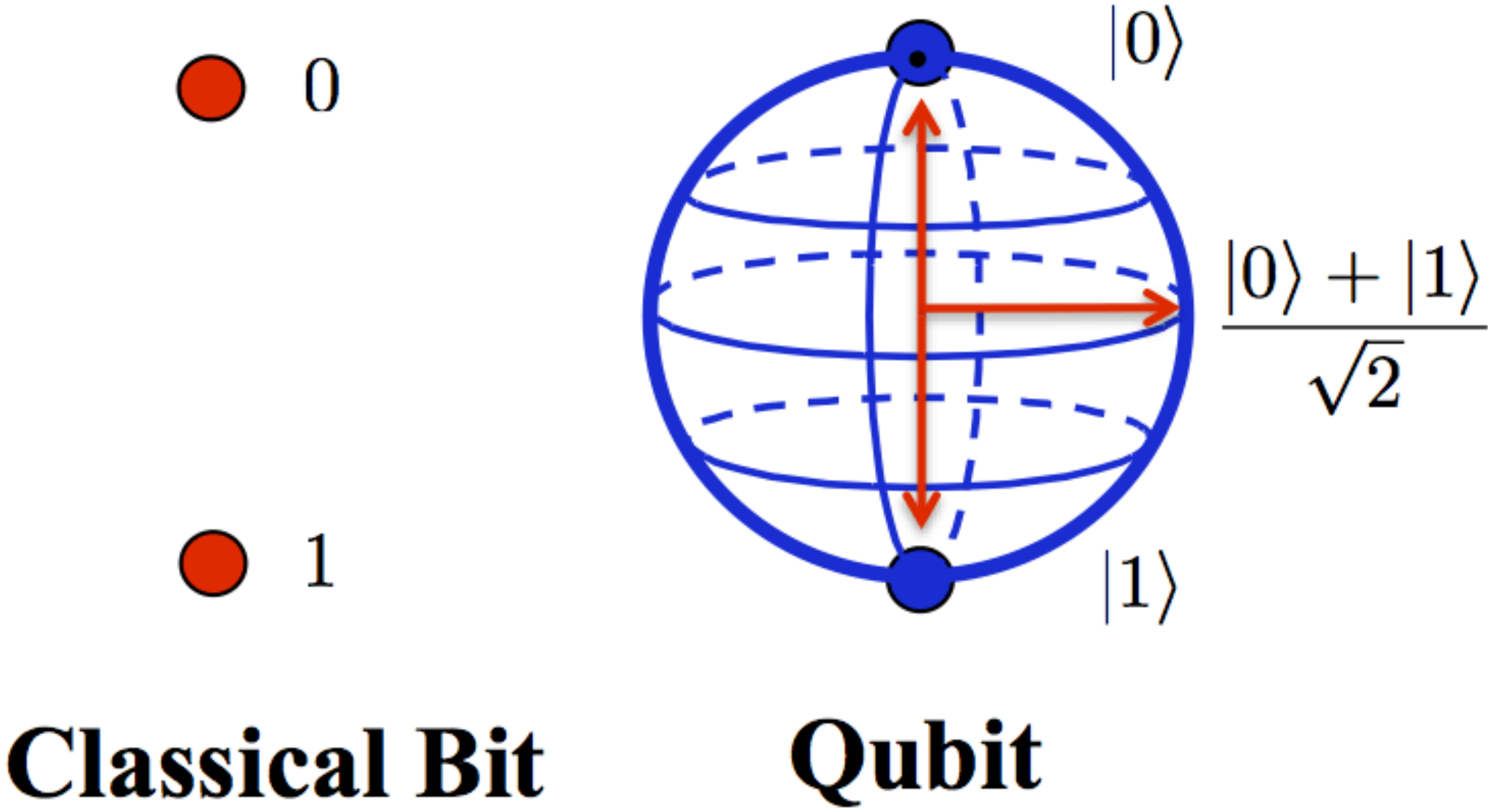


Fig 4. Difference between states of a classical bit and Qubit

Quantum Entanglement

- Multiple Qubits are represented using Tensor Product, But under ONE condition!
- Qubits are said to be entangled if their tensor product can't be refactored.
- Entangled Qubits can't exist or be described independently.
- They are correlated and exhibit ***Faster than Light Co-ordination***.
- Once measured, they come down to one of two states, ie., either 0 or 1, and when measured, both are same.

$$\binom{a}{b} \otimes \binom{c}{d} = \begin{pmatrix} ac \\ ad \\ bc \\ bd \end{pmatrix}$$

$$\|ac\|^2 + \|ad\|^2 + \|bc\|^2 + \|bd\|^2 = 1$$

$$\begin{pmatrix} \frac{1}{\sqrt{2}} \\ 0 \\ 0 \\ \frac{1}{\sqrt{2}} \end{pmatrix} = \binom{a}{b} \otimes \binom{c}{d}$$

$$ac = \frac{1}{\sqrt{2}}$$
$$ad = 0$$
$$bc = 0$$
$$bd = \frac{1}{\sqrt{2}}$$

What is so special about Quantum Computing?

- It is **THE FUTURE**! QC can change the way we compute, especially Optimization problems.
- At atomic level, quantum computing simulates **nature**! Therefore could help us find new materials or identify new chemical compounds for drug discovery.
- Can solve those problems that could take a normal computer billions of years to solve and can do it in seconds. *Quantum Speed-Up right?*
- Quantum Computing can exponentially optimize tasks in Defense, Communications, Financial Trading, Metrology, Drug Discovery and Chemoinformatics! *Can you guess what it can't do?*

Literature Survey

- M. V. Altaisky [1] suggested a quantum neural network (QNN) using the principles of quantum information processing in 2001.
- C. Zhao et al., [2] introduced a general quantum DNN, consisting of a fully quantum structured layers with better representation power than the classical DNN, while still keeping the advantages of the classical DNN such as the non-linear activation, the multi-layer structure, and the efficient backpropagation training algorithm.
- I. Cong et al., [3] proposed a novel quantum machine learning model motivated by convolutional neural networks. This model makes use of only O(log(N)) variational parameters for input sizes of N qubits, allowing for its efficient training and implementation on realistic, near-term quantum devices.

Literature Survey

- I. Kerenidis et al., [4] proposed a quantum algorithm for applying and training deep convolutional neural networks with a potential speedup. They also presented numerical simulations for the classification of the MNIST dataset to provide practical evidence for the efficiency of the QCNN.
- K. Beer et al., [5] presented a truly quantum analogue of classical neurons, which form quantum feedforward neural networks *capable of universal quantum computation*. The efficient training of these networks are described using ***fidelity*** as a cost function, providing both classical and efficient quantum implementations.
- Debanjan Konar et al., [7] proposed fully self-supervised novel quantum-inspired neural network model referred to as Quantum-Inspired Self-Supervised Network (QIS-Net) and tailored for fully automatic segmentation of brain MR images to obviate the challenges faced by deeply supervised Convolutional Neural Network (CNN) architectures.

Classical Convolutional Neural Network

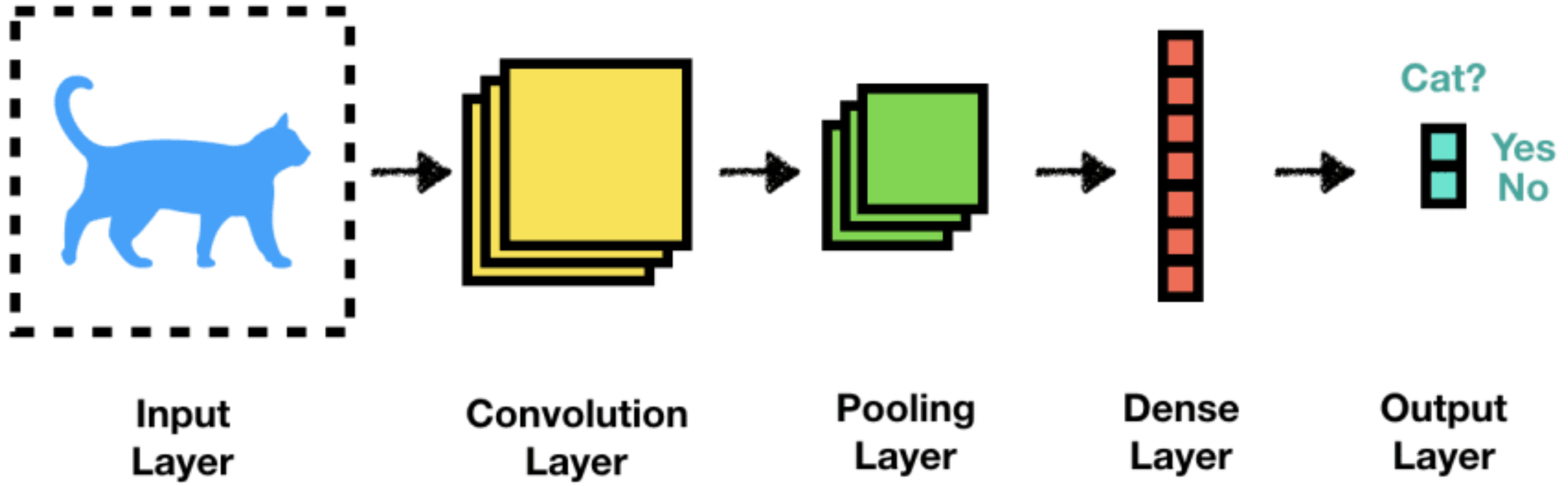


Fig 5. Major Steps involved in Convolutional Neural Network for Image Classification

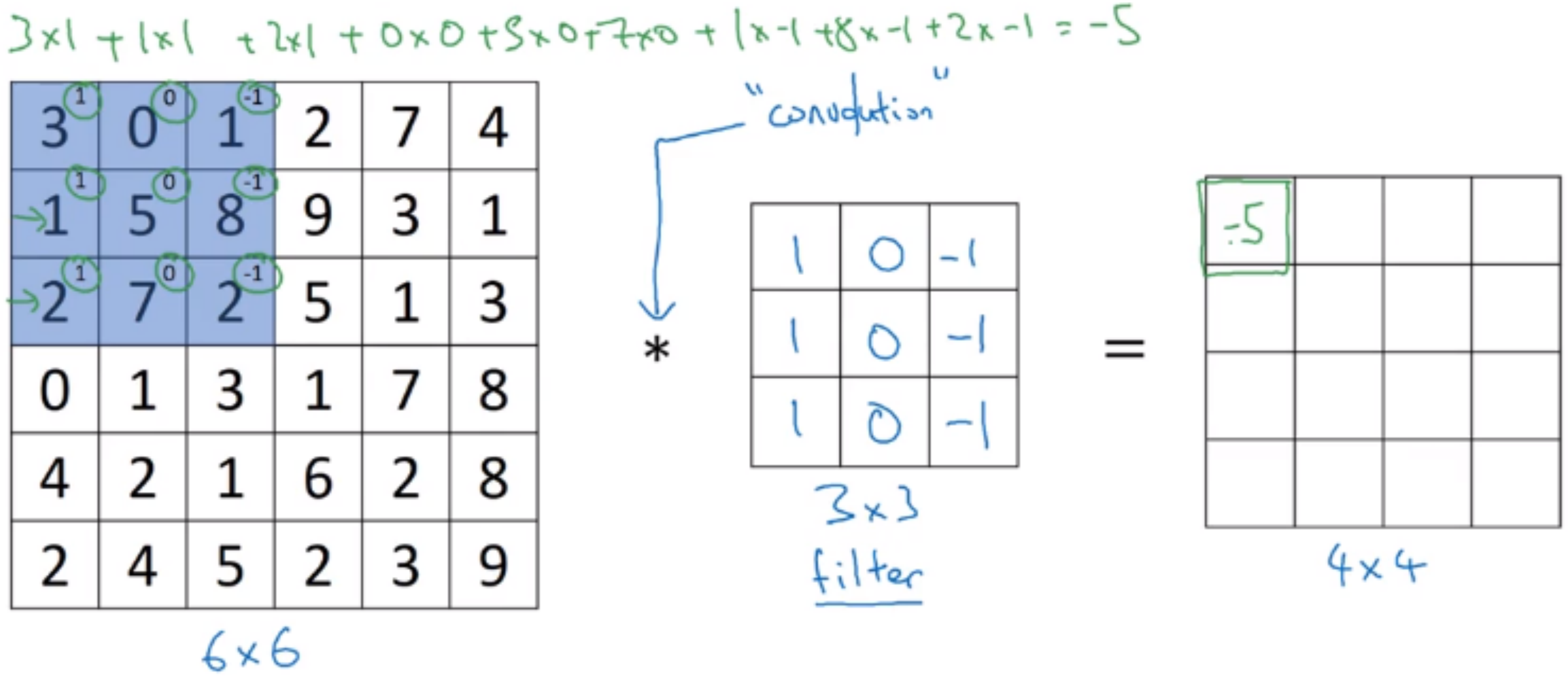


Fig 6. Convolutional Layer/ Filter/ Kernel

Quantum Convolutional Neural Network

PROPOSED: Hybrid Quantum-Classical Convolutional Neural Network

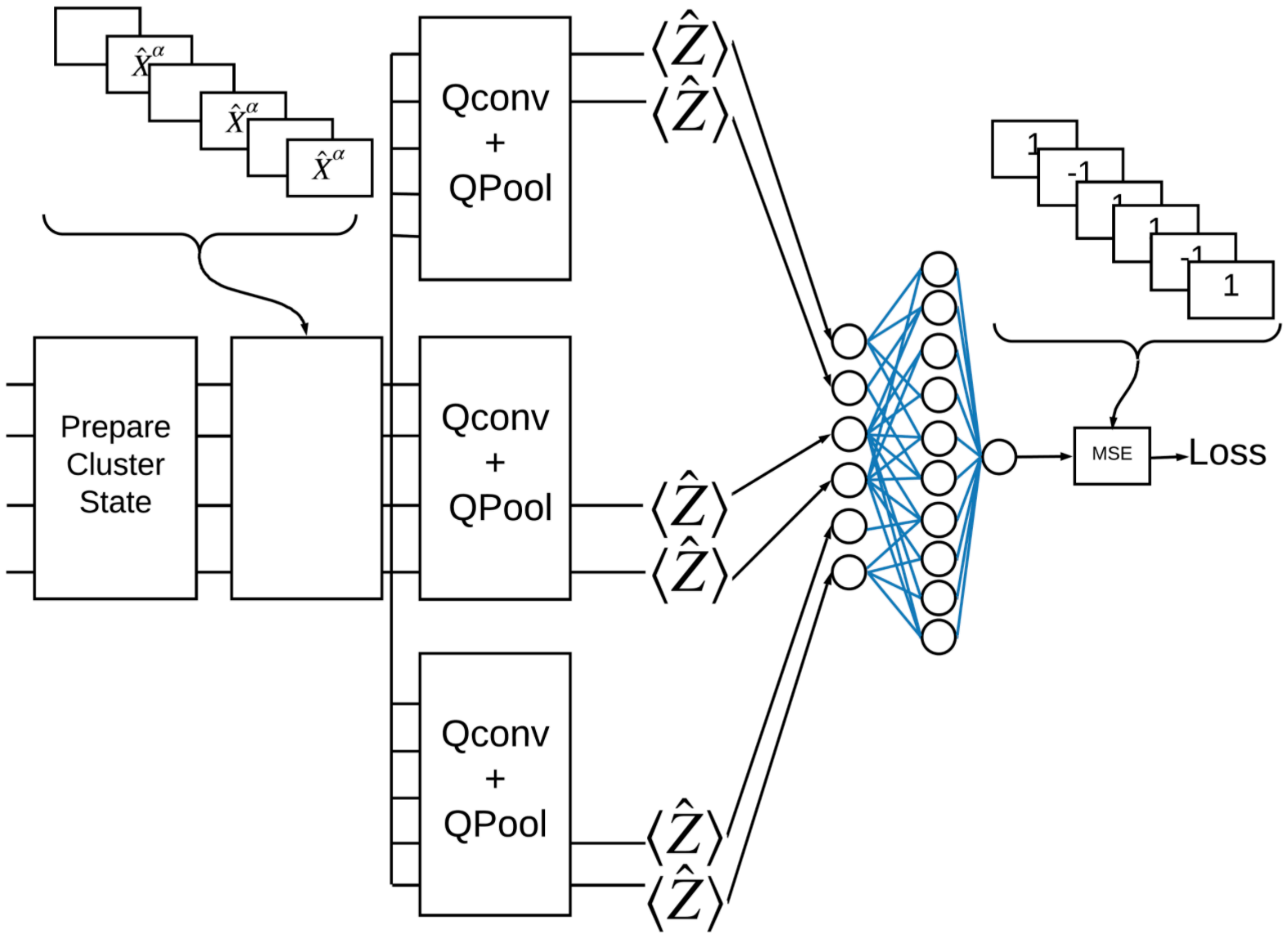


Fig 7. Architecture of the Hybrid Quantum-Classical Convolutional Neural Network

It has the following components:

- $\hat{X}^a$
- Cluster State
- QConv - Quantum Convolutional
- QPool - Quantum Pooling
- Classical Neural Network
- MSE- Mean Squared Loss

METHODOLOGY:
Hybrid Quantum-Classical Convolutional Neural Network

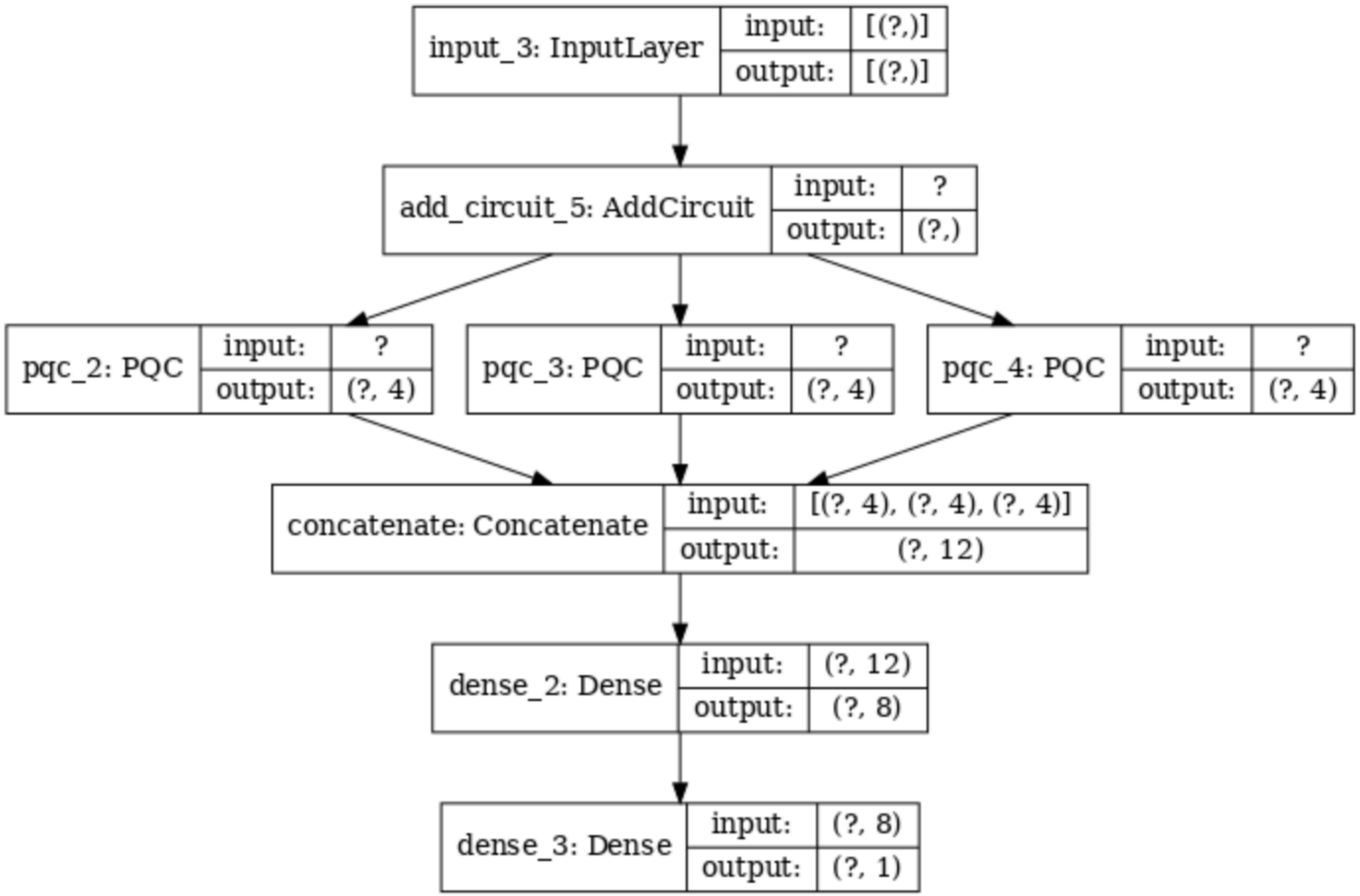
- Assemble Quantum Circuits using TensorFlow Quantum's (TFQ) Layer class
- Load data from Kaggle (Brain MRI Scans dataset)
- Preprocessing of image data:
    A. Resize images to 4x4, as quantum computer is not capable of processing large amounts of data **YET!**
    B. Remove Contradictory examples
    C. Convert each pixel to a Qubit, by setting a threshold value* for pixels.

* Farhi, E., & Neven, H. (2018). Classification with quantum neural networks on near term processors. *arXiv preprint arXiv:1802.06002*.

METHODOLOGY:
Hybrid Quantum-Classical Convolutional Neural Network

- Defining Layer:
  A. Cluster Layer: It is a highly entangled quantum state/ layer for performing measurement-based quantum computation.
  B. Parametrized Quantum Circuit (PQC) Layers: Comprises of the Quantum Convolutional (Qconv) and Quantum Pooling (Qpool) layers.
  C. Classical Dense Layer: The Dense layer of a classical Neural Network is concatenated at the end of the PQC.
- The model is then assembled and trained using TensorFlow's compile() method.
- The model's performance will be judged using Accuracy of prediction as metric

FLOW DIAGRAM OF THE ARCHITECTURE:
Hybrid Quantum-Classical Convolutional Neural Network



Results & Discussions

The proposed model and the Classical NNs were trained and tested using the Brain MRI dataset obtained from Kaggle website. Our proposed model obtained the highest results with 99.8% accuracy. The results obtained are juxtaposed in a graphical manner in the figure below.

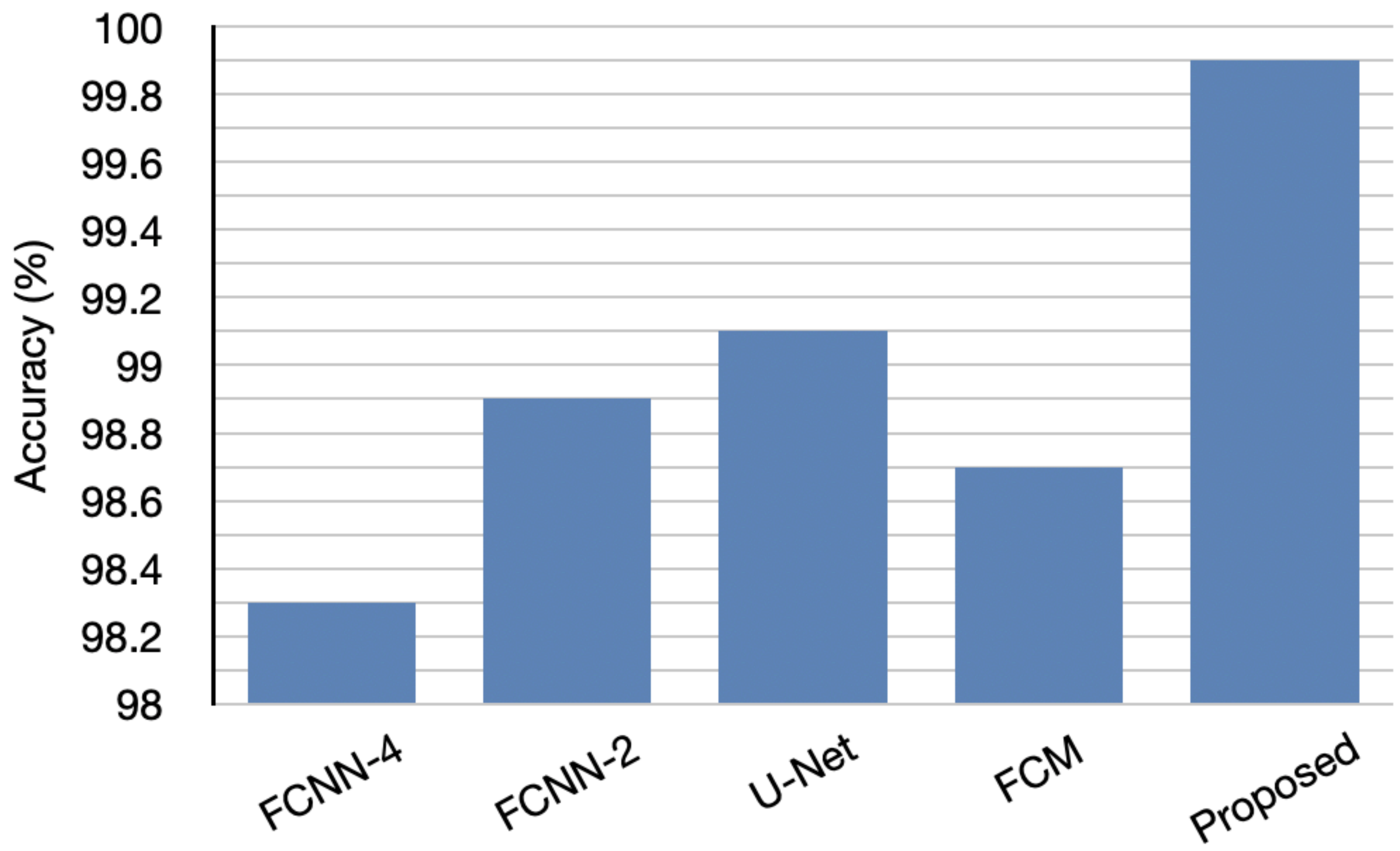


Fig 7. Comparison of accuracies obtained by previous models and the proposed hybrid model.

Conclusion & Future Works

- In this Project, we have looked at the problem of automatically segmenting tumors from the brain MR images and have further classified the tumors into three types, namely, Glioma, Meningioma and Pituitary Tumor.
- We proposed a hybrid architecture using Quantum Convolutional Neural Networks for the purpose of segmenting and classifying the brain tumors using MR images.
- Regarding further work, approaches for database augmentation (e.g., increasing number of subjects) in order to improve the generalization capability of the network can work wonders.
- One of the main improvements will be adjusting the architecture so that it could be used during brain surgery, classifying and accurately locating the tumor. Detecting the tumors in the operating room should be performed in real-time and real-world conditions; thus, in that case, the improvement would also involve adapting the network to a 3D system.

References:

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2. Zhao, C., & Gao, X. S. (2019). QDNN: DNN with Quantum Neural Network Layers. *arXiv preprint arXiv:1912.12660*.
3. Cong, I., Choi, S., & Lukin, M. D. (2019). Quantum convolutional neural networks. *Nature Physics*, *15*(12), 1273-1278.
4. Kerenidis, I., Landman, J., & Prakash, A. (2019). Quantum algorithms for deep convolutional neural networks. *arXiv preprint arXiv:1911.01117*.
5. Beer, K., Bondarenko, D., Farrelly, T., Osborne, T. J., Salzmann, R., Scheiermann, D., & Wolf, R. (2020). Training deep quantum neural networks. *Nature communications*, *11*(1), 1-6.
6. https://www.kaggle.com/sartajbhuvaji/brain-tumor-classification-mri
7. Konar, D., Bhattacharyya, S., Gandhi, T. K., & Panigrahi, B. K. (2020). A Quantum-Inspired Self-Supervised Network model for automatic segmentation of brain MR images. *Applied Soft Computing*, 106348.

Thank you!