Quantum-Classical Convolutional Neural Network for Multi-class Brain Tumor MRI Classification

Schrödinger's kittens

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Primary reference : 'An improved hybrid quantum-classical convolutional neural network for multi-class brain tumor MRI classification'
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Background

- Brain tumors are one of the most challenging diseases to diagnose and treat, with high morbidity and mortality rates. Magnetic Resonance Imaging (MRI) has become a widely used diagnostic tool for brain tumor detection, but the accurate classification of tumor types remains a significant challenge.
- Recently, machine learning techniques, particularly Convolutional Neural Networks (CNNs), have shown promising results in accurately classifying brain tumors using MRI images. However, the performance of CNNs can be limited by the size and complexity of the dataset.
- Hybrid quantum-classical CNN can be used to improve the results by incorporating a quantum convolutional layer used to extract shallow features along with the classical convolutional neural network used for completing the classification.

Classical CNN

- Convolutional neural networks (CNNs) for brain tumor MRI classification use specialized layers that can learn spatial features of the input images, allowing the network to recognize patterns regardless of their location in the image.
- The first layer of a CNN typically performs a series of convolutions between the input image and a set of learnable filters. These filters identify features such as edges and texture in the image.
- Subsequent layers use pooling operations to reduce the spatial dimensions of the output from the previous layer, and additional convolutions to learn increasingly complex features. The final layer of the network outputs a probability distribution over the possible classes, which can be used to make a prediction for a given input image.

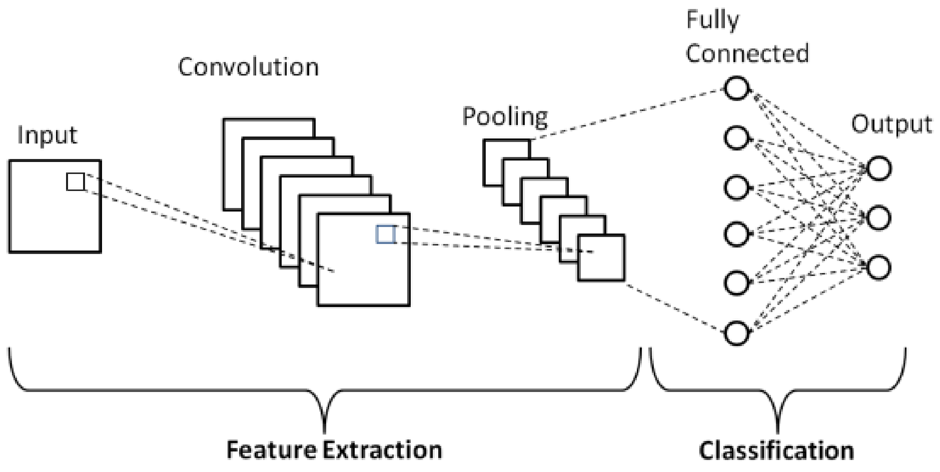
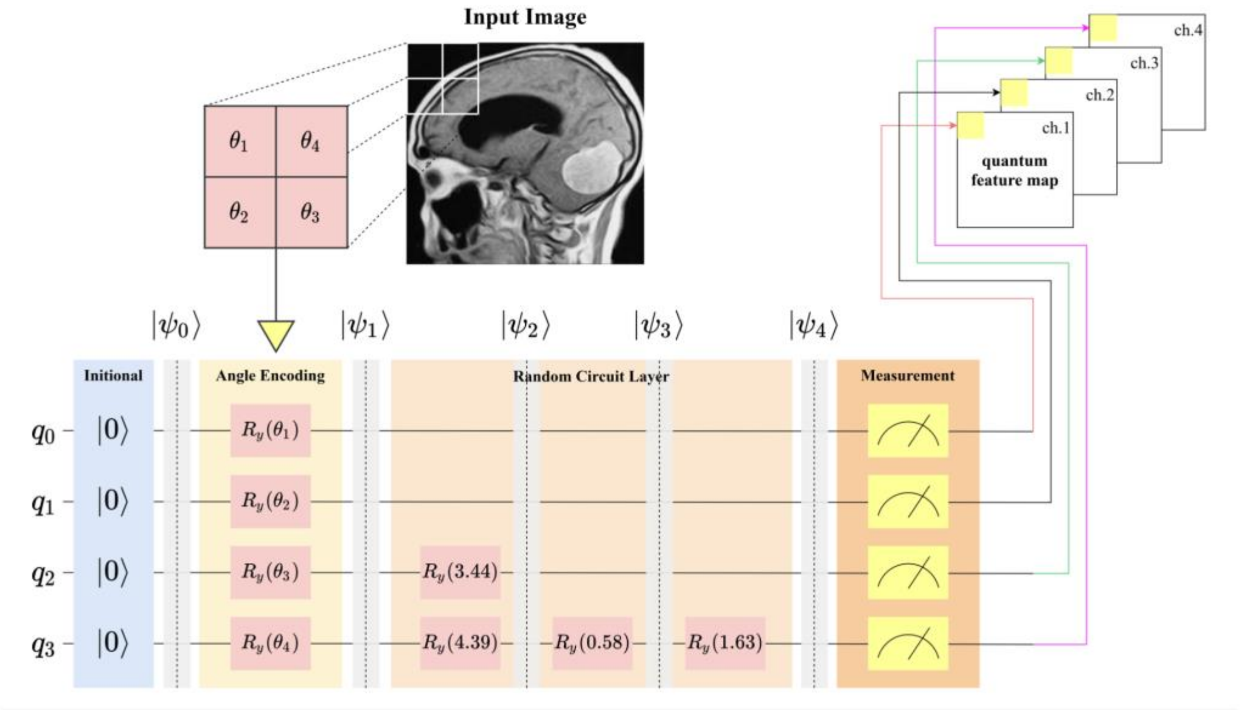


Image from :A High-Accuracy Model Average Ensemble of Convolutional Neural Networks for Classification of Cloud Image Patches on Small Datasets - Scientific Figure on ResearchGate. Available from: https://www.researchgate.net/figure/Schematic-diagram-of-a-basic-convolutional-neural-network-CNN-architecture-26_fig1_336805909 [accessed 27 Feb, 2023]

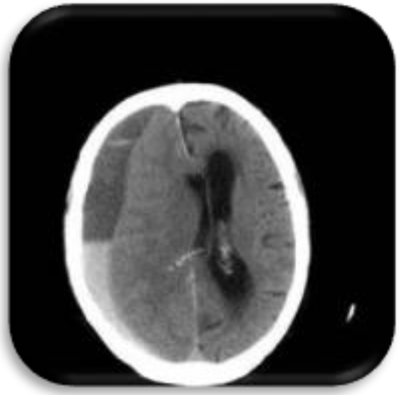
Quantum convolutional layer



- Quantum convolutional layers offer parallel operations that can significantly improve the operational efficiency of traditional machine learning when dealing with massive amounts of data and achieve efficient information extraction and classification.
- Quantum convolutional layers consist of parametric quantum filters for feature extraction, preserving the properties of local connectivity and weight sharing in convolutional neural networks.
- Quantum CNN can effectively extract image features, reduce the complexity of network models, and significantly improve the computational efficiency of the models. In addition, an improved quantum convolution layer is proposed by not using the CNOT Gate, greatly reducing the complexity of the network model and shortening the training time of the model.

The dataset

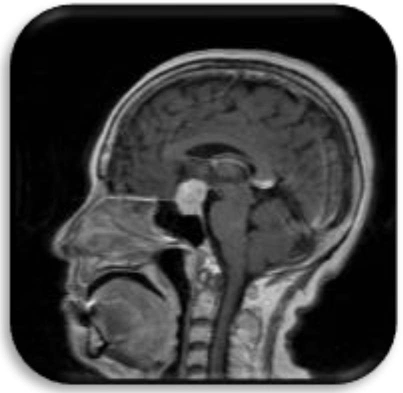
- The dataset consists of four categories of brain MRI images: glioma tumor, meningioma tumor, pituitary tumor and no tumor visible, with each image labelled as such.
- Each category contained between 300 and 900 images for training and approximately 100 images each for testing. All images were in JPEG format and were preprocessed to ensure consistent size and quality across the dataset.



No tumor

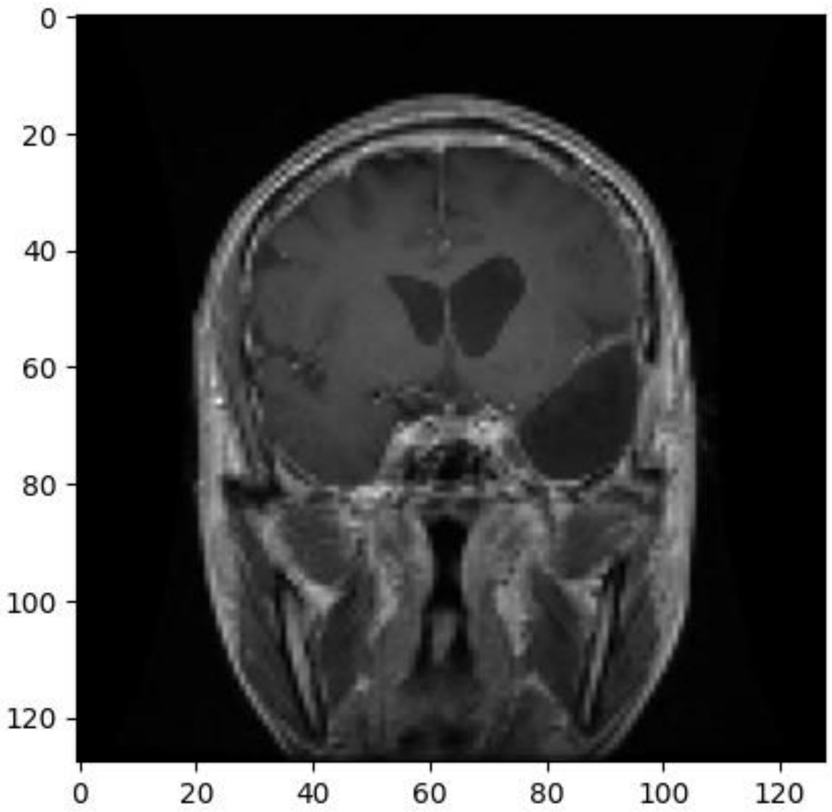
Glioma tumor

Meningioma tumor

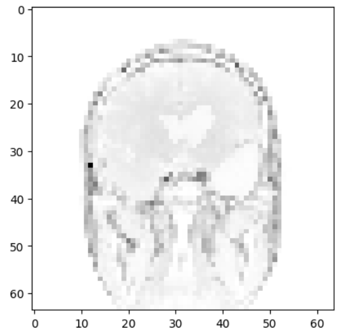


Pituitary tumor

Visualization of four output channels generated by quantum convolution layer.



Input image for Glioma tumor



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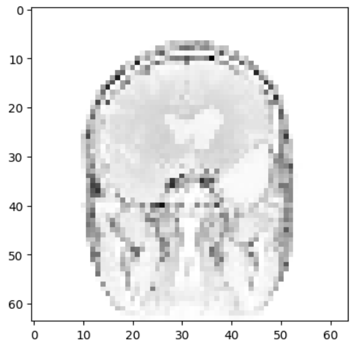

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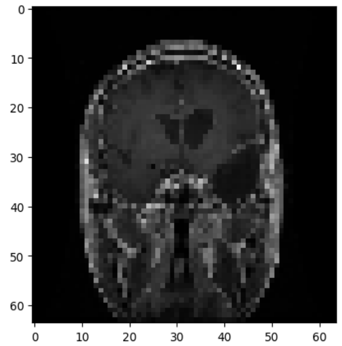
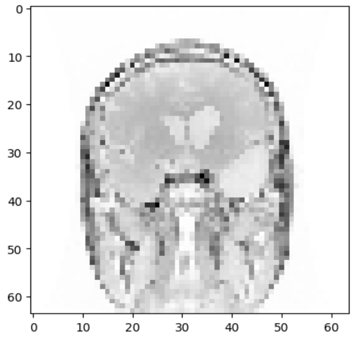
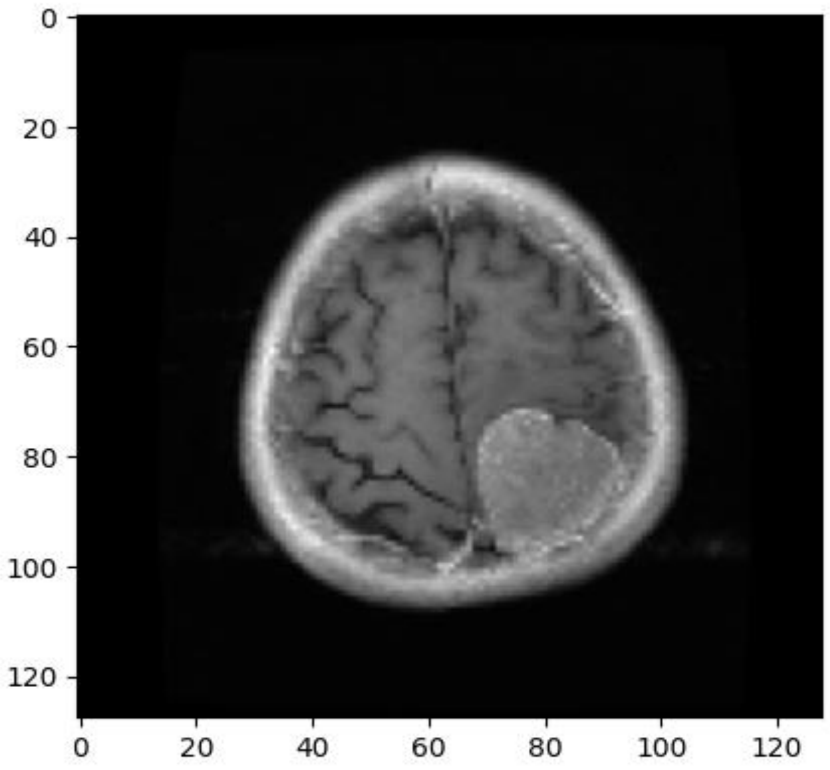


Channel 3

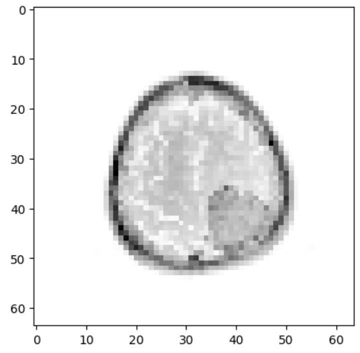


Channel 4

Visualization of four output channels generated by quantum convolution layer.



Input image for Meningioma tumor



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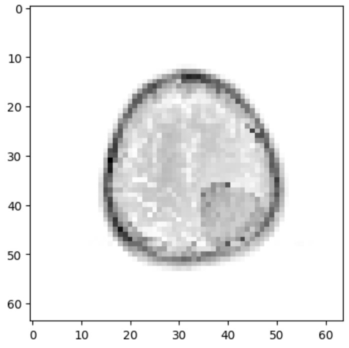

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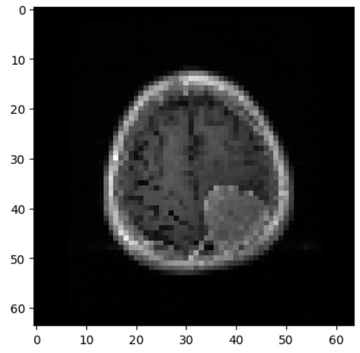

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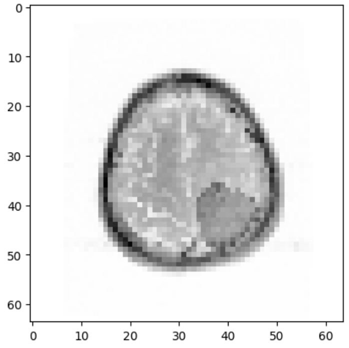
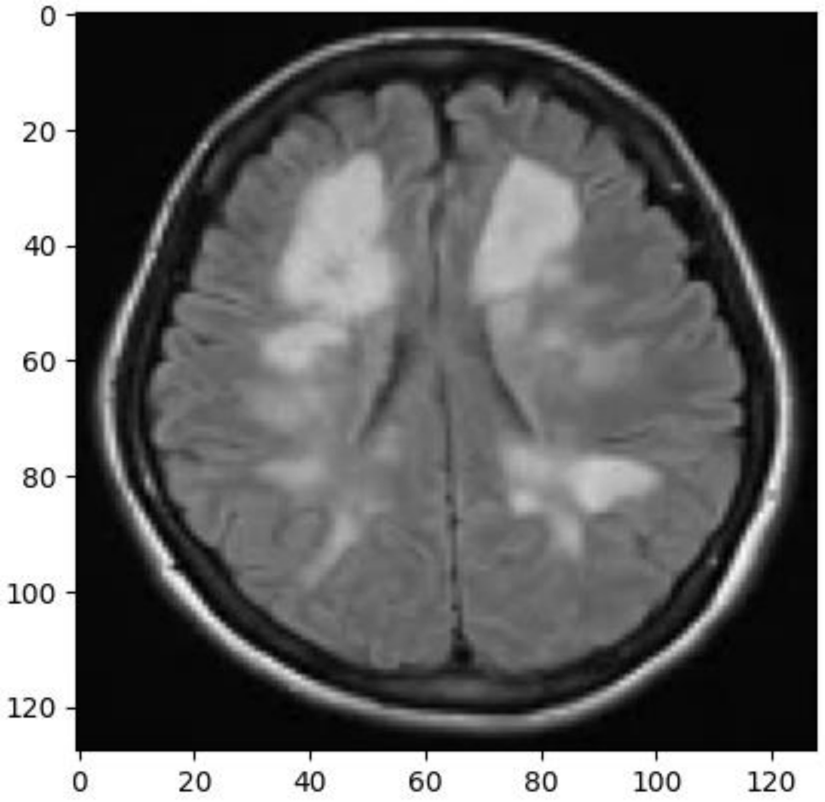
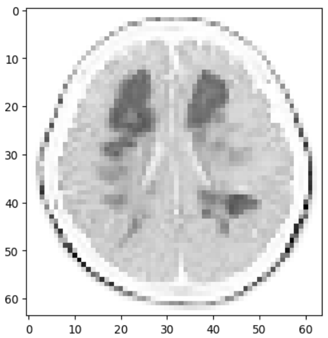


Channel 4

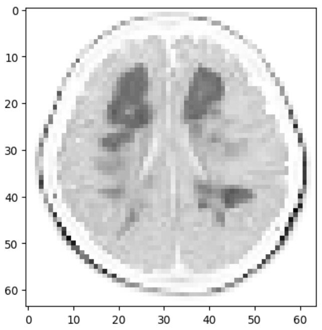
Visualization of four output channels generated by quantum convolution layer.



Input image for no tumor



Channel 1



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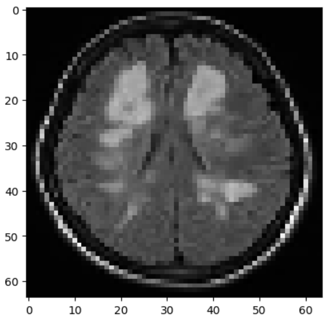

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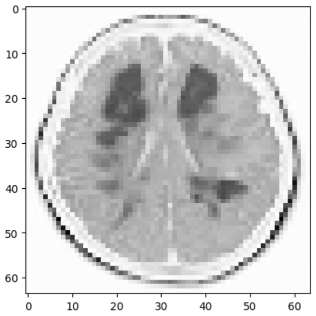
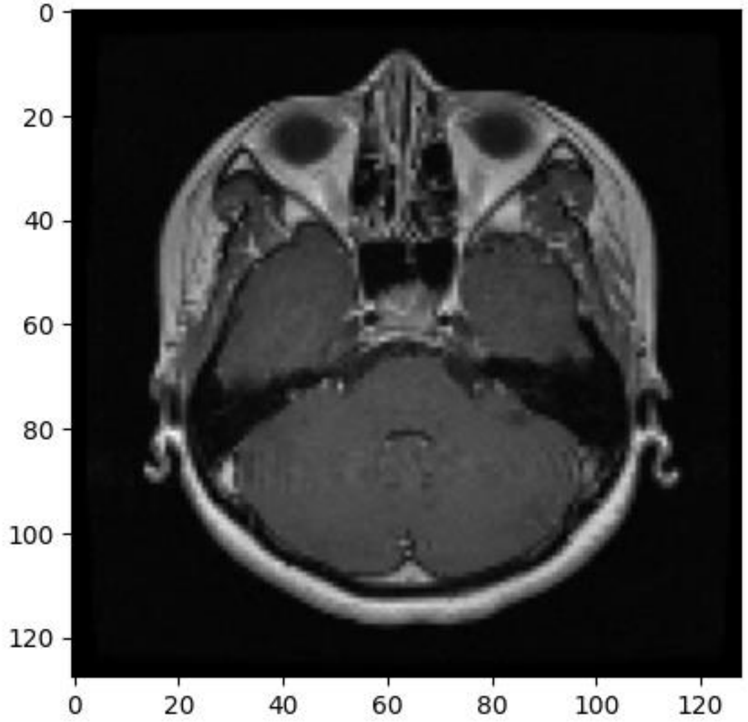
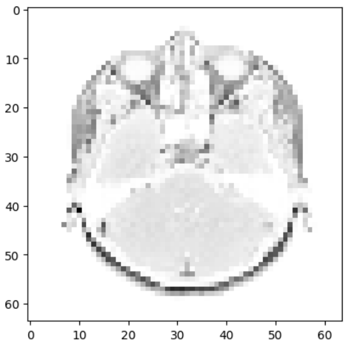


Channel 4

Visualization of four output channels generated by quantum convolution layer.



Input image for Pituitary tumor



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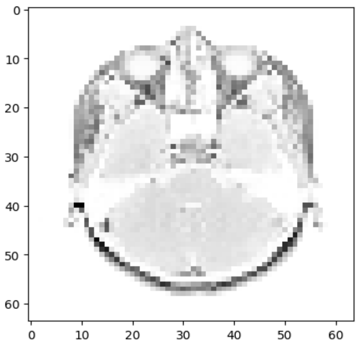

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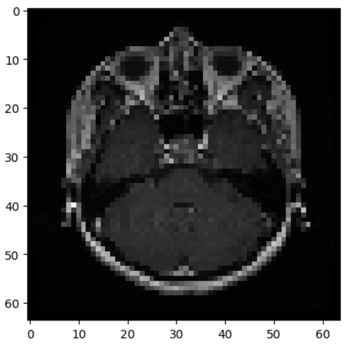

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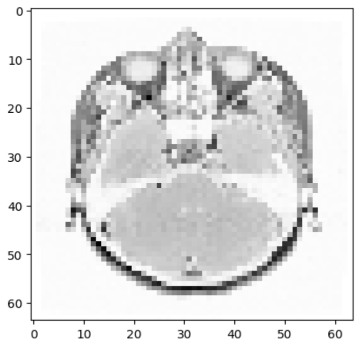


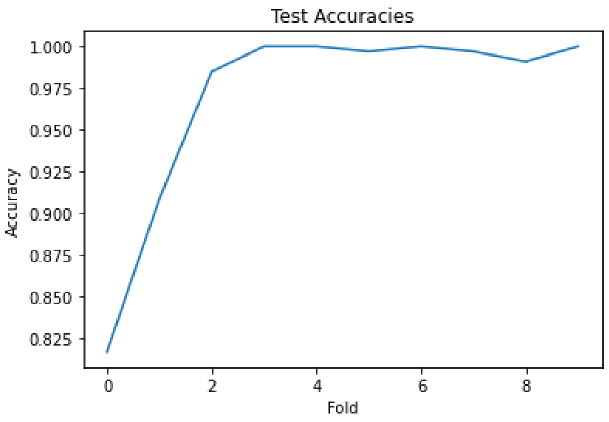
Channel 4

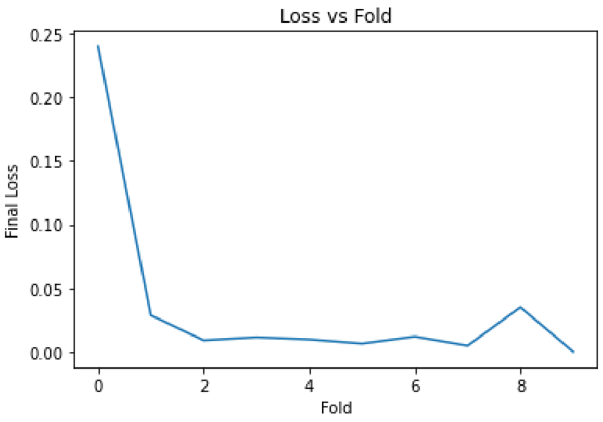
Results: Accuracy

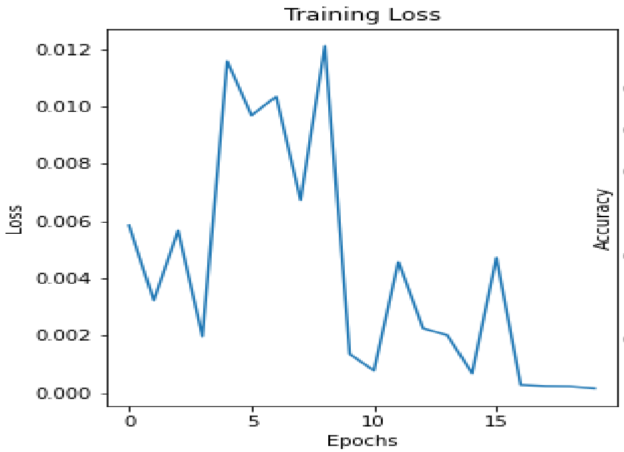
- Accuracy is one of the most popular indexes in multi-class classification
- The accuracy is given as follows:

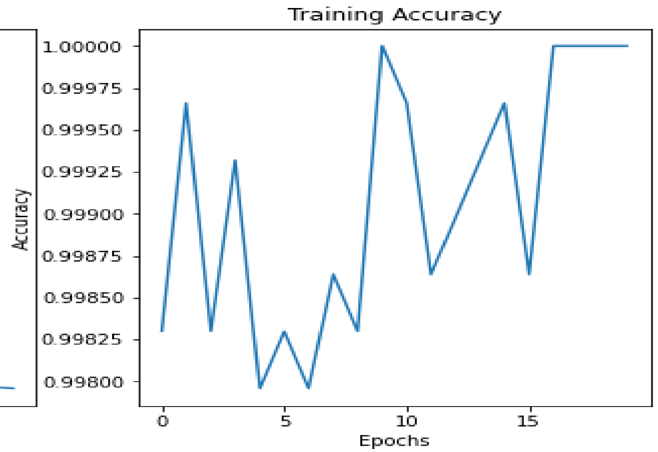
$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

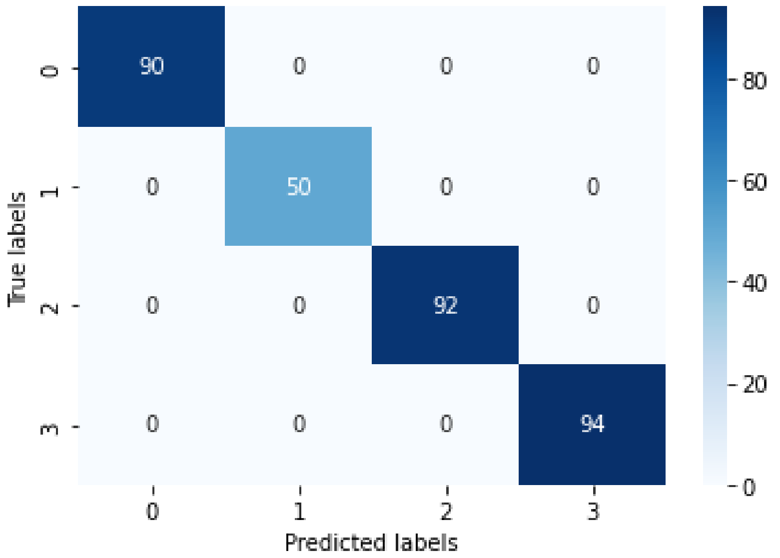
- The accuracy achieved was 96.94% with an average loss of 0.0357 for 10 folds
- For more epochs, accuracy reaches 1 which possibly could be because of the overfitting of the model











Precision	Recall	F1 Score	Support
1.00	1.00	1.00	326
1.00	326	weighted	avg
macro	avg	1.00	1.00
94	accuracy	1.00	326

Results

- 0: Glioma tumor
- 1: Meningioma tumor
- 2: No tumor
- 3: Pituitary tumor

Conclusion and future work

- In this project, an improved hybrid-classical-quantum CNN is implemented on MRI brain scans.
- The method consisted of two parts: quantum convolutional layer and classical CNN.
- We uniformly use a tenfold stratified sampling strategy. As the dataset is uneven, we use the stratified K fold to perform the cross validation
- Results show that the model stands out on the brain tumor MRI dataset with fewer number of parameters as well as accuracy and finally achieves a classification result of 96.94%.

Future work

- The importance of the model is that it should be made user based; i.e. Doctors and patients should be able to use it to predict the results more accurately.
- The model only uses shallow quantum convolution kernels as preprocessing, and deeper quantum convolution kernels may have better performance. The different encoding methods in the quantum convolutional layer can affect the classification effect.
- The results are only for one type of dataset; One needs to implement it on more dataset in order to generalize it.
- These are future directions of the project.