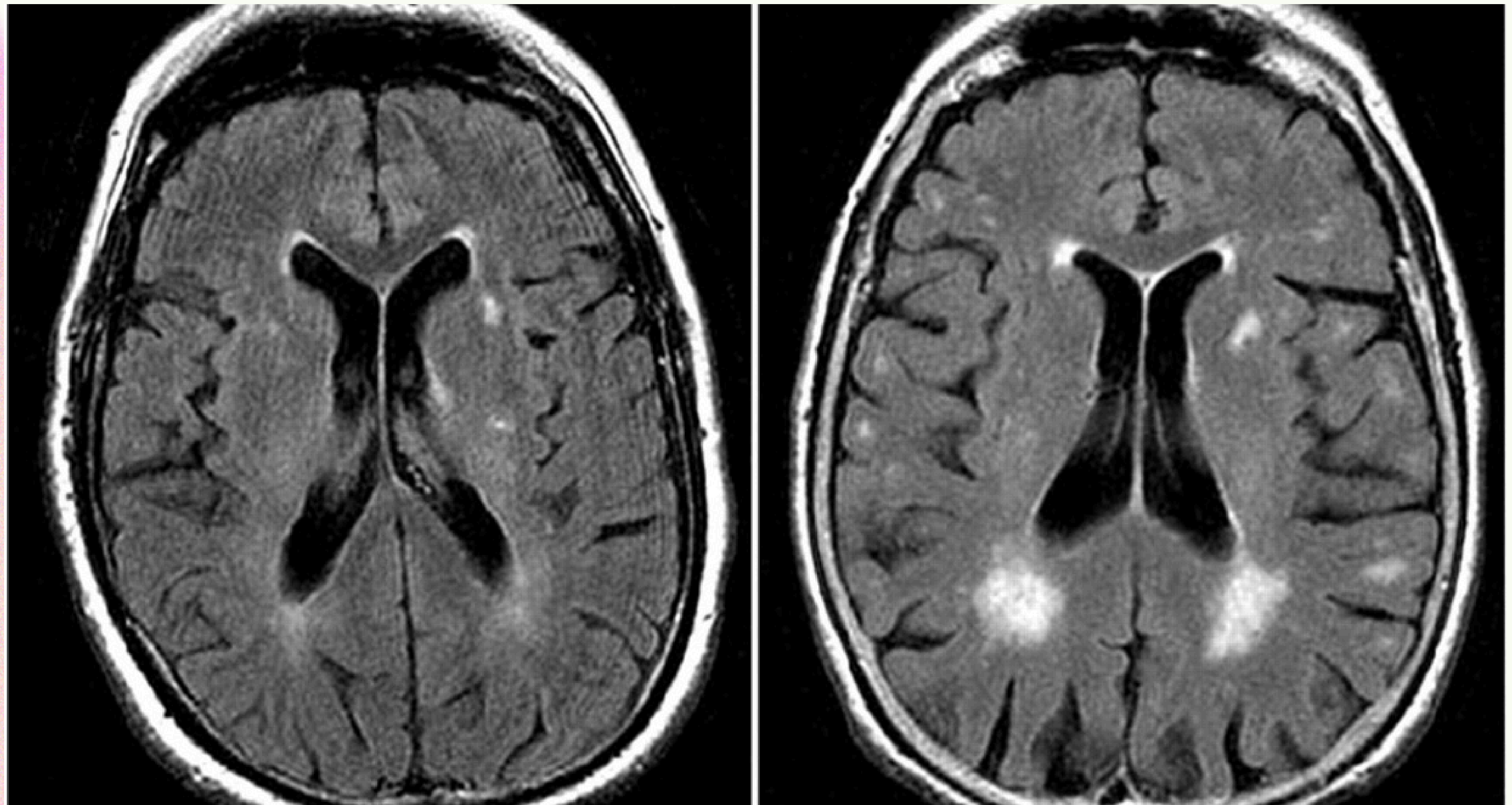
4th International Convention on Green Environment, Technology & Entrepreneurship through Innovation Conference

Advanced Innovation Augmented With Intelligent Analytics(AIAIA)

Image Classification of Alzheimer's disease using quantum computing with convolutional neural neural networks.



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Agenda

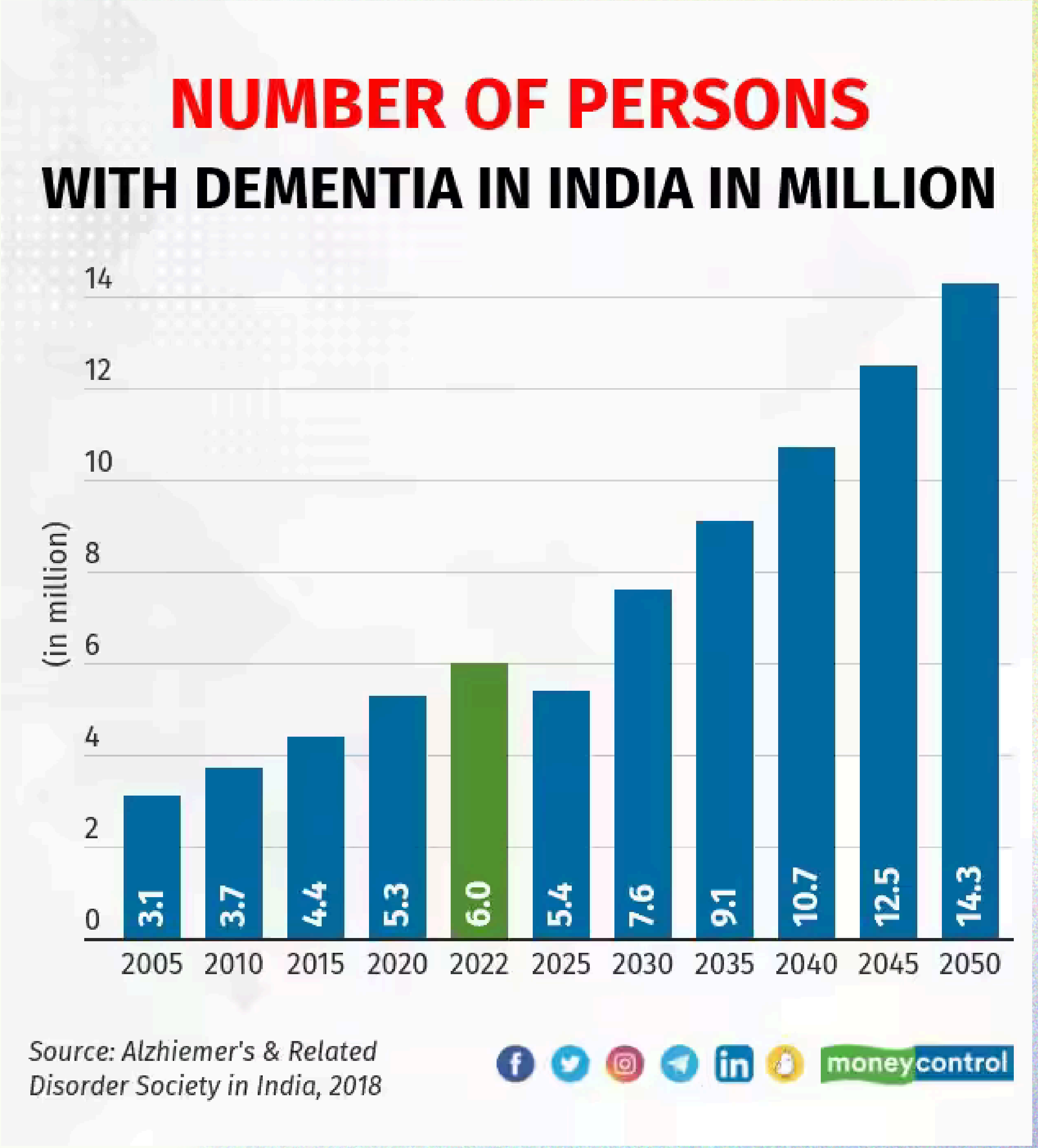
- Introduction
- Methodology
- Result and discussion
- Conclusion and future work
- Refrences

Introduction

- **Alzheimer's disease,** a progressive neurodegenerative disorder, poses significant challenges to global healthcare systems and affects millions of lives worldwide

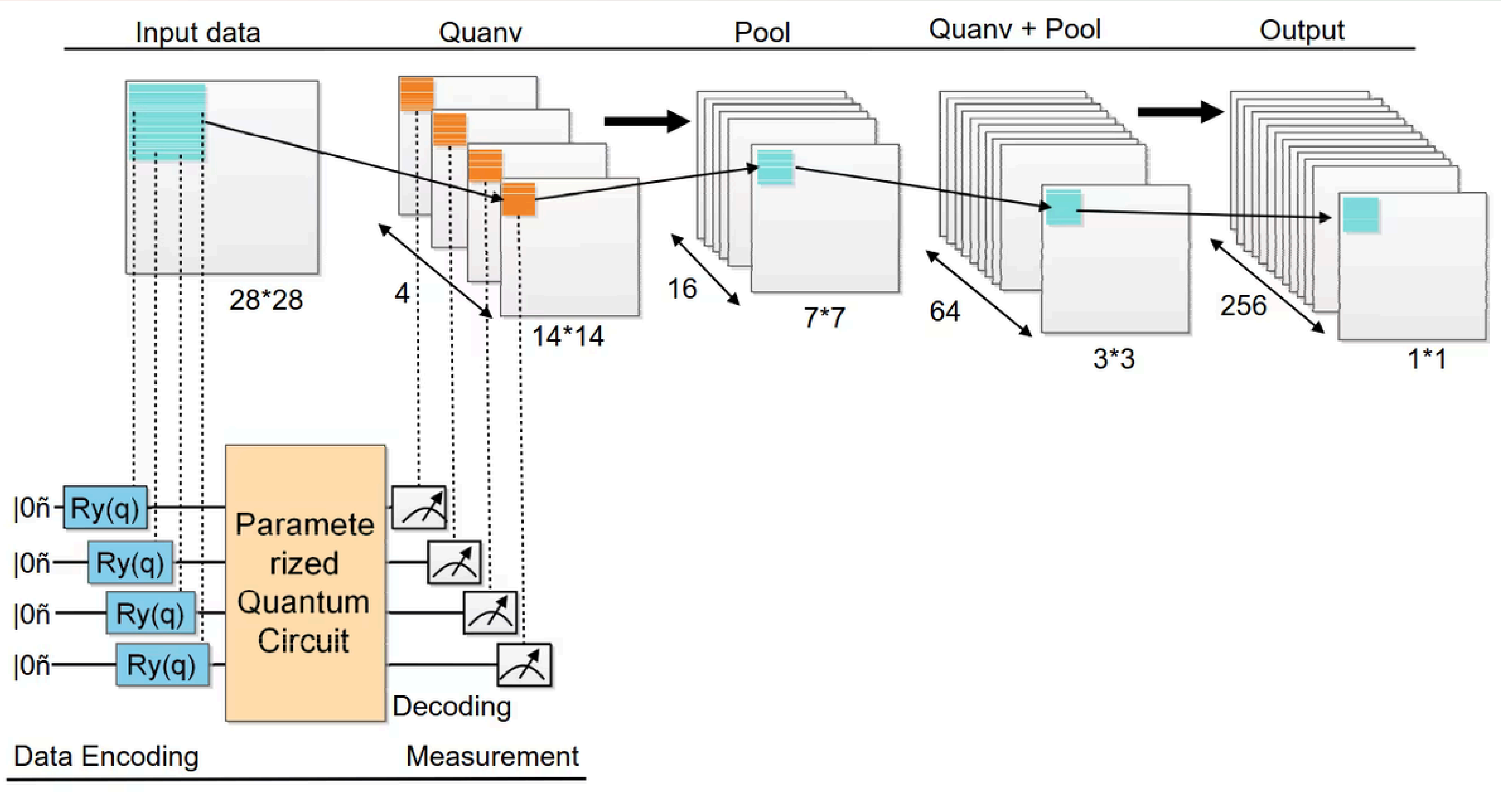
- This research explores an innovative approach to Alzheimer's disease diagnosis by combining two cutting-edge technologies: quantum computing and convolutional neural networks (CNNs). This novel integration aims to enhance the accuracy and efficiency of image classification for Alzheimer's detection.

- This research not only contributes to the field of Alzheimer's diagnostics but also paves the way for broader applications of quantum machine learning in healthcare.



- Quantum convolutional neural networks (QCNNs) extend the capabilities of CNNs by leveraging certain potentially powerful aspects of quantum computation. It operate on input data by locally transforming the data using a number of random quantum circuits.

- It has been shown that quantum circuits are able to model complex functional relationships, which is infeasible using polynomial sized classical computational resources, QNNs add a new type of transformational layer to the standard **CNN architecture: the quantum convolutional (or quanvolutional)** layer.
- It is a made up of a group of **N quantum filters**, which operate much like their classical convolutional layer counterparts by producing features maps through locally transforming input data..



Methodology

- We considered a single **quanvolutional filter** uses a random quantum circuit q, which takes as input spatially-local subsections of images from dataset .
- We imported the Alzheimer’s Disease dataset from **Kaggle** which is further divided into:

1. Mild Demented,
2. VeryMild Demented,
3. Moderate Demented
4. Normal

- Total **5120** MRI images for training and **1481** images for testing.
- Each input (ui) is a 2D matrix of size n*n wherein n >1.
- We initialized a **PennyLane** default.qubit device, simulating a system of 4 qubits.
- The Model uses Python Libraries such as **TensorFlow Quantum**, **Keras, Pennylane** etc.

The quantum circuit consisting of:

- An embedding layer of local Ry rotations:
- A random parametrized quantum circuit of n layers;
- A final measurement in the computational basis, estimating the 4 expectation values.

The image is divided into squares of **2*2 pixels** and each square is processed by the **quantum circuit** and finally 4 expectation values are mapped into 4 different channels of a single output pixel.

Results and Discussion

the **4 output channels** generated by the quantum convolution are visualized in gray scale. It can be clearly observed that some local distortion is introduced by the quantum kernel and down sampling the resolution.Although, the global shape of the image is preserved as it is as expected for a
convolution layer.

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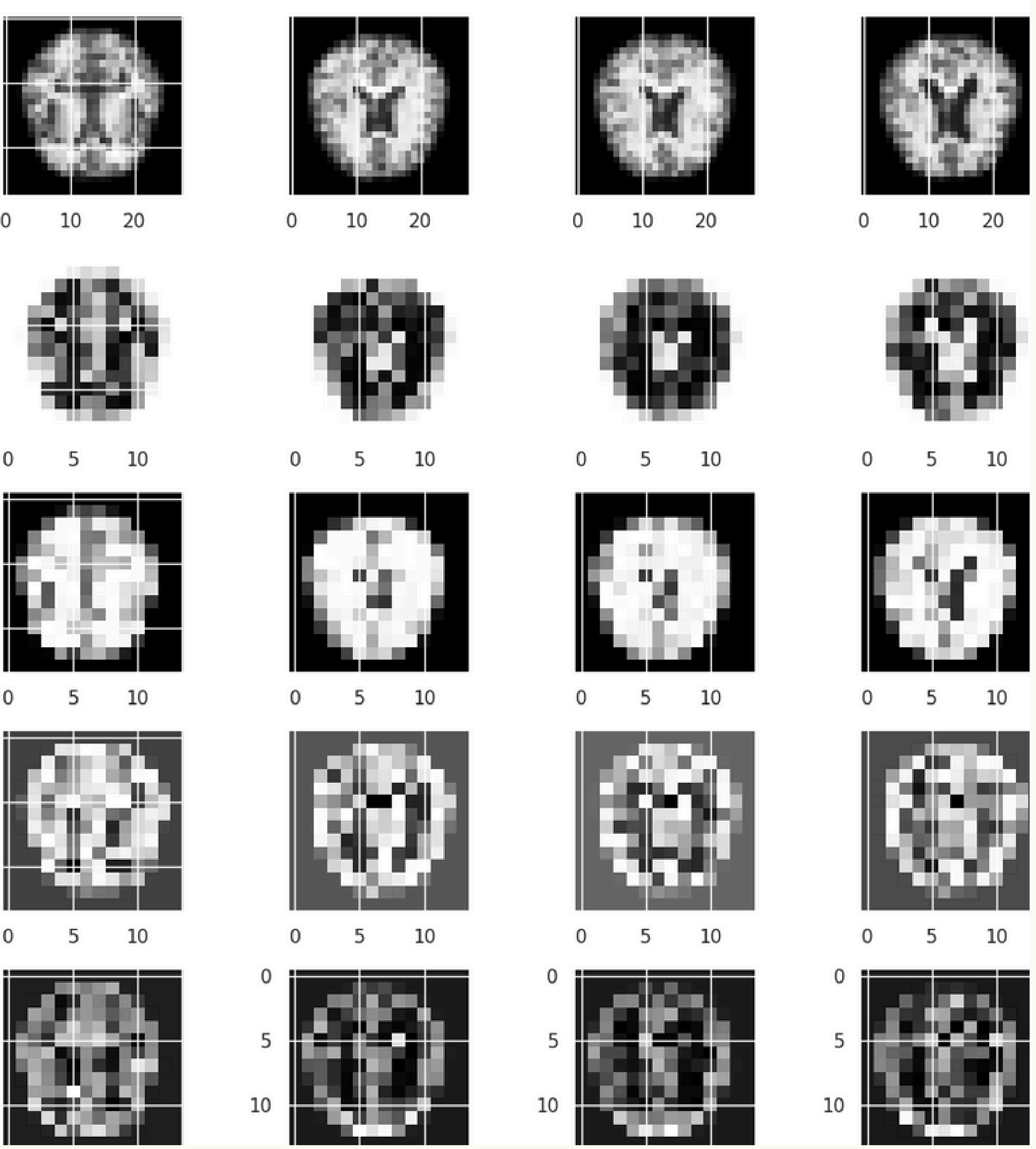
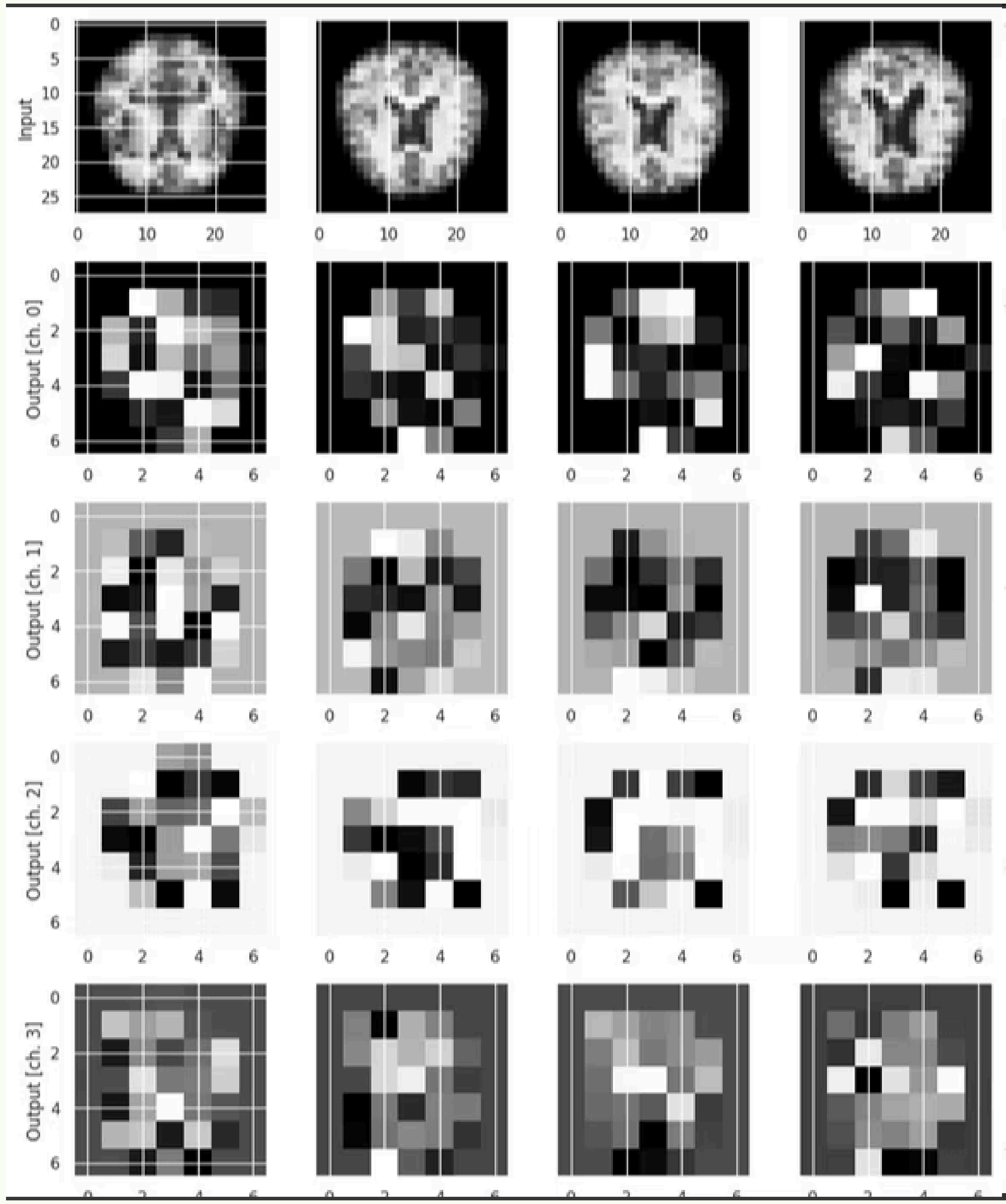
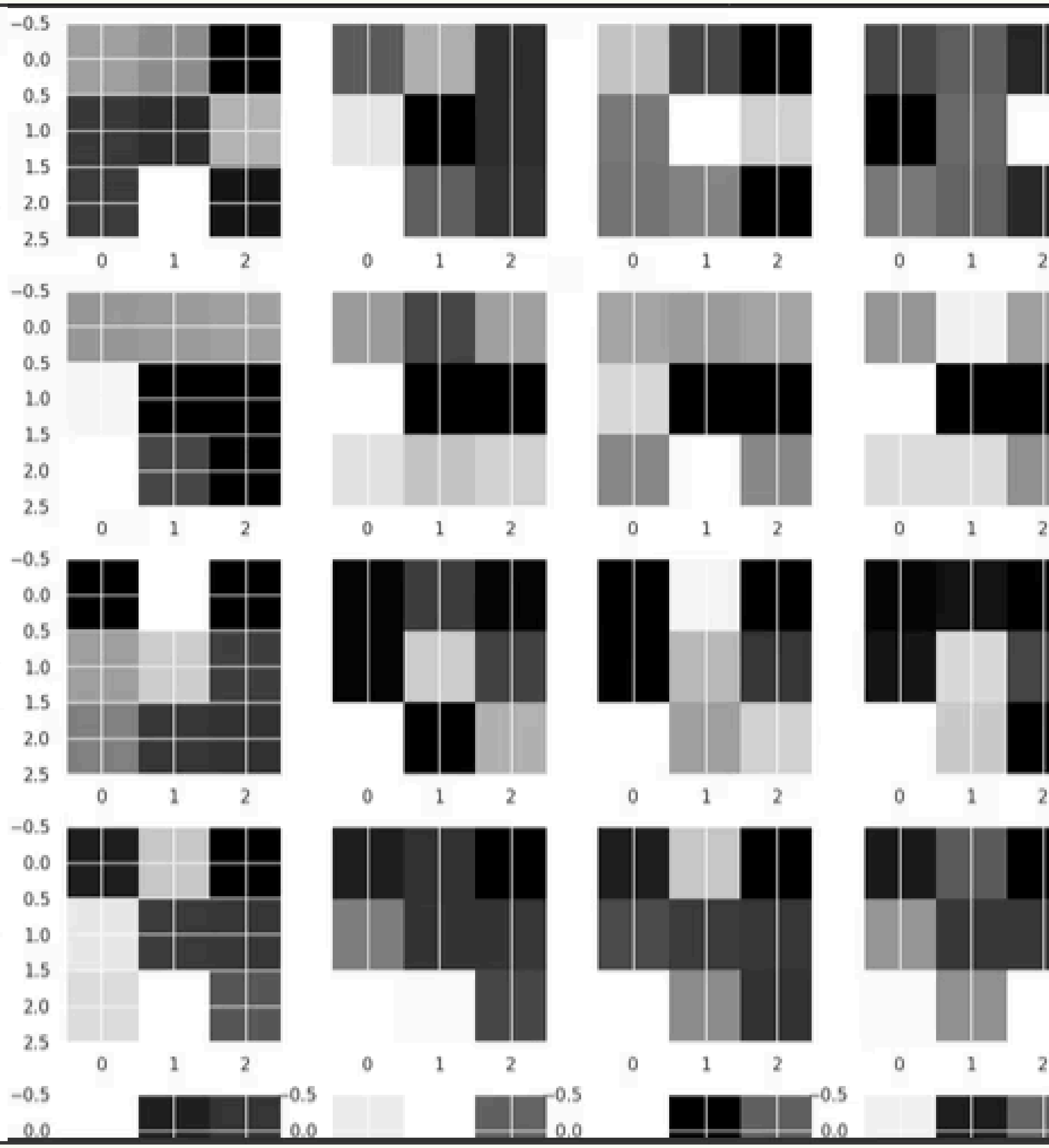
- initially each images data is flattened to a single dimension and uploaded to the csv. So here we again reshaped the data to 28x28 format.
- This first Quanvolutional layer when implemented on a (28x28x3) image data, it creates output data of (14x14x4) dimension.
- This second Quanvolutional layer when implemented on a (14x14x4) image data, it creates output data of (7x7x16) dimension.
- Quantum circuit is applied on 2x2 blocks of the images and returns 4 dimensional output each time same as the previous one.
- This first Quanvolutional layer when implemented on a (7x7x16) image data, it creates output data of (3x3x64) dimension.
- Quantum circuit is applied on 3x3 blocks of the images and returns 4 dimensional output each time, the block selection here is little different from first and second layer circuit.
- This first Quanvolutional layer when implemented on a (3x3x64) image data, it creates output data of (1x1x256) dimension.
- Quantum circuit is applied on 3x3 blocks of the images and returns 4 dimensional output each time, the block selection here is little different from first or second layer circuit and similar to the third layer circuit.







$14 \times 14 \times 4$

$7 \times 7 \times 16$

$3 \times 3 \times 64$

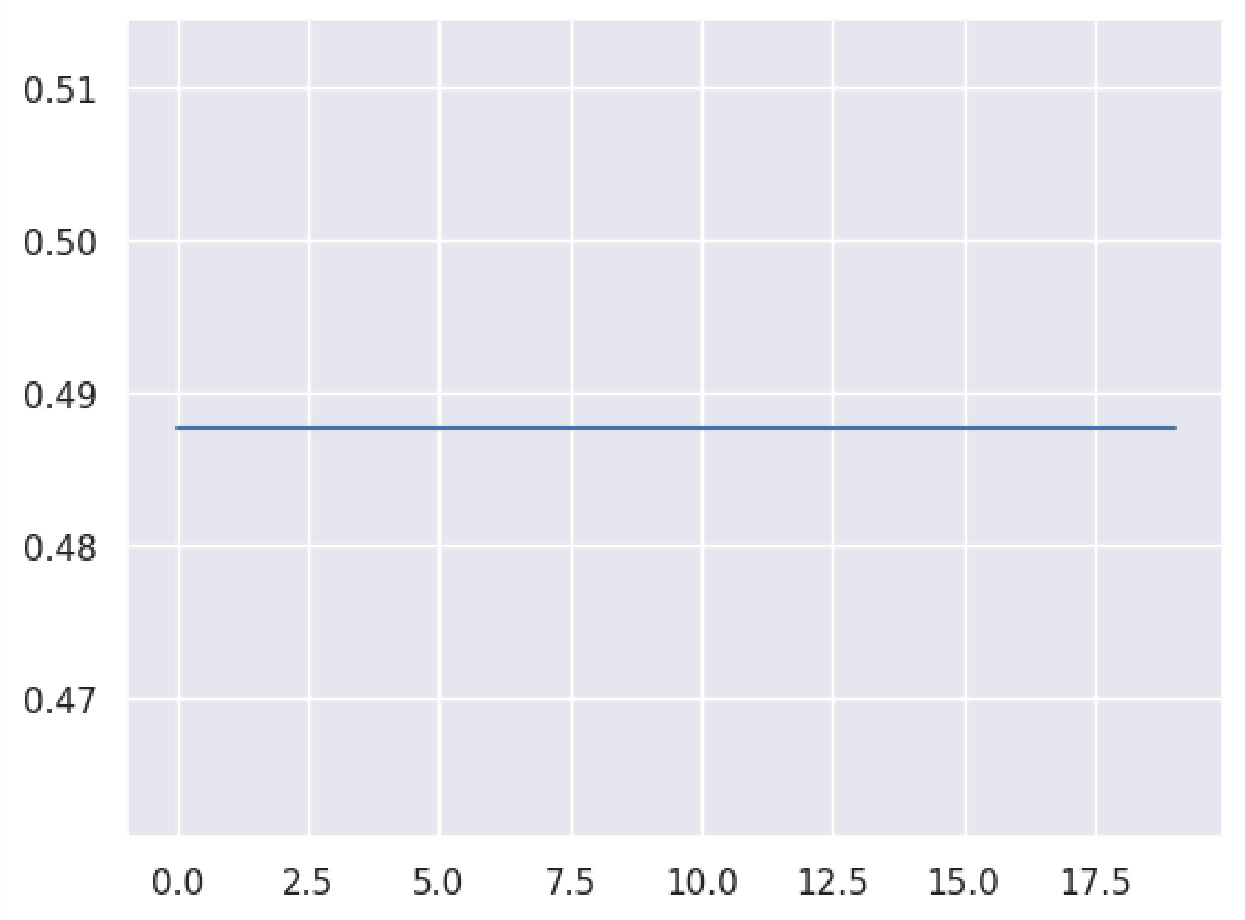


Fig .a (Training Accuracy Plot)

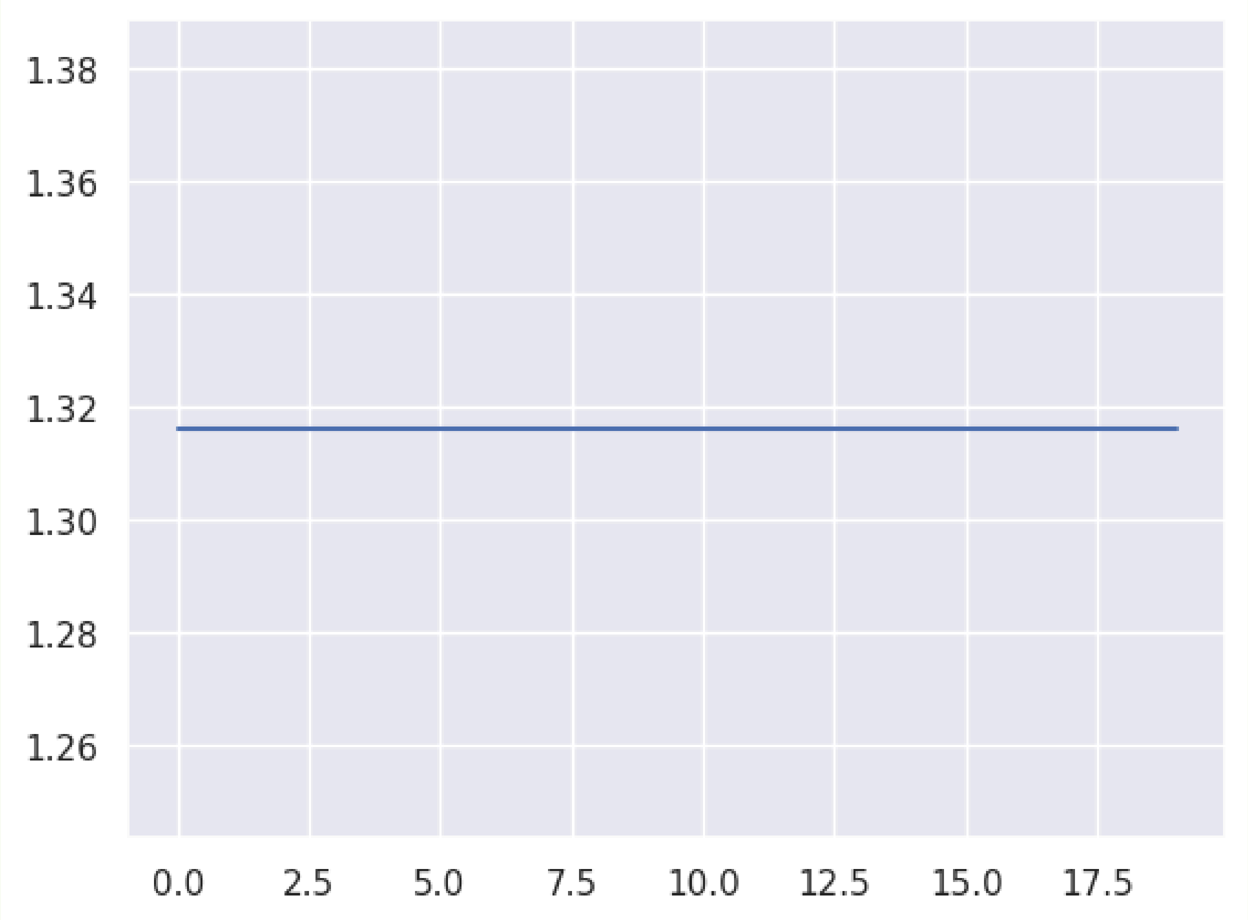
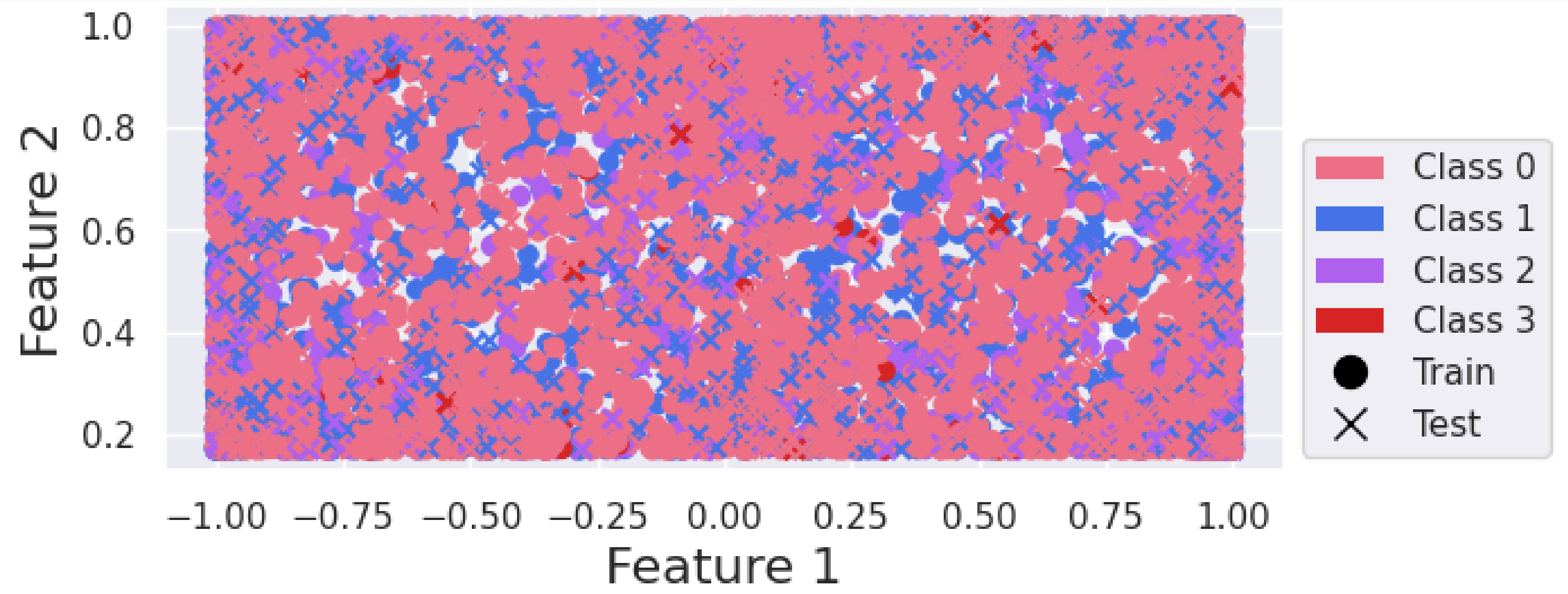


Fig.b (Cost Plot)

Figure.a shows the accuracy around 48%. Moreover, the cost is evaluated as 1.31 shown in Figure.b



scatter plot using **LinearSVC Quantum Machine Learning** visualizing the 2D dataset with four classes:

Class 0 - Normal

Class 1 - Very Mild Demented

Class 2 - Mild Demented

Class 3 - Moderate Demented

Conclusion & Future Work

The main benefit is that quantum circuit can generate highly complex kernels whose computation could be, at least in principle, classically intractable.

- The real MRI images in the dataset is enough large to contain a lots of information.
- Due to lack of computational resources we reduced the size to 28x28 using openCV library, which may have suppressed a lot of important information.
- Later with the availability of more computational resources, we can use 256x256 dimensional image which can increase the accuracy of the model.
- After applying **Quanvolution and flattening** the data, we had **256 features** of each image and **11 features** are used by feature selection method due to **lack of qubits**.
- This work can be implemented on a real-time quantum computer with more number of available qubits and real-time simulation of the quantum circuit to get a feel of the quantum system.
- Moreover, we can experiment with training of four **quanvolutional layers** on the randomly generated image data with the availability of more qubits.

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Thank you!