Hybrid Quantum Convolutional Neural Network for Tuberculosis Prediction Using Chest X-Ray Images

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Abstract – *The rise in quantum algorithm research in recent years has sparked the development of a new paradigm of computing that outsource classically intractable portions of an algorithm to a quantum computer .These hybrid quantum – classical approaches are applied to image classification specifically to Convolutional Neural Networks(CNNs).*

In this work, a hybrid quantum-classical image classification algorithm inspired by CNN called quanvolutional neural network(QNN) is used for the diagnosis of Tuberculosis from images of chest x-ray. A new variant of the QNN is proposed where Novel Enhanced Quantum Representation (NEQR) image encoding is used to encode the pixel values present in image patches into a quantum state. The model showed a validation accuracy of 87% while training.

Key Words: Quantum Computing, Quanvolutional Neural Network, NEQR, Quantum Machine Learning

1. INTRODUCTION

Tuberculosis (TB) is one of the most lethal infectious diseases in the world. According to World Health Organisation (WHO), a total of 1.5 million people died from TB in 2020[1]. An estimated 10 million people fell ill with tuberculosis globally. It is the 2nd leading infectious killer after COVID-19[1]. The disease is airborne and caused by Mycobacterium Tuberculosis. Many of these deaths could be prevented with earlier detection. These days many accurate diagnostic techniques are available based on molecular analysis and bacteriological culture. However, most of them are costly and cannot be used for mass adoption by the developing countries which are usually the most affected ones.

The usage of frontal chest radiographic images is one of the popular diagnosis methods. But this requires skilled radiologists and good quality imaging equipment which are again limited in developing nations. Thus, the need was felt for computer-aided detection systems for the preliminary diagnosis of the disease which could offer an effective solution in areas where skilled radiologists are scarce and would make widespread early -stage tuberculosis screening a reality.

With technological advancements, various approaches, from pattern recognition and neural networks to present day deep learning have been used for medical image analysis and computer aided detection systems.

Quantum computing harnesses the laws of quantum mechanics to solve computational problems that modern day computers cannot solve easily. Quantum machine learning exploits the potential of quantum computing to improve machine learning solutions. Noisy Intermediate-Scale Quantum (NISQ) devices with smaller number of qubits are available and has led to the hybrid quantum-classical solutions where quantum circuits play a powerful role in an overall machine learning application pipeline.

In this paper, we present a hybrid quantum convolutional neural network inspired by the architecture proposed by Henderson et al. as *quanvolutional neural networks* [2] for detecting Tuberculosis from images of chest radiographs. Data encoding has a significant impact on the overall complexity of the quantum circuit. In [2], although threshold encoding was used, however the question of finding an optimal image encoding was left open. Mari [3] proposed another variant where angle encoding was used. The present work proposes a new variant where Novel Enhanced Quantum Representation (NEQR) [4] is used for encoding the pixel values into a quantum state. The choice for NEQR can be mainly attributed to the faster image preparation due to elimination of complex quantum rotation operations which in-turn reduces circuit depth and accurate image retrieval via quantum measurements [4].

The paper is structured as follows: Section 2 gives a background about the concepts of quantum image representations and includes the recent works on hybrid quantum classical approaches. Section 3 introduces the theoretical background of quanvolutional neural network. Section 4 describes the proposed model and results. Section 5 presents the conclusions on the findings of this study with any future works that can be done for improvement.

2. REVIEW OF LITERATURE

This section is divided into two sub-sections. The first discusses different quantum image formats and the second discusses the works on quantum machine learning techniques pertaining to image classification problems.

2.1 Quantum Image Representations

Quantum image processing (QIP) involves exploiting quantum properties to represent, manipulate, and compress images in a quantum computer [5].

Qubit Lattice: This is the first quantum image format and was proposed by Venegas-Andraca [6]. Here the frequency value(color) of the light wave is mapped to the probability amplitude of a qubit. So, the pixel value of i^{th} row and the j^{th} column can be stored in the amplitude angle shown in equation (1), and the whole image can be represented as a qubit string (equation (2)).

$$|pixel_{i,j}\rangle = \cos\frac{\theta_{i,j}}{2}|0\rangle + \sin\frac{\theta_{i,j}}{2}|1\rangle \quad (1)$$

$$|image\rangle = \{\ |pixel_{i,j}\rangle\ \}\ i=1,2,3.....n_1,\ j=1,2,3.....n_2 \quad (2)$$

The essence of this representation is to map the image's spatial information to the amplitude of a single qubit without using superposition and entanglement.

Real Ket: This quantum image format was proposed by Latorre [7]. Here an image is divided into 4 blocks, each numbered from left to right, starting with the top row. These blocks were again divided into 4 blocks and numbered in the same manner until the smallest block with only 4 pixels was obtained. These four pixel's grayscale values are mapped to the probability amplitude of every component of a quantum state with 2 qubits. Equation (3) describes the quantum state, where $i_1 = 1$ is the index of the top-left pixel, $i_1 = 2$ is the index of the top-right pixel, $i_1 = 3$ is the bottom-left pixel, and $i_1 = 4$ is the bottom-right pixel. C_i stores the mapping value of each pixel and satisfies $\sum_{i_1=1,2,..4}\left|C_{i_1}\right|^2 = 1$.

$$|\psi_{2^1 \times 2^1}\rangle = \sum_{i_1=1,2,..4} C_{i_1}|i_1\rangle$$

$$\text{such that } \sum_{i_1=1,2,..4}\left|C_{i_1}\right|^2 = 1 \quad (3)$$

FRQI: Flexible Representation of Quantum Images

Le et al. [8] proposed the Flexible Representation of Quantum Images (FRQI) as an upgraded version of Qubit Lattice, which used quantum state superposition. It still maps each pixel's grayscale value to the amplitude but introduces an auxiliary qubit to denote the position of each pixel.

Equation (4) depicts a $2^n \times 2^n$ quantum image, where i can be regarded as an indicator of pixels' position (row × column converted to a one-dimensional vector).

In comparison to a classical image, the representation (storage) space of quantum states decreases rapidly due to the superposition effect.

$$|pixel_i\rangle = \cos\theta_i|0\rangle+\sin\theta_i|1\rangle$$

$$|image\rangle = \frac{1}{2^n}\sum_{i=0}^{2^{2n-1}}(\cos\theta_i\,|0\rangle + \sin\theta_i|1\rangle) \otimes |i\rangle$$

$$\text{where } \theta_i\in[0,\tfrac{\pi}{2}] \quad (4)$$

NEQR: Novel Enhanced Quantum Representation

A novel enhanced quantum representation (NEQR) for digital images proposed by Zhang et al.[4] uses the basis state of a qubit sequence to store the gray-scale value of each pixel in the image instead of the probability amplitude of a qubit. Different basis states of qubit sequence are orthogonal, so different gray scales can be distinguished in the NEQR quantum image. The representation transforms square images with size $2^n \times 2^n$ into a state $|I\rangle$. If XY denotes the two n-bit values of the pixel location, then C^i_{XY} denotes the i-th bit of the 8-bit grayscale intensity of the pixel in position (X, Y).

$$|I\rangle=\frac{1}{2^n}\sum_{Y=0}^{2^n-1}\sum_{X=0}^{2^n-1}\otimes_{i=0}^{7}\ |C^i_{XY}\rangle|\mathbf{XY}\rangle$$

Performance comparisons with FRQI revealed that NEQR achieved a quadratic speedup in quantum image preparation. The compression ratio of quantum images was increased by approximately 1.5X, and the image retrieved after measurement was accurate.

2-D QSNA

This approach proposed by Madhur et al.[9] uses the two-dimensional (2- D) quantum states to locate each pixel in an image through row-location and column-location vectors for identifying each pixel location. The quantum state of an image is the linear superposition of the tensor product of the m-qubits row-location vector and the n-qubits column-location vector of each pixel. The amplitude/intensity of each pixel is incorporated into the coefficient values of the pixel's quantum state without using any qubits.

2.2 Related Works on Hybrid Quantum Classical Methods

Despite being in a developing phase, several quantum implementations of the classical ML counterparts are already proposed.

In [10], a method for image classification with quantum neural networks is proposed. Handwritten numeric image data for digit 3 and digit 6, obtained from the MNIST dataset, is classified with 100% accuracy using the quantum circuit simulator provided by Cirq and TensorFlow Quantum.

The first quantum algorithm to adapt the classical convolutional neural network (CNN) was developed to solve quantum many-body problems, which are complex systems that are too difficult to solve theoretically [11]. This algorithm took the convolutional and pooling layers from a classical CNN and implemented them in the quantum space. But it suffered from two problems: It has no image processing uses like a classical CNN, and second, it requires more qubits than are feasible on current quantum hardware to solve a complex problem.

In [12], image processing was kept in mind. The algorithm is a complete translation of the classical CNN into the quantum realm having convolutional layers, pooling layers, an activation function, and a fully connected layer with backpropagation. But this approach suffered two main problems: the need for quantum RAM (QRAM) having no reliable implementation and a need for a higher number of qubits to implement this algorithm efficiently on current hardware. The authors, however, did run a numerical simulation of their algorithm against a classical CNN of similar architecture and showed that the quantum CNN was significantly faster than its classical counterpart while providing a similar accuracy. This showed that quantum CNN has the potential to outperform a classical CNN. But until quantum hardware improves enough, it cannot be definitively said that the quantum algorithm is better.

To address the problems, Hybrid quantum-classical algorithms are developed where NISQ devices can be used in conjunction with classical computers. The idea here is to outsource portions of a classical algorithm that can either benefit from quantum phenomena, or is classically intractable, or both to a quantum computer.

In [2], Henderson et al. proposed image classification with hybrid quantum convolution neural network architecture termed "Quanvolutional Neural Networks (QNNs)." The proposed architecture extends the capabilities of CNNs by leveraging certain potentially powerful aspects of quantum computation. A new transformational layer termed "quanvolutional layer" is added to the standard CNN architecture that operates on the input data by locally transforming the data using a series of random quantum circuits to produce feature maps. This layer acts as a pre-processing layer. The features produced by the quanvolutional circuits increased the accuracy of the machine learning models for classification. The results of the proposed approach exhibit consistency with those of Wilson et al. 2018 [13]; that is, quantum transformations feeding into a linear model could give a performance enhancement over linear models built on the data directly.

In [14], a hybrid quantum-classical convolutional Neural Networks (HQCNN) model that used the random quantum circuits (RQCs) is proposed as a base to detect COVID-19 patients with Chest X-Ray images. This approach is based on the works done in [2] by Henderson et al.

In [3], the approach proposed by Henderson et al. is implemented with angle encoding for the MNIST dataset, and similar accuracy has been obtained for both the hybrid quantum-classical model and the traditional CNN.

In [15], detection of COVID-19 from CT images using the quantum transfer learning method is proposed. The authors performed experiments on real quantum processors and simulators and achieved success of 94% with a 4-qubit quantum system. They also showed that the quantum approach is advantageous in classification in the case of smaller datasets compared to traditional machine learning due to the superior properties of quantum.

In [16], the effect of different quantum image encoding on the performance of the model proposed by Henderson et al. is studied. They concluded that there is no best encoding, and the choice of encoding depends on a specific application.

In [17], a novel quantum edge extraction algorithm is proposed based on the NEQR model using Kirsch Operator. The quantum algorithm showed a better extraction effect than traditional methods and can perform real-time image processing with high accuracy.

3. HYBRID QUANTUM CONVOLUTIONAL NEURAL NETWORK

As mentioned earlier, the present work follows the hybrid quantum-classical approach proposed by Henderson et al.[2].The authors of [2] provide a quantum analog for the classical convolutional layer and name it the "quanvolutional" layer. Similar to the classical convolutional layer, the proposed layer extracts high-level spatial features from the input image. The layer consists of a quantum circuit that encodes pixel data on n × n qubits (where n represents the kernel size), applies a random quantum circuit on these qubits, and then measures them to produce a feature matrix. Henderson et al. used the threshold encoding for encoding the pixel values where pixel values higher than a limit were encoded to |1⟩ while those less than or equal to the limit were encoded to |0⟩.

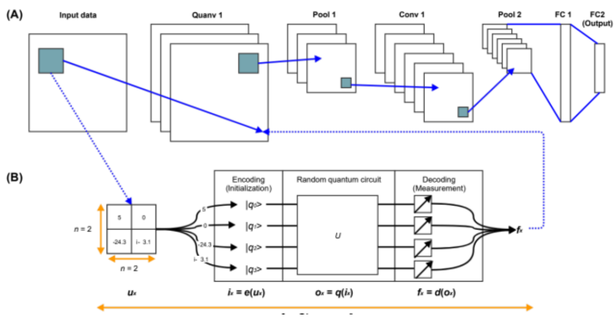

Fig -1: Schematic illustration of Quanvolutional Neural Network proposed by Henderson et al. [Image: 2]

Another encoding method was taken by Mari [3]. As shown in Fig. 2, rather than performing element-wise matrix multiplications, the 2 × 2 windows in the image are encoded onto the qubits using the Ry gate. This particular encoding is also known as 'angle encoding.' This is then passed to the random circuit, transforming the quantum state through a series of two-qubit gates like C-NOT and parameterized one-qubit gates and then measured.

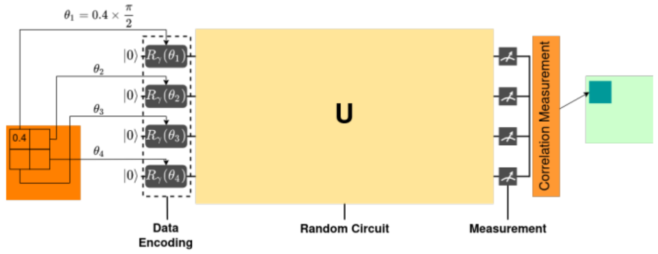

Fig -2: The random quantum convolutional layer. [Image:18]

Classical neural network layers can process the measurement results for the final classification step, or further convolution and pooling layers can be applied.

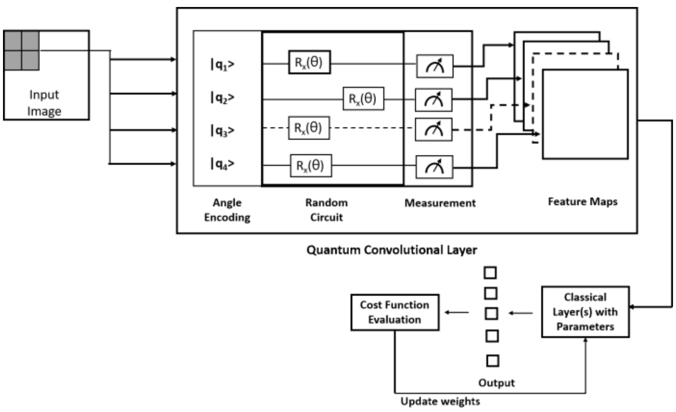

Fig -3: Schematic illustration of Quanvolutional Neural Network proposed by Mari

4. PROPOSED METHOD AND EXPERIMENTAL RESULTS

4.1 Proposed Method

This work combines the advantage of the 'quanvolutional neural networks (QNNs)'[2] with CNNs and proposes an implementation of a Hybrid Quantum Convolutional Neural Network for the diagnosis of Tuberculosis from images of Chest X-Ray. This model uses the NEQR quantum image format [4] for encoding the pixel values in the quantum state, which is different from threshold encoding as proposed in [2] and angle encoding as proposed in [3].

The proposed architecture consists of the following components:

1. Encoding: Image patches corresponding to the filter size (2X2) is extracted from the entire input image and encoded to a quantum state vector. NEQR [4] is the image encoding used in this work.

2. Quantum convolution or the Quanvolutional layer: Random Quantum circuit performs local transformations on each quantum state representing a single image patch and produces feature maps as output.

3. Classical Convolutional Neural network layer(s) with Pooling: Sequentially applied classical convolution layers with Max pooling and ReLU activation process the generated feature maps and outputs the classification prediction.

Fig. 4 and 5 shows the steps followed while training and the detailed architecture of the proposed method respectively.

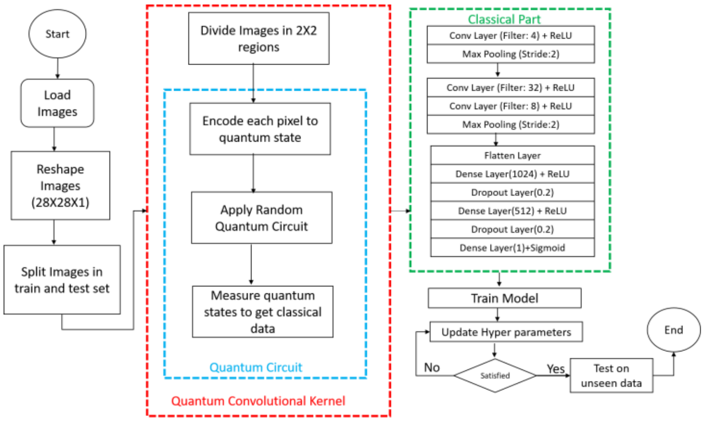

Fig -4: Flowchart of proposed method

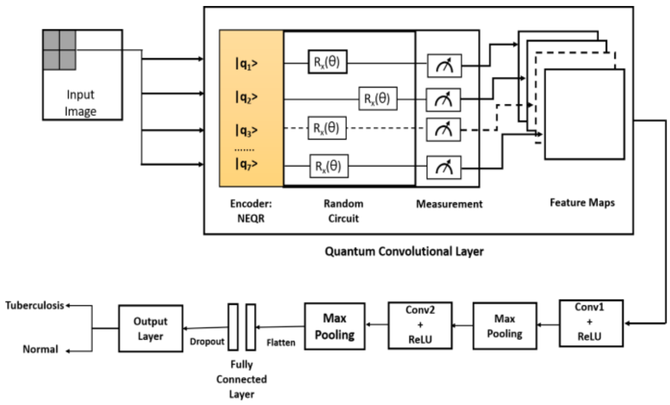

Fig -5: Schematic illustration of proposed method

Quanvolutional Layer

Here, every image patch of size (2X2) from the input image is encoded using NEQR[4] into a quantum state, and then quantum transformations are applied using a random circuit. Lastly, the qubits are measured, and a feature map is produced.

1. **Encoding:** The NEQR circuit is constructed with 10 qubits, of which 8 qubits are used for the intensity

values (0-255 for grayscale), referred to as $i_0, i_1, i_2, \ldots i_7$, and 2 qubits are used for pixel position, referred as i_{idx}, j_{idx}. Hadamard gate is applied to i_{idx}, j_{idx} to put the qubits in superposition. For every pixel, the value is converted to an 8-bit binary string, and the bit for which the value is 1, Toffoli gate is applied to that qubit keeping the i_{idx}, j_{idx} as the control qubits.

2. **Random Quantum Circuit:** The random circuit is constructed from randomly chosen one-qubit and two-qubit gates. The rotations applied in these gates are also chosen randomly using Numpy's random method. Only one random layer is used in the circuit.

3. **Measurement:** Pauli-Z gates are used for measurement and the expected values that are obtained forms the real-valued output vector for each image patch. The output vector has an entry for every qubit representing the intensity values. In the present work, for the implementation of NEQR with 2X2 image patches, Toffoli gates are used as 2n-CNOT gates. Thus, for the NEQR implementation, 2 Hadamard gates for the positional qubits, 2 NOT gates to construct and deconstruct all on-off combinations of the positional qubits, and for every pixel, a maximum of eight times the number of gates required to form one Toffoli gate are used. The quantum convolution layer uses a maximum of 4098 gates to process an entire image of size 28X28, with a maximum of 3876 gates used for NEQR encoding. However, the quantum convolution layer with angle encoding required a maximum of 392 gates to process an entire image of size 28X28.

Classical Convolution Layers

The classical convolutional layers with a 2X2 kernel followed by ReLU activation is used. The first classical CNN layer takes the feature maps produced in the quanvolution step as input. Max Pooling with stride 2 reduces computational learning by selecting the most important and valuable features.

Fully Connected Layers

The features obtained in the convolution step are flattened and fed to a fully connected layer with a dropout value of 0.2 to reduce overfitting.

Output Layer

The output layer uses the sigmoid function and calculates a value between 0 and 1. A value greater than 0.5 is classified as Tuberculosis, and less than 0.5 is classified as Normal.

4.2 Data Set

Two datasets were used for this work. The first one is the Montgomery County - Chest X-ray Dataset created by the National Library of Medicine in collaboration with the Department of Health and Human Services, Montgomery County, Maryland, USA, and the second is the Tuberculosis (TB) CHEST X-RAY DATABASE created by researchers from Qatar University, the University of Dhaka with collaborators and doctors from Malaysia. Both the datasets had images belonging to two classes, TB and normal.

A total of 1114 images were taken for training and validation from both these datasets, with 554 cases of Tuberculosis and 560 normal cases. The training and validation set consists of 890 images and 223 images, respectively. The images were down-sampled to (28X28 px). The test set consists of 400 images with 200 cases of Tuberculosis and 200 Normal cases.

4.3 Experimental Results

The hybrid quantum-classical model and the image encoding were implemented in Python using PennyLane, a cross-platform python library for quantum machine learning and the classical parts of the model were implemented in Keras. The model was trained on a classical computer using Quantum Simulator.

The model showed validation accuracy of 87.00% during training. On the test set, the model showed 84.00% accuracy.

	Actually Positive	Actually Negative
Predicted Positive	163 (TP)	27 (FP)
Predicted Negative	37 (FN)	173 (TN)

Table -1: Confusion Matrix of the Results for the proposed Hybrid Quantum CNN on the mentioned dataset

The dataset was also trained using the same hybrid quantum-classical model but with angle encoding as a comparison (angle encoding proposed by Mari[3]), and a validation accuracy of 87.00% was obtained during training. On the test set, the model's accuracy was noted to be 88.75%.The results obtained are shown in Fig. 6, which shows the classification results in accuracy and loss of the training and validation data using the hybrid quantum convolutional method with angle encoding.

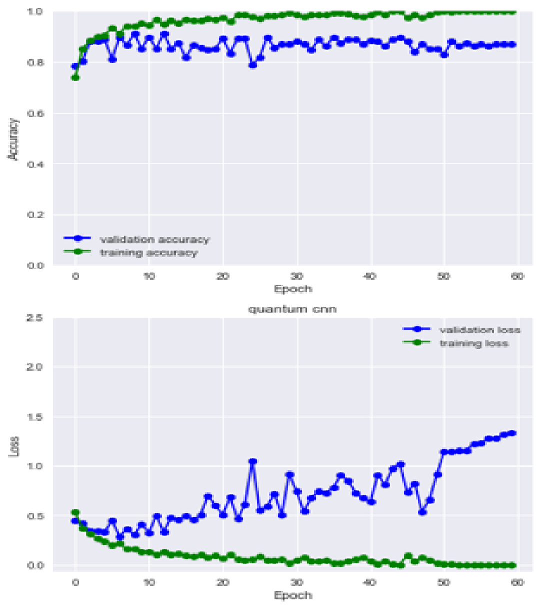

Fig -6: Results for the Hybrid Quantum CNN on the mentioned dataset using angle encoding

The same dataset was also trained on a classical CNN having the same architecture but replacing the quanvolutional layer with a classical convolution layer. This showed a validation accuracy of 93% during training.

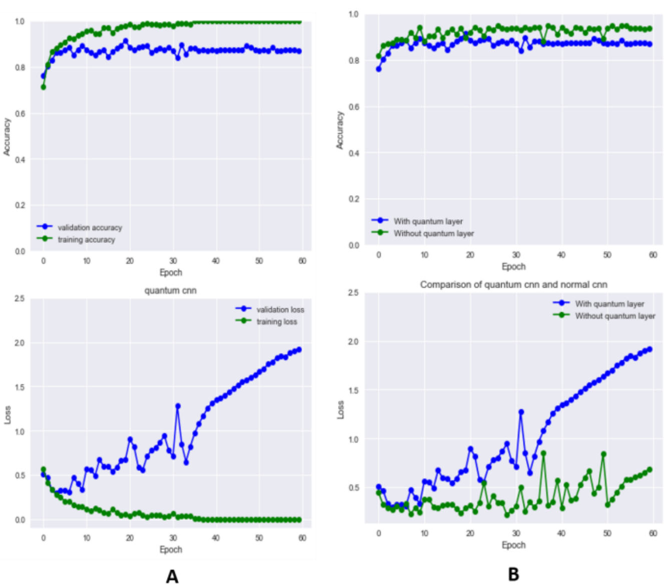

Fig -7: Results for the proposed Hybrid Quantum CNN on the mentioned dataset

Fig -8: Predictions of proposed method

The results obtained for the proposed model are shown in Fig. 7. Fig .7(A) shows the results for classification in terms of accuracy and loss on the training and validation data using the proposed hybrid quantum convolutional method. Fig. 7 (B) compares the quantum and the classical CNN.

5. CONCLUSIONS

The results show that NEQR image encoding produced similar accuracy to angle encoding on the same dataset (Fig. 6, Fig. 7). This demonstrates that image encoding had little impact on the model's accuracy for this dataset. This might be because the images are grayscale, and angle encoding captures pixel information similar to NEQR encoding.

The results (Fig. 7 B) show that Classical CNN outperformed the hybrid quantum CNN. This contradicts the results obtained in [2] and [14]. This discrepancy between the results obtained in this work and those obtained in previous work may be because the simulators used must have been analogs for perfect quantum computers. The proposed method does, however, demonstrate how to use the concept of a quantum circuit to augment a quantum layer to a classical CNN for classifying Tuberculosis from chest x-rays using NEQR image encoding.

The results obtained in this work are an encouraging preliminary to continue further research in different directions. A continuation path for the presented work would focus on improving the accuracy of the model by adopting: multiple quantum convolution layers, making the weights of the random circuit trainable.

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