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

A thesis

submitted in partial fulfillment of the requirement for the Degree of Master of Technology in Computer Technology of

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By

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This is to certify that the dissertation entitled "**Hybrid Quantum Convolutional Neural Network For Tuberculosis Prediction using Chest X-Ray Images**" has been carried out by **Sayantika Debnath** (UniversityRegistration No: 149852 of 2019-2020, Examination Roll No: M6TCT22019) under my guidance and supervision and be accepted in partial fulfillment of the requirement for the Degree of Master of Technology in Computer Technology. The research results presented in the thesis have not been included in any other paper submitted for the award of any degree in any other University or Institute.

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I hereby declare that this thesis entitled – **Hybrid Quantum Convolutional Neural Network For Tuberculosis Prediction using Chest X-Ray Images** contains a literature survey and original research work by the undersigned candidate, as part of her Degree of Master of Technology in Computer Technology.

All information has been obtained and presented in accordance with academic rules and ethical conduct.

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CHAPTER 1: INTRODUCTION

Tuberculosis (TB) is one of the most lethal infectious diseases in the world. According to the World Health Organization (WHO), a total of 1.5 million people died from TB in 2020 [1]. An estimated 10 million people fell ill with tuberculosis globally, among which 5.6 million men, 3.3 million women and 1.1 million are children [1]. It is the 13th leading cause of death worldwide and is the second leading infectious killer after COVID-19 [1].

The bacteria Mycobacterium tuberculosis causes this global disease found in every country. TB is airborne that spreads primarily by coughing and sneezing and affects the lungs.

Many of these deaths could have been prevented if the disease had been detected earlier. These days, many highly 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.

Among the popular diagnosis methods are the usage of frontal chest radiographic images. But this requires skilled radiologists and good quality imaging equipment which are again limited in developing nations.

Thus, the need was felt for a computer-aided detection system for the preliminary diagnosis of the disease. The system could be an inexpensive and effective method to make widespread tuberculosis screening a reality. In smaller medical facilities where skilled radiologists are limited, populations would be screened for possible TB manifestations and the probable patients can be sent for further diagnosis. This early-stage screening can potentially save many lives.

With technological advancements, various approaches, from pattern recognition and neural networks to present-day deep learning, have been used for the detection system. In recent years deep learning techniques of Convolutional Neural Networks (CNNs) have surpassed other traditional algorithms.To date, computer-aided systems embedded with deep-learning algorithms have proven to help detect medical diseases by offering various high-quality diagnostic solutions.

Quantum computing is a rapidly emerging technology that harnesses the laws of quantum mechanics and promises to solve computational problems that modern-day computers cannot solve easily. Quantum machine learning came up as a field of study which explores the interplay of ideas from quantum computing and machine learning. This has led to the research for developing newer algorithms that try to make the best of both worlds. Some of these attempts were successful in their applications to real-world problems.

1.1 TUBERCULOSIS

1.1.1 BACKGROUND

One of India's most serious public health issues is tuberculosis. According to World Health Organization (WHO) estimates, India notified more than 2.4 million TB cases in 2019 and continues to have the largest share of the global TB burden [2].

The disease is responsible for economic collapse and the poverty and illness cycle that has engulfed families, towns, and even entire countries. Also,growing resistance to available drugs is seen, implying that the disease is becoming more deadly and difficult to treat.

Tuberculosis infections can be perceived in chest X-Rays by detecting the presence of specific patterns in the image. According to[3], the most common manifestations of tuberculosis in chest radiographs are:

a) Air space consolidation(appears as opacity in the lobes)

b) Miliary patterns (a sand-like pattern appearing throughout the lungs)

c) Adenopathy (enlargement of the lymph nodes)

d) Airways enlargement (appears as tubular rings) and

e) Pleural effusion (indistinctness in lateral and medial regions).

a) Chest x-ray showing dense homogenous opacity in the right, middle and lower lobe of primary pulmonary TB

b) Chest x-ray showing bilateral diffuse miliary opacities of primary pulmonary TB.

c) Chest x-ray showing bilateral hilar adenopathy of primary pulmonary TB

e) Chest x-ray showing dense opacity pleural effusion in the lower left lung of primary pulmonary TB

Figure 1: Most common manifestations of Tuberculosis
[Image: 4]

1.1.2 COMPUTER-AIDED DETECTION METHODS

Historically, computer-aided detection systems mainly relied on feature extraction and pattern recognition technology.

In recent years with the advances in deep learning, convolutional neural networks (CNNs) have consistently surpassed other traditional recognition algorithms in achieving superior performance for image-based classification problems.The ability to automatically extract useful features from the inherent characteristics of data makes CNN the first choice for solving complex medical problems.

In most of the published works, CNNs are applied to image classification in four different manners [5,6]:

a) Training the network weights from scratch (usually done only when there is a huge dataset available)
b) Fine-tuning the weights of an existing pre-trained CNN (achieves similar results to training from scratch but may work in smaller datasets [7])
c) Using unsupervised pre-training to set initial weights before training the CNN
d) Using a pre-trained CNN (sometimes called an off-the-shelf or out-of-box CNN) as a feature extractor.

Some of the relevant works on Tuberculosis detection are discussed in section 2.3.1.

1.2. QUANTUM COMPUTERS

1.2.1. FROM CLASSICAL TO QUANTUM

The simplest definition of a computer is a machine that stores and processes information. Computers store information in memory and apply operations to perform a task.

Both of a computer's key tricks -storage and processing- are accomplished using transistors, like microscopic versions of the switches we have for turning on and off the lights. A transistor can be turned on or off, much like light can be turned on or off. If it's on, we can use a transistor to store a number one (1).If it's off, it stores a number zero (0).Using a binary code, long strings of ones and zeros can store any number, letter, or symbol.

Computers calculate by using circuits called logic gates, which are made from several transistors connected together.Logic gates compare patterns of bits stored in temporary memories called registers and then turn them into new patterns of bits.In physical terms, the algorithm that performs a particular calculation takes the form of an electronic circuit made from several logic gates, with the output from one gate feeding in as the input to the next.

So, it can be understood that conventional computers depend on transistors. Looking at the fantastic progress in electronics over the last few decades, this strong dependence on transistors seems to be a boon. Back in 1947,when transistors were invented,they replaced the traditional vacuum tube switches(which had the size of a thumb).Now a single microprocessor chip packs hundreds of millions of transistors. Integrated Chips are an incredible feat of miniaturization.

In the 1960s, Gordon Moore stated his observation that the power of computers would double every two years while the cost would be halved. Though it sounds amazing, it means that the number of transistors in an integrated circuit will double, suggesting the decreasing size and complexity of the transistors.

As Moore’s law advances, the number of intractable problems is diminishing. Computers get more powerful, and with the increase in computational power, many deep learning approaches which were earlier limited have gained popularity.

But the trouble is,transistors are just about as tiny as we can make them.We are getting to a point where the laws of physics seem to stop Moore’s law.Since the size of transistors is shrinking to the size of a few atoms, transistors cannot be used as switches.Quantum effects will then interfere with the devices' functioning due to the circuit's smaller size.

Unfortunately, difficult computing problems still exist because even the most powerful computers find them intractable. That's one of the reasons why a new and different computing paradigm that employs quantum mechanics is gaining importance.

1.2.2 QUANTUM THEORY

Quantum theory is the branch of physics that explores the world of subatomic particles. At this level, particles behave differently, and the classical laws of physics no longer apply.

The wave-particle duality is one of the key ideas of quantum theory.A beam of light sometimes behaves as if it's made up of particles (like a steady stream of cannonballs), and sometimes as if it's waves of energy rippling through space (like waves on the sea). It is hard to comprehend that something can be two things at once: a particle and a wave,because it is unfamiliar to our everyday experience. However, this behavior is possible in quantum theory.

Based on wave-particle duality, the ideas of superposition and entanglement are conceptualized, forming the basis for quantum bits or qubits, which are the basic unit of information in quantum computers.

1.2.3 QUANTUM INFORMATION

The question is whether computers designed in a way where it follows the quantum mechanical laws can do things our conventional computers can't.

In 1980, physicist Paul Benioff from Argonne National Laboratory tried to envisage a quantum Turing machine that would work similarly to an ordinary computer but follow the principles of quantum physics.

Richard Feynman sketched roughly how a machine using quantum principles could perform basic computations. He proposed the first quantum computer for simulating experiments in physics.He stated in [9] about the need for a quantum system that provides the platform for computation that is impossible to simulate in classical computers.

As a result, Quantum computers are emerging and applied to problems intractable on classical computers. Quantum computing exploits quantum-mechanical effects of superposition and entanglement, which are not seen in classical computing environments.

Classical computers have bits analogous to which a quantum computer has a quantum bit or qubit. A bit can store either a 0 or 1, while a qubit can store a 0, a 1, both 0 and 1, or an infinite number of values in between.This suggests that a qubit can be in multiple states,i.e., can store multiple values simultaneously.This is analogous to light being a particle and a wave simultaneously, Schrödinger's cat being alive and dead. In simpler words,qubits store information using the concept of superposition.

Since qubits can store multiple values at once, a quantum computer can process them simultaneously. Instead of processing in serial, the quantum computer can work in parallel. Only when we measure a qubit, or in other words, we try to find out the value present in the qubit at any given moment(which is given by its state), the qubit "collapses" into one of its possible states of 0 or 1. As per estimates, a quantum computer's ability to work in parallel would make it millions of times faster than any conventional computer.

An intuition of the difference in the approach between the classical and quantum computer can be further explained with an example:

Let us take 4 bits in a classical computer. Combining these 4 bits can represent 2^4=16 values or states in total. Only one state can be accessed at an instant.

But in a quantum computer with a combination of 4 qubits, all the 16 states can be accessed simultaneously.

1.2.4 REALISING A QUANTUM COMPUTER

To realize a quantum computer, qubits need to be created. In reality, qubits have to be stored by atoms, ions (atoms with too many or too few electrons), or even smaller things such as electrons and photons (energy packets).Therefore, mechanisms for containing atoms, ions, or subatomic particles, putting them into certain states (so that information can be stored), converting them into other states (so that the stored information can be processed), and figuring out what their states are after applying particular operations are needed.

Some of the approaches to realizing a qubit are:

a) Ion traps: Electrons are taken away from an atom to make an ion. The ion is kept steady in a kind of laser spotlight and then flipped into different states with laser pulses

b) Superconductors: Qubit is implemented in a superconducting circuit where an electric current oscillates around the microscopic circuit etched on a chip.When cooled to temperatures just a few hundredth above absolute zero,the circuit behaves as a quantum object. Radio waves of the right frequency can put the circuit in energy levels corresponding to quantum 0 or 1

1.2.5 IMPACTS OF QUANTUM COMPUTER

Although it may appear that quantum computers must automatically be better than conventional ones, that's by no means certain. Research is conducted in many domains applying the quantum computing scenarios to determine the quantum supremacy over the classical counterparts.

Some potential application domains are discussed below:

a) Cryptography: In 1994, mathematician Peter Shor demonstrated an algorithm to find a large number's "prime factors" using a quantum computer. Shor’s algorithm runs in polynomial time in a quantum computer. This proved that if a quantum computer with sufficient qubits could operate without succumbing to noise, Shor's algorithm could be used to break public-key cryptography schemes.

b) Optimization Problems: The machines are great for optimization problems as they can quickly crunch through many potential solutions.

c) Machine Learning: Quantum analogues to classical machine learning algorithms like quantum SVM, quantum neural networks, etc., are attempted. Hybrid quantum-classical approaches are researched. Studies are conducted on whether quantum information will bring a new perspective on how machines recognize patterns in the data.

1.3 QUANTUM MACHINE LEARNING

Training a machine to learn from data is the core of machine learning. The classical machine learning methods help classify images, recognize patterns and speech, handle big data, and many more. However, a huge amount of data is being generated, and new approaches are required to manage, organize and classify such data.

Machine learning and quantum computing are expected to play a role in how the information will be processed in the future.As a result, Quantum machine learning comes up as an alternative.This field explores the interplay of ideas from the two areas.

One of the ways quantum computations could be advantageous in machine learning is the time it takes to train a model due to the inherent nature of how information is represented in a quantum computer.

In the quantum machine learning techniques, quantum algorithms analogous to classical algorithms are developed. Thus, data can be classified, sorted, and analyzed using the quantum algorithms of supervised and unsupervised learning methods. These methods are again implemented through models of a quantum neural network,quantum support vector machines,and quantum decision trees.

Apart from these,research is conducted on whether quantum information will bring a new perspective on how machines recognize patterns in the data, whether systems can learn from fewer training data, and how new machine learning methods combine quantum and classical approaches.

1.4 MOTIVATION

The motivation behind this work is to understand the fundamental concepts of quantum computing, its application, and its claims that it is faster than traditional computers.

Hybrid quantum-classical algorithms pertaining to a convolutional neural network have shown a significant research interest and are applied to medical image analysis. In accordance with this,Detection of Tuberculosis from Chest X-Ray images is taken up as a usecase,and a hybrid quantum convolutional neural network is presented.

1.5 CONTRIBUTION

In this work, the Hybrid Quantum Convolutional Neural Network proposed by Henderson et al.[27] is taken up. In [27], threshold encoding was used to convert the classical information (pixel values) to a quantum state.The question of finding an optimal encoding for classical data was left open.Mari [36] proposed a model variant where angle encoding was used.

Many quantum image representations have evolved as discussed in section 2.3.2. Among these,Flexible Representation of quantum images (FRQI)[21] and Novel Enhanced Quantum representation (NEQR) [22] are significant.NEQR offered certain advantages like (a)quadratic speedup for quantum image preparation,(b)higher compression ratio of quantum images,(c)accurate retrieval of images and (d)complex color operations[22].

In the present work, a new model variant is proposed whereNEQR [22] is used for encoding pixel values present in image patches to a quantum state.The choice for NEQR can be mainly attributed to the faster image preparation due to the elimination of complex quantum rotation operations which in turn reduces circuit depth and accurate retrieval via quantum measurements instead of probabilistic measurements in FRQI.

Implementation details about the NEQR circuit used in this work are present in section 4.1.1

The experimental results for the proposed approach,as discussed in section 4.2,shows 87.00% validation accuracy on training which is similar to the validation accuracy with angle encoding on the same dataset.This demonstrates that image encoding had little impact on the model's accuracy for this dataset. Angle encoding may have captured pixel information similar to NEQR encoding because the images are grayscale.

1.6 ORGANIZATION OF THE THESIS

This thesis is divided into 5 different chapters.

In Chapter 1, a general introduction to Tuberculosis, the need for an inexpensive detection system is presented. The chapter also introduces quantum technology, its impact,and quantum machine learning. The chapter ends with the motivation for the present work.

In Chapter 2,a primer on the quantum basics and technologies that are currently available is presented. This helps in understanding the following chapters. Additionally, it also includes the literature survey for the present work.

In Chapter 3, a brief introduction of the methods applied for the present work is presented.

In Chapter 4, the proposed model, details of the implementation,and the obtained result are provided.

In Chapter 5,the conclusions on the findings of this study with any future works that can be done to improve the results are presented.

CHAPTER 2: BACKGROUND RESEARCH

This section explains some of the basic concepts of quantum computing used in this work, followed by a literature review.

The state of any quantum system is always represented by a vector in a complex vector space (usually called a Hilbert space). Quantum algorithms are expressible as transformations acting on this vector space. These basic facts follow from the axioms of quantum mechanics[37].

2.1 QUBIT

2.1.1 SINGLE QUBIT

At the heart of a classical computer is the concept of bit. A bit is the most basic unit of classical information. A bit can be in state 0 or 1. For example:

- A bit can be thought of as a switch turned “ON” or “OFF”
- A bit is a way of denoting “TRUE” or “FALSE”

The condition of a bit to be in one of the two states was sufficient for the classical world. Either a switch is ON, or it is not. A proposition is either True or False.

But this is not sufficient in the quantum world as there are situations where the quantum system is simultaneously in both states. In the quantum world, there are systems where a switch is both ON and OFF simultaneously. A quantum system can be in states 0 and 1 simultaneously. Thus,we are led to the concept of a Quantum Bit (also known as a qubit).

Like classical computers, a quantum computer's heart is a generalization of the concept of a bit called the Quantum bit or Qubit. Like a classical bit, a qubit is the fundamental information-carrying unit used in a quantum computer.

A qubit can be in 0 or 1 or a combination of both states simultaneously, known as linear superposition. The state of a qubit can be written as:

$$|q\rangle = \alpha\,|0\rangle + \beta\,|1\rangle \qquad (1)$$

Here:

- α and β are complex numbers such that, $|\alpha|^2 + |\beta|^2 = 1$.
- In the ket-notation, $|0\rangle = \begin{bmatrix}1\\0\end{bmatrix}$ and $|1\rangle = \begin{bmatrix}0\\1\end{bmatrix}$ are shorthands for the vectors encoding the two orthonormal basis states of a two-dimensional vector space.

The amplitudes α and β are linked to the probabilities of observing either 0 or 1 when measuring the qubit. In simple words,$|\alpha|^2$is to be interpreted as the probability that after measuring the qubit, it will be found in state |0⟩. $|\beta|^2$is to be interpreted as the probability that after measuring the qubit, it will be found in state |1⟩.

Whenever we measure a qubit, it automatically collapses to 0 or 1, and we get a bit. It is essential to note that the state of a qubit cannot be measured without changing it. Measuring a qubit, whose state is given by Eq. (1) above, will yield the classical value of either zero (|0⟩) with probability $|\alpha|^2$ or one (|1⟩) with probability $|\beta|^2$.

Before the measurement,any superposition is possible, giving a quantum system special ability in terms of computation.

To represent the qubit's state with real numbers, equation (1) can be re-written to equation (2) where a = cos θ/2 and b = sin θ/2.

$$|q\rangle = \cos\frac{\theta}{2}|0\rangle + e^{i\varphi}\sin\frac{\theta}{2}|1\rangle \qquad (2)$$

To visualize a single qubit, we use the Bloch Sphere.

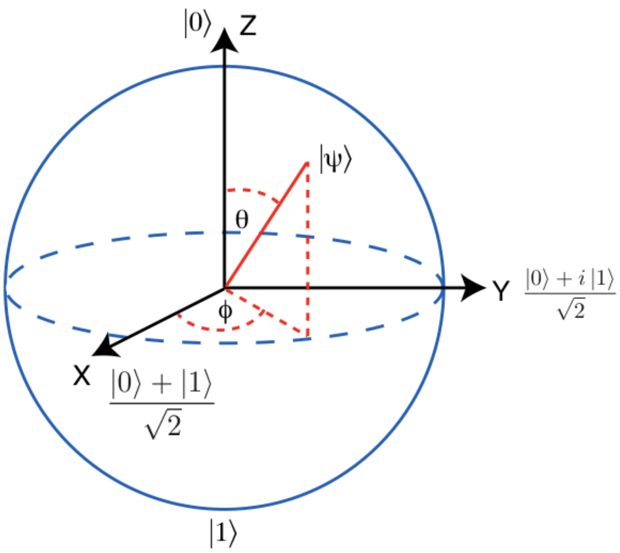


Figure 2: Representation of a qubit in Bloch Sphere as obtained from Qiskit

2.1.2 SYSTEM OF QUBITS

A single qubit, although attractive, offers no computational advantage. So, the true power of quantum computing is realized through the interaction of multiple qubits.

As seen in the previous section, a single qubit is represented using the two basis states $|0\rangle$ and $|1\rangle$,having two complex amplitudes, α, and β, respectively. Similarly, a two-qubit system would have four basis states: $|00\rangle$, $|01\rangle$, $|10\rangle$, $|11\rangle$, and the state can be represented as:

$$|a\rangle = a_{00}|00\rangle + a_{01}|01\rangle + a_{10}|10\rangle + a_{11}|11\rangle \qquad (3)$$

The concept of measurement works in the same way and $|a_{00}|^2+|a_{01}|^2+|a_{10}|^2+|a_{11}|^2=1$

Equation (3) can be written in the form of a vector as:

$$\begin{bmatrix} a_{00} \\ a_{01} \\ a_{10} \\ a_{11} \end{bmatrix}$$

It is important to note that the vector represented by a two-qubit system is four-dimensional. This means that for an n-qubit system, the vector would be 2^n dimensional, and keeping track of these many complex amplitudes is difficult [10].

These vectors grow exponentially with the number of qubits.That is why quantum computers with large numbers of qubits are challenging to simulate.

A modern laptop can only simulate a general quantum state of around 20 qubits, but simulating 100 qubits is too difficult for the largest supercomputers.

2.2 QUANTUM GATES

Analogous to gates in a classical computer that performs certain operations on the input to generate the expected output, quantum computers have quantum gates which are rudimentary quantum circuits operating on a small number of qubits.

Quantum gates are represented as matrices and as rotations around the Bloch Sphere.

2.2.1 SINGLE QUBIT GATES

THE X-GATE

This is similar to the classical NOT gate flipping 0 to 1 and 1 to 0.

The Pauli-X matrix represents the X-gate as:

$$X=\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

This gate flips the probabilities associated with the basis states. If a qubit is in the state $|q\rangle = \alpha\,|0\rangle + \beta\,|1\rangle$, and we apply X-gate as shown below, we get $|q'\rangle = \beta\,|0\rangle + \alpha\,|1\rangle$.

$$|q'\rangle = X\,|q\rangle = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}\begin{bmatrix} \alpha \\ \beta \end{bmatrix} = \begin{bmatrix} \beta \\ \alpha \end{bmatrix} = \beta\,|0\rangle + \alpha\,|1\rangle$$

As a more straightforward example,we can see that the X-gate switches the amplitudes of the states $|0\rangle$to $|1\rangle$

$$X\,|0\rangle = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}\begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} = |1\rangle$$

The Pauli-X gate rotates a single-qubit by π radians around the x-axis.

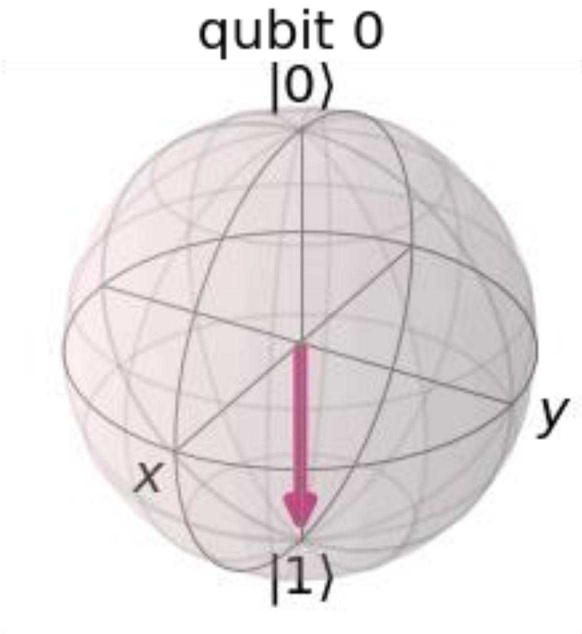


Figure 3: Rotation of a single qubit in on applying X-gate as obtained from Qiskit

HADAMARD GATE

The Hadamard gate is one of the most helpful quantum gates.When the Hadamard Gate is applied to a qubit in state |0⟩,the qubit enters a superposition state where the probability of measuring 0 equals the probability of measuring 1.

$$H|0\rangle = \frac{1}{\sqrt{2}}\begin{bmatrix}1 & 1\\ 1 & -1\end{bmatrix}\begin{bmatrix}1\\ 0\end{bmatrix} = \begin{bmatrix}\frac{1}{\sqrt{2}}\\ \frac{1}{\sqrt{2}}\end{bmatrix}$$

The matrix represents the gate as:

$$H = \frac{1}{\sqrt{2}}\begin{bmatrix}1 & 1\\ 1 & -1\end{bmatrix}$$

THE Y-GATE

The Pauli-Y gate rotates the state vector of a qubit along the y axis by π radians.

The matrix represents the gate as:

$$Y=\begin{bmatrix}0 & -i\\ i & -0\end{bmatrix}$$

It changes |0⟩ to $i|1\rangle$ and |1⟩ to$-i|0\rangle$.

THE Z-GATE

The Pauli-Z gate rotates the state vector of a qubit along the z-axis by π radians.

The matrix represents the gate as:

$$Z=\begin{bmatrix}1 & 0\\ 0 & -1\end{bmatrix}$$

It keeps |0⟩ unchanged but flips the sign of |1⟩to -|1⟩.

THE PARAMETERIZED GATES

These gates accept a parameter and operate based on this parameter

The Parameterized gates perform a rotation of ϕ around the Z-axis direction. It has the matrix form:

$$R_\phi = \begin{bmatrix} 1 & 0 \\ 0 & e^{i\phi} \end{bmatrix}$$

2.2.2 MULTI QUBIT GATES

C-NOT GATE

The C-NOT gate is a two-qubit operation.Here the first qubit is the control qubit, and the second qubit is the target qubit. This gate performs a Pauli-X gate on the target qubit when the control qubit is$|1\rangle$ and leaves the target qubit unchanged when the control qubit is$|0\rangle$.The control qubit remains unchanged.

The gate is represented as:

$$\text{CNOT} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

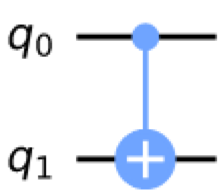


Figure 4: C-NOT gate from Qiskit with q_0 as control and q_1 as target qubit

TOFFOLI GATE

The Toffoli gate is a three-qubit gate having two controls and one target.

It performs an X operation on the target only if both controls are in the state |1⟩. The target's final state is then equal to the AND or NAND of the two controls, depending on whether the target's initial state was |0⟩ or |1⟩.

Also known as the CCX gate,the Toffoli gate can also be thought of as a controlled-controlled-NOT operation.

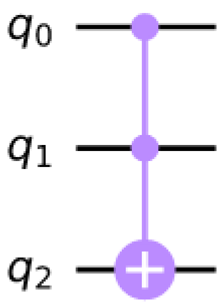


Figure 5:Toffoli gate from Qiskit with q_0,q_1 as control and q_2 as target qubit

2.3 REVIEW OF LITERATURE

This section is organized into three sub-sections. The first discusses some relevant works on Tuberculosis detection with image processing and machine learning techniques. The second discusses different quantum image formats.The third discusses the works on quantum machine learning techniques pertaining to image classification problems.

2.3.1 RELATED WORKS ON TUBERCULOSIS DETECTION

Jaeger et al. [11] proposed an automatic TB detection system by combining many standard computer vision algorithms to extract features of radiographic images. The proposal is divided into three steps: segmentation of the region of interest, feature extraction using a combination of algorithms (such as histogram of oriented gradients [13], local binary patterns [12]), and classification in which the extracted features are fed to a binary classifier to identify the image as healthy or not healthy. The classifiers examined were the Multilayer Perceptron (MLP), SVM, decision trees, and logistic regression. The logistic regression and linear SVM with an AUC of 0.87 for the Montgomery dataset and 0.90 for the Shenzhen dataset showed the best performance. The accuracies were respectively 0.78 and 0.84

The application of a CNN to tuberculosis detection was proposed for the first time by Hwang et al. [14]. The proposal specifies creating a custom network, adapting an existing CNN to the specific problem of tuberculosis detection, and recalculating the existing weights. The architecture described here is a variant of the AlexNet network with a larger input layer (500 X 500 pixels), a new convolutional layer right after the input layer (to process the higher-resolution images), and a new max-pooling layer. The network was trained to utilize a sizeable private dataset of an estimated 10,000 images. The initial weights of the network were set in two different configurations: random and using the weights learned by the standard AlexNet in the ImageNet dataset. Unsatisfactory results were obtained by randomly initializing the weights, producing an accuracy of 0.77 and an AUC of 0.82. In the case of the network trained with pre-learned weights, the accuracy and AUC reached 0.90 and 0.96, respectively.

Bogomasov et al. [15] use image processing techniques for feature extraction from CT scans and use artificial neural networks (ANN) for predicting probabilities for different lung irregularities associated with pulmonary tuberculosis and tuberculosis severity assessment. However, they directly use U-net and VGG19 as classification networks without comparing different CNN models. They get an accuracy of 0.6923, which is too low for clinical use.

Xiong et al. [16] built a CNN model named tuberculosis AI (TB-AI) to recognize TB bacillus. They achieve 97.94% sensitivity and 83.65% specificity. TB bacillus is the classification object in this work, so this approach could help doctors distinguish what they see in the microscope. But, the training set consists of only 45 samples, with 30 positive and 15 negative examples. More training examples appear to be more beneficial.

2.3.2 QUANTUM IMAGE REPRESENTATION

Quantum computing has entered the era of NISQ (Noisy Intermediate Scale Quantum)and is assumed to be ready to show supremacy in some application areas. Image processing is one such field.

Quantum image processing (QIP) involves exploiting quantum properties to represent, manipulate, and compress images in a quantum computer [18].

In the following section, we discuss some quantum image representation techniques.

2.3.2.1 QUBIT LATTICE

This is the first quantum image format and was proposed by Venegas-Andraca [19].

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 (4), and the whole image can be represented as a qubit string (equation (5)).

$$|pixel_{i,j}\rangle = \cos\frac{\theta_{i,j}}{2}|0\rangle + \sin\frac{\theta_{i,j}}{2}|1\rangle \qquad (4)$$

$$|image\rangle=\{\ |pixel_{i,j}\rangle\ \}i=1,2,3.....n_1,\ j=1,2,3.....n_2 \ (5)$$

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.

2.3.2.2 REAL KET

This quantum image format was proposed by Latorre[20].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 pixelswas obtained. These four pixel's grayscale values are mapped to the probability amplitude of every component of a quantum state with 2 qubits.

Equation (6) 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$\sum_{i_1=1,2,..4}|C_{i_1}|^2 = 1$.

$$|\psi_{2^1 x 2^1}\rangle = \sum_{i_1=1,2,..4} C_{i_1}|i_1\rangle \text{ such that } \sum_{i_1=1,2,..4}|C_{i_1}|^2 = 1(6)$$

2.3.2.3 FRQI

Le et al. [21] proposed the Flexible Representation of Quantum Images (FRQI) proposed 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 (7) 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.

$$|pixel_i\rangle = \cos\theta i|0\rangle + \sin\theta i|1\rangle$$

$$|image\rangle = \frac{1}{2^n}\sum_{i=0}^{2^{2n}-1}(\cos\theta i|0\rangle + \sin\theta i|1\rangle) \otimes |i\rangle \theta i \in [0, \frac{\pi}{2},] \qquad (7)$$

2.3.2.4 NEQR

A novel enhanced quantum representation (NEQR) for digital images proposed by Zhang et al.[22] 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⟩. If XY denotes the two n-bit values of the pixel location, thenC^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.

2.3.2.5 2-D QSNA

This approach was proposed by Madhur et al.[23] 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

2.3.3 RELATED WORKS ON QUANTUM MACHINE LEARNING FOR IMAGE CLASSIFICATION PROBLEM

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

In [24], 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 [25]. 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 [26], 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 implementationand a need for a higher number of qubits needed 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 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 either can benefit from quantum phenomena, is classically intractable, or both to a quantum computer.

In [27], 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 [28]; that is, quantum transformations feeding into a linear model could give a performance enhancement over linear models built on the data directly.

In [29], 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 CXR images. This approach is based on the works done in [20] by Henderson et al.

In [36], 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 [30],detection of COVID-19 from CT images using the quantum transfer learning methodis 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 advantageousin classification in the case of smaller datasets compared to traditional machine learning due to the superior properties of quantum.

In [31],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 [32],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.

CHAPTER 3: METHODS ANDMETHODOLOGY

The present work focuses on the hybrid quantum-classical approach, specifically the quantum convolutional neural network proposed by Henderson et al. [27]. This section provides a theoretical foundation of classical CNN and the hybrid quantum CNN.

3.1 CONVOLUTIONAL NEURAL NETWORK

CNN is a specific neural network that has shown remarkable success,particularly for computer vision applications. Though introduced by Yann LeCun in the 1980s, CNNs gained popularity when AlexNet won the ImageNet computer vision contest in 2012.

ARCHITECTURE

A CNN comprises three main operations: Convolution operation, most often followed by an Activation Function, and Pooling operation.In the end,some Fully Connected layers act as the classifier. These layers can be compiled and stacked in any order.

Convolution Operation: Image (a 2-D matrix)is convolved by a set of filters called kernels. A convolution by a single kernel can be seen as a feature detector.The kernel will go over all regions of the input and perform a convolution operation which is the element-wise multiplication of the kernel and the image.

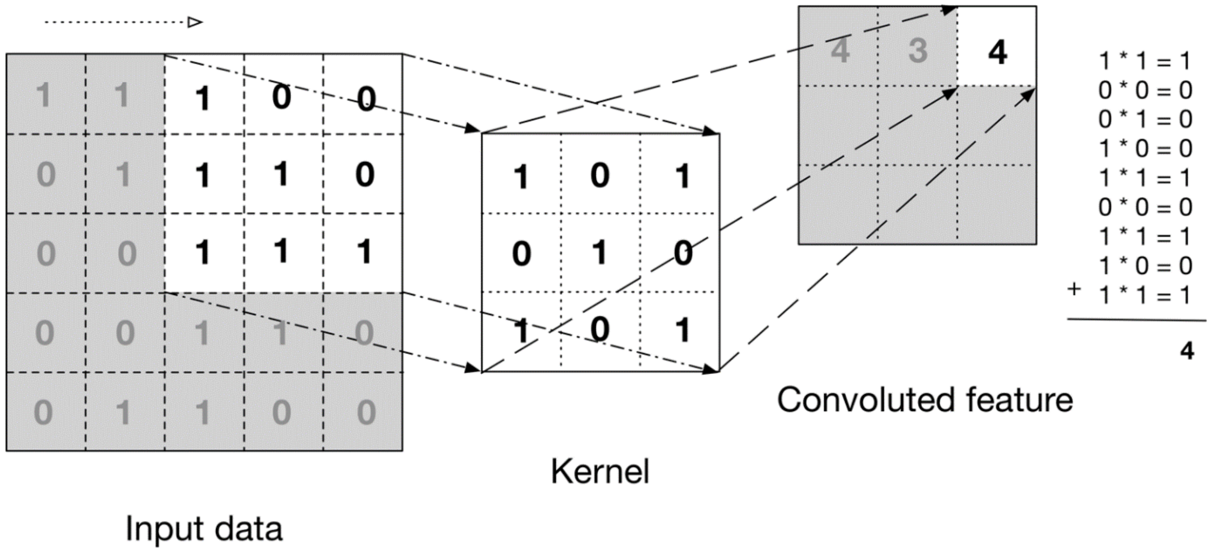


Figure 6: Convolution Operation [Image:33]

If the feature represented by the kernel,for instance, a vertical edge is present in some part of the input, there will be a high value at the corresponding position of the output.

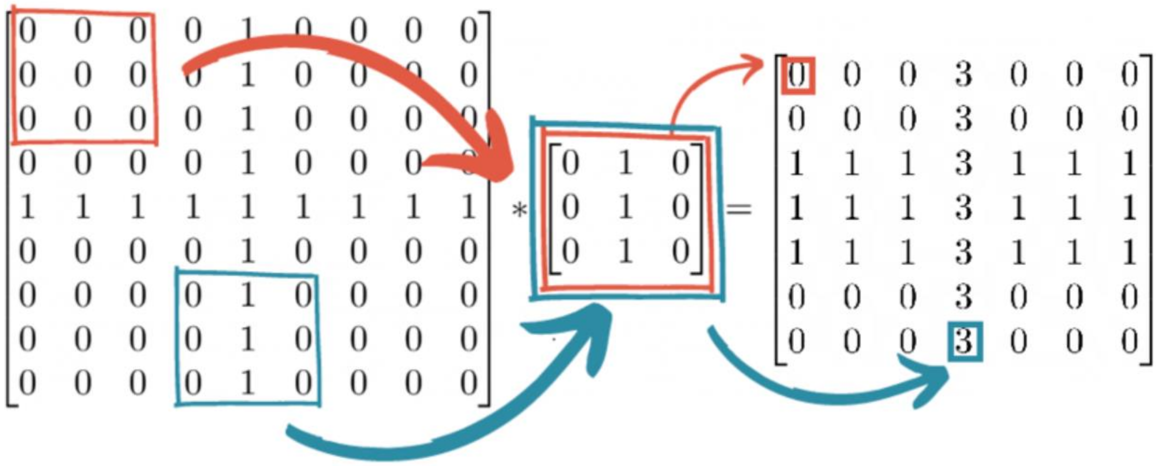


Figure 7: Convolution Operation [Image:34]

In Fig 7, the kernel is a vertical edge detector.For the parts of the original image which contained a vertical line as represented by a blue box, the kernel has returned a value of 3, whereas it has returned a value of 1 for the horizontal line and 0 for the empty areas of the image as represented by a red box.

The output obtained after a convolution is commonly called the feature map.

Activation Function: Activation functions are added to insert some non-linearity. These are mandatory for a neural network to learn any function. For CNN, each convolution is often followed by a Rectified Linear Unit function or ReLu. This is a simple function that puts all negative values of the output to zero and lets the positive values as they are.

Pooling Layer: This down-sampling technique reduces the dimensionality of the output obtained from the convolutional layer to improve the computation. Moreover,the CNN gets the ability to learn a representation that is invariant to small translations. Most of the time, a Maximum Pooling or an Average Pooling is applied.MaxPooling consists of replacing a subregion of P × P elements only with the one with the maximum value. Average Pooling does the same by averaging all values.

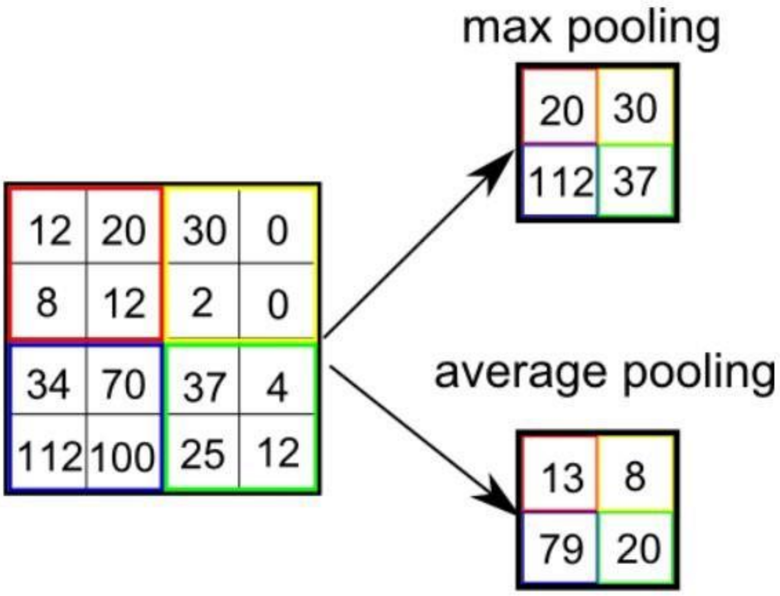


Figure 8: Pooling Operation [Image:33]

Fully Connected Layer: After applying a certain number of convolution layers, the input has been sufficiently processed.A Fully connected network is applied at the end. Weights connect each input to output, where inputs are all elements of the previous layer. In case of an image classification problem, the fully connected layer acts as a classifier, and this network's last layer should have one node per possible label. Each node value can be interpreted as the probability of the initial image belonging to the corresponding class.

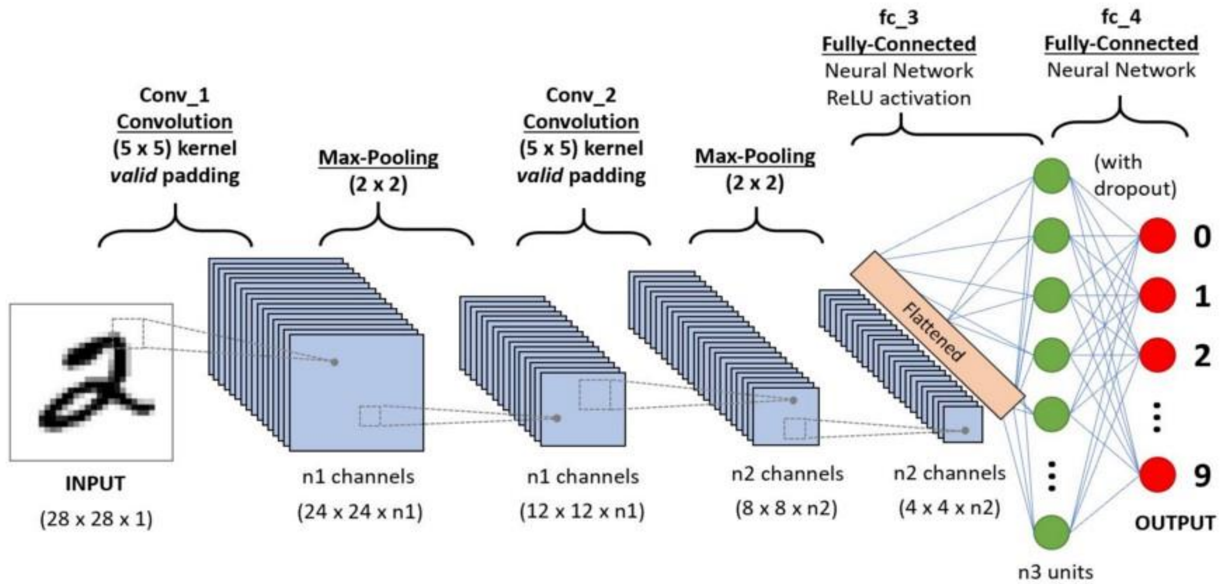


Figure 9: Neural Network for classifying handwritten digits of MNIST dataset [Image: 33]

3.2 HYBRID QUANTUM-CONVOLUTIONAL NEURAL NETWORK

As mentioned earlier, the present work follows the hybrid quantum-classical approach proposed by Henderson et al.[27].The authors of [27] 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 spatialfeatures 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⟩.

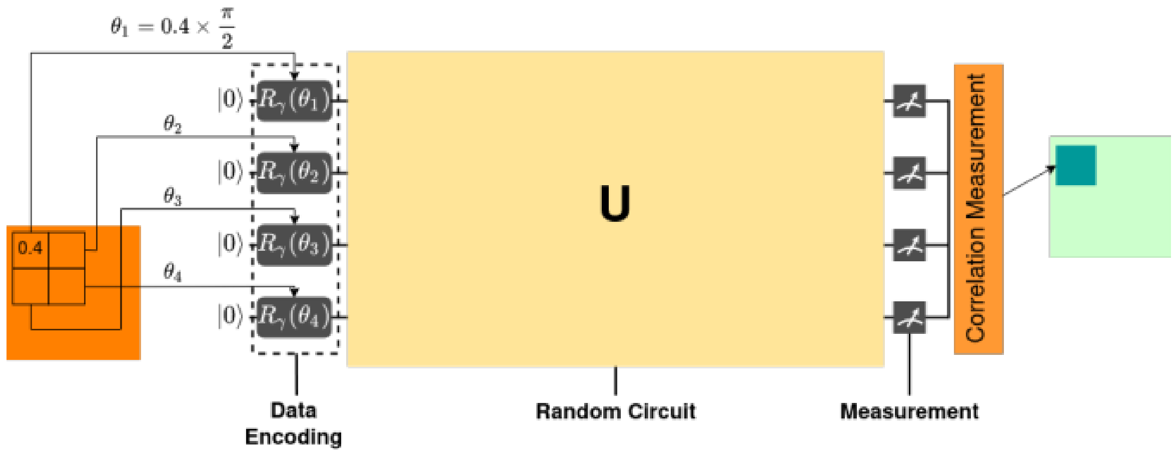


Figure 10: The random quantum convolutional layer. [Image:35]

Another encoding method was taken by Mari [36]. As shown in Fig. 10, 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 encodingis 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 gatesand then measured.

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

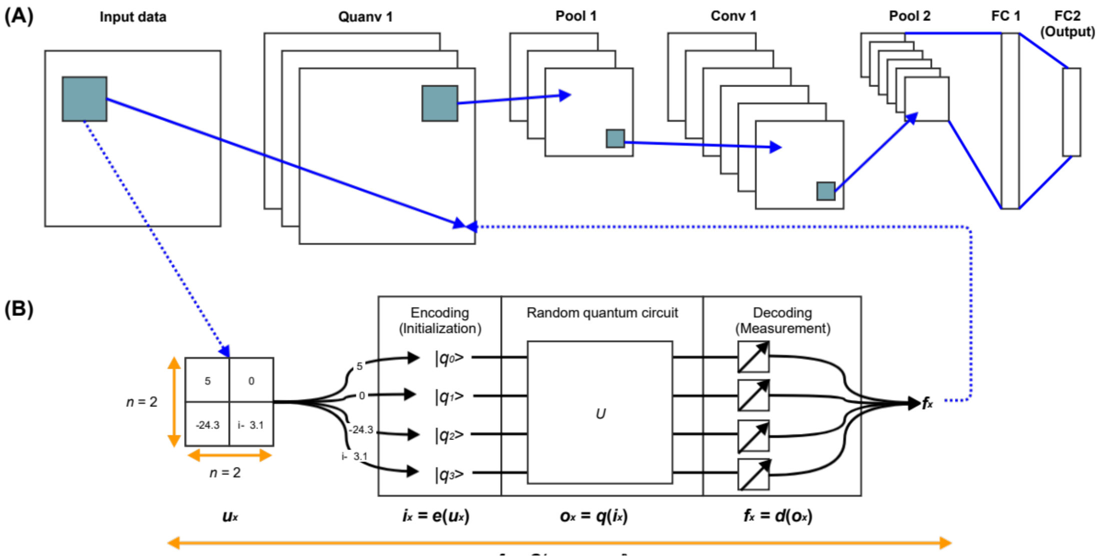


Figure 11: Schematic illustration of Quanvolutional Neural Network proposed by Henderson et al. [Image: 27]

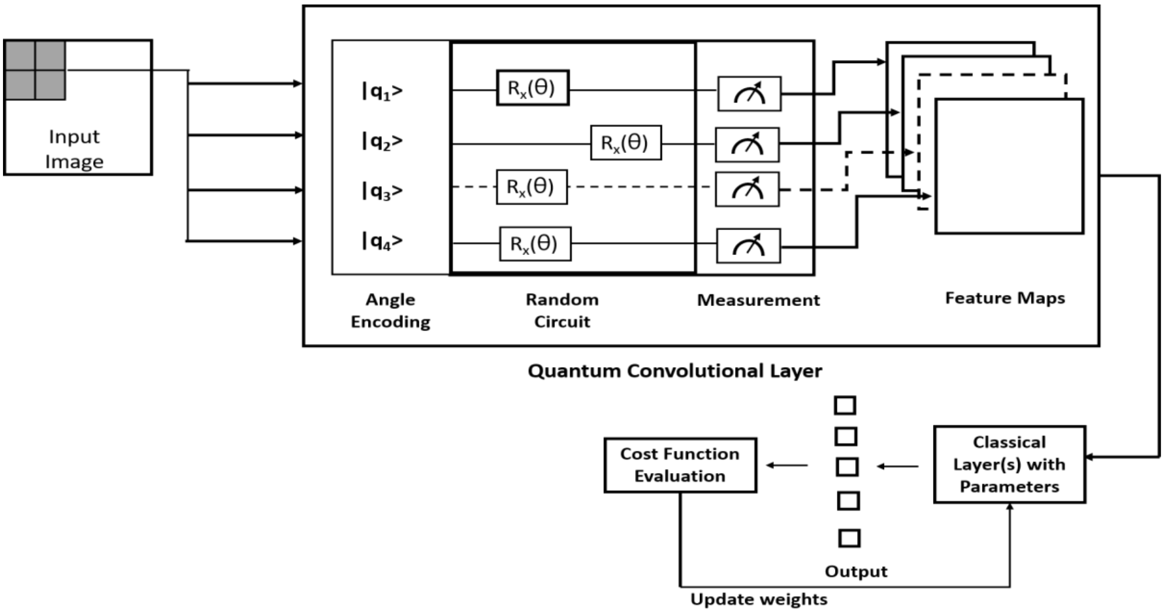


Figure 12: Schematic illustration of Quanvolutional Neural Network proposed by Mari.

CHAPTER 4: PROPOSEDAPPROACH WITH RESULT AND DISCUSSION

4.1 PROPOSED MODEL

This work combines the advantage of the ‘quanvolutional neural networks (QNNs)’[27]with CNNs and proposes an implementationof 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 [22] for encoding the pixel values in the quantum state, which is different from threshold encoding as proposed in [27] and angle encoding as proposed in [36].

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 [22] 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.

Details about each of the above components are given in the next section.

4.1.1 IMPLEMENTATION DETAILS

The implementation follows the implementation of Mari[36] in that the measured values of the qubits are written in a separate layer of the feature map.

Fig.13 shows the steps followed while training the model and the detailed architecture. It is important to note that the input images are converted to grayscale and resized to (28 X 28 X 1).

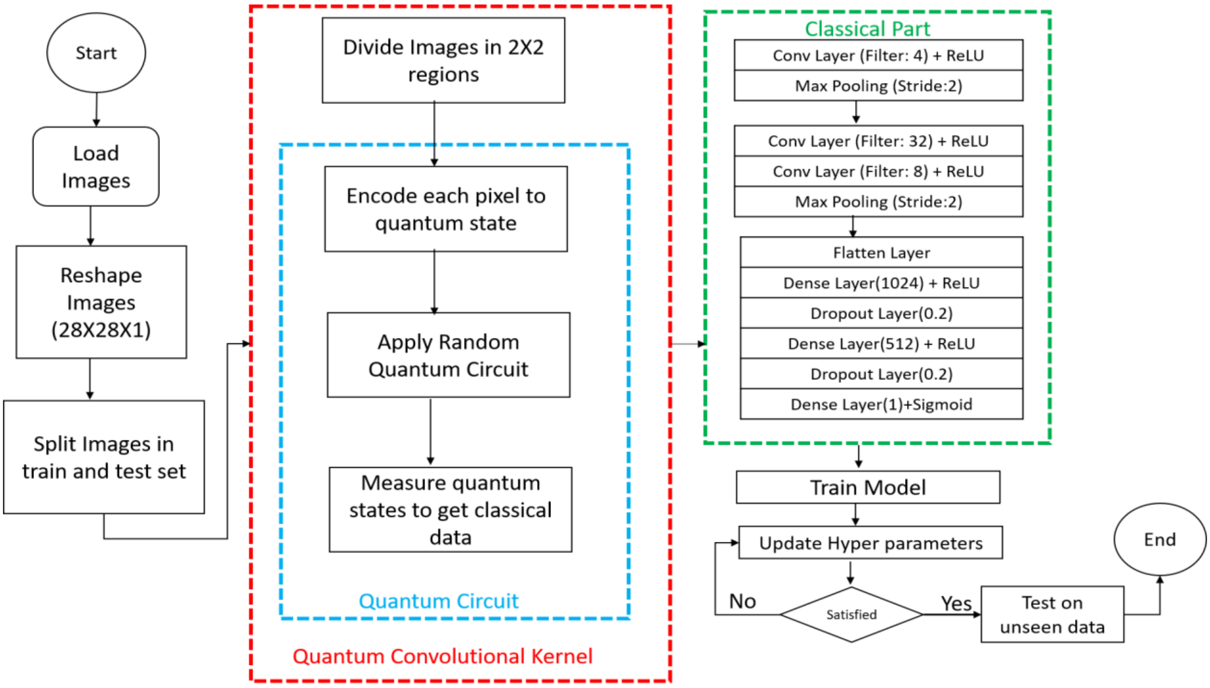


Figure 13: Flowchart of the proposed model

The model consists of four layers, as shown in Fig 14. The first one is the quanvolutional layer,followed by two classical convolutional layers with max-pooling, and lastly, the fully connected layer, followed by the output layer.

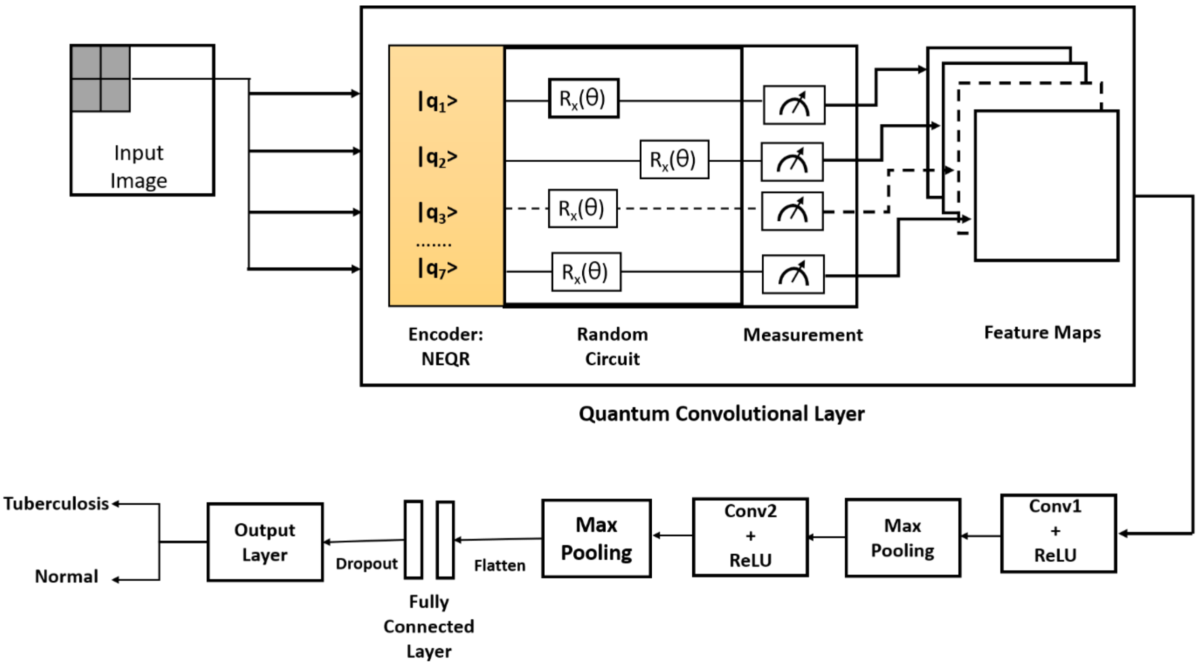


Figure 14: Schematic illustration of Proposed Model

The steps followed in each layer are explained below:

QUANVOLUTIONAL LAYER

Here, every image patch of size (2X2) from the input image is encoded using NEQR[22] 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.

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.

Suppose, the pixel value is '01100100' then the NEQR encoding circuit would be as shown in Fig. 15. This particular circuit has reversed the value so $intensity_0=0$, $intensity_1=0$, $intensity_2=1$, $intensity_3=0$, $intensity_4=0$, $intensity_5=1$, $intensity_6=1$, $intensity_7=0$.

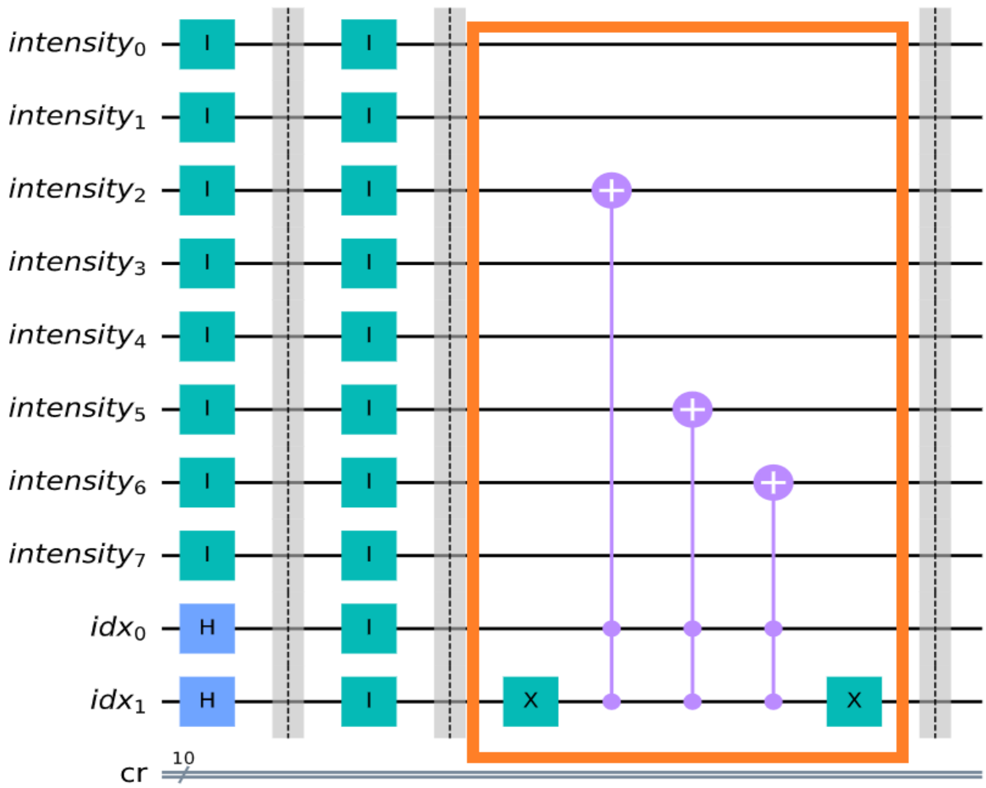


Figure 15: NEQR circuit showing the encoding '01100100' (Region marked in orange color) as obtained from qiskit.

Random Quantum Circuit

This 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.

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 CONVOLUTIONAL LAYERS

The next two layers are the classical convolutional layers with a 2X2 kernel followed by ReLU activation. The first one 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.

Figure 16: Input image and the feature maps produced by quantum convolutional layer.

4.1.2 DATASET

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.

4.2 EXPERIMENTAL RESULT

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. Out of 200 cases of TB,163 were correctly classified (True positive),and out of 200 Normal cases,173 were correctly classified (True Negative). 37 Tuberculosis cases were misclassified as Normal(False Negative), while 27 Normal cases were misclassified as Tuberculosis(False Positive).

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

Figure 17: 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[36]), 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. 20, which shows the classification results in accuracy and loss of the training and validation data using the hybrid quantum convolutional method with 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.

Some of the test case outputs of the proposed model are shown in Fig 18.

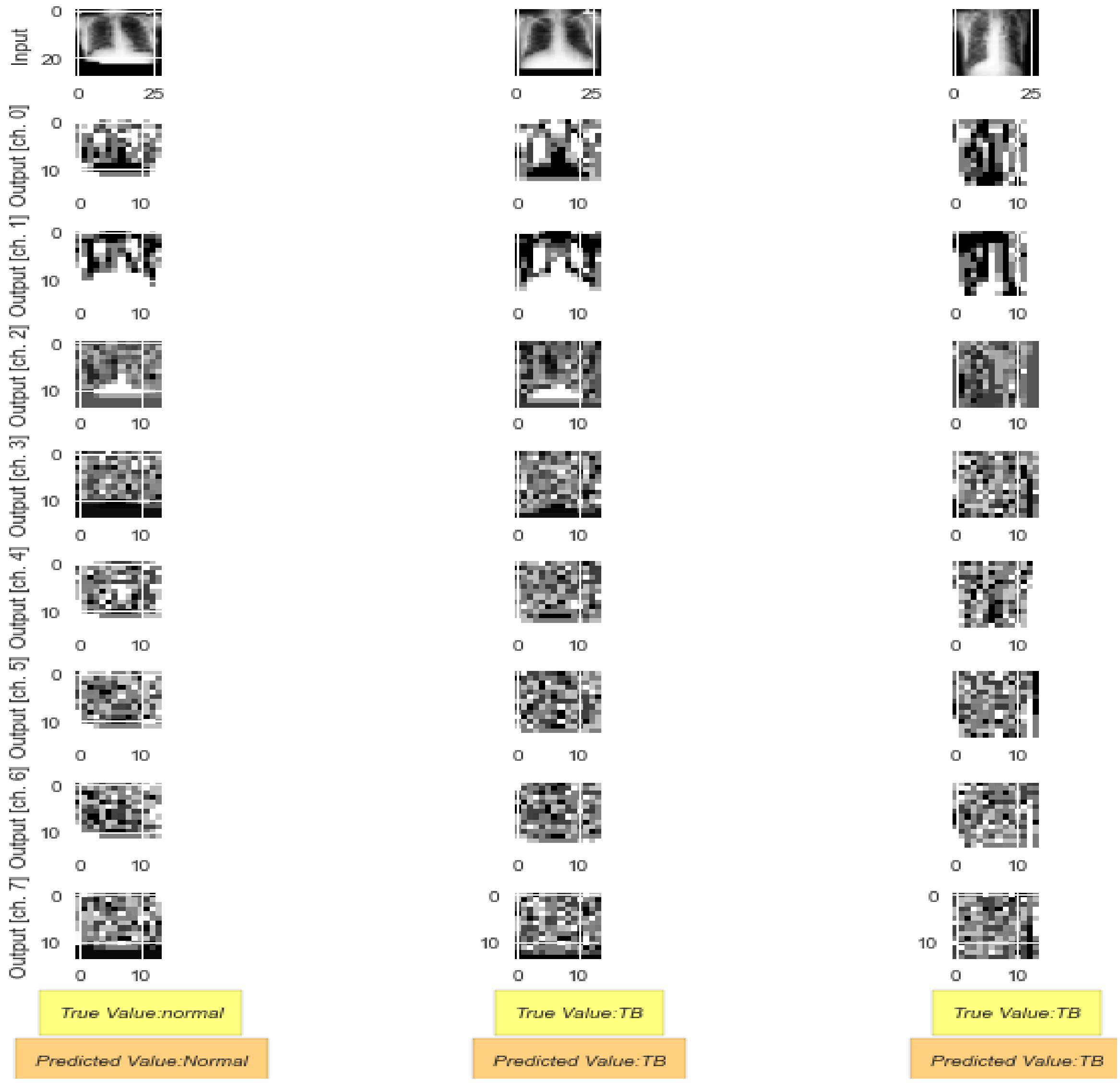
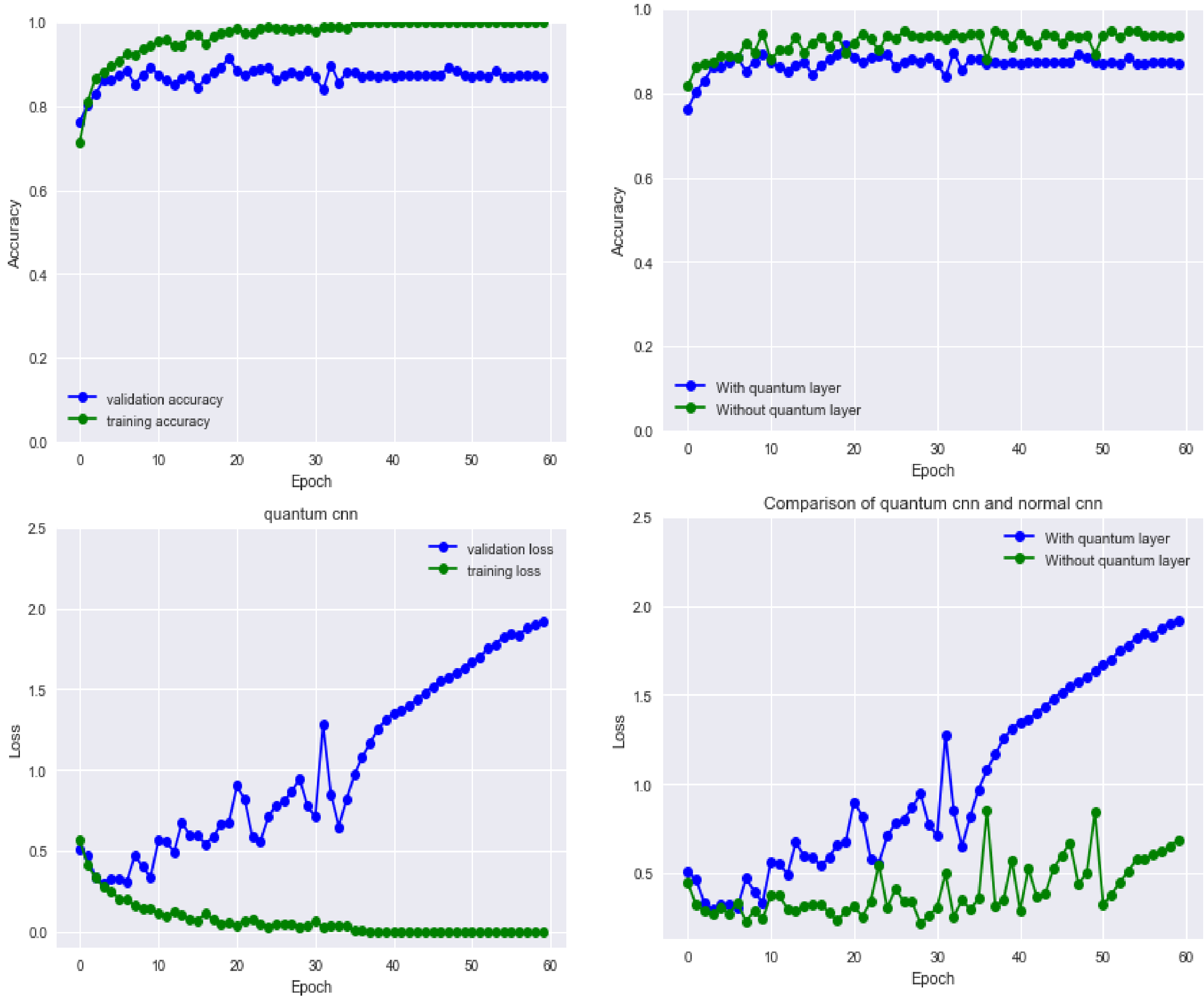


Figure 18: Prediction outputs of the model.

The results obtained for the proposed model are shown in Fig. 19. Fig 19 (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 19 (B) compares the quantum and the classical CNN.



(A) (B)

Figure 19 : Results for the proposed Hybrid Quantum CNN on the mentioned dataset.

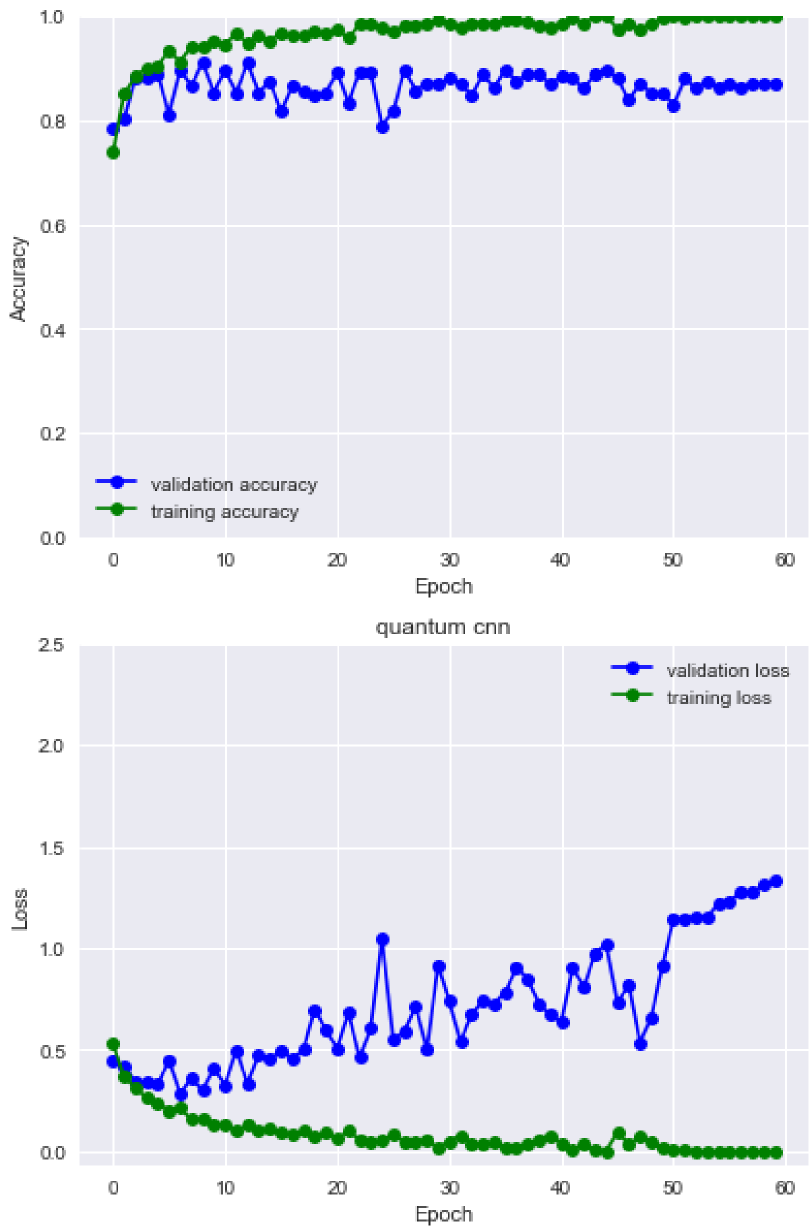


Figure 20: Results for the Hybrid Quantum CNN on the mentioned dataset using angle encoding

4.3 DISCUSSION

The results show that NEQR image encoding produced similar accuracy to angle encoding on the same dataset (Fig. 19, Fig. 20).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. 19 B) show that Classical CNN outperformed the hybrid quantum CNN. This contradicts the results obtained in [27] and [29]. 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. Also,the size of the training setmight have affected the results.

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.

CHAPTER 5: CONCLUSION

This work studied the fundamental concepts of quantum computing, its implications and applications specific to image classification problems.

A binary classification problem of detecting Tuberculosis from chest radiographs was taken as a use case, and a hybrid quantum-classical CNN model with NEQR image encoding has been proposed. The model combines traditional CNN witha quantum convolution layer implemented using the random quantum circuit.

A comparison between the angle encoding scheme by Mari[36] and the proposed approach showed similar validation accuracy on training.

Though results obtained in this work contradicted that the quantum-CNN would provide better accuracy than traditional CNN, it still provided an acceptable accuracy of 84% on 400 test samples with a precision of 85.7% and recall of 81.5%.

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:

a. Multiple quantum convolution layers
b. Making the weights of the random circuit trainable
c. Applying transfer-learning using pre-trained CNN

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