Analytical Estimation of Quantum Convolutional Neural Network and Convolutional Neural Network for Breast Cancer Detection

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Abstract:- Experts predict that the use of artificial intelligence and quantum computing will transform medicine including medical imaging. One of the common malignant tumors in women and seriously threatens women's physical and mental health is breast cancer. The high incidence and mortality of breast cancer are seriously threatening women's physical and mental health. The long time it took to get breast cancer's test result and the conditions which make delay without being treated which caused the loss of lives due to latency. Early screening for breast cancer *via* mammography, ultrasound (US) and magnetic resonance imaging (MRI) can significantly improve the prognosis of patients. Artificial intelligence has been extensively researched for breast cancer screening and has demonstrated good performance in image identification tests. This research was introduced analytical estimation for quantum Convolutional Neural Network for breast cancer detection, such as in the identification, segmentation and classification of lesions, breast density assessment and breast cancer risk assessment. Objectives will be to: To detect the breast cancer on a quantum convolutional neural network algorithm using image recognition, to create and develop a CNN and QCNN algorithm that will detect breast Cancer using Deep Learning and to early predict pathological complete response to neoadjuvant chemotherapy and survival analysis using Deep Learning. Data was analyzed through the use of descriptive and deep learning models like CNN and QCNN models. This research used also Google Collab to analyze the data and used data analysis tools python as programming language. From the study results, we have demonstrated the efficacy of quantum convolutional neural networks (QCNNs) to detect breast cancer cells. Using the techniques of deep learning and supervised learning in the quantum framework, we have proposed and tested the effectiveness of quantum CNN on the quantum simulator available at the IBM quantum experience platform.

Keywords:- *Quantum Computing, Artificial Intelligence, Machine Learning, Deep Learning, Breast Cancer Detection, Medical Imaging.*

I. INTRODUCTION

One of the main causes of death for women and a serious public health issue is breast cancer. The definition of artificial intelligence (AI), according to this definition, is "a system's capacity to appropriately interpret external data, to learn from such data, and to use those learnings to fulfill specific goals and tasks through flexible adaptation." The exponential rise of computer functions linked to large data penetration during the previous 50 years has pushed AI applications into new areas. Currently, Artificial Intelligence can be found in voice recognition, face recognition, driverless cars and other new technologies, and the application of Artificial Intelligence and Quantum Computing in medical imaging have gradually become an important topic of research. Deep learning (DL) algorithms, in particular, have made significant strides in image identification tasks. We will attempt to build a quantum convolutional neural network models, exhibiting the use of several algorithms to handle the data set. Deep neural networks offer a wide range of applications, and we have focused on breast cancer detection. Artificial Intelligence has made great contributions to early detection, disease evaluation and treatment response assessments in the field of medical image analysis for diseases like pancreatic cancer , liver disease , breast cancer , chest disease and neurological tumors.

II. METHODOLOGY

- *Data Analysis*

The process of discovering solutions through investigation and interpretation is known as data analysis. Understanding survey and administrative source results and presenting data information require data analysis. Data analysis is anticipated to provide light on the subject of the study and the respondents' perceptions, as well as to increase readers' understanding of the subject and pique their interest in this portion of the research. Google Collab will be used to analyze the data and present the results using data analysis tools used in scientific analysis. (Burns, 2022)

Deep learning has an advantage over conventional data processing techniques, coupled with supervised and unsupervised learning. The architecture of a neural network is what these methods produce. These artificial neural networks aid the system in learning data handling thanks to their layered nature. The training data, also known as the input set of data, contains some label values. After that, it is processed through the network's layers so that the output label produced is quite near to the real label. Then, this fundamental foundation is expanded to include applications for speech recognition, text classification, image and pattern recognition, and many others.

➢ *Convolutional Neural Networks model (CNN)*

CNNs are the one of the best algorithms in regard to image content identification and have shown exemplary performance in several tasks. Its complexity is one of its major drawbacks, though. Since features end up collecting and recombining as we move deeper into a neural network, the more complex features it can recognize. When training models that need detailed images as input, like mammograms, speeding up these networks can make a significant difference.. (Huang et al. 2017).

- *Process CNN*

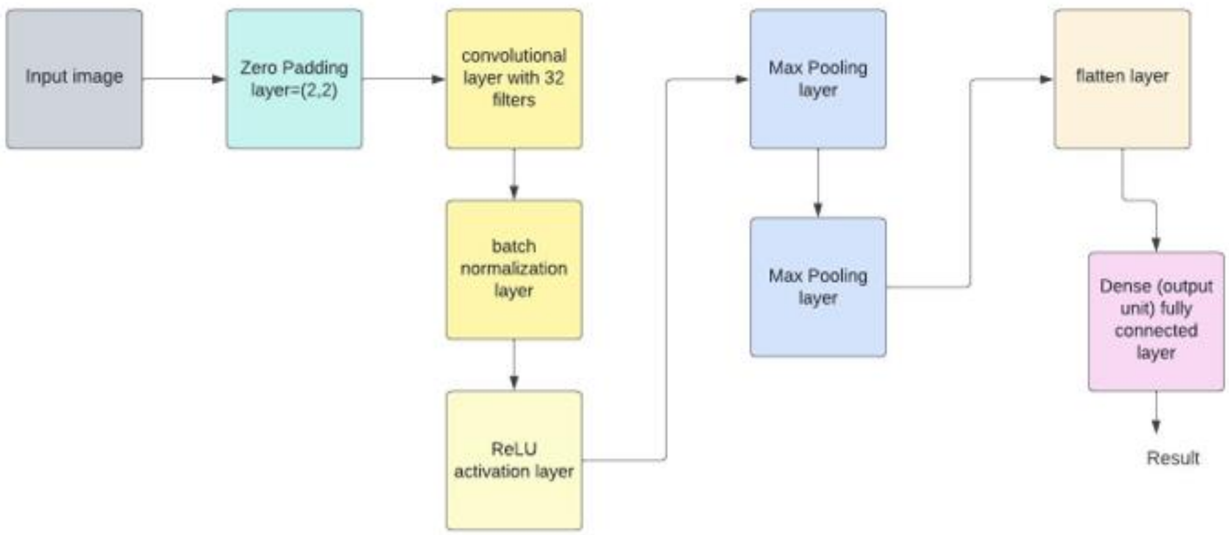

Fig 1 Source: My Own Design, 2022

- *Helper Functions*
- ✓ import numpy as np
- ✓ import pandas as pd
- ✓ import os
- ✓ from os import listdir
- ✓ import tensorflow as tf
- ✓ from keras.preprocessing.image import ImageDataGeneratorimport cv2
- ✓ import matplotlib.pyplot as plt
- ✓ %matplotlib inline
- ✓ import imutils
- ✓ from tensorflow.keras.models import Model,load_model
- ✓ from tensorflow.keras.layers import
- ✓ Conv2D,Input,ZeroPadding2D,BatchNormalization,Flatten,Activation,Dense,MaxPooling2D
- ✓ from sklearn.model_selection import train_test_split
- ✓ from sklearn.utils import shuffle #shuffling the data improves the model

➢ *Quantum Convolutional Neural Networks model (QCNN):*

In quantum computing (QC), we deal with quantum bits, where 0 and 1 can overlap in time, rather than binary digits (bits). The two potential states for the qubit (unit of quantum information) are |0〉 and |1〉 . In the context of QC, the Hilbert space is an abstract vector space that permits, for instance, a quantum superposition, or the simultaneous existence of multiple states in a physical system. Deep learning and quantum computing have made considerable strides in the recent few decades. Huge volumes of data are currently being produced, which is boosting interest in research at the intersection of the two domains and resulting in the creation of quantum deep learning and quantum-inspired deep learning methods. The following subject is determined by Schuld's description. (Schuld, 2018).

➢ *Build a QCNN*

- *Assemble circuits in a TensorFlow graph:*

TensorFlow Quantum (TFQ) provides layer classes designed for in-graph circuit construction. One example is the tfq.layers.AddCircuit layer that inherits from tf.keras.Layer. This layer can either prepend or append to the input batch of circuits, as shown in the following figure.

- *The Following Snippet Uses this Layer:*

```
qubit=cirq.GridQubit(0,0)

#Define some circuits.
circuit1 = cirq.Circuit(cirq.X(qubit))
circuit2 = cirq.Circuit(cirq.H(qubit))
```

```
# Convert to a tensor.
input_circuit_tensor = tfq.convert_to_tensor([circuit1, circuit2])

# Define a circuit that we want to append
y_circuit = cirq.Circuit(cirq.Y(qubit))
# Instantiate our layer
y_appender = tfq.layers.AddCircuit()


# Run our circuit tensor through the layer and save the output.
output_circuit_tensor = y_appender(input_circuit_tensor, append=y_circuit)
```

Examine the input tensor:

```
print(tfq.from_tensor(input_circuit_tensor))
[cirq.Circuit([
    cirq.Moment(
        cirq.X(cirq.GridQubit(0, 0)),
    ),
 ])
 cirq.Circuit([
    cirq.Moment(
        cirq.H(cirq.GridQubit(0, 0)),
    ),
 ])
                    ]
```

And examine the output tensor:

```
print(tfq.from_tensor(output_circuit_tensor))
[cirq.Circuit([
    cirq.Moment(
        cirq.X(cirq.GridQubit(0, 0)),
    ),
    cirq.Moment(
        cirq.Y(cirq.GridQubit(0, 0)),
    ),
 ])
 cirq.Circuit([
    cirq.Moment(
        cirq.H(cirq.GridQubit(0, 0)),
    ),
    cirq.Moment(
        cirq.Y(cirq.GridQubit(0, 0)),
    ),
 ])                     ]
```

While it is possible to run the examples below without using tfq.layers.AddCircuit, it's a good opportunity to understand how complex functionality can be embedded into TensorFlow compute graphs.

- *Process of Image Recognition:*

Demonstrating the idea of using image recognition as a tool to detect the disease on a quantum convolutional neural network. Background: The process of detection of a disease such as breast cancer can be carried out through the method of image recognition. The image is analysed as a gray scale 2-dimensional matrix, whose cell value corresponds to relative brightness. The quantum setting of the process: The process of image recognition is based on the grey scale data of the image. The system assigns values to each pixel, ranging from 0 to 1 based on its brightness. These values are then fed as the input training set in the form of an array. We also input the true label (whether the cell is cancerous or not) for the image in the training stage, which is either 0 or 1. The network is then trained to find the label value of the input set.

This will be a value between 0 and 1, and the error is calculated based on its deviation from the true label. We collect the data set on images from Kanombe Military Hospital, which consist of the MRI images of the cells. The process involves entering the pixel matrix as the input to the neural network. In theory, we may consider such a system to be built. However,for a reasonably high resolution image, the size of the matrix is too large to be given as input to the currently available quantum simulator circuit. As a test of a modified system, we chose a 4×4 matrix of pixels from the image and enter it as the dataset. The training parameter is thus calculated which gives the minimum error or loss. To minimize the loss function, we have implemented the optimization algorithm like variational quantum eigensolver (VQE).

We are able to determine the training parameter which gives the minimum error while calculating the label function. The parameters are thus chosen which are optimal to the given problem.

- *Data Set Containing of Information on Cell Features:*

The detection of breast cancer in early stages has been done by studying subtle morphological changes due to broken collagen fibers for disease progression. The MRI cell dataset of KMH Breast Cancer consists of features of lumps on the patient’s breast, such as, radius, roughness, concavity, and so on.

The data was taken from KMH, is where the data was obtained. Implementing a QCNN, we use the data containing details on the size, radius, etc. of the damaged cell to determine whether the subject has breast cancer. This technique benefits from a lower initial data collection and can be used with simulators that are currently in use.

III. ARCHITECTURE OF QCNN

Neural networks may be implemented in quantum computers by treating the qubits as neurons. We act on neurons with rotation gates which have parameters, which are then optimized in our model. The inputs are implemented as initial rotations on each qubit. The operational block diagrams of classical Convolutional Neural Network (CNN) and Quantum Convolutional Neural Network (QCNN), on breast cell samples are shown in Figure 2 and 3. Let us make a comparison based on the equivalence between CNN and QCNN to understand the structure of the QCNN circuit. (Bikash K. Behera, 2019).

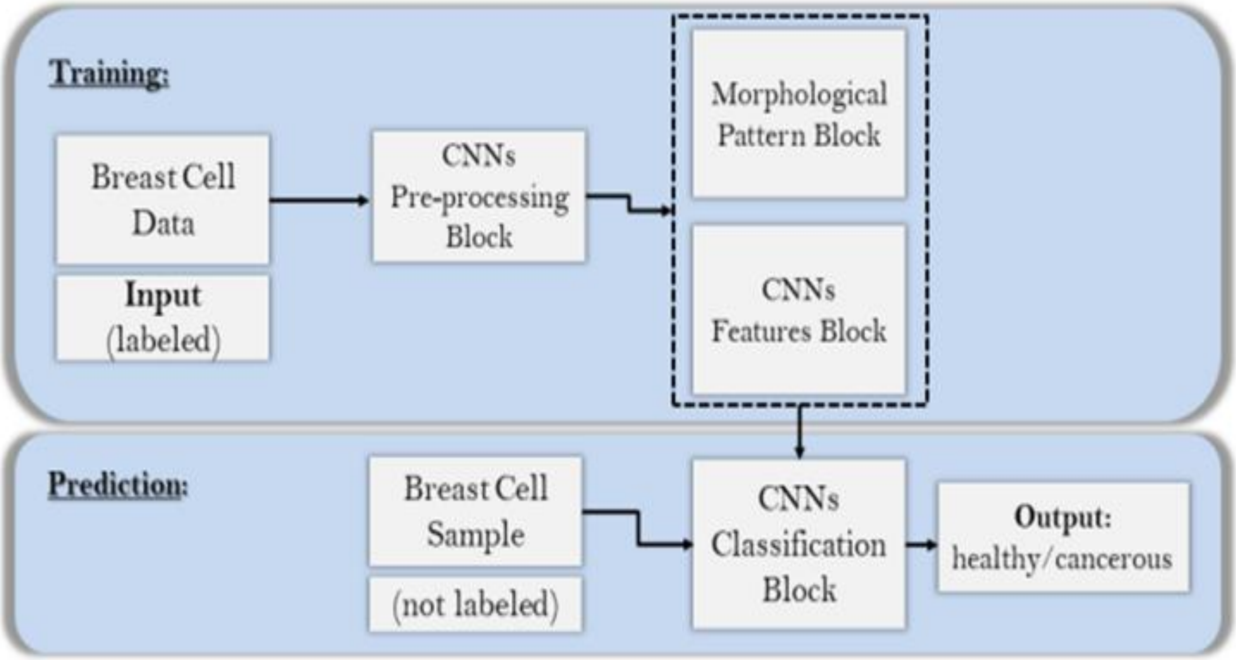

Fig 2 Classical Convolutional Neural Network Based Approach for Breast Cell Sample

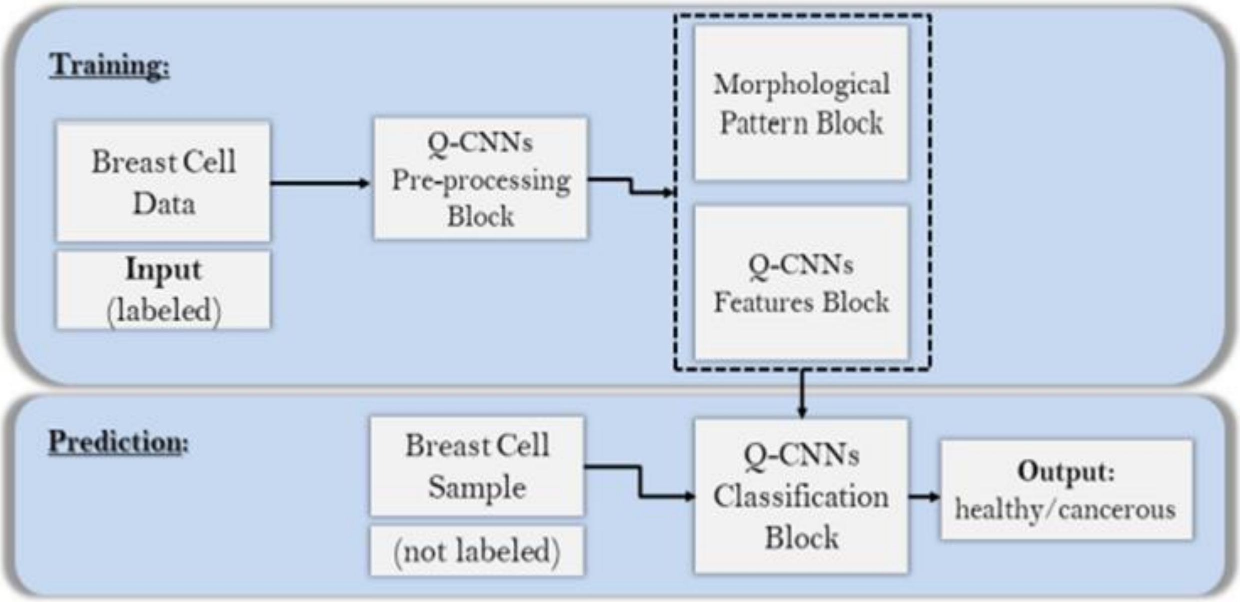

Fig 3 Quantum Convolutional Neural Network Based Approach for Breast Cell Sample

Figure 2) Classical Convolutional Neural Network based approach for breast cell sample. Figure 3) Quantum Convolutional Neural Network based approach for breast cell sample. A quantum convolutional neural network (QCNN), capable of operating on a 10-qubit system, is designed. The designed QCNN is capable of carrying out several algorithms for optimizations. This design helps in obtaining the training vector to calculate the label value of the string given as input. Demonstrating the implementation of the network, we have tried to use the basic principles of deep learning to handle data, for detecting breast cancer.

We have analysed two methods here. First by training the network through the numerical dataset and secondly, tried to utilize the method of image recognition. All the network implementation and simulation of results were carried out on the cloud-based platform provided by IBM.label function. The parameters are thus chosen which are optimal to the given problem.

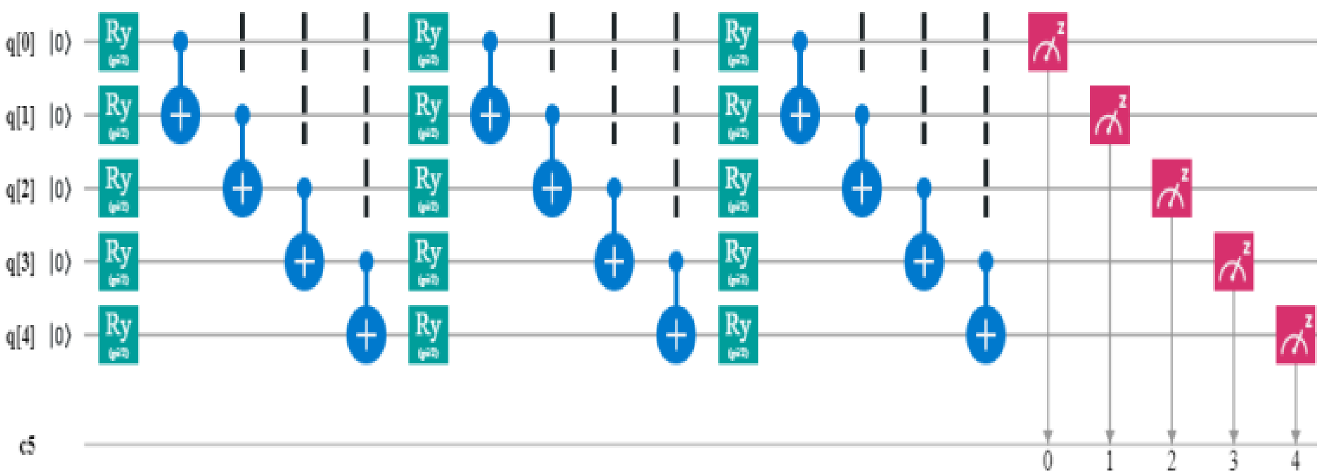

Fig 4 IBMQ System Demonstrating How Partial Entanglement Can be Used to Reduce the Number of Parameters Required in a Quantum Convolutional Neural Network To O(Log(N)).

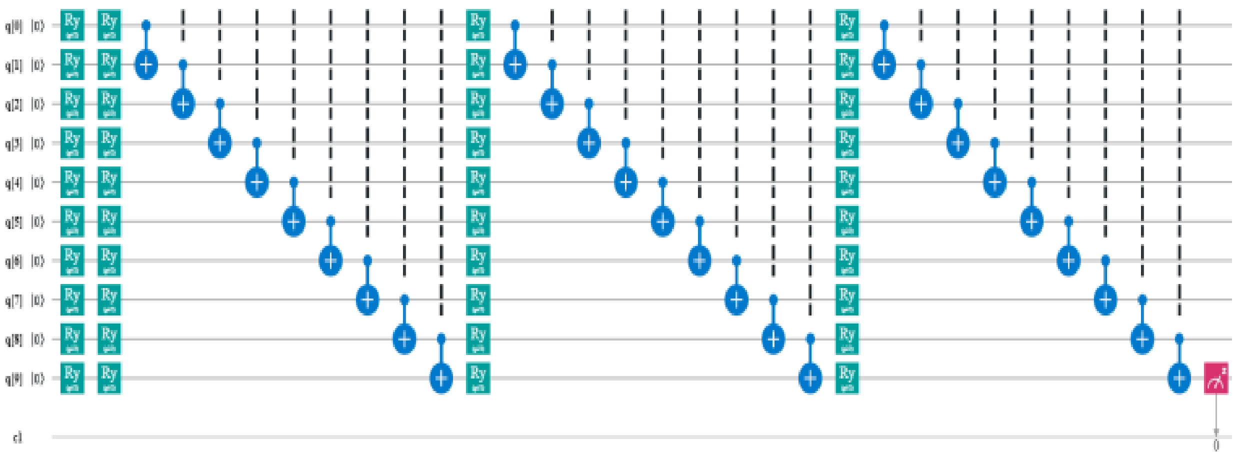

Fig 5 10 Qubits Partially Entangled Quantum Convolutional Neural Network.

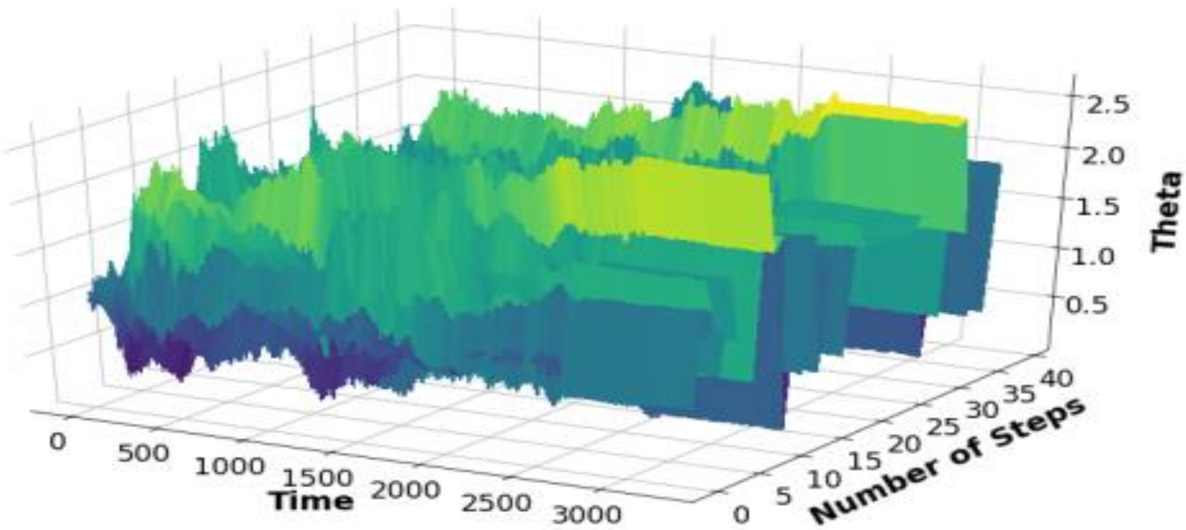

Fig 6 Variation in All Parameters on the Vertical Axis. The X Axis Denotes the Number of Iterations and the Y Axis Depicts the Parameter Index Running from 0 To 40.

- Both CNN and QCNN input data, the first take for example an image to perform computation on it, while the second is a quantum circuit which takes in an unknown quantum state $|\psi\rangle$.
- CNN relies on convolutional layers of image processing, called feature maps, each contains a number of pattern detectors − filters, that calculate new pixel values from the previous map by a linear combination of nearby pixels.

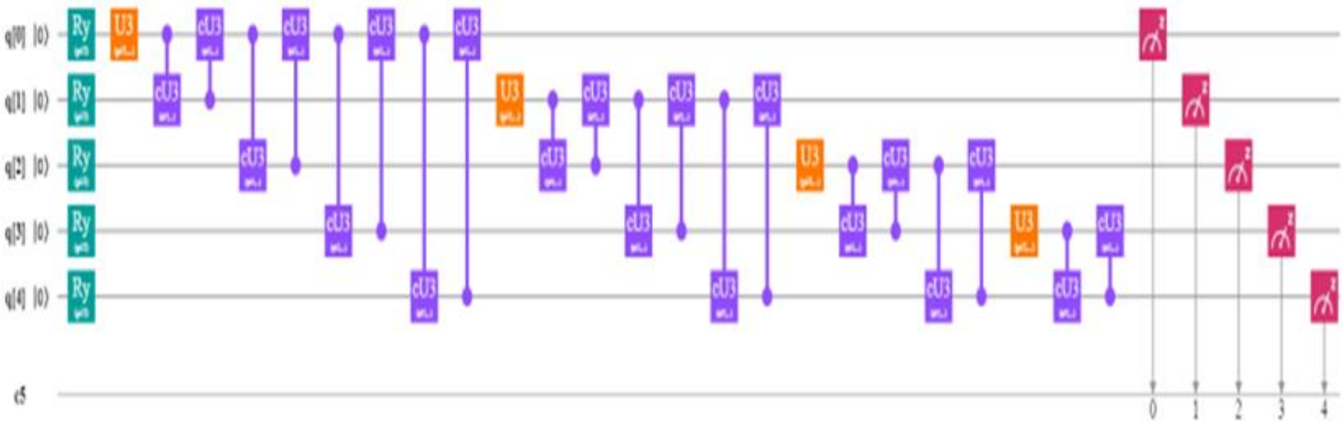

Fig 7 The Maximally Entangled Qubit Network is Represented on IBMQ. This System Scales Up as O(N2) With the Number of Qubits.).

IV. BREAST CANCER DETECTION

We have attempted to use our simplified QCNN to detect breast cancer as per given patient data. However, 256 qubit systems cannot be simulated efficiently on current available systems, and the exercise reduces to one of the theoretical interest for QCNNs. The breast cancer dataset of Wisconsin consists of features of lumps of the patient's breast, e.g., radius, roughness, concavity, etc. We take 10 parameters and assign each to one qubit. The initial Y rotations are set up so that |0i corresponds to the minimum value of the variable and |1i to the maximum. As we only want to determine whether a lump is cancerous or not, we need one output bit so we only measure the last qubit's value. We assign 0 to benign and 1 to malignant stages. The loss function is logarithmic. If l is the obtained label, and 1 is the expected label, loss = −(1 − l) · log(1 − l) − l · log(l) (3) We then compute by varying each parameter one at a time. The parameters are then moved in the direction opposite the gradient, controlled by a learning rate r. As the differences in values become smaller, r is also set to smaller values. p~0 = ~p − r · ∇~ (loss) ∇~ (loss) (4) The data set is of size 600. We first take the whole data set as our training set, and then sample a subset for training, to treat the remaining as test data.

V. RESULT

The simulation is carried out in two ways. The first is a test to fit the parameters to the entire data set. The risk associated to this is the over-fitting to the input set. The loss function over time is shown in Figure 9, and the final loss function over the entire data space is also depicted here. The second method involved training on a subset of the data, consisting of 100 images. After the training, the algorithm is subjected to the entire data set. This method is a more rigorous implementation of deep learning methods. The results are shown in Figure 10, and are extremely accurate considering the size of the training data set.

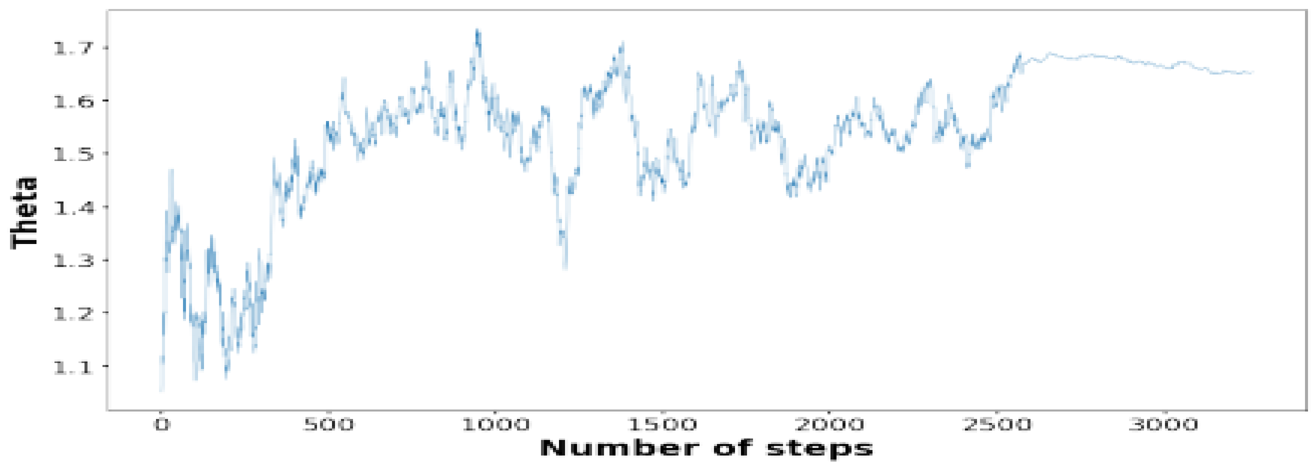

Fig 8 Representative variations of a parameter θ depicted on the y axis vs number of iterations of the simulations on the x axis. Easily visible is the definite upward trend towards a limiting value, and the point where the learning rate is manually decreased

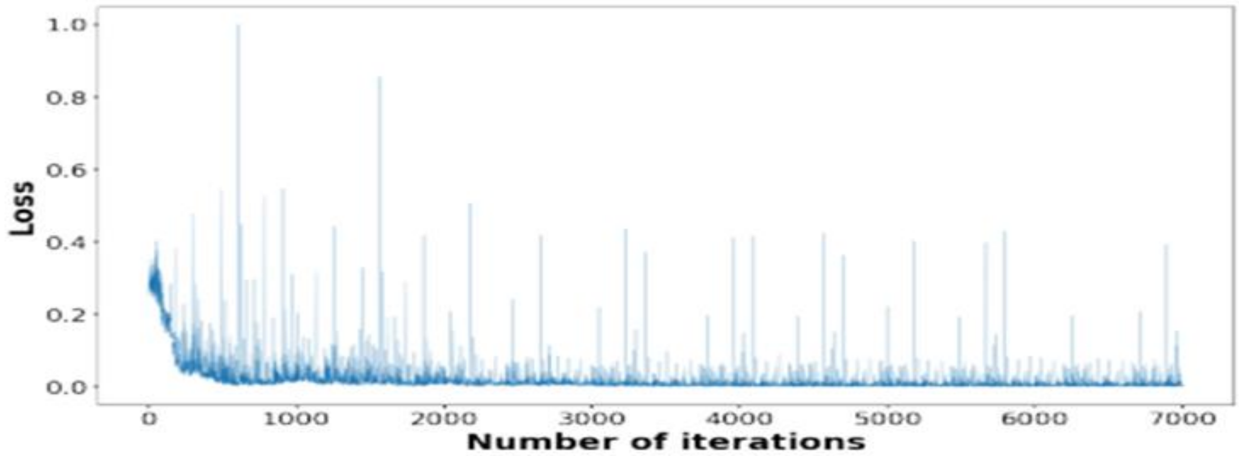

Fig 9 The value of the loss function depicted on the y axis vs the number of simulation iterations on the x axis. The peaks correspond to anomalous data, but the overall decrease is clearly visible.

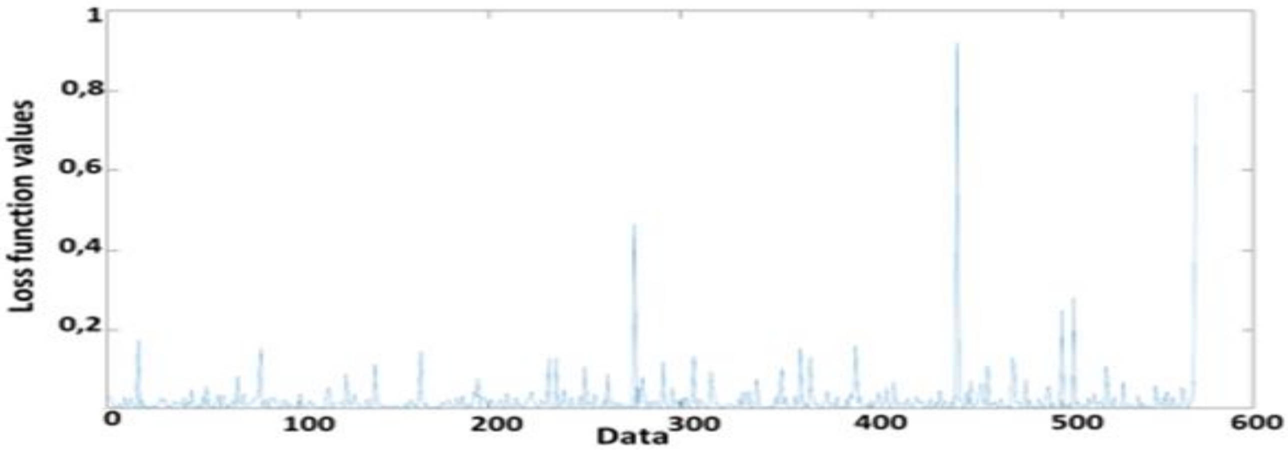

Fig 10 The final result for both training and testing on the entire set. The y axis is the value of the loss function for the parameter set obtained, and the x axis denotes the particular data point in the set.

The variation of the parameters over time is shown in Figure 6 and also depicted one of them as a representative parameter in Figure 8. This the point where the learning rate is manually changed and also can be observed. This is done as an emerging cyclic nature, and a change to the learning rate would disrupt the loop and allow convergence to a higher precision. The loss over most inputs slowly decreased. Some anomalous inputs resulted in wrong answers and excessive losses. The final losses for all 600 inputs are shown in Figure 11. The average loss is 1.4%. To a remarkable precision, the network is sufficiently trained in breast cancer detection.

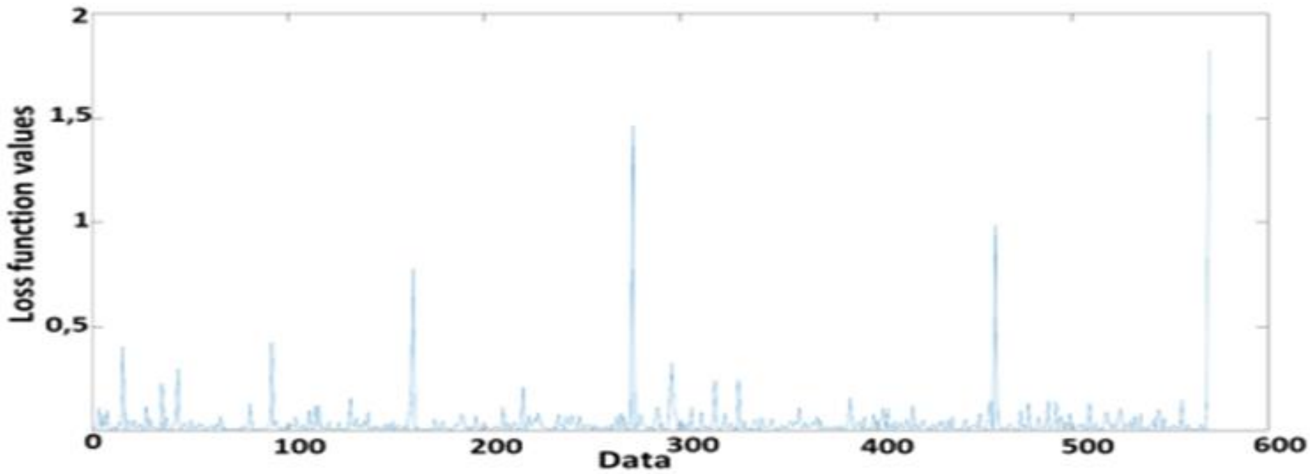

Fig 11 The final result when training is done on the first 100 elements and testing on the entire set. The y axis is the value of the loss function for the parameter set obtained, and the x axis denotes the particular data point in the set.

As we can see in Figure 9, the plot describes the training accuracy versus the number of training steps. Here we remark how the optimization work as expected, and All rights reserved. No reuse allowed without permission. (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. medRxiv preprint doi: https://doi.org/10.1101/2020.06.21.20136655; this version posted June 23, 2020. The copyright holder for this preprint 7 like the classical case, adjusting weight and biases via back-propagation. Relying upon QCNN, this process is carried out with optimizing gates parameters using VQE algorithms where it shows a high performance regarding time complexity and accuracy.

Looking at the Figure 8, we can see that the variations of one parameter from 40 ones in the quantum circuit, where the overall variance is seen in Figure 5. We can mention about one parameter here to explain the general change. A parameter adapting to the optimum value results in the loss function convergence to the ideal value 0 as shown in Figure 9. This is achieved by an angle modification of the qubit, which attempts to shoot the correct value to eventually become stabilized, this process is worked out as follows.

Theta in the figure is a parameter that we have. Depending on how accurate the guess is, we send it an input that produces one. The theta initially varies with a relatively large step size from a starting angle, which is visible in the range between 0 and nearly 2500 on the time axis, where it fluctuates rapidly. After that, we reduce this step (in the gradient function) so it takes less movement and does not over-shoot the desired value and finally, it gets balanced. We can change the parameters in the direction of the maximum (or minimum) gradient and shift them by a small amount. Back to Figure 5, this procedure is completed for all the remaining parameters.

For developing accurate predictions of benign (the negative class) and malignant (the positive class) breast cell samples, sensitivity, specificity, and accuracy are determined using the True positive (TP), true negative (TN), false negative (FN), and false positive (FP) indicators. Table 1 makes it very evident that a classical CNN can attain an accuracy of 98.6%, a sensitivity of 97.5%, and a specificity of 99.4%. In the meanwhile, we can see that the QCNN can obtain a 98.9% accuracy rate, a 97.7% sensitivity rate, and a 99.6% specificity rate. As a result, QCNN offers better results than the classical CNN.

Table 1 Comparative study on the performances of Convolutional Neural Network and Quantum Convolutional Neural Network

	Accuracy	**Sensitivity**	**Specificity**
CNN	98.6%	97.5%	99.4%
QCNN	98.9%	97.7%	99.6%

From the time complexity plot in Figure 11, it is clearly visible that the QCNN works exponentially faster than the classical algorithm.

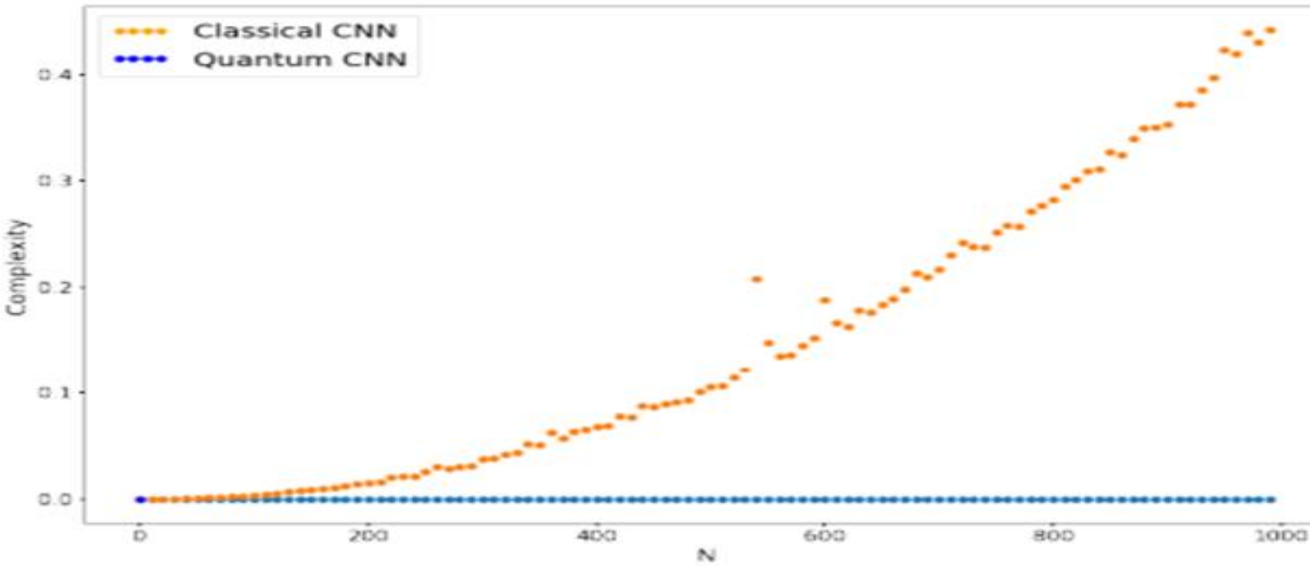

Fig 12 Complexity Comparison Between Classical and Quantum CNN Where N Denotes the Number of Training Samples

In the days of initial work performed with deep learning CNNs for breast cancer detection in mammography, studies were performed to compare the difference in performance between the current technology, i.e. conventional CADe/CADx, and the up-and-coming CNN-based technology. For example, Fotin et al. compared conventional CADe to the performance of deep learning CNNs for the task of mass detection in DBT. Moving from conventional to deep learning approach resulted in an increase of sensitivity, at the ROI level from 83.2%–89.3% for ROIs marked as containing suspicious lesions, and 85.2%–93.0% for ROIs containing malignant lesions.

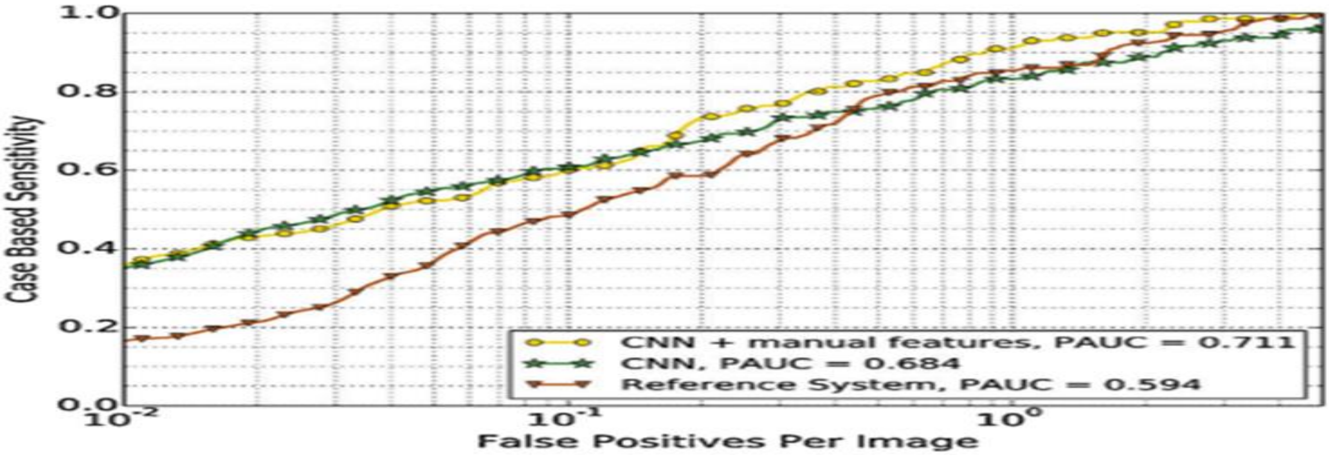

Fig 13 FROC curve showing the reduction in sensitivity with decreased false positives per image for a deep learning CNN, the deep learning CNN combined with hand-crafted features, and the conventional (reference) CADe algorithm.
Reprinted with permission

The proposed CNN, when having access to only the image patch, with no external information, making the conditions equivalent to those available to the conventional CADe, resulted in a non-significant increase in the area under the receiver operating characteristics (ROC) curve (AUC) compared to latter. The performance of the CNN increased with the incorporation of the handcrafted features. As has been discussed, the major pitfall of conventional CADe in real world use was the number of false positive marks per image. Therefore, beyond the comparison of the overall performance, the new AI-based technology would be expected to make a significant impact on health care only if it outperforms conventional CAD in the high specificity.

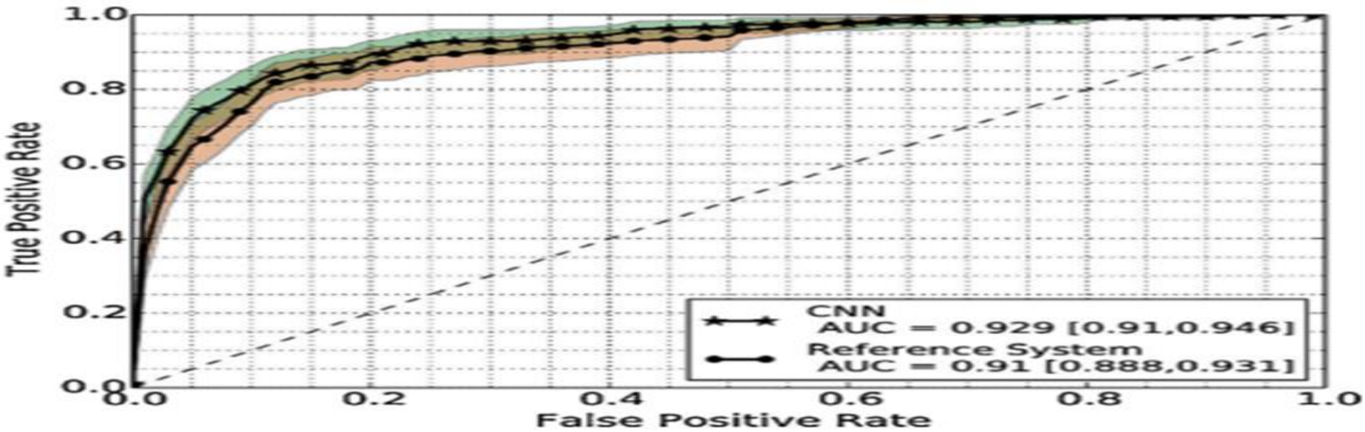

Fig 14 Stand-alone ROC performance of a deep learning CNN compared to a conventional (reference) CADe, when restricting the CNN to analyze only image patches, with no additional information, to be on par with the information available to the conventional CADe

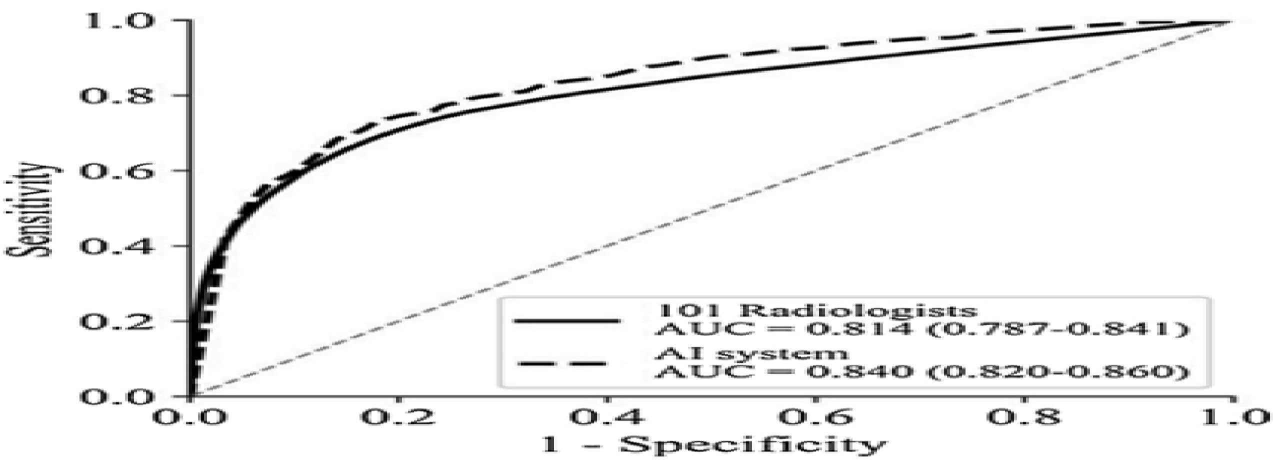

Fig 15 Stand-alone ROC performance of a commercial AI system compared to the reader-averaged radiologist interpreting over 2 600 mammograms during retrospective observer studies. Reprinted with permission from Rodriguez Ruiz et al. Stand-Alone AI

- The Figure 15 is the Results After Analytical Estimation of Quantum Computing for Breast Cancer Detection

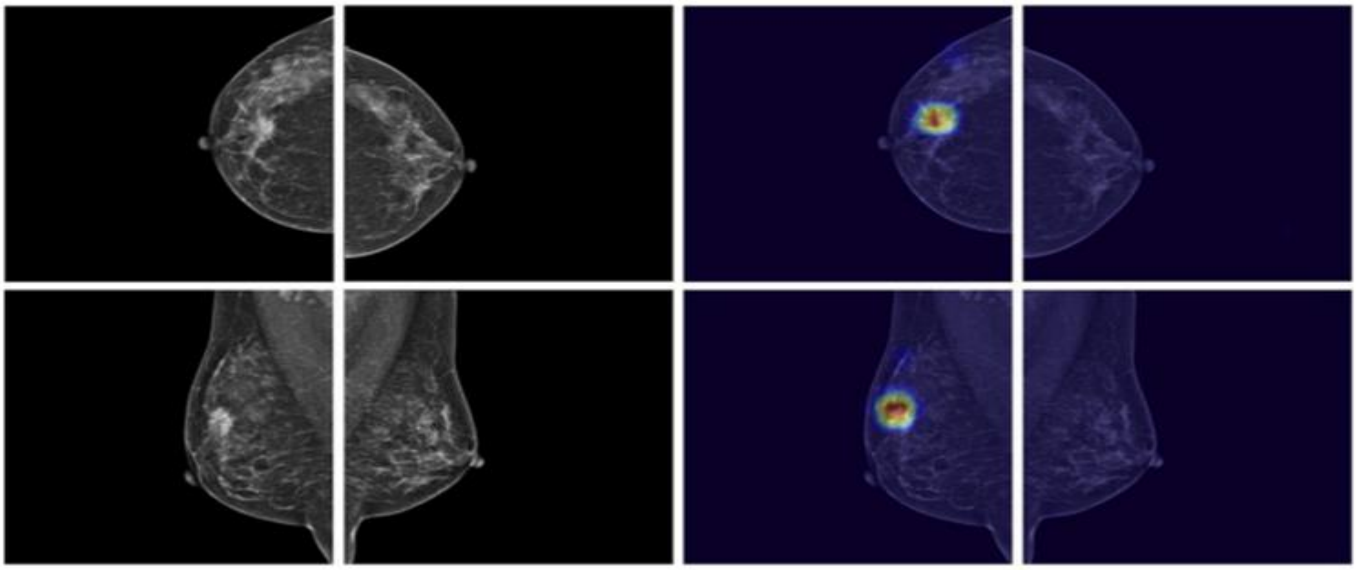

Fig 16 (left) Digital mammography of a 44-year old woman with invasive ductal carcinoma in the right breast, with (right) an overlaid heat map highlighting the area that most strongly contributed to the final classification decision.

VI. CONCLUSION

From the study results, we have demonstrated the efficacy of quantum convolutional neural networks (QCNNs) to detect breast cancer cells. Using the proposed algorithms, we have run the circuit for different parameters and optimized it for the accurate predictions of the breast cancer cell. Using the techniques of deep learning and supervised learning in the quantum framework, we have proposed and tested the effectiveness of quantum CNN on the quantum simulator available at the IBM quantum experience platform.

We have considered the application of breast cancer detection to explicate the working of our quantum convolutional neural network. We have trained the network of ten qubits in such a way that it can learn from the labeling of the given data set and can optimize the circuit parameters to obtain results with the minimum errors. Finally we also have pointed out that QCNN is not only optimum in terms of the accuracy in comparisons with classical CNN but produces results with better time complexity than the classical counterpart.

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