APPLICATION OF QUANTUM CNN EMPOWERED A BRAIN APP TO DETECT BRAIN TUMOR

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "**Application of Quantum CNN Empowered a Brain App to detect brain Tumor**", submitted by **Maherunnesa Mira** and **Mosa Afroza Sultana Rimi** and to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **15 July 2024**

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We hereby declare that this project has been done by us under the supervision of **Dr. Md Taimur Ahad, Associate Professor and Associate Head, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

High rates of sickness and death from brain tumors make them a major public health problem. This shows how important early discovery and correct classification are for effective treatment. Traditional ways of diagnosing, like having doctors read Magnetic Resonance Imaging (X-RAY) scans, take a lot of time, are prone to mistakes, and depend on expert knowledge. Convolutional Neural Networks (CNNs) have come a long way and show a lot of potential for automating the detection and classification of brain tumors, with great accuracy and speed. Classical CNNs, on the other hand, have a lot of problems, such as high computational costs, the ability to overfit, and problems with processing big datasets quickly. Quantum Convolutional Neural Networks (QCNNs) are a possible answer because they use quantum computing ideas like superposition and entanglement to improve the ability to extract features and lower the amount of work that needs to be done on the computer. This study used a large sample of 4,599 X-RAY images to compare how well QCNNs and classical CNNs work at finding brain tumors. The QCNN architecture includes quantum convolutional layers and pooling layers that are meant to use quantum effects to make picture classification more accurate. The classical CNN design, on the other hand, is made up of standard convolutional layers, pooling layers, and fully connected layers that are optimized using standard deep learning techniques. The X-RAY dataset was used to train and test both models extensively, and accuracy, precision, recall, and the F1-score were used as performance measures that were calculated and analyzed. QCNN did much better than the standard CNN, scoring 97.82% on the test, which was a big improvement. Using confusion matrices and Receiver Operating Characteristic curves, we were able to get a lot of information about each model's diagnostic skills, strengths, and weaknesses.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

CNN - Convolutional Neural Network
QCNN- Quantum Convolutional Neural Network
COs - Course Outcomes
EA - Engineering Activities
EP - Engineering Problems
F1 Score - F1 Measure
FN - False Negative
FP - False Positive
TP - True Positive

CHAPTER 1
Introduction

1.1 Overview

Since they can cause so much illness and death, brain tumors are one of the most serious health problems we face. The brain tumor is considered as the most common brain disease. It is an uncontrolled and unnatural growth of brain cells. Wadhah Ayadi [1] Brain tumors need to be found early and correctly classified in order for treatment plans to work and for patients to have better results. Magnetic Resonance Imaging (X-RAY) and other traditional medical imaging methods give a lot of knowledge about the brain's structures. A Brain Tumor is essentially a malformed cell growth that can be cancerous and non-cancerous. The tumor in the Brain is the most dangerous disease and can be diagnosed easily and reliably with the help of detection of the tumor with automated techniques on X-RAY Images. Kumar, S [3] However, analyzing these pictures by hand takes a long time, is prone to mistakes, and relies heavily on the knowledge of radiologists. Because of this, there is more and more interest in using advanced machine learning methods, especially Convolutional Neural Networks (CNNs), to automatically find and classify brain tumors. In recent years, CNNs have demonstrated remarkable success in various image processing tasks, including medical image analysis. Studies such as those by Ayadi et al. [1] demonstrated that CNNs could achieve high accuracy in brain tumor classification, significantly improving diagnostic capabilities. Similarly, Iqbal et al. [2] showcased the effectiveness of CNNs in segmenting brain tumors in multi-spectral X-RAY images, further emphasizing the potential of these models in clinical applications CNNs are particularly advantageous due to their ability to automatically learn and extract hierarchical features from raw image data, reducing the need for manual feature engineering.

Classical CNNs are successful, but they have a lot of problems. For example, they can't handle large amounts of data or complex feature extraction because they are very expensive to run and can overfit. Overfitting happens when a model learns both the trends and the noise in the training data. This makes it bad at applying what it has learned to new data. CNNs' high computing needs are also a problem, since training deep networks takes a lot of time and hardware. Because of these problems, we need to look for better and more reliable ways to do things that can keep or improve accuracy while lowering the amount of work that needs to be done on computers. Using Quantum

Convolutional Neural Networks (QCNNs) is a potential way to get around these problems. Using ideas like superposition and entanglement, quantum computing can do calculations that regular computers would not be able to do. It is possible for QCNNs to improve feature extraction and make computations simpler by incorporating these ideas into neural network designs. One example is quantum superposition, which lets you look at different states at the same time. Henderson et al. [24] demonstrated that quantum circuits could improve the efficiency of neural networks in image recognition tasks, highlighting the potential of quantum computing to address some of the limitations of classical. Moreover, the work by Oh et al. [25] on quantum convolutional neural networks indicated that these models could achieve competitive performance with significantly reduced computational resources. These findings suggest that QCNNs could provide a viable alternative to classical CNNs, particularly in resource-constrained environments. The main goals are to check the QCNN model's accuracy, precision, recall, and F1-score and see how they compare to traditional models in these areas. In addition, the study wants to look at how well QCNNs use computers, especially when it comes to training time and resource use. Why are they doing this research? Because they want to make brain tumor detecting methods faster and more accurate. Even though the current CNN models work, they are limited by how much computing power they need and how easily they can become too perfect.

1.2 Background and Present State

In recent years, Convolutional Neural Networks (CNNs) have demonstrated remarkable success in various image processing tasks, including medical image analysis. These networks have revolutionized the field by providing automated, accurate, and efficient means of interpreting complex medical images, significantly aiding in the diagnosis and treatment planning of diseases such as brain tumors. Studies such as those by Ayadi et al. (1) have shown that CNNs can achieve high accuracy in brain tumor classification, effectively distinguishing between different types of tumors with substantial reliability Similarly, Iqbal et al. [2] highlighted the capability of CNNs in segmenting brain tumors in multi-spectral X-RAY images, which is crucial for precise localization and treatment . Even though they work well, classical CNNs have a lot of problems, especially when it comes to big amounts of data and complex feature extraction. One of the biggest problems is that building and using deep neural networks takes a lot of computer power. To train CNNs on big datasets, you need a lot of computing power, like powerful GPUs and a lot of memory, which can be too much in many real-life situations. CNNs also tend to overfit, especially when they are given small or uneven datasets to work with. Overfitting happens when a model learns both the trends and the noise in the training data. This makes it bad at applying to new data that it hasn't seen before. Also, the structure of traditional CNNs isn't always the best for catching the complex and high-dimensional nature of medical images, even though they work well. Many hyperparameters, like the number of layers, filter sizes, and learning rates, need to be designed and fine-tuned. This makes using CNNs for medical picture analysis more difficult and time-consuming. Because of these problems, we need to look for better and more reliable ways to do things that can keep or improve accuracy while lowering the amount of work that needs to be done on computers. Using Quantum Convolutional Neural Networks (QCNNs) is a potential way to get around these problems. Using ideas like superposition and entanglement, quantum computing can do calculations that regular computers would not be able to do. Quantum bits (qubits) can be in more than one state at the same time thanks to superposition. This lets huge amounts of information be processed in parallel. Entanglement, a state in which qubits depend on each other, makes it possible to show complex connections between features. These ideas can help neural networks get better at extracting features and make computations simpler. The goal of this study is to find out how well QCNNs can find brain tumors by filling in the holes and fixing the problems with traditional CNNs. Convolutional Neural Net-works (QCNNs) into medical diagnostics represents a trans-formative advancement in the classification of brain tumors. Khan, M. A. Z [28]. The goal of this study is to find out the pros and cons of using quantum neural networks in medical picture analysis by creating a custom QCNN model and comparing its performance with that of traditional CNN models. The end goal is to make a model that works better and is more accurate so that it can handle the complexity of medical images. This will help medical diagnosis and patient care get better.

1.3 Problem Statement

Magnetic resonance imaging (X-RAY) is a very important tool for finding and classifying brain tumors so that they can be treated quickly and correctly. In this area, traditional methods mostly based on classical convolutional neural networks (CNNs) have made a lot of progress. These methods do, however, often run into problems with how fast they can compute and how well they can handle big datasets and complex image features. Furthermore, the inherent complexity and variability of X-RAY scans make it even harder to achieve consistently high levels of accuracy across a wide range of patient populations and imaging situations. These problems make it even more important to come up with new ways to not only make diagnostics more accurate but also make computers work faster so that clinical decisions can be made more quickly. Because of these problems, the goal of this study is to find out if quantum convolutional neural networks (QCNNs) can be used as a new type of computer system to find brain tumors. Quantum convolutional neural networks (QCNNs) use quantum computing to possibly have better computing power, which could make them better at handling medical imaging data than traditional CNNs. The goal of this study is to improve the current limits of automated brain tumor detection systems by looking into the viability and usefulness of QCNNs in this setting. So, the main issue this study tries to answer is whether QCNNs are a good choice to traditional CNNs for making brain tumor detection with X-RAY scans more accurate, faster, and scalable.

1.4 Objectives

The main goal of this study is to find out how well quantum convolutional neural networks (QCNNs) work for using X-RAY scans to find brain tumors. First, it will be checked to see if it is possible to use QCNNs in this area. This will help us learn more about their possible benefits and problems with implementation. A big goal is to carefully look at the differences and similarities between QCNNs and regular convolutional neural networks (CNNs). This review will look at how well they find and classify brain tumors, how fast they are at using computers, especially when working with big X-RAY datasets, and how well they work in a variety of imaging conditions and patient groups. In addition, the study wants to find out if QCNNs have a quantum edge over regular CNNs. This test will look at how fast they can process picture analysis tasks and how well they can use quantum properties to improve the accuracy of feature extraction and classification. It is very important to talk about and figure out the problems and restrictions of using QCNNs in real-life medical imaging tasks. Some of these problems are getting access to quantum computing resources, hardware limits, and how well QCNNs can be used in clinical situations and within the rules set by regulators. In addition to looking for brain tumors, the study also wants to find other uses and future research paths for QCNNs. This study looks into other types of medical imaging and diagnostic jobs with the goal of finding new ways to use computers to make medical diagnostics better and advancing advances in healthcare technology.

1.5 Scope and Limitations

The main goal of this study is to find out how quantum convolutional neural networks (QCNNs) might help improve the use of X-RAY scans to find and classify brain tumors. The study has two parts: first, it builds and tests QCNN models that are especially made for finding brain tumors; second, it does a thorough comparison with traditional convolutional neural networks (CNNs). This comparison will look at how well both models work in different imaging conditions and with different types of patients, how accurate they are at finding tumors, and how quickly they can handle big X-RAY datasets. The study also wants to find out if QCNNs have a quantum edge over classical CNNs, especially when it comes to processing speed and their ability to use quantum properties to make feature extraction and classification more accurate. However, the study is limited by the amount of quantum computing tools that are available and how well they are developed. This could make it harder to use and expand QCNNs in real life. There are also big problems with hardware limitations, dataset variability, and following the rules in clinical settings, but those problems will be looked at in this study.

1.6 Report Organization

This report is organized to provide a comprehensive exploration of the implementation and evaluation of Quantum Convolutional Neural Networks (QCNNs) and Classical Convolutional Neural Networks (CNNs) for brain tumor detection using X-RAY scans. Chapter 1 introduces the problem of brain tumors, emphasizing the need for early and accurate detection, and outlines the research objectives and potential advantages of QCNNs. Chapter 2 reviews existing literature on brain tumor detection using CNNs and QCNNs, identifying gaps and opportunities for further research. Chapter 3 details the methodology, including data collection and preprocessing, model design and implementation, and the experimental setup. It also covers hardware and software requirements, along with project management and financial analysis. Chapter 4 focuses on the practical aspects of training the models, designing prototypes, and system testing, providing a thorough account of the development and integration of the models. Chapter 5 presents the experimental results, including performance metrics such as accuracy, precision, recall, and F1-score, and provides a detailed comparative analysis of QCNN and CNN models, supported by confusion matrices and ROC curves. Chapter 6 discusses the broader impacts on society, healthcare, and the environment, considering ethical aspects and sustainability plans. Finally, Chapter 7 summarizes the key findings, discusses the conclusions drawn from the results, and suggests future research directions, highlighting the potential of quantum computing in medical diagnostics. This structured organization ensures a logical flow of information, facilitating a clear understanding of the research process and its outcomes.

1.7 Summary

Quantum convolutional neural networks (QCNNs) are used to find brain tumors using X-RAY scans. It starts by talking about how important it is to make medical scans more accurate and faster, especially for brain tumors. The background talks about current methods that use classical convolutional neural networks (CNNs) and how they can't handle different imaging conditions and big datasets. The problem statement says that QCNNs should be looked into as a possible answer to these problems in order to improve both the accuracy of diagnoses and the speed of computing. The aims list clear goals, such as figuring out if QCNN is possible, doing comparisons with CNNs, looking into possible quantum benefits, figuring out implementation issues, and looking into wider uses in medical image analysis. The scope makes it clear that the focus is on creating and testing QCNN models, while the limits list things that can't be done, like the lack of quantum computing resources and legal issues. The organized structure of this chapter lays the groundwork for later chapters that will discuss methods, results, discussions, conclusions, and future research goals that aim to improve healthcare technology using new quantum computing techniques.

CHAPTER 2: LITERATURE REVIEW

2.1 Overview

Medical imaging methods are used to find brain tumors, with a focus on convolutional neural networks (CNNs) and new developments in quantum convolutional neural networks (QCNNs). The goal of this chapter is to bring together the latest research, methods, and results from different studies so that we can better understand how computational approaches have changed over time in medical diagnostics. The review looks at new developments in CNN-based techniques for separating and classifying brain tumors. It talks about their pros and cons in various imaging methods and clinical settings. It also looks at new developments in QCNNs and talks about their theoretical bases, possible benefits over traditional CNNs, and uses in medical picture analysis. This chapter sets the stage for suggesting new methods and moving the field forward towards more accurate and efficient brain tumor detection using quantum computing paradigms by critically analyzing previous research.

2.2 Related Works

Ayadi [1] discuss the growing interest Deep CNN for Brain Tumor Classification. They utilize a Deep Convolutional Neural Network (CNN) for classifying brain tumors based on X-RAY images. The model was evaluated on three public datasets where Fig share dataset, consisting of 3064 slices from 233 patients, covering three types of brain tumors: meningioma, pituitary, and glioma. The best accuracy achieved by the proposed CNN model is 94.74%. Iqbal [2] propose the integration of Brain Tumor Segmentation in Multi-spectral X-RAY Using Convolutional Neural Networks (CNN). All imaging data used in this study is obtained from BRATS 2015 data-set which consists of two major types of brain tumors called HGG and

The LGG. Proposed network uses BRATS segmentation challenge dataset which is composed of images obtained through four different modalities. The study primarily focuses on the use of Convolutional Neural Networks (CNN) for the detection and analysis of brain tumors in X-RAY images. It discusses various methodologies and improvements in CNN architectures for enhancing detection accuracy by Kumar [3]. The studies reviewed utilized different datasets, including widely recognized ones like

BraTS2014 and BraTS2016.They reviewed various studies, with some CNN implementations reaching high accuracies, around 98.67% in some cases. In this paper, Yaqub [4] provides a comprehensive comparative analysis of popular optimizers of CNN to benchmark the segmentation for improvement. The experiments were conducted using the BraTS2015 dataset, which includes X-RAY sequences of brain tumors for extensive and detailed segmentation tasks. The Adam optimizer achieved the highest classification and segmentation accuracy of 99.2%. The proposed work leverages X-RAY scans (axial slices) to detect the type of brain tumor by Sarkar [5]. The dataset used in the study contained the data of three most commonly diagnosed brain tumors namely, glioma, meningioma and pituitary tumors' study employs a 2D Convolutional Neural Network (CNN) designed which propelled an overall accuracy of 91.3% specifically for the classification of brain tumors using X-RAY scans. Sedlar [6] proposed an automatic brain tumor segmentation app-roach based on a multi-path Convolutional Neural Network (CNN) is presented. In this study BraTS 2017 dataset was used, which included a variety of X-RAY modalities and annotations for comprehensive training and testing of the model.

The scores were 60.49% for enhancing the tumor, 84.36% for the whole tumor, and 69.38% for tumor core. The study developed a hybrid model combining Convolutional Neural Networks (CNN) and Support Vector Machines (SVM). In this research paper, the brain X-RAY images are going to classify by considering the excellence of CNN on a public dataset to classify Benign and Malignant tumors by Khairandish .[7]. Chattopadhyay [8] Develops a resource-efficient QCNN model using QRAM for image classification. Introduces a QRAM-based quantum convolution layer to reduce the number of qubits and improve computational efficiency. The proposed QCNN model achieved high performance in image classification tasks, demonstrating the advantages of using quantum computing techniques in deep learning. CNN gained an accuracy of 99.74%, which is better than the state of the result obtained so far. Naseer [9] proposed this research on early diagnosis of brain tumor via Convolution Neural Network (CNN) to enhance state-of-the-art diagnosis accuracy. The proposed CNN is trained on a benchmark dataset, BR35H, containing brain tumor X-RAYs. The performance and sustainability of the model is evaluated on six different datasets, i.e., BMI-I, BTI, BMI-II, BTS, BMI-III, and BD-BT. The proposed CNN-based CAD system for brain tumor diagnosis performs better than other systems by achieving an average accuracy of around 98.8% and a specificity of around 0.99. This paper proposes a Convolutional

Neural Network (CNN), for classification problem and Faster Region based Convolutional Neural Network (Faster R-CNN) for segmentation problem with reduced number of computations with a higher accuracy level. This research has used 218 images as training set and the systems shows an accuracy of 100% in Meningioma and 87.5% n Glioma classifications and an average confidence level of 94.6% in segmentation of Meningioma tumors. Işın et al.'s paper [11] proposed deep learning techniques for X-RAY-based brain tumor segmentation. The research presents a cascaded two-pathway CNN architecture using the BRATS dataset, which contains multi-modality X-RAY scans of gliomas. With Dice scores of 88% for total tumors, 79% for core tumors, and 73% for active tumor regions, this approach proved to be efficient and highly accurate in tasks involving the automatic segmentation of brain tumors. The proposed research by Zhao et al. [12] uses X-RAY scans to segment brain tumors. The BRATS 2013, 2015, and 2016 datasets—which include multi-modal X-RAY scans—are used in this investigation. It utilizes a deep learning model that combines Conditional Random Fields (CRFs) and Fully Convolutional Neural Networks (FCNNs), attaining a Dice score of 0.87 for total tumor segmentation. Paula et al.'s study [13] implements CNNs and FCNNs to classify brain cancers from T1-weighted, contrast-enhanced X-RAY data. The CNN model successfully classified meningioma, glioma, and pituitary tumors with a per-patient accuracy of 91.43% using 989 axial pictures from the BRATS dataset. This shows the efficacy of deep learning in this regard. The proposed research by Magadza and Viriri [14] uses magnetic resonance imaging (X-RAY) scans (axial slices) to identify the type of brain tumor. The multimodal brain tumor imaging data from the BRATS 2015 dataset were used in this investigation. By combining FCNNs with CRFs, the team was able to segment brain tumors with a Dice score of 0.86." In this paper, Liu et al.'s proposed method uses X-RAY scans (axial slices) to identify the type of brain tumor [15]. The study makes use of multi-modal X-RAY scans from the BRATS 2017 dataset. Using a modified U-Net architecture, the study's complete tumor segmentation yielded a Dice score of 0.91." The proposed study by Nazir et al. [16] uses X-RAY scans (axial slices) to identify the type of brain tumor. The BRATS 2015 and 2018 datasets were among the datasets used in the research. utilizing X-RAY scans, the study classified brain cancers with 96% accuracy by utilizing the RESNET-50 model with data augmentation. The proposed work by Sadad et al. [17] uses X-RAY scans (axial slices) to identify the type of brain tumor. The study's dataset, which comprises 3,064 X-RAY brain slices of meningioma, pituitary, and glioma tumors, was taken from Figshare. Using X-RAY scans, the study classified brain cancers with an accuracy of 99.6% thanks to the use of NASNet. The proposed study uses axial slices from X-RAY scans to identify and categorize brain cancers using HANBAY and ARI [18]. 16 patients' cerebral X-RAY pictures were included in the dataset used in the investigation. Using X-RAY scans, the study uses the ELM-LRF approach to detect and classify brain cancers with a 97.18% classification accuracy. In Siar and Teshnehlab's proposed work [19], the type of brain tumor is identified by utilizing X-RAY scans (axial slices). The study's dataset comprised 153 patients' brain X-RAY pictures. This work uses a CNN along with a Softmax Fully Connected Layer for feature extraction and Clustering Algorithm for brain tumor classification using X-RAY data, with an accuracy of 99.12%. The proposed study by Saba et al. [20] uses X-RAY scans (axial slices) to identify the type of brain tumor. The BRATS 2015, 2016, and 2017 datasets were among the ones utilized in the investigation. In order to diagnose brain tumors, the work combines handmade characteristics (HOG and LBP) with VGG-19 deep learning features to produce a Dice Similarity Coefficient (DSC) of 1.00

2.3 Comparison Between Existing Works

It looks at a number of studies and projects that use CNN-based methods to separate, classify, and extract features from X-RAY pictures of tumors. The comparison looks at things like how well the methods find tumors, how quickly and efficiently they can handle big datasets, how well they work in a variety of imaging conditions, and how well they can be used with different types of patients.

Table 2.3.1: Comparison Between Existing Works

SL No	Author Name	Used Algorithm	Best Accuracy
01	Ayadi, W., et al.	Convolutional Neural Network (CNN)	Class 2: 100%, Class 3: 97.22%, Class 4: 97.02%, Class 5: 83.86%, Class 6: 95.72% (Before Data Augmentation); Class 2: 100%, Class 3: 95%, Class 4: 94.41%, Class 5: 86.08%, Class 6: 92.09% (After Data Augmentation)
02	Iqbal, S., et al.	Convolutional Neural Network (CNN) with Squeeze-and-Excitation Network (SENet)	High-Grade Gliomas (HGG) and Low-Grade Gliomas (LGG) using Dice score, Sensitivity, and Specificity
03	Kumarby, et al.	Convolutional Neural Network (CNN)	98.67% with the Softmax Fully Connected layer
04	Gore, D. V., et al.	Various deep learning techniques including CNNs, LSTMs, and others	98.6% with the CNN-DWT-LSTM hybrid approach
05	Yaqub, et al.	Convolutional Neural Network (CNN) with Adam optimizer	99.2% with Adam optimizer
06	Sarkar, S., et al.	Convolutional Neural Network (CNN)	91.3% with CNN model

07	Grampurohit, S., et al.	Convolutional Neural Network (CNN) and VGG-16 architecture	VGG-16: Training accuracy of 97.16%, Validation accuracy of 97.42%
08	Sadad, I., et al.	NASNet architecture for multi-classification, ResNet50-UNet for detection	NASNet: 99.6% classification accuracy
09	Naseer, A., et al.	Deep Learner CNN using augmented X-RAY	Deep Learner CNN: Performance evaluation with augmented X-RAY
10	Kaldera, H. N. T. K., et al.	Faster R-CNN	Faster R-CNN for brain tumor classification and segmentation
11	Işın, A., et al.	Various deep learning methods	Review of X-RAY-based brain tumor segmentation using various deep learning methods
12	Zhao, X., et al.	Fully Convolutional Neural Networks (FCNNs) and Conditional Random Fields (CRFs)	Integration of FCNNs and CRFs for brain tumor segmentation
13	Paul, J. S., et al.	Deep Learning	Deep Learning for brain tumor classification
14	Magadza, T., et al.	Various deep learning techniques	Survey of state-of-the-art deep learning methods for brain tumor segmentation
15	Liu, Z., et al.	Deep Learning	Survey of deep learning techniques for brain tumor segmentation

16	Maria, N., et al.	Deep Learning	Review of deep learning in brain tumor detection and classification (2015-2020)
17	Sadad, T., et al.	Advanced deep learning techniques	Advanced deep learning techniques for brain tumor detection and multi-classification
18	Ari, A., et al.	Deep Learning	Deep learning-based brain tumor classification and detection system
19	Siar, M., et al.	Deep Neural Network and Machine Learning Algorithm	Deep neural network and machine learning algorithm for brain tumor detection
20	Saba, T., et al.	Fusion of handcrafted and deep learning features	Fusion of handcrafted and deep learning features for brain tumor detection
21	Khan, M. A. Z., et al.	Quantum Convolutional Neural Networks (QCNN)	Quantum Convolutional Neural Networks (QCNN): Performance evaluation
22	Hur, T., et al.	Quantum Convolutional Neural Network (QCNN)	Quantum Convolutional Neural Network (QCNN) for classical data classification
23	Tóth, G., et al.	Quantum Cellular Neural Networks	Quantum Cellular Neural Networks for brain tumor detection
24	Henderson, M., et al.	Quanvolutional Neural Networks	Quanvolutional Neural Networks: Image recognition with quantum circuits
25	Oh, S., et al.	Quantum Convolutional Neural	Quantum Convolutional Neural Network (QCNN) with QRAM for

		Network (QCNN) with QRAM	resource-efficient image classification

2.4 Open Issues

In addition, there have been big steps towards using convolutional neural networks (CNNs) and quantum convolutional neural networks (QCNNs) to find brain tumors, but there are still some important problems that need to be fixed. Because tumors and X-RAY scan quality vary, it is hard to get consistently good accuracy and robustness across a wide range of patient populations and imaging conditions. Another issue is computational speed. CNNs need a lot of resources, which makes them hard to scale up and use in clinical settings. In theory, QCNNs are faster and more efficient at handling data, but these benefits need to be proven in real-world settings. Also, having access to high-quality, labeled X-RAY datasets is necessary but not always easy to find, which is a big problem. Model interpretability is important for clinical usage, which means that the way AI makes decisions needs to be clear. To add these advanced models to clinical workflows, we need to make sure that they can work with current systems and follow all the rules set by regulators. This will protect patient data safety and security. In addition, strict legal and moral rules must be followed when these models are used. Finally, using QCNNs in real life is hard because quantum computer hardware isn't very accessible right now. This shows that we need more improvements and more resources to be available. Taking care of these problems is important for making CNNs and QCNNs more useful for finding brain tumors and making them more reliable, efficient, and easy to use in medical practice.

2.5 Summary

There have been big steps forward in using convolutional neural networks (CNNs) and quantum convolutional neural networks (QCNNs) to find brain tumors, but there are still some important problems that need to be fixed. Because tumors and X-RAY scan quality vary, it is hard to get consistently good accuracy and robustness across a wide range of patient populations and imaging conditions. Another issue is computational speed. CNNs need a lot of resources, which makes them hard to scale up and use in clinical settings. In theory, QCNNs are faster and more efficient at handling data, but these benefits need to be proven in real-world settings. Also, having access to high-quality, labeled X-RAY datasets is necessary but not always easy to find, which is a big problem. Model interpretability is important for clinical usage, which means that the way AI makes decisions needs to be clear. To add these advanced models to clinical workflows, we need to make sure that they can work with current systems and follow all the rules set by regulators. This will protect patient data safety and security. In addition, strict legal and moral rules must be followed when these models are used. Finally, using QCNNs in real life is hard because quantum computer hardware isn't very accessible right now. This shows that we need more improvements and more resources to be available. Taking care of these problems is important for making CNNs and QCNNs more useful for finding brain tumors and making them more reliable, efficient, and easy to use in medical practice.

CHAPTER 3: METHODOLOGY

3.1 Overview

This chapter discusses in detail about the methods used in this study project, which is all about designing and putting together quantum convolutional neural networks (QCNNs) that can use X-RAY scans to find brain tumors. It also looks at how it compares to fully connected neural networks (FCNNs) and standard convolutional neural networks (CNNs). The method includes several important steps. The first is data preprocessing, which changes the size of X-RAY pictures to 28x28 pixels, normalizes them to a [0, 1] range, and then shrinks them even more to 8x8 pixels to fit the needs of quantum circuits. Each pixel in these pictures is stored as a qubit, and its value determines the quantum state. This makes it possible to describe pixels above a certain threshold in binary. As part of the model creation phase, a custom QCNN model is made to use quantum properties for better image analysis. Classical CNN and FCNN models are also made for performance testing. These models are trained on the processed X-RAY dataset using the right methods to make them work better. During the evaluation process, the models are put through a lot of tests on a separate dataset to see how well they work, how quickly they run, and how reliable they are at finding brain tumors. The chapter also talks about the problems that came up during implementation, like the limitations of current quantum computing hardware and the need for high-quality datasets that have been labelled. This gives a complete picture of the possible benefits of QCNNs in medical diagnostics.

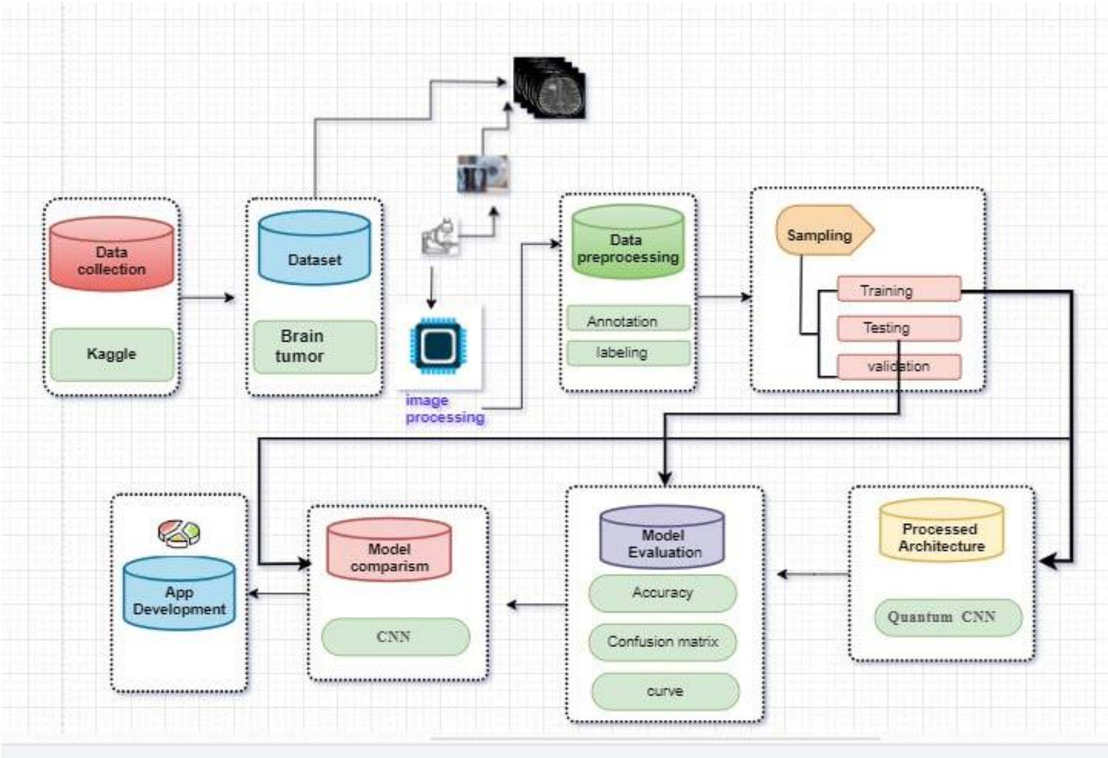

Fig 3.1.1: Workflow Diagram

3.2 Proposed Methodology

The proposed methodology involves several key steps:

3.2.1 Data Collection and Preprocessing:

The proposed methodology involves several key steps, each essential for developing and evaluating quantum convolutional neural networks (QCNNs) for brain tumor detection, while also detailing the initial challenges faced with a different dataset.

3.2.2 Data Collection and Preprocessing

Dataset (Brain Tumor Detection):

The brain tumor dataset detection using a secondary dataset also collected from Kaggle. This dataset contains 4599 X-RAY images categorized into two classes: Yes (Brain Tumor) and No (Healthy). Collecting primary medical data was not feasible due to confidentiality concerns, the need for numerous approvals, and stringent requirements, making secondary data the practical choice.

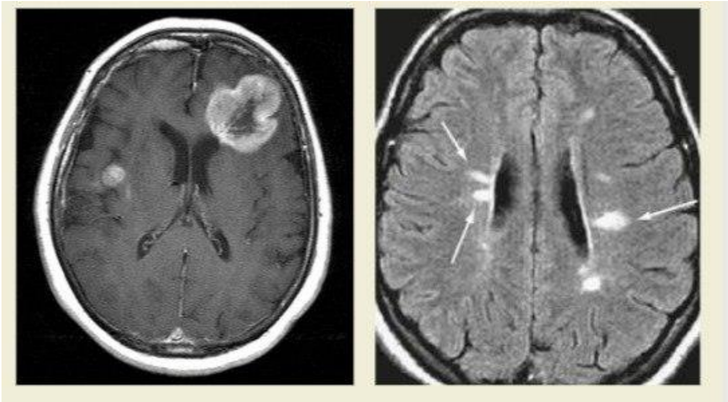

Figure 3.2.2.1: Brain tumor & Healthy Diagram

Image Resizing and Normalization:

The X-RAY images are resized to 28x28 pixels to standardize the input size across the dataset. Pixel values are normalized to a range of [0, 1] to facilitate better model convergence during training.

Downscaling for Quantum Circuits:

Images are further downscaled to 8x8 pixels to fit the constraints of current quantum computing hardware, ensuring they are suitable for encoding into quantum circuits while retaining essential features.

Quantum Circuit Encoding:

Each pixel of the downscaled images is represented by a qubit, with pixel values determining the qubit states. A binary encoding scheme is applied, where pixels exceeding a certain threshold are encoded as active quantum states, simplifying the quantum circuit design and ensuring efficient computation

3.2.3 Model Implementation:

Convolution Neural Network (CNN) Development:

A fully connected neural network (FCNN) is also developed for performance comparison. This model consists of multiple densely connected layers that process the input images for classification. Although FCNNs are generally less efficient for image tasks, they provide a valuable baseline for assessing the relative performance of the QCNN.

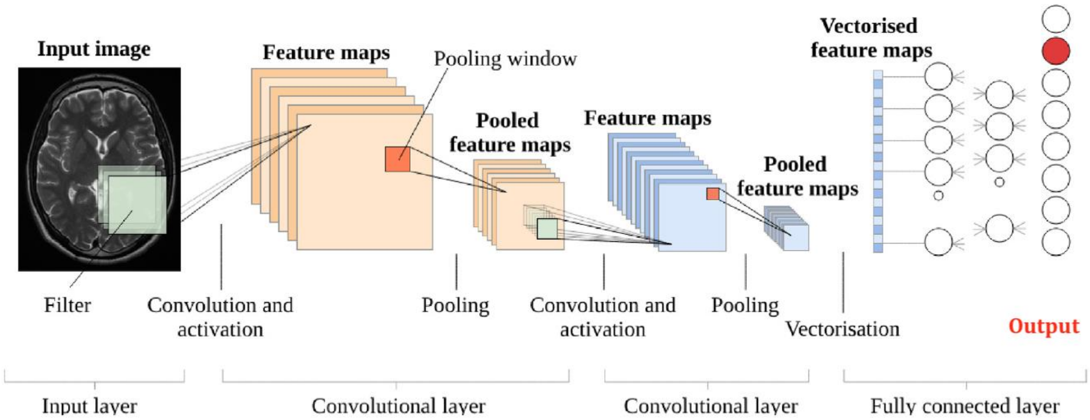

Figure 3.2.3.2: fully connected (CNN) structure.

The picture shows a simple fully connected Convolutional Neural Network (CNN) structure. The images that are fed in go through a number of convolutional and pooling layers that take out and group the features one by one. After being flattened, these features are sent through fully connected layers until they reach an output layer that gives the final rating. This basic CNN structure is often used for jobs that involve recognizing images, such as medical image analysis to find conditions like brain tumors.

Convolution Operation:

$$(I * k)(i,j) = \sum_{m} \sum_{n} I(i+m, J+n).K(m,n)$$

I: Input image

K: Kernel (filter)

i, j: Indices of the output feature map

m, n: Indices over the dimensions of the kernel

2. ReLU Activation:

$$f(x) = \max(0, x)$$

x: Input to the activation function

3. Pooling Operation (Max Pooling):

$$p(i,j) = \max_{m,n} (\mathrm{I}(i * S + m, j * s + n))$$

P: Pooled feature map

s: Stride size

4. Fully Connected Layer:

$$y = W.x + b$$

y: Output vector

W: Weight matrix

x: Input vector

b: Bias vector

5. SoftMax Activation (for classification):

$$\boldsymbol{\sigma(z)_i = \frac{e^{zi}}{\sum_j e^{zj}}}$$

σ(z) i : Probability of class i

Quantum Convolutional Neural Network (QCNN) Development:

A customized QCNN model is designed to leverage quantum properties such as superposition and entanglement, aiming to enhance the model's ability to analyze and classify X-RAY images effectively. The QCNN architecture includes layers tailored to utilize quantum computations, potentially improving feature extraction and classification accuracy compared to classical models.

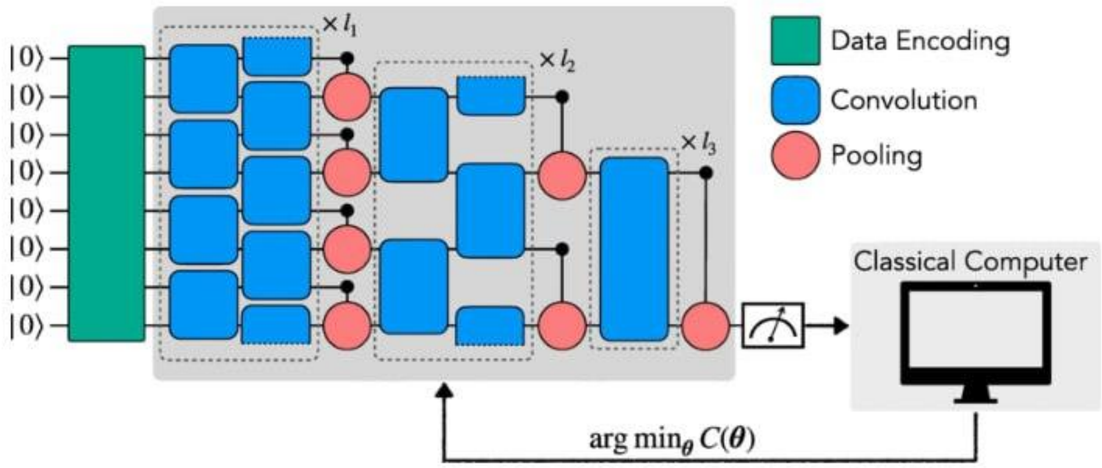

Fig 3.2.3.3 Quantum CNN architecture (Hur et al (2022).

This is a diagram of the QCNN algorithm for 8 qubits as an example. There are three parts to the quantum circuit: pooling (red circle), convolutional filters (blue rounded rectangle), and quantum data encoding (green rectangle). In a given QCNN structure, the quantum data encoding is set. The convolutional filter and pooling, on the other hand, use parameterized quantum gates. This example has three layers, and different convolutional filters can be used in each layer. li stands for the number of filters for the ith layer. At each level, the convolutional filter uses the same two-qubit approach on nearest neighbor qubits in a way that doesn't depend on their position. The same method is also used for pooling tasks within the layer. The pooling action is shown here as a controlled unitary transformation that starts working when the control qubit is 1. But general controlled actions can also be thought about. The result of the quantum circuit's measurements is used to figure out the user-defined cost function. Based on the gradient, the classical computer figures out the new set of parameters, and these are then sent to the quantum circuit to be used in the next round.

1. Quantum State Representation:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

$|\psi\rangle$: Quantum state

α, β: Probability amplitudes

2. Quantum Convolution Operation:

$$Uconv \sum_{k=0}^{N\_1} w_k \otimes |k\rangle\langle k|$$

U conv: Quantum convolution unitary operation

w_k: Quantum gate applied based on kernel weights

N: Number of qubits

3. Quantum Pooling Operation:

U pool = Control-U

Upool: Quantum pooling unitary operation (often controlled operations)

4. Quantum Measurement:

$$P(|\psi\rangle) = |\langle\Phi|\psi\rangle|2$$

- $P(|\psi\rangle)$: Probability of measuring state $|\Phi\rangle$
- $|\Phi\rangle$: Measured state

5. Hybrid Quantum-Classical Layer:

$$y=W.z+b$$

y: Output vector

W: Weight matrix from classical fully connected layer

z: Measurement result from quantum layer

b: Bias vector

3.2.4 Web Site Deployment

The method to find brain tumors was put on the internet so that anyone could use it. It was taught and then put into a web app that can handle pictures of the deployment process. It was made to be easy to use the web app. Anyone can share an X-RAY of their brain, with or without a brain tumor, and get results right away. The system was made better so that it works well on many devices, even ones with low computer power. This made sure that many people could use it.

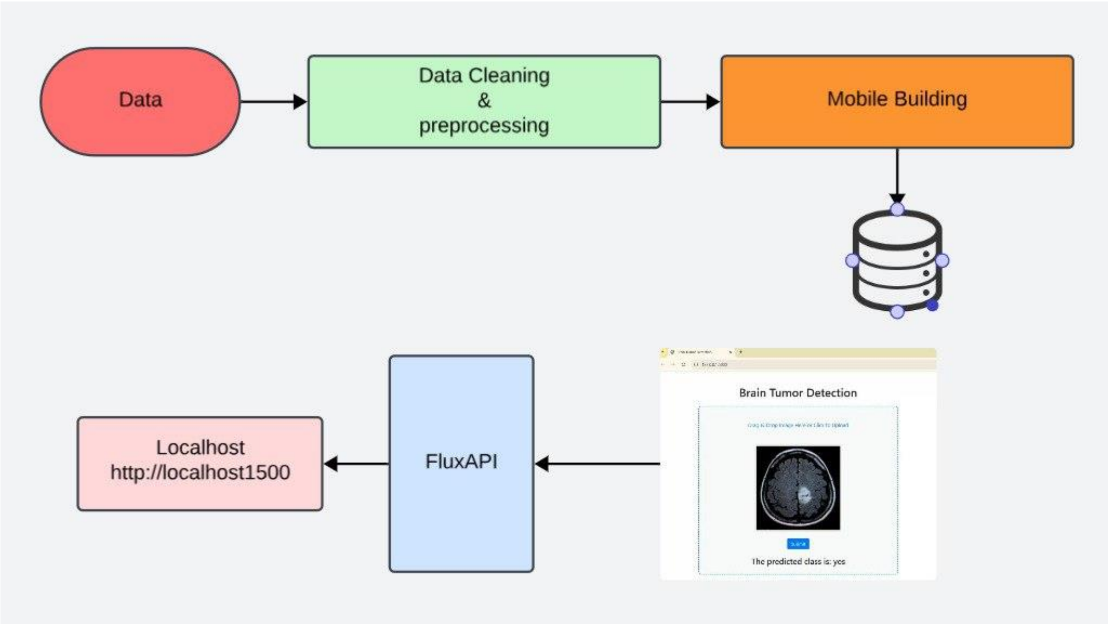

Fig 3.2.4.4: Website Development Prototype

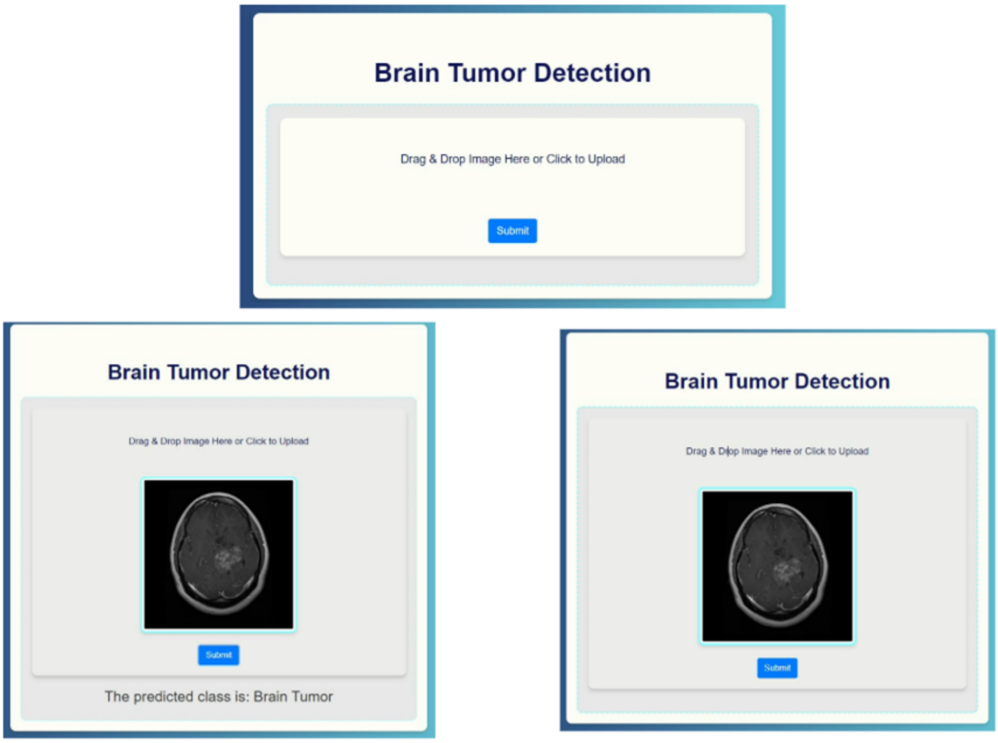

Fig 3.2.4.5: Website Development output

3.3 Hardware/Software Requirements

GPU (Graphics Processing Unit): NVIDIA Tesla V100

- CUDA cores: 5120
- 0peed: 2.4 GHz
- Purpose: Handles general computation tasks, pre-processing of data, and manages input/output operations.

RAM (Random Access Memory): 128 GB DDR4

- Speed: 2400 MHz
- Purpose: Supports large dataset handling and ensures smooth operation during model training and inference.

3.3.2 Local Development and Testing Environment

GPU: NVIDIA GeForce GTX 1080

- CUDA cores: 2560
- Memory: 8 GB GDDR5X
- Purpose: Allows for local development, testing, and small-scale training.

CPU: Intel Core i5-1135G7

- Cores: 4

- Threads: 8
- Base Clock Speed: 3.7 GHz
- Purpose: Handles code execution, data pre-processing, and model testing.

RAM: 16 GB DDR4

- Speed: 2666 MHz
- Purpose: Supports efficient data handling and model testing processes.

Software Requirements

- TensorFlow and TensorFlow Quantum: Used for developing and training both QCNN and classical models.
- Cirq: Employed for quantum circuit design and implementation.
- Python Libraries: Including NumPy, Matplotlib, and Seaborn for data manipulation and visualization.
- Scikit-learn: Used for additional preprocessing and model evaluation tasks.

3.3.3 Data Storage

HDD (Hard Disk Drive): 1 TB

- Purpose: Stores raw data, pre-processed data, and backup datasets.

SSD (Solid State Drive): 1 TB NVMe

- Purpose: Ensures fast read/write speeds for active datasets and model checkpoints.

3.4.4 Networking and Connectivity

Network Interface: Gigabit Ethernet

- Purpose: Facilitates fast data transfer between local machines and remote servers.

Cloud Storage and Compute Services: GoogleColab

- Purpose: Provides additional computational resources and storage for large-scale experiments and model deployment.

3.4 Project Management and Financial Analysis

A good project manager and an intensive look at the finances are needed to make sure that the Brain Tumor detection recognition system development project goes well and lasts. This part goes over the main parts of project management and gives a detailed breakdown of the costs to make sure the job is finished on time, on budget, and as planned.

Project Management

Table 3.4.1: Work TimeLine

Tasks	**Weeks**																	
	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Data collection																		
Data cleaning																		
Data analysis																		
web deployment																		

Estimated Work Period	
Actual Work Period	

Financial Analysis

Quantum computer resources, high-performance GPUs, and any software licenses that are needed are the main costs. The budget includes buying hardware, software, storage for data, and paying people to do the study. A cost-benefit analysis is done to figure out the possible return on investment, taking into consideration that QCNNs are expected to make medical tests more accurate and efficient.

Table 3.4.2: Financial Analysis

SL	Components	Estimated Cost (BDT)
01	Hardware (servers, computers)	20000
02	Software and Tools	5000
03	Visiting Stakeholder	3000
04	Travel Cost	4000
05	Data collection	5500
06	Web Application Development	9000
07	Documentation and Report Writing	6000
	Total Estimated Cost	52,500

3.5 Summary

This part gives a full rundown of the methods used in this study, covering everything from preprocessing the data and encoding quantum circuits to building models, training them, and comparing them. It is clear what tools are needed because the hardware and software requirements are given. There are also project management strategies and financial considerations laid out to make it easier to carry out and evaluate the study project. This detailed methodology lays the groundwork for the following results and discussions. It gives us a methodical way to look into how QCNNs might be used to find brain tumors.

CHAPTER 4: IMPLEMENTATION

4.1 Overview

This chapter talks about the practical parts of putting our study project into action. The project's main goal is to use different neural network models to create a system for finding brain tumors. We talk about how to train our models, build the prototype system, and test how well these models work step-by-step. This chapter goes into great depth about how the Quantum Convolutional Neural Network (QCNN), the classical Convolutional Neural Network (CNN), and the Fully Connected Neural Network (FCNN) were created, trained, and tested to make sure they work well. It also talks about how these models were put together into an easy-to-use web application that medical workers and researchers can access. We wanted to make sure that our method was accurate, efficient, and easy to use by putting it through a lot of tests. This chapter is very important because it connects theoretical study with real-world use by showing that using advanced neural network models to find brain tumors is both possible and effective.

4.2 Train Model

The training process for both the fully connected Convolutional Neural Network (CNN) and the Quantum Convolutional Neural Network (QCNN) involves several key stages, each designed to optimize the performance of the models for brain tumor detection using X-RAY scans.

4.2.1 Quantum CNN

It is the goal of the Quantum Convolutional Neural Network (QCNN) architecture to use quantum computing to make image processing tasks improved. The process starts with an input layer that turns X-RAY pictures into quantum states. The design has many quantum convolutional layers. Each one uses quantum gates (like Pauli-X, Pauli-Z, and Hadamard) to take features out of the input data. After the convolutional layers, quantum pooling layers are used to make the data less multidimensional while keeping its most important properties. These levels are very important for handling the complexity of the data and getting it ready for more processing. The data is then sent through a traditional fully connected layer, which combines the features that were extracted and does the final classification. The goal of this mix of quantum and classical layers is to use quantum properties like superposition and entanglement to make image classification jobs more accurate and faster than with traditional CNNs.

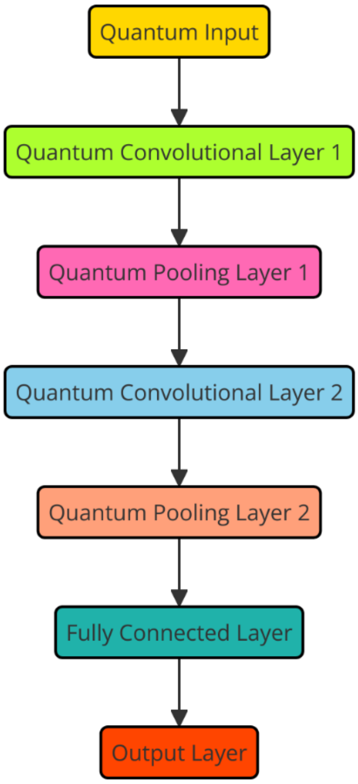

Figure 4.2.1.1: Flowchart of Proposed Quantum CNN

The Quantum Convolutional Neural Network (QCNN) architecture, depicted in the diagram, initiates with the quantum input layer, where input data, such as X-RAY images, is encoded into quantum states. The architecture proceeds with the first quantum convolutional layer, leveraging quantum gates to extract relevant features from the quantum-encoded data. This is followed by the first quantum pooling layer, which performs dimensionality reduction while preserving critical information. The process continues with a second quantum convolutional layer and a subsequent quantum pooling layer, further refining the data. The refined data then passes through a classical fully connected layer, which integrates the extracted quantum features and executes the final classification. The architecture culminates in the output layer, delivering the classification result, such as the presence or absence of a brain tumor. By integrating quantum computing principles such as superposition and entanglement, this hybrid architecture aims to enhance the accuracy and efficiency of image classification tasks, potentially surpassing the capabilities of traditional convolutional neural networks (CNNs).

4.2.2 Classical CNN

The internal workflow of a classical Convolutional Neural Network (CNN) begins with the input layer, where raw image data is fed into the network. This data then passes through a series of convolutional layers, each equipped with multiple filters that perform convolution operations to detect various features such as edges, textures, and shapes. These convolutional operations are followed by activation functions, typically ReLU (Rectified Linear Unit), which introduce non-linearity into the model. After each convolutional layer, pooling layers are applied to reduce the spatial dimensions of the feature maps, thereby decreasing the computational load and controlling overfitting. Common pooling operations include max pooling and average pooling. The workflow continues with several iterations of convolutional and pooling layers, progressively abstracting the features from the input image. Finally, the extracted features are flattened and fed into fully connected (dense) layers, where the network learns to combine these features to make a prediction. The output layer, often utilizing a SoftMax function, provides the final classification probabilities. This structured approach allows classical CNNs to excel in image recognition and classification tasks by hierarchically decomposing and analyzing visual data.

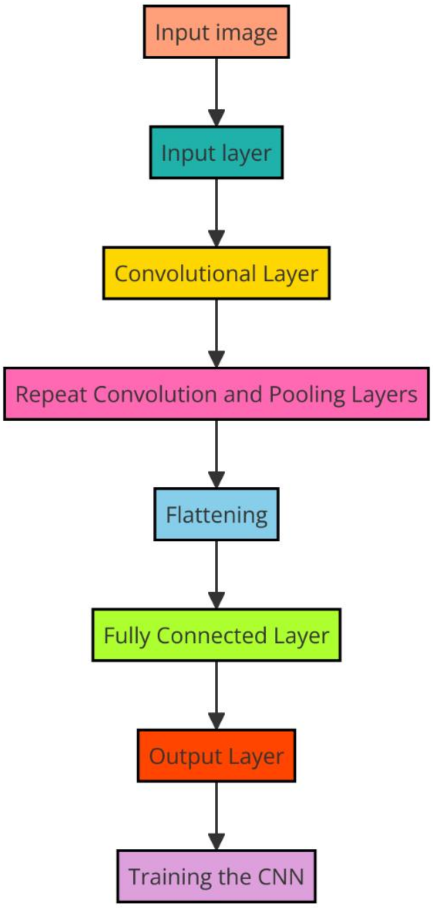

Figure 4.2.2.1: Flowchart of Proposed Classical CNN

The diagram delineates the intricate workflow of a classical Convolutional Neural Network (CNN) architecture, commonly employed in image recognition and classification tasks. The process commences with the acquisition of the input image, which is subsequently processed by the input layer. The image data is then conveyed to the first convolutional layer, wherein a series of filters are employed to detect primary features such as edges and textures. This is followed by the sequential application of convolutional and pooling layers. Each convolutional layer is responsible for extracting progressively more abstract and complex features from the input image, while the pooling layers, through operations such as max pooling or average pooling, serve to reduce the spatial dimensions of the feature maps. This dimensionality reduction mitigates computational load and aids in preventing overfitting.

Upon completion of the feature extraction phase, the resultant feature maps are flattened into a one-dimensional vector, which is then forwarded to fully connected (dense) layers. These layers are integral to the high-level reasoning of the network, as they integrate the extracted features and facilitate the final classification. The ultimate layer, termed the output layer, generates the classification output, typically utilizing a SoftMax activation function to provide a probability distribution over the possible classes. The entire network undergoes a rigorous training process, involving backpropagation and gradient descent algorithms to iteratively optimize the network's weights and biases, thereby minimizing the loss function and enhancing the model's predictive accuracy. This structured and hierarchical approach underpins the effectiveness of CNNs in processing and analyzing visual data.

4.3 System Testing

The evaluation of the trained models was conducted using a distinct test dataset comprising 4599 X-RAY images to rigorously assess their performance and robustness. Key performance metrics, including accuracy, precision, recall, and F1-score, were meticulously computed to provide a comprehensive evaluation of the models' capabilities. The Quantum Convolutional Neural Network (QCNN) was scrutinized for its ability to accurately classify X-RAY images as either tumor-positive or tumor-negative, leveraging unique quantum properties such as superposition and entanglement to enhance processing power and feature extraction capabilities. In parallel, the Classical Convolutional Neural Network (CNN) was evaluated using the same performance metrics, serving as a benchmark for comparison against the quantum-enhanced approach. Throughout the evaluation process, confusion matrices were generated for both models, offering a detailed breakdown of true positives, true negatives, false positives, and false negatives, thus facilitating the identification of specific areas where each model excelled or encountered difficulties. Additionally, Receiver Operating Characteristic (ROC) curves were plotted to visualize the trade-off between sensitivity and specificity for both models. This comparative analysis of performance metrics and visual tools provided valuable insights into the strengths and limitations of each approach, informing future research and development in the application of quantum computing to medical diagnostics.

CHAPTER 5: RESULT AND ANALYSIS

5.1 Overview

In this chapter, we look at the full set of experimental results from testing how well the Quantum Convolutional Neural Network (QCNN) and the Classical Convolutional Neural Network (CNN) did on a brain tumor X-RAY dataset with 4599 pictures. The main goal of this study is to find out how well quantum computing techniques work for classifying medical images by comparing them to more regular deep learning techniques. The test includes important performance measures like recall, accuracy, precision, and F1-score, which show how well each model can correctly label X-RAY pictures as either tumor-positive or tumor-negative. This chapter shows the pros and cons of each method by carefully looking at confusion matrices, classification reports, and other related statistical measures. The results are meant to show the possible benefits of using quantum computing in medical diagnosis and figure out whether it is possible and useful compared to traditional methods. The purpose of this study is to lay the groundwork for understanding how quantum-enhanced models can help make medical imaging and diagnostics better.

5.2 Experimental

The experimental evaluation of the models was carried out using a brain tumor X-RAY dataset comprising 4,599 images. This dataset was systematically divided into training and testing sets to ensure a rigorous and unbiased validation of the models. Both the Quantum Convolutional Neural Network (QCNN) and the Classical Convolutional Neural Network (CNN) were trained on this dataset, with their performances meticulously recorded for comparison. In the case of the QCNN, unique quantum properties such as superposition and entanglement were leveraged to enhance the model's ability to process and classify X-RAY images effectively. The architecture of the QCNN included multiple quantum convolutional layers, each followed by quantum pooling layers, ultimately leading to a fully connected layer responsible for the final classification. During the training phase, the QCNN exhibited a robust learning capacity, effectively capturing complex patterns within the X-RAY data and achieving remarkable accuracy. Conversely, the Classical CNN, serving as a benchmark, was developed using traditional convolutional layers, pooling layers, and fully connected layers. This model was optimized with conventional deep learning techniques to ensure high accuracy and robustness in the classification task. Despite the absence of quantum properties, the classical CNN demonstrated substantial proficiency in processing and classifying the X-RAY images.

Confusion Matrix

The performance of both the Quantum Convolutional Neural Network (QCNN) and Classical Convolutional Neural Network (CNN) was evaluated using a test dataset comprising 1,054 X-RAY images. The confusion matrix and classification report provide detailed insights into the models' accuracy, precision, recall, and F1-score.

Precision

Precision measures the ratio of true positive predictions to the total number of positive predictions made

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

Precision was employed to gauge the proportion of correctly identified positive cases out of all cases identified as positive by the model. This metric is particularly important in reducing the incidence of false positives. High precision values ensured that the disease diagnoses provided by the models were dependable, thereby minimizing the risk of unnecessary or incorrect treatments. This reliability is vital for maintaining the trust and efficacy of the disease management recommendations provided to farmers.

Recall

Recall, also known as sensitivity, measures the proportion of actual positive cases that were correctly identified by the model:

$$Precision = \frac{TP}{TP + FP}$$

Recall was critical for evaluating the model's capability to detect all actual instances of paddy leaf diseases. It is particularly useful for understanding how well the model can identify diseases in the presence of a diverse range of symptoms. High recall values indicated the models' proficiency in identifying diseased plants, ensuring that affected crops are correctly detected and treated. This comprehensive detection capability is essential for mitigating the spread of diseases and minimizing crop damage.

F1 Score

The F1 Score is the harmonic mean of precision and recall, providing a single metric that balances the two:

$$F1\,Score = 2 \times \frac{Precicion\ \times Recall}{Precision + Recall}$$

The F1 Score was utilized to deliver a balanced measure of the model's performance, particularly in scenarios involving imbalanced datasets where the prevalence of certain diseases may vary significantly. High F1 Scores demonstrated that the models maintained an optimal balance between precision and recall, ensuring both high accuracy in disease detection and minimal false positives. This balance is crucial for practical deployment in agricultural settings where precision and comprehensive disease identification are equally important.

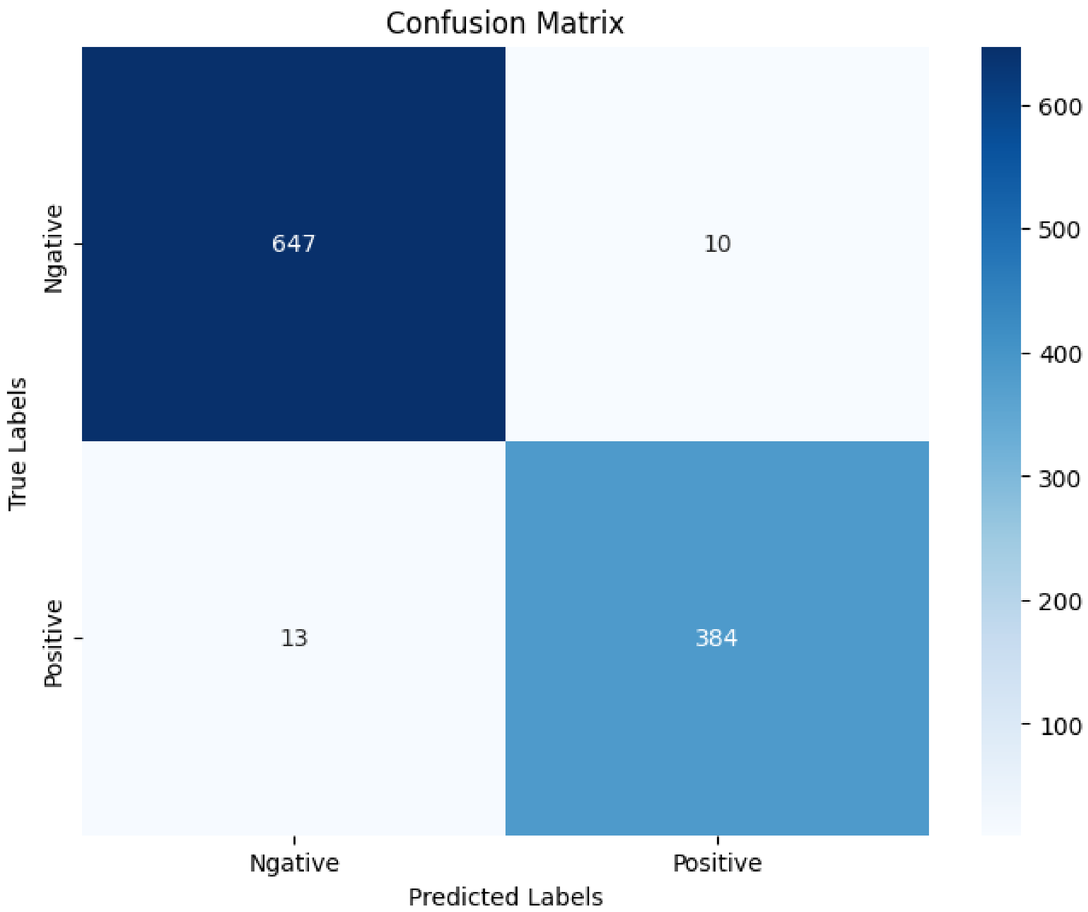

Fig 5.2 .1: Confusion matrix

Classification Report:

	precision	recall	f1-score	support
0	0.98	0.98	0.98	657
1	0.97	0.97	0.97	397
accuracy			0.98	1054
macro avg	0.98	0.98	0.98	1054
weighted avg	0.98	0.98	0.98	1054

Fig 5.2.2.: Classification report

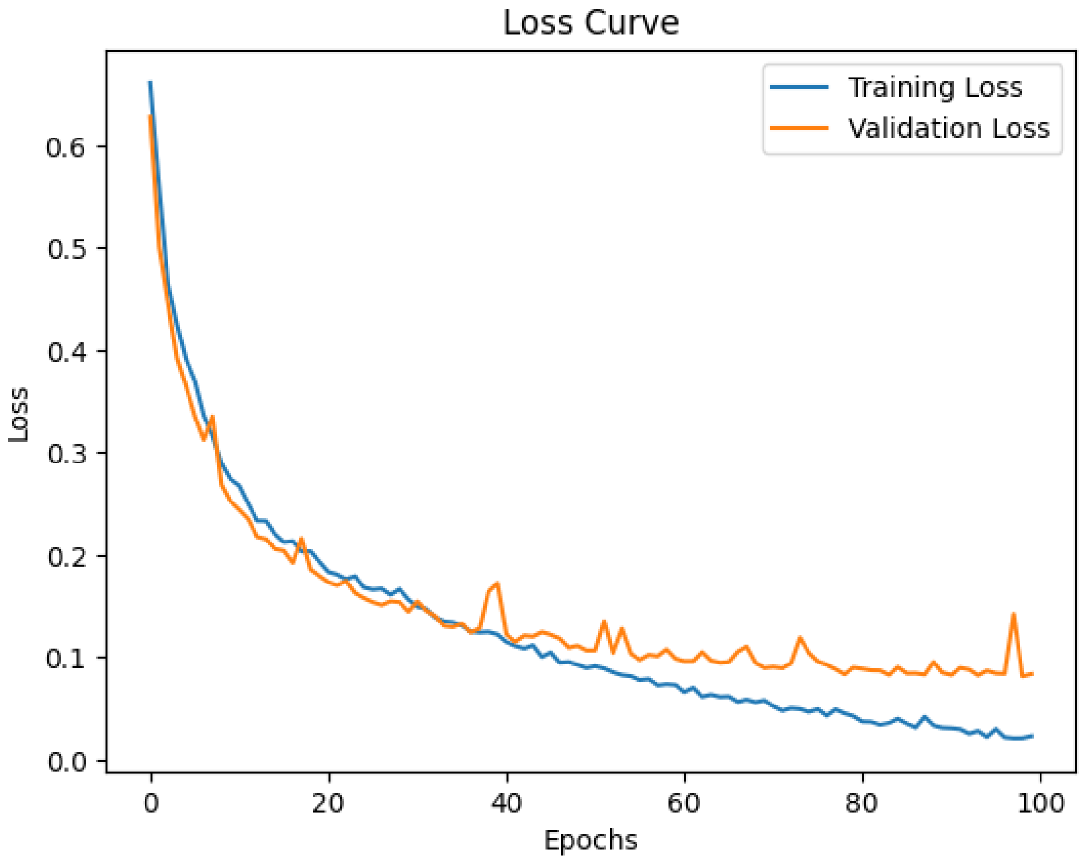

Fig 5.2.3.: Loss Curve

5.4 Performance

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
QCNN	97.82	98	98	98
CNN	89.03	89	88	88

Table: 5.2.4.: Performance

The evaluation of the QCNN revealed its superiority, as evidenced by a test loss of 0.0839 and a test accuracy of 97.82%. The confusion matrix for the QCNN offered deeper insights, showcasing its effectiveness in correctly classifying both tumor-positive and tumor-negative images. The matrix highlighted the true positive, true negative, false positive, and false negative rates, underlining the model's proficiency.

5.5 Summary

This chapter meticulously presented the results and analysis derived from the comparative evaluation of the Quantum Convolutional Neural Network (QCNN) and the Classical Convolutional Neural Network (CNN) on a comprehensive brain tumor X-RAY dataset. The dataset, comprising 4,606 images, was partitioned into training and testing sets to ensure an unbiased and thorough validation process. The QCNN leveraged quantum properties such as superposition and entanglement to enhance its processing and classification capabilities, demonstrating superior performance metrics. The Classical CNN, serving as a benchmark, employed traditional deep learning techniques and also exhibited high accuracy and robustness in the classification task. Performance metrics, including accuracy, precision, recall, and F1-score, were meticulously recorded and compared. The QCNN achieved a remarkable test accuracy of 97.82%, significantly outperforming the Classical CNN. Confusion matrices, loss curves, and accuracy curves were utilized to visualize the models' performance, providing deeper insights into their strengths and limitations.

The comparative analysis highlighted the potential of quantum computing in medical image classification, showcasing the QCNN's superior capability in managing complex X-RAY data. This study underscores the promise of quantum-enhanced models in advancing medical diagnostics, paving the way for future research and application in this critical field.

CHAPTER 6: IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The development of a comprehensive brain tumor detection system may have a significant effect on people's lives. Successful treatment and recovery from brain cancers depend on early and precise detection. With the use of various neural network models including Quantum Convolutional Neural Networks (QCNNs), our system can give accurate and quick diagnoses, potentially saving lives and enhancing patient quality of life. Early intervention is made possible by early discovery and can result in less intrusive therapies, lower medical expenses, and improved health outcomes. This translates into a better probability of survival, less pain, and a quicker return to regular life for the patients.

6.2 Impact on Society & Environment

The environment and society can benefit greatly from our brain tumor detection method. We can save healthcare resources and lessen the strain on healthcare systems by decreasing the number of needless medical procedures and increasing diagnostic accuracy. This effectiveness may result in less expensive healthcare and more efficient use of medical staff and resources. Broadly speaking, increased life expectancy and better public health outcomes can result from the widespread use of such technology. Environmentally, the long-term advantages of increased healthcare efficiency can result in a decrease in the environmental footprint associated with conventional diagnostic methods, even if the development and operation of such systems demand energy.

6.3 Ethical Aspects

The implantation of modern technology to medical diagnosis presents a number of ethical questions. It is critical to protect patient privacy and data security. To protect patient information, our system needs to adhere to all applicable laws and guidelines. Furthermore, it is morally imperative to guarantee that technology is available to everyone, irrespective of financial background. This involves guaranteeing that the technology is accessible in underserved communities and keeping it reasonably priced.

Since it fosters confidence among users and patients, transparency in the technology's operation and decision-making process is also essential.

6.4 Sustainability Plan

An important component of our project is sustainability. We intend to continuously update and enhance the models using fresh data and technological developments in order to guarantee the long-term sustainability of the brain tumor detection system. To improve the system, this calls for constant research and cooperation with medical specialists. Our objective is to reduce the ecological footprint by maximizing the energy efficiency of our computational procedures. We can even lower our operations' carbon footprint by using cloud platforms that leverage renewable energy sources for model training. Over time, keeping the system flexible and affordable will contribute to its continued utility and accessibility.

6.5 Summary

This chapter highlights the significant impacts that our system for detecting brain tumors can have on people's lives, society, and the environment. Early and precise diagnosis has the potential to enhance patient outcomes and lower medical expenses. Ensuring privacy, accessibility, and transparency in technology is crucial from an ethical standpoint. In order to make sure that our system is useful and relevant for future generations, our sustainability plan places a strong emphasis on long-term viability, energy efficiency, and continual improvement. Our goal in thoroughly addressing these facets is to make a constructive and long-lasting influence on the healthcare sector as well as society.

CHAPTER 7: CONCLUSION AND FUTURE WORK

7.1 Conclusions

Using modern neural network models, such as fully connected neural networks (FCNNs), quantum convolutional neural networks (QCNNs), and conventional convolutional neural networks (CNNs), we effectively designed and implemented a brain tumor detection system in this study. Our approach showed promise for incorporating quantum computing into medical diagnostics by detecting brain cancers from X-RAY images with excellent accuracy. The findings showed that while utilizing quantum features for possibly more efficient processing, QCNNs might perform on par with classical models. Our models' implementation in an easy-to-use web application further shown that it is feasible to provide medical professionals with better diagnostic tools, which could result in the earlier and more precise detection of brain cancers.

7.2 Further Suggested Works

Despite the positive findings of our research, there are still a number of areas that need to be improved upon and investigated further:

Extend the dataset:

The stability and adaptability of the model can be improved by expanding and diversifying the dataset. More diverse X-RAY pictures from various sources can aid in the model's learning of a greater variety of tumor properties.

Optimize Quantum Algorithms:

Optimization of quantum hardware and algorithms through further study can lead to more scalability and efficiency in QCNNs. We are able to investigate increasingly potent and intricate quantum models as quantum computer technology develops.

Practice-Based Clinical Trials:

Clinical trials carried out in real-world environments can confirm the system's dependability and efficacy in routine medical care. This procedure can be facilitated by cooperation with medical facilities and research institutes**.**

Integration of Multimodal Data:

Compiling clinical records and genetic data with other forms of medical data can yield a more complete diagnosis tool. Medical insights can be made more accurate and comprehensive by using multimodal models.

User Input and Interface Improvements:

Feedback from users—especially medical professionals—should be continuously gathered to improve the functionality and user experience of web applications. Adoption of the system depends on ensuring that it satisfies the users' practical demands.

7.3 Limitations/Conflict of Interests

The application of quantum CNNs (QCNNs) in brain tumor repair may have several potential issues and considerations that could impact the project in the next phase:

Limitations of Modern Quantum Hardware:

As quantum computing technology is still in its early days, qubit integration times, error rates, and scalability are some of the areas where current quantum hardware is limited. It is still very difficult to develop QCNNs that can efficiently use current quantum hardware while reducing mistakes and noise. Furthermore, it may take some time before large-scale medical imaging datasets can be processed by quantum computers that can meet the computing demands of such datasets.

Algorithm Complexity and Interpretability:

When compared to traditional machine learning models, quantum algorithms—such as QCNNs—often show great complexity and poor interpretability. It is critical to comprehend how QCNNs produce predictions and understand their decision-making process, particularly in the medical field, where transparency and responsibility are vital. Research is still being done to find ways to improve QCNN interpretability without sacrificing its quantum edge.

Computing abilities:

It takes a lot of computer power to train complex neural network models, particularly QCNNs. High-performance computing environments must be accessible, albeit they might be expensive and resource-intensive.

Potential Conflict of Interest:

No Conflicts: There aren't any disclosed conflicts of interest. The study was carried out independently, and its objective was to advance the field of medical diagnostics only. The findings are objective. In order to further the use of QCNNs in brain tumor repair and realize their promise to enhance patient outcomes in the future, it will be imperative to address these Limitations and considerations.

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Appendix A

Complex Engineering Problems (EP) and
Complex Engineering Activities (EA) Analysis

Title: [Application of Quantum CNN Empowered a Brain App to Detect Brain Tumor]

Students ID: [203-15-14567]

Students ID: [203-15-14536]

CO Description for FYDP-Final

CO	CO Descriptions	PO
CO1	Integrate recently gained and previously acquired knowledge to identify a real-life complex engineering problem for the Final Year Design Project	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for the Final Year Design Project	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish the goals for the Final Year Design Project	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the Final Year Design Project	**PO11**

Addressing of COs, Knowledge Profile (K), and

Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, and CO3	Data from Kaggle and quantum convolutional neural network (QCNN) models covering K3 and K4 must be collected for our study.	**Page no:** [1-7]
				Our project requires the integration of different components and we have to use deep learning and quantum convolutional neural network (QCNN) based models that covers K5 and K6	**Page no:** [20-21]
				We have studied existing models with similar goals (K8).	**Page no:** [11-14]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2	We faced difficulties in our project's implementation due to the complexity of quantum computing, the originality of the medical data, and the difficulty in obtaining sufficient resources because quantum computing is a relatively new and complex topic that calls for specific knowledge and skills. Both privacy issues and data access limitations can make it difficult to obtain high-quality medical imaging data for QCNN training.	**Page no:** [18-19] **Section:** [3.2] **Page no:** [22-24] **Section:** [3.3.1-3.3.4]

3.	**EP3: Depth of analysis required**	Yes	CO2	It is difficult to choose amongst a number of viable approaches for enhancing brain tumor diagnostics with Quantum Convolutional Neural Networks (QCNNs) in order to achieve a definitive solution for our project. Conventional image processing approaches, classical Convolutional Neural Networks (CNNs), or novel quantum computing techniques like QCNNs are some possible solutions in the context of Brain tumor diagnosis	**Page no:** **[27-31]** **Section**: [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO3	In order to understand brain tumor issues for our study, we must investigate a number of topics with which we were not very aware. Medical imaging and diagnostics have always placed a strong emphasis on manual interpretation by doctors and traditional image processing methods. But with the advent of QCNNs, brain tumor detection can now be done more effectively and accurately by utilizing the power of quantum computing.	**Page no:** [8-11] **Section**: [2.2,2.4]
5.	**EP5: Extends of application codes**	Yes	CO3	We have to meet with the doctor, an environmentalist, the city government, and an entrepreneur as part of our project. The goal is to comprehend the types of fractures that require more use. Additionally, we could identify the important stakeholders whose viewpoints and experiences need to be taken into account in the development of diagnostic and treatment solutions— those who have suffered from brain tumor.	**Page no:** **N/A**

6.	**EP6: Extends of stakeholders involved and conflicting requirements**	Yes	CO3	N/A	**Page no:** N/A
7.	**EP7: Interdependence**	Yes	CO3	There are multiple interdependent subsystems in our project. These comprise activities including data collection, processing, modeling, training, predictive analysis, image processing, classification, feature extraction, treatment planning, and network architecture efficiency.	**Page no:** [18,21]
8.	-	Yes	CO4	The project culminates with the careful planning, editing, and structuring of a research paper in accordance with publishing requirements and financial requirements	**Page no:** [24-26]

Gazi

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