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Hybrid Quantum Neural Architecture in Biomedical Image Recognition

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ABSTRACT

Superposition states that, similar to waves in classical physics, you can combine two or more quantum states to create another acceptable quantum state. whereas, every quantum state can be represented as the sum of two or more distinct states. This superposition of qubits provides quantum computers with inherent parallelism, allowing them to perform millions of operations at the same time. Quantum entanglement happens when two systems are so closely linked that knowledge of one provides immediate knowledge of the other, regardless of how far apart they are. Quantum processors can infer judgments about one particle after measuring another. For example, they can decide that if one qubit spins up, the other always spins down, and vice versa. Quantum entanglement enables quantum computers to solve complicated problems more quickly.When a quantum state is measured, the wavefunction collapses, resulting in either a zero or a one. In this known or predictable condition, the qubit functions like a conventional bit. Entanglement refers to qubits' capacity to associate their states with other qubits. Decoherence means the loss of a quantum state in a qubit. Environmental influences, like as radiation, can cause the qubits' quantum states to collapse. A significant engineering issue in establishing a quantum computer is designing the numerous characteristics that seek to delay state decoherence, such as building specialist structures that screen the qubits from external influences.[17] Using Qiskit, we built a Quantum Convolutional Neural Network (QCNN) to categorize MRI brain tumor pictures into two categories: tumor and no tumor. To circumvent the dimensionality constraints of quantum systems, Principal Component Analysis (PCA) was used to condense the visual data into core components appropriate for quantum encoding. The model was trained on a quantum simulator and its performance measured using measures such as classification accuracy, precision, recall, and f1-score. Despite existing hardware limits, the experiment shows that hybrid quantum-classical models may be used to perform challenging medical picture categorization tasks. The EstimatorQNN is a neural network that accepts a parametrized quantum circuit with specified parameters for input data and/or weights, as well as an optional observable(s), and returns its expectation value(s).A blended quantum circuit is implemented. Such a circuit is composed of two circuits: a feature map, which gives input parameters to the network, and an ansatz (weight parameters).[b] To apply Grover's approach for n qubits from a resister Q, initialize the state H⊗n|0n⟩ and then run G repeatedly. G=H⊗nZORH⊗nZf the sets of not solved and solved approaches. A0 = {x∈ Σn | f(x)=0} and A1 = {x ∈ Σn: f(x)=1} may be used to create a uniform superpositions of the following form: |A0⟩ = 1 √ |A0| ∑ |x⟩ x∈A0 |A1⟩ = 1 √ |A1| ∑ |x⟩ x∈A1.[c]

INTRODUCTION

Background and Motivation:

Quantum computing is founded on a fundamentally different physical phenomenon than traditional computation. It is a fast-expanding field of study that aims to apply quantum mechanics concepts to the development of new computing technology. Unlike classical computing, which utilizes bits that can only exist in one of two states (0 or 1), quantum computing uses quantum bits, or qubits, which can be in several states at the same time, resulting in an exponential boost in machine capacity. Quantum computing has the potential to transform a wide range of industries, from encryption to drug development, by enabling the solution of problems that are currently outside the scope of classical computers. However, the construction of workable quantum cosmputing remains a serious issue.Quantum computing is a sort

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of computing system that uses the collective properties of quantum states, such as superposition, interference, and entanglement, to perform calculations. Although classical computing has advanced significantly over the last few decades, many issues remain that cannot be solved by these machines. Quantum machines give an exponential speedup that even a parallel computer cannot match. It provides a promising path for problem-solving, opening up new applications, and advancing research and technology in areas like materials science and cryptography. The creation of useful quantum computers is therefore critically needed in the upcoming years.[1]

Problem Definition:
Using the aid of qiskit to solve the binary classification problem since no one solve with qiskit all work previously done in pennylanne, pytorch cirg etc. but nobody has done this approach, thus I am doing this sort of problem to work.

Objective of the Problem:
A Hybrid approach for efficient binary classification
QCNN on Qiskit is built by modeling both the convolutional and pooling layers using a quantum circuit. After creating such a network, we train it to distinguish between horizontal and vertical lines in a pixelated image.[2]

Scope of the work:
Analyze a unique quantum machine learning model based on convolutional neural networks. quantum convolutional neural network (QCNN) uses only variational parameters for qubit input sizes, making it suitable for efficient training and implementation on practical, near-term quantum devices. The QCNN architecture combines the multi-scale entanglement renormalization approach with quantum error correction.[3]

LITERATURE REVIEW

IoT is rapidly transforming the healthcare sector with new innovative approaches. luckily proposed V-Doctor. The module monitors patient health using several sensors. Utilizing Arduino and sensors to monitor pulse and temperature, we identified numerous health conditions. This IoT gadget can monitor temperature and heart rate. The proposed V-doctor module continuously updates an IoT platform with ambient temperature and pulse rate, identifying human illnesses based on these parameters.[4] To explore the possibility of quantum computing for efficiently processing and classifying picture data, even with low feature availability. It examines how QCNNs can discriminate between normal and pneumonia cases using chest X-ray pictures in a feature-constrained scenario. Our findings indicate that QCNNs may effectively categorize images with reduced feature dimensions, demonstrating its robustness and potential for use in machine learning and computer vision. This study demonstrates the scalability and adaptability of QCNNs across training test splits, highlighting their potential to improve computational efficiency in machine learning tasks. This indicates a potential paradigm evolution.[5] QML is becoming increasingly used in various disciplines, including RS, finance, energy, space exploration, medicine, and physics.QML classifiers surpassed conventional approaches for accuracy, high-dimensional data management, and computational efficiency. However, problems remain, like noisy quantum equipment and the need for hybrid and creative quantum algorithms.[6]

Brain imaging provides comprehensive images and is crucial for detecting abnormalities, such as tumors. It is challenging to appropriately categorize different types of cancers. Advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have showed promise in accurately classifying brain cancers using MRI data. However, CNNs' performance may be limited by the size and complexity of the dataset.

This study applies the Hybrid Quantum Classical Convolutional Neural Network (HQC-CNN) and DenseNet121 model to three types of brain malignancies: meningioma, glioma, and pituitary tumors. The HQC-CNN and DenseNet121 models successfully classified brain tumor images with accuracies of 88% and 94%, respectively.[7]

Medical image analysis studies require rigorous experiments to demonstrate the effectiveness of proposed approaches. However, experiments frequently use pre-selected data.

Researchers can originate from various institutions, scanners, and demographics. Comparing evaluation methods might be challenging due to the usage of different measures. This research presents a dataset of 7909 breast cancer histopathology images from 82 patients, which is currently publically available at Breast -Cancer-Database [a]. The collection includes both benign and cancerous photos. The task is related with

Demonstrate preliminary results from cutting-edge image categorization methods. Accuracy ranges between 80% and 85%, indicating potential for improvement. Our dataset and standardized evaluation process aim to bring together experts from medical and machine learning fields to develop clinical applications.[8]

COVID-19 is a contagious virus that can infect lung cells and respiratory systems, creating a serious threat to human lives. Identifying appropriate infection patterns on lung CT images is a tough task for researchers.

COVID-19 diagnostics are automated. A new semi-supervised shallow neural network system uses a Parallel Quantum-Inspired Self-supervised Network (PQIS-Net) to automatically segment lung CT images, followed by Fully Connected (FC) layers.[9]

Diagnosing an illness involves laborious and error-prone procedures. Using AI prediction approaches improves autodiagnosis and minimizes detection mistakes compared to relying solely on human expertise.

Current literature during the last ten years, January 2009–December 2019. The study analyzed the eight most often used databases and discovered 105 articles. A rigorous study of the publications was undertaken to classify the most often used AI techniques for medical diagnostic systems. We cover numerous diseases and AI techniques such as Fuzzy Logic, Machine Learning, and Deep Learning. This research paper seeks to provide insights into current and prior AI strategies utilized in medical research, focusing on heart disease prediction, brain disease, prostate, liver illness, and kidney disease.[10]

Quantum physics' stochastic nature allows for random computation, making data science crucial for developing quantum computation and information.This article provides an overview of quantum computing and encourages collaboration between quantum research and data science.[11]

Excessive data or model dimensions can make CNN learning difficult.

Quantum Convolutional Neural Network (QCNN) offers a quantum computing-based solution to a problem or enhances an existing learning model's performance.
Shor’s algorithm is famous for factoring integers in polynomial time. Since the best-known classical algorithm requires greater-than-polynomial time to factor the product of two primes, the widely used cryptographic protocol, RSA, relies on factoring being impossible for large enough integers.[12]

Summary of Previous work:

Index & Years	Work	Methodology	Finding	Limitation
[4] 2023	IOT controller,	Arduino,Sensor ,v-Doctor module	Pulse rate	Applicable in rural area,WIFI module
[5] 2024	X-ray image	Quantum Support Vector Machine(QSVM)	Distinguish normal and pneumonia	Low feature scenarios,Robustness
[6] 2025	Engineering,medicine,economics	520 research article,23 research review (years 2013 to 2023)	Review on QML applications	Noisy quantum hardware,intricate diseases
[7] 2025	Magnetic Resonance Imaging (MRI)	HQC-CNN Accuracy (88%) & DensNet121 Accuracy (94%) quantum simulator	Classify complex image Detection	Aids medical image analysis
[8] 2016	Histopathological image classification	State -of-the-art accuracy 80% to 85%	Image Classification	Challenge for multiclass malignant and benign image
[9] 2021	Covid -19 Lung CT images	State-of-the-art QIS-Net,3D-Unet and ResNet50	Mycoplasma Pneumonia screening	Models face serious
[10] 2020	Medical Diagnostic Systems Principles and Perspectives Jan. 2009 to Dec. 2019	Fuzzy Logic,Machine Learning and Deep Learning	Heart disease prediction 91% AI methods reported positive impact	Alzheimer's disease and Parkinson's Disease
[11] 2022	Multiple frontiers computer Science to mathematics		Quantum information,Quantum speedup	

	and statistics			
[12] 2020	MNIST Dataset	QCNN ,Ansatz	Use o(log(n))	Correlation information of data
[13] 2019	Tutorials	Implementing convolutional layers and pooling layers	Qiskit	Binary classification
[14] 2019	Optimum quantum circuit			Nature Physics

PQIS-Net : Parallel Quantum-Inspired Self-supervised Network
QCNN: Quantum Convolutional Neural Network

Justification Approach:
Over all past work with Tensorflow, Keras, Pythorch, Pennylane, and Cirag to handle quantum machine learning problems using this type of simulator that they use, therefore in my project, I will implement the quantum circuit, convolution neural network, pooling layers, and anstaz.

METHODOLOGY

Dataset Description:

A Brain tumor is considered as one of the aggressive diseases, among children and adults. Brain tumors account for 85 to 90 percent of all primary Central Nervous System(CNS) tumors. Every year, around 11,700 people are diagnosed with a brain tumor. The 5-year survival rate for people with a cancerous brain or CNS tumor is approximately 34 percent for men and36 percent for women. Brain Tumors are classified as: Benign Tumor, Malignant Tumor, Pituitary Tumor, etc. Proper treatment, planning, and accurate diagnostics should be implemented to improve the life expectancy of the patients. The best technique to detect brain tumors is Magnetic Resonance Imaging (MRI). A huge amount of image data is generated through the scans. These images are examined by the radiologist. A manual examination can be error-prone due to the level of complexities involved in brain tumors and their properties.

Application of automated classification techniques using Machine Learning(ML) and Artificial Intelligence(AI)has consistently shown higher accuracy than manual classification. Hence, proposing a system performing detection and classification by using Deep Learning Algorithms using Convolution-Neural Network (CNN), Artificial Neural Network (ANN), and Transfer-Learning (TL) would be helpful to doctors all around the world.

Brain tumours are complex. There are several variations in the size and location of the brain tumor(s). This makes it extremely difficult to gain a thorough knowledge of the malignancy. In addition, MRI analysis requires the services of a skilled neurosurgeon. Often, in developing nations, a lack of skilled doctors and information about tumors makes generating MRI results extremely difficult and time-consuming. So a cloud-based automated system can fix this problem.

The dataset is divided into three folders: yes, no, and pred, which contain 3060 brain MRI images.which is 1500 yes_tumor and 1500 no_tumor with value 60.[1][d]

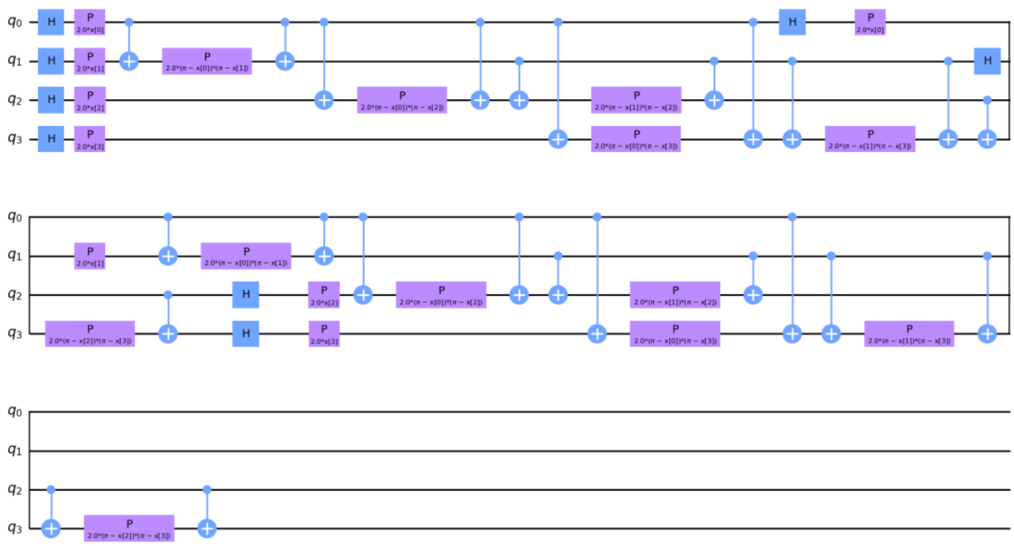
Preprocessing Technique:
My dataset already has annotations with the help of loading the dataset, then splitting the dataset into x_train, X_test, y_train, y_test 70 and 30, applying angle encoding for data augmentation, normalizing for how many data are distributed, then principal component analysis to extract the important features without the loss of important features to insert the important features.

```
Size of dataset: (3000, 2, 2), Label: (3000,)
```

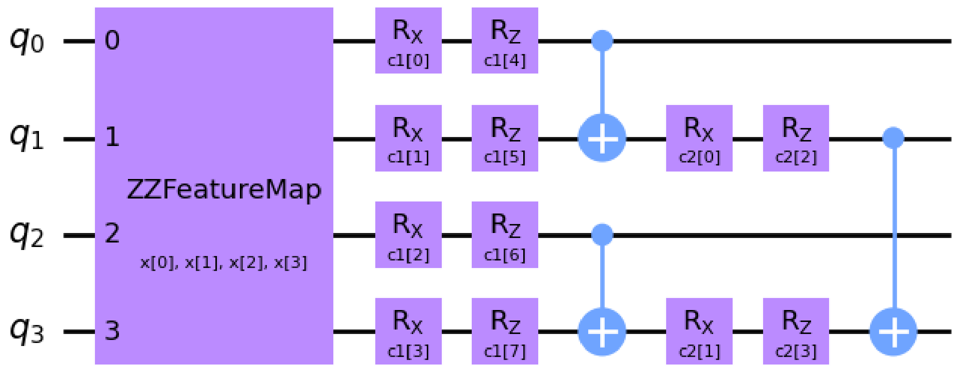
```
Processed train data shape: (2100, 4)
Processed test data shape: (900, 4)
Original train data shape: (2100, 4), Labels: (2100,)

Original test data shape: (900, 4), Labels: (900,)
```

Quantum Model:
To classical data to encode quantum state form (2,2) qubit into feature map for quantum state ZZfeaturemap, quantum support vector machine learning.



Integration of Quantum Convolution and Pooling Layer:
Adding a quantum convolution and pooling layer to extract important features of classical data, using the Ansatz with a first convolution layer c1 connected to four qubits, then pooling in chronological order, adding in the quantum circuit, and encoding the data in the quantum state format. This is the process used here.



Tools and Platform :

Using several library packages in this project, including qiskit == 1.3.1, qiskit_machine_learning == 0.8.2, pylatexenc, and qiskit qiski-aer ==0.13.3. We then import several parts, such as QuantumCircuit for feature map, ZZFeatureMap for quantum state, COBYLA for maxtier, PCA, Classification_report,AerEstimator, and class_weight.

```
import json
import pickle
import cv2
import matplotlib.pyplot as plt
import numpy as np
from IPython.display import clear_output
from qiskit import QuantumCircuit,transpile
from qiskit.circuit import ParameterVector
from qiskit.circuit.library import ZFeatureMap,ZZFeatureMap
from qiskit.quantum_info import SparsePauliOp
from qiskit.primitives import StatevectorEstimator as Estimator
from qiskit_machine_learning.optimizers import COBYLA
from qiskit_machine_learning.utils import algorithm_globals
from qiskit_machine_learning.algorithms.classifiers import NeuralNetworkClassifier
from qiskit_machine_learning.neural_networks import EstimatorQNN
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.utils import class_weight
from sklearn.metrics import classification_report
from qiskit_machine_learning.optimizers import SPSA,NFT
from qiskit_aer import AerSimulator
from qiskit_aer.primitives import Estimator as AerEstimator
from sklearn.utils import class_weight
#from imblearn.over_sampling import RandomOverSampler

algorithm_globals.random_seed = 12345
estimator = Estimator()
```

There is no use of any quantum simulator, such as IBM, because of the qubit issue. If the performance of the qubit model is increased, the results will be better.This is pure documentation of the qiskit tutorial that is used here.

IMPLEMENTATION

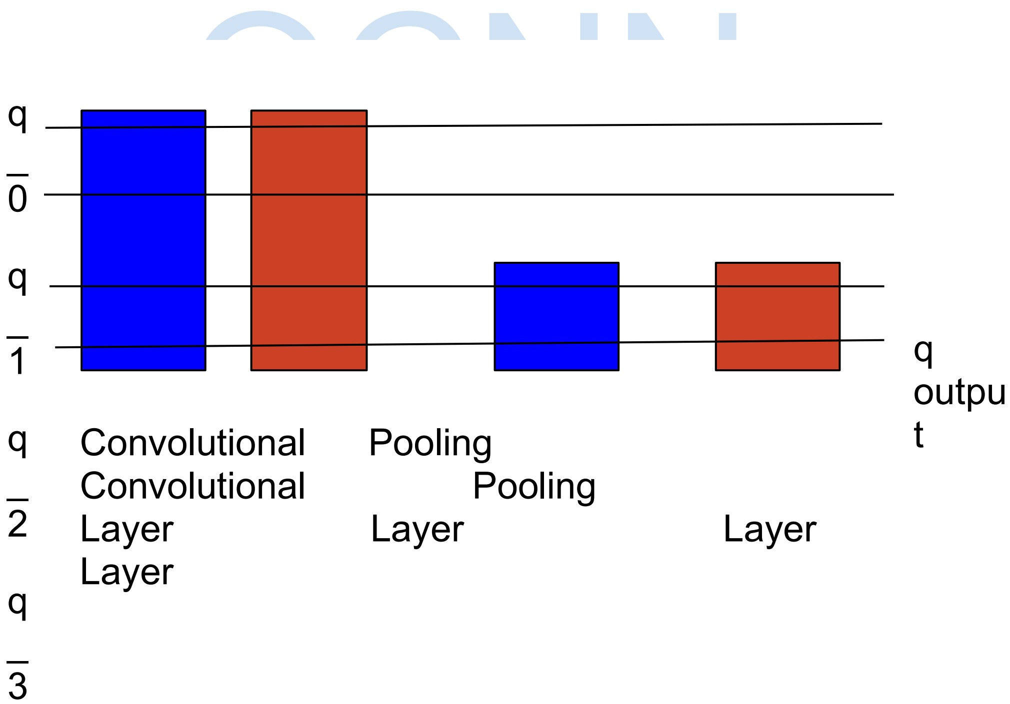
Hardware and Software setup:

In the classical computer, there are various issues that occur: quantum decoherence, quantum pruning, and quantum error fixing. To increase the model correctness, here are some basic things that are available in the PC. This is the simple, practical way to implement this term.

Software	Hardware
Python 3.8+,Google Colab	Local Classical Machine Core Intel i5
Qiskit framework	8 GB RAM
qiskit.visualization	Windows 10
numpy	Classical Simulator AerSimulator
matplotlib	Google Drive
scikit-learn	Ubuntu 20.04+

Step by Step Explanation:

The components of a QCNN include data generation, building, training, and testing.



component of QCNN encoding, then applying ZZFearMap for quantization of the data and extracting the new information from the convolution layer, pooling layer becoming the final qubit by using the order of complexity (o(n)/2) methodology, data generation, training, and testing the MRI tumor data of binary classification.

Error Handling and Model Tuning:
During information transfer, the coherence time is around 100 microseconds, with a correction time of 10 microseconds. Quantum mechanics theory predicts collapse. Fixing errors and breaking quantum states, however, is at the heart of quantum computing.

There are two types.
Bit flip fault (X error): Act as a NOT gate, changing the qubit value from classical 0 to 1 or 1 to 0. Pauli X gate $|\psi\rangle=\alpha|0\rangle+\beta|1\rangle$ becomes $|\psi\rangle=\alpha|1\rangle+\beta|0\rangle$.
Error during phase flip: Pauli Z Gate The amplitude remains constant, but the phase (sign) changes from + to - or - to +. For example, $|\psi\rangle=\alpha|0\rangle+\beta|1\rangle$ becomes $|\psi\rangle=\alpha|0\rangle-\beta|1\rangle$.
Combined Error: Bit + Phase Flip = Y-error. Pauli-Y gate equals iXZ.used the COBYLA optimizer for tunning.

RESULT AND DISCUSSION

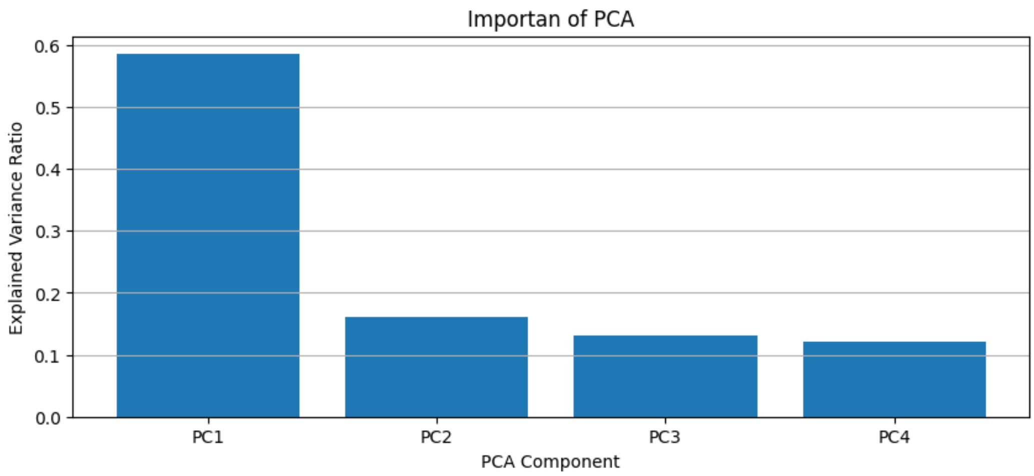
Model Accuracy :

Label	Precision	Recall	F1-Score	Support
No Tumor	0.48	0.49	0.48	439
Tumor	0.51	0.50	0.50	461
Accuracy			0.49	900
Macro Avg	0.49	0.49	0.49	900
Weighted Avg	0.49	0.49	0.49	900

Precision : Model Predicted a class(Tumor /No Tumor), how many times was it correct?
Recall: How many did the model correctly identify?
F1-Score: Harmonic Mean of precision and recall.Good when balance between the precision and recall.
Support: The number of actual occurrence for each class in the testing MRI dataset.

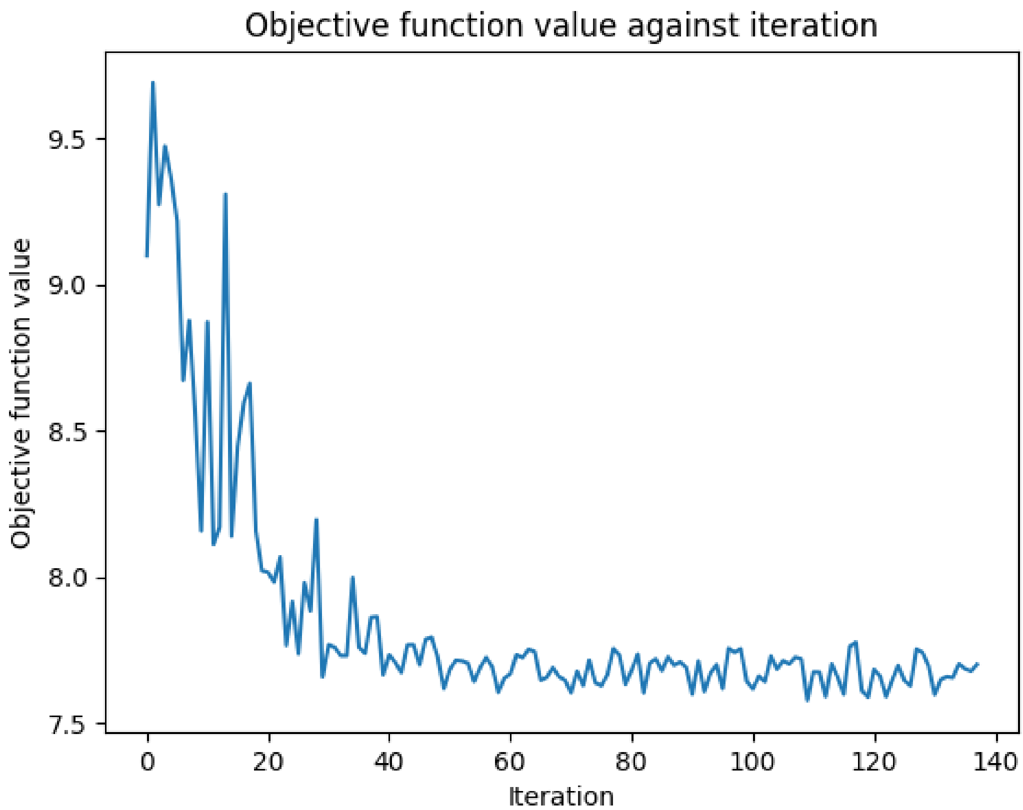
Accuracy: 49% it means only half is correct prediction,Weighted Avg is 0.49 it means model is not biased toward one class,but not effective for either class.

5.2 Visualization and Garph:
Distribution of **Principle component Analysis** in term of Explain Variance how the information capture the information.



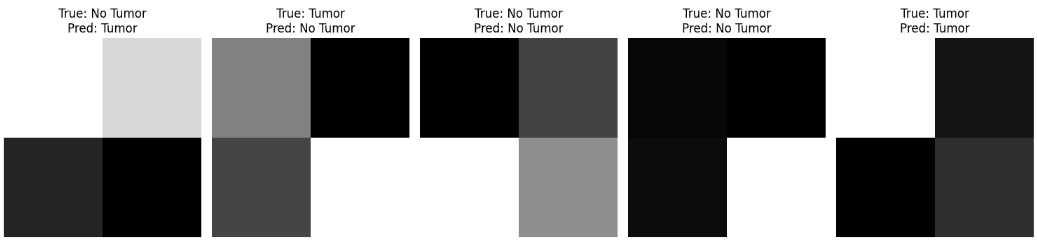
Principle Component Analysis	**Variance Explanation**	**Means**
PC1	~59%	MRI data capture information in term of variance
PC2	~17%	Moderate variance
PC3	~13%	More less
PC4	~12%	Most less

Objective Function Value vs Iteration
It means aims function consistently decrease, which is a good indicator.



Above graph (0-30) iterations, the curve is rapidly declining, while the medium phase (30-70) iterations is nearly flat, and the later phase (70+ iterations) is around 7.6 to 7.8. then learning improves not according, therefore after using just 70 iteration use only.

Five randomly selected images are used to forecast if a tumor exists or not.



CONCLUSION

Summary and Achievements :

We investigated a hybrid classical-quantum approach to MRI brain tumor classification utilizing Quantum Convolutional Neural Networks (QCNNs) implemented using Qiskit. The goal was to use a binary classification approach on a multiclass MRI dataset to discriminate between the "Tumor" and "No Tumor" categories.Preprocessed MRI scans were used to extract significant features. To reduce dimensionality while keeping important variance, we utilized Principal Component Analysis (PCA).

Classical data was converted into quantum circuits using Qiskit's amplitude encoding. Built and trained a quantum convolutional neural network (QCNN) model.

Performance has been assessed using classification measures as well as visual tools.Extracted insights using PCA, revealing that the first principle component accounts for more than 58% of the variance.

Limitation :

Limited accuracy (~49%) which means model did not perform out perform and also this could not be use in multiclass causing loss of information.Quantum hardware Constrants because model was simulated on classical hardware using Qiskit's rather than other simulator,limited qubit,data size and complexity even MRI images (2,2) a small number of qubits results in significant dimensionality reduction,training Instability optimization methods still lack the robustness and consistency of their classical counterparts,so due to real time medical medical application lack due to accuracy limitations and current quantum infrastructered and model is not ready for clinical or diagnostic use.

Future scope and Application :

Drug discovery

Covid-19 (deadly mutation to forecast spread and save lives.

Vaccine development involves studying cancer protein folding (mutations) and human life span biology (DNA level) to create anti-agent drugs and improve medical facilities.Space industry to decrease quantum loss to develop models like blackhole quantum, gravity precisely, dark energy, dark matter, and the mystery of the universe.The exact position of stars, planets, asteroid, and planetary motion is determined every second.To journey to Mars, millions of variables are solved for the exact course of a spacecraft.New material design, alien life, biosignature, and dark equation-like planetary dataset scan in which alien life is active.The impact of physics and mathematics formulas on technological advancementsAI (self-learning) + Quantum computing: how human life advances and never stops.

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