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A Review on Image Classification of Medical Images for Tumor Detection Using Quantum Convolutional Neural Networks

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Abstract: Quantum Convolutional Neural Networks (QCNNs) have became a promising field for quantum advantage in feature extraction and classification of different datasets like Handwritten datasets, Fashion datasets, particularly useful for complex datasets like medical images. Medical image classification has emerged as a critical component in modern healthcare diagnostics, particularly for tumor detection and cancer diagnosis. Normally, Classical CNN is used for image classification but they may face certain challenges in achieving further improvements in accuracy, computational efficiency, processing time. Also, it becomes difficult to train for high-dimensional medical datasets and extracting complex feature representations. Therefore, In this proposal, Image classification through a Scalable and Resource efficient QCNN is proposed which integrates classical CNN with quantum computing. This review examines the current state of medical image classification for tumor detection, analyzes the transition from classical CNNs to quantum-based architectures, and explores the potential of QCNNs in revolutionizing medical diagnostics. This research includes QCNN architecture which will include selective feature encoding using encoding technique such as Z Feature map and quantum circuits for convolutional layers and pooling layers to handle multi-modal medical data (e.g., MRI and CT scans). We aim to achieve superior accuracy with reduced parameters over classical CNNs. This work advances quantum ML toward practical deployment in resource-limited healthcare settings.
Keywords: Quantum computing, quantum circuit, convolutional neural network, quantum convolution, quantum pooling, quantum convolutional neural network, image classification, deep learning, medical imaging, Tumor detection

I. INTRODUCTION

The study and analysis of medical images remains a cornerstone of diagnostics. Classical convolutional neural networks (CNNs) struggle with the high-dimensional, noisy, and multi-modal nature of such data and often it requires vast computational resources. Quantum computing offers potential exponential speed-ups through quantum phenomenon such as superposition and entanglement, but NISQ devices limit scalability due to qubit counts and noise. Recent research has addressed these through hybrid quantum-classical models and circuit optimizations making the way for efficient QCNNs.

This proposal addresses the gap in scalable, symmetry-aware QCNNs for multi-modal medical data imaging. By combining distributed hybrid techniques, we propose medical image classification using QCNN for Tumor detection using medical datasets like MRI, CT scan etc. QCNN based model enhance feature extraction while minimizing qubit overhead.

In this paper, we expect faster and better performance in terms of accuracy as compared to Classical methods which will form basis for broader quantum-enhanced AI applications

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II. LITERATURE REVIEW

Recent advancements in QCNNs have focused on hybrid architectures, feature optimization, and symmetry preservation to bridge quantum theory and practical implementation. Some of the previous works include:

In [1], Author compares CNN and QCNN architecture for image-based tasks, to enhance feature extraction capabilities. Better QCNN accuracy (91.57%) and processing speed was achieved for covidx-cxr3 datasets. But, More methods for features extraction needs to be carried out to explore the interpretability and performance improvement of QCNN models.

In [2], This introduces QINN that has been developed to improve image recognition capabilities. The study's findings indicated that QINN displayed superior accuracy rates compared to traditional methods and revealed faster convergence throughout the training process. Here, expansion of network scalability to accommodate bigger datasets and exploration of security measures are needed to be explored.

In [3], The study had combined (MERA) and quantum error correction(QEC) with QCNN. It simultaneously optimizes both encoding and decoding procedures and find that the resultant scheme outperforms known quantum codes of comparable complexity. However, this study only present the QCNN circuit structure for recognizing 1D phases and more research is needed for 2D and 3D

In [4] The research consisted of multiple small quantum devices. It combined classical devices and quantum computing, achieving fewer parameters on Datasets like Chest X-ray Images (Pneumonia) using Simulator like PennyLane and PyTorch. Studies suggest, it not only achieved an average accuracy of 97.71% on the test set, but also obtains an F1-score of 98.46%, an AUC value of 99.47%, However, there is still research space in quantum device security.

In [5], The Study integrates quantum convolutional filters, classical CNN layers, and a trainable quantum neural network (QNN) classifier. Three datasets MNIST, Fashion-MNIST and MRI brain tumor were used. It achieves competitive performance in terms of accuracy and convergence behaviour when compared to both classical even in the presence of such quantum noise. However, Results are still constrained to small-scale circuits, which may not directly generalize to large-scale, high-dimensional tasks.

Similarly, more papers based on medical data image classification were reviewed.

III. MOTIVATION

The integration of AI (Machine Learning) and medical imaging has emerged revolutionary in diagnostic accuracy and clinical decision-making over the past decade [12]. Classification of medical images, speciallyTumor detection, represents critical applications of machine learning in medical field which directly impact patient outcomes and survival rates [19]. Traditional approaches rely mainly on radiologist expertise and manual interpretation. It can be time-consuming and challenging because of increasing volume of medical imaging data generated globally. Deep learning, specifically Convolutional Neural Networks has emerged as the dominant field for medical image analysis [15][21]. These architectures have demonstrated remarkable capabilities in learning hierarchical feature representations from raw pixel data, achieving performance levels that can exceed human expertise in specific diagnostic tasks. Studies have shown that CNN-based systems can achieve accuracy rates exceeding 95% in certain tumor-based classification tasks, with applications including brain tumor detection, lung cancer screening, and skin lesion classification [8][13].

However, as medical imaging datasets grow in size and complexity, classical computing methods encounter fundamental limitations. High-resolution three-dimensional medical scans, multi-modal imaging data and the need for real-time processing create computational bottlenecks. These limitations have prompted researchers to explore quantum computing as a potential solution which uses quantum mechanical phenomena to process information in different ways than classical computers [25]

A. The Promise of Quantum Computing in Medical Imaging

Quantum computing represents a revolutionary computational paradigm that exploits quantum mechanical properties—superposition, entanglement, and interference to perform certain calculations exponentially faster than classical computers [26]. While still in early developmental stages, quantum computers have demonstrated potential advantages in optimization problems, pattern recognition, and machine learning tasks that align closely with the challenges faced in medical image analysis [22].

Quantum Convolutional Neural Networks (QCNNs) represent a nascent but promising approach that combines the architectural principles of classical CNNs with quantum computing capabilities shown in Fig1. The theoretical foundations suggest that QCNNs could offer several advantages: (1) exponential reduction in the number of parameters required for feature representation through quantum state encoding, (2) enhanced pattern recognition through quantum interference effects, (3) potential for processing high-dimensional data more efficiently through quantum parallelism, and (4) novel feature extraction mechanisms not available in classical systems.

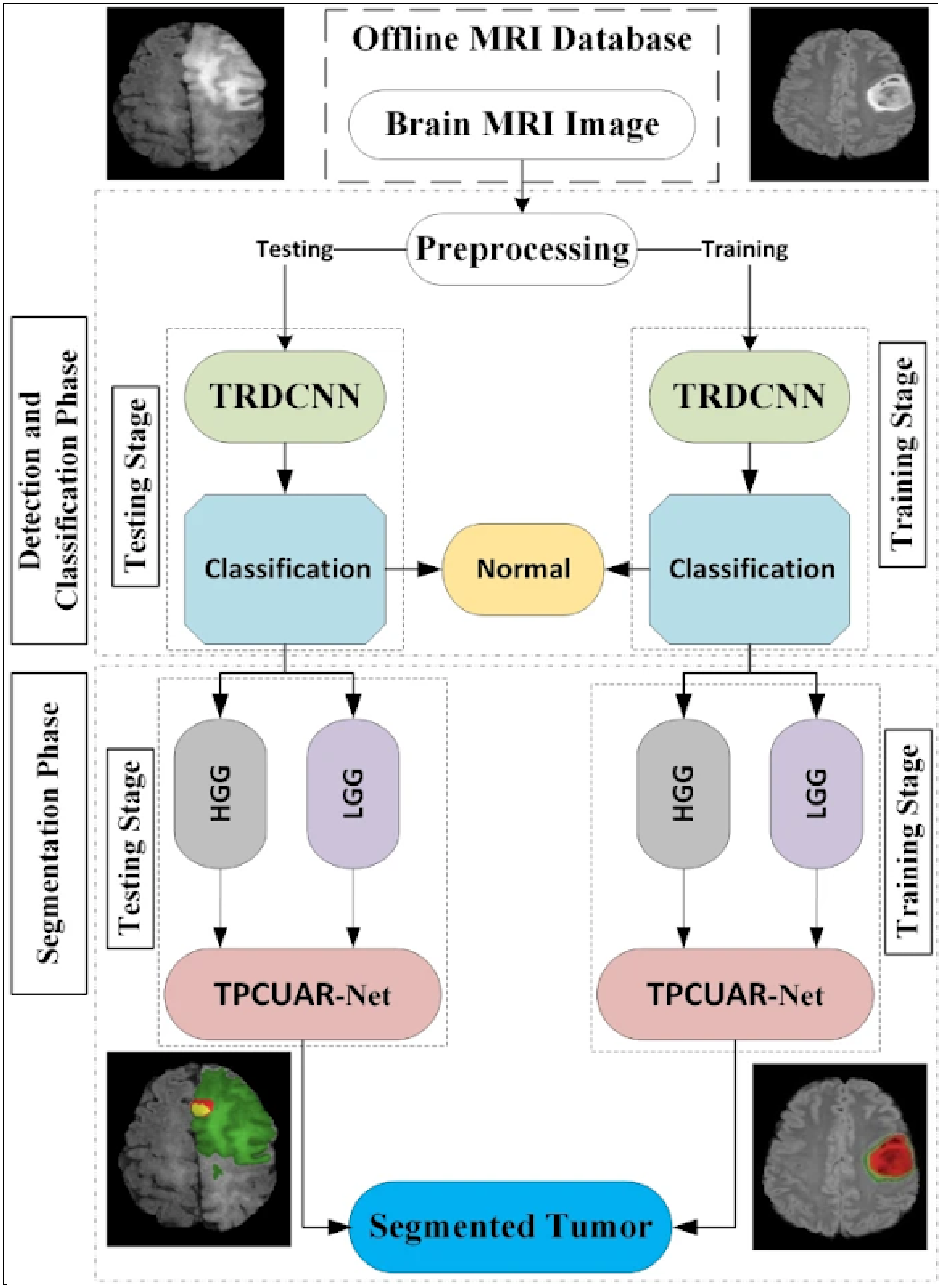

Fig.1The two phases and illustrating the two distinct types of CNN employed. The two-pathway with residual-based deep convolutional neural network (TRDCNN) architecture is used in the detection and classification phases, and two parallel cascaded U-Nets with an asymmetric residual (TPCUAR-Net) is employed in the segmentation phase.

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IV. RESEARCH OBJECTIVES AND SCOPE

This comprehensive review aims to bridge the gap between classical CNN-based medical image classification and emerging quantum approaches for tumor detection. Specifically, we address the following research questions:

1) What are the current state-of-the-art classical CNN architectures for medical image classification?
2) What are the fundamental principles and mechanisms underlying Quantum Convolutional Neural Networks?
3) How do QCNNs compare to classical CNNs in terms of computational complexity, feature extraction capabilities, and theoretical advantages?
4) What are the current implementations, experimental results, and practical challenges in applying QCNNs to medical imaging?
5) What future research directions and technological developments are necessary for clinical translation of quantum-enhanced medical image analysis?

A. BACKGROUND

Quantum Computing Fundamentals and Quantum Machine Learning

1) Principles of Quantum Computing

Quantum computing represents a fundamentally different computational paradigm that leverages quantum mechanical phenomena to process information. The quantum bit (qubit) forms the basic unit of quantum information, existing in a superposition of the classical states $|0\rangle$ and $|1\rangle$. Unlike classical bits that must be definitively 0 or 1, a qubit can be represented as $\alpha|0\rangle + \beta|1\rangle$, where α and β are complex amplitudes satisfying $|\alpha|^2 + |\beta|^2 = 1$. This superposition enables quantum systems to represent exponentially more information than classical systems with the same number of bits.

Quantum entanglement, another key quantum phenomenon, creates correlations between qubits that have no classical analogue. When qubits are entangled, measuring one qubit instantaneously affects the state of others, regardless of spatial separation. This property enables certain quantum algorithms to achieve computational speedups by processing [7]. entangled states in parallel. Quantum interference, the third pillar of quantum computing, allows constructive and destructive interference of probability amplitudes to amplify correct solutions while suppressing incorrect ones.

Quantum gates manipulate qubit states, analogous to classical logic gates but operating on superposition states. Single-qubit gates like the Hadamard gate create superposition's, while multi-qubit gates like the CNOT (Controlled-NOT) gate generate entanglement. Quantum circuits composed of these gates implement quantum algorithms. However, quantum states are fragile and susceptible to decoherence—loss of quantum properties due to environmental interactions—limiting the depth and duration of quantum computations achievable with current technology.

2) Quantum Machine Learning Paradigms

Quantum machine learning explores how quantum computing can enhance or accelerate machine learning algorithms. Several paradigms have emerged: quantum algorithms for analyzing classical data, classical algorithms for analyzing quantum data, quantum algorithms for quantum data, and quantum-enhanced classical algorithms that use quantum subroutines within otherwise classical frameworks [16].The most relevant paradigm for medical imaging involves quantum algorithms analyzing classical data, where medical images are encoded into quantum states for quantum processing.

Variational quantum algorithms represent a near-term approach suitable for noisy intermediate-scale quantum (NISQ) devices currently available. These hybrid quantum-classical algorithms use parameterized quantum circuits (quantum neural networks) to process data, with classical optimization updating circuit parameters based on measurement outcomes. This approach mitigates the impact of quantum noise by limiting circuit depth while leveraging quantum effects for computation.

Quantum kernel methods map data into high-dimensional quantum feature spaces where linear classification may be easier than in the original space. The quantum kernel represents inner products between quantum states, potentially providing computational advantages over classical kernel methods for certain data distributions. Quantum support vector machines employing quantum kernels have shown promise in proof-of-concept studies, though practical advantages on real-world data remain under investigation.

3) Quantum Feature Encoding

Encoding classical data into quantum states represents a critical step for quantum machine learning applications. Several encoding strategies have been developed, each with different properties and computational requirements. Basis encoding directly maps classical bit strings to computational basis states, requiring one qubit per classical bit.

While conceptually simple, this approach is impractical for high-dimensional data like medical images.

Amplitude encoding represents classical data as amplitudes of quantum superposition states, enabling exponentially compact representation. An n-qubit system can encode 2^n classical values, making this approach highly efficient for high-dimensional data. However, preparing arbitrary amplitude-encoded states can be computationally expensive, potentially negating advantages for some applications. Angle encoding maps classical features to rotation angles of qubit gates, with each feature encoded as a rotation around the Bloch sphere. This approach naturally handles continuous features and admits efficient circuit implementations.

For medical images, hierarchical encoding schemes that encode image patches or features at multiple scales may prove most practical. Quantum convolutional approaches can process locally encoded regions, reducing the total number of qubits required while maintaining spatial structure. The choice of encoding significantly impacts both the quantum resources required and the types of patterns quantum circuits can efficiently recognize.

4) Quantum Neural Network Architectures

Quantum neural networks implement learnable transformations on quantum states through parameterized quantum circuits [23].These circuits consist of layers of quantum gates with adjustable parameters, analogous to weights in classical neural networks. Training proceeds by measuring quantum states, computing loss functions classically, and updating parameters through gradient-based optimization. Variational quantum circuits with alternating layers of single-qubit rotations and entangling gates form a common architecture [10]

Quantum convolutional layers apply local quantum transformations to subsets of qubits, mimicking classical convolutional operations. These local operations can be applied in parallel across different spatial regions, followed by pooling operations that reduce the quantum state dimension. The quantum pooling operation typically involves measuring some qubits and discarding them, analogous to classical pooling but with fundamentally quantum characteristics due to measurement's irreversible nature [11].

Barren plateau phenomena, where gradients vanish exponentially with increasing circuit depth or qubit count, present a significant challenge for training quantum neural networks. Careful architecture design, including initialization strategies and structured ansatzes, helps mitigate this issue. Hardware-efficient ansatzes tailored to specific quantum processors' connectivity and gate sets may prove more practical for near-term applications than theoretically optimal but physically challenging architectures.

B. Quantum Convolutional Neural Networks: Architecture and Theory

1) Fundamental Concepts and Definitions

Quantum Convolutional Neural Networks represent the intersection of quantum computing and convolutional architectures for image processing [6][8][9]. The core concept involves replacing classical convolutional operations with quantum transformations acting on quantum-encoded image data. A QCNN typically consists of quantum convolutional layers, quantum pooling layers, and measurement operations that produce classical outputs for final classification.

The quantum convolutional operation applies parameterized quantum circuits to local regions of the quantum-encoded image, analogous to sliding classical convolutional kernels across an image. These local quantum transformations can entangle qubits within each region, potentially capturing correlations that classical operations would miss. Multiple convolutional layers can be stacked, with each layer's outputs serving as inputs to subsequent layers, building hierarchical feature representations in the quantum domain.

Quantum pooling reduces the dimensionality of quantum states between convolutional layers [22]. Unlike classical pooling which typically selects maximum values or averages within regions, quantum pooling performs partial measurements that project high-dimensional quantum states onto lower-dimensional subspaces. This operation irreversibly collapses the quantum state, similar to classical pooling's information reduction, but through fundamentally quantum mechanisms.

2) Quantum Advantage in Pattern Recognition

The potential advantages of QCNNs stem from several quantum properties. Quantum superposition allows processing multiple input configurations simultaneously, potentially enabling parallel evaluation of different pattern hypotheses. Quantum entanglement can capture complex correlations between spatially distant image regions that might require very deep classical networks to detect. Quantum interference can amplify features relevant for classification while suppressing noise or irrelevant patterns.

Theoretical analyses suggest that certain pattern recognition tasks may exhibit exponential speedup on quantum computers compared to classical algorithms. For instance, quantum algorithms for solving systems of linear equations, a common operation in machine learning, can achieve exponential speedup under certain conditions. However, translating theoretical advantages into practical gains for real medical imaging tasks remains an open question, as advantages often depend on specific problem structure and data properties.

The quantum feature space accessible through quantum circuits may enable more efficient representation of certain patterns. Classical neural networks approximate functions through compositions of simple nonlinearities, requiring many layers and parameters for complex functions. Quantum circuits can implement highly nonlinear transformations through unitary evolution, potentially requiring fewer parameters for equivalent representational capacity. However, measurement constraints limit which quantum computations produce useful classical outputs.

3) QCNN Architecture Components

A complete QCNN architecture for medical image classification typically includes several components. The encoding layer maps classical image data into quantum states, often employing amplitude encoding or parameterized rotation gates. This layer determines the quantum computational basis for subsequent processing and influences which patterns the network can efficiently recognize.

Quantum convolutional layers apply parameterized quantum gates to local groups of qubits. These local transformations, often implemented as variational quantum circuits with trainable parameters, extract features from encoded image regions. Multiple convolutional layers can be stacked, with each layer potentially capturing increasingly abstract features. The specific gate sequences and connectivity patterns significantly impact both computational efficiency and representational power.

Quantum pooling layers reduce state dimensionality between convolutional layers through partial measurement or other dimension-reduction techniques. These layers control the depth and width tradeoffs in the quantum network architecture. Measurement and classical output layers convert the final quantum state into classical information for interpretation and classification. Observable selection and measurement strategies critically influence what information the quantum network makes accessible.

4) Training Algorithms for QCNNs

Training QCNNs requires adapting classical optimization algorithms to the quantum setting. The parameter-shift rule enables exact gradient computation for parameterized quantum circuits by evaluating the circuit at shifted parameter values, avoiding numerical differentiation inaccuracies. For a quantum gate with parameter θ, the gradient can be computed by evaluating the circuit at $\theta + \pi/2$ and $\theta - \pi/2$, providing an exact derivative through quantum measurements.

Gradient-based optimization algorithms including Adam, RMSprop, and stochastic gradient descent can be applied to update quantum circuit parameters based on computed gradients. However, the shot noise inherent in quantum measurements introduces stochasticity beyond classical mini-batch sampling. Multiple measurements may be required to accurately estimate expectation values, increasing computational overhead. Variance reduction techniques, including importance sampling and control variates, can improve gradient estimation efficiency.

Quantum natural gradient methods account for the geometry of quantum state space, potentially improving optimization convergence. The quantum Fisher information metric defines the natural gradient direction in parameter space, enabling more efficient navigation of the optimization landscape. Studies suggest quantum natural gradients can mitigate barren plateau effects and accelerate training for certain quantum architectures . However, computing the quantum Fisher information matrix adds computational overhead that may limit practical applicability.

Evolutionary and metaheuristic optimization approaches represent alternatives to gradient-based methods, particularly when gradients are difficult to compute or unreliable. Genetic algorithms, particle swarm optimization, and simulated annealing can optimize quantum circuit parameters by treating them as black-box optimization problems. These approaches may prove more robust to measurement noise and barren plateaus but typically require many more circuit evaluations than gradient-based methods.

5) Theoretical Computational Complexity

Analyzing the computational complexity of QCNNs compared to classical CNNs reveals both potential advantages and limitations. Classical CNNs require $O(n^2k^2d)$ operations for processing an $n \times n$ image with $k \times k$ kernels across d channels, plus additional operations for pooling and fully connected layers. As image resolution and network depth increase, computational requirements grow substantially, presenting challenges for high-resolution medical imaging.

Quantum circuits can represent and manipulate exponentially large state spaces using only polynomial numbers of qubits. An n-qubit system spans a 2^n-dimensional Hilbert space, enabling compact representation of high-dimensional data. If this exponential representational capacity translates to computational advantages, QCNNs could process high-dimensional medical images more efficiently than classical approaches. However, measurement collapse limits how much quantum information can be extracted as classical outputs.

The query complexity number of times the input must be accessed may be reduced for certain pattern recognition tasks on quantum computers. Quantum algorithms like Grover's search achieve quadratic speedup for unstructured search, while quantum walks can provide polynomial speedups for certain graph problems. Whether similar advantages apply to realistic medical image classification tasks remains an active research question requiring both theoretical analysis and empirical validation.

Circuit depth the number of sequential gate layers determines quantum computation time and susceptibility to decoherence. Shallow circuits minimize decoherence effects but may have limited expressiveness. Deep circuits can represent more complex transformations but accumulate errors from quantum noise. This depth-expressiveness trade-off critically impacts QCNN design for practical applications. Current NISQ devices typically support circuits with depths up to several hundred gates before de-coherence dominates.

6) Entanglement and Feature Correlations

Quantum entanglement enables QCNNs to capture correlations between image regions in ways that may be difficult for classical networks. In medical imaging, tumors often exhibit characteristics that extend across multiple spatial scales—textural patterns, shape irregularities, and relationships to surrounding tissues. Classical CNNs capture such multi-scale features through hierarchical processing, but quantum entanglement could potentially encode these relationships more efficiently.

Entangling gates in quantum convolutional layers create quantum correlations between qubits representing different image regions. These correlations persist through subsequent layers, potentially enabling the network to maintain and process relationships between distant features without requiring the deep hierarchies classical networks need. However, entanglement also makes quantum states more susceptible to decoherence, as errors affecting one qubit can propagate through entangled systems.

The volume law scaling of entanglement in quantum circuits presents both opportunities and challenges. As quantum circuits deepen, entanglement entropy typically grows, indicating increasingly complex quantum states. High entanglement may correlate with expressiveness—the ability to represent complex patterns—but also with trainability challenges. Barren plateaus occur more frequently in highly entangled quantum circuits, potentially hindering optimization

Quantifying the role of entanglement in QCNN performance remains an active research area. Some studies suggest that entanglement provides measurable advantages for specific classification tasks, while others find that carefully designed classical networks can match quantum performance. Disentangling the contributions of quantum superposition, entanglement, and interference to [23]. practical performance advantages requires rigorous comparative studies on realistic datasets.

V. PROPOSED METHODOLOGY

Model Architecture will include distributed hybrid architecture by incorporating subspace-preserving elements using different layers such as:

1) Classical Pre-Processing Layer : Multi-modal inputs (e.g., 2D MRI/CT scan datasets) are encoded by Z feature map.
2) Distributed Quantum Convolutional Layers : Using quantum circuit splitting, an n-qubit QCNN (n=6-8) is partitioned across 4-5 qubits per node. It involves parameterized RY/RZ rotation gates and CNOT entanglement gate.
3) Pooling Layer: Pooling uses measurement-based max operations and circuits to reduce the dimensions and reduce the number of Qubits.
4) Hybrid Integration : After a series of Convolution and pooling layers, Quantum outputs are fed into a classical fully connected layer for final classification, with end-to-end variational training.
5) The circuit depth is capped at 3 layers to suit NISQ devices like IBM Quantum or IonQ.

VI. CONCLUSION AND FUTURE WORK

Quantum Convolutional Neural Networks (QCNNs) have emerged as a promising field for quantum advantages in feature extraction and image classification, particularly for complex datasets like medical images like MRI, X ray, CT scan etc.

The primary goal of the proposed research is based on Quantum Convolutional Neural Networks (QCNN) for medical image classification for Tumor detection to harness the power of quantum computing to significantly enhance the accuracy as well as efficiency of image recognition tasks with fewer resources.

Expected Outcomes and Impact

We anticipate 10-20% accuracy gains over traditional models on multi-modal tasks, with fewer parameters and polynomial speed-ups in training time. This could lead to edge-deployable quantum AI for telemedicine.

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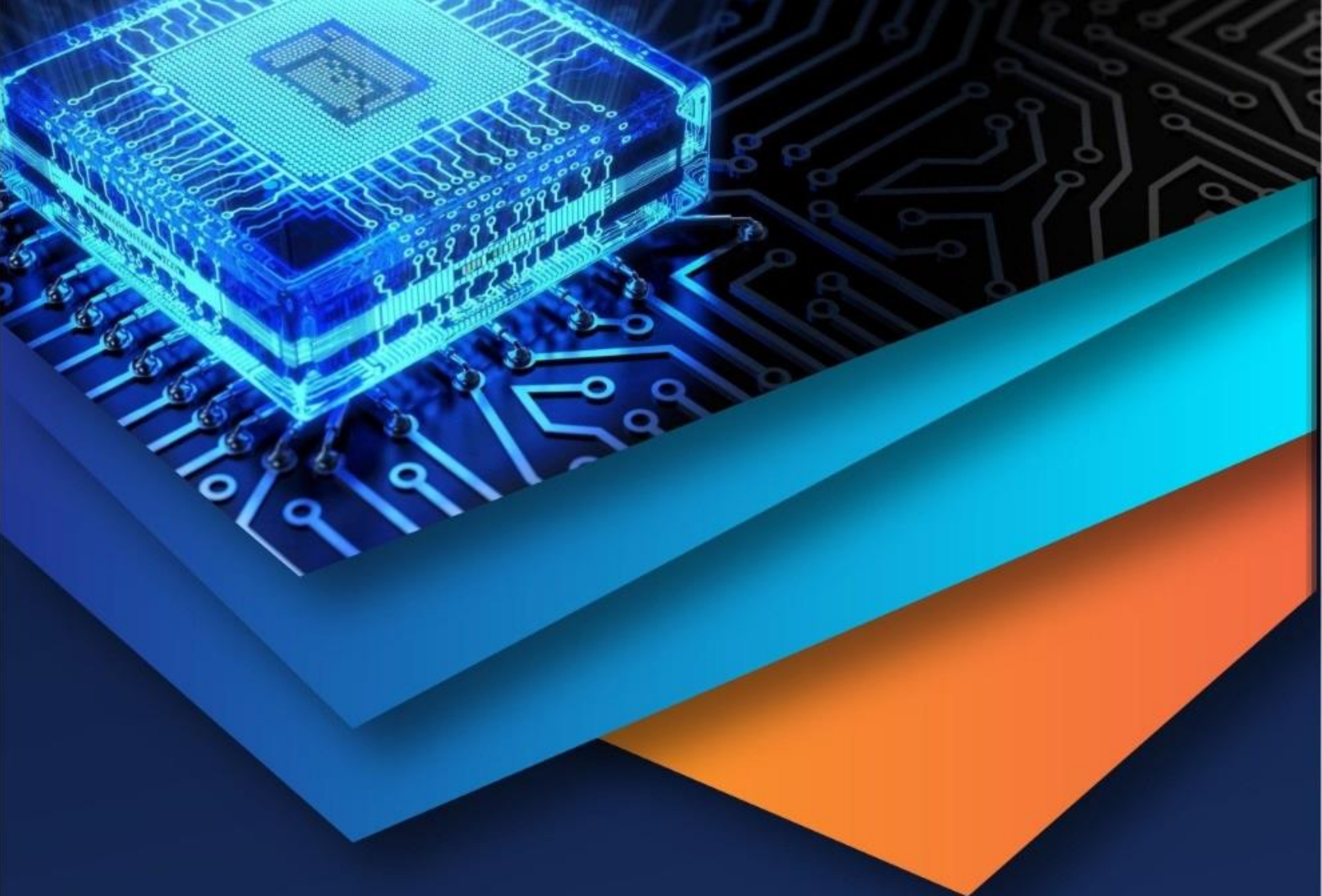

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