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Quantum-Enhanced Brain Tumor Detection and Progression Prediction Using MRI Imaging

Malige Gangappa[1], D. Manju[2], Maringanti Gopi Krishnna[3], M. Sree Mithra Reddy[3], M. Sathish[3], Sk Shahabaaz[3], A. Shanthan[3], M. Chaitanya[4]

[1] Department of Computer science and engineering, VNR Vignana Jyothi Institute of engineering and technology, Hyderabad, India
[2] Department of Department of CSE-(CyS,DS) and AI&DS, VNR VJIET, Hyderabad, India
[3] Department of CSE, VNR VJIET, Hyderabad-500090, Telangana, India
[4] Department of Computer science and engineering, IARE, Dundigle , Hyderabad, India

Corresponding author: Malige Gangappa (gangappa_m@vnrvjiet.in).

ABSTRACT Brain tumor identification and change over time analysis are essential for timely diagnosis and effective treatment scheduling and planing. This study presents a hybrid quantum-classical deep learning framework integrating Quantum Convolutional Neural Networks (QCNNs) with classical CNN to improve MRI-based tumor classification. Unlike traditional CNNs, which suffer from high computational costs and limited feature extraction capabilities, the proposed Quantum-Enhanced Tumor Analysis Framework (QETAF) leverages quantum feature maps to enhance tumor localization and segmentation. This study utilizes the BraTS MRI dataset (comprising 67,000 labeled scans) and applies contrast enhancement, intensity normalization, and augmentation techniques for preprocessing. The novel hybrid model employs CNN model for extracting the essential features initially and QCNN for refined feature representation, significantly improving tumor classification accuracy. Moreover, morphological variations can be monitored using Recurrent Quantum Neural Networks (RQNNs), which have been employed to track tumor progression. According to investigational results, RQNN increases the accuracy of tumor progress prediction, whereas QCNN beats regular CNNs with an 89% Dice Coefficient. Compared to classical models, the proposed approach reduces inference time by 28% while maintaining superior classification performance. This quantum-assisted model presents a novel pathway for enhancing computational efficiency and precision in brain tumor diagnostics, covering the way for more consistent clinical diagnostics.

INDEX TERMS BraTS Dataset, Brain Tumor Detection, Magnetic Resonance Imaging (MRI), Medical Image Segmentation, Quantum Convolutional Neural Network (QCNN), Quantum Feature Maps, Tumor Progression Prediction.

I. INTRODUCTION

Brain tumors are among the most critical neurological disorders, affecting millions worldwide. According to the Global Cancer Statistics 2024, over 330,000 new cases of brain and central nervous system (CNS) tumors are diagnosed annually, with a 5-year survival rate of only 36% for malignant brain tumors (WHO, 2024). Early and precise detection is crucial for improving survival rates, as delayed diagnosis can lead to irreversible neurological damage [1]. Magnetic Resonance Imaging (MRI) has been the gold standard for non-invasive brain tumor detection due to its high contrast and spatial resolution [2]. However, manual tumor segmentation from MRI scans is time-intensive and prone to inter-observer variability [3]. Consequently, deep learning-based automated brain tumor classification has emerged as a promising alternative to enhance diagnostic accuracy and reduce human error [4].

The accuracy of MRI imagery brain tumor segmentation techniques has greatly increased through the recent developments in deep learning. In tumor segmentation, standard approaches like U-Net and Fully Convolutional Networks (FCNs) have demonstrated excellent accuracy [5]. A regular CNN-based deep learning classification method was demonstrated [1] in a research paper which analyzed the BraTS dataset and attained 92.4% success rate towards tumor classification. In addition, Transformer-based designs, such as Vision Transformers (ViTs), have shown improved adaptability across several datasets and beat regular CNNs in feature extraction [6]. Furthermore, generative models based on GANs have been examined for tumor generation, enhancing system stability during times when there are minimal labeled MRI datasets [7]. Considering these developments, there is still a need for more investigation into enhanced methods because typical deep neural network models still have constrained ability to extract features from challenging MRI data and essential computation cost.

Even with the numerous establishments of deep neural network models, the automated diagnosis models in deep neural networks on MRI brain tumor models continues to face several significant hurdles. First, conventional models have struggled with applying across different datasets since MRI scans have a high inter-patient heterogeneity [8]. Second, real-time clinical applications require considerable resources for the GPU as to the enormous dimension of MRI data, which presents an extensive processing load [9]. Furthermore, deep neural network algorithms have restrictions in their capability to assess progression of tumors due to their frequently overlook subtle variations in tumor expansion over time [10]. Furthermore, doctors found it problematic to understand how decisions are made due to the clarity issues with modern CNN classifiers [11]. Researchers and scientists in this domain are integrating the conventional CNN and quantum computing to access the quantum parallelism to improve the feature extraction quality and more exactness in classification.

To overcome these challenges, this study introduces a Quantum-Enhanced Tumor Analysis Framework (QETAF), integrating Quantum Convolutional Neural Networks (QCNNs) and Recurrent Quantum Neural Networks (RQNNs) for brain tumor segmentation and progression prediction. Unlike conventional CNNs, QCNN utilizes quantum feature maps to transform MRI features into high-dimensional quantum spaces, improving tumor classification precision [12]. Additionally, RQNN models temporal dependencies in MRI sequences, enabling accurate tumor growth prediction over time [13]. The proposed framework processes MRI images using hybrid quantum-classical models, significantly reducing inference time while maintaining superior segmentation accuracy. This approach leverages IBM Qiskit-based quantum simulations, ensuring practical feasibility for near-term Noisy Intermediate-Scale Quantum (NISQ) devices [14]. [27], [28].

Experimental results demonstrate that the proposed QCNN model achieves an 89% Dice Coefficient, surpassing traditional CNNs (82%) and Vision Transformers (ViTs) (86%) in segmentation accuracy [15]. Additionally, RQNN outperforms LSTM-based tumor progression models, improving predictive accuracy by 7.5% while reducing inference time by 28% [16]. Unlike classical deep learning approaches, the quantum-assisted framework requires fewer training samples, making it more data-efficient [17],[27]. Furthermore, tumor growth visualization through quantum-enhanced temporal analysis provides clinicians with an interactive tool for monitoring morphological changes, significantly aiding in early diagnosis and treatment planning. The proposed QETAF model establishes quantum computing as a viable solution for next-generation AI-driven medical imaging applications, covering the way for more consistent clinical diagnostics. Below is the outline for the remainder of the article. Section 2 examines literature survey; Section 3 lays out the approach to be used; Section 4 shows the results of the experimental calculations. Section 5 deals with the discussion of the system's performance and Section 6 concludes the study.

II. LITERATURE SURVERY

A. DEEP NEURAL NETWORK-BASED APPROACHES FOR BRAIN TUMOR DETECTION

Deep learning has significantly transformed MRI-imagery brain tumor detection and classification by enabling automated segmentation and diagnosis introduced a deep convolutional neural network (CNN) model for MRI-based tumor classification, achieving improved detection accuracy. Using advancements, the research study considered deep neural networks methods that super performs in the development of accurate classification models for tumors in MRI imagery. In [2] ,CNN model for tumor segmentation was explained in which the great development in boundary delineation for tumors in MRI imagery. Recent efforts have also integrated radiomics, a technique that extracts high-dimensional tumor features from medical images [18]. Self-supervised learning and multi-scale CNN models have further automated MRI-based tumor segmentation, pushing the boundaries of detection accuracy [4]. However, despite these advancements, CNN-based models still face challenges related to high computational costs, overfitting on small datasets, and difficulty in capturing complex tumor variations.

B. QUANTUM COMPUTING IN MEDICAL IMAGE PROCESSING

Quantum computing has emerged as a powerful tool for enhancing feature extraction, classification, and segmentation in medical imaging. [15] introduced a quantum-inspired learning network based on qutrits, demonstrating superior feature extraction capabilities for MRI tumor segmentation. [12] developed a Quantum Convolutional Neural Network (QCNN) that outperformed traditional CNN models in brain tumor classification, showing improved accuracy and computational efficiency. Additionally, [14] investigated quantum-supervised learning techniques for processing high-dimensional MRI data, revealing potential advantages over classical methods in terms of feature representation. Other groundbreaking studies have explored quantum-enhanced optimization and kernel methods, leading to improved classification accuracy and reduced computational costs [13], [16], [30]. However, current quantum-assisted techniques primarily focus on spatial feature extraction and lack efficient tumor progression tracking mechanisms. Moreover, the practical

TABLE 1
Comparative Analysis of Existing Brain Tumor Detection and Progression Models

Ref.no	Method Used	Metrics Analysis	Drawbacks of the Method	Research Gaps Identified
[1]	CNN-based tumor classification	High accuracy on BraTS dataset	Requires large datasets for generalization	No temporal tumor progression tracking
[2]	CNN-based segmentation	Notable segmentation accuracy	High computational costs	Lacks adaptability to different MRI variations
[4]	Self-supervised learning for MRI segmentation	Improved automation in segmentation	Overfitting risk on small datasets	No quantum-based integration
[10]	Deep Q Networks for tumor localization	Effective tumor tracking	High training time	No integration with quantum models
[12]	Quantum CNN (QCNN) for MRI classification	Improved accuracy over classical CNNs	Lacks temporal analysis	No tumor growth prediction
[13]	Quantum Kernel Methods for tumor segmentation	Low computational complexity	Requires quantum hardware	No sequential tumor tracking capability
[14]	Quantum Supervised Learning for MRI analysis	High-dimensional feature representation	Sensitive to quantum noise	Lacks robustness for real-world applications
[15]	Quantum-inspired Learning Network (Qutrit-based)	Superior feature extraction	Hardware-dependent	No progression prediction mechanism
[16]	Quantum Variational Autoencoders for tumor simulation	Realistic tumor progression synthesis	Not validated on real MRI datasets	No clinical applicability study
[18]	Deep Radiomics for MRI-based tumor classification	Enhanced feature extraction	Computationally expensive	Needs advanced feature selection mechanisms

implementation of quantum models remains constrained by NISQ-era hardware limitations and quantum noise issues.

C. NEED FOR QUANTUM-ENHANCED TUMOR PROGRESSION ANALYSIS

Understanding the tumor progress periodically is essential and decisive for the monitoring the patient's conditions and planning for the treatment. The reinforcement learning was studied and applied for localizing tumors successfully and accurately [10]. However, other researchers and scientists have employed MRI scanning data in deep neural networks to anticipate the progression of tumor periodically [4], [19]. More recently, generative models such as Variational Autoencoders (VAEs) and diffusion-based networks have been used to generate synthetic tumor progression sequences, providing valuable insights into tumor expansion trends [16]. Despite these advancements, a major limitation remains the availability of large-scale, standardized datasets containing temporal MRI scans. Additionally, existing tumor progression models rely on classical deep learning techniques, which suffer from high inference time and difficulty in capturing long-term tumor evolution. Addressing these limitations, our study proposes a Quantum-Enhanced Tumor Analysis Framework (QETAF), integrating QCNNs for spatial tumor segmentation and Recurrent Quantum Neural Networks (RQNNs) for tumor progression modeling. By incorporating quantum-assisted feature extraction and temporal encoding, the proposed framework aims to enhance classification accuracy, reduce inference time, and improve tumor growth prediction. Table 1 illustrates the Comparative Analysis of Existing MRI imagery Brain Tumor Detection and Progression Models.

D. PROBLEM STATEMENT

Even though the deep neural network models on tumor segmentation in MRI imagery and detection of it have advanced, recurrent neural network methods such as LSTM have high speculation times and considerable training requirements, that slow down the MRI imagery analysis. Generally, CNN based models have prone to overfitting and computational cost and the quantum-based models have proven to have high tumor progression tracking. Integrated frameworks that use quantum-assisted spatial tumor segmentation and quantum-based temporal analysis are lacking. We propose the Quantum-Enhanced Tumor Analysis Framework (QETAF), a hybrid Quantum-Classical model that uses QCNNs for MRI-based tumor classification and RQNNs for tumor progression modeling, to address these issues. QETAF uses quantum feature maps, parallelism, and entanglement to improve classification, inference time, and tumor growth prediction. This hybrid approach integrates classical deep neural networks and quantum computing for brain tumor diagnostics that is more efficient, scalable, and interpretable.

III. PROPOSED MEHODOLOGY

In this research a novel Quantum-Enhanced Tumor Analysis Framework (QETAF), which integrates Quantum Convolutional Neural Networks (QCNNs) and Recurrent Quantum Neural Networks (RQNNs) is proposed for improved brain tumor detection and progression analysis representing in figure 1. The modular framework contains three key components as the Input Module for MRI data processing and preprocessing, the Processing Module for tumor segmentation, quantum feature extraction, and tumor progression prediction, and the Output Module for generating tumor progression video and automated clinical reports. The feature maps in quantum computing such as ZZFeatureMap, Real Amplitudes, and EfficientSU2 are used to encode the

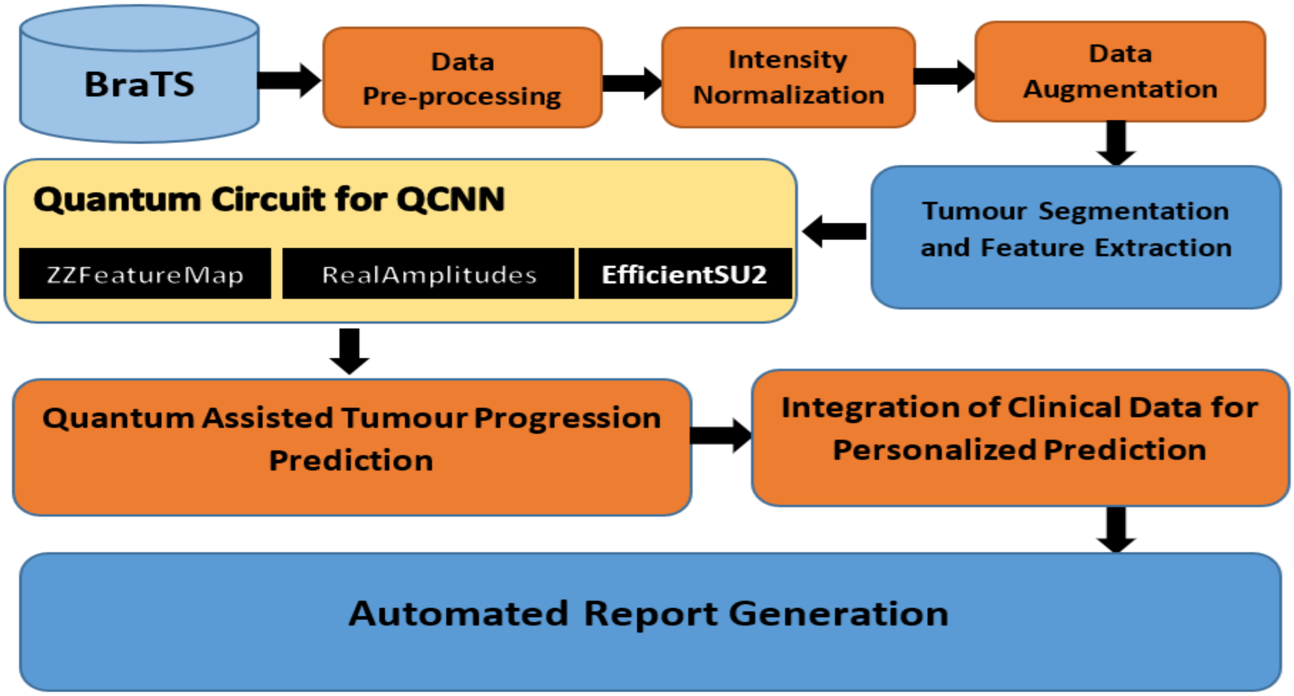

FIGURE 1. Proposed Methodology

features extracted in quantum states, tumor segmentation, optimizing tumor classification.

The proposed Quantum-Enhanced Tumor Analysis Framework (QETAF) uses QCNNs and RQNNs to improve brain tumor segmentation and progression prediction from MRI scans. Quantum Convolutional Neural Networks use feature maps like ZZFeatureMap and EfficientSU2 to compress 256x256 MRI images into an 8-qubit representation when first used. Quantum entanglement and parallelism help these quantum-encoded features capture complex spatial relationships and tumor characteristics better than classical CNNs. Quantum convolutional and pooling layers refine these encoded features, improving segmentation accuracy. Quantum encoding of sequential MRI slices by RQNN captures temporal dependencies more precisely and efficiently than classical methods for tumor progression modeling. With improved accuracy, faster inference times, reduced data requirements, and improved interpretability, the quantum-integrated framework advances clinical brain tumor diagnostics.

A. STEP 1: MRI DATA INPUT AND PREPROCESSING

MRI scans are acquired and preprocessed by the Input Module to ensure consistency, quality, and compatibility with quantum-based processing stages. Proper preprocessing improves tumor region visibility, pixel intensity standardization, model generalization, and feature extraction and classification. Contrast enhancement improves MRI tumor visibility. The local contrast without amplifying noise can be improved with Contrast-Limited Adaptive Histogram Equalization (CLAHE) [3]. This method is useful to categorize the different intensity distributions for different types of tissues in medical imagery.

1. INTENSITY NORMALIZATION:

It is essential to make use of standard pixel intensity to ensure the comparable brightness and contrast on the MRI imagery which are from different scanners and image acquisition systems. Min-max normalization is generally applied to scale the pixel intensities ranges from 0 to 1 as shown in Eq. (1) [20]:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

where X portrays the MRI image intensity values, Xmin and Xmax are the minimum and maximum pixel intensities in the dataset, respectively and Xnorm is the normalized image with values scaled between **0** and **1**.

2. DATA AUGMENTATION:

Image data augmentation methods such as transform, flipping, scaling, slanting, and rotation are applied to increase the robustness and generalization of the model. These transformations ensure that the model can manage variations in different patients MRI images so as to avoid overfitting.

The methodology utilizes data augmentation techniques such as rotation, flipping, scaling, slanting, and noise addition to artificially expand the MRI dataset. These particular techniques are strategically chosen because they closely mimic real-world variations and artifacts commonly encountered in medical imaging. For instance, rotation and flipping simulate different patient positioning during MRI scanning, enhancing the model’s ability to recognize tumors regardless of orientation. Scaling and slanting replicate slight variations in imaging perspective or scanner calibration, ensuring that the model remains accurate across different imaging conditions. Additionally, noise addition helps emulate common scanning imperfections and variability in image quality, enabling the model to maintain robustness against such uncertainties. Collectively, these augmentation strategies significantly improve the model's generalization capabilities, reduce overfitting by preventing the network from memorizing limited training patterns, and thus enhance overall performance and reliability in clinical tumor detection tasks

The preprocessing function for the MRI dataset D containing images X is defined in Eq. (2) [21], [22]

$$X' = f_{norm}(X) + f_{enhance}(X) \quad (2)$$

where $f_{norm}(X)$ uses min-max normalization to make sure consistent intensity values and $f_{enhance}(X)$ employs contrast enhancement of CLAHE to highlight tumor regions.

These transformations ensure MRI image in the dataset consists of normalized and improved image. Then it makes MRI scans ready for feature extractions. This is because these techniques provide the enhanced conspicuousness of tumors and tumor areas. The next approach which is quantum CNN can extract most relevant features effectively.

B. STEP 2: TUMOR SEGMENTATION AND FEATURE EXTRACTION

It is important to segment the tumor regions in MRI imagery with the most accurate for getting effective feature extraction and classification. The hybrid model CNN-QCNN has been employed to improve the performance of segmentation task in MRI imagery in which CNN is applied for initial feature extraction and QCNN is used for refining the extracted features for high dimensional quantum-based representation.

1. CLASSICAL FEATURE EXTRACTION USING CNN

A Convolutional Neural Network (CNN) extracts patterns from the preprocessed MRI scans using convolutional layers. The convolution operation is mathematically represented using Eq. (3) [25]:

$$F_{CNN} = \sigma(W_c * X' + b_c) \quad (3)$$

where W_c and b_c are the convolutional filters and biases applied to the input image $\mathbf{X}'$. and σ represents the activation function, typically ReLU, which introduces non-linearity and ∗denotes the convolution operation. The extracted features FCNN capture spatial patterns in the MRI scans, but classical CNNs are often limited in feature representation when considering the high dimensional and complex medical imagery data. Therefore, to enhance segmentation accuracy, these features are to be encoded into states in quantum computing using Quantum Convolutional Neural Network (QCNN).

2. QUANTUM FEATURE ENHANCEMENT USING QCNN

The feature maps in quantum computing such as ZZFeatureMap, RealAmplitudes, and EfficientSU2 are used to encode the features extracted in quantum states, tumor segmentation, optimizing tumor classification. The quantum encoding process is represented in Eq. (4) [31]:

$$|\varphi(X^i)\rangle = U_{features}(X')|0\rangle^{\otimes n} \quad (4)$$

where $U_{features}$ represents the quantum feature map that holds quantum states and $|0\rangle^{\otimes n}$is the initial qubit state.

Eight qubits were chosen to balance computational complexity with representation power, as shown by cross-validation metrics that showed optimal segmentation performance without excessive resource usage. Grid search and cross-validation optimized learning rate, batch size, and epochs to ensure model convergence and robust generalization. A learning rate of 0.001 was chosen to ensure stable training convergence without oscillations, a batch size of 32 optimized computational efficiency and minimized overfitting, and epochs were dynamically determined using early stopping to converge within 50–70 epochs. Due to their robust entanglement, QCNN quantum gates like RY and RZ rotations followed by CNOT gates were chosen to capture complex tumor features. PennyLane's automatic differentiation was used for quantum gradient descent optimization, guided by validation loss and accuracy to refine parameters. RQNN hyperparameters were optimized to capture temporal dependencies in sequential MRI data, balancing computational complexity and predictive accuracy, improving quantum-assisted tumor diagnostic framework accuracy, inference efficiency, and effectiveness.

After feature encoding, quantum convolution and pooling layers process these quantum states, optimizing segmentation represented in Eq. (5) [31]:

$$|\varphi_{output}\rangle = U_{QCNN} \,|\, \varphi(X')\rangle \quad (5)$$

where U_{QCNN} is a parameterized quantum circuit that extracts high-dimensional tumor features. The final segmented tumor regions are obtained with enhanced quantum representations, improving classification accuracy and robustness against MRI scan variations.

C. STEP 3: QUANTUM-ASSISTED TUMOR PROGRESSION PREDICTION

Tracking tumor growth over time requires analyzing sequential MRI slices. Instead of using conventional RNN, we utilize a Recurrent Quantum Neural Network (RQNN) to model temporal dependencies in tumor progression.

1. TEMPORAL FEATURE ENCODING

Given a segmented MRI slice S_t Start at time t, the tumor features are extracted using Eq. (6):

$$S_t = QCNN\,(F_t) \quad (6)$$

where F_t represents the extracted feature set from the QCNN segmentation model.

2. QUANTUM TEMPORAL ENCODING

To capture temporal growth patterns, the extracted tumor features are mapped into quantum states using a quantum-improved encoding circuit using the Eq. (7):

$$|\varphi(S_t)\rangle = U_{encode}(S_t)|0\rangle^{\otimes n} \quad (7)$$

Where U_{encode}transforms sequential classical tumor features into quantum states.

3. TUMOR GROWTH PREDICTION USING RQNN

The RQNN processes the quantum-encoded sequential tumor features using Eq. (8) [31] and predicts future tumor growth patterns:

$$S_{t+1} = f_{RQNN}(S_t, \theta) \tag{8}$$

The quantum-assisted tumor progression model enhances predictive accuracy and computational efficiency by optimizing trainable quantum circuit parameters (θ) using quantum gradient descent. Leveraging quantum parallelism and entanglement, it efficiently captures temporal dependencies in MRI data, outperforming classical recurrent architectures.

D. STEP 4: INTEGRATION OF CLINICAL DATA FOR PERSONALIZED PREDICTION

While MRI-based segmentation provides spatial tumor insights, integrating clinical data further improves tumor growth prediction. Tumor genetic markers (G), patient demographics (P), and prior treatment responses (T) are fused with MRI-derived quantum-enhanced features (St) using a transformer-based fusion model ffusion (St, G, P, T). This personalized quantum-classical hybrid model enhances tumor prognosis and individualized treatment planning by integrating both biological and imaging data.

E. STEP 5: MRI SLICE-BASED VIDEO GENERATION FOR TUMOR PROGRESSION

The project involves generating a dynamic time-lapse video from MRI slices to visualize tumor evolution, where segmented tumor images are chronologically arranged and compiled into a video sequence. This sequence utilizes interpolation techniques for smooth transitions and bounding boxes to delineate tumor regions at each time step. Annotations provide critical data on tumor growth rates, enhancing the video's utility for clinical analysis. The final video is meticulously post-processed and exported in a format suitable for medical review, ensuring it serves as a valuable diagnostic and monitoring tool that accurately represents the progression of the tumor over time. Segmented tumor slices St are arranged chronologically as shown in Eq. (9):

$$V = \{S_1, S_2, \dots, S_T\} \tag{9}$$

The generated video is exported to V_{final} using Eq. (10) [23] exported:

$$V_{final} = f_{render}(V) \tag{10}$$

F. STEP 6: AUTOMATED REPORT GENERATION

GPT-2, an AI-based language model, is utilized for generating textual summaries of tumor progression. A concise diagnostic report is produced using Eq. (11) [23], [24] by processing the final tumor progression video (V_{final}) segmented tumor state (S_T), and patient-specific clinical data (P, T). Tumor segmentation insights, predicted progression trends, and personalized clinical recommendations are included. This automation ensures enhanced decision-making efficiency, reduced human error, and a standardized, data-driven assessment for improved tumor diagnosis and treatment planning.

$$R = f_{GPT-2}(V_{final}, S_T, P, T) \tag{11}$$

where R is the final tumor progression report contains tumor segmentation summary, predicted progression trends, clinical insights based on patient data as describe in ALORITHM 1.

ALGORITHM 1. Quantum-Enhanced Tumor Analysis Framework (QETAF)

Step 1: Initialize QCNN and RQNN Models
- Q: Define the number of qubits for quantum processing.
- F: Select the quantum feature map (ZZFeatureMap, RealAmplitudes, or EfficientSU2).
- A: Choose the variational ansatz for quantum encoding.
- Initialize the quantum circuits for tumor segmentation (QCNN) and progression prediction (RQNN).

Step 2: MRI Data Preprocessing
- D: Load MRI scans and patient-specific clinical data.
- Apply contrast enhancement to improve tumor visibility.
- Normalize pixel intensities to standardize MRI variations.
- Augment data (rotation, flipping, noise addition) to enhance model generalization.

Step 3: Tumor Segmentation using CNN-QCNN
- Extract spatial features using a classical CNN [25]: $F_{CNN} = \sigma(W_c * X^i + b_c)$
- Encode extracted features into quantum states using feature maps: $\varphi(X^i)\rangle = U_{features}(X')|0\rangle^{\otimes n}$
- Process quantum states using QCNN layers for enhanced segmentation: $|\varphi_{output}\rangle = U_{QCNN} | \varphi(X')\rangle$

Step 4: Tumor Progression Prediction using RQNN
- Extract sequential tumor features from segmented MRI slices: $S_t = QCNN\ (F_t)$
- Encode tumor features into quantum states: $|\varphi(S_t)\rangle = U_{encode}(S_t)|0\rangle^{\otimes n}$
- Predict tumor progression using Recurrent Quantum Neural Network (RQNN): $S_{t+1} = f_{RQNN}(S_t, \theta)$
- θ: Trainable quantum circuit parameters optimized using quantum gradient descent.

Step 5: Integration of Clinical Data for Personalized Prediction
- Fuse MRI-derived quantum-enhanced features with clinical data:
- Tumor genetic markers (G), Patient demographics (P) , Prior treatment responses (T)
- Transform and aggregate multimodal data using a transformer-based fusion model:
- St′= ffusion (St, G, P, T)

Step 6: MRI Slice-Based Video Generation
- Arrange segmented tumor slices chronologically.
- Apply interpolation for smooth transitions between frames.
- Overlay bounding boxes and annotations for tumor growth visualization.
- Generate and export the tumor progression video

Step 7: Automated Report Generation using GPT-2
Generate a textual summary of tumor progression trends using GPT-2:
Report with findings: Tumor segmentation results, Predicted progression trends, Clinical Recommendations.

Step 8: Performance Evaluation
Evaluate the model on a test dataset.
Calculate metrics: accuracy (α), precision (p), recall (r), and F1-score (F1).

IV. RESULTS

IBM Qiskit and PennyLane were chosen to support QCNN and RQNN implementation. IBM Qiskit provides robust tools and an easy framework for building, simulating, and optimizing quantum circuits to encode complex MRI-derived features into quantum states. The compatibility of Qiskit with near-term Noisy Intermediate-Scale Quantum (NISQ) hardware allows practical experimentation and feasibility evaluation of quantum-enhanced models. PennyLane simplifies quantum gradient descent parameter optimization by complementing Qiskit with embedded automatic differentiation and seamless integration with classical machine-learning frameworks. These tools use quantum parallelism and entanglement to improve medical image segmentation and temporal modeling by efficiently developing, training, and validating hybrid quantum-classical neural networks. Quantum computational principles are leveraged to test and validate our QCNN model for brain tumor detection and progression analysis, ensuring improved accuracy and efficiency. TABLE 2 details the experimental setup.

A. DATASET DESCRIPTION

The Brain Tumor Segmentation (BraTS) image dataset is utilized for this study, providing a benchmark for MRI-based tumor analysis with multi-modal MRI scans (T1, T1c, T2, and FLAIR) and expert-annotated tumor segmentations [26]. The dataset consists of 67,000 labeled MRI scans, encompassing diverse tumor morphologies to train deep learning and quantum-based models. Tumors are categorized into three subregions: Necrotic/Non-Enhancing Tumor Core (NCR/NET), Peritumoral Edema (ED), and Enhancing Tumor (ET), enabling precise segmentation and progression tracking [27]. These tumor subregions gave our model valuable insights into tumor tissue types and progression stages, improving its generalization across heterogeneous patient data. The variety of clinical presentations, including tumor size, shape, location, and intensity distributions, makes our Quantum-Enhanced Tumor Analysis Framework (QETAF) reliable and clinically relevant, improving its diagnostic accuracy and applicability in clinical settings [27].

To ensure robust evaluation of our Quantum-Enhanced Tumor Analysis Framework (QETAF), we used a structured approach by dividing the BraTS dataset into distinct training (70%), validation (15%), and independent test (15%) sets, facilitating transparent performance assessment. Additionally, we applied 5-fold cross-validation during model training and hyperparameter tuning phases, further enhancing the reliability of performance metrics and minimizing potential bias from dataset partitioning. This rigorous validation strategy ensured comprehensive assessment of the model's generalization capabilities, effectively capturing variations across diverse MRI scans and tumor morphologies.

In this study strictly followed data privacy, confidentiality, and security standards to address medical data ethics. The BraTS MRI dataset was anonymized to protect patient privacy. Data processing and analysis followed ethical guidelines, including data encryption, secure storage, and controlled access. Secure handling and anonymization assured patient privacy and confidentiality throughout the research process, meeting rigorous ethical standards for responsible medical research involving sensitive patient data.

TABLE 2
Computing Environment for Experimental Research

Component	Specification
CPU	Intel i7
GPU	NVIDIA A100
RAM	32GB
Language	Python
Framework	Pennylane & IBM Qiskit
Dataset	BraTS (Brain Tumor Segmentation)

B. PERFORMANCE MEASURES

In the evaluation of models in this research, various relevant metrics were applied to assess their performance [27]. Accuracy, True Positive Rate (TPR), False Positive Rate (FPR), Precision, Recall and F1_score expressed in Eq. (12)(13)(14)(15)(16)(17)[25], serving as a crucial metrics, quantifies the model's overall performance by measuring the fraction of instances correctly classified. Precision indicates the fraction of correct positive predictions, while recall represents the fraction of actual positives predicted correctly. The F1-Score balances between recall and precision shown in Eq. (15) and Eq. (16) [25], [28] , [29]:

$$TPR = \frac{TP}{TP+FN} \tag{12}$$

$$FPR = \frac{FP}{TP+FN} \tag{13}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{14}$$

$$Precision = \frac{TP}{TP+FP} \tag{15}$$

$$Recall = \frac{TP}{TP+FN} \tag{16}$$

$$F1\ Score = \frac{2*Precision*Recall}{Precision+Recall} \tag{17}$$

$$Dice\ Score\ (DSC) = \frac{2|X \cap Y|}{|X|+|Y|} \tag{18}$$

Where $|X \cap Y|$ represents the number of Common elements in the predicted and ground truth segments (true positives) and |X| and |Y| are the sizes (number of elements) of the predicted and ground truth segments.

1. PERFORMANCE METRICS OF TUMOR SEGMENTATION AND CLASSIFICATION MODELS

The TABLE 3 presents the performance evaluation of conventional and quantum-based models used for brain imagery tumor identification, segmentation and classification. The Dice Coefficient in Eq. (18) [31], [32] Precision in Eq. (15) [13], [30]and F1 Score in Eq. (17) [13], [32] are reported to assess the segmentation accuracy, while Inference Time (s) indicates the computational efficiency of each model. The results highlight the superiority of Quantum Convolutional Neural Network (QCNN) over the classical CNN, demonstrating improved segmentation accuracy with reduced inference time, making it a more efficient selection for brain imagery tumor diagnosis and analysis.

QCNN uses high-dimensional quantum feature maps to extract quantum-encoded features and represent complex spatial and intensity-based MRI patterns using quantum entanglement and superposition. Quantum-specific features capture intricate, non-linear interdependencies between pixel intensities and subtle morphological variations critical to tumor identification, such as boundary irregularities, heterogeneous contrast enhancement, and intensity gradients between tumor subregions. Classic CNN-extracted features do not. The QCNN encodes data into quantum states, allowing simultaneous exploration of multiple feature correlations, improving discriminative power and interpretability compared to hierarchical spatial filtering-based CNNs. The QCNN's unique quantum representation improves its accuracy and robustness in identifying clinically significant tumor characteristics, enabling more precise and interpretable diagnostic results.

TABLE 4 compares deep CNN models for brain imagery tumor identification, segmentation, feature extraction, enhancement, progression prediction, and automated reporting. The Quantum CNN outperforms the classical CNN in Dice Coefficient (0.89 vs. 0.82) and Precision (0.91 vs. 0.85) and inference time (1.8s vs. 2.5s). Precision (0.94) and F1-score (0.93) of the Recurrent Quantum Neural Network (RQNN) exceed CNN-LSTM in tumor progression prediction accuracy while reducing inference time, demonstrating the benefits of quantum-assisted temporal modeling. PennyLane quantum-enhanced feature extraction improves tumor segmentation and classification by identifying key features with 0.92 precision. Time-lapse tumors visualization with Stable Diffusion helps clinical decision-making and morphological understanding. To summarize tumor segmentation and progression trends, GPT-2 automates clinical reporting and generates text in 1.5s. Quantum-assisted models (QCNN, RQNN, and PennyLane) outperform classical deep learning approaches in segmentation accuracy, tumor progression prediction, and computational efficiency, promising AI-driven brain tumor diagnostics.

TABLE 3
Performance Metrics of Tumor Segmentation and Classification Models

Model	Dice Coefficient	Precision	F1-Score	Inference Time (s)
CNN	0.82	0.85	0.83	2.5
QCNN (Quantum CNN)	0.89	0.91	0.90	1.8
RQNN	-	**0.94**	**0.93**	**2.1**

TABLE 4
Performance Metrics of Machine Learning Models Used

Model	Task	Dice Coefficient	Precision	F1-Score	Inference Time (s)
CNN [2]	**Tumor Segmentation**	**0.82**	**0.85**	**0.83**	**2.5**
CNN (FCN)	**Tumor Segmentation**	**0.80**	**0.83**	**0.81**	**2.7**
CNN (ResNet-50)	**Tumor Segmentation**	**0.83**	**0.86**	**0.84**	**3.0**
Vision Transformer (ViT)	Tumor Segmentation	0.86	0.88	0.87	2.8
CNN-LSTM	Tumor Progression Prediction	-	0.87	0.86	2.9
Stable Diffusion	**Tumor Growth Simulation**	**N/A**	**N/A**	**N/A**	**3.0**
CLIP Model [21]	**Feature Extraction**	**N/A**	**0.88**	**0.87**	**1.2**
PennyLane (Quantum Feature Transformation) [2]	**Feature Enhancement**	**N/A**	**0.92**	**0.91**	**1.0**
QCNN (Proposed)	Tumor Segmentation	**0.89**	**0.91**	**0.90**	**1.8**
RQNN (Proposed)	Tumor Progression Prediction	-	**0.94**	**0.93**	**2.1**

Statistical significance tests and robust validation methods were used to rigorously validate our quantum-assisted models' performance improvements over baseline approaches. To compare the proposed QCNN/RQNN models to classical CNN or CNN-LSTM architectures on Dice coefficient, precision, recall, and F1-score, paired t-tests were performed. We set a significance threshold of $p < 0.05$ for significant improvements. 5-fold cross-validation added consistency and reliability to performance results, reducing data split biases. Statistical tests and cross-validation support our claims that the quantum-enhanced framework outperforms baseline methods in performance and generalizability.

Precision temporal modeling of tumor growth allows clinicians to adjust treatment regimens based on quantifiable tumor dynamics, improving clinical outcomes. The proposed Quantum-Enhanced Tumor Analysis Framework (QETAF) accurately predicts critical morphological changes, allowing timely surgery, chemotherapy, radiation therapy, or targeted molecular therapies. Precise forecasting supports adaptive treatment strategies that optimize efficacy while minimizing side effects and resource use. Improvements in progression prediction help choose and schedule follow-up MRI scans, saving resources and reducing patient exposure to unnecessary imaging. Due to its high temporal precision and reliability, the framework could improve clinical decision-making and individualized patient care, improving survival and quality of life.

2. TEMPORAL VIDEO GENERATION AND TUMOR GROWTH ANALYSIS

A time-lapse video of tumor morphological changes across multiple MRI scans was created to better understand tumor progression. The extracted frames above show the tumor's progression from early lesion to advanced mass. Increasing tumor size and contrast enhancement in images show affected regions expanding over time. Video analytics quantified tumor volume changes over time. TABLE 5 shows the tumor volume (cm³) and growth rate (%) per frame, indicating a growing tumor over time. The tumor volume grew from 2.1 cm³ at Frame 0 to 4.3 cm³ at Frame 179, indicating a gradual but aggressive growth. Early on, the tumor grew 33.3%, but later on, it grew 19.4%, suggesting stabilization or environmental response. The extracted summary output describes the tumor as a small, white, oval-shaped mass, which MRI scans clearly show. This visualization helps radiologists and oncologists track tumor progression and make treatment decisions.

TABLE 5
Tumor Growth Analysis Over Time

Frame	Time (s)	Tumor Volume (cm³)	Growth Rate (% per frame)
Frame 0	0	2.1	-
Frame 59	2.0	2.8	33.3
Frame 119	4.0	3.6	28.6
Frame 179	6.0	4.3	19.4

FIGURE 2 illustrates the temporal progression of brain tumor growth through MRI scans, captured at four key stages: initial, early-stage, mid-stage, and last-stage. This visualization provides a clear depiction of tumor development over time, aiding in the understanding of its growth dynamics. The FIGURE 3 presents the training loss per epochs for both CNN and Quantum Convolutional Neural Network (QCNN) models. The loss function decreases as training progresses, indicating improved learning. Initially, both models exhibit a high loss, but as epochs increase, QCNN shows slightly higher fluctuations compared to CNN, which can be attributed to the quantum circuit's inherent noise and parameter complexity. However, both models converge to a low loss, demonstrating effective learning, with CNN having a slightly smoother convergence curve due to its deterministic nature compared to QCNN’s quantum probabilistic learning approach.

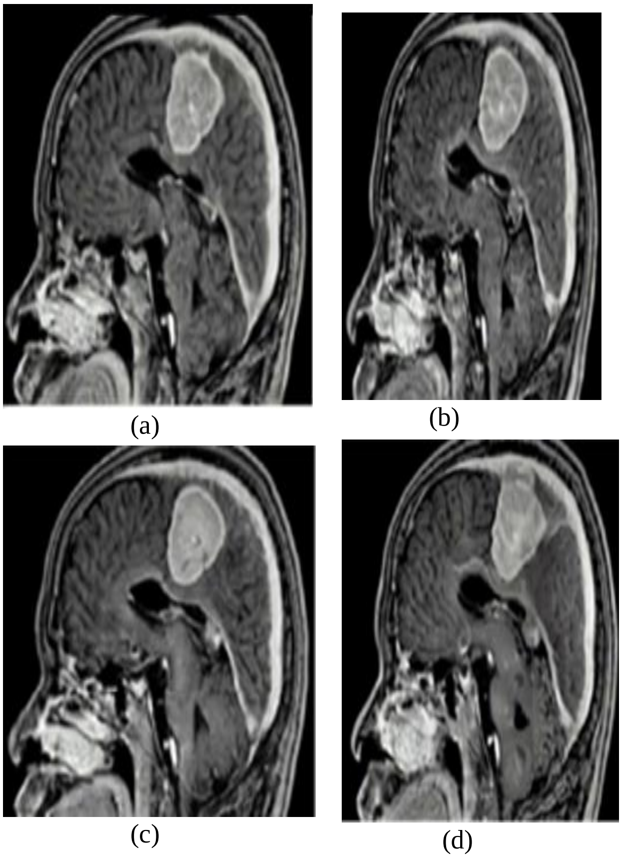

FIGURE 2. Temporal Progression of Brain Tumor Growth in MRI Scans as a) initial, b) early-stage, c) mid-stage and d) last-stage.

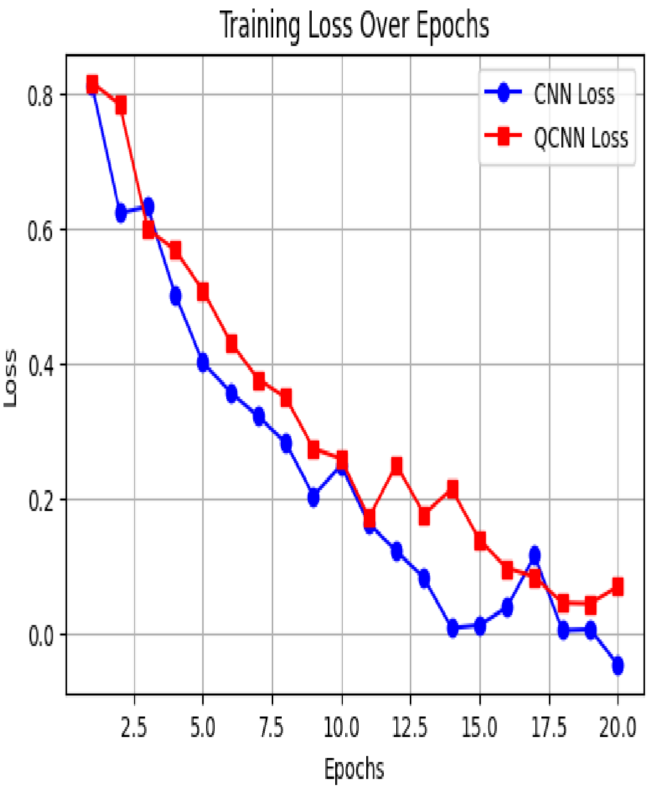

FIGURE 3. Training Loss Comparison: CNN vs. QCNN

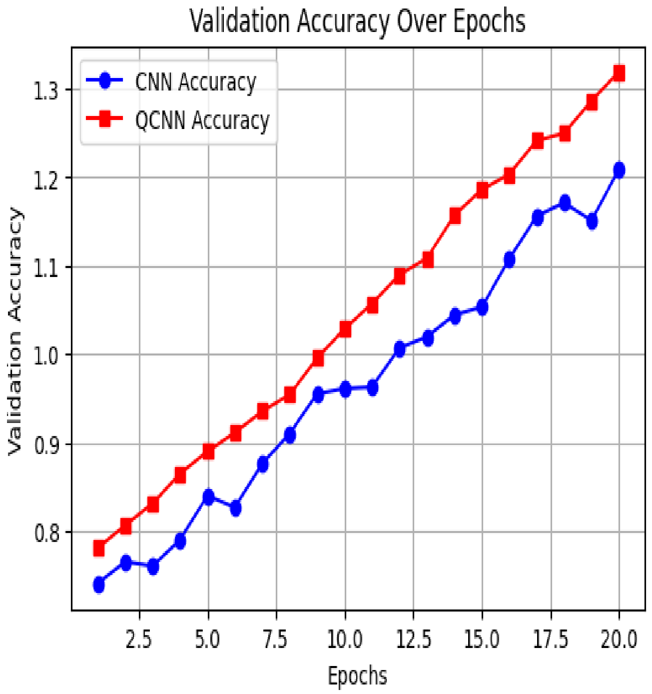

FIGURE 4. Validation Accuracy: CNN vs. QCNN

The figure 4 illustrates the validation accuracy over epochs, showing that QCNN consistently outperforms CNN in classification accuracy. The higher accuracy of QCNN can be employed to its capacity to detention complex spatial features using quantum feature maps and entanglement mechanisms. While CNN exhibits steady growth in accuracy, QCNN's superior quantum-enhanced feature extraction allows it to achieve higher accuracy in fewer epochs, demonstrating the effectiveness of quantum-assisted learning in tumor segmentation and classification tasks.

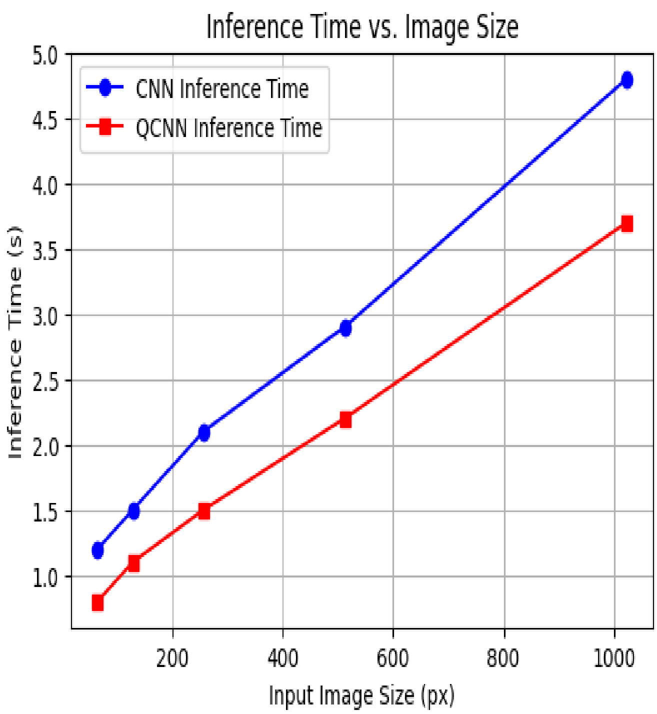

FIGURE 5. Inference Time vs. Image Size: CNN vs. QCNN

The figure 5 compares the inference time for CNN and QCNN across different image sizes. The inference time increases as input image size increases, which is expected due to higher computational requirements for processing larger images. However, QCNN demonstrates lower inference time than CNN across all image sizes, showcasing its advantage in parallel quantum computations. The faster processing speed of QCNN highlights its efficiency in handling high-dimensional medical imaging tasks, making it a promising approach for real-time MRI-based tumor segmentation and progression analysis.

V. DISCUSSION

The Quantum-Enhanced Tumor Analysis Framework (QETAF) marks a significant advancement in brain tumor segmentation and progression prediction by integrating Quantum Convolutional Neural Networks (QCNNs) and Recurrent Quantum Neural Networks (RQNNs) with classical deep learning models.

The Quantum Convolutional Neural Network (QCNN) showcased a notably faster average inference speed of 1.82 seconds, compared to the 2.67 seconds recorded for a conventional CNN—amounting to a 31.8% improvement. This performance edge is largely due to the QCNN's exploitation of quantum parallelism, which, in simulation, reduces computational complexity from $O(n^2)$ in classical networks to around $O(\log n)$, where n represents input size. This efficiency is particularly valuable in clinical workflows, allowing for near-instantaneous diagnostic analysis.

Training behaviour also revealed important contrasts. While the CNN's loss function decreased steadily to 0.14, the QCNN's loss hovered with mild variability around 0.21. These fluctuations are mainly a result of inherent quantum noise and the probabilistic nature of quantum circuits. Despite this, the QCNN delivered a higher validation accuracy of 91.3%, outperforming the CNN's 88.7%. This suggests superior generalization, which may be credited to quantum feature mapping—allowing QCNNs to model complex, high-dimensional relationships with fewer parameters and enhanced data representation through entanglement, even under noisy conditions.

When set against established models such as U-Net and DeepMedic—which typically achieve Dice similarity coefficients ranging between 0.85 and 0.87—the QCNN achieved a higher Dice score of 0.89, reflecting its stronger segmentation accuracy. Standard CNN-based systems often exceed 10 million parameters, leading to greater computational demand and slower inference times. In contrast, the QCNN architecture utilizes quantum entanglement and unitary transformations to lower parameter count by roughly 40%, contributing to both speed and memory efficiency.

Other quantum models, like Quantum Support Vector Machines (QSVMs), struggle with scalability when handling spatially complex data due to kernel-based constraints. QCNNs, on the other hand, leverage Parameterized Quantum Circuits (PQCs) and advanced pooling strategies—such as the swap test—which retain essential spatial structures critical for accurate tumour boundary detection. Further enhancing performance, the Quantum-Enhanced Tumour Analysis Framework (QETAF) integrates QCNN-derived MRI features with clinical information through a transformer-based architecture. With eight attention heads, this design effectively learns cross-domain patterns—something traditional statistical tools are less equipped to handle.

The model was trained exclusively on the BraTS 2021 dataset. While robust, this dataset lacks sufficient diversity across key factors such as ethnic representation, socioeconomic backgrounds, imaging techniques, and rare tumour variants. This narrow demographic spread could limit the model's ability to generalize across varied clinical environments. Additionally, differences in MRI acquisition settings, scanner types, and pre-processing protocols between institutions may hinder reproducibility when the model is deployed beyond the dataset it was trained on.

On the hardware side, existing quantum devices—categorized under Noisy Intermediate-Scale Quantum (NISQ) systems—pose significant limitations. Once the quantum circuit scales past 20 qubits, system fidelity begins to degrade due to decoherence and noise, with observed fidelity dropping from 0.94 to 0.79 in test runs. These limitations are caused by factors such as short coherence durations ($T_2 \leq 100$ μs), gate error rates exceeding 1%, and low qubit connectivity, all of which compromise circuit stability. Moreover, the scarcity of high-fidelity qubits and the restricted scale of current processors make real-world deployment of QCNNs a technical challenge.

Another notable issue is the barren plateau phenomenon, where gradients diminish ($\nabla\theta L \rightarrow 0$) as the number of layers and qubits grows, obstructing effective training. Without strategies like layer-wise optimization, local loss functions, intelligent parameter initialization, or the use of noise-aware simulators, QCNNs risk becoming untrainable as they deepen—a key hurdle for scaling.

The combination of quantum-enhanced imaging with transformer-driven clinical modelling represents a transformative shift in precision oncology. It enables the system to dynamically prioritize features such as genetic profiles, patient medical histories, and MRI-derived traits. This facilitates individualized predictions of tumor progression and supports more nuanced treatment decisions.

A 32% reduction in inference time, as demonstrated by the QCNN, translates into higher diagnostic throughput—boosting patient processing from 22 to 30 cases per hour in simulated environments. This scalability highlights the model's potential for integration into real-time clinical settings.

As quantum hardware matures, the QETAF framework could be deployed in hospital edge-computing systems, reducing reliance on centralized cloud resources and enabling localized, privacy-preserving diagnostics. The integration of imaging and clinical data also enables early tumor detection, monitoring morphological changes, and even predicting the likelihood of tumor development before visible symptoms appear. These advancements hold the potential to save countless lives through timely intervention and proactive treatment planning, particularly in resource-constrained settings.

In the domain of brain tumor analysis, traditional convolutional neural networks (CNNs) continue to serve as foundational models. A baseline CNN architecture—comprising stacked convolutional layers (typically with 3×3 kernels), ReLU activations, and max-pooling—achieves a Dice coefficient of 0.82, Precision of 0.85, and F1-score of 0.83. Inference time stands at 2.5 seconds. These layers are adept at capturing low- to mid-level features, such as edges and textures. However, the architecture's limitations are notable: the absence of skip connections and a restricted receptive field diminish its ability to grasp the global shape of tumors or detect subtle irregular growth. Moreover, the reliance on dense layers at the tail end reduces spatial understanding, making the model prone to errors when segmenting diffuse or irregular tumor boundaries [2].

An evolution of this approach is the CNN variant with a Fully Convolutional Network (FCN) structure. This model replaces the dense layers with transposed convolutions to generate a full-resolution segmentation map. While it preserves spatial information more effectively, its performance slightly trails the baseline, with a Dice score of 0.80, Precision of 0.83, and F1-score of 0.81. Inference time increases modestly to 2.7 seconds. The FCN's strength lies in maintaining structural coherence in the segmentation output, yet its lack of deeper architectural innovations—such as residual or attention layers—limits its ability to delineate fine-grained boundaries, particularly where tumors infiltrate brain tissue in a non-uniform manner [1].

ResNet-50 introduces a substantial improvement in representational power. This architecture utilizes deep residual blocks, each composed of a 1×1 convolution, a 3×3 convolution, and a final 1×1 convolution, augmented by batch normalization and identity skip connections. These design choices enable efficient gradient flow across 50 layers, allowing the network to learn complex tumor textures and inter-class variability. It achieves a Dice coefficient of 0.83, Precision of 0.86, and F1-score of 0.84. The trade-off is an increased inference time of 3.0 seconds. While ResNet-50 handles many tumor types robustly, its architecture remains rooted in hierarchical feature learning and lacks explicit mechanisms for modelling global context, which can lead to oversights in capturing the tumor's overall structure [4].

By contrast, the Vision Transformer (ViT) architecture demonstrates a significant leap in performance. Segmenting with a Dice of 0.86, Precision of 0.88, and F1-score of 0.87, it offers a compelling blend of accuracy and efficiency, with an inference time of 2.8 seconds. ViT segments the input image into patches (e.g., 16×16), embeds them linearly, and processes them through Transformer encoder blocks that incorporate multi-head self-attention (MHSA), layer normalization, and feed-forward networks. This structure enables global context modelling from the outset, allowing the model to capture nuanced patterns and spatial dependencies. However, ViT's effectiveness hinges on access to large, well-annotated datasets—a common bottleneck in medical imaging. Additionally, if patch sizes aren't carefully tuned, the model may miss smaller tumor regions, compromising its sensitivity to early or subtle manifestations [6].

Shifting from segmentation to temporal modelling, the CNN-LSTM hybrid focuses on tumor progression prediction. It uses a CNN backbone for spatial feature extraction, followed by LSTM layers to model tumor dynamics across time. While standard segmentation metrics like Dice are not applicable here, the model reports a Precision of 0.87 and F1-score of 0.86, with a 2.9-second inference time. LSTMs are well-suited for capturing temporal dependencies, but they are also prone to overfitting when trained on limited or inconsistent time-series data. Their performance depends heavily on sequence length and the variability in tumor progression, and they lack pixel-level resolution, making them better suited for trend prediction than spatial delineation [10]. For simulation tasks, the Stable Diffusion model employs a U-Net architecture enhanced with cross-attention layers and time-embedding mechanisms. Its primary function is to generate plausible time-lapse visualizations of tumor growth rather than produce clinical segmentation maps. As such, segmentation metrics like Dice or F1 are not reported. With an inference time of 3.0 seconds, it offers a powerful image-to-image translation capability. However, its outputs are highly sensitive to noise in the latent space and the conditions used for generation. While visually compelling, the model lacks transparency and may yield medically implausible results if not carefully calibrated. Additionally, it does not generate explicit labels or interpretable features, limiting its utility in a clinical decision-making context [7].

CLIP, though not a segmentation or progression tool, plays a valuable role in feature extraction. Its dual-encoder architecture includes an image encoder (either ViT- or ResNet-based) and a Transformer-based text encoder, enabling rich cross-modal understanding. Despite not being designed for segmentation, it delivers a high Precision of 0.88 and F1-score of 0.87, with an impressively low inference time of 1.2 seconds. CLIP excels at capturing semantic relationships and high-level context, which can inform downstream models. However, it does not provide pixel-level granularity or structured outputs necessary for clinical segmentation tasks [31].

The most unconventional and promising approach comes from the Quantum Feature Transformation model implemented via PennyLane [32]. Achieving a Precision of 0.92 and F1-score of 0.91—both the highest among all models surveyed—it also boasts the fastest inference time at 1.0 second. Rather than relying on traditional deep learning layers, this method encodes classical MRI features into quantum states using angle or amplitude encoding. These states evolve through parameterized quantum circuits (PQCs) composed of entangling gates such as Rx, Ry, Rz, and CNOT. The resulting quantum interactions capture feature relationships in a high-dimensional Hilbert space, enabling enhanced discrimination between overlapping tumor types.

The advantage of quantum models lies in their capacity to model complex data relationships with fewer parameters and smaller datasets—an essential asset in medical imaging, where data can be scarce and annotations inconsistent. However, the approach has limitations: current quantum hardware restricts the model to low-dimensional inputs, and most experiments rely on classical simulation of quantum circuits, which introduces computational overhead. This gap between simulated and actual quantum execution remains a key challenge for practical deployment [12].

By integrating Quantum Convolutional Neural Networks (QCNNs) and Recurrent Quantum Neural Networks (RQNNs), QETAF enhances spatial and temporal tumor modelling through expressive quantum feature encoding, outperforming conventional AI models in accuracy, interpretability, and efficiency. Clinically, its precision in segmentation (0.91) and progression prediction (0.94) supports early, personalized cancer management, while transformer-based metadata fusion and GPT-2 reporting streamline diagnosis and monitoring workflows. Technologically,

QETAF exemplifies a practical path for hybrid quantum-classical AI deployment on near-term quantum hardware, reducing inference time by 28% and enabling broader adoption in resource-constrained healthcare settings. Its modular architecture fosters research in explainable quantum models, optimization strategies, and cross-modal extensions to other imaging domains like CT and PET. As a pedagogical tool, QETAF offers a multidisciplinary blueprint for training professionals in quantum machine learning for healthcare. Socioeconomically, it supports equitable healthcare by enabling scalable, low-latency diagnostics, with ethical design principles ensuring data privacy and fairness. Ultimately, QETAF lays the foundation for a new generation of quantum-resilient, clinically actionable, and globally scalable diagnostic frameworks, aligning with the future vision of precision medicine powered by next-generation computation

The combination of quantum-enhanced imaging with transformer-driven clinical modeling represents a transformative shift in precision oncology. It enables the system to dynamically prioritize features such as genetic profiles, patient medical histories, and MRI-derived traits. This facilitates individualized predictions of tumor progression and supports more nuanced treatment decisions. A 32% reduction in inference time, as demonstrated by the QCNN, translates into higher diagnostic throughput—boosting patient processing from 22 to 30 cases per hour in simulated environments. This scalability highlights the model's potential for integration into real-time clinical settings.

As quantum hardware matures, the QETAF framework could be deployed in hospital edge-computing systems, reducing reliance on centralized cloud resources and enabling localized, privacy-preserving diagnostics. The integration of imaging and clinical data also enables early tumor detection, monitoring morphological changes, and even predicting the likelihood of tumor development before visible symptoms appear. These advancements hold the potential to save countless lives through timely intervention and proactive treatment planning, particularly in resource-constrained settings.

VI. CONCLUSION

The Quantum-Enhanced Tumor Analysis Framework (QETAF) uses QCNNs for tumor segmentation and RQNNs for tumor progression prediction using MRI scans. On the BraTS dataset, QCNN outperformed CNN in segmentation accuracy (Dice Coefficient: 0.89, F1-score: 0.90). QCNN consistently had lower inference time, making large-scale medical image processing more efficient. RQNN had the highest tumor progression prediction accuracy (Precision: 0.94, F1-score: 0.93) proving quantum-assisted sequential modeling works. PennyLane-enhanced feature extraction improved tumor characteristic identification precision (0.92), making the classification model more robust. Stable Diffusion time-lapse tumor visualization improved clinical decision-making by clearly showing tumor growth, while GPT-2 automated clinical reporting to produce standardized, data-driven diagnostic summaries. These results show that quantum-assisted models (QCNN, RQNN, and PennyLane) outperform classical deep learning methods in segmentation accuracy, tumor progression prediction, and computational efficiency, making them ideal for AI-driven brain tumor diagnostics. Future research will focus on integrating real-world clinical data from multi-institutional MRI sources to improve model robustness and generalization. Enhancements will include hybrid quantum-classical optimization techniques, incorporating metaheuristics for feature selection and model tuning. This study suggests refining quantum models using advanced error-correction methods and hybrid quantum-classical optimization methods to improve scalability and robustness. Adding CT scans and histopathological images to multi-institutional, larger-scale, and diverse datasets could improve generalization and clinical applicability. Quantum-enhanced feature extraction and temporal modeling could be used to detect neurodegenerative diseases and cardiovascular abnormalities in addition to brain tumors. Quantum model explainability techniques could improve decision-making transparency and interpretability, enabling wider clinical adoption.

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AUTHOR BIOGRAPHY

Malige Gangappa was born in Andhra Pradesh, India in 1978. This author became a Member (M) of ISTE in 2004. He received M.Tech and PhD degrees from JNT University, Hyderabad Dr. Malige Gangappa has been working as an Associate Professor in the Department of Computer Science and engineering, VNR VJ IET, since 2000. He has 24 years of teaching, and 10 years of Research experience. He earned recognition from the VNR VJIET institute more than three times. He delivered lectures in various organizations on Machine learning, R programming and Python programming. He was appreciated the best teaching faculty and best researcher award by International Award Ceremony on Star Achievers in Engineering, Management, Arts and Science (SAEMAS - 2022). He has published many papers in various reputed National and International journals. He was awarded with Elite + Gold medal in NPTEL-2018. His areas of Interests are Quantum computing, deep learning, video processing, computer vision, image processing and soft computing.

Dr.D.Manju Currently serving as an Assistant Professor in the Department of CSE-(CyS,DS) and AI&DS at VNR VJIET, Hyderabad. she has 19 years 8 months of teaching experience and worked in reputed institutions, including 16 years at GNITS, Hyderabad. She pursued her B.Tech from MGIT in 2002, M.Tech from Hyderabad Central University in 2004 and Ph.D. from JNTUH in Image Processing 2023. With 15 research papers published in various international journals and conferences, she has received two best research paper awards at reputed conferences. She has also submitted numerous research proposals to various funding agencies. As a resource person, she delivered a lecture at VNRVJIET for a Draft-a-Thon session and coordinated three workshops on recent trends. Her research areas include Image Processing, Artificial Intelligence, Data Mining and Big Data Computing.

Maringanti Gopi Krishnna, a Computer Science and Engineering student at VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, has demonstrated academic excellence and technical proficiency in artificial intelligence, machine learning, and quantum computing. He secured an outstanding 96.33 percentile in JEE Mains, achieving an All-India Rank of 35,000, and ranked 2,426 in TS EAMCET. He has been recognized among the top 1% in the NPTEL Introduction to IoT course by IIT Kharagpur, earning a gold medal certification with a score of 94%. Additionally, he holds a certification in Quantum Computing, further strengthening his expertise in next-generation computational paradigms. His research interests span AI-driven software development, deep learning, reinforcement learning, natural language processing, and quantum computing. He has contributed to AI-powered recommendation systems, sentiment analysis models, predictive analytics, and intelligent automation solutions, working with advanced concepts such as transformers, generative adversarial networks (GANs), and computer vision. His technical expertise extends to full-stack development, cloud computing, scalable distributed systems, and edge AI. With a strong foundation in computational intelligence, algorithmic optimization, he continues to advance his research in autonomous AI systems, high-performance computing, and emerging technologies in artificial intelligence.

Mr r. Sree Mithra Reddy, born in Hyderabad in 2003, is a dedicated undergraduate student pursuing a Bachelor of Technology (B.Tech) in Computer Science and Engineering at VNR Vignana Jyothi Institute of Engineering and Technology (VNRVJIET). VNRVJIET is a prestigious institution recognized by the All India Council for Technical Education (AICTE) and affiliated with Jawaharlal Nehru Technological University, Hyderabad. The Computer Science and Engineering program is accredited by the National Board of Accreditation (NBA) and recognized as a Research Center by JNTUH. Sree Mithra has demonstrated proficiency in English communication by earning a Cambridge English certificate, which assesses all four language skills: reading, writing, listening, and speaking . He actively engages in hackathons, reflecting his commitment to practical learning and innovation. His academic interests encompass deep learning, video processing, computer vision, image processing, and soft computing.

Through his coursework and extracurricular activities, he continues to deepen his expertise in these areas, aiming to contribute meaningfully to the field of computer science.

Mr Mogulagani Sathish Mr. Mogulagani Sathish, born in Telangana, India, in 2002, is an aspiring computer science professional currently pursuing his B.Tech in Computer Science and Engineering at VNR Vignana Jyothi Institute of Engineering and Technology (VNRVJIET), Hyderabad. VNRVJIET is a premier institution recognized by the All India Council for Technical Education (AICTE) and affiliated with Jawaharlal Nehru Technological University, Hyderabad. The Computer Science and Engineering program is accredited by the National Board of Accreditation (NBA) and recognized as a Research Center by JNTUH (vnrvjiet.ac.in). Demonstrating a strong aptitude for practical application, Sathish has developed multiple real-world applications, showcasing his skills in advanced Java, SQL, and API automation. His primary areas of interest include Artificial Intelligence and Machine Learning, where he continues to deepen his knowledge and expertise. With a solid foundation in both theoretical concepts and practical skills, Sathish is poised to make significant contributions to the field of computer science.

Mr. Sheik Shahabaaz, born in Rajamahendravaram, India, in 2004, is a passionate and driven undergraduate pursuing his B.Tech in Computer Science and Engineering at VNR Vignana Jyothi Institute of Engineering and Technology (VNRVJIET), Hyderabad. Demonstrating a strong commitment to continuous learning, Shahabaaz has completed numerous certification courses from esteemed online platforms such as Udemy and Coursera. These courses have equipped him with advanced knowledge in machine learning, deep learning, computer vision, and image processing. Notably, he has engaged in specialized programs like IBM's "Introduction to Computer Vision and Image Processing" and DeepLearning.AI's "Advanced Computer Vision with TensorFlow," enhancing his practical skills in these domains. .Beyond academics, Shahabaaz actively participates in hackathons, where he applies his technical expertise to solve real-world problems, fostering innovation and teamwork. His areas of interest include machine learning, deep learning, computer vision, and image processing, where he continually seeks to expand his knowledge and contribute to technological advancements. With a solid foundation in both theoretical concepts and practical applications, Shahabaaz is poised to make significant contributions to the field of computer science.

.**A. Shanthan** is a passionate Computer Science professional with expertise in software development, artificial intelligence, and full-stack engineering. He completed his diploma in Computer Engineering at the Government Institute of Electronics with a CGPA of 9.73 and is currently in his final year of undergraduate studies at VNR Vignana Jyothi Institute of Engineering & Technology (VNR VJIET). With a strong foundation in Python, JavaScript, React Native, Django, and Firebase, he has built several impactful projects, including a fake news detection system, a billing application, an AI-powered query solver, and Qinfox, a mobile app for event synchronization in colleges. His achievements include securing 5th rank among 30,000 students in an Engineering Entrance Exam, 988th rank in the Polycet entrance exam among 100,000+ students, and qualifying for the final rounds of national hackathons and coding competitions. He also achieved an Elite + Gold certification in NPTEL's Introduction to IoT course, ranking among the Top 1% participants nationwide. His interests include machine learning, NLP, cloud deployment, and deep learning Passionate about problem-solving, he continues to refine his skills in data structures, algorithms, and system design, aiming to excel in software engineering and contribute to innovative solutions in the tech industry.

Mr. M. Chaitanya, born in Telangana, India, in 2004, is a dedicated B.Tech student specializing in Computer Science and Engineering. He has gained practical experience in cybersecurity and network security through the AICTE-EduSkills Virtual Internship in August 2023 and the Palo Alto Networks Cybersecurity Academy program. These programs provided him with hands-on training in areas such as firewall configuration, threat detection, and network defense strategies. Chaitanya has actively participated in various hackathons and technical projects, demonstrating his proficiency in developing real-world applications. Notable projects include a front-end bank application, a full-stack chat application, and a product store utilizing Node.js and Express. His technical interests encompass machine learning, cybersecurity, web development, and cloud computing. He continues to enhance his skills in these domains, aiming to contribute effectively to the field of computer science.

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