Multidisciplinary Journal of Research in Engineering and Technology
ISSN: 2348-6953
Volume 13 Issue 2s (2026) | Pages: 49-53

Quantum-Powered Vision Network for Intelligent Brain Analysis

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Peer Review Information

Type: *Article*
Received: *26 March 2026*
Revised: *10 April 2026*
Accepted: *24 May 2026*
Published: *15 June 2026*

Abstract

Brain tumor detection from magnetic resonance imaging (MRI) plays a vital role in early diagnosis and effective treatment planning. However, conventional manual analysis and classical deep learning models often face challenges related to high computational complexity, long training time, and limited scalability when handling high-dimensional medical image data. This project presents a Quantum-Powered Vision Network for Intelligent Brain Analysis, which integrates classical image pre-processing with quantum-assisted machine learning techniques to improve classification performance.
The proposed system follows a hybrid quantum–classical workflow that includes MRI image preprocessing, quantum data encoding using unary amplitude encoding, and quantum-assisted learning layers for feature extraction and classification. The model is designed to classify brain MRI images and identify tumor presence and levels efficiently. A structured methodology is implemented, and the working of the system is demonstrated through step-by-step output results.
Experimental observations show that the proposed approach achieves reliable classification behavior while maintaining com-putational efficiency compared to purely classical methods. The results highlight the feasibility and potential of quantum-assisted learning techniques in medical image analysis. This project demonstrates that hybrid quantum-classical models can serve as a promising direction for future intelligent healthcare and diagnostic systems.

Keywords: Hybrid Quantum–Classical Learning; Automated Brain Tumor Diagnosis; Tumor Classification and Staging; Quantum Feature Encoding; Healthcare Image Analytics; Deep Learning Models.

How to Cite This Article

Fegade, M., Chaudhari, V., Bodake, T., Rupnar, P., & Manjare, V. (2026). Quantum-powered vision network for intelligent brain analysis. *Multidisciplinary Journal of Research in Engineering and Technology*, 13(2s), 49–53.

Introduction

The growing intersection of intelligent computing and med-ical diagnostics has opened new possibilities for improv-ing brain tumor analysis from Magnetic Resonance Imaging (MRI). Brain tumors remain one of the most critical neuro-logical disorders, where precise identification at an early stage directly influences treatment outcomes and patient prognosis. However, analyzing tumor patterns from MRI data remains inherently difficult because of irregular tumor morphology, subtle intensity variations, and the complexity of multidimen-sional brain imaging.

MRI has long been considered a fundamental imaging modality for neurological diagnosis because it captures de-tailed structural information of soft tissues without invasive procedures. While these images provide valuable diagnostic insight, extracting meaningful tumor-related patterns through manual examination is often demanding, highly dependent on specialist expertise, and challenging to scale with increasing clinical data. These practical limitations have encouraged the search for intelligent systems capable of assisting or augment-ing conventional diagnosis.

The evolution from traditional machine learning toward deep representation learning has significantly reshaped auto-mated medical image analysis. Earlier approaches relied heav-ily on manually engineered descriptors, which often struggled to generalize across diverse tumor characteristics. In con-trast, deep neural architectures introduced data-driven feature discovery, allowing classification models to learn complex spatial patterns directly from MRI scans. Although these methods have demonstrated strong performance, their reliance on intensive computation, extensive optimization, and large annotated datasets presents notable challenges for efficient and scalable deployment.

An emerging perspective for addressing these limitations is found in quantum-enhanced learning. Rather than treating computation solely through classical optimization, quantum-inspired and hybrid quantum–classical frameworks introduce a fundamentally different approach to feature representation and learning. Through quantum states capable of encoding com-plex relationships in high-dimensional spaces, these models offer a new pathway for exploring richer representations that may complement conventional deep learning systems.

Motivated by this perspective, this research introduces a Quantum-Powered Vision Network for Intelligent Brain Anal-ysis, designed as a hybrid diagnostic architecture for brain tumor classification. The framework combines classical MRI preprocessing with quantum-assisted representation learning to construct a unified pipeline for intelligent tumor analysis. Instead of viewing quantum computation as a replacement for classical methods, the proposed approach leverages both paradigms collaboratively, utilizing classical learning strengths alongside quantum-enhanced feature modeling.

A central focus of this work lies in translating quantum machine learning concepts into an implementation-oriented framework suitable for practical medical imaging tasks. Struc-tured preprocessing stages are incorporated to improve input consistency, while quantum encoding mechanisms transform extracted image information into representations suitable for hybrid learning. This integrated strategy is intended to support robust classification behavior while maintaining feasibility for near-term quantum systems.

Beyond classification performance, the proposed framework is designed with adaptability and future clinical integration in mind. Its modular structure supports possible expansion toward tumor staging, segmentation-oriented analysis, and decision support applications. By linking theoretical advances in hybrid quantum intelligence with practical diagnostic workflows, the study explores a pathway toward next-generation computa-tional healthcare systems.

Literature Survey

Research in brain tumor detection and classification using Magnetic Resonance Imaging (MRI) has advanced consid-erably with the development of intelligent image analysis techniques. Traditional approaches have primarily focused on classical machine learning and deep learning methods for automated diagnosis. Among these, Convolutional Neural Networks (CNNs) have been widely used because of their ability to extract complex hierarchical features from MRI images and perform accurate tumor detection, segmentation, and classification. Despite their success, these models often require large annotated datasets, significant computational resources, and long training times. In addition, challenges such as overfitting, vanishing or exploding gradients, and instability in deeper architectures can affect their practical performance. To address these challenges, researchers have recently ex-plored quantum computing-based approaches for enhancing neural network models. Quantum machine learning intro-duces a different computational framework that uses principles such as superposition and entanglement for processing high-dimensional data efficiently. One important contribution in this area is Quantum-Assisted Neural Networks (QANN), where quantum circuits are integrated with classical neural networks to accelerate computationally intensive operations such as inner-product estimation. This hybrid approach combines clas-sical learning with quantum-assisted computation, making it suitable for complex data analysis tasks including brain MRI classification.

Another notable advancement is Quantum Orthogonal Neu-ral Networks (QOrthoNN), proposed to improve gradient stability and model generalization through orthogonality-preserving quantum circuits. Unlike classical orthogonal neu-ral networks, QOrthoNN uses parametrized quantum gates for optimization, reducing computational complexity while maintaining exact orthogonality. This contributes to efficient training and improved scalability in deep learning models.

In addition to these methods, Variational Quantum Circuits (VQCs) have also been investigated for image classification on near-term quantum devices. Although these models show significant potential, optimization challenges such as barren plateaus may affect their learning performance. Structured quantum architectures such as QOrthoNN help address these limitations through constrained circuit designs that stabilize training dynamics.

Experimental studies reported in recent literature suggest that hybrid quantum–classical models can provide classifica-tion performance comparable to conventional neural networks while offering advantages in computational efficiency and optimization behavior. Evaluations on simulators and emerging quantum hardware further support their applicability in medi-cal image analysis. Overall, the literature reflects a shift from purely classical deep learning models toward hybrid quantum-enhanced frameworks, which forms the motivation for the pro-posed quantum-powered vision network for intelligent brain tumor analysis.

Proposed System and Methodology

The proposed methodology presents an implementation-oriented hybrid framework for intelligent brain tumor analysis using quantum-assisted learning techniques. The workflow is designed to integrate classical image processing with quantum-inspired computation while remaining feasible on current computing platforms.

Data Collection and Preprocessing

The process begins with the collection of brain MRI images from an annotated dataset. To ensure uniformity and improve learning performance, preprocessing operations such as image resizing, normalization, and noise reduction are applied. These steps enhance image quality and prepare the data for further analysis. The preprocessed images are then converted into numerical representations suitable for feature extraction and learning.

Feature Representation and Quantum Encoding

After preprocessing, relevant image features are represented in vector form and prepared for quantum-assisted processing. The feature vectors are encoded into quantum states using quantum data encoding techniques, such as amplitude-based encoding, to preserve essential information. This encoding enables efficient handling of high-dimensional data and allows the learning process to benefit from quantum-inspired feature representation.

Quantum-Assisted Learning Model

The encoded features are processed using a hybrid quantum-assisted learning model that combines classical neural network layers with quantum-inspired computations. The model per-forms feature learning and transformation while maintaining compatibility with classical optimization techniques. This hy-brid structure enables efficient learning without requiring a fully quantum architecture.

Classification and Prediction

The learned feature representations are passed to a classi-fication layer that performs brain tumor detection and tumor-level identification. Depending on the task, suitable activation functions are applied to generate final prediction results. The classification output indicates whether a tumor is present and determines its corresponding level.

Training Process

The training process is carried out using classical optimiza-tion algorithms such as gradient descent. Model parameters are updated iteratively based on prediction error until conver-gence is achieved. The hybrid design ensures stable training while leveraging quantum-assisted computations during fea-ture learning.

Evaluation and Output Generation

The trained model is evaluated using standard performance metrics such as accuracy, precision, recall, and F1-score. The complete working of the system is demonstrated through step-by-step output screenshots, including input images, intermedi-ate processing results, and final classification outputs. These results validate the effectiveness of the proposed methodology for intelligent brain tumor analysis.

Algorithm

Hybrid Brain Tumor Classification Algorithm

Require: MRI Brain Image
Ensure: Tumor Class (Glioma / Meningioma / Pituitary / No Tumor)
Step 1: Classical CNN (like ResNet or EfficientNet) extracts high-level features.

Step 2: Dimensionality reduction (PCA or Linear layer) shrinks features to match qubit count (e.g., 4–10).
Step 3: Angle Encoding maps features into a Quantum Variational Circuit (VQC).
Step 4: Quantum Entanglement layers (CNOT gates) find non-linear relationships.
Step 5: Measurement produces probability for "Tumor" vs "No Tumor".

System Architecture

The system architecture represents the workflow of the proposed quantum-powered vision network for brain tumor analysis. The process begins with MRI brain image acquisition followed by preprocessing operations such as noise reduction, resizing, normalization, and region of interest extraction. The processed images are then encoded into quantum states using angle encoding, amplitude encoding, and FRQI techniques. A parameterized quantum circuit processes the encoded features to learn meaningful patterns. Measurement operations generate probabilistic outputs that are mapped to tumor class labels. A feedback mechanism is used to refine model parameters and improve classification accuracy.

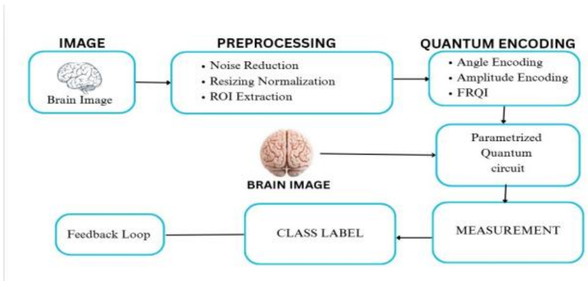

Fig. 1. *System Architecture*

Result Analysis

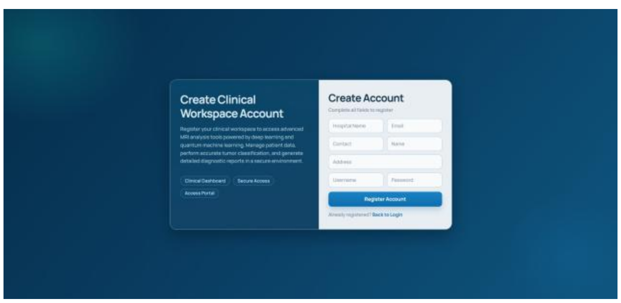

Fig. 2. *Register Page*

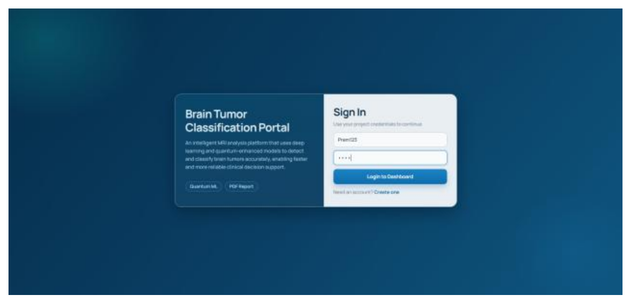

Fig. 3. *Login Page*

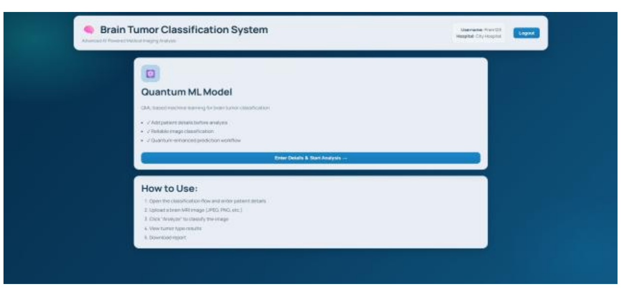

Fig. 4. *Main Dashboard*

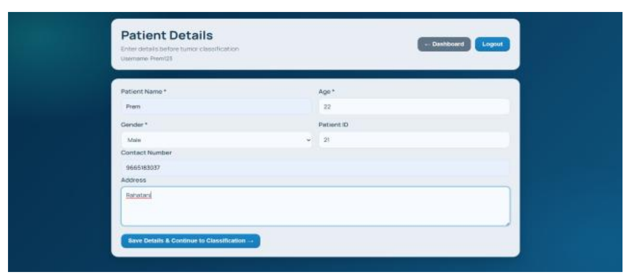

Fig. 5. *Patient Details*

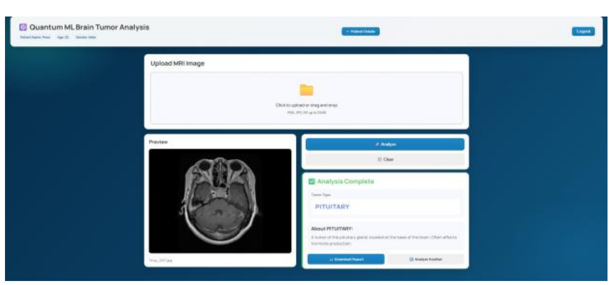

Fig. 6. *Classify Tumor*

Conclusion

This research presents an intelligent brain tumor classifi-cation framework that integrates medical image analysis with advanced computational techniques to support early diagnosis of brain tumors. The proposed system processes MRI brain images through a structured pipeline involving preprocess-ing, feature extraction, and automated classification. Various statistical and structural image characteristics such as mean intensity, entropy, edge strength, and spatial concentration are analyzed to identify tumor-related patterns within the MRI scans.

The developed model is capable of classifying brain MRI images into four major categories: glioma, meningioma, pitu-itary tumor, and normal brain tissue. By analyzing distinctive visual features present in different tumor types, the system can effectively differentiate between tumor classes and assist in accurate detection. The implementation also incorporates automated testing mechanisms to evaluate prediction accuracy and validate the reliability of the classification process.

A key contribution of this work is the integration of classical machine learning methods with quantum-inspired computational approaches within a unified system architec-ture. The backend prediction models are exposed through API endpoints, enabling real-time tumor classification through image uploads. Additionally, a web-based interface built using modern frontend technologies allows users to interact with the system easily, making the solution practical and user-friendly. The experimental results demonstrate that the proposed framework can successfully analyze MRI images and identify tumor patterns with promising accuracy. This highlights the potential of combining artificial intelligence, quantum-inspired computation, and medical imaging for intelligent healthcare applications. Such systems can support radiologists and health-care professionals by providing fast and consistent preliminary diagnostic insights.

Although the current system demonstrates encouraging per-formance, further improvements can be achieved by train-ing the models on larger clinical datasets, integrating more advanced deep learning architectures, and conducting exten-sive medical validation. Future research may also explore fully quantum machine learning models and improved hybrid AI–quantum approaches for enhanced diagnostic precision.

In conclusion, this work demonstrates the feasibility of developing an intelligent, scalable, and accessible brain tumor detection system that leverages modern computational tech-nologies to assist medical professionals in early diagnosis and treatment planning.

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