# Hybrid Quantum-Classical Neural Network for Brain Tumor Detection: A Literature Survey Towards Sustainable Healthcare

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**Abstract:** Brain tumor detection from Magnetic Resonance Imaging (MRI) is essential for early diagnosis, treatment planning, and improved patient outcomes. Recent advances in Deep Learning (DL), particularly Convolutional Neural Networks (CNNs) and transfer learning models, have enhanced automated brain tumor classification. However, conventional DL approaches often require significant computational resources and may struggle to capture complex nonlinear patterns in high-dimensional medical imaging data. Quantum Machine Learning (QML) has emerged as a promising alternative by integrating quantum computing principles with machine learning to improve feature representation and classification performance. This paper presents a comprehensive survey of hybrid quantum-classical approaches for MRI-based brain tumor detection. The review examines recent developments in Quantum Neural Networks (QNNs), Quantum Convolutional Neural Networks (QCNNs), Variational Quantum Circuits (VQCs), and hybrid learning frameworks applied to medical image analysis. Existing studies demonstrate encouraging results, but challenges related to scalability, limited quantum hardware, class imbalance, false-negative reduction, and clinical deployment remain unresolved. The survey identifies key research gaps and discusses a future research direction that combines EfficientNet-B2 with Variational Quantum Circuits for enhanced brain tumor classification. The proposed direction supports Sustainable Development Goal (SDG) 3 and SDG 9 by promoting intelligent and innovative healthcare technologies.

**Keywords:** Brain Tumor Detection, Hybrid Quantum-Classical Neural Networks, Quantum Neural Networks, Variational Quantum Circuits, Sustainable Healthcare.

## 1. Introduction

Brain tumors remain a major healthcare challenge, requiring timely and accurate diagnosis to improve treatment outcomes. MRI is widely used for brain tumor assessment because of its ability to provide detailed anatomical information. However, manual interpretation of MRI scans is time-consuming and subject to inter-observer variability, creating a need for automated diagnostic systems. Recent advances in deep learning, particularly CNNs and transfer learning models, have significantly improved brain tumor classification from MRI images. Despite their success, conventional deep learning approaches often demand substantial computational resources and large training datasets, motivating the exploration of alternative intelligent computing paradigms. QML combines quantum computing principles with machine learning techniques and has recently emerged as a promising direction for medical image analysis. Hybrid quantum-classical frameworks seek to leverage the strengths of both quantum and classical computing to improve feature learning and classification performance. This paper presents a survey of hybrid quantum-classical neural network approaches for MRI-based brain tumor detection. The survey reviews recent developments, analyzes existing methodologies, identifies current challenges, and discusses future research opportunities in quantum-enhanced healthcare systems.

## 2. Related Work

Recent advances in Artificial Intelligence (AI) and DL have significantly improved MRI-based brain tumor classification. CNNs, transfer learning, and ensemble learning approaches have demonstrated promising performance by automatically extracting discriminative features from medical images [3], [4]. However, these approaches often require large annotated datasets and substantial computational resources, motivating the exploration of alternative learning paradigms. QML has emerged as a promising research direction by integrating quantum computing principles with machine learning techniques. Early studies established the potential of quantum-enhanced learning through Variational Quantum Classifiers and Quanvolutional Neural Networks, demonstrating improved feature representation and classification capabilities for image recognition tasks [5], [14]. These developments laid the foundation for applying quantum computing techniques to medical image analysis. Building on these advancements, several researchers have investigated QCNNs and other quantum-based architectures for brain tumor diagnosis. Yani et al. [1] proposed a QCNN framework using a four-qubit architecture for binary and multiclass MRI brain tumor classification. Similarly, Pulicherla and Namineni [7] explored a QCNN-based approach for multiclass brain tumor classification, while Ticku et al. [12] and Alamri et al. [13] demonstrated the applicability of quantum-enhanced techniques for neuroimaging and tumor analysis. These studies indicate the potential of quantum models to improve feature extraction and classification performance in medical imaging applications. To leverage the advantages of both classical and quantum computing, hybrid quantum-classical architectures have gained increasing attention. Hafeez et al. [2] introduced a Hybrid Quantum-Classical Neural Network (H-QNN), while Fan et al. [6] proposed a hybrid quantum-classical convolutional framework integrating classical feature extraction with quantum processing layers. Further advancements include the transfer learning-based hybrid model of Srivastava et al. [3], the ensemble transfer learning and Quantum Variational Classifier approach of Amin et al. [4], and the quantum-assisted deep learning framework proposed by Muniasamy et al. [8]. More recently, Wang et al. [9] developed HQNet for multiclass MRI brain tumor classification, whereas Akpinar et al. [10] proposed Hybrid Quantum-Classical Integrated Neural Network (HQCINN) models incorporating shallow and deep quantum circuits. Ranga et al. [11] further demonstrated the feasibility of hybrid quantum-classical neural networks for brain tumor diagnosis. Collectively, these studies highlight the growing interest in combining deep learning and quantum computing to enhance diagnostic performance. Despite encouraging results, several challenges remain unresolved. Most studies focus primarily on classification accuracy while giving limited attention to false-negative reduction, class imbalance, model interpretability, and deployment on real quantum hardware. Furthermore, the reliance on simulator-based implementations and limited quantum resources restricts scalability and practical clinical adoption. These limitations motivate the need for more robust, scalable, and clinically relevant hybrid quantum-classical frameworks for brain tumor diagnosis.

### 3. Comparative Analysis of Existing Studies

Table 1 presents a comparative analysis of recent studies on quantum and hybrid quantum-classical approaches for brain tumor detection. The comparison highlights the classification type, quantum techniques employed, key strengths, and existing limitations.

| Ref. | Approach | Classification Type | Quantum Technique | Key Strength | Limitation |
|---|---|---|---|---|---|
| [1] | QCNN | Binary & Multiclass | Quantum Convolutional Neural Network | Effective MRI feature extraction | Limited qubit architecture |
| [2] | H-QNN | Binary | Hybrid Quantum Neural Network | Improved classification performance | General image dataset |

| Ref. | Approach | Classification Type | Quantum Technique | Key Strength | Limitation |
|---|---|---|---|---|---|
| [3] | Transfer Learning + QNN | Brain MRI | Quantum Neural Network | Enhanced feature learning | Simulator dependency |
| [4] | Ensemble Transfer Learning + VQC | Brain MRI | Variational Quantum Classifier | Improved classification accuracy | Computational complexity |
| [5] | Variational Quantum Classifier | Binary | VQC | Compact parameter space | Limited medical application |
| [6] | Hybrid QCNN | Image Classification | Hybrid Quantum-Classical CNN | Enhanced feature representation | Scalability challenges |
| [7] | QCNN | Multiclass Brain MRI | QCNN | Promising diagnostic results | Limited hardware implementation |
| [8] | Hybrid Quantum-Assisted DL | Brain MRI | Hybrid QML | Improved diagnosis | Limited dataset validation |
| [9] | HQNet | Multiclass Brain MRI | Hybrid Quantum Network | Better feature transformation | Hardware constraints |
| [10] | HQCINN | Multiclass Brain MRI | Deep Quantum Circuits | Improved circuit expressibility | NISQ limitations |
| [11] | Hybrid Quantum-Classical NN | Brain MRI | Quantum Layers | Effective tumor diagnosis | Simulator-based evaluation |
| [12] | QCNN | Neuroimaging | QCNN | Enhanced tumor detection | Limited scalability |
| [13] | Quantum Entropy + DL | Brain MRI | Quantum Entropy Methods | Improved edge detection | Increased computational cost |
| [14] | Quanvolutional Neural Network | Image Classification | Quanvolution | Quantum feature extraction | Early-stage framework |

## 4. Research Gaps

• Most existing studies focus primarily on improving classification accuracy while giving limited attention to reducing false-negative predictions, which are critical in brain tumor diagnosis.
• Current hybrid quantum-classical models are predominantly evaluated on quantum simulators rather than real quantum hardware, limiting their practical applicability and scalability.

• Existing QNN and QCNN architectures often employ shallow quantum circuits and do not effectively address class imbalance in MRI datasets, affecting model robustness and generalization.
• The integration of advanced transfer learning models, such as EfficientNet, with expressive VQCs for brain tumor classification remains insufficiently explored.
• Explainability, computational efficiency, and alignment with sustainable healthcare goals (SDG 3 and SDG 9) are largely overlooked, creating barriers to clinical adoption.

These gaps highlight the need for a robust, scalable, interpretable, and sustainable hybrid quantum-classical framework for accurate brain tumor diagnosis.

## 5. Conclusion and Future Directions

Brain tumor detection using MRI is an important research area due to its significance in early diagnosis and treatment planning. While deep learning techniques have achieved remarkable success in automated tumor classification, challenges related to computational complexity, large data requirements, and model generalization continue to persist. In this context, QMLhas emerged as a promising approach for enhancing medical image analysis through the integration of quantum computing and machine learning. This survey reviewed recent advances in QNNs, QCNNs, VQCs, and hybrid quantum-classical frameworks for brain tumor classification. The reviewed studies indicate that quantum-enhanced models can improve feature representation and classification performance, offering new possibilities for intelligent diagnostic systems. However, challenges such as limited quantum hardware availability, dependence on simulators, class imbalance, scalability issues, and limited interpretability remain significant barriers to practical adoption. Future research should focus on developing expressive and hardware-efficient hybrid architectures, integrating advanced transfer learning techniques with variational quantum circuits, improving diagnostic sensitivity, and enhancing model explainability. In addition, validation on real quantum hardware and the development of computationally efficient healthcare solutions will be essential for translating quantum-enhanced diagnostics into clinical practice. Overall, hybrid quantum-classical frameworks represent a promising pathway toward next-generation brain tumor diagnosis, with the potential to support accurate, reliable, and sustainable healthcare technologies aligned with SDG 3 and SDG 9.

## References:

[1]. Yani, Sitti, et al. "Quantum convolutional neural network for MRI brain tumor analysis: Binary and multiclass classification using a four-qubit architecture." *Radiation Physics and Chemistry* (2025): 113545.
[2]. Hafeez, Muhammad Asfand, Arslan Munir, and Hayat Ullah. "H-QNN: A hybrid quantum–classical neural network for improved binary image classification." *AI* 5.3 (2024): 1462-1481.
[3]. Srivastava, Alok Kumar, et al. "A hybrid classical-quantum model for enhanced MRI-based brain tumor classification using transfer learning and quantum neural networks." *2025 3rd International Conference on Communication, Security, and Artificial Intelligence (ICCSAI)*. Vol. 3. IEEE, 2025.
[4]. Amin, Javeria, et al. "A new model for brain tumor detection using ensemble transfer learning and quantum variational classifier." *Computational intelligence and neuroscience* 2022.1 (2022): 3236305.
[5]. Maheshwari, Danyal, Daniel Sierra-Sosa, and Begonya Garcia-Zapirain. "Variational quantum classifier for binary classification: Real vs synthetic dataset." *IEEE access* 10 (2021): 3705-3715.
[6]. Fan, Fan, et al. "Hybrid quantum-classical convolutional neural network model for image classification." *IEEE transactions on neural networks and learning systems* 35.12 (2023): 18145-18159.
[7]. Pulicherla, Rajyalakshmi, and Gireesh Namineni. "A Quantum CNN Approach for MRI Based Multi-Class Brain Tumor Classification." *2026 IEEE Madhya Pradesh Section Conference (MPCON)*. IEEE, 2026.
[8]. Muniasamy, Anandhavalli, et al. "Investigating hybrid quantum-assisted classical and deep learning model for MRI brain tumor classification." *Journal of Image and Graphics* 13.1 (2025): 123-129.
[9]. Wang, Aijuan, et al. "HQNet: A hybrid quantum network for multi-class MRI brain classification via quantum computing." *Expert Systems with Applications* 261 (2025): 125537.
[10]. Akpinar, Emine, Sardar MN Islam, and Murat Oduncuoglu. "Multi-classification of brain tumors using proposed hybrid quantum–classical integrated neural network (HQCINN) models: shallow and deep circuit approaches." *Neural Computing and Applications* 37.27 (2025): 22891-22922.

[11]. Ranga, Deepak, et al. "Brain tumor diagnosis using hybrid quantum-classical neural networks." *Neural Computing and Applications* 37.30 (2025): 25535-25554.
[12]. Ticku, Amrita, et al. "Advancing neuroimaging with quantum convolutional neural networks for brain tumor detection." *International Journal of Information Technology* (2025): 1-8.
[13]. Alamri, Ahmed, et al. "Innovative deep learning and quantum entropy techniques for brain tumor MRI image edge detection and classification model." *Alexandria Engineering Journal* 122 (2025): 588-604.
[14]. M. Henderson, S. Shakya, S. Pradhan, and T. Cook, "Quanvolutional neural networks: Powering image recognition with quantum circuits," Quantum Mach. Intell., vol. 2, no. 1, p. 2, Jun. 2020.