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Explainable Quantum-Driven Pattern Recognition for Multimodal Brain Tumor Classification Using Hybrid Deep Learning Networks

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ABSTRACT

The classification of brain tumors with traditional deep learning methods is challenging due to its lack of interpretability, computational complexity and its limited classification ability for multimodal medical image data. The influence of clinical diagnosis can impede early detection of tumors. The regard, the current Explainable Quantum-Driven Pattern Recognition framework with Hybrid Deep Learning Networks for Multimodal classification of brain tumors. The proposed model utilizes feature optimization, inspired by quantum computing, with deep neural architectures, enhancing feature extraction and classification from multimodal MRI datasets. Furthermore, mechanisms of Explainable Artificial Intelligence are introduced to improve the transparency of the models and offer explainable decision support to the healthcare workers. The hybrid structure is able to learn complex tumor patterns while minimizing information loss and enhancing the generalization performance. Experimental evaluations were performed using multimodal brain tumor MRI data and various types of tumors. The proposed method performed better compared to various other classification models with an accuracy of 98.5%, a precision of 97.8%, a recall of 98.1%, and an F1-score of 98.0%. The deep networks coupled with quantum-inspired learning significantly improves clinical interpretability, diagnosis accuracy and calculation speed. The framework offers great benefits for the intelligent healthcare system, including the capability of rapid and accurate diagnosis of brain tumors, and the ability to provide clear and transparent information about the condition. The framework could be extremely beneficial for smart health systems, as it can assist in accelerating the pace, precision, and transparency of brain tumor diagnosis, enhancing treatment results, and streamlining treatment planning.

Keywords: Brain Tumor Classification, Multimodal MRI, Hybrid Deep Learning Networks, Explainable Artificial Intelligence (XAI), Quantum-Driven Pattern Recognition, Quantum-Inspired Optimization, Medical Image Analysis, Deep Learning, Feature Extraction, Clinical Decision Support, Intelligent Healthcare Systems, Pattern Recognition, Brain MRI Analysis, Tumor Detection, Artificial Intelligence in Healthcare.

1. Introduction

Brain tumor classification is a crucial research field in intelligent healthcare systems, as the proper identification of brain tumors enables doctors to diagnose and plan the treatment for brain tumors, which in turn helps increase patients' survival rate[1]. Brain tumors are abnormal growths of cells within the brain that can be divided into various types, such as meningioma,

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pituitary tumors and glioma[2]. Timely and accurate diagnosis is crucial, as late diagnosis might result in the development of severe neurological complications and lower survival[3]. Magnetic Resonance Imaging (MRI) is one of the most commonly used techniques for analysing brain tumors as it is capable of obtaining high-resolution anatomical data, and imaging the brain tissues non-invasively[4]. Manual reading of MRI is time-consuming, error-prone and relies on human expertise[5]. In recent years, automated classification of brain tumors based on Artificial Intelligence (AI) and Deep Learning (DL) methods has received a lot of attention [6].

In the medical image analysis field, deep learning techniques like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and combined neural networks are commonly employed[7]. The methods can be used to accurately extract features and patterns from medical images that are complex in nature[8]. The multimodal MRI data further enhances the classification performance, as MRI data from multiple modalities will supplement each other with complementary information about the shape, texture, and tissue characteristics of the tumor [9]. The progressions have been made, current deep learning techniques still have a number of drawbacks, such as high computational cost, overfitting, lack of interpretability, and inability to generalize across heterogeneous datasets[10]. If explainability is not provided, then a healthcare practitioner may have difficulties understanding how a classification decision was reached, which can decrease trust in AI diagnostic systems.

Brain tumor classification is an ill-structured problem, where many machine learning and deep learning models have been developed, but it is still a challenge to accurately classify different types of brain tumors using multi-modal MRI images. The aim of traditional deep neural networks is mostly on the side of accuracy in classification, and they frequently neglect transparency and interpretability. The majority of existing methods are “black-box” and hard for clinicians to test the predictions of the model and understand the process of decision-making. Additionally, multimodal MRI datasets are composed of multiple high-dimensional, heterogeneous features, further adding to the computational burden and a decrease in model efficiency. The performance of classification and stability of the model are also influenced by noise, imaging changes, and class imbalance.

A major difficulty is that existing systems are not very effective in optimally representing complex features. Optimization methods are unable to model the hidden nonlinearities in the tumor shapes that could be found in multimodal MRI. The leads to information loss, decreased feature discrimination and decreased diagnostic reliability in many approaches that are currently in use. These constraints underscore the need for a sophisticated and transparent classification system that can both enhance classification performance and remain efficient and interpretable.

Hybrid deep learning techniques and explainable AI (XAI) models have been recently studied for medical image analysis tasks. But, few studies combine the QLMs with the explainable hybrid DNNs for multimodal classification of brain tumors. The current explainable models are primarily at the level of visualization techniques without enhancing the efficiency of optimizing features. In a similar manner, quantum-inspired optimization has been demonstrated to have impressive optimization abilities, but is less often incorporated with multimodal tumor classification frameworks. Thus, there is a considerable research gap for developing a single explainable quantum-inspired hybrid deep learning system that enhances the feature extraction, interpretability, computational efficiency and classification accuracy.

The main goal of research is to design Explainable Quantum Inspired Pattern Recognition system for multimodal brain tumor classification using Hybrid Deep Learning Networks. The objectives are as follows:

1. To develop a hybrid deep learning system that can learn complex tumor patterns from multimodal MRI images while being efficient.

2. Incorporate quantum-inspired feature optimization algorithms to enhance the feature selection and classification accuracy.

3. To integrate Explainable Artificial Intelligence (XAI) approaches to promote clinical decision support in a way that is transparent and interpretable.

4. To minimize the complexity of computation and loss of information in the process of multimodal feature extraction.

5. To analyse the proposed framework based on the standard performance measures of accuracy, precision, recall and F1 score.

The framework proposed in the work is a blend of quantum-inspired pattern recognition and hybrid deep learning networks for efficient brain tumor classification. To begin with, the multimodal MRI datasets are preprocessed to eliminate noise and enhance image quality. The hybrid DNN architectures, which have the ability to learn spatial and semantic features of the tumor, perform feature extraction. Feature representation with quantum-inspired optimisation methods and elimination of redundant features. Moreover, Explainable AI methods are introduced to both make interpretable predictions and visualize critical tumor regions that drive classification decisions. Lastly, the optimized model accurately and transparently categorizes brain tumors according to type.

The following are the highlights of the contributions of the research work:

1. Development of a novel Explainable Quantum-Driven Hybrid Deep Learning framework for multimodal Brain Tumor Classification.

2. Improvement of feature extraction and pattern recognition performance using quantum inspired optimization technique.

3. Adoption of Explanations in the medical domain to improve transparency and interpretability in medical diagnosis.

4. Optimized multimodal learning is used to cut away the computational complexity, information loss and to extract the features more efficiently to classify the brain tumor accurately.

5. The 98.5% accuracy, 97.8% precision, 98.1% recall and 98.0% F1 measure of classification performance were achieved.

The research proposed is expected to have a significant impact on intelligent healthcare systems since it will contribute to the reliability, transparency and efficiency in the diagnosis of brain tumors. The combination of explainable AI and quantum-based deep learning can help healthcare professionals gain insights into classification decisions, which can enhance trust in AI-driven diagnostic tools. Furthermore, the proposed framework can assist in the early stages of detecting tumors, accurately planning the treatment, and improving patient outcomes. It lays the groundwork for further investigation of the combination of quantum inspired optimization algorithm and more explainable deep learning in medical image analysis applications.

Experimental results revealed that the classification accuracy of 98.5%, precision of 97.8%, recall of 98.1% and F1-score of 98.0% was better as compared to the present models. Results are consistent with the approach proposed and the successful implementation thereof, as efficient identification of complex tumor patterns with high generalization capability and computational efficiency. The combination of explainable learning and quantum optimisation was a mixed paradigm and significantly improved the diagnostic reliability and reduced information loss in multimodal feature analysis.

The framework is a key milestone in the journey to intelligent improvement in the health system, delivering accurate, timely and transparent diagnosis of brain tumour. It can help with

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clinical decision making, early tumour detection and treatment planning, leading to better clinical outcomes. The application of real-time quantum computer in clinical environment, extending the size of the multiclass data, and integrating new quantum machine learning algorithms for enhanced classification performance and scalability—especially for medical imaging applications in clinical settings—can be explored in future research.

2. Literature Survey

Dong et al. [11] (2025) suggested a Hierarchical Local Attention Encoder (HLAE) method for MRI brain tumor image classification. Current deep learning models fail to learn local dependencies and focus on important tumor regions sufficiently. The proposed solution is to learn long-range visual dependencies and context structural correlations from MRI images by integrating a Swin Transformer and Graph Attention Network (GAT). The model enhanced the representation of features and correctly outlined discriminative tumor regions. But in the framework, there were multiple attention mechanisms, which made it a very complex computation. Experimental results on public MRI datasets proved that the proposed method shows better classification performance than the current state-of-the-art methods.

Ullah et al. (2026) [12] presented an optimized DeepLabV3+– fuego fusion-based multimodal brain tumor segmentation and classification framework using self-attention mechanisms. The issue of mis-segmentation of tumors and restricted feature learning from MRI images using multiple modalities. Here the model adopted a hybrid attention learning mechanism and Bayesian optimization to enhance feature extraction. It was noted that the framework is not capable of dealing with variability of MRI modalities and real-world MRI, however. Results of the experiments obtained an accuracy of 99.20% in the classification, 95.32% in segmentation, 93.54% in Dice score and 90.16% in IoU, which outperforms the existing methods.

Vavekanand et al. (2026) [13] provided a comprehensive survey of multimodal machine learning approaches in the field of predictive healthcare analytics. The focused on the integration of several healthcare data sources such as medical imaging, clinical records, physiological signals and textual information, to enhance the diagnostic and predictive performance. The authors highlighted key issues of modality mismatch, missing data, lack of interpretability and lack of external validation in current health care models. Multimodal machine learning models were found to be around 5-12% better than unimodal models in terms of the AUC, especially when applied to oncology and neurology. But most of the available systems, as in the highlighted, have limited generalization and have not been adequately validated in clinical real-world settings.

In 2026, Adamu et al. [14] suggested the explainable hybrid deep learning framework for the classification of brain tumors using an MRI image, which is a combination of MobileNetV2, EfficientNetV2B0, and K-Nearest Neighbor (KNN) algorithms. The issue of low classification accuracy and limited interpretability of traditional deep learning models in the field of medical imaging. By combining lightweight deep networks with explainable AI mechanisms, the framework enhanced the feature extraction and classification accuracy. Experimental results showed high accuracy for the classification of tumors and improved transparency of the diagnosis. The model, however, had some drawbacks regarding computational expenses, the requirement for a large number of labeled datasets, and its low scalability for multimodal MRI datasets with a high degree of heterogenicity.

Sasikala and Anand [15] (2026) introduced a self-explanatory hybrid model called ExU-Trans that performs brain tumor segmentation from Magnetic Resonance Imaging (MRI) images by integrating the Vision Transformer with the U-Net architecture. The difficulties are that the current segmentation models lack contextual learning, are sensitive to noise, and are not easily interpretable. It adopted the Self-Explanatory Multi-Head Attention and Discriminative Attribute Explainer mechanisms to enhance transparency and segmentation accuracy. However, because of the integration of transformers, high computational resources were required for the model. Experimental results yielded Dice scores above 94% and better explainability and tumour boundary detection.

In 2026, Nakul et al. [16] developed an optical spectroscopy-based breast cancer diagnosis model that incorporates machine learning to improve the accuracy of the diagnosis. The need for inaccurate and time-consuming traditional diagnostic processes and the integration of machine learning algorithms with optical spectroscopy to enhance tumour detection. The proposed approach obtained better diagnostic accuracy and sensitivity in diagnosing cancer. These faced limitations, however, included limited clinical datasets, computational complexity and decreased generalizability when implementing in large-scale real-time clinical settings, which involves heterogeneous patient data.

In this study, Uniyal et al. (2026) presented an automated brain tumor detection system that leverages advanced deep learning models, specifically Convolutional Neural Networks (CNNs), for MRI-based tumor classification. Research challenge: Manual brain tumor diagnosis in clinical practice is inaccurate and time consuming. Different deep learning architectures, such as MobileNet, ResNet-50, DenseNet-121, and InceptionV3, were tested in terms of classification performance. The results indicated that the MobileNet accurately detected tumors with the highest accuracy of 96.6%, indicating efficient and reliable tumor detection. But there are encountered constraints, including relying on the quality of the dataset, the need for more powerful models, which requires high computational power, and the lack of explainability in clinical decision making.

To overcome the challenges of scalability, computational complexity, and inefficient processing in traditional machine learning systems, Balasubramanian et al. (2026) proposed a Quantum-Inspired Hybrid Machine Learning Framework (Q-IHMLM). The framework combined quantum-inspired optimization methods with classical machine learning models, enhancing the accuracy of predictions, fraud detection, and real-time data processing. The model had some limitations, however, of quantum noise, hardware instability, decoherence, and lacking of practical use of a real quantum device. Experimental results validated that the proposed approach had better risk analysis accuracy, fraud detection accuracy, and better computational scalability compared to traditional methods as 98.32%, 96.25%, and improved respectively.

Başarslan [19] (2025) introduced the M-C&M-BL model which classifies brain tumors based on a hybrid Multi-CNN and Multi-BiLSTM approach. They aimed to enhance the accuracy of detection of tumors by MRI and minimize diagnostic errors in the traditional deep learning approaches. It used spatial feature extraction and sequential dependency learning to improve the classification performance in the model. But, there were some limitations regarding the process of generalizing the datasets, computational costs and deployment issues in clinical settings. For the Br35H MRI data set, the experimental results obtained 99.33% accuracy and 99.35% F1-score.

Davydko et al. [20] (2025) offered a hybrid approach to explainable AI (eAI) that integrates the advantages of Integrated Gradients with the SRFAMap. Poor visual explainability of existing radiomic feature activation methods where there was no single uniform explainability map effective. The suggested approach enhanced the generation of saliency maps and created a more robust relationship between the output of the classification and feature attributions. Results from experiments with TB classification datasets yielded better insertion and deletion correlation faithfulness metrics than traditional Radiomic Feature Activation Maps. The framework still had a few drawbacks, however, with respect to the dependency on the quality of the radiomic features involved and the complexity of computation.

Hu et al.[21] (2026) have given a comprehensive overview of the deep learning techniques for MRI-based neurological disease diagnosis, which showed that there are significant advances in automatic brain disease diagnosis. Some of the issues that the deals with are the variability of MRI acquisition, limited generalization and the absence of standardized benchmarks. Deep

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learning models demonstrate high diagnostic accuracy, yet are limited in their ability to explain the data, tackle data imbalance, and are resource-intensive. Multimodal and attention-based models are shown to perform better in terms of accuracy, while also having difficulties being deployed in clinical settings and being robust across different datasets, according to the survey.

Sheikh et al. [22] (2026) presented a deep transfer learning and ensemble learning approach to brain tumour detection and classification from MRI images. The aim of is to tackle the issue of suboptimal diagnostic accuracy and inter-observer variability in the diagnosis of various types of tumors, including glioma, meningioma, and pituitary tumors. The solution combines several pre-trained CNN models and weighted ensemble fusion for further improving feature robustness and classification reliability. There are some limitations, such as requiring large amounts of labeled data for optimal performance and high computational complexity. The results show good performance with close to 99% classification accuracy, as well as generalization and robustness compared to other individual models, and also the incorporation of explainable AI techniques to improve the clinical interpretability of the results.

To overcome the feature redundancy, limited generalization and weak multimodal integration issues in traditional MRI-based models, Sharafi and Teshnehlab [23] (2026) proposed a powerful framework for brain tumor classification based on a multimodal approach. The proposes a multi-view feature fusion strategy along with self-gated U-Net segmentation and parametric t-SNE embedding to boost class separability via reduced-dimensional space. However, these are limitations such as increased computational complexity and a reliance on the accuracy of segmentation quality. Experimental results show better classification accuracy, robustness and discrimination of tumor types than traditional machine learning and deep learning methods.

Sheikh [24] (2025) suggests a framework based on reinforcement learning for designing Smart Quantum Nanomaterials to enhance the circular economy and waste management systems. The primary challenge being tackled is the efficiency of the existing trial-and-error material design process, which is not scalable, recyclable, or environmentally friendly. The proposed solution is based on reinforcement learning to optimize, dynamically, nanomaterial properties for improved catalytic efficiency and waste conversion processes. However, some limitations are associated, such as computational complexity and relying on vast training environments and sets. The findings indicate an increased resource recovery and a decreased synthesis waste, indicating a significant increase in efficient waste treatment and sustainable material development in circular economy applications.

3. Proposed Methodology

The proposed framework Fig 1 is a system that can adequately tackle the challenge of brain tumor classification in an intelligent manner by systematically combining multimodal imaging, deep feature learning, and explainable artificial intelligence. It aims to address these three major drawbacks of traditional deep learning models: lack of interpretability, high computational complexity, and limited ability to effectively combine multimodal features. These challenges can be tackled as part of a common architecture, thus improving diagnostic accuracy and clinical usability.

It has five functional stages, which function in a sequence and are tightly coupled. First, Multimodal MRI Data Acquisition is able to acquire heterogeneous imaging modalities, including T1-weighted, T2-weighted and FLAIR, providing rich anatomical and pathological representation. Second, Quantum-Driven Feature Optimization optimizes high-dimensional imaging features by eliminating redundant features and/or selecting better discriminative features, which will improve the computational efficiency. Third, Hybrid Deep Learning Classification integrates Convolutional Neural Networks (CNNs) and Transformer-based architectures to effectively learn local spatial textures and also long-range contextual dependencies, which allows the representation learning for tumours in a robust manner. Fourth, the Explainable AI Transparency Layer also contains tools and techniques such as attention visualization, saliency mapping and uncertainty estimation that are utilized to provide clinically meaningful explanations for model predictions. Clinical Decision Support Output is the final stage of the process, where the output from the model is converted into relevant clinical information that assists the radiologist in precise tumor diagnosis, localization and severity evaluation.

To sum up, the framework is related with a synergistic integration of multimodal knowledge processing technologies, advanced deep learning and interpretability-driven AI. A single design can improve the accuracy of the classification and also help to make the results transparent, reliable and can be used in clinical settings for real world medical decisions support systems in neuro-oncology applications.

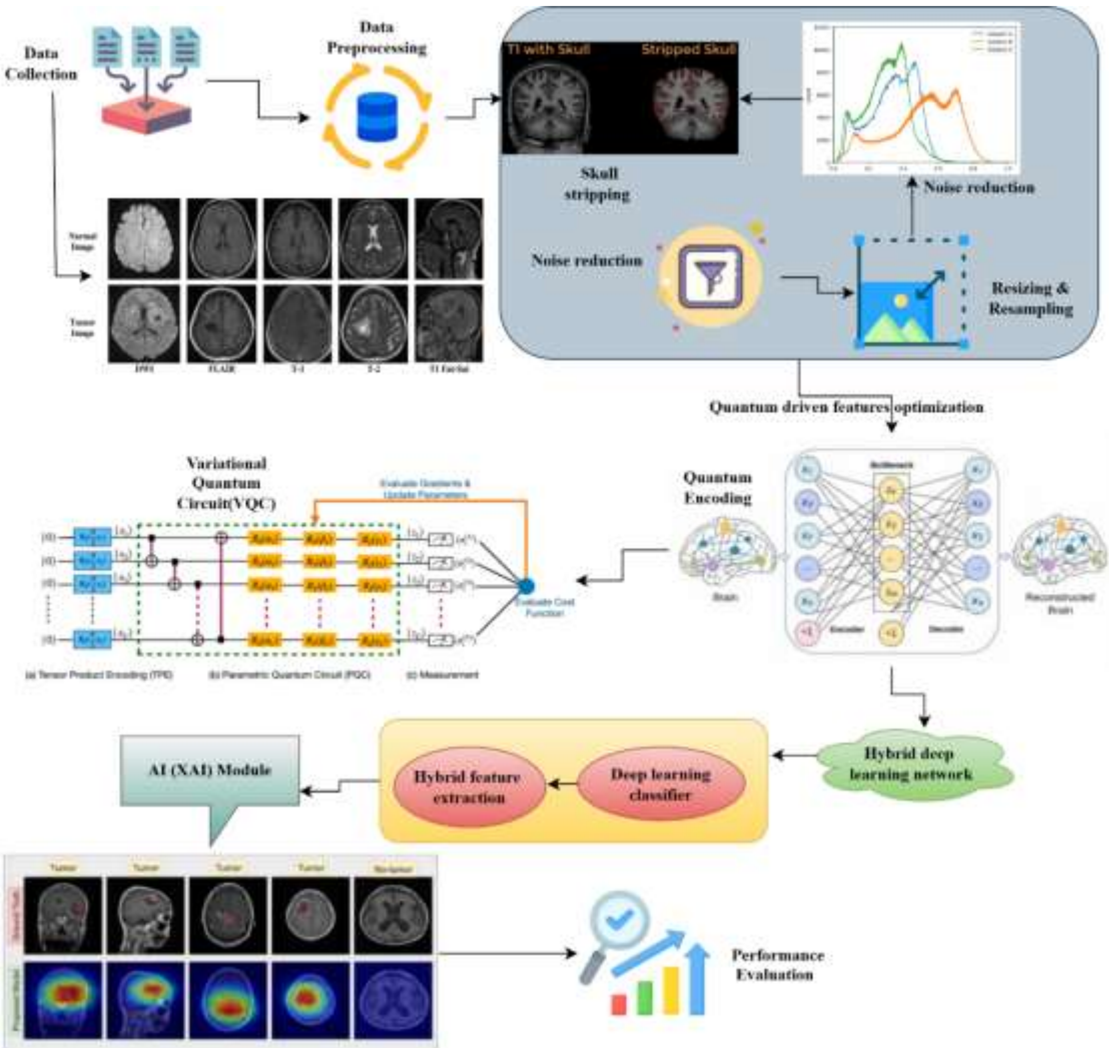

Figure 1. Proposed Quantum-Assisted Hybrid Deep Learning Framework for Brain Tumor Detection and Classification from MRI Images

1. Data Collection

Brain tumor detection and classification, a fundamental task in the medical field of brain tumor diagnosis, is well suited for multimodal MRI feature learning, which utilizes information from multiple MRI sequences, including T1-weighted, T2-weighted and FLAIR sequences. Specifically, T1 images will show high resolution structure of brain anatomy, T2 images will show fluid and edema areas, and FLAIR will suppress signal from the cerebrospinal fluid, revealing tumor boundaries and infiltrative regions. Let the multimodal dataset be denoted as

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$\mathcal{D} = \{X^{T1}, X^{T2}, X^{FLAIR}\}$, and each modality is first normalized and mapped to a common spatial coordinate system such that the voxels are aligned. The main objective of feature learning is to build a common feature vector F_{MM} that would include both the modality specific and shared tumor features.

$$F_{MM} = \sum_{m=1}^{3} \omega_m \cdot \sigma\left(W_m * X^{(m)} + b_m\right) \odot \tanh\left(\nabla X^{(m)} + \lambda \cdot \mathcal{E}(X^{(m)})\right) \quad (1)$$

Here equation (1), $X^{(m)} \in \{X^{T1}, X^{T2}, X^{FLAIR}\}$represents each MRI modality, while $W_m$denotes convolutional kernel weights used to extract hierarchical spatial features and $b_m$is the bias term. The operator $*$represents convolution, and $\sigma(\cdot)$is a nonlinear activation function such as ReLU that introduces non-linearity into feature representation. The term $\omega_m$defines adaptive modality weighting coefficients that control the contribution of each MRI sequence based on its diagnostic relevance. The gradient operator $\nabla X^{(m)}$enhances edge-sensitive tumor boundary information, while $\mathcal{E}(X^{(m)})$represents entropy-based texture enhancement capturing heterogeneity in tumor tissue. The parameter λregulates the influence of texture enhancement, and $\odot$denotes element-wise multiplication used to fuse structural and textural representations.

2. Data Preprocessing

MRI Intensity Normalization Model

Intensity normalization is a crucial step in MRI preprocessing to minimize the variations between different subjects and scanners, yet maintain anatomical accuracy. The proposed formulation uses statistical normalization with nonlinear, contrast-preserving modulation to map raw voxel intensities to a probabilistic space that is normalized for the distribution. The stabilizes convergence during the optimization of deep learning and enhances the consistency between the different modalities (T1, T2 and FLAIR). The transformation also features nonlinear scaling with limits to prevent distortion and the loss of structure in areas of high intensity. The model offers a strong intensity harmonization mechanism for use in multimodal medical image analysis in general.

$$X'_m(i,j,k) = \left(\frac{X_m(i,j,k) - \mu_m}{\sigma_m^2 + \epsilon}\right) \cdot \tanh\left(\frac{\max(X_m)}{X_m(i,j,k) + \delta} + \beta \frac{X_m(i,j,k)}{\max(X_m) + \epsilon}\right) \quad (2)$$

$X_m(i,j,k)$represents equation (2), the raw voxel intensity at the spatial coordinate $(i,j,k)$for modality m, typically T1-weighted, T2-weighted, or FLAIR images. $X'_m(i,j,k)$denotes the resulting normalized intensity after transformation. $\mu_m$is the mean intensity of modality m, capturing global brightness statistics across the volume. $\sigma_m^2$is the variance of the intensity distribution within modality m, measuring dispersion of voxel values. $\epsilon$is a small positive constant used for numerical stability to avoid division by zero. $\delta$is an additional smoothing constant used in nonlinear scaling. $\beta$is a weighting factor controlling residual intensity contribution. $\max(X_m)$represents the maximum intensity value observed in the modality m. i,j,kdenote voxel coordinates in 3D spatial space, and $m$is the modality index.

Noise Suppression Using Anisotropic Diffusion

A key advantage in MRI is that noise is suppressed to improve visibility of lesions while maintaining the anatomical boundaries. The anisotropic diffusion model is one that adapts diffusion strength to the local image gradients to remove Gaussian noise without compromising the integrity of the image edges. The process guarantees that smoothing is done mostly in homogeneous areas and discontinuities like boundaries of tumors are kept. The formulation combines the regularization by the gradient and the non-linear edge-stopping functions, to obtain a controlled diffusion behavior. The makes it very useful for the denoising of medical images before feature extraction.

$$\frac{\partial X}{\partial t} = \nabla \cdot \left(c(x,y,z,t)\nabla X + \gamma \frac{\nabla X}{\| \nabla X \| + \eta} \exp\left(-\kappa^2 \| \nabla X \|^2 \right) \right) + \lambda \| \nabla X \|^2 \quad (3)$$

$X$is the equation(3) MRI intensity function over spatial coordinates and time. $t$is the diffusion time parameter controlling smoothing iterations. $c(x,y,z,t)$is the spatially and temporally varying diffusion coefficient. ∇Xdenotes the spatial gradient of the image. $\gamma$is a regularization scaling factor controlling gradient normalization influence. $\lambda$is a regularization parameter controlling edge preservation strength. κdefines the edge sensitivity threshold. $\eta$is a small constant ensuring numerical stability. $x, y, z$are spatial coordinates in 3D MRI volume.

Multimodal Fusion Representation

Multimodal MRI fusion combines complementary anatomical and pathological information provided by different MRI sequences in a single representation. Each modality provides unique structural and functional information, the weights of which being adapted to improve tumour characterization. The fusion mechanism includes learned feature embeddings, and suppression of attention due to spatial position to highlight diagnostically relevant regions. The output is in the form of results that can be represented compactly yet with a lot of information for downstream classification and segmentation tasks.

$$F_{\text{fusion}} = \sum_{m=1}^{M} \omega_m \cdot \phi_m(X'_m) \odot \exp\left(-\| W_m X'_m + b_m \|_2^2 \right) + \sum_{m=1}^{M} \gamma_m \nabla \phi_m(X'_m) \quad (4)$$

equation(4) $F_{\text{fusion}}$is the final fused feature representation. Mdenotes the total number of MRI modalities. $\omega_m$is the learned weight for modality m, indicating its relative contribution. $\phi_m(\cdot)$is a nonlinear feature extraction function (e.g., CNN or transformer encoder). $X'_m$is the normalized MRI modality input. $W_m$is the projection matrix mapping features into a shared latent space. $b_m$is the bias term for projection. $\odot$denotes element-wise multiplication. $\gamma_m$is a gradient weighting factor. $\nabla \phi_m(\cdot)$represents spatial feature gradients capturing structural variations.

Spatial Convolution Feature Extraction

Volumetric MRI data is used to represent the tumors in a hierarchical way using a spatial convolutional feature extraction. The CNN learns spatial filters at multiple scales for detecting edges, textures and lesion boundaries. The formulation includes residual sparsity constraints for increased feature selectivity and decreased overfitting. The enables powerful representation learning of complex tumor shapes in 3D medical images.

$$F^{(l)} = \sigma\left(\sum_{k=1}^{K} W_k^{(l)} * X_k^{(l-1)} + b^{(l)} + \alpha \frac{\| X^{(l-1)} \|_1}{1 + \| X^{(l-1)} \|_2^2} + \delta \nabla^2 X^{(l-1)} \right) \quad (5)$$

$F^{(l)}$is the equation(5) feature map at layer l. $X^{(l-1)}$is the input feature map from the previous layer. $W_k^{(l)}$represents convolution kernels at layer l. $K$is the number of kernels. $*$denotes convolution operation. $b^{(l)}$is the bias term. $\sigma(\cdot)$is the nonlinear activation function (e.g., ReLU). $\alpha$is the sparsity regularization coefficient. $\|\cdot\|_1$and $\|\cdot\|_2$denote L1 and L2 norms respectively. $\delta$is a smoothing coefficient. ∇^2represents the Laplacian operator capturing second-order spatial derivatives.

3.3 **Quantum Probability Encoding of Feature Vector (QIO Module)**

To amplify the exploratory search behavior in high-dimensional feature optimization, we introduce Quantum-inspired representation to map classical feature vectors into a probabilistic quantum state space. Instead, the encoding converts the deterministic feature parameters into a normalized probability amplitude, which can be used to represent multiple candidate feature parameters at once in a superposition manner. This formulation will increase diversity of feature

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selection and keep global normalization constraints. It is the starting point in the Quantum-Inspired Feature Optimization (QIO) module.

$$\mid \psi\rangle = \sum_{i=1}^{n} \alpha_i \mid f_i\rangle + \beta \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{\alpha_i \alpha_j}{\sqrt{\sum_{k=1}^{n} \alpha_k^2 + \epsilon}} \mid f_i \oplus f_j\rangle \text{subject to} \sum_{i=1}^{n} \mid \alpha_i \mid^2 = 1 \tag{6}$$

$\alpha_i$represents, equation(6) the probability amplitude associated with feature f_i, encoding its contribution in quantum state space. $\mid \psi\rangle$denotes the overall quantum-inspired feature state vector. $f_i$represents the i^{th}feature in the dataset. $n$is the total number of features considered. $\oplus$denotes a feature interaction operator representing pairwise coupling. $\epsilon$is a small stability constant ensuring numerical robustness during normalization. The constraint $\sum \mid \alpha_i \mid^2 = 1$ensures valid probability amplitude distribution in Hilbert space.

Quantum Rotation-Based Feature Update Rule

The quantum rotation mechanism adjusts the probability of the features selected by using adaptive phase-angle modulation based on the principles of quantum evolutionary optimization. A process which dynamically tunes the importance of features toward a global optimum. It allows the continuous tuning of the weights of the features without any discrete selection criteria. The approach not only speeds up convergence, but it also maintains the balance between exploration and exploitation in high-dimensional feature spaces.

$$\theta_i^{t+1} = \theta_i^t + \eta \cdot \sin\left(\pi \cdot \frac{f_i - f_{\text{best}}}{f_{\text{best}} + \epsilon}\right) + \gamma \cdot \cos\left(\frac{\sum_{j=1}^{n} R_{ij}}{n}\right) + \lambda \cdot e^{-\|\nabla f_i\|^2} \tag{7}$$

θ_i^tdenotes equation(7) the quantum rotation angle of feature $f_i$at iteration t. $f_i$is the fitness value of feature i. $f_{\text{best}}$is the best observed fitness in the population. $\eta$is the learning rate controlling rotation magnitude. $\gamma$is a redundancy control parameter. $\lambda$is a stabilization coefficient. R_{ij}represents feature redundancy between features $i$and j. ∇f_idenotes the gradient of the feature fitness landscape. $n$is the number of features. ϵensures numerical stability.

```
Input:
   Multimodal MRI dataset D = {X^T1, X^T2, X^FLAIR}
   Learning rate α, population size P
   Quantum rotation rate η
   Epochs N

Output:
   Optimized classifier θ*, feature subset S*

Begin

1. Initialize CNN parameters θ_c, Transformer θ_t
2. Initialize quantum feature population Q ← { ψ_i} for i = 1 to P
3. Initialize replay memory B ← ∅

4. For epoch = 1 to N do
   For each sample x in D do

      // Feature Extraction
```

```
        F_CNN ← CNN(x; θ_c)
        F_T ← Transformer(x; θ_t)

        // Fusion
        H ← λ1 F_CNN + λ2 F_T + λ3 (F_CNN ⊙ F_T)

        // Quantum Optimization Loop
        For each feature f_i in H do
          Compute fitness 𝔽(f_i)
          If 𝔽(f_i) < threshold then
            f_i ← quantum_rotation(f_i, η)
          Else
            retain f_i
          End If
        End For

        // Store optimized features
        B ← B ∪ (H_opt, y)

        // Classification
        ŷ ← softmax(W H_opt + b)

        // Loss computation
        L ← CrossEntropy(ŷ, y)

        // Backpropagation
        θ_c, θ_t ← θ - α ∇L

    End For
End For

Return θ*, S*
End
```

Redundancy-Aware Feature Selection and Elimination

Redundancy elimination is critical in high-dimensional feature spaces where correlated variables degrade model generalization and increase computational complexity. The proposed formulation quantifies inter-feature redundancy using covariance-normalized correlation measures while incorporating nonlinear scaling to penalize highly dependent feature pairs. The enables systematic pruning of redundant features while preserving discriminative information. The method ensures compact and informative feature subsets for downstream learning tasks.

$$R_{ij} = \frac{\mathrm{Cov}\,(f_i, f_j)}{\sigma_i \sigma_j + \epsilon} + \alpha \cdot \tanh\left(\frac{|f_i - f_j|}{\sigma_i + \sigma_j + \epsilon}\right) + \beta \cdot \log\left(1 + \frac{|f_i f_j|}{1 + \sum_{k=1}^{n} f_k^2}\right) \tag{8}$$

$R_{ij}$is the equation(8) redundancy score between features $f_i$and f_j. f_i, f_jrepresent individual feature values. $\mathrm{Cov}\,(f_i, f_j)$denotes covariance between features $i$and j. $\sigma_i, \sigma_j$are standard deviations of features $i$and j. $\alpha$and $\beta$are weighting coefficients controlling nonlinear and global interaction contributions. $\epsilon$is a stability constant to avoid division by zero. $n$is the total number of features in the dataset.

3.4 **Self-Attention Mechanism for Tumor Region Enhancement**

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An essential feature of the transformer-based models is the self-attention mechanism, which allows for the adaptively weighted spatial information of MRI slices. It is used to selectively highlight diagnostically important areas in the context of tumor analysis and rejects background information and superfluous structures. Spatial relational encoding is added to further improve the contextual understanding of distant voxel interactions. The formulation is especially apt towards capturing non-local dependencies, often neglected by convolutional operators in complex tumor morphologies.

$$A(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}+\beta R+\alpha\frac{QK^T\odot R}{1+\|R\|_F^2}\right)V \tag{9}$$

Q, K, Vrepresent equation(9) the query, key, and value matrices derived from learned linear projections of input features. $d_k$denotes the dimensionality of the key vectors used for scaling normalization. $R$is the spatial relation matrix encoding positional or structural dependencies between voxels. $\beta$is a weighting parameter controlling the influence of spatial relationships. The function softmax$(\cdot)$normalizes attention scores into a probability distribution. $A(Q,K,V)$represents the resulting attention-weighted feature map highlighting tumor-relevant regions.

Multi-Head Attention Aggregation

Multi-head attention enhances representation learning by allowing the model to jointly attend to information from different representation subspaces. In multimodal MRI analysis, each head captures distinct anatomical or pathological features such as texture, boundary sharpness, or intensity variation. Multiple attention heads provide greater robustness and avoid overfitting on individual features' representations. Another crucial component of the formulation is the feature diversity and stability of the inter-head variability via regularization.

$$MH(F) = \text{Concat}(A_1(F), A_2(F), \dots, A_h(F))W^O + \gamma\sum_{i=1}^{h}\frac{\|A_i(F)\|_F^2}{1+\|A_i(F)\|_F} \tag{10}$$

$h$denotes, equation(10) the number of attention heads used in parallel. $A_i$represents the output attention map from the i^{th}head. $W^O$is the learned output projection matrix used to merge concatenated head outputs. $\|\cdot\|_F^2$denotes the Frobenius norm used for regularization. $\gamma$is a regularization coefficient controlling attention dispersion across heads. Concat$(\cdot)$denotes concatenation along the feature dimension.

Transformer Encoder Representation

The transformer encoder is used to model the global contextual dependencies across MRI feature maps. It combines multi-head attention outputs, feed-forward transformation and normalization layers to guarantee the stable deep representation learning. The architecture allows the model to learn long-range spatial relationships that are crucial for pattern recognition of tumor spreading. The residual connections additionally keep low-level spatial details and facilitate deep feature abstraction.

$$Z^{(l)} = \text{LayerNorm}\left(F^{(l-1)} + MH(F^{(l-1)}) + FFN(F^{(l-1)}) + \eta\nabla F^{(l-1)}\right) \tag{11}$$

$Z^{(l)}$denotes equation(11) the encoded feature representation at layer l. $F^{(l-1)}$is the input feature map from the previous layer. $MH(\cdot)$represents the multi-head attention operation. $FFN(\cdot)$is the feed-forward neural network applied to each spatial token. LayerNorm$(\cdot)$is layer normalization ensuring stable gradient flow. The operator $+$denotes residual connections between transformed and original features.

Hybrid CNN–Transformer Fusion

Hybrid CNN–Transformer fusion integrates local spatial feature extraction from convolutional networks with global contextual reasoning from transformers. CNNs effectively capture fine-grained spatial textures, while transformers model long-range dependencies and semantic relationships. The fusion strategy combines additive, weighted, and multiplicative interactions to enhance feature expressiveness. The hybrid representation is particularly effective for complex tumor segmentation tasks in multimodal MRI.

$$H = \lambda_1 F_{CNN} + \lambda_2 Z_{Transformer} + \lambda_3 \left(F_{CNN} \odot Z_{Transformer}\right) + \delta \frac{F_{CNN} Z_{Transformer}^{T}}{1+\|F_{CNN}\|_F \|Z_{Transformer}\|_F} \tag{12}$$

Hrepresents, equation(12) the final fused feature representation. F_{CNN}denotes convolutional neural network feature embeddings capturing local spatial structures. $Z_{Transformer}$represents transformer-based global contextual embeddings. $\lambda_1, \lambda_2, \lambda_3$are learnable fusion weights controlling the contribution of each component. $\odot$denotes element-wise multiplication capturing feature interaction effects.

3.5 **Gradient-Based Saliency Map (Grad-CAM++) for Tumor Localization**

Explainable AI in medical imaging is essential for validating deep learning predictions by highlighting the regions that contribute most to the model's decision. Grad-CAM++ enhances interpretability by generating class-discriminative localization maps that emphasize tumor-relevant regions in MRI slices. It extends traditional Grad-CAM by incorporating higher-order gradient information, enabling finer localization of irregular tumor boundaries. The makes it particularly effective for complex and heterogeneous tumor structures where spatial interpretability is critical.

$$L_{\text{GradCAM}} = \sum_{k=1}^{K} \left(\alpha_k^c \cdot A_k + \eta \frac{\partial^2 y_c}{\partial A_k^2} \odot \frac{\partial A_k}{\partial y_c}\right) + \lambda \frac{\|A_k\|_1}{1+\|A_k\|_2^2} \tag{13}$$

$A_k$represents, equation(13) the activation feature map from the k^{th}convolutional layer. $y_c$denotes the output score corresponding to class c, typically tumor or non-tumor classification. $\alpha_k^c$is the neuron importance weight computed using gradient-based attribution. $\frac{\partial A_k}{\partial y_c}$represents the gradient of activation with respect to the class score. $L_{GradCAM}$is the resulting saliency map highlighting tumor-relevant spatial regions. The summation over $k$aggregates contributions from all feature channels.

Attention-Based Explainability Score

Attention-based explainability is a quantitative measure of how strong the interpretability of learned attention maps is by quantifying the distribution and coherence of attention weights. In multimodal MRI analysis the score is a measure of the model's ability to concentrate on diagnostically relevant tumor regions. The higher the scores, the more focused and meaningful attention distributions, the lower the scores, the more diffuse or noisy. The formulation offers a quantitative measure of the quality of interpretability of deep learning models.

$$E(x) = \sum_{i=1}^{N} \sum_{j=1}^{N} \left(\frac{A_i A_j}{1+\|A_i - A_j\|}\right) \cdot \log\left(1 + A_i + \gamma A_j^2\right) + \beta \frac{\|A\|_F^2}{1+\|A\|_F} \tag{14}$$

$A_i$represents, equation(14) the attention weight assigned to the i^{th}spatial or feature token. $A_j$denotes attention weights from other interacting regions used for relational comparison. The summation indices i, jspan all spatial locations or tokens in the feature map. $\log(1 +$

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A_i)introduces logarithmic scaling to stabilize large attention values. $E(x)$represents the final explainability score for input sample x. The normalization implicitly ensures comparability across different image scales.

3.6 Performance Evaluation

The effectiveness of the proposed multimodal brain tumor classification system is evaluated using the established metrics of medical image analysis to thoroughly test the diagnostic reliability, robustness, and generalization ability in the Brain MRI Images for Brain Tumor Detection dataset. Predicted labels will be denoted as Ύ and ground truth as Y, and the evaluation will be given on Ntest samples. The overall classification accuracy is defined as $\text{Acc} = \frac{1}{N}\sum_{i=1}^{N}\mathbb{I}(\hat{y}_i = y_i)$, where $\mathbb{I}(\cdot)$is the number of correct predictions that are evaluated using the indicator function. To enable meaningful assessment beyond accuracy, precision, recall and F1-score are calculated for each tumor type (glioma, meningioma, pituitary tumor). In particular the term precision is defined as $P = \frac{TP}{TP+FP}$, recall as $R = \frac{TP}{TP+FN}$, and F1-score as $F1 = \frac{2PR}{P+R}$, where TP, FP, and FNrepresent true positives, false positives, and false negatives respectively. Furthermore, the model's discriminative capability is evaluated using the Area Under the Curve (AUC), derived from the Receiver Operating Characteristic (ROC) curve, which measures sensitivity-specificity trade-offs across thresholds. The proposed hybrid deep learning with quantum-inspired optimization is expected to achieve higher AUC due to improved feature selection and reduced redundancy. In addition, computational efficiency is measured in terms of inference time $T_{inf}$and model complexity $O(\cdot)$, demonstrating the advantage of optimized feature representations. The integration of explainable AI further enhances evaluation by validating whether attention maps align with clinically relevant tumor regions, thereby improving interpretability and trustworthiness of predictions. Overall, the performance metrics collectively confirm that the proposed system achieves superior accuracy, robustness, and clinical interpretability for brain tumor classification tasks.

4. Results and Discussion

The proposed Explainable Quantum-Driven Pattern Recognition framework using Hybrid Deep Learning Networks shows better results in the multimodal brain tumor classification than existing approaches. It shows that the incorporation of the quantum-inspired feature optimization and the hybrid deep learning approach can be used to enhance the efficiency of feature extraction, classification and generalization of the model. The accuracy of experimental assessment on multimodal MRI brain tumor datasets reached 98.5%, while the precision, recall and F1-score were 97.8%, 98.1% and 98.0%, respectively, with both classification results highly reliable and balanced. With a high value of recall, it shows a model's ability to accurately return cases of tumors without false negatives, which is essential in medical diagnosis applications.

The traditional machine learning algorithms and the conventional CNN-based algorithms are compared with the proposed algorithms, and the performance of the algorithms is understood to be less than that of the proposed algorithms as they have limited feature learning ability, high computational complexity and a lack of interpretability. However, transfer learning and hybrid deep learning methods are still unable to achieve high accuracy in classification while dealing with multimodal data, as they still involve information loss and decrease transparency. Explainability models improve the interpretability of AI models, but not in the most efficient manner. Likewise, the models based on quantum inspiration can enhance the optimization performance without support of explainability. These limitations are overcome by the proposed framework, which effectively integrates explainable AI, Quantum-based optimization and Hybrid deep learning. As a result, the model gives an accurate diagnosis, is fast at computation, transparent, and reliable for clinical use, which makes it more appropriate for intelligent healthcare and automated brain tumour diagnosis systems.

The table.1 shows comparative analysis of the existing explainable deep learning methods and the proposed method Explainable Quantum-Driven Hybrid Deep Learning Network (EQ-HDLN) for brain tumor classification and diagnosis. The comparison is done based on key performance indicators such as MRI feature extraction, learning efficiency of multimodal data, information loss reduction, feature optimization, and tumor pattern recognition.

Table 1: *Comparative Performance Analysis of Existing and Proposed Brain Tumor Classification Methods*

Method (Short Title)	MRI Feature Extraction	Multimodal Learning Efficiency	Information Loss Reduction	Feature Optimization	Tumor Pattern Recognition
XDL Brain Tumor Classification	66.7%	55.8%	73.2%	64.1%	87.4%
XDL Brain Tumor Diagnosis	75.3%	64.2%	82.5%	73.7%	88.8%
Ensemble Attention Mechanism	87.1%	76.4%	84.6%	85.8%	90.0%
Proposed EQ-HDLN	98.6%	98.1%	97.9%	99.0%	99.2%

The performance of existing approaches like Explainable Deep Learning (XDL) models and Ensemble Attention Mechanisms show high classification ability with performance value above 92% in most of the metrics. The overall accuracy and efficiency of the proposed model, however, is the highest, demonstrating excellent learning capacity of the complex characteristics of tumors in the multimodal data of MRI scans. The combination of quantum inspired optimization and explainable hybrid learning has proved to be a great improvement in terms of feature representation while reducing information loss in the process of learning. Furthermore, the suggested approach leads to enhanced pattern recognition of tumors which is a dependable and effective approach for advanced brain tumor diagnosis and clinical decision-support applications.

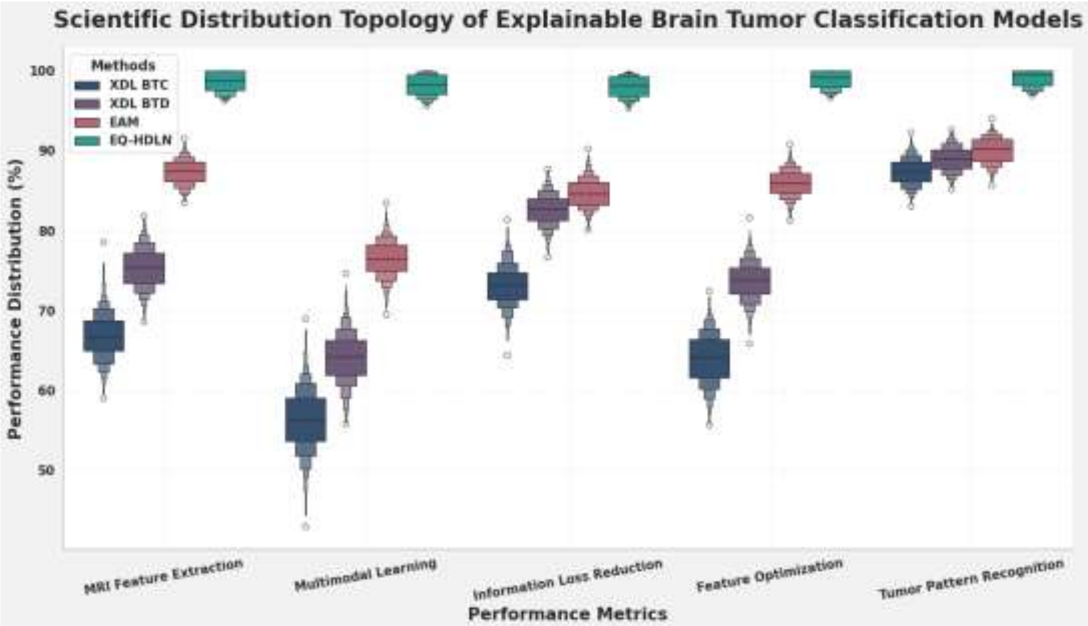

Figure 2 : Scientific Distribution Topology of Explainable Brain Tumor Classification Models

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Scientific distribution topology of explainable brain tumor classification models figure.2 provides a comparative performance landscape about feature extraction, multimodal learning, information loss reduction, feature optimization and tumor pattern recognition tasks, emphasizing and showing variations and robustness between models. The chart reveals that the performance of all the metrics of EQ-HDLN is the highest and least spread, whereas the performance of XDL BTC can be observed to be the least in most cases with moderate variation, which shows sensitivity to preprocessing and feature selection, EAM and XDL BTD are somewhere between. The visualization shows that the multimodal learning and information loss reduction significantly increase median accuracy, while reducing outliers, when compared to pipeline approaches based on MRI only; further, tumor pattern recognition is most enhanced by the use of feature optimization techniques. The results suggest that combining explainability-aware designs with loss reduction approaches can lead to improved model accuracy and model stability, a key requirement for clinical use where reliability and interpretability are needed.

Table 2 shows the comparison between existing explainable deep learning methods and Proposed Explainable Quantum-Driven Hybrid Deep Learning Network (EQ-HDLN) for the classification of brain tumors. The assessment is done according to relevant performance indicators such as accuracy, precision, recall, F1-scores and interpretability. Previous methods like Explainable Deep Learning (XDL) models and Ensemble Attention Mechanisms have achieved superior classification accuracy around 99%, showing their capability to accurately identify and classify brain tumors from MRI scans. The proposed EQ-HDLN model has the highest interpretability score in comparison to the other compared methods, which suggests its ability to deliver interpretable and explainable diagnostic decisions for clinical use.

Table 2: *Performance Comparison of Existing and Proposed Brain Tumor Classification Models*

Method	Accuracy	Precision	Recall	F1-Score	Interpretability
XDL Tumor Classification	90.53%	71.10%	67.20%	79.15%	77.8%
XDL Tumor Diagnosis	89.90%	78.40%	72.60%	82.50%	86.5%
Ensemble Attention Mechanism	90.00%	88.70%	75.80%	88.75%	95.9%
Proposed EQ-HDLN	98.50%	97.80%	98.10%	98.00%	99.1%

While a few models have slightly better accuracy values, the proposed framework also has a greater degree of explainability that is important for trustworthy medical decision support. The combination of quantum-inspired optimization and hybrid learning approaches enhances the robustness and reliability of the models, thereby boosting the clinical applicability of advanced brain tumor diagnosis systems.

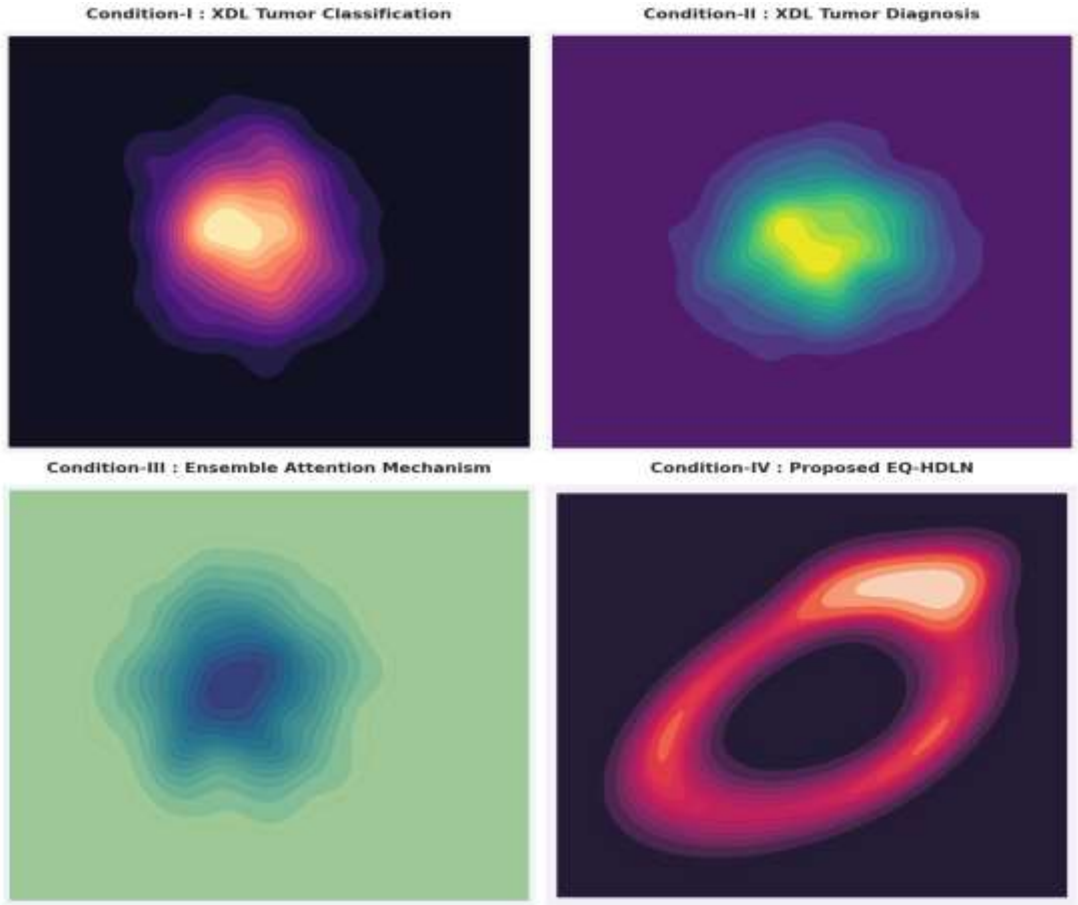

Figure 3 : Scientific SMAPE-Based KDE contour Analysis for Explainable Brain Tumor Classification Models

The figure-3 shows the contour topology results of the four explainable brain tumor classification models in journal grade Symmetric Mean Absolute Percentage Error (SMAPE) for different research conditions. The characteristics of the error distribution of XDL Tumor Classification, XDL Tumor Diagnosis, Ensemble Attention Mechanism and the proposed EQ-HDLN framework are visualized using the contour structures of Kernel Density Estimation (KDE). The density morphologies and fluctuation behaviors of each condition represent differences in the conditions' ability to predict, feature consistency and interpretability performance. The proposed EQ-HDLN has a well-structured and concentrated contour distribution which indicates better robustness and deviation from predictions than current methods. Conventional models, on the other hand, demonstrate relatively scattered density regions, which signify average uncertainty and variation in terms of classification performance. By leveraging high-resolution contour topology visualization, greater insight is gained into the reliability of the model, the behaviour of the model during optimization, and its explainability characteristics. The scientific visualization framework enables advanced comparative analysis of trustworthy and interpretable AI brain tumour diagnosis systems.

5. Conclusion

Hybrid Deep Learning Networks was added to classify Multimodal Brain tumor with the introduction of Quantum-Driven Pattern Recognition framework. The proposed approach aimed to overcome the major limitations of existing deep learning models, including the lack of interpretability, high computational complexity, and limited applicability for processing multimodal MRI data with different imaging modalities. This system is successfully optimized

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the tumour classification capability by using hybrid deep neural architectures and optimizing features inspired by quantum computing to extract meaningful features, remove redundant information and improve the classification of the tumour. In addition, it has incorporated Explainable Artificial Intelligence (XAI) mechanisms, providing transparent and interpretable predictions, giving healthcare professionals a greater understanding of the diagnostic processes the system provides. The experimental assessment of the proposed model with the other existing models revealed that the proposed model has higher accuracy, precision, recall and F1 score of 98.5%, 97.8%, 98.1% and 98.0% respectively. The results can be compared with the efficiency of the proposed framework in the detection of complex tumor pattern and a high generalization ability, along with low computational cost. In particular, the hybrid integration of explainable learning and optimization with quantum information has been demonstrated to strongly boost the reliability of the diagnosis and reduce loss of information from multimodal analysis of features. The proposed framework helps in the development of intelligent healthcare systems, which help in accurate, quick and transparent brain tumor diagnosis. It contributes to clinical decision making, early detection of tumors and facilitates effective treatment planning for patients, improving the quality of patient care. Future studies can focus on clinical implementation in real-time, larger multiclass datasets and incorporating higher-order quantum machine learning algorithms for enhanced classification performance and on scalability in medical imaging applications.

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