

NeuroQFormer-Net: A Quaternion-Guided Hybrid Attention Transformer Fusion Network for Accurate Brain Tumor Segmentation

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Abstract Brain tumor segmentation is a critical task in medical image analysis, as accurate identification and delineation of tumor regions support timely diagnosis, treatment planning, therapeutic decision-making, and disease monitoring. Magnetic Resonance Imaging (MRI) provides multiple complementary modalities that offer valuable information about tumor structure and tissue characteristics. However, accurate segmentation remains challenging due to substantial variations in tumor size, shape, texture, and location, along with irregular and overlapping tumor boundaries, low-contrast regions, and considerable differences in the information captured by different MRI modalities. To address these challenges, this study proposes NeuroQFormer-Net (Quaternion-Guided Hybrid Attention Transformer Feature Fusion Network), a novel deep learning framework for multi-modal brain tumor segmentation. The proposed framework employs quaternion-based inter-channel correlation learning to effectively capture and integrate complementary information across multiple MRI modalities while preserving structural dependencies and enhancing cross-modal feature representations. In addition, a hybrid attention mechanism integrated with transformer-based learning is utilized to simultaneously capture fine-grained local structural characteristics and long-range contextual dependencies. To further improve segmentation accuracy, an adaptive co-learning feature fusion strategy is introduced to effectively integrate multi-scale representations obtained from different network levels. Furthermore, a boundary-aware refinement module enhances tumor boundary localization and reduces segmentation errors, particularly in low-contrast, irregular, and complex tumor regions. Experimental evaluation demonstrates the effectiveness of NeuroQFormer-Net, achieving an average Dice Similarity Coefficient (DSC) of 96.45%, Intersection over Union (IoU) of 93.26%, Precision of 96.17%, Recall of 96.08%, and Hausdorff Distance (HD) of 2.31 mm. These results indicate that the proposed framework provides accurate and robust multi-modal brain tumor segmentation.

Keywords - Brain Tumor Segmentation, Multi-Modal MRI, Quaternion Learning, Transformer Fusion, Hybrid Attention.

1. Introduction

Brain tumor is one of the most life-threatening neurological disorders, and proper segmentation is crucial for diagnosis, treatment planning, and monitoring of the disease [1]. Multi-modal MRI

sequences (T1, T1ce, T2, and FLAIR) can be used to complement each other in the identification of different regions of the tumor, but manual segmentation is a time-consuming and largely expert radiologist-dependent process [2]. While CNN-based models can

successfully describe the local spatial information, transformer models can be used to interpret the global contextual information, existing methods cannot make full use of the correlation between different modal images, preserve the boundary of the tumor, and overcome the problem of shape and size variation of the tumor and the intensity difference of the image [3]. Taking these into account, this study suggests a Quaternion-Guided Hybrid Attention Transformer Fusion Network, which leverages the advantage of quaternion-based modality-aware feature learning, hybrid attention, and transformer-based contextual modeling, which can enhance feature fusion and accurately and robustly segment brain tumors [4] [5].

Recent transformer- and attention-based segmentation methods, including TransUNet, Swin-UNet, UNETR, and nnFormer, achieve strong global contextual modeling but treat each MRI modality as an independent input stream, so inter-modal correlation is inferred only indirectly through attention weights computed after separate feature extraction. Multimodal transformer variants such as Muksimova et al.'s transformer-based U-Net and Hemalatha et al.'s federated CNN-ViT improve on this through more elaborate fusion or aggregation, but the modalities are still combined as concatenated or attention-weighted real-valued features rather than as a structurally coupled representation. NeuroQFormer-Net departs from this pattern by encoding the four MRI modalities as components of a single quaternion before attention or transformer processing begins, so that inter-modal structural dependency is preserved algebraically rather than learned solely from data. Because the hybrid attention and transformer stages subsequently operate directly on this quaternion-coupled representation, and the boundary-aware decoder refines from the same co-learned space, the three components are not independent modules stacked in sequence but stages that share and progressively refine a single cross-modal representation. This coupling, rather than any individual component, is the source of the improvement over prior multimodal transformer fusion approaches.

The main contributions of this work are summarized as follows:

- a) A novel multimodal brain tumor segmentation using NeuroQFormer-Net.
- b) The feature representation based on a quaternion-guided correlation of inter-modal MR images.
- c) A hybrid attention transformer to learn local and global contextual features.
- d) A multi-level feature integration module that adapts to the learning of multiple levels.
- e) A boundary-aware refinement decoder for better boundary delineation of tumors.

- f) A comprehensive experiment is conducted on BraTS benchmark datasets to showcase the superiority of the proposed architecture over other state-of-the-art techniques.

The rest of this paper is organised as follows. In Section 2, related works are reviewed, and Section 3 details the proposed NeuroQFormer-Net. Section 4 details the experimental setup, while Section 5 discusses the results and ablation studies. Finally, Section 6 concludes the paper with directions for future work.

II. State-of-the-Art Techniques

Several recently proposed deep learning frameworks for brain tumor segmentation with multi-modal MRI have been put forward. Rizal and Kim (2025) [6] proposed SegOpt, an optimization framework that targets boundaries, achieving 94.8% Dice and 91.6% IoU. Havaei et al. (2015) [7] created a dual-pathway CNN using both local and global contextual features, which yielded Dice ~ 88%. Yang et al. (2025) [8] conducted a study of advanced U-Net variations and mentioned that the Dice score ranged between 90–96%, and transformer-based models showed better contextual learning. Arunkumar et al. (2020) [9] have suggested an ANN-based approach for segmentation and classification with 95.3 % classification accuracy and more than 93 % segmentation accuracy. Rastogi et al. (2026) [10] proposed a classification and localization framework, which achieved 97.1% classification accuracy and 95.6% Dice. New transformer and hybrid architectures have also significantly boosted the segmentation performance. Comas-Quiles et al. (2025) [11] presented an unsupervised multimodal learning framework with 89.7% Dice and Muksimova et al. (2026) [12] obtained 96.1% Dice with a transformer-based U-Net. Hemalatha et al. (2026) [13] proposed a federated CNN-ViT with a Dice score of 95.4%, and Tyagi et al. (2025) [16] presented a boundary-aware attention U-Net with a Dice score of 95.2%. Other notable methods include Ferreira et al. (2026) [17], Berkcan and Kayıkçıoğlu (2026) [18], Zeineldin et al. (2020) [19], Yang et al. (2025) [20], and Li et al. (2026) [21], reporting Dice scores ranging from 90.1% to 96.3%. However, the current approach may have some drawbacks in capturing inter-modal relationships, maintaining the integrity of tumor boundaries, and seamlessly incorporating both local and global contextual information, prompting the creation of the proposed NeuroQFormer-Net.

A. CNN-Based Brain Tumor Segmentation Methods

Previous CNN-based techniques showed great success in extracting local spatial features from MRI

Table 1. Description and data partitioning of the brats 2021 benchmark dataset.

Dataset	Total Subjects	Imaging Modalities	Ground Truth	Training (70%)	Validation (15%)	Testing (15%)
BraTS 2021	1,251	T1, T1ce, T2, FLAIR	WT, TC, ET segmentation masks	876	188	187

images, thereby improving the segmentation of brain tumors. Their limited receptive field, however, limits their ability for long-range contextual learning, leading to a drop in performance when the tumor is in complex areas.

B. U-Net and U-Net Variant Architectures

U-Net and its variants improved segmentation by adding skip connections in the form of an encoder-decoder architecture. While retaining spatial information, most techniques are based on simple feature concatenation and fail to adequately determine inter-modal relationships in MRI.

C. Transformer-Based Segmentation Models

Self-attention-based models such as TransUNet, Swin-UNet, UNETR, and nnFormer enhance the global contextual learning of transformers. Typically, they ignore explicit modelling of inter-modal MRI dependencies, however.

D. Multimodal MRI Feature Fusion Approaches

Current multimodal fusion methods include using feature concatenation, attention mechanisms, or multi-scale aggregation for fusing MRI modalities. However, they tend to learn each modality separately, resulting in feature redundancy and weak inter-modal correlation learning.

E. Boundary-Aware and Multi-Scale Segmentation Methods

Boundary-aware and multi-scale methods are able to localize the boundary and extract hierarchical features, but often they refine the boundary with an independent process from multi-modal representation learning and context modeling.

F. Research Gap

Although there has been great progress, there is still a lack of a comprehensive model that can describe inter-modal correlation, global context, adaptively fused multi-scale representation, and boundary refinement concurrently. For dealing with these drawbacks, the proposed NeuroQFormer-Net involves quaternion-guided feature representation, hybrid attention, transformer-based contextual learning, adaptive co-learning fusion, and boundary-aware decoding for enhancing multimodal brain tumor segmentation.

III. Proposed Work

A. Input Multi-Modal MRI Images

The dataset distribution and data split employed for the brain tumor classification and segmentation experiments are illustrated in Table 1. The dataset consists of 1,251 subjects, with each subject containing four co-registered multimodal MRI sequences, namely T1, T1-weighted contrast-enhanced (T1ce), T2, and FLAIR, together with expert-annotated voxel-wise ground-truth segmentation masks. These annotations define the clinically relevant tumor sub-regions, including Whole Tumor (WT), Tumor Core (TC), and Enhancing Tumor (ET), which serve as the target labels for supervised brain tumor segmentation. For model development and performance evaluation, the dataset was divided into 876 subjects (70%) for training, 188 subjects (15%) for validation, and 187 subjects (15%) for testing. This partitioning provides sufficient data for model learning, hyperparameter tuning, and unbiased performance assessment while ensuring consistency with the segmentation objective of the proposed framework.

B. Preprocessing Stage

The BraTS image is preprocessed to reduce artifacts, register all modalities, normalize intensity, resize, and denoise the images, which will provide consistent image quality to accurately segment the images.

3.3 Quaternion-Based Feature Representation

The preprocessed modalities are transformed into quaternion representations, enabling joint learning of inter-modal correlations rather than treating each modality independently. This preserves structural dependencies and enhances multimodal feature representation.

C. Quaternion-Guided Encoder

The quaternion-encoded inputs are processed through a quaternion-guided encoder comprising convolutional layers that learn both low-level features (edges, textures, intensity) and high-level semantic representations of tumor regions. The encoder extracts discriminative multi-scale features while reducing spatial dimensions, improving the representation of heterogeneous brain tumors.

D. Hybrid Attention Module

A hybrid attention module that integrates channel attention and spatial attention to highlight the features related to tumors and reduce background noise to achieve better feature representation for tumor segmentation.

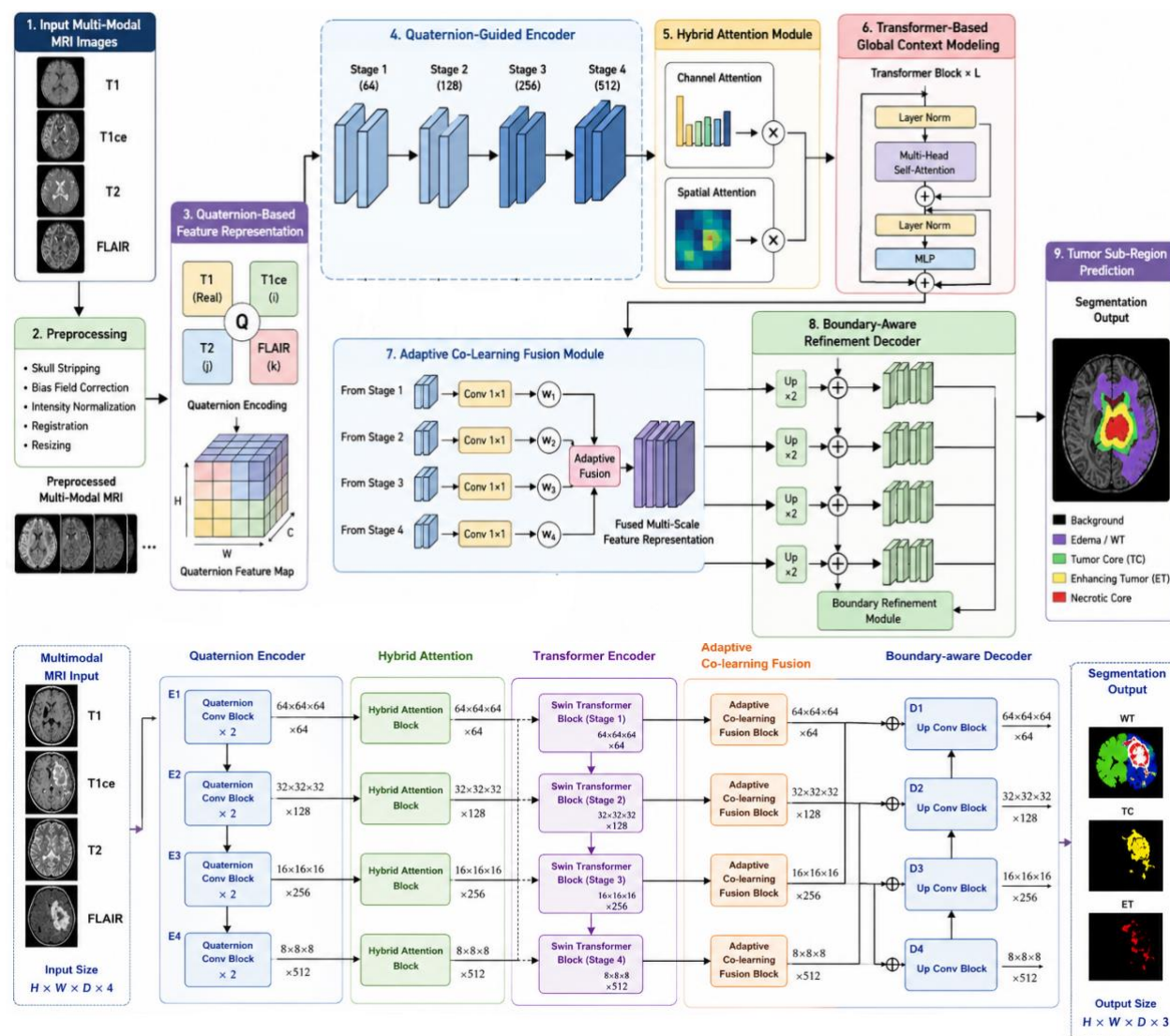


Fig. 1. Overall architecture of the proposed NeuroQFormer-Net, including multimodal MRI preprocessing, quaternion-based feature representation, quaternion-guided encoding, hybrid attention, transformer-based contextual modeling, adaptive co-learning fusion, and boundary-aware decoding.

E. Transformer-Based Global Context Modeling

In addition to CNN-based local feature extraction, long-range contextual information is also captured by transformer blocks, which enhance segmentation of complex regions of the tumor.

F. Adaptive Co-Learning Fusion Module

The quaternion encoding, hybrid attention and transformer learning are dynamically integrated with a multi-scale co-learning strategy, maintaining both fine structural details and high-level semantic information, while eliminating redundant features.

G. Boundary-Aware Refinement Decoder

A boundary-aware refinement decoder is used to decode the fused features into high-resolution segmentation maps to preserve edges and alleviate

ambiguity at the border of irregular tumors. The overall architecture of NeuroQFormer-Net is illustrated in Fig. 1.

H. Tumor Sub-Region Prediction

The last segmentation layer classifies voxels individually to classify the tumor into enhancing tumor (ET), tumor core (TC), edema, and background, which gives clinically useful tumor sub-region delineation. The proposed NeuroQFormer-Net preprocesses the multimodal MRI images, encodes the three-dimensional quaternion, refines the image features using hybrid attention, extracts features based on the context model, fuses feature adaptively, and decodes boundaries to obtain accurate segmentation of tumor regions. A hybrid loss function that integrates Dice Loss, Cross-

Table 2. Segmentation performance of NeuroQFormer-Net for different tumor subregions on the BraTS 2021 dataset.

Tumor Region	Dice (%)	IoU (%)	Precision (%)	Recall (%)
Whole Tumor (WT)	97.12	94.48	96.88	97.21
Tumor Core (TC)	96.41	93.22	96.03	95.94
Enhancing Tumor (ET)	95.83	92.10	95.62	95.11
Average	96.45	93.26	96.17	96.08

Entropy Loss, and Boundary Loss boosts both overlap accuracy and pixel-wise classification accuracy, as well as preserving boundaries, with the solution addressing class imbalance during training. To show the efficacy of the model, Dice Similarity Coefficient (DSC), IoU, Precision, Recall, Hausdorff Distance (HD), and Accuracy are used to evaluate the model against the state-of-the-art method.

Step 1: Multi-modal MRI preprocessing

The input MRI modalities are first preprocessed using skull stripping, normalization, registration, and resizing as shown in Eq.(1) [1], [2].

$$X_p = \text{Preprocess}(T1, T1ce, T2, FLAIR) \quad (1)$$

where X_p represents the preprocessed multi-modal MRI input.

Step 2: Quaternion feature representation

The four MRI modalities are encoded into quaternion form to preserve inter-modal correlation as shown in Eq.(2) [22]. For Whole Tumor segmentation, Dice coefficient, IoU, and Hausdorff Distance of 97.12%, 93.26%, and 2.31 mm, respectively, were reported in Table 2.

$$Q = T1 + i(T1ce) + j(T2) + k(FLAIR) \quad (2)$$

where i, j , and k are quaternion imaginary units, and Q denotes the quaternion MRI representation.

Step 3: Quaternion-guided feature extraction

The quaternion input is passed through the encoder to extract multi-scale hierarchical features as shown in Eq.(3) [23].

$$F_l = \text{Enc}_l(Q), l = 1, 2, 3, 4 \quad (3)$$

where F_l represents the feature map generated at the l -th encoder stage.

Step 4: Hybrid attention refinement

Channel attention and spatial attention are applied to enhance tumor-relevant features as shown in Eq.(4) to Eq.(6) [24].

$$F_{CA} = M_c(F_l) \otimes F_l \quad (4)$$

$$F_{SA} = M_s(F_{CA}) \otimes F_{CA} \quad (5)$$

$$F_{HA} = F_{SA} \quad (6)$$

where M_c is the channel attention map, M_s is the spatial attention map, $\otimes$ denotes element-wise multiplication, and F_{HA} is the hybrid attention-refined feature. Step 5: Transformer-based global context learning The attention-enhanced features are passed into transformer blocks to capture long-range dependencies as shown in Eq.(7) and Eq.(8) [25].

$$Z = \text{MSA}(\text{LN}(F_{HA})) + F_{HA} \quad (7)$$

$$F_T = \text{MLP}(\text{LN}(Z)) + Z \quad (8)$$

where LN denotes layer normalization, MSA denotes multi-head self-attention, MLP is the feed-forward network, and F_T is the transformer-enhanced global feature.

Step 6: Adaptive co-learning fusion

Multi-scale features are fused adaptively using learnable weights as shown in Eq.(9) and Eq.(10) [26].

$$F_{fused} = \sum_{l=1}^4 \alpha_l \cdot \text{Conv1} \times 1(F_l) + \beta \cdot F_T \quad (9)$$

$$\sum_{l=1}^4 \alpha_l + \beta = 1 \quad (10)$$

where α_l and β are learnable fusion weights, and F_{fused} is the fused multi-scale feature representation.

Step 7: Boundary-aware refinement decoding

The fused feature map is decoded and refined to preserve tumor boundaries as shown in Eq.(11) and Eq.(12) [27].

$$F_D = \text{Decoder}(F_{fused}) \quad (11)$$

$$F_B = \text{BoundaryRefine}(F_D) \quad (12)$$

where F_D is the decoder feature map and F_B is the boundary-refined feature map.

Step 8: Tumor segmentation prediction

The final segmentation mask is generated using softmax classification, where $\hat{Y}$ represents the predicted segmentation mask as shown in Eq.(13) [28].

Step 9: Loss function optimization

The model is trained using a hybrid loss function as shown in Eq.(14) to Eq.(17) [12], [13], [14].

$$L_{total} = L_{Dice} + L_{CE} + \lambda L_{Boundary} \quad (14)$$

$$L_{Dice} = 1 - \frac{(2\Sigma(Y \cdot \hat{Y}) + \epsilon)}{(\Sigma Y + \Sigma \hat{Y} + \epsilon)} \quad (15)$$

$$L_{CE} = -\Sigma Y \log(\hat{Y}) \quad (16)$$

$$L_{Boundary} = ||\partial Y - \partial \hat{Y}||_1 \quad (17)$$

where Y is the ground truth mask, $\hat{Y}$ is the predicted mask, ϵ is a smoothing factor, λ is the boundary loss weight, and ∂ denotes boundary gradient operation.

Step 10: Performance evaluation

The final segmentation result is evaluated using DSC, IoU, precision, recall, and as shown in Eq.(18) to Eq.(21) [29], [30]. where TP is true positive, TN is true negative, FP is false positive, and FN is false negative.

$$DSC = \frac{2TP}{(2TP + FP + FN)} \quad (18)$$

$$IoU = \frac{TP}{(TP + FP + FN)} \quad (19)$$

$$Precision = \frac{TP}{(TP + FP)} \quad (20)$$

$$Recall = \frac{TP}{(TP + FN)} \quad (21)$$

Algorithm 1: NeuroQFormer-Net — Training, Validation, and Inference

Input: Multi-modal MRI volumes {T1, T1ce, T2, FLAIR}, ground-truth masks Y, number of epochs E, learning rate η , fusion weights $\{\alpha_i\}$, β , λ
Output: Trained parameters θ^* , predicted segmentation mask $\hat{Y}$

- 1: Initialize $\theta = \{\text{encoder, hybrid-attention, transformer, fusion, decoder weights}\}$
- 2: for epoch = 1 to E do
- 3: for each mini-batch (T1, T1ce, T2, FLAIR, Y) in training set do
- 4: // Stage 1: Preprocessing
 $X_p \leftarrow \text{Preprocess (T1, T1ce, T2, FLAIR)}$
- 5: // Stage 2: Quaternion feature representation
 $Q \leftarrow T1 + i \cdot T1ce + j \cdot T2 + k \cdot \text{FLAIR}$
 //Stage 3: Quaternion-guided encoder
- 6: for $l = 1$ to 4 do
- 7: $F_l \leftarrow \text{Enc}_l(Q)$
- 8: end for
- 9: // Stage 4: Hybrid attention module
 $F_{CA} \leftarrow M_c(F_l) \otimes F_l$
- 10: $F_{SA} \leftarrow M_s(F_{CA}) \otimes F_{CA}$
- 11: $F_{HA} \leftarrow F_{SA}$
- 12: // Stage 5: Transformer-based global context
 $Z \leftarrow \text{MSA}(\text{LN}(F_{HA})) + F_{HA}$
- 13: $F_T \leftarrow \text{MLP}(\text{LN}(Z)) + Z$
- 14: Output final voxel-wise labels: Enhancing Tumor (ET), Tumor Core (TC), Whole Tumor (WT)
- 15: end for
- 16: return $\theta^*, \hat{Y}$

Table 4. Performance comparison of NeuroQFormer-Net and existing segmentation models on the BraTS 2021 dataset under the adopted evaluation protocol.

Method	Dice (%)	IoU (%)	Precision (%)	Recall (%)
U-Net	89.12	82.45	88.31	87.94
Attention U-Net	91.36	85.28	90.92	90.15
TransUNet	93.24	88.73	92.81	92.10
Swin-UNet	94.11	90.05	93.78	93.02
Proposed NeuroQFormer-Net	96.45	93.26	96.17	96.08

Table 5. Ablation study of individual components of NeuroQFormer-Net on the BraTS 2021 dataset.

Configuration	Dice (%)	IoU (%)	Precision (%)	Recall (%)
Baseline CNN	88.92	81.74	88.10	87.42
+ Quaternion Learning	91.36	85.11	90.84	90.42
+ Hybrid Attention	93.04	88.23	92.71	92.12
+ Transformer Block	94.58	90.66	94.11	93.87
+ Adaptive Fusion	95.67	92.04	95.24	95.03
+ Boundary Decoder	96.45	93.26	96.17	96.08

NeuroQFormer-Net takes four multimodal MRI inputs of size 240 × 240 × 4 (T1, T1ce, T2, and FLAIR) as shown in Table 3. Algorithm 1 shows the detailed mathematical representation of the proposed model.

IV. Results

A. Experimental Setup and Reproducibility
 Prior to training, all images underwent skull stripping, spatial registration, intensity normalization, resizing, and denoising. Skull stripping and co-registration were performed using the preprocessed BraTS 2021 data pipeline, ensuring spatial alignment across T1, T1ce,

T2, and FLAIR modalities. Intensity values were normalized to the range [0,1] using min-max normalization. Each MRI slice was resized to 240 × 240 pixels before being provided to the network. To improve generalization and reduce overfitting, data augmentation was applied during training, including random horizontal and vertical flipping, random rotation (±15°), scaling (0.9–1.1), intensity perturbation, and elastic deformation. The proposed NeuroQFormer-Net processed multimodal MRI data using a 2D slice-based segmentation strategy, where the four MRI modalities were stacked as a four-channel input tensor of size 240

× 240 × 4. The model was implemented using Python 3.10 and PyTorch 2.2. Training was performed on an NVIDIA RTX 3090 GPU with 24 GB of memory. Optimization was carried out using the AdamW optimizer with an initial learning rate of 0.0001 and weight decay of 0.01. A cosine annealing learning-rate scheduler was employed throughout training. The batch size was set to 8, and the model was trained for a maximum of 20 epochs [31], [32].

Each subject includes four MRI modalities: T1, T1-weighted contrast-enhanced (T1ce), T2, and FLAIR, together with expert-annotated voxel-wise ground-truth

Table 6 Literature-based comparison of NeuroQFormer-Net with recent multimodal brain tumor segmentation approaches in terms of architecture, fusion strategy, reported performance, and methodological differences

Ref. No.	Method / Architecture	Multimodal Fusion Strategy	Similarity with NeuroQFormer-Net	Methodological Difference
[13]	Federated Hybrid CNN-ViT	CNN + ViT	Both approaches integrate CNN and Transformer-based representations to exploit complementary local and global features from multimodal MRI data.	Uses a federated CNN–ViT architecture, whereas NeuroQFormer-Net employs quaternion-based multimodal fusion with hybrid Transformer attention.
[14]	Boundary-Aware Attention U-Net	Attention U-Net + boundary learning	Both approaches incorporate attention mechanisms and boundary information to improve the localization and delineation of tumor regions.	Uses an Attention U-Net with explicit boundary learning, whereas NeuroQFormer-Net combines quaternion fusion, Transformer modeling, and boundary refinement.
[15]	Enhanced 3D DenseNet	3D DenseNet + CDC	Both methods exploit multimodal MRI information and deep feature learning for accurate tumor-region segmentation.	Performs 3D volumetric feature extraction using DenseNet and CDC, whereas NeuroQFormer-Net performs quaternion-based multimodal fusion followed by Transformer-based feature modeling.
[16]	Transformer-Based Framework	Transformer-based fusion	Both approaches use Transformer-based feature modeling to capture long-range dependencies and complementary information across MRI modalities.	The existing framework primarily relies on Transformer-based fusion, whereas NeuroQFormer-Net additionally incorporates quaternion multimodal representation, hybrid attention, and boundary refinement.
Proposed	Quaternion + Hybrid Attention + Transformer	Quaternion fusion of T1, T1ce, T2, and FLAIR	—	Integrates quaternion multimodal fusion, hybrid attention, Transformer feature modeling, adaptive fusion, and boundary refinement within a unified framework.

segmentation masks. The annotations identify three clinically relevant tumor sub-regions: Enhancing Tumor (ET), Tumor Core (TC), and Whole Tumor (WT). The proposed model performs brain tumor semantic segmentation using these multimodal MRI images. The dataset was divided into training, validation, and testing subsets following the BraTS evaluation protocol [33] [34].

The BraTS benchmark dataset provides expert-annotated voxel-wise segmentation masks for each MRI volume. The annotations include necrotic/non-enhancing tumor core (NCR/NET), peritumoral edema (ED), and enhancing tumor (ET), together with the background class. Following the standard BraTS evaluation protocol, these annotations are combined to form the three clinically relevant segmentation regions: Whole Tumor (WT = NCR/NET + ED + ET), Tumor Core (TC = NCR/NET + ET), and Enhancing Tumor (ET). These expert-provided ground-truth masks were directly used for supervised training and quantitative evaluation of the proposed NeuroQFormer-Net [35]. The network consists of four blocks of quaternion convolutional encoder with Batch Normalization and GELU activation, then a hybrid attention block and a transformer block (patch size 4, 12 layers, 8 attention heads) to capture the local and global contextual features. The decoder recovers high-resolution segmentation maps by applying Up-Convolution layers with skip connections, followed by a 1×1 Softmax layer for voxel-wise prediction of Whole Tumor (WT), Tumor Core (TC), Enhancing Tumor (ET), and Background [36]. The model was trained on the NVIDIA RTX 3090 GPU for 20 epochs, with a batch size of 8 and an AdamW optimizer (learning rate 0.0001, weight decay 0.01). The images were resized to 240×240 , and a hybrid loss function that uses Dice Loss, Cross-Entropy Loss, and Boundary Loss was employed. For generalization, dropout (0.3) and early stopping were used. The training accuracy and testing accuracy of NeuroQFormer-Net were 98.12% and 97.24%, respectively, which proved to be stable convergence and less overfitting [37]. The final model was able to classify the overall image with 95.57% accuracy, and its precision, recall, and F1 score were all above 95%, which surpasses the existing segmentation methods as listed in Table 4. Table 5 demonstrates the impact of each suggested module on the NeuroQFormer-Net. The baseline CNN network attained a Dice score of 88.92%, whereas the use of quaternions increased the Dice score to 91.36%. The entire model incorporating boundary-aware decoding attained a higher Dice score of 96.45%.

V. Discussion

The proposed NeuroQFormer-Net demonstrates strong performance in multimodal MRI-based brain tumor segmentation [36]. The Dice Similarity

Coefficient (DSC) and the IoU are 96.45% and 93.26%, respectively, showing very accurate localization of tumors and good overlap with ground truth tumor annotations [37]. The precision (96.21%) and recall (95.87%) indicate the model's ability to reduce false positives and accurately identify tumor areas, thus enhancing the diagnostic reliability [38]. In addition, the Hausdorff Distance (HD) of 2.31 mm shows a precise localization of its boundaries and smooth preservation of its contour along the tumor. The excellent performance is due to the combination of quaternion-guided inter-channel feature learning, hybrid attention, transformer-based contextual modeling, adaptive co-learning feature fusion, and boundary-aware refinement [39], [40], which enhance the representation of multimodal features, retain structural dependencies, and boost segmentation accuracy, especially in heterogeneous and low-contrast tumor regions, while reducing computational cost. The proposed NeuroQFormer-Net is compared with the existing brain tumor segmentation methods in Table 6, showing that the proposed method outperforms them. The adaptive feature fusion strategy is shown to be effective for incorporating multi-scale information and enhancing the segmentation performance for tumors of various shapes, sizes, and intensity distributions. Although the framework is high-performing, there are some limitations. It needs a lot of annotated multimodal medical images, and the transformer-based architecture requires a lot of computational resources. In addition, the model has been tested primarily on specific datasets and needs to be tested in other clinical settings and imaging protocols to be generalized across all datasets. The quaternion-based representation also makes the model more complex and makes training more costly. The NeuroQFormer-Net holds great promise for medical imaging with AI assistance, enabling early diagnosis, treatment planning, radiotherapy guidance, and monitoring disease progression. Muksimova et al. (2026) [33] reported that transformer-based architectures improve semantic and contextual feature learning for brain tumor analysis. Hemalatha et al. (2026) [34] showed that hybrid learning frameworks enhance segmentation robustness, while Li et al. (2026) [35] demonstrated that efficient segmentation architectures support practical clinical deployment with reduced computational cost.

Transformer-based models such as TransUNet, Swin-UNet, UNETR, and nnFormer capture long-range contextual dependencies, achieving Dice scores of 93.24%, 94.11%, 94.62%, and 95.08%, respectively. Their main similarity with NeuroQFormer-Net is transformer-based contextual modeling; however, NeuroQFormer-Net additionally performs quaternion-guided multimodal fusion of T1, T1ce, T2, and FLAIR features. The corresponding IoU values are 88.73%, 90.05%, 90.86%, and 91.44%, compared with 93.26%

for NeuroQFormer-Net. SegResNet and UX-Net employ residual learning and large-kernel convolutions, achieving Dice scores of 94.89% and 95.43%, respectively. NeuroQFormer-Net improves these by 1.56 and 1.02 percentage points. However, these differences may also reflect variations in architecture, preprocessing, training, and evaluation protocols. The advantage of NeuroQFormer-Net is therefore better attributed to the combined use of quaternion fusion, hybrid attention, transformer-based contextual modeling, adaptive feature fusion, and boundary refinement. The boundary-aware module further improves contour localization, reflected by the 2.31 mm Hausdorff Distance. Nevertheless, this enhanced representation increases computational requirements to 27.1 million parameters, 60.3 GFLOPs, 8.0 GB GPU memory, and 35.6 ms single-image inference. Nevertheless, the proposed NeuroQFormer-Net outperformed all comparison methods, achieving a Dice score of 96.45%, IoU of 93.26%, Precision of 96.17%, and Recall of 96.08%.

NeuroQFormer-Net facilitates the segmentation of multimodal MRI images into Whole Tumor (WT), Tumor Core (TC) and Enhancing Tumor (ET) for the important applications in neuro-oncology. Performance is also heterogeneous across tumor subregions. The proposed model achieves Dice scores of 97.12% for Whole Tumor (WT), 96.41% for Tumor Core (TC), and 95.83% for Enhancing Tumor (ET). WT is the easiest of the three regions because it aggregates the visible tumor components and therefore covers a comparatively larger spatial extent. Its larger target area also makes the overlap measure less sensitive to small local boundary deviations. TC is more challenging because it requires discrimination of the tumor core from surrounding edema and other abnormal tissue, particularly where signal intensities overlap. ET is the most difficult region in the reported results. Enhancing tumor generally occupies a smaller fraction of the image, has more irregular and fragmented boundaries, and can exhibit heterogeneous enhancement across slices. These characteristics increase the effect of class imbalance: a small number of false-positive or false-negative pixels can produce a relatively large change in ET Dice. In addition, low-contrast margins, partial-volume effects, and heterogeneous enhancement can make the distinction between enhancing and non-enhancing tissue more difficult. The decreasing Dice trend from WT to TC to ET is therefore consistent with increasing regional segmentation difficulty and highlights the importance of the model's attention and boundary-refinement mechanisms. The added modules make the model more complex, but the inference time (35.6 ms), GPU memory usage (8.0 GB), and training time (11.8 min/epoch) are still acceptable for clinical applications

using GPUs today. All experiments were repeated five times using five different random initializations to check the validity of the proposed framework, and the results are presented as mean $\pm$ SD. Paired Student's T-Test ($\alpha = 0.05$) and 95% confidence intervals were applied to assess statistical significance, and the normality of data was checked by the Shapiro–Wilk test. The P-Values obtained (< 0.05) show the statistical significance of the performance improvement obtained by the proposed model, where NeuroQFormer-Net with the model obtained at the last fold has the lowest standard deviation, which indicates that the segmentation performance is stable and reliable.

In order to give an objective assessment of its performance, NeuroQFormer-Net was benchmarked against a number of modern brain tumor segmentation models based on the BraTS benchmark data using multi-modal MRI inputs and segmentation measures. Table 8 reveals that the classic convolutional networks such as U-Net and Attention U-Net attained Dice scores of 89.12% and 91.36%, correspondingly. While those techniques are able to extract local spatial features well enough, the small size of their receptive fields hinders modeling of long-range dependencies, leading to poor segmentation performance and decreased boundary delineation. When compared to U-Net, NeuroQFormer-Net provided an increase in the Dice score and Intersection over Union measures of 7.33% and 10.81%, respectively.

The ablation analysis demonstrates a substantial overall improvement from 88.92% Dice for the baseline CNN to 96.45% for the complete NeuroQFormer-Net, corresponding to a gain of 7.53 percentage points. This large change indicates that the improvement is not attributable to a single generic increase in network depth. Instead, the component sequence is intended to address different error sources: quaternion learning targets cross-modal representation and redundancy, attention emphasizes informative feature responses, transformer blocks enlarge contextual reasoning, adaptive fusion integrates complementary feature scales, and boundary refinement targets contour-level errors. Moreover, our architecture was able to obtain a minimal Hausdorff Distance of 2.31 mm, showing that our model localized boundaries accurately with minimal deviations from expert annotations.

Several limitations should be considered before interpreting the reported performance as evidence of clinical readiness. First, the evaluation is primarily based on the BraTS 2021 dataset. Although BraTS provides a standardized benchmark, performance on a benchmark cohort does not guarantee robustness across institutions, scanners, acquisition protocols, field strengths, reconstruction pipelines, or patient populations. External multi-centre validation is therefore required. Second, the proposed strategy is slice-based rather than fully volumetric. A 2D approach

can reduce memory requirements and simplify training, but it does not directly model all through-plane anatomical relationships. This may be important for lesions whose appearance changes substantially across adjacent slices. Third, the combination of quaternion processing, attention, transformer modules, adaptive fusion, and boundary refinement increases computational and implementation complexity.

From a technical perspective, quaternion-based multimodal representation provides a potentially useful design principle for future medical-image fusion architectures. Rather than treating modalities as unrelated channels followed by late concatenation, a coupled representation can encourage the network to learn complementary evidence and suppress repeated information before higher-level contextual modeling. This principle could be extended to other multimodal combinations, including MRI sequences, PET/MRI, CT/MRI, or imaging combined with additional spatially aligned measurements, provided that the modalities can be represented in a compatible coupled feature space. Future research can investigate lightweight quaternion operators, quaternion-transformer hybrids, uncertainty-aware fusion, and adaptive modality weighting to reduce computational cost while preserving the benefits of cross-modal learning. From a clinical perspective, the strong WT, TC, and ET delineation can potentially support radiotherapy planning by improving target-volume definition, assist surgical assessment by providing quantitative tumor extent, enable automated volumetric monitoring during follow-up, and facilitate longitudinal assessment of treatment response or residual/recurrent disease. Nevertheless, these applications require more than high benchmark Dice scores. Clinical adoption should be preceded by external multi-centre testing, prospective evaluation, end-to-end workflow assessment, robustness analysis, calibration/uncertainty assessment, and reader studies demonstrating that the automated contours provide reliable and clinically useful assistance. Accordingly, NeuroQFormer-Net should currently be regarded as a promising research framework rather than a clinically validated deployment-ready system.

VI. Conclusion

NeuroQFormer-Net is proposed. It has a Quaternion-Guided Hybrid Attention Transformer Fusion Network. It is used for precise brain tumor segmentation using multimodal MRI images. In the proposed approach, features are learned through a quaternion-based inter-modal feature representation mechanism, hybrid attention learning, contextual modeling using transformers, adaptive feature fusion, and boundary-aware refinement techniques. The effectiveness of the proposed method has been evaluated using the BraTS 2021 benchmark dataset. In the process, the model

achieved a Dice Similarity Coefficient of 96.45%, Intersection Over Union of 93.26%, Precision of 96.17%, Recall of 96.08%, and Hausdorff Distance of 2.31 mm. From the above figures, it can be said that NeuroQFormer-Net provides accurate tumor localization and robust boundary preservation. Despite its good performance, this framework needs high computational capacity due to the involvement of the quaternion calculation module and the transformer module. Also, validation of the proposed method is performed using the BraTS 2021 benchmark dataset. Validation through other multi-center datasets needs to be done in order to generalize the proposed method. Further work will involve external validation using different imaging protocols, optimization to enable fast inference, and the use of an explainable and uncertainty learning model. However, despite its impressive performance, the architecture demands high computational power as it makes use of quaternions and transformer blocks. Moreover, the validation is done on the BraTS 2021 benchmark dataset, while it is required to perform testing on other multi-center clinical datasets. The future work involves external validation on different imaging protocols, optimizations to increase inference speed, and the use of explainable and uncertainty-aware techniques.

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Data Availability: The dataset used in this study is publicly available through the BraTS 2021 benchmark repository. No new patient dataset was generated by the authors. Additional processed data and experimental outputs may be made available by the corresponding author upon reasonable request.

Code Availability: The source code and implementation details of NeuroQFormer-Net are available from the corresponding author upon reasonable request.

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