A Multi-Domain Feature Fusion Framework Integrating DCT, DWT, and Deep CNN for Brain Tumor Classification

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Background: The study investigates brain tumor diagnosis using MRI, a fundamental task in neuro-oncology, as accurate tumor type identification determines diagnostic outcomes and treatment strategies. Deep learning techniques have achieved substantial success with Convolutional Neural Networks (CNNs), which primarily extract spatial features while often overlooking other essential information, such as frequency and multi-scale information.

Method: The study proposes a hybrid multi-domain framework that combines spatial features from a Pretrained ResNet-50 model with frequency-domain data obtained via the Discrete Cosine Transform (DCT) and multi-scale data from the Discrete Wavelet Transform (DWT). A channel attention mechanism fuses the extracted features by dynamically selecting the most discriminative ones. The model uses 5-fold stratified cross-validation to assess its performance on the TCIA MU-Glioma-Post dataset.

Results: The proposed hybrid model reached an overall classification accuracy of 97%, with weighted precision, recall, and F1-score all at about 0.97. It also showed strong performance across tumor types, with AUC-ROC values close to 0.99. Compared to baseline models, this framework improved accuracy by 3-5%, supporting the value of integrating features from multiple domains.

Discussion: The combination of spatial, frequency, and multi-scale representations emerges as a superior approach for MRI data classification, as it captures complementary information from the data. The attention mechanism enhances the model's ability to adaptively weight each feature during processing. The findings suggest that medical image analysis benefits from multi-domain feature fusion, and the developed framework demonstrates high-precision classification of brain tumors.

Keywords: Brain Tumor Classification; Magnetic Resonance Imaging (MRI); Deep Learning; Discrete Cosine Transform (DCT); Discrete Wavelet Transform (DWT); Attention-Based Feature Fusion

Introduction:

The global healthcare system faces a major healthcare challenge from brain tumors, which cause severe health outcomes and develop in complex ways within the central nervous system [1][2]. Accurate diagnosis is essential throughout the clinical process, as Magnetic Resonance Imaging (MRI) is the best non-invasive method for identifying brain tumors [1][3]. The process of manually interpreting multimodal MRI scans, including T1, T2, and FLAIR sequences, is time-consuming and may yield inconsistent interpretations across observers [4][5].

Recent advances in Artificial Intelligence (AI) have enabled the development of fully automated diagnostic systems. Comprehensive reviews in [1] and [6] demonstrate that Deep Learning (DL) currently leads the field of neuro-oncology research and clinical practice. Technological development has advanced from basic Machine Learning (ML) systems to advanced systems capable of handling multiple classes and delivering accurate segmentation results [7][8]. The survey papers demonstrate that Convolutional Neural Networks (CNNs) and their variations, including U-Net, serve as the standard approach for all clinical segmentation tasks [8][9].

Current systems demonstrate advanced capabilities, yet they still exhibit fundamental limitations. Systematic reviews highlight major concerns regarding clinical explainability, as many DL medical models function as "black boxes." that medical professionals cannot understand [3][10]. The use of TransUNet models [11] for segmentation has achieved higher accuracy, but the system still struggles to maintain consistent performance across datasets from different institutions due to data scarcity and domain shifts [4][5].

Although deep learning has improved brain tumor classification, most current methods mainly use spatial features from CNNs and do not fully integrate other types of features. Some hybrid models exist, but they usually do not combine frequency-domain and multi-scale information in a structured way. Attention mechanisms are also mostly used within single domains, not across different types of features. As a result, there is still a need for a unified approach that brings together spatial, frequency, and multi-scale features with adaptive weighting.

The rest of this paper is structured as follows. Section II reviews related work and highlights current methods for brain tumor classification and segmentation. Section III explains our methodology, covering preprocessing, feature extraction, and the hybrid fusion model. Section IV shares our experimental results, including both quantitative and qualitative evaluations. Section V discusses our findings and offers insights into how our approach performed. Section VI wraps up the paper and suggests directions for future work.

Research Objectives:

The objectives of this study are as follows:

To develop a hybrid framework that integrates spatial, frequency-domain, and multi-scale features for brain tumor classification.

To investigate the effectiveness of combining CNN, DCT, and DWT features within a unified architecture.

To evaluate the impact of attention-based feature fusion on classification performance.

To compare the proposed model with baseline methods using standardized evaluation metrics.

Contributions:

The key contributions of this work are summarized as follows:

A novel hybrid framework is proposed that integrates deep spatial features extracted from a pretrained CNN backbone with frequency-domain descriptors derived from DCT and multi-scale wavelet features obtained via DWT. This combination enables the model to capture complementary information that is not fully represented by any single modality.

A channel attention module is introduced to adaptively reweight the fused feature representations, allowing the model to emphasize the most informative components across spatial, spectral, and multi-resolution domains.

Comprehensive ablation studies are conducted to determine optimal configurations for DCT coefficient selection and wavelet basis functions, providing empirical validation of design choices and demonstrating the importance of balanced feature representation.

The proposed model is evaluated against multiple baseline approaches, including standalone CNN, DCT-based, and DWT-based classifiers, under a consistent cross-validation framework, demonstrating superior performance in terms of accuracy, FI-score, and AUC.

The study provides empirical evidence that combining spatial, frequency, and multi-scale representations leads to improved classification performance, highlighting the importance of multi-domain feature integration in medical image analysis.

Novelty:

This study introduces an approach that integrates spatial, frequency, and multi-scale feature representations within a unified attention-based framework. In contrast to existing methods that use only a single domain or combine multiple feature types without structured fusion, the proposed model employs a structured fusion of features derived from the Discrete Cosine Transform (DCT), the Discrete Wavelet Transform (DWT), and Convolutional Neural Networks (CNNs). Additionally, a channel attention mechanism is applied across these feature spaces, enabling adaptive feature weighting and thereby enhancing both classification performance and interpretability.

Background & Related Work:

Deep Learning (DL) and Machine Learning (ML) technologies have transformed neuro-oncology by enabling advanced analysis of brain tumors from MRI scans. The section presents the current state of the art through a dedicated investigation of three main areas: detection methods, classification techniques, and segmentation methods, along with their corresponding optimization methods and security systems.

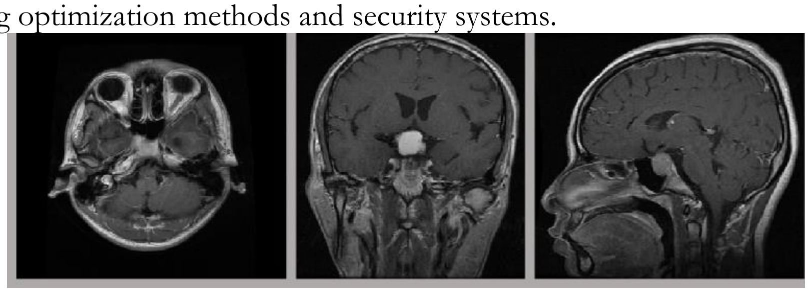

Figure 1 MRI of Tumors, (a) glioma, (b) meningioma, (c) pituitary tumors.

Automated classification is essential for distinguishing between various tumor pathologies such as glioma, meningioma, and pituitary tumors, as shown in

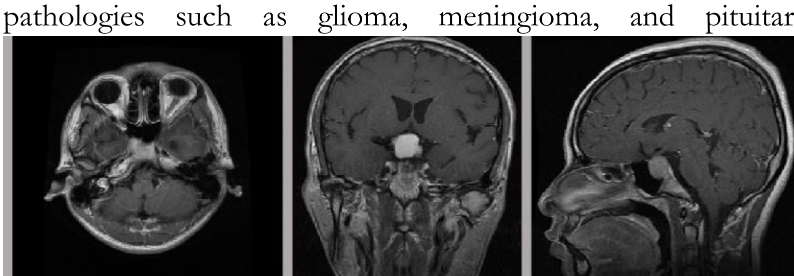

Figure 1. Traditional approaches have been superseded by Convolutional Neural Networks (CNNs) because they provide better feature extraction capabilities according to research [12][13]. The study by [14] demonstrated an improved DL method for more precise diagnostic results, while [15] developed a comprehensive system to improve the processing of MRI images.

Transfer learning has emerged as a particularly effective strategy for classification when researchers have limited access to annotated medical datasets. [16] used transfer learning methods, achieving high detection rates, while [17] employed T1-weighted MRI data and hybrid models to enhance their classification system. [18] introduced soft attention mechanisms to enhance the model's focus on subtle tumor features, while [19] combined metaheuristic optimization with gene expression data to develop a multidimensional diagnostic framework.

Segmentation accuracy plays a crucial role in both treatment planning and surgical navigation processes. The literature shows a clear evolution from basic architectures to models that prioritize boundary precision, as reported in research studies. The Sparse Dynamic Volume TransUNet system introduced an advanced approach that uses multi-level edge fusion to effectively capture complex tumor shapes, as reported by [11]. The research conducted by [20] introduced two methods, including spatial information enhancement and boundary shape correction, to improve standard CNN performance for tumor border detection.

Segmentation efficiency has now become an essential focus area. [21] created an EfficientNet-enhanced [21] developed an EfficientNet-enhanced UNet system that achieves optimal performance through a balanced trade-off between computational complexity and system capabilities. IC-weighted knowledge distillation technology was introduced to reduce the computational requirements of heavy models. Hybrid diagnostic systems, which combine Fuzzy C-Means (FCM) with Support Vector Machines (SVM), demonstrate strong potential to enhance segmentation accuracy in complex MRI scan analysis, according to research by [22]. Combines multiple algorithms to create systems that overcome their inherent limitations. The system developed by Celik and Inik [23] fuses deep learning with optimized machine learning algorithms to achieve accurate and reliable multiclass classification, according to research findings [24].

Recent progress in medical imaging has focused on hybrid deep learning models to improve the accuracy of brain tumor identification and segmentation. Some researchers have created secure hybrid systems that combine classification and detection, while others have used attention mechanisms to make these models both accurate and interpretable in clinical settings. New methods also use dynamic weighted knowledge distillation to sharpen segmentation boundaries, and deep learning pipelines designed specifically for MRI analysis. Recent reviews and studies show a shift from traditional CNNs to more advanced, explainable models such as CNN-TumorNet, underscoring the need for transparency in automated cancer diagnosis [25][26][27][28][29][30].

Optimization techniques adjust the operational parameters that control the performance of complex network systems. The research conducted by [31], together with [32], introduced optimized learning systems that significantly reduce error rates. The comparative analysis of the different models has shown that optimized hybrid frameworks currently provide the best solution for managing diverse brain tumor datasets according to research studies [33]. Attention to Explainable AI (XAI) and data security has become increasingly important as automated systems are increasingly applied in medical settings. The "black-box" nature of early DL models is being addressed by frameworks like CNN-TumorNet, which prioritize clinical explainability alongside hybrid models with transparent design. The development of secure hybrid frameworks followed the emergence of medical data privacy issues, as these frameworks protect patient privacy while enabling efficient diagnostics, according to research by [25]. The medical imaging field has reached a "neural frontier" that provides both precision and secure trust, according to studies.

Table 1. Comparison of Existing Brain Tumor Classification Approaches with the Proposed Method

Study	Method Used	Feature Domain	Attention / XAI Used	Performance	Limitation	Comparison with Proposed Study
[12]	Deep CNN-based brain tumor detection and classification	Spatial CNN features	No explicit attention	High classification performance reported	Mainly depends on spatial features; frequency and wavelet information are not considered.	The proposed method improves by combining CNN spatial features with DCT frequency and DWT multi-scale features.
[13]	Deep learning model for MRI-based brain tumor classification	Spatial image features	No	Improved classification accuracy	Single-domain feature learning; limited feature diversity	The proposed model uses multi-domain feature fusion instead of relying only on deep spatial features
[16]	Transfer learning-based brain tumor detection	Spatial transfer learning features	No	High detection rate reported	Performance depends heavily on pretrained CNN representations	The proposed method adds handcrafted frequency and wavelet descriptors to improve feature complementarity
[18]	Feature-enhanced deep learning with soft attention	Spatial CNN features	Yes, soft attention	Improved MRI classification performance	Attention is applied mainly to spatial features; no explicit DCT/DWT integration.	The proposed method applies attention after fusing spatial, frequency, and multi-scale features.
[23]	Hybrid deep learning and optimized machine learning for multi-classification	Deep + optimized ML features	No explicit attention	Strong multi-classification performance	Hybridization is present, but lacks structured multi-domain feature fusion	The proposed method provides a structured CNN + DCT + DWT fusion with channel attention

[24]	Hybrid ensemble deep learning model	CNN ensemble features	Limited / not central	Improved detection performance	Ensemble models may increase computational cost and complexity	The proposed model achieves strong performance using targeted multi-domain fusion rather than heavy ensemble dependency
[22]	FCM-SVM-based segmentation and classification	Handcrafted/classical ML features	No	Improved segmentation and classification	Limited deep representation learning capability	The proposed method combines classical transform-based features with deep CNN features.
[14]	Deep learning-based MRI classification	Spatial CNN features	No explicit attention	Accurate diagnosis reported	Does not explicitly model frequency-domain or wavelet-based information	The proposed method improves representation richness through DCT and DWT branches
[26]	Hybrid deep learning with attention and explainability	Spatial + optimized deep features	Yes	Strong performance with explainability	Does not explicitly integrate DCT frequency and DWT multi-scale features	The proposed method extends attention-based learning using structured spatial, frequency, and multi-scale fusion
[10]	A hybrid explainable ML and DL model	ML + DL features	Explainability included	High classification performance reported	Feature fusion is not centered on DCT/DWT frequency-wavelet complementarity.	The proposed method specifically targets complementary CNN, DCT, and DWT representations.
[33]	Comparative analysis of significant deep learning models	CNN/deep features	Not central	Multi-model comparison reported	Focuses on comparing existing DL	The proposed study introduces a new fusion framework

					models rather than proposing structured multi-domain fusion	rather than only comparing CNN models
Proposed Study	Hybrid DCT + DWT + CNN with Channel Attention	Spatial + frequency + multi-scale	Yes, channel attention + Grad-CAM	97% accuracy, weighted F1-score 0.970, AUC close to 0.99	Limited to 2D MRI slices and single-dataset validation	Provides structured multi-domain feature fusion and outperforms individual CNN, DCT, and DWT baselines

Table 1 shows that most current approaches mainly use spatial features from deep learning models and include little frequency-domain or multi-scale information. In addition, many hybrid models are poorly integrated and lack attention mechanisms for adaptive feature selection. These gaps support the need for the unified multi-domain framework proposed in this study.

Methodology:

This section presents the proposed hybrid framework for brain tumor classification, which integrates spatial, frequency-domain, and multi-scale representations within a unified learning architecture. As illustrated in

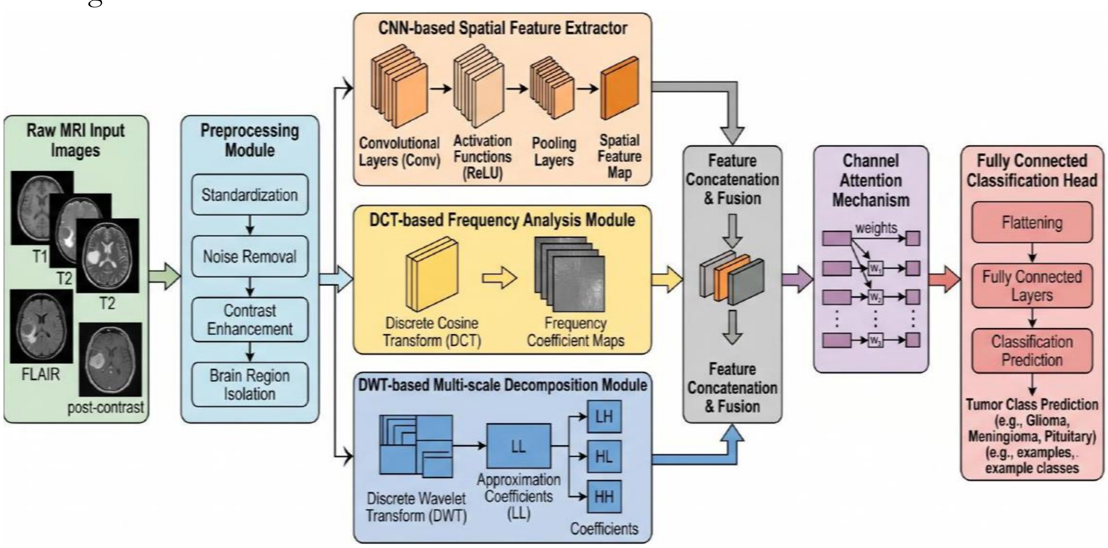

Figure 2, the overall pipeline consists of four major stages: preprocessing, multi-domain feature extraction, feature fusion using attention, and final classification.

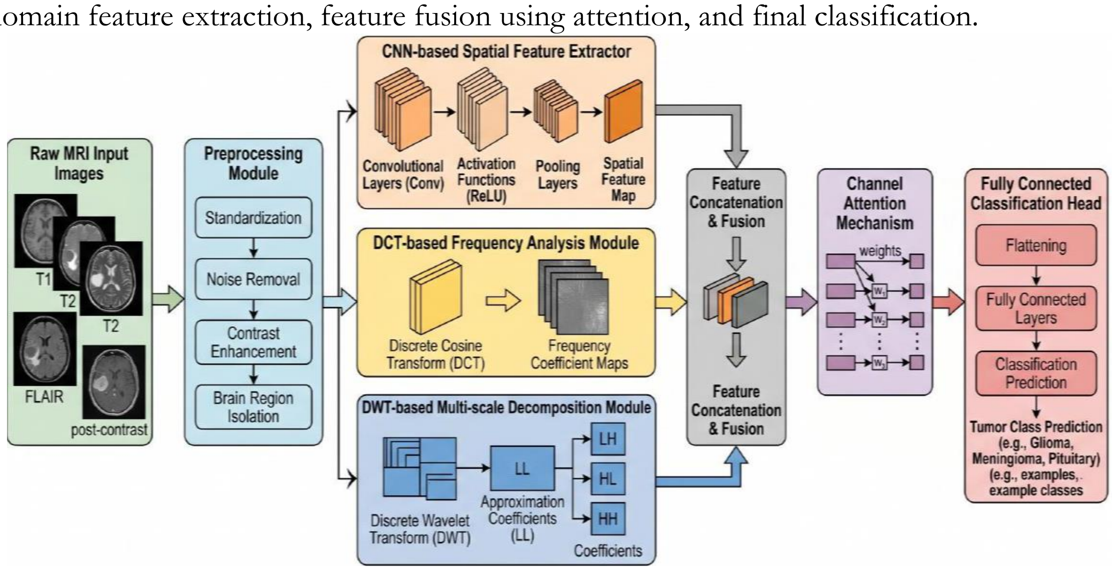

Figure 2. Overall pipeline of the proposed hybrid brain tumor classification system. The framework integrates preprocessing, multi-domain feature extraction, and attention-based fusion.

The process begins with raw MRI input images, which are initially processed by a preprocessing module to standardize intensity distributions, remove irrelevant regions, and improve feature consistency. This step involves grayscale conversion, resizing, contrast enhancement using CLAHE, skull stripping, and normalization to ensure the input data is suitable for subsequent feature extraction. Following preprocessing, the normalized image is input into three parallel feature-extraction branches. The first branch employs a pretrained ResNet-50 model to extract deep spatial features, capturing hierarchical patterns such as edges, textures, and structural tumor characteristics. The second branch applies the Discrete Cosine Transform (DCT) to convert the spatial image into the frequency domain, facilitating the extraction of global intensity patterns and spectral energy distributions. The third branch uses the Discrete Wavelet Transform (DWT) for multi-level decomposition, capturing both coarse and fine-grained features at different spatial resolutions. Feature vectors from these three branches are projected into compatible embedding spaces and concatenated to form a unified multi-domain feature representation. This fused feature vector integrates complementary information from spatial, frequency, and multi-scale domains. To further enhance discriminative capability, a channel attention mechanism is applied to the fused features. This module learns adaptive weights for each feature dimension, emphasizing the most relevant components while suppressing less informative ones. The attention-refined feature vector is then passed through a fully connected classification head that maps the features to class probabilities via a SoftMax function. The pipeline illustrated in

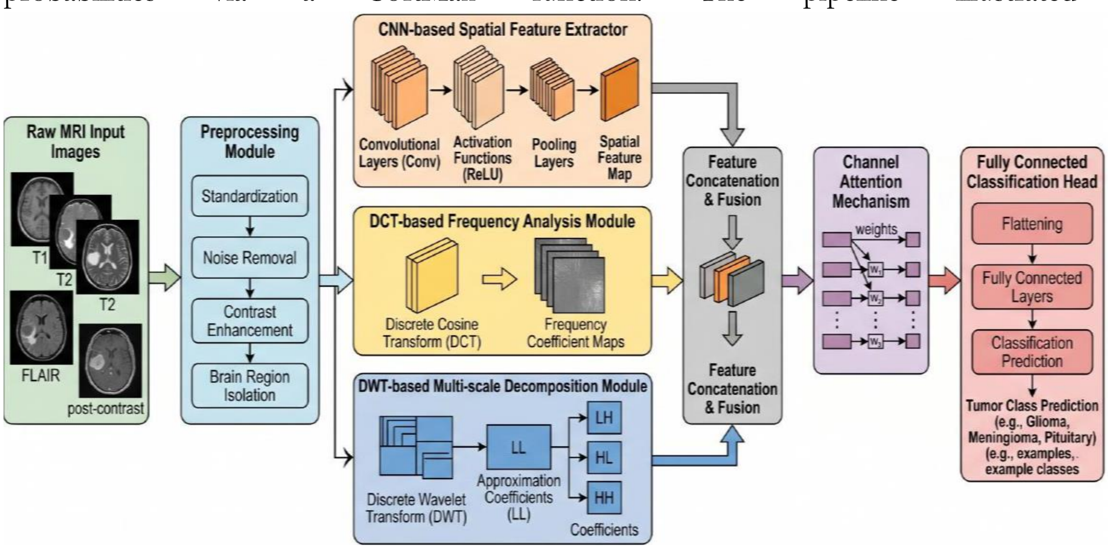

Figure 2 demonstrates how the proposed model integrates heterogeneous feature representations within a unified architecture, thereby enabling robust and accurate classification of brain tumor types.

Dataset Description:

The dataset used in this study is the publicly available Brain Tumor MRI Classification dataset, sourced from The Cancer Imaging Archive (TCIA) collection MU-Glioma-Post, accessible at https://www.cancerimagingarchive.net/collection/mu-glioma-post/. The dataset contains T1-weighted MRI brain scans organized into four clinically distinct categories: Glioma, Meningioma, No Tumor, and Pituitary Tumor. These classes represent the most commonly diagnosed intracranial tumor types encountered in clinical neuro-oncology practice. Each image in the dataset is a 2D grayscale axial MRI slice stored in standard image format. The dataset provides a diverse set of imaging characteristics across the four classes, reflecting real-world variation in tumor size, location, morphology, and signal intensity, all of which are exploited during feature extraction.

Let the dataset be represented as:

$$\mathcal{D} = \{(X_i, y_i)\}_{i=1}^{N} \ (1)$$

Where $X_i \in R^{H \times W}$ denotes the input MRI image and $y_i \in \{1,2,3,4\}$ represents the corresponding tumor class label.

The dataset comprises 8,118 TI-weighted axial MRI images across four classes: Glioma, Meningioma, No Tumor, and Pituitary Tumor. To ensure unbiased evaluation, the dataset is partitioned using stratified sampling into training, validation, and testing sets while preserving class distribution. Furthermore, a 5 -fold cross-validation strategy is employed to enhance robustness and minimize variance in performance estimation.

Preprocessing Pipeline:

MRI images exhibit variability in intensity distribution and structural noise, which can negatively impact model performance. Therefore, a standardized preprocessing pipeline is applied, as shown in Fig. 2.

Given an input image$X$, the preprocessing steps are defined as follows. First, the image is converted to grayscale:

$$X_g = \mathrm{Gray}(X) (2)$$

Next, the image is resized to a fixed resolution:

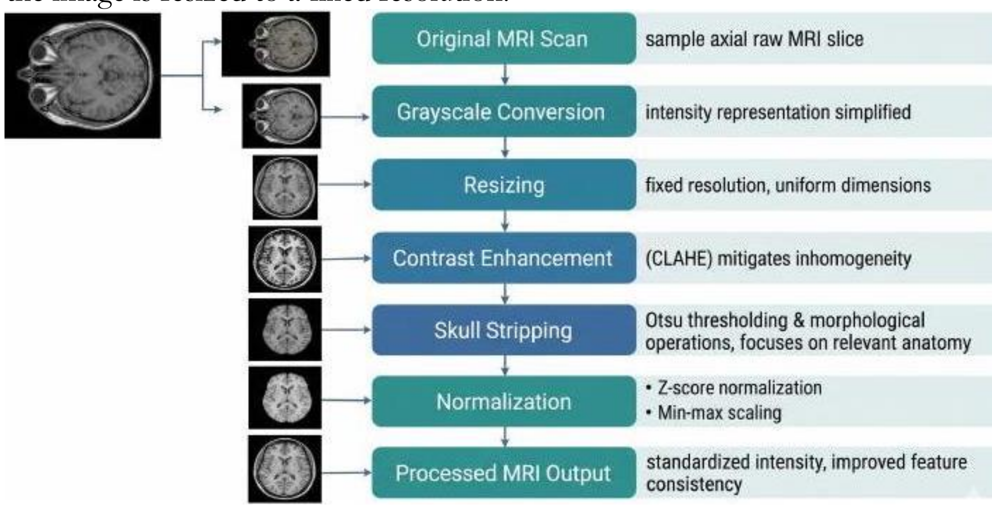

Figure 3. Preprocessing pipeline applied to MRI images

$$X_r = \mathrm{Resize}\left(X_g, 256 \times 256\right) (3)$$

To address intensity inhomogeneity, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied:

$$X_c = \mathrm{CLAHE}(X_r) (4)$$

Subsequently, skull stripping is performed using Otsu thresholding to generate a binary mask:

$$M = 1(X_c > \tau_{\mathrm{Otsu}}) (5)$$

The brain region is extracted as:

$$X_s = X_c \odot M (6)$$

Finally, normalization is applied using the Z-score transformation:

$$X_n = \frac{X_s - \mu}{\sigma} (7)$$

Followed by min-max scaling:

$$X_{\mathrm{norm}} = \frac{X_n - \min(X_n)}{\max(X_n) - \min(X_n)} (8)$$

Multi-Domain Feature Extraction: To capture complementary information, features are extracted from three domains: spatial, frequency, and multi-scale. The overall feature extraction pipeline is illustrated in Figure 3.

Spatial Feature Extraction Using CNN: Deep spatial features are extracted using a pretrained ResNet-50 model. The model is trained for 50 epochs with a batch size of 16 using the AdamW optimizer with a learning rate of 10^{-4}. Early stopping is applied based on validation loss to prevent overfitting.

Let $\phi_{\text{CNN}}(\cdot)$ denote the feature extraction function. The output feature vector is:

$$F_{\text{CNN}} = \phi_{\text{CNN}}(X_{\text{norm}}) \in R^{2048} \quad (9)$$

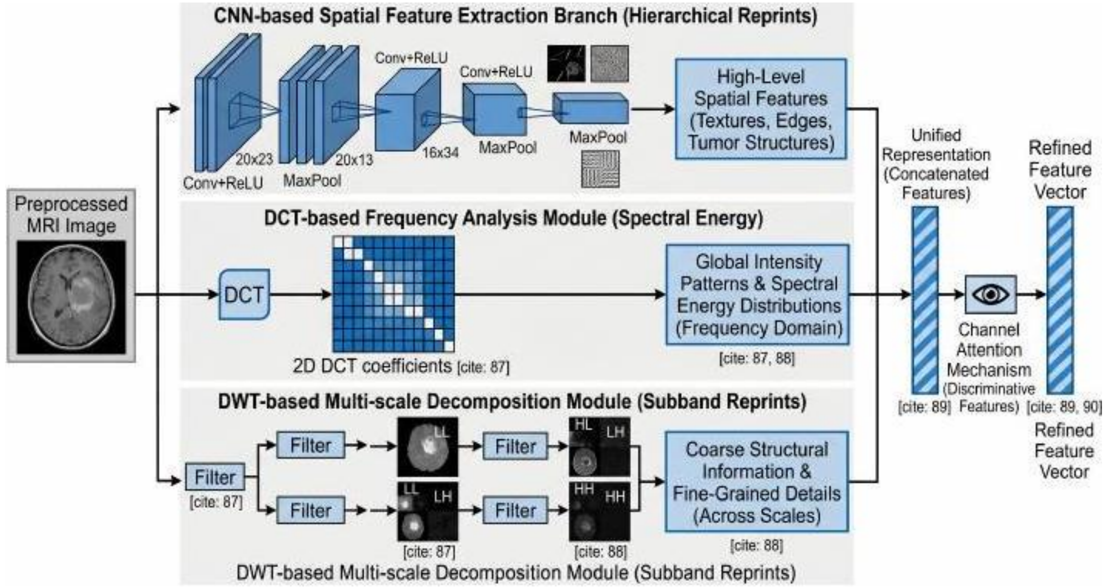

Figure 4. Parallel feature extraction pipeline

This representation encodes hierarchical spatial information such as edges, textures, and structural tumor patterns.

Frequency-Domain Feature Extraction Using DCT:

The Discrete Cosine Transform (DCT) converts the spatial image into frequency components:

$$C(u,v) = \alpha(u)\alpha(v) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} X_{\text{norm}}(x,y) \cos\left[\frac{\pi(2x+1)u}{2N}\right] \cos\left[\frac{\pi(2y+1)v}{2N}\right] (10$$

To retain the most informative features, only the top k

$$C' = \{C(u,v) \mid |C(u,v)| > T_k\} \quad (11)$$

Statistical descriptors are then computed:

$$F_{\text{DCT}} \in R^{12} \quad (12)$$

Multi-Scale Feature Extraction Using DWT:

The Discrete Wavelet Transform (DWT) decomposes the image into multiple frequency bands:

$$X_{\text{norm}} \xrightarrow{\text{DWT}} \{LL_i, LH_i, HL_i, HH_i\}_{i=1}^{L} \quad (13)$$

For each sub-band S, statistical features are computed:

$$\mu_S = \frac{1}{|S|} \sum_{x \in S} x \quad (14)$$

$$\sigma_S^2 = \frac{1}{|S|} \sum_{x \in S} (x - \mu_S)^2 \quad (15)$$

The final feature vector is:

$$F_{\text{DWT}} \in R^{40} \quad (16)$$

Proposed Hybrid Fusion Model:

The Hybrid Fusion Model combines information from multiple feature domains to improve brain tumor classification. Instead of using only CNN-based spatial features, the model combines three types of data: deep spatial features from a pretrained ResNet-50, frequency-domain descriptors from Discrete Cosine Transform (DCT), and multi-scale texture features from Discrete Wavelet Transform (DWT). These features are converted into compatible embeddings and merged into a single feature vector. A channel attention mechanism then highlights the most important features and reduces the impact of less useful ones. The refined feature vector is fed into fully connected layers for tumor type classification. By fusing spatial, spectral, and multi-scale features from MRI images, this approach makes the model more robust than methods that use only one type of feature, as shown in

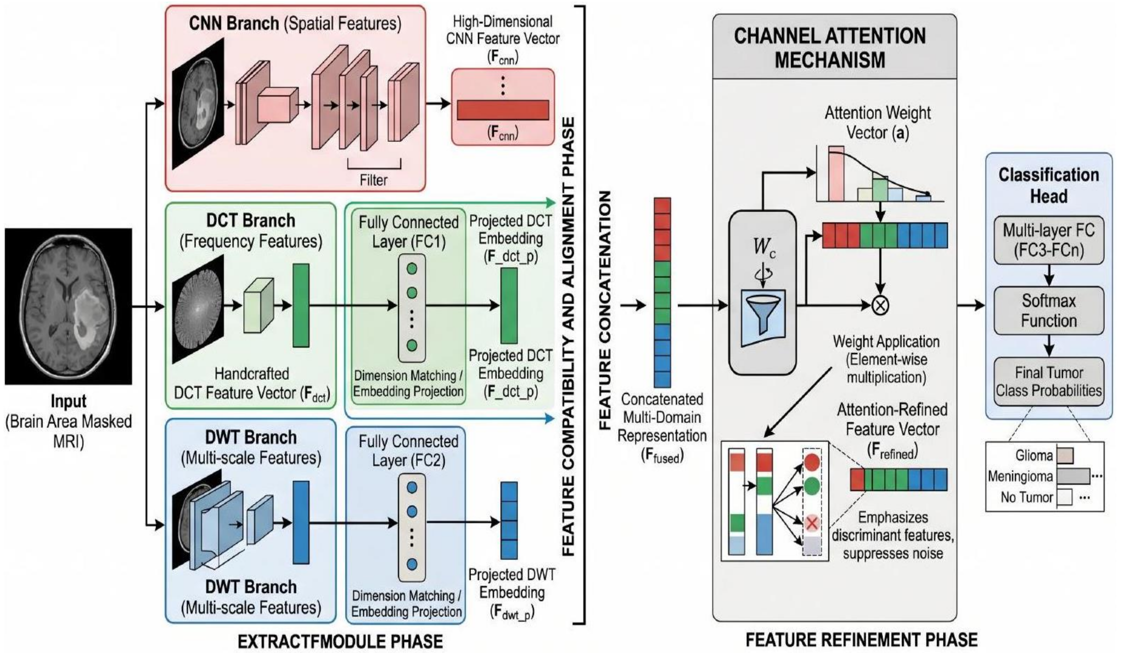

Figure 5.

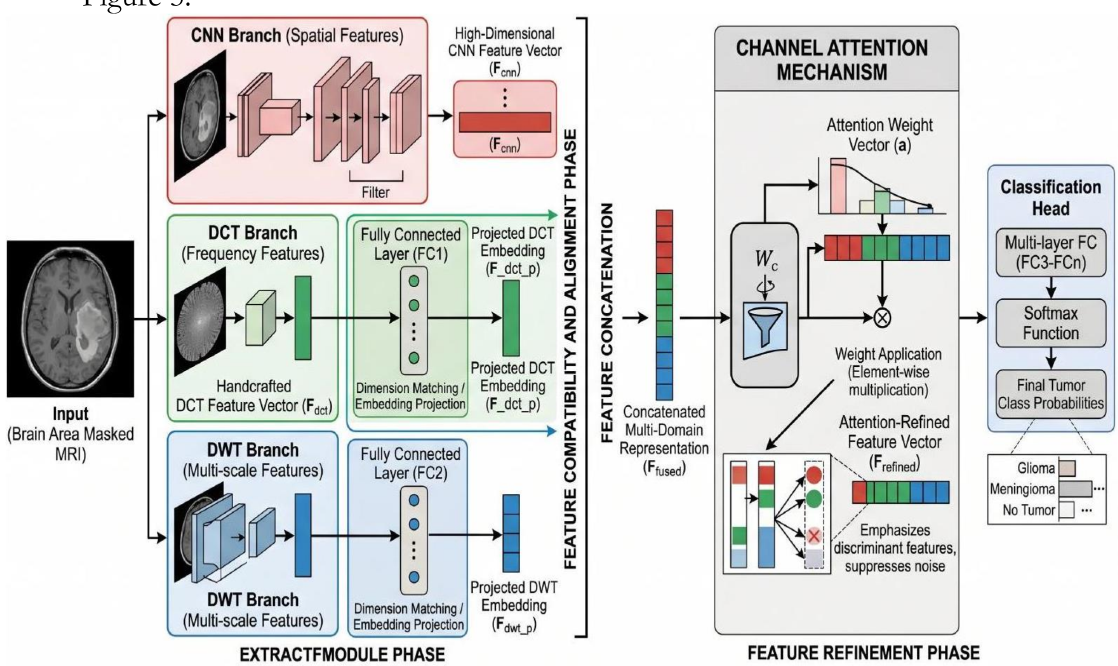

Figure 5. Hybrid fusion model combining CNN, DCT, and DWT features with channel attention

First, DCT and DWT features are projected into higher-dimensional representations:

$$F'_{\mathrm{DCT}} = W_d F_{\mathrm{DCT}} + b_d \ (17)$$

$$F'_{\mathrm{DWT}} = W_w F_{\mathrm{DWT}} + b_w \ (18)$$

The combined feature vector is formed as:

$$F_{\text{fusion}} = [F_{\text{CNN}}, F'_{\text{DCT}}, F'_{\text{DWT}}] \quad (19)$$

To enhance discriminative features, a channel attention mechanism is applied:

$$A = \sigma\left(W_2 \cdot \text{ReLU}\left(W_1 \cdot F_{\text{fusion}}\right)\right) \quad (20)$$

$$F_{\text{att}} = A \odot F_{\text{fusion}} \quad (21)$$

Finally, classification is performed using:

$$\hat{y} = \text{Softmax}(W_c F_{\text{att}} + b_c) \quad (22)$$

Training Strategy: The model parameters are optimized using the AdamW optimizer:

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta \mathcal{L} \quad (23)$$

Where $\mathcal{L}$ is the cross-entropy loss:

$$\mathcal{L} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \quad (24)$$

Data augmentation techniques such as rotation, flipping, and scaling are applied during training to improve generalization.

Evaluation Metrics: Model performance is evaluated using standard metrics:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (25)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (26)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (27)$$

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (28)$$

Overall, the proposed method integrates preprocessing, multi-domain feature extraction, and attention-based fusion into a single framework for classifying brain tumors. By combining CNN-based spatial features, DCT-derived frequency information, and DWT-based multi-scale representations, the model can capture different aspects of MRI data. Adding a channel attention mechanism helps the model adaptively weight features, improving its ability to distinguish between tumor types. Systematic preprocessing, careful feature selection, and a robust training approach help the model remain consistent and generalize well across tumor classes. The next section presents experimental results demonstrating the effectiveness of this framework.

Results:

This section reports both quantitative and qualitative evaluations of the proposed hybrid fusion model. We assessed its performance using 5 -fold stratified cross-validation and compared it to baseline methods to show how multi-domain feature integration improves results.

Model Performance:

Table **2** shows the overall classification results for our method and the baseline models. The hybrid fusion model achieved **97%** accuracy and a weighted F_1score of 0.970, outperforming all individual approaches.

Figure 5 further illustrates that the hybrid model consistently outperforms the individual models on all evaluation metrics.

The observed improvement demonstrates that integrating spatial, frequency, and multi-scale features provides a more discriminative representation compared to single-domain approaches.

Table 2. Model Performance Comparison

Model	Accuracy	FI-Score
CNN (ResNet-50)	92%	0.919
DCT + SVM	94%	0.938
DWT + RF	93%	0.929
Hybrid Fusion	**97%**	**0.970**

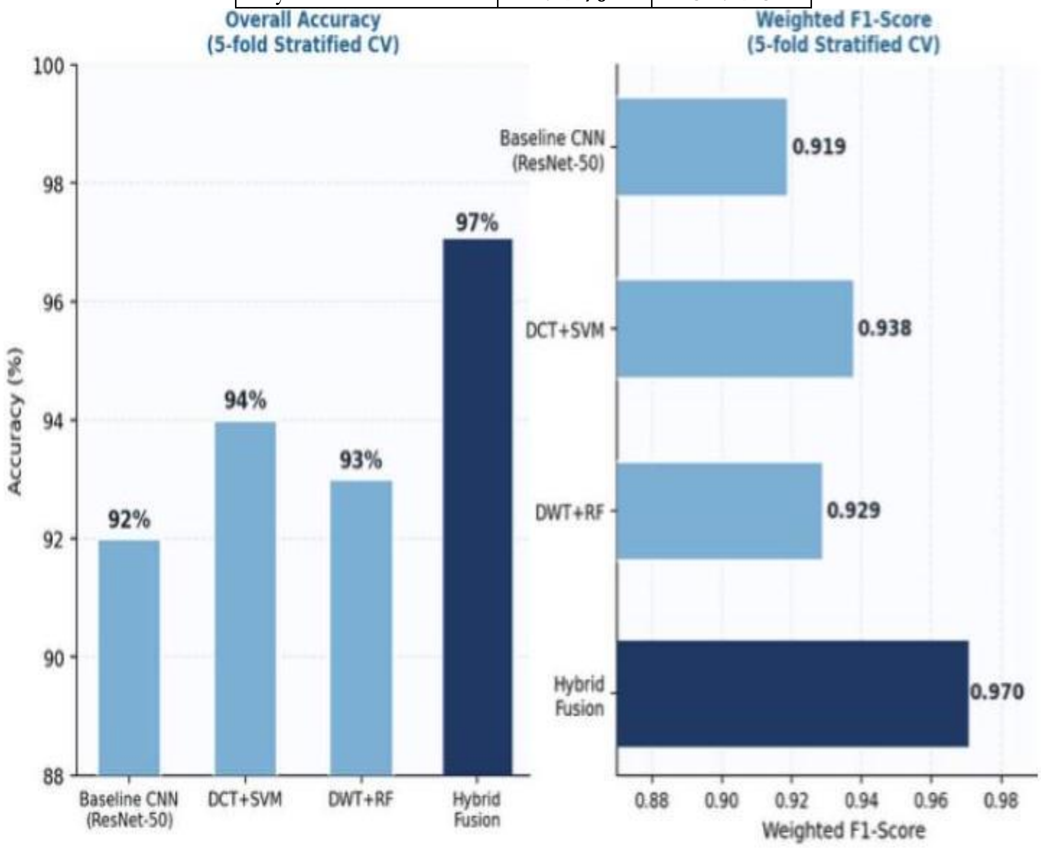

Figure 6. Comparison of model performance in terms of accuracy and FI-score

Class-Wise Performance Analysis: Table 3 shows how the proposed model performed on each class in the test set.

Table 3. Per-Class Classification Performance of the Hybrid Model

Class	Precision	Recall	F1-Score	AUC
Glioma	0.97	0.97	0.97	0.99
Meningioma	0.95	0.96	0.95	0.98
No Tumor	0.99	0.99	0.99	1.00
Pituitary	0.98	0.97	0.97	0.99

The results show that the model performs well across all classes, with the highest accuracy for the "No Tumor" class. The Meningioma class had slightly lower performance, likely because its visual features sometimes overlap with Glioma in MRI images.

Confusion Matrix Analysis: The confusion matrix of the proposed model is shown in Fig. 6. The confusion matrix shows that most predictions lie along the diagonal, indicating correct classifications. The most frequent misclassifications occur between the Glioma and Meningioma classes, as expected given their similar MRI morphological patterns. Overall, the model achieves a low error rate of approximately2.9%, confirming its robustness.

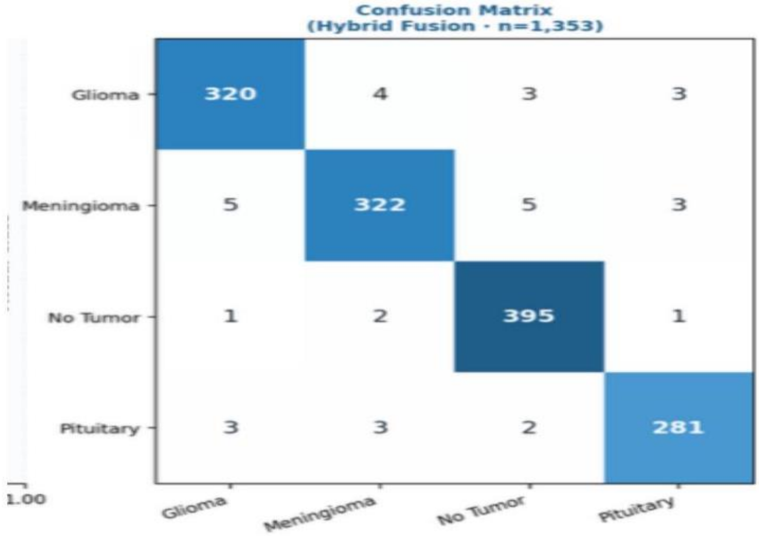

Figure 7. Confusion Matrix of Hybrid Fusion Model

Ablation Study on DCT Coefficient Selection: To evaluate the impact of frequency feature selection, an ablation study was conducted by varying the percentage of retained DCT coefficients. The results are summarized in Table 4.

Table 4. DCT Coefficient Selection Ablation Study

Top Coefficients	Accuracy	FI-Score
10%	89.3%	0.891
30%	94.0%	0.938
50%	92.1%	0.919
70%	91.5%	0.913

The results show that retaining 30% of DCT coefficients yields the best performance. Lower percentages fail to capture sufficient information, while higher percentages introduce noise from high-frequency components.

Wavelet Type Analysis: Table 5 presents how different wavelet bases affect classification performance.

Table 5. DWT Wavelet Comparison

Wavelet	Accuracy	F1-Score
Haar	90.4%	0.902
Sym4	91.7%	0.915
Db4	93.0%	0.929

The db4 wavelet gives the best results, showing it can capture both smooth structures and detailed boundaries well.

Qualitative Analysis Using Grad-CAM: We used Grad-CAM visualizations to help interpret the model's predictions, as shown in Fig. 7.

The heatmaps show that the model focuses on clinically relevant tumor regions. For example, Glioma predictions highlight irregular tumor edges, while Pituitary tumor predictions focus on the brain's center. This suggests the model learns spatial features that match radiological findings.

The experimental results show that the proposed hybrid fusion approach outperforms the other methods. By combining spatial (CNN), frequency (DCT), and multi-scale (DWT) features, the model can capture a wide range of MRI image characteristics.

CNN features capture spatial patterns, DCT features provide global frequency information, and DWT captures local changes at different scales. The attention mechanism improves results by adjusting the importance of each feature type. This combined approach yields greater accuracy and robustness than using individual models.

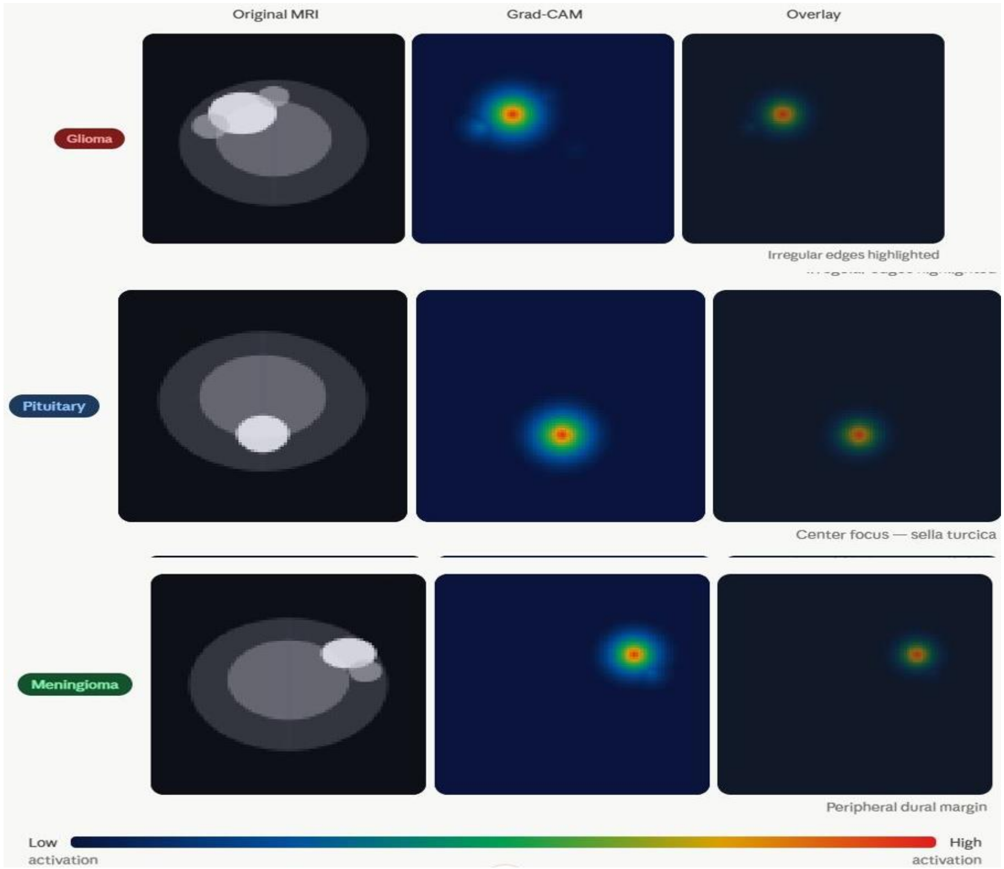

Figure 8. Grad-CAM Visualizations Highlighting Regions Influencing Model Predictions.

Practical Implications:

The proposed framework has potential applications in clinical decision support systems, where automated tumor classification can assist radiologists in diagnosis. The integration of multi-domain features improves reliability, while the attention mechanism enhances interpretability, making the system suitable for real-world deployment.

Discussion:

The results show that the proposed hybrid fusion model outperforms traditional single-domain methods for brain tumor classification. This is mainly because it combines three types of features: CNN-based spatial features, DCT-based frequency features, and DWT-based multi-scale features. Each feature type captures important information on its own, but together they give the model a fuller understanding of MRI data.

CNN-based features are effective at capturing spatial patterns such as edges, textures, tumor shapes, and local structures. However, CNNs mostly focus on spatial information and may miss global intensity or frequency details in MRI images. To address this, DCT features are added to capture frequency characteristics, such as overall energy distribution and low-frequency patterns. These are helpful because tumors can change the intensity and texture of MRI scans.

DWT features add multi-scale information by breaking down the MRI image into different sub-bands. This helps the model capture both large anatomical structures and small local details. Multi-scale representation is important in brain tumor analysis because tumor boundaries and texture changes can appear at different resolutions. Combining CNN, DCT, and DWT features helps the model better distinguish tumor types than using a single feature type alone.

The channel attention mechanism strengthens the framework by adjusting the weights each feature receives. Since features from different domains are not always equally useful across images or tumor types, attention helps the model focus on the most important features and ignore less useful ones. This selective weighting is especially helpful when combining features from multiple domains, as it allows the model to choose which features matter most for classification. As a result, attention improves both the model's ability to distinguish between classes and its overall performance.

The class-wise results also provide useful insights into the behavior of the proposed model. Looking at each class, the model performs best on the "No Tumor" class, which makes sense because normal brain MRIs usually look more distinct than those with tumors. The Meningioma class has slightly lower results, mainly because it looks similar to Glioma in some 2D MRI slices. Both tumor types can have overlapping features, especially when only axial slices are used. This is why most mistakes happen between Glioma and Meningioma. Still, the low overall misclassification rate shows that the model is robust across all four classes. The best DCT performance was achieved when 30% of the coefficients were retained. This indicates that selecting too few coefficients may remove useful frequency information, while retaining too many coefficients may introduce high-frequency noise and reduce classification performance. Similarly, the db4 wavelet produced better results than Haar and Sym4, suggesting that db4 provides a better balance between smooth structural representation and detailed boundary information. These findings confirm that careful feature selection and appropriate transformation choices are important for improving hybrid model performance.

Compared with other deep learning and hybrid methods, the proposed framework employs a more structured and comprehensive fusion strategy. Many current models focus mostly on CNN-based spatial features or loosely mix deep learning with traditional methods. In contrast, this model clearly integrates spatial, frequency, and multi-scale features into a single system and applies attention-based weighting after fusion. This helps the model capture a broader range of tumor characteristics, thereby improving classification reliability.

In practice, the proposed method could be a helpful tool for automated brain tumor classification. It provides accurate results and Grad-CAM visual explanations, helping clinicians see which image regions affect the prediction. However, this system is not meant to replace expert radiologists. Instead, it can support decision-making, help reduce workload, improve consistency, and assist with initial screening in clinical settings.

Although the model performs well, there are some limitations. First, it uses 2D MRI slices, which may miss some 3D tumor details. Second, the results are based on a single dataset, so testing on other datasets is needed to assess generalization. Third, while Grad-CAM gives some interpretability, more advanced explainable AI methods are needed to better understand the model's decisions. Finally, real-world use would need more testing for robustness, speed, scanner differences, and integration with clinical systems.

Future work will aim to extend the framework to 3D MRI data to better capture relationships between slices. Adding multimodal MRI sequences such as T1, T2, and FLAIR could also improve tumor characterization by providing additional anatomical and tissue information. Future studies should test the model on clinical datasets from different institutions to check its robustness. Further research may also look into advanced explainable AI methods and ways to optimize the model for real-time use in clinical decision-support systems.

Conclusion:

The study introduced an innovative hybrid system that leverages spatial, frequency, and multi-scale image representations to build a combined attention-based framework for brain tumor detection. The model demonstrates its ability to extract vital information by combining deep CNN features with DCT- and DWT-based handcrafted descriptors that capture data across multiple domains. The experimental results show that the hybrid fusion model outperforms baseline methods, achieving 97% composite accuracy and a weighted F1-score of 0.970. The system achieved performance enhancement through two primary components: multi-domain feature integration and a channel attention mechanism, which support adaptive feature selection while boosting discriminative strength. The study results prove that medical image analysis requires diverse feature representation methods for effective analysis. The combination of spatial, spectral, and multi-scale information enables researchers to gain a comprehensive understanding of tumor properties, thereby improving classification results. The present technique works effectively, although it uses only 2D MRI slices from a single dataset. Future studies will extend the framework to 3D volumetric data by adding multimodal MRI sequences and will test the model against external clinical datasets. The research will improve system interpretability and clinical usability by further developing explainable AI methods. The hybrid fusion method creates a reliable, expandable system that enables brain tumor classification while advancing in multi-domain medical image analysis.

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