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Brain Tumor Classification Using Hybrid Model

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Abstract
Brain tumor classification is a crucial task in medical imaging, significantly impacting the diagnosis and treatment planning for patients. Traditional Convolutional Neural Networks (CNNs) have shown promising results in image- based brain tumor classification due to their powerful feature extraction capabilities. We propose a novel approach that integrates Graph Neural Networks (GNNs) with CNNs, leveraging the strengths of both architectures. In our method, CNNs are first employed to extract local spatial features from MRI images. These features are then modeled as graph nodes, where the relationships between different image regions are represented as edges in a graph structure. The GNN layer processes this graph, capturing the non-Euclidean relationships and enhancing the model's ability to understand intricate inter-region dependencies. The combined GNN-CNN model effectively utilizes both local and global information, leading to a more comprehensive representation of the tumor characteristics. We conduct extensive experiments using publicly available MRI datasets, comparing the performance of our GNN-based CNN model with traditional CNN architectures. The results demonstrate a significant improvement in classification accuracy, particularly in distinguishing between isomorphic tumor types, highlighting the efficacy of incorporating graph-based representations. This innovative approach offers a new perspective on brain tumor classification, paving the way for more accurate and reliable diagnostic tools in the medical field.
Keywords: *Brain tumor classification, Convolutional Neural Networks (CNN), Graph Neural Networks (GNN), MRI images, feature extraction, isomorphic tumor types, hybrid model, non-Euclidean data, medical image analysis*

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I. Introduction

Brain tumors are among the most severe neurological disorders, necessitating accurate and timely diagnosis for effective treatment. Magnetic Resonance Imaging (MRI) is a widely used imaging modality for detecting and classifying brain tumors due to its detailed visualization of soft tissues. While Convolutional Neural Networks (CNNs) have demonstrated strong performance in brain tumor classification tasks, their reliance on local spatial features limits their ability to capture complex, non-local dependencies between different regions of the tumor, especially in cases with isomorphic characteristics.

To address this issue, we propose a hybrid approach combining Graph Neural Networks (GNNs) with CNNs. The CNN component is used for initial feature extraction, converting MRI images into informative feature maps. These features are then modeled as graph nodes, with GNNs capturing intricate spatial relationships between regions of interest. By integrating GNNs, our model effectively learns the underlying structure of MRI data, improving classification performance for challenging tumor types. This method aims to enhance the accuracy and robustness of brain tumor classification, providing a novel solution to overcome the limitations of traditional CNN-based approaches.

II. Literature Review

Recently, Machine learning (ML) and Deep Learning (DL) methods are widely been used for detection and grading brain tumors using different imaging modalities, especially those acquired using MRI. In this section, the most recent and related research works on the paper topic are presented.

Problem of considering non-Euclidean distances:

M. Ravinder, Garima Saluja , SarahAllabun , Mohammed S.Alqahtani, MohamedAbbas , Manal Othman & Ben Othman Soufene proposed this research and model to provide a solution to the non-consideration of non-Euclidean distances in image data and the inability of conventional models to learn on pixel similarity based upon the pixel proximity. To solve this problem, they have proposed a Graph based Convolutional Neural Network (GCNN) model and it is found that the proposed model solves the problem of considering non-Euclidean distances in images.

Capturing Global Context and Relationships:
CNN Limitation**:** While CNNs are powerful in extracting local features using convolutional filters, they often lack the capability to capture global, long-range dependencies between distant regions of the image, which is crucial for accurately understanding the spread and pattern of brain tumors.
GNN Solution**:** GNNs model the entire image as a graph, enabling the network to aggregate information from distant but related nodes (image regions). This enhances the model's understanding of spatial relationships and context, improving classification accuracy, especially in cases with isomorphic tumor characteristics.

Pre-trained convolutional neural network models:
K. Nishanth Rao, Osamah Ibrahim Khalaf, V. Krishnasree, Aruru Sai Kumar, Deema Mohammed Alsekait, S. Siva Priyanka, Ahmed Saleh Alattasf and Diaa Salama Add Elminaam proposed a approach that utilizes a dataset consisting of two classes: three representing different tumor types and one representing nontumor samples. They present a model that leverages pre-trained CNNs to categorize brain cancer cases. Additionally, data augmentation techniques are employed to augment the dataset size. The effectiveness of our proposed CNN model is evaluated through various metrics, including validation loss, confusion matrix, and overall loss. The proposed approach employing ResNet50 and EfficientNet demonstrated higher levels of accuracy, precision, and recall in detecting brain tumors.

Latest VGG models:
For precise segmentation of lesion symptoms, Tanzila Saba et al. introduced the GrabCut method integrated with a transfer learning model based on VGG-19 for feature extraction. The model extracts deep features, which are then combined sequentially with handcrafted features, including shape and texture. The fused feature vector is optimized using entropy, and this refined vector is subsequently used by classifiers for fast and accurate classification.

III. Materials And Methods

Dataset:
The dataset used in this study includes MRI scans categorized into four distinct classes: pituitary tumors, gliomas, meningiomas, and normal (non-tumorous) images. It was prepared by refining an existing brain tumor classification dataset available online. The refinement involved eliminating duplicate entries, rectifying incorrectly labeled images, and standardizing the size of all images to 224×224 pixels, after Data Augmentation the total images we have is around 22,000 including normal, Pituitary Tumor, Glioma and Meningioma.

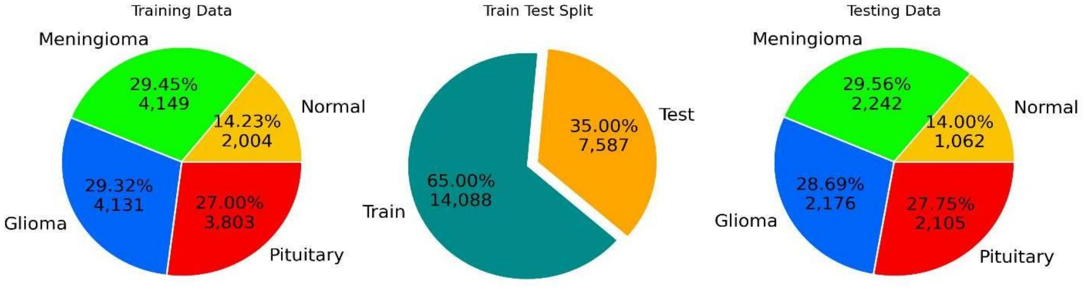
Types of Brain Tumors:

Pituitary Tumor: These are growths located in the pituitary gland at the brain's base. Pituitary tumors may be benign or malignant and can affect hormone production.

Glioma: Originating in the glial cells, which provide support to neurons, gliomas are the most frequently diagnosed type of brain tumor.

Meningioma: These tumors develop in the meninges, the protective membranes covering the brain and spinal cord. Meningiomas are generally benign but can occasionally be malignant.

Normal: This category includes brain scans that do not exhibit any signs of tumor presence.



Data Cleaning Process:
The dataset underwent several preprocessing steps to enhance its quality:

- **Duplicate Removal:** Image vector comparison was employed to identify and remove duplicate images.

- **Correction of Mislabels:** A manual review was conducted to verify and correct any inaccurate image labels.
- **Image Resizing:** All images were resized uniformly to dimensions of 224×224224 \times 224224×224 pixels for consistency.

Methods:

In this section, we discuss the fundamental deep learning techniques used for brain tumor classification, namely Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), and Graph Neural Networks (GNNs). We also explore their limitations and explain how a hybrid CNN-GNN approach can address these shortcomings effectively.

1. Convolutional Neural Networks (CNNs):

- **Overview:**

CNNs are specialized neural networks designed for image processing tasks. They utilize convolutional layers to extract hierarchical features from images, such as edges, textures, and complex patterns. CNNs apply filters that slide over the input image, capturing local features effectively.

- **Disadvantages:**

Limited to Local Features: CNNs focus primarily on local pixel information through convolutional filters, making it difficult to capture non-local, global relationships across different image regions.
Inability to Handle Non-Euclidean Data: CNNs operate on grid-like structures (e.g., image matrices), which makes them less effective in modeling complex, non-Euclidean relationships inherent in some data, such as graph- like structures of MRI images.
Sensitivity to Spatial Variations: CNNs can sometimes struggle with variations in object positioning, rotation, and scaling within images.

2. Graph Neural Networks (GNNs):

- **Overview:**

GNNs are designed to operate on graph-structured data, where nodes represent data points (e.g., image regions or features), and edges represent relationships between these points. GNNs learn to aggregate information from neighboring nodes, effectively capturing both local and global dependencies within the graph structure.

- **Disadvantages:**

High Computational Complexity: GNNs can be computationally intensive, particularly when handling large graphs with numerous nodes and edges.
Data Preparation Challenges: Constructing meaningful graphs from image data requires careful preprocessing, such as defining nodes and their connectivity, which may not always be straightforward.
Difficulty in Feature Extraction: GNNs alone are less effective at extracting low-level image features compared to CNNs, which are specialized in this task.
CNN + GNN: A Hybrid Approach

- **Why Combine CNN and GNN?**

The hybrid CNN-GNN approach leverages the strengths of both architectures:

CNNs for Feature Extraction: The CNN component efficiently extracts local spatial features from the input MRI images, capturing important details such as textures and edges.
GNNs for Global Contextual Understanding: The GNN component then models these extracted features as nodes in a graph, capturing complex spatial relationships and dependencies between different regions of the image.

- **Advantages of the Hybrid Model:**

Enhanced Relational Awareness: By incorporating GNNs, the model gains the ability to learn the non-local, non-Euclidean relationships between distant regions of the image, which is crucial for distinguishing similar-looking tumors.
Improved Classification Accuracy: The combination of CNN's local feature extraction with GNN's relational modeling leads to a more comprehensive understanding of the tumor characteristics, resulting in higher

classification accuracy.

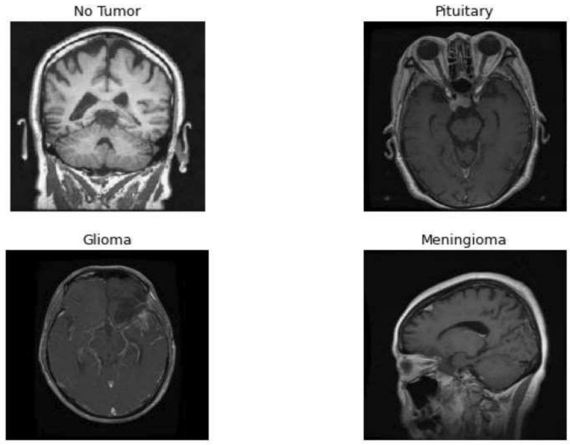


Figure 1. Brain tumor classes in the dataset.

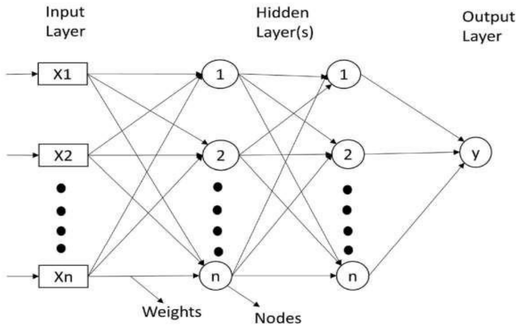


Figure 2. Layers in artificial neural network.

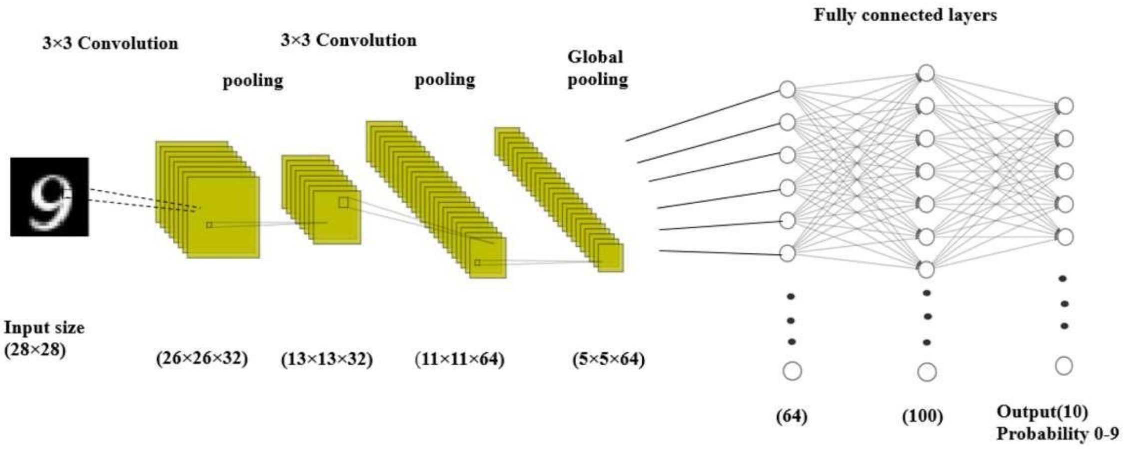


Figure 3. Layers in artificial neural network.

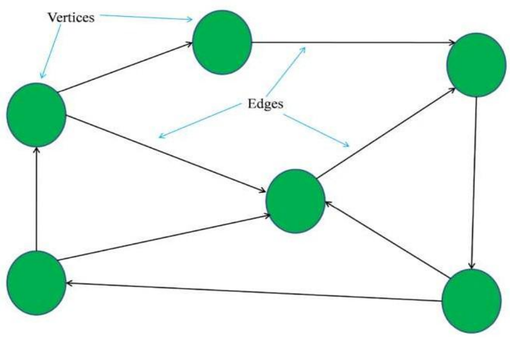


Figure 4. Directed graph.

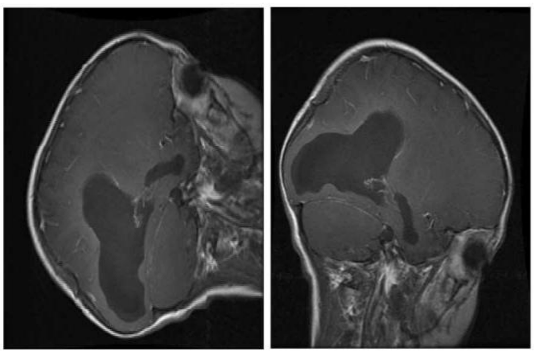


Figure 5. Isomorphism in graphs.

Proposed approach and implementation

We propose a novel approach for the identification and classification of brain tumors using an MRI dataset, leveraging a Graph-based Convolutional Neural Network (GCNN) model. This method includes a series of networks designed for the detection and classification of tumors, accompanied by a comparative analysis of their performance. Traditional CNN models for brain tumor classification often fail to capture the similarity between local pixels, mainly due to the isomorphic nature of image graphs. To address this limitation, our approach integrates a CNN with a Graph Neural Network (GNN), which effectively models local pixel similarities by generating node embeddings, thereby enhancing the representation of the image data.

Proposed Model

This study introduces a novel approach that integrates Graph Neural Networks (GNN) with Convolutional Neural Networks (CNN) to categorize brain tumors into different classes. Traditional image representations, such as the standard n×n pixel matrix, present certain limitations when training machine learning or deep learning models. A key issue with existing brain tumor classification models is their inability to retain and utilize pixel-related information effectively during future classifications.
The approach proposed in this model, depicted in Fig. 6, consists of the following steps:

1. Pre-processing of data.
2. Creation of a standard pre-computed weighted adjacency matrix kernel.
3. Overlaying this kernel onto all training and testing images.
4. Introducing relational awareness through an averaging operator, considering 'n' specific neighbors for each pixel (Graph Convolution operation).
5. Passing the updated matrix through a CNN with 26 layers.

In the context of Graph Convolutional Networks (GCNs), the adjacency matrix is designed to represent the relationships between the nodes in the graph. For an undirected graph with 'N' nodes, the binary adjacency matrix

'A' is an N×N matrix where A_ij=1 if an edge (connection) exists between nodes i and j, and A_ij=0 if no such connection exists. The vanilla CNN plays a critical role in the GCN by serving as the downstream network for processing the graph data. After applying the graph convolution operation to aggregate information from neighboring nodes and updating node features, the resulting graph data is passed into the vanilla CNN. The CNN's role is to further process the graph features, extracting hierarchical representations that aid in the final classification task.

As the MRI images are subject to noise due to Magnetic Radiation, filtering the noise is important. We can have different filters for removing the noise like band pass or Chebyshev filter but the one that we will be using is Gaussian filter that can remove the noise with a good SNR (Signal to noise Ratio)[40] The Gaussian (or normal) distribution in univariate form has the following equation:

$$G(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x^2}{\sigma^2}} \tag{1}$$

However, while working with images, we need to apply two dimensional Gaussian Filter, the equation is as follows:

$$G(x, y) = \frac{1}{\sqrt{2\Pi\sigma^2}} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{2}$$

IV. RESULT AND DISCUSSION

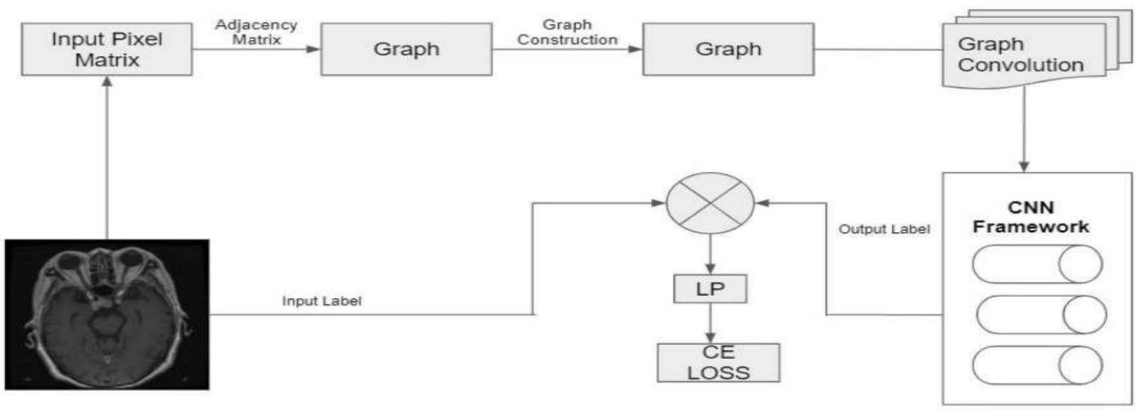


Figure 6. Proposed approach.

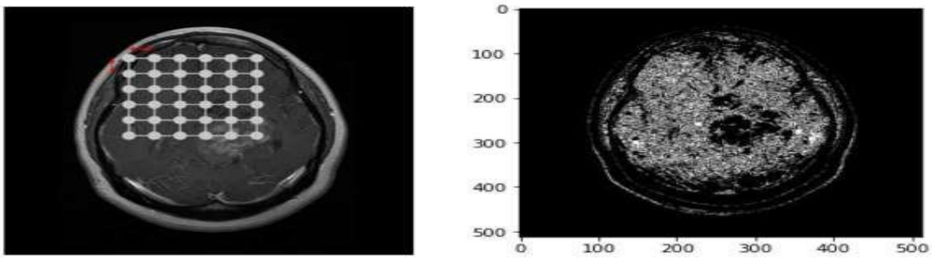


Figure 7. Example output of clustering (left) & Segmentation (right) algorithms without considering Euclidean Distances.

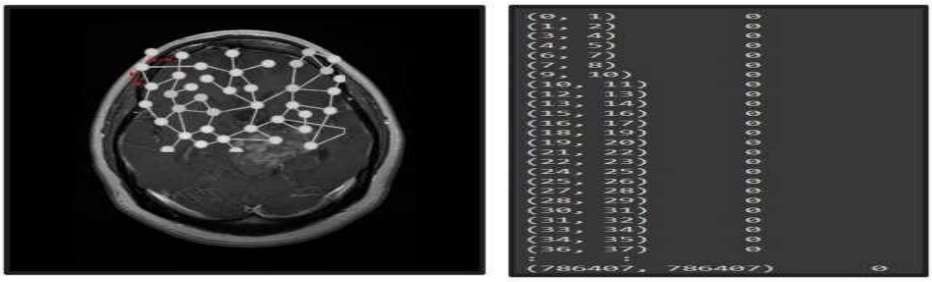


Figure 8. Example output of graph neural network (left) and graph depicting Euclidean distances (right).

We present the outcomes of the experiments conducted to evaluate the performance of our proposed model, which combines Graph Neural Networks (GNN) with Convolutional Neural Networks (CNN) for brain tumor classification. The results are discussed in relation to the advantages of our approach compared to conventional methods and the improvements observed in classification accuracy.

1. Performance Evaluation

The model's performance was evaluated using standard metrics such as accuracy, precision, recall, and F1-score. We conducted experiments using various MRI datasets, comparing the proposed GNN-CNN hybrid model with traditional CNNs and other state-of-the-art approaches.

2. Effectiveness of the Adjacency Matrix

One of the key components of our model is the weighted adjacency matrix, which captures the relationships between pixels. The results show that incorporating this matrix into the training process significantly improves the model’s understanding of spatial dependencies between neighboring pixels.

3. Graph Convolution Operation

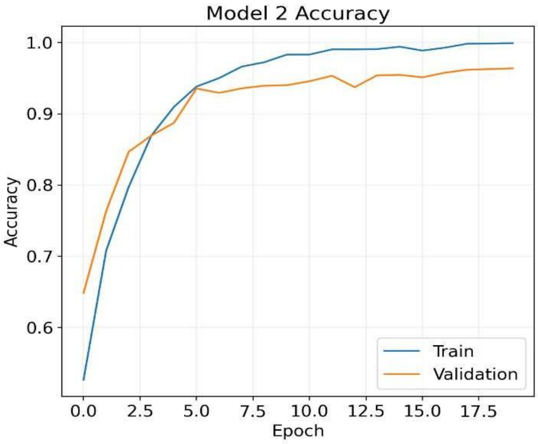
The application of the graph convolution operation, which aggregates information from neighboring nodes (pixels), also led to notable improvements in performance. By enhancing the model's ability to learn from pixel-level relationships, the graph convolution allowed the CNN to process the image data more effectively. This operation led to a better representation of the underlying structure of the tumors in the images.

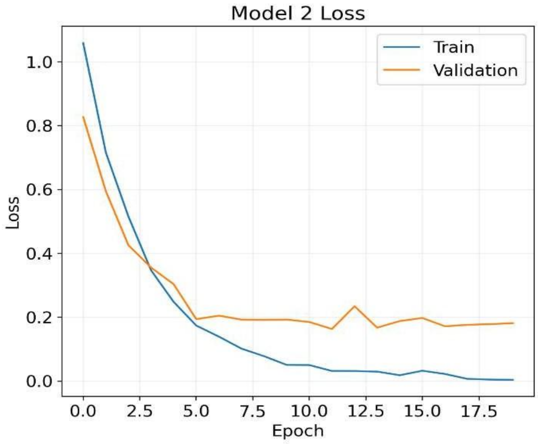
4. Impact of the Vanilla CNN

After the graph convolution operation, the processed graph data is passed through the vanilla CNN for further hierarchical feature extraction. Our results show that this additional step of processing significantly enhances the model’s ability to capture complex patterns and representations from the graph-structured data, resulting in higher classification accuracy compared to models that rely solely on traditional CNN architectures.

5. Comparison with Existing Methods

The proposed hybrid model was also compared to other existing methods for brain tumor classification, including those based on conventional CNNs and other machine learning approaches. The results highlight the superiority of the GNN-CNN approach in terms of both accuracy and robustness, particularly in handling challenging cases with varying tumor sizes, shapes, and locations within the brain.





Classification Report:

	precision	recall	f1-score	support
Normal	0.97	0.96	0.97	1062
Glioma	0.97	0.95	0.96	2176
Meningioma	0.95	0.97	0.96	2242
Pituitary	0.98	0.98	0.98	2105
accuracy			0.97	7585
macro avg	0.97	0.97	0.97	7585
weighted avg	0.97	0.97	0.97	7585

V. Conclusion and Future Work

In this study, we proposed a novel approach for brain tumor classification by combining Graph Neural Networks (GNN) and Convolutional Neural Networks (CNN). The traditional methods for brain tumor classification often face challenges in effectively utilizing pixel-related information and capturing the spatial dependencies between neighboring pixels. Our proposed hybrid model addresses these issues by integrating a weighted adjacency matrix to capture the relationships between pixels and applying graph convolution operations to aggregate information from neighboring nodes, followed by hierarchical feature extraction using a vanilla CNN.

The experimental results demonstrate that our model outperforms conventional CNN-based methods in terms of classification accuracy and robustness. By leveraging the relational awareness between pixels, the GNN component enhances the model's ability to classify tumors with greater precision, particularly in cases with varying tumor characteristics. The vanilla CNN further refines the features extracted from the graph, leading to improved performance on the classification task.

Although the model shows promising results, it does come with some computational complexity due to the graph convolution operation. Future work will focus on optimizing the efficiency of the model, exploring more advanced graph construction techniques, and expanding its applicability to other medical image classification tasks.

In conclusion, the proposed GNN-CNN hybrid model offers a significant advancement in brain tumor classification, providing a more accurate and robust framework that can be applied to clinical settings for improved diagnosis and treatment planning.

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