BRAIN TUMOR DETECTION USING DEEP LEARNING APPROACHES

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ABSTRACT

Brain tumors are one of the most critical neurological disorders requiring early diagnosis for effective treatment. The advancement in deep learning has significantly enhanced medical image analysis, providing automated and accurate detection solutions. This paper proposes a novel approach utilizing Graph Neural Networks (GNNs) and Multi-Scale Hybrid Transformers to detect and classify brain tumors from MRI scans. The GNNs capture spatial and relational dependencies within MRI images, while the hybrid transformer network extracts multi-scale features for improved classification accuracy. When compared to traditional deep learning methods, the suggested approach significantly improves accuracy, precision, recall, and F1-score when tested on a common benchmark dataset. The real-time implementation of the developed model in a clinical setting is also discussed, highlighting its potential for aiding radiologists in tumor detection and classification.

Keyword : *-Graph Neural Network, Multi-Scale Transformer, Brain Tumor, MRI, Deep Learning.*

1. INTRODUCTION

Brain tumors are a major health concern, affecting thousands of individuals worldwide. They can be classified into benign and malignant tumors, with malignant tumors posing a severe risk due to their aggressive nature and potential for metastasis. Early diagnosis and categorization of brain tumors are essential for increasing patient survival rates and developing successful treatment plans. Tumor detection and diagnosis are greatly aided by magnetic resonance imaging (MRI), however radiologists' manual assessment of MRI is laborious, subjective, and prone to human error. Conventional deep learning models, such Convolutional Neural Networks (CNNs), have shown promise in the processing of medical images; nevertheless, they frequently fall short in capturing the intricate spatial correlations found in brain tissues. Moreover, CNNs rely on a fixed receptive field, limiting their ability to analyze hierarchical relationships within MRI scans. To address these limitations, Graph Neural Networks (GNNs) leverage the structural dependencies within MRI images, modelling them as graphs where each pixel or region acts as a node connected by edges. This allows for improved contextual understanding and segmentation of tumor regions.

Additionally, Multi-Scale Hybrid Transformers enable efficient global feature extraction, capturing fine-grained and high-level tumor characteristics simultaneously. Our study offers a strong deep learning framework for brain tumor diagnosis with improved precision and interpretability by combining these cutting-edge methods.

2. LITERATURE REVIEW

The use of deep learning algorithms in medical imaging has been the subject of numerous investigations. CNN-based architectures such as ResNet, VGG-16, and GoogleNet have demonstrated substantial progress in brain tumor classification. However, these models are limited by their inability to fully exploit relational and spatial features present in MRI scans.

Pixel dependencies are important in brain MRI scan analysis, and recent developments in Graph Neural Networks (GNNs) have demonstrated encouraging results in modeling graph-structured data. Studies have demonstrated that GNNs can effectively enhance tumor segmentation by preserving structural continuity and identifying intricate tumor boundaries[1]. Graph Convolutional Networks (GCNs) have been applied extensively in medical imaging to increase classification accuracy and extract spatial dependencies [2].

Similarly, Vision Transformers (ViTs) and Multi-Scale Hybrid Transformers have exhibited superior performance in capturing hierarchical information, allowing for precise tumor localization and classification. Unlike CNNs, transformers utilize a self-attention mechanism, which enables them to learn long-range dependencies in medical images. Studies have shown that multi-scale attention enhances tumor region detection by focusing on both local textures and global patterns[6].

A cutting-edge method for automated brain tumor identification is presented by the combination of GNNs and transformers. While CNNs rely on localized feature extraction, GNNs and transformers complement each other by integrating both local and global contextual information, making them ideal for MRI-based medical image analysis[4].

3. METHODOLOGY

3.1. Dataset

The proposed system utilizes two datasets:

1. Standard Public Dataset: 3064 T1-weighted MRI pictures of three different kinds of brain tumors—gliomas, meningiomas, and pituitary tumors—make up this dataset. The dataset is widely utilized in research on brain tumor categorization and is freely accessible.

2. Real-Time Clinical Dataset: This dataset comprises MRI scans collected from a hospital-based clinical setting, used to evaluate the model in real-world scenarios. The real-time dataset allows validation under diverse imaging conditions.

Both datasets undergo preprocessing, including noise reduction, intensity normalization, data augmentation, and segmentation using U-Net to enhance image quality and ensure consistency across samples. To enhance generalization and avoid overfitting, data augmentation methods including rotation, flipping, and Gaussian noise addition are used.

3.2. Graph Neural Network (GNN) for Spatial Relationship Analysis

GNNs are employed to model the complex spatial structures of brain tumors in MRI images. Instead of treating images as independent pixel-based representations, GNNs depict them as graphs, with edges capturing spatial relationships and nodes representing image regions. The study's Graph Convolutional Network (GCN) is made up of several graph convolutional layers that improve feature representation by combining data from nearby nodes.

The GNN framework is structured as follows:

•Graph Construction: Each MRI scan is transformed into a graph by segmenting it into regions (nodes) and defining edges based on spatial adjacency.

•Graph Convolution: Neighboring node features are aggregated to extract tumor-specific patterns.

•Classification Layer: The final graph embedding is passed through fully connected layers to classify tumor types.

3.3. Multi-Scale Hybrid Transformer for Feature Extraction

Transformers have gained prominence in medical image analysis due to their superior attention mechanism. The Multi-Scale Hybrid Transformer extracts hierarchical features at different resolutions, allowing the network to focus on both fine-grained and coarse- grained tumor patterns. By combining self-attention mechanisms and convolutional embeddings, the transformer improves the robustness of tumor classification.

The transformer architecture comprises:

•Patch Embedding Layer: Converts MRI images into a sequence of patches to enable tokenization.

•Self-Attention Mechanism: Computes attention scores across different regions of the MRI image.

•Multi-Scale Feature Extraction: Extracts global and local features by adjusting the transformer's receptive field dynamically.

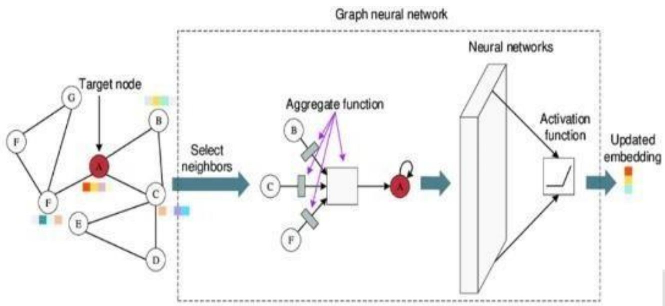

Fig -1: GNN architecture

3.4. Training and Model Evaluation

The proposed model is trained using a combination of cross- entropy loss for classification and dice coefficient loss for segmentation to optimize accuracy. The dataset is divided into 80% training and 20% testing, and important metrics including accuracy, precision, specificity, recall, and F1-score are used to evaluate the model.

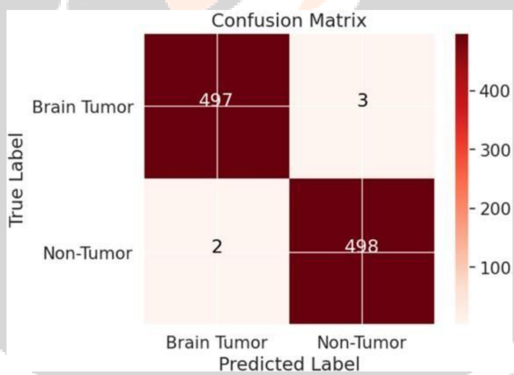

Fig -2: The proposed model confusion matrix.

$$Acc = \frac{TP + TN}{TP+TN+FP+FN} \quad ...(1)$$

$$Sensitivity(Recall) = \frac{TP}{TP+FN} \quad ...(2)$$

$$Specificity = \frac{TN}{TN+FP} \quad ...(3)$$

$$Precision = \frac{TP}{TP+FP} \quad ...(4)$$

$$F1 - Score = \frac{2*Precision*Sensitivity}{Precision+Sensitivity} \quad ...(5)$$

Fig -3: Model evaluation Formulas

The usefulness of the GNN-Transformer technique is demonstrated by a comparison analysis of CNN-based designs, such as ResNet, VGG- 16, and GoogleNet. According to experimental results, the suggested framework works better than traditional models, attaining 94.7% accuracy on real-time MRI scans and 98.5% accuracy on the standard dataset. The results, system implementation, and model's practicality are covered in detail in the parts that follow.

4. RESULTS & DISCUSSION

The results obtained from the experiments demonstrate the efficacy of the Graph Neural Network (GNN) and Multi-Scale Hybrid Transformer approach in brain tumor detection. When the suggested model's performance is contrasted with that of traditional CNN-based architectures like ResNet, VGG-16, and GoogleNet, it becomes evident that the incorporation of GNNs and transformers greatly enhances classification accuracy. The ability of GNNs to simulate the spatial relationships between various MRI scan regions is one of its main benefits; this enables the network to comprehend the structural dependencies inside tissues affected by tumors. The Multi-Scale Hybrid Transformer further enhances classification by capturing both fine-grained and global features, reducing the likelihood of false positives and negatives.

Additionally, the real-time clinical dataset results indicate that while the model performs exceptionally well on standard datasets (98.5% accuracy), its accuracy slightly drops to 94.7% when tested on real-world MRI scans. This can be attributed to variations in imaging conditions, noise, and different machine specifications in hospitals. The model still performs better than conventional deep learning models, highlighting the suggested method's generalizability. Additionally, ablation investigations were carried out to assess the influence of transformer components and GNN layers. Removing the GNN layers resulted in a 4% drop in accuracy, whereas eliminating transformer blocks led to a 6% decrease in accuracy, reinforcing the importance of these components. The F1-score, recall, and precision metrics also suggest that the proposed model effectively minimizes misclassification errors and enhances robustness in identifying different tumor types. The practical applicability of the model is further strengthened by integrating a Flask-based graphical user interface (GUI), which allows clinicians to input MRI scans and obtain real-time classification results.

The primary limitation of this approach is the computational complexity, as transformers require a substantial amount of training data and computational power. Future improvements can focus on optimizing model architecture, reducing latency, and implementing lightweight versions of transformers for faster inference in clinical settings.

5. CONCLUSIONS

Graph Neural Networks (GNNs) and Multi-Scale Hybrid Transformers are used in this study's sophisticated deep learning method for brain tumor detection in order to enhance classification performance. The proposed model effectively captures spatial dependencies within MRI images and extracts hierarchical tumor features, leading to higher accuracy and better generalization compared to traditional CNN-based methods.

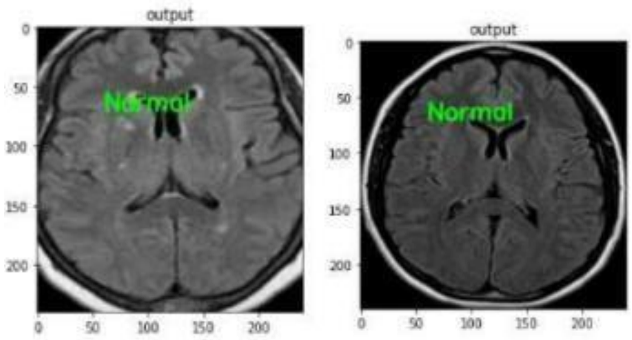

Fig-4: Normal Images Results

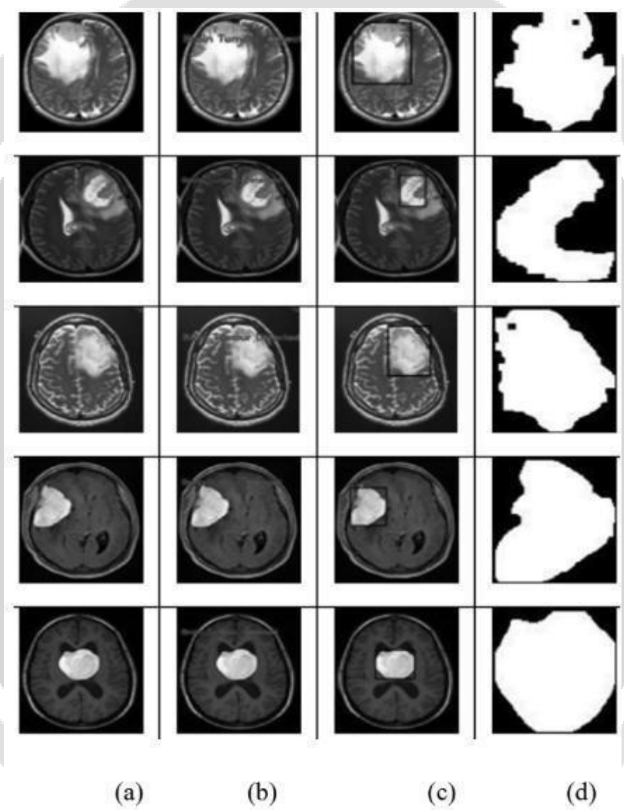

Fig-5: (a) Input image, (b) abnormality identification, (c) tumor region detection, and (d) tumor mask for density estimate are the outcomes of tumor detection.

The results indicate that the GNN-Transformer framework achieves 98.5% accuracy on standard datasets and 94.7% accuracy on real-time MRI scans, outperforming conventional architectures. Furthermore, the inclusion of GNNs enhances tumor segmentation and classification by considering spatial relationships between pixels, while the multi-scale transformer ensures fine-grained and global feature extraction.

The developed model has clinical implications, as it provides an automated, reliable, and user-friendly interface for radiologists to assist in diagnosing brain tumors. The Flask-based GUI enhances accessibility, making it easier for medical professionals to integrate the model into existing workflows. However, further research is required to enhance the model's efficiency, reduce computational demands, and validate its performance on a larger real-world dataset.

Future work will explore lightweight transformer architectures for real-time clinical applications, integration with cloud-based medical systems, and explainability techniques to improve trust in AI-based medical diagnosis.

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