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Multi-class Brain Tumor Segmentation using Graph Attention Network

Authors:
Dhrumil Patel, Dhruv Patel, Rudra Saxena, and Thangarajah Akilan

Presenters:
Dhrumil Patel and Dhruv Patel

Presentation Overview

- Introduction
- Literature review
- Proposed Solution
- Experimental study and results
- Conclusion

Introduction

- Background:
  - **Brain tumors** can be **fatal**, significantly impact the quality of life, and fundamentally change the lives of both the patient and their loved ones.

  - **Malignant tumors** have a **limited** chance of **surviving**, so **early detection** and **diagnosis** of brain tumors **are essential**.

- Motivation:
  - **Gliomas** are one of the most **prevalent** forms of brain tumors among all others. Most gliomas are classified as Low-grade gliomas (LGG) and High-grade gliomas (HGG).

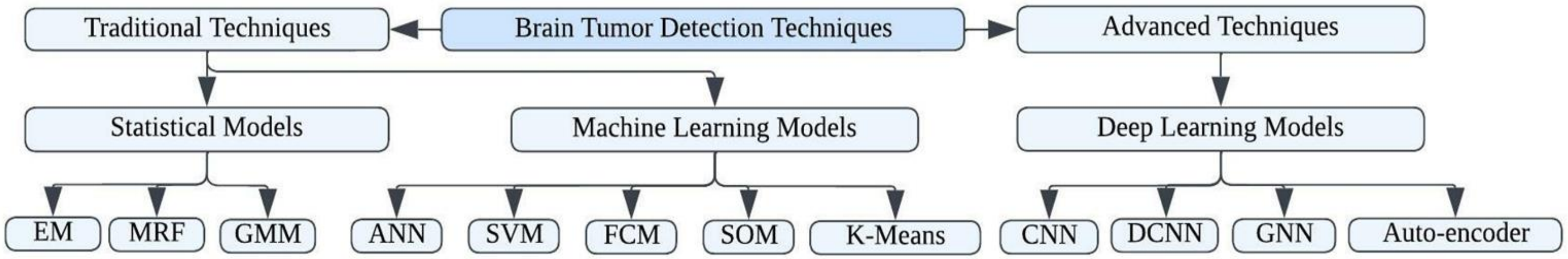
  - A study by the US National Cancer Institute (NCI) found that every year, 18,000 Americans are diagnosed with a glioma brain tumor, most of which pass away within 14 months.

Introduction Cont.

- Challenges:
    - Processing of the entire brain.
    - Applying graph neural network (GNN) on legacy datasets (i.e., non-graphical data).

- Contributions:
    - A computationally efficient and accurate model for brain tumor segmentation as compared to relevant state-of-the-art methods.
    - Exhaustive experimental analysis on benchmark datasets and thorough comparative analysis.

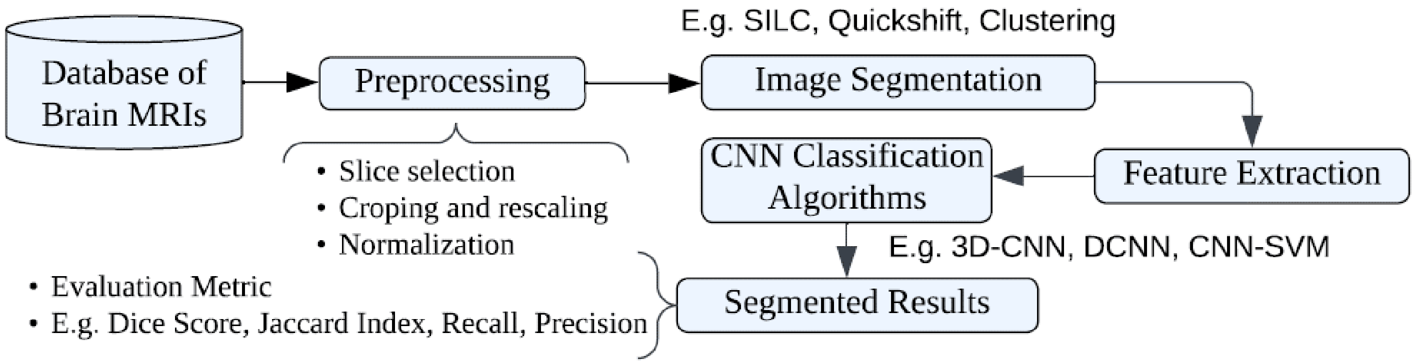
Literature Review



- Methodologies for brain tumor detection: ANN- Artificial Neural Network, SVM- Support Vector Machine, FCM-Fuzzy c-means SOM- Self Organized Map, CNN-Convolution Neural Networks, GNN-Graph Neural Networks, DCNN-Deep Convolution Neural Networks, EM- Expectation Maximization MRF-Markov Random Fields, GMM-Gaussian Mixture Model

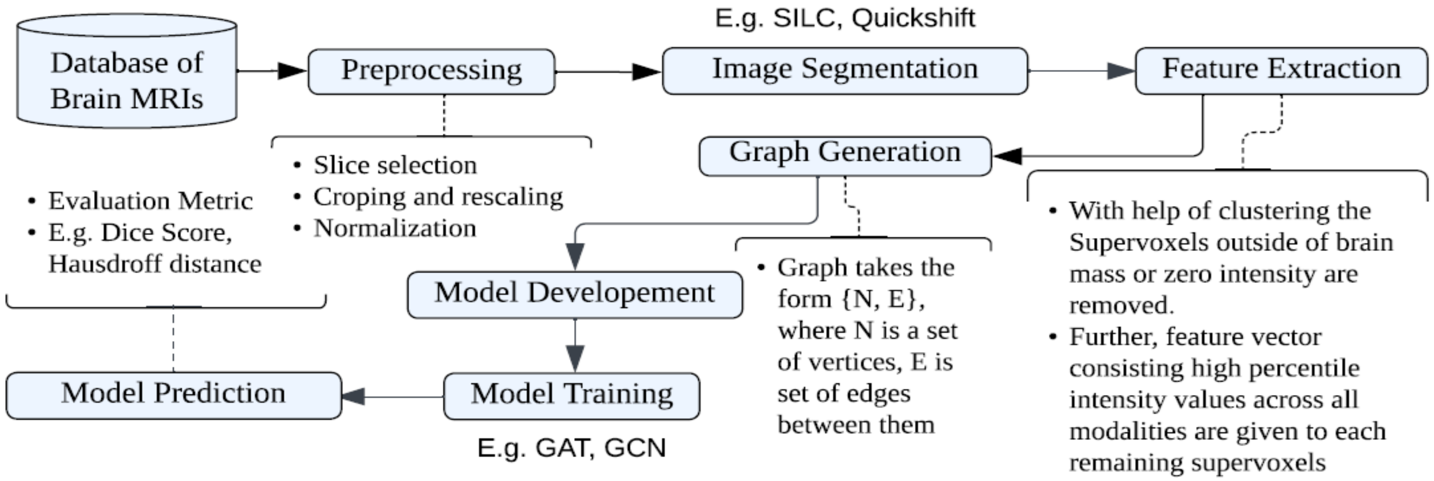
- Traditional Methods:
  - SVM concept was studied by Shubhangi *et al.* [5] who combined knowledge-based approaches with multi-spectral analysis.
  - In 2010, Gopal *et al.* [6] proposed work on MRI brain tumor detection using fuzzy c-means along with intelligent optimization tools.
  - Javaid *et al.* [8] presented a sophisticated fully automated tumor recognition model using kernel-based fuzzy C-means, achieving an accuracy of 98.7%.

Literature Review Cont.



- Advanced methods:
  - In recent years, **deep convolutional neural networks** (DCNNs) have shown excellent results in various medical image segmentation tasks.
    - Longet *et al.* [9], in 2015, developed a fully convolutional network (FCN) for pixel-level classification.
    - Following this idea, several DL-based segmentation models have been developed for various applications, including brain tumor segmentation.

Literature Review Cont.

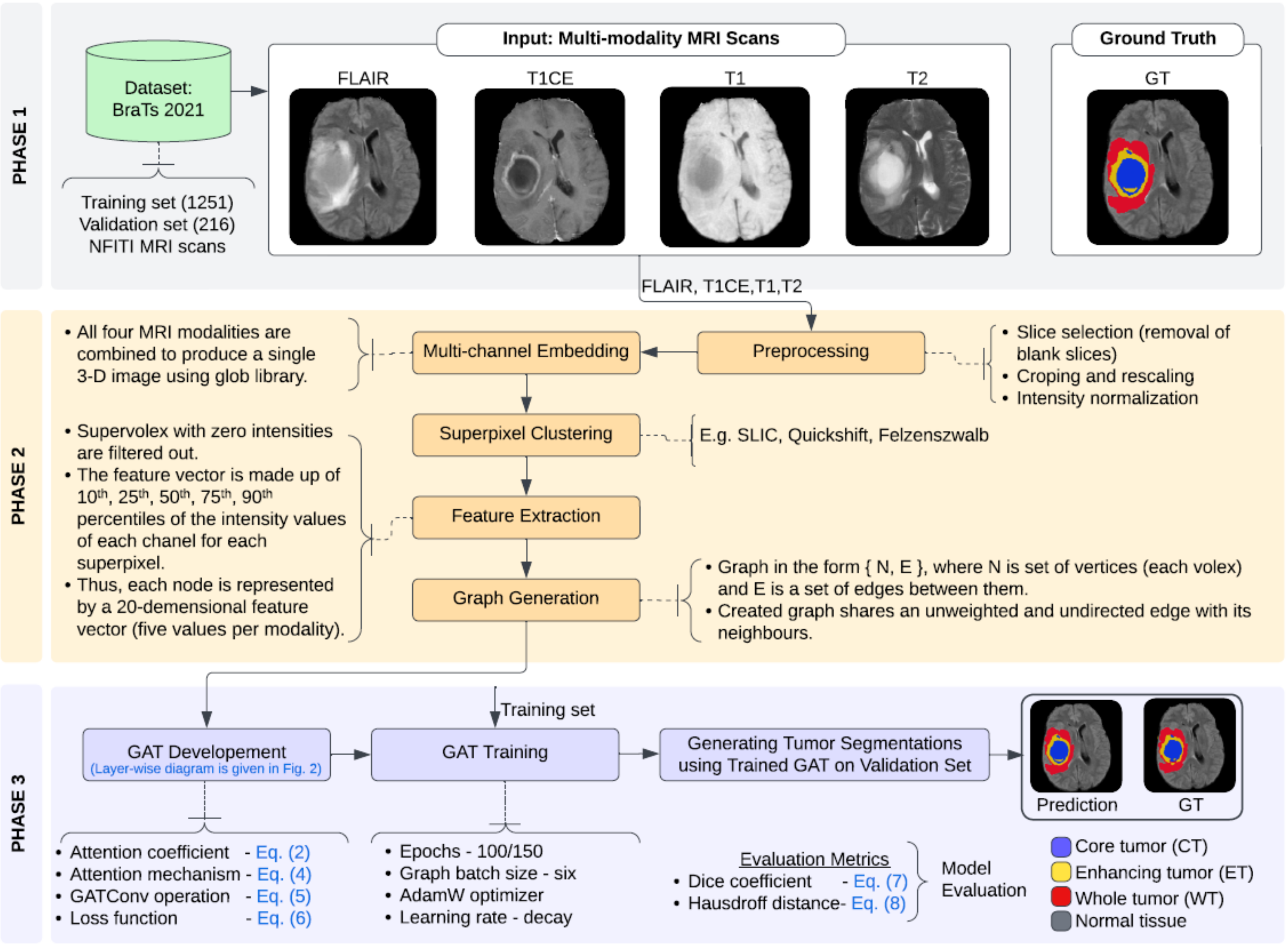


- **Graph Neural Network (GNN)**:
    - DL-based graph data processing, known as GNN, was first introduced by Gori *et al.,* in 2005 [15].
    - One of the most advanced techniques, in this category, is the **graph attention network** (GAT), which was introduced by Yoshua Bengio's research team, in 2018.
    - Hyeonwoo et al. [16] combined a multi-view representation using multiple simultaneous self-constructing graph (SCG) modules to transform image data into a graph representation and applied **graph convolutional network** (GCN) to learn segmentation.
    - Similarly, Wei et al. [19] proposed a method to determine isocitrate dehydrogenase mutation status in glioma using structural brain networks and GNNs.

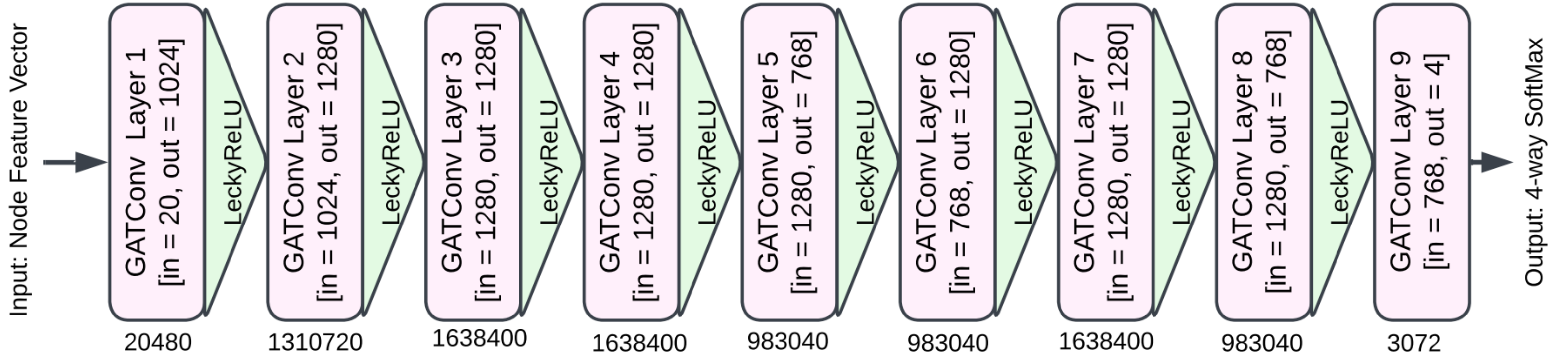
Proposed Solution

Detailed functional flow diagram of the proposed GAT-based MRI brain tumor segmentation framework.

- It consists of three abstract phases :
  - Phase 1: Input
  - Phase 2: Data curation
  - Phase 3: Model building and evaluation.



Proposed Solution: Layer-wise Schematic of the GAT



Computation carried out in a GATCov layer: $h_p^{[l]} \Longrightarrow \boxed{\|_{k=1}^{K} \sigma \left(\sum_{q \in N_p} a_{pq}^{k} W_k^{[l]} h_q^{[l]} \right)} \Longrightarrow h_p^{[l+1]}$

GATConv

$h_p^{[l+1]}$- output feature of node *p* in layer *l*

$h_p^{[l]}$ - input feature of node *p* in layer *l*

- It subsumes ~10 M total number of trainable parameters.
- It stacks eight GATConv layers with LeakyReLu activation, and the top layer is formed by a GATConv layer with Softmax activation.

Proposed Solution: The Mathematical Formulation of the GAT

- The mathematical formulation of the GATs learning layer :
  (Eq (5) in the paper)

$$\mathbf{h}_p^{[l+1]} = \Big\Vert_{k=1}^{K} \sigma \left(\sum_{q \in N_p} a_{pq}^{k} W_k^{[l])} h_q^{[l]} \right)$$

- Attention coefficient e as:
  (Eq (2) in the paper)

$$e_{pq} = a\left(W\vec{h_p}, W\vec{h_q}\right)$$

- Attention mechanism:
  (Eq (4) in the paper)

$$\sigma_{pq} = \frac{exp\left(LeakyReLU\left(\vec{a^T}\left[W\vec{h_p} \parallel W\vec{h_q}\right]\right)\right)}{\sum_{k \in N_p} exp\left(LeakyReLU\left(\vec{a^T}\left[W\vec{h_p} \parallel W\vec{h_k}\right]\right)\right)}$$

- Multi-label cross-entropy loss:
  (Eq (6) in the paper)

$$Loss = \sum_{c=0}^{C} (1_{c=y}) W_c \log(\widehat{P}_y)$$

Proposed Solution: Hyperparameter Setting

- The GAT is trained for **300 epochs** on **mini-batches of 6 graphs.**
  Note: The training converges between 100 and 150 epochs in different runs depending on the graph mini-batch size.
- We used the **AdamW optimizer** with a **weight decay of 0.0001** and exponentially decrease learning rate.
- **SLIC** configuration: **k = 15000** and **m = 0.5** has the best achievable segmentation accuracy.
- The cross-validation phase’s top-performing GAT model comprised **8 layers** with **256 neurons** each.
- Attention heads and Residuals used for the model training are [4, 5, 5, 5, 3, 5, 5, 3] and [False, False, False, False, True, False, False, False], respectively.

Experimental Study and Analysis

- Environment:
  - System specifications: AMD Ryzen 7 4800HS 2.90 GHz processor, a Tesla K80 GPU with 2496 CUDA cores, and 35 GB of DDR5 VRAM on Google Colab, the model was trained and tested.
  - The per-sample prediction time was 1.7 seconds on the above configurations.

- Evaluation Metrics**:**
  - Dice score and the 95th percentile of the symmetric Hausdorff distance are two measures used to assess the performance of the models.

$$Dice = \frac{2TP}{2TP + FP + FN}$$

(Eq (7) in the paper)

$$HD95 = 95\% \left(d\left(\hat{Y}, Y\right) \middle\| d\left(Y, \hat{Y}\right) \right)$$

(Eq (8) in the paper)

Experimental Study and Analysis: Quantitative Analysis

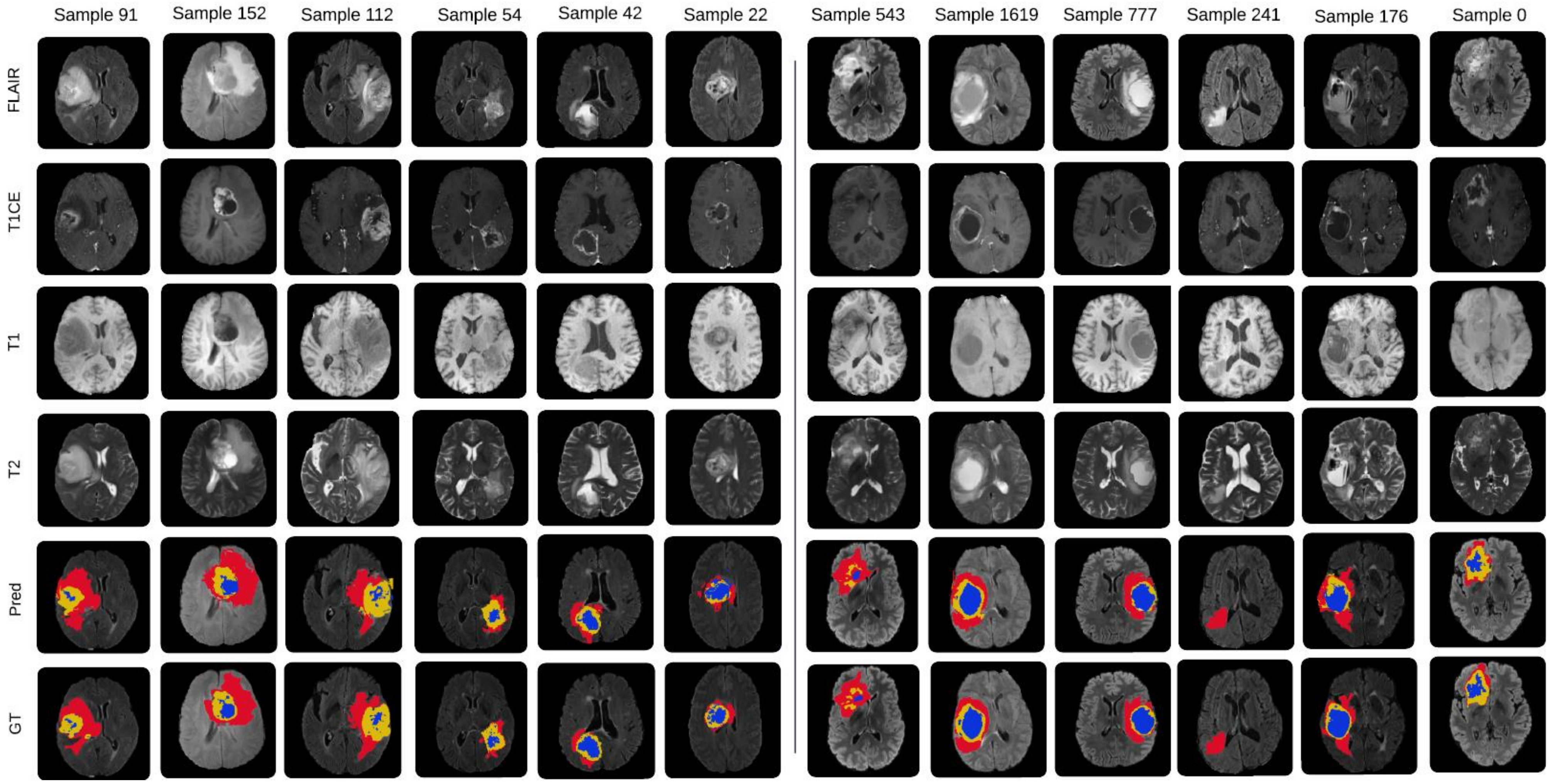
Performance of various models on the BRATS2021 validation dataset and their % of improvement compared to the baseline model introduced in [18].

Models	Dice Score (%)				HD95				Avg. % of Improvement	
	WT	CT	ET	Average	WT	CT	ET	Average	Dice Score	HD95
GNN [18]	0.87	0.78	0.74	0.80	6.92	16.67	20.40	14.66	**Baseline**	
GNN-CNN [18]	0.89	0.81	0.73	0.81	6.79	12.62	28.20	15.87	1.3 ↑	8.3 ↓
3D CMM-Net [27]	0.84	0.81	0.75	0.80	10.16	24.64	35.00	23.26	0	58.7 ↓
3D-UNet [28]	0.87	0.76	0.73	0.79	6.29	14.70	30.50	17.16	1.3 ↓	17.1 ↓
3D ResUNet [29]	0.90	0.85	0.82	0.86	4.3	9.89	17.89	10.69	7.5 ↑	27.1 ↑
DNN [30]	0.90	0.84	0.81	0.85	7.3	22.32	19.58	16.4	6.3 ↑	11.9 ↓
GAT (this work)	0.91	0.86	0.79	0.85	5.91	6.08	9.52	7.17	6.3 ↑	51.1 ↑

Note: Dice coefficient (higher is better), and hd95 (lower is better).

↓ And ↑ stand for '+' and '-' Improvement, respectively. The best performances are inked in blue

Experimental Study: Qualitative Analysis



(a) BRATS 2020 **(a) BRATS 2021**

Conclusion

- Exploiting advancement in **AI and computer vision** for lifesaving **medical diagnosis** is **extremely significant**.
- In response to that, this work proposes a **graph attention-based neural network** for effectively segmenting **multi-class tumors** from **multi-modality MRI** scans.
- Exploiting graph attentional layer that is computationally efficient (does not require expensive matrix operations and is parallelizable across all nodes in the graph).
- The exhaustive experimental studies and comparative analysis on the benchmark datasets show that the **proposed model** can **achieve competitive performances**.
- It shows an **overall improvement > 6%** and **> 50%,** respectively in **dice score** and **HD95** evaluation metrics **compared** to an existing GNN-based **baseline model**.

Acknowledgment

This work was inspired in part by the pioneering research conducted by various researchers in graph neural networks and MRI segmentation.

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End of the Presentation

- **Thank you** for attending and listening

- Q&A: Please let us know if you have any questions