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Advancing Brain Tumor MRI Segmentation

Utkarsh Kant Mishra[1,*], Anand Prakash Yadav[1], Satyam Kumar[1]

Abstract

Segmentation of brain tumors in MRI scans is an integral part of neuroimaging carried out for diagnostic and therapeutic interventions. Given that manual segmentation is cumbersome and highly variable, there arises a need for automated, more precise segmentation solutions. This project, 'Machine Learning and Deep Neural Networks to Advance Brain Tumor MRI Segmentation' will develop a better, efficient, and accurate segmentation model to help clinicians identify brain tumors with greater accuracy. The most commonly used imaging technique applied in the evaluation of brain tumors is magnetic resonance imaging, which allows radiologists to view the interior of the brain using radio waves and magnets. However, it is time-consuming and complex to differentiate between tumorous and nontumorous regions due to the complexity of the region involved with the tumor. Therefore, automatic reliable segmentation and predictability are required in brain tumor segmentation. This gives us a trustworthy and efficient variant of neural network-based segmentation, which we propose to incorporate attention into convolutional neural networks for brain tumor segmentation. The encoder component of UNET's pre-trained VGG19 network induces noise in segmentation through adjacent decoder components with attention gates while employing a denoising mechanism to counter overfitting. Our address here in Segmentation is with the dataset from BRATS'20 containing four different MRI modalities along with one target mask file. For the tumors identified in enhancing core and whole parts, respectively, the algorithm described above yielded a dice similarity coefficient equal to 0.83, 0.86, and 0.90.

Keywords: Magnetic resonance imaging (MRI), convolutional neural network (CNN), attention mechanism, deep learning, embedded medical systems, electronic health diagnostics

INTRODUCTION

Brain tumors are one of the most serious and life threatening diseases among all the human diseases which require early detection and accurate diagnosis for giving better treatment to the patients. Generally, Magnetic Resonance Imaging (MRI) is widely used to diagnose brain tumors because it provides non-invasive high resolution images of the anatomical structures of brain. But, manual extraction or segmentation process for extracting brain tumor from an MRI image is a very time consuming and error-prone task which depends upon skills and knowledge of radiologists. In addition to this, inter-observer variation and complexity in shape, size and location of tumor may be more challenging issues while doing segmentation [1].

Glioma ranks as most common tumor type, notoriously tricky to spot, boasting a dismal 22% survival rate and accounting for roughly 33% of brain tumors. Some brain tumors are benign with a high survival rate but others are malignant and have a low survival rate. Brain tumors originate from two distinct sources basically. Primary brain tumors originate in brain tissue and arise from abnormal brain cells; these are also referred to as mutations. Cells undergo rapid mutation and then grow exponentially, resulting in a wildly

***Author for Correspondence**
Utkarsh Kant Mishra
E-mail: mishrautkarshkant@gmail.com

Student, Department of Computer Science and Engineering (Artificial Intelligence), Galgotias College of Engineering and Technology, Greater Noida, Uttar Pradesh, India

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uncontrolled proliferation that forms a grotesque mass. A brain tumor ranks high up on death's leading causes list apparently. Tumors originating elsewhere in the body that spread to the brain are dubbed secondary brain tumors or brain metastasis. A 2019 report by London Institute of Cancer and World Health Organization reveals that roughly 18 million cancer cases are logged globally nowadays. Brain tumors comprise 286,000 cases roughly and Asia sees most of these with 156,000 cases reported yearly somehow. Approximately nine million fatalities globally can be attributed directly to cancer. Most notably, 241 deaths stem from brain tumors; meanwhile Asia had the highest mortality rate of 129 cases [2].

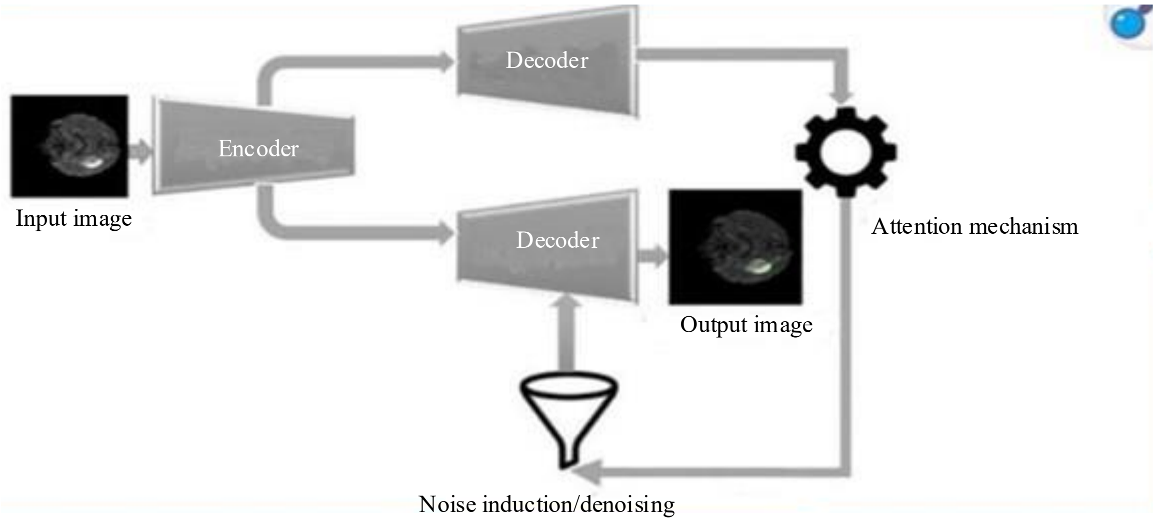

Figure 1. Detailed overview of sequential research methodology.

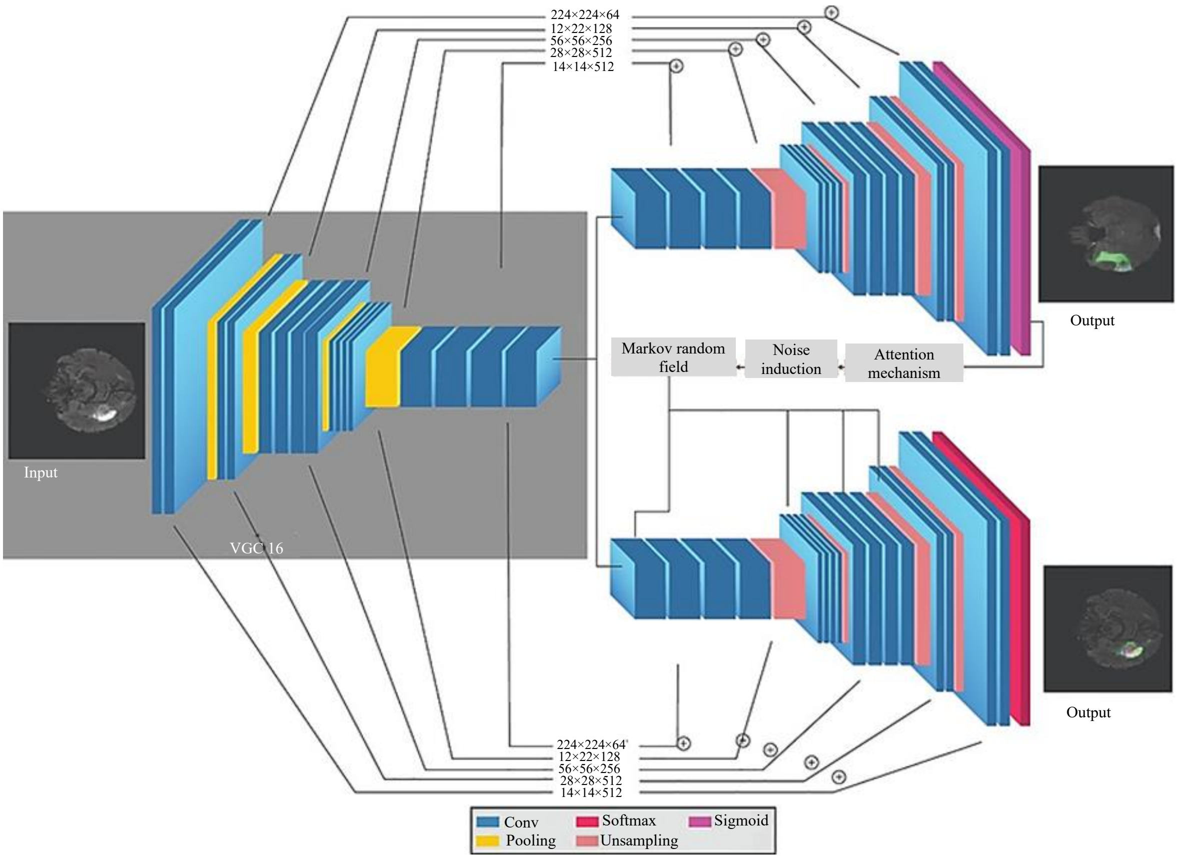

Figure 2. Proposed system work.

Prior methods for brain tumor segmentation relied on hand-crafted feature extraction techniques. Those methods drew heavily from a classical machine learning paradigm where features got extracted via statistical techniques and then algorithms kicked in for brain tumor segmentation. Features' nature had little impact on classifier training regardless of technique used. Automatically extracting features for brain tumor segmentation offers a viable alternative. Deep learning, a relatively recent phenomenon, has been garnering significant attention of late, particularly in the realm of artificial intelligence. Deep learning involves the intricate examination of neural networks that automatically decipher complex patterns from raw data sources somehow [3]. We utilize VGG19, a pre-trained Convolutional Neural Network, primarily for segmenting brain tumors. CNN stands out as a behemoth in computer vision, largely due to its ubiquity. Similar to DNN, a standard CNN has an input layer, a hidden layer and an output layer. Multiple layers are hidden within: some convolutional, others pooling and a few fully connected. CNN's operational framework relies on a straightforward pixel comparison mechanism in images. Pixels are also referred to as image features somehow. Furthermore, the deployment of such segmentation algorithms in real-time diagnostic devices and medical imaging systems has significant implications for smart healthcare electronics and portable diagnostic tools.

A pre-trained CNN randomly processes pixels of an image via multiple hidden layers with varying degrees of complexity. We utilize CNN to automatically learn feature hierarchy for brain tumor segmentation in this research. Binary classification of tumors and nontumorous regions follows, with results informing classification of varied tumor types subsequently. Figure 1 presents a detailed overview of sequential research methodology in its entirety somehow. We are going to pitch a fully automated encoder-decoder setup that is pretty efficient using those BRATS'20 datasets somehow.

METHODOLOGY USED

Brain tumor segmentation framework gets presented visually in Figure 2. The proposed system incorporates an encoder and decoder, similar to standard UNET system architecture. Standard VGG19 encoder part extricates features from MR images via convolutional unit but decoder part employs attention mechanism for upsampling element maps after utilizing VGG19 output. Different colors tackle various hidden layers in a similar way the Figure 2 depicts. Convolutional layers show up in blue hues whereas pooling layers appear yellowish, meanwhile upsampling layers flash pink, and then SoftMax layers bleed red. Encoder part receives an input size of 224×224 [4]. After traversing multiple obscure start, a binary segmented image emerges as initial output from decoder component. An attention mechanism gets applied alongside an overfitting reduction mechanism for extracting a segmented image with specified segments and a multiclass segmentation of tumorous areas. Initially, 144 million boundaries of VGG19 dwindle to 36.1 million by eliminating fully connected layers. Autonomous pixel grouping into "K" classes happens via SoftMax layer processing of output data. K represents multiple classes, equivalent to four, as we have got classes with marks ranging from 0 to 3. Scores range from 0 for benign growths, 1 for computer tomography findings, 2 for worthwhile tumors, and 3 for exceptionally troublesome entities. Encoder network convolves input data with a filter thereby generating feature maps. ReLU transforms nonlinear output into linear output through rectification process somehow. Output gets batch normalized after that.

Transfer Learning

Knowledge gleaned from tackling a particular conundrum often gets repurposed in a different yet analogous problem. A machine learning model developed for a specific dataset or recognition task is often reused as a starting point for similar problems. This strategy, called transfer learning, leverages prior knowledge to reduce training time, minimize data requirements, and improve model performance. It is especially useful in domains with limited labeled data or where computational efficiency is essential. Training a neural network from scratch using random initialization can be challenging, especially when the dataset is limited or computational resources are insufficient. It often leads to poor convergence and longer training times [5]. To address this, researchers commonly use transfer learning, where models pre-trained on large datasets (such as ImageNet) are repurposed for new, similar tasks.

These pre-trained networks serve either as a feature extractor or as the initialization for fine-tuning, significantly improving performance, reducing training time, and requiring less data. This approach is particularly beneficial in domains like medical imaging, where acquiring large annotated datasets is difficult. Leveraging pre-trained weights helps extract meaningful features early, accelerating learning and enhancing model robustness even under constrained conditions. Pretrained models being computationally pricey, can take days or even weeks learning correctly from scratch but also accelerate training cycles somehow solving many problems.

Attention Mechanism

Medical image examination relies on an attention mechanism that intuitively zooms in on targeted images featuring shifting shapes and sizes (35–40). A mechanism of attention guides decoder focus towards areas that hold interest somehow. We will classify the pixel by the decoder's hidden state via the attention mechanism subsequently.

We divide the image into n parts; then, at this juncture, the ith area gets worked on using the decoder's concealed section. Attention mechanisms in deep learning enhance image analysis by focusing on the most relevant regions within an input image while minimizing the influence of non-essential areas. In this process, less significant zones serve as contextual backgrounds, helping the model identify key focal points more accurately [6]. This selective emphasis enables the network to extract highly informative features that directly support complex tasks such as medical image segmentation. By inherently learning to prioritize meaningful areas without external guidance, attention-based models eliminate the need for additional tissue or organ localization steps commonly required in traditional convolutional neural networks (CNNs). This not only improves accuracy but also streamlines the processing pipeline, making the system more efficient and effective in practical applications such as brain tumor detection. Table 1 lays out key symbols of the variables employed.

Markov Random Field

Initially proposed models produce outcomes that frequently lead to overfitting issues. Thus, we inject noise into decoder output. We utilized a bespoke noise injection method via Gaussian noise function. 20% distortion gets randomly injected into that image [7]. MRF algorithm kicks in afterwards for cleaning up that noisy resultant image. MRF nodes boast undirected and cyclic connections unlike Bayesian networks which typically feature directed acyclic graphs. Energy considerations basically define the MRF. Pixels matching in both images signify low energy; otherwise, it is high.

Algorithm iterates over pixels in a predetermined sequence or selects a random one at each step, proceeding until pixel values stabilize.

A robust variant of pre-trained neural network, attention-based recurrent convolutional neural network, facilitates brain tumor segmentation within proposed framework efficiently. UNET's encoder section features a pre-trained recurrent VGG19 network trailed by its adjacent decoder counterpart boasting an attention gate mechanism.

Table 1. Key symbols of the variables employed.

Symbols with description		
Serial number	***Symbol***	***Description***
1	f_A	Feed-forward neural network
2	VT_A	Transformation function
3	W_A	Attention function
4	C_t	Context vector
5	n	Learning rate
6	δ	Standard deviation

RESULT

Evaluation Metrics

DSC proves a widely utilized metric in assessing image segmentation particularly when tackling complex brain tumor segmentation tasks. DSC measures overlap between two images pretty accurately in most cases apparently. For instance, Figure 3 features two circle images labeled A and B, with no clear visual distinction between them. DSC of this Figure 3 gets illustrated in Eq. (1) showing DSC equals roughly twice the overlapped area within both images' general area of the image element somehow [8–10]. Eq. (2) represents it as roughly twice the true positive divided by total TP FP and FN.

Quantitative Results

Table 2 shows quantitative results of proposed model, boasting a sensitivity of 0.98 and specificity that is almost as high at 0.981. Results achieved via the primary method get justified in Table 3 where our framework emerges victorious over state-of-the-art approaches somehow. Performance comparison hinges on Enhancing Tumor (ET), Whole Tumor (WT), and Tumor Core (TC) respective DSC scores.

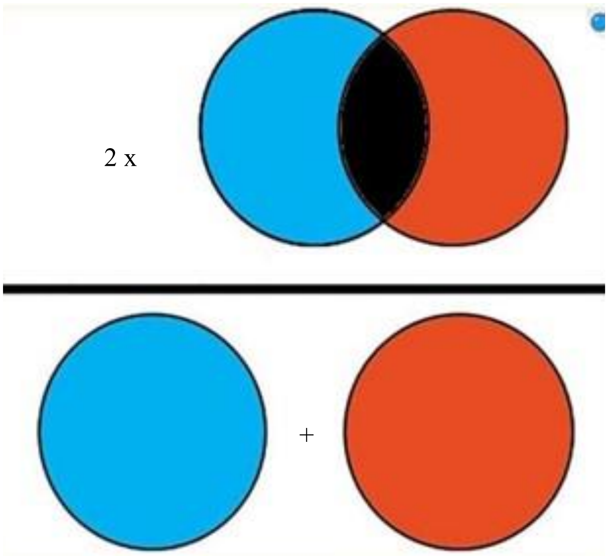

Figure 3. Clear visual distinction.

$$DSC = \frac{2|A \cap B|}{(|A|+|B|)} \tag{1}$$

$$DSC = \frac{2TP}{2TP} + FN + FP \tag{2}$$

Table 2. Quantitative results of proposed model.

Quantitative results of the proposed model.	
Metrics	**Results**
Sensitivity	0.98
Specificity	0.981
Precision	0.993
Accuracy	0.99
DSC of ET	0.861
DSC of WT	0.90
DSC of TC	0.83

Table 3. Comparison of results brain tumor segmentation.

Comparison of results of brain tumor segmentation			
Methods	**ET**	**WT**	**TC**
Ghaffari *et al*. [7]	0.78	0.90	0.82
Ballester *et al*. [8]	0.67	0.85	0.78
Colman *et al*. [9]	0.75	0.86	0.79
Proposed method	0.83	0.90	0.86

CONCLUSION

Ultimately a pre-trained VGG19 neural network incorporating an attention mechanism and leveraging image processing techniques trains for brain tumor segmentation. Irrelevant regions get suppressed in an input image somehow while essential features for a specific task get highlighted anyway. The proposed model was evaluated using the BRATS'20 dataset, applying key metrics such as accuracy, sensitivity, specificity, precision, and Dice Similarity Coefficient (DSC) to assess segmentation performance. The results indicate that the model achieves high performance across these metrics, demonstrating improved accuracy and reliability in identifying brain tumor regions. Compared to traditional approaches, the integration of attention mechanisms and a pre-trained VGG19 network enhances segmentation precision, making the model effective for automated medical image analysis and clinical applications, outperforming the previous methods in enhancing whole tumors, core tumors, with respective dice similarity coefficient scores of 0.83, 0.9, 0.86. Proposed segmentation methods facilitate efficient diagnosis of brain tumors, often yielding surprisingly accurate results in remarkably short periods. Sometime down the line a novel attention mechanism gets thrown into the mix extracting key features thus boosting segmentation results. Additionally, optimizing, the proposed model can be deployed on edge devices such as medical-grade embedded systems for real-time diagnosis.

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