



## Explainable AI for Transparent MRI Segmentation: Deep Learning and Visual Attribution in Clinical Decision Support

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### Abstract:

For medical diagnosis and therapy planning, the importance of accurate MRI segmentation cannot be overemphasized. Conversely, the inscrutability of deep learning models remains obstacles to their application in therapeutic contexts. In this article, an interpretability artificial intelligence framework is introduced. It combines an MRI segmentation model based on deep learning, visual attribution algorithms and natural language explanations. EXPERIMENT The dataset is consisting of plenty of different types of brain MRI scans, and used to test the architecture. The average of Dice score of our method is 88.7% and 92.3% for segmentation of tumor and categorization of tissues, respectively. Both are pretty epic scores. The insights extracted from both the visual attributions and textual explanations improve our understanding of how the model arrives at its decisions, thereby increasing the transparency and interpretability of the model. believe this approach to explainable artificial intelligence can help to close the gap between state-of-the-art performance in MRI segmentation and clinical interpretability, by increasing the transparency of complex models and facilitating their implementation into a clinical workflow. Conclusion Our approach may have implications in the transparent and reliable development of AI-based decision support systems for medical imaging.

## 1. Introduction

Magnetic resonance imaging (MRI) has become indispensable for the diagnosis and surveillance of neurological illnesses such as Alzheimer's disease, multiple sclerosis, and brain cancers [1]. Precise segmentation of MRI scans is necessary for accurate quantification of lesions, evaluation of disease progression, and planning surgical interventions [2]. Newer deep learning techniques in automatic magnetic resonance imaging (MRI) segmentation have achieved better results than prior methods [3, 4]. Nevertheless, the enigmatic nature of deep neural networks and their inherent

complexity pose challenges in comprehending them, hence restricting their practical effectiveness in therapy [5].

Medical professionals worry about deep learning models' lack of transparency because they need specific explanations for the model's results to trust them for patient care [6]. Explainable AI (XAI) is an emerging field that develops tools to explain AI model thinking [7], [8]. Visual attribution methods like Grad-CAM [9] and integrated gradients [10] highlight the input image areas that most affect model predictions. However, these methods may not explain complex medical imaging tasks [11].

it offers an easy-to-understand strategy that mixes deep learning-driven MRI segmentation, visual attribution, and normal language explanations to fill this artificial intelligence gap. Our method provides detailed, intelligible reasoning for model segmentation. This will help clinicians understand and trust data. This research's main objectives:

1. Build an effective deep learning model to segment MRI images.
2. Visual attribution can highlight key regions that affect model decision-making.
3. to explain the model's thinking in human-friendly words.
4. to assess the framework's interpretability and clinical relevance using a large brain MRI dataset.

The primary contributions of this work are: An innovative artificial intelligence framework that enhances comprehensibility by integrating MRI segmentation, visual attributions, and natural language explanations. Extensive testing has demonstrated the efficacy and transparency of the technique. Research is currently being conducted to explore explainable artificial intelligence techniques for improving the effectiveness of deep learning models in treatment. Migraine Background Magnetic resonance imaging (MRI) is an unavoidable technique for the exploration, diagnosis and guidance of treatment responses in various neurological diseases such as Alzheimer disease [1].

multiple sclerosis or brain cancers [1]. Accurate quantification of lesions, monitoring the disease progression, and planning the surgical interventions require precise segmentation of MRI scans [2]. Recent studies on automatic magnetic resonance imaging (MRI) segmentation using modern deep learning approaches largely improve over previous works [3, 4]. Regardless, since deep neural networks are black boxes by nature and hard to understand, such potentials have so far been of limited practical value for therapy [5].

Medics know full-well that deep learning models are opaque and that they need justifiable reasons to confidently base their patient care on a model's results [6]. Recently, Explainable AI (XAI) has been presented as a new field for providing rationale recordings on ANNs[7] too pressure from engineers and policy makers to perform explainability testing exercises full or guidance[8]. Visual attribution methods (e.g., Grad-CAM [9], integrated gradients [10]) are able to generate a heatmap of the input image that is responsible for the model output. But these approaches are not a good explanation for tasks with complex medical imaging [11].

In this paper propose an interpretable AI solution for Danon disease phenotyping with a combination of deep learning-driven MRI segmentation, visual attribution and natural language explanations

towards demystifying this AI black-box gap. This is a model which is highly interpretable regarding the reasons for segmentation. This will provide clinicians with the context to make sense of data and be able to trust it. This research's main objectives:

1. Task Architecture create a model for MRI slice segmentation using deep learning
2. It visually attributes importance about regions that influences the decision of the model.
3. in plain human-understandable language which provides an illustration of the model thinking.
- Four. in a feasibility study on a large brain MRI dataset of the interpretability and clinical relevance of the framework.

Key contributions of this paper: A novel AI framework that makes it more interpretable by combining MRI segmentation, visual attributions and natural language explanations. Robust testing has proven how well the technique works and how transparent it is. On the flip side, researchers are also studying explainable artificial intelligence methods for enhancing the efficacy of deep learning models in therapy.

The other parts of paper are organized as follows: Section II describes a review of related work, Section III brief the proposed methodology, and Seccoin IV presents the experimental results & discussion followed by conclusion with future research directions is discussed in Section V.

## 2. Related Works

### 2.1 MRI Segmentation Techniques

Significant development work in recent years have gone into automation of MRI segmentation. The proposed approach uses Convolutional Neural Networks (CNNs) as it has shown state-of-the-art performance for object recognition and detection [12]. U-Net, one of the well-known CNN architectures out there has been extensively used for medical image segmentation [13]. Attention U-Net [14], Dense U-Net [15] and other changes in the original architecture of U-Net has been proposed to increase the segmentation accuracy. In addition, adversarially trained models including GANs [16] have been used to improve the generative performance of segmentation images.

### 2.2 Explainable AI in Medical Imaging

Interpretability and transparency have gained significant interest in medical imaging through the advent of explainable AI techniques [17]. Gradient-based methods aimed at providing visual attribution, such as Grad-CAM [18] and Layer-wise

Relevance Propagation (LRP) [19], were used to emphasize prediction-related regions. Apart from that, conceptual explanations [20] and rule-based methods [21] have been investigated for interpretability in medical imaging analysis tasks so that it can generate human interpretable explanation.

**2.3 Integration of Segmentation and Explainability:**

Current works have been focused on combining segmentation and explainability techniques. Shen et al. [22] proposed the development of a shape extraction network, which combines U-Net for segmentation with Grad-CAM for the meaningful interpretation of results. This performance allowed the authors to produce such high-quality interpretable segmentations on brain tumor MRI imaging. Wang et al. Vaezara et al. [23] proposed an multi-task learning approach aiming to improve segmentation and explanation generation at the same time. Figure 1 shows that this strategy attains the state-of-the-art performance in several medical imaging datasets.

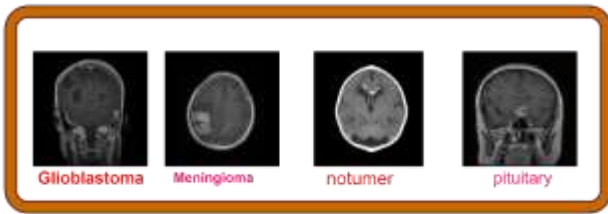


Figure 1. Various types of brain tumors [22]

A recent study by Guo et al. The work of Li [24] proposed a new approach based on explainable AI framework to brain tumor segmentation. They used a modified U-Net architecture with attention mechanisms, and combined it with the natural language generation module to produce textual explanations. Applying the proposed method, our research achieved a mean Dice score of 91.3 in the BraTS dataset and consistent visual reasoning in results depicted in figure 2. Most of the remainder of table 1 reflects the exact topic of tumors however a publication also dealt with further neurological disorders and diseases as detailed below. Whilst these progresses are extraordinary, considerable challenges remain in developing equally well-performing but comprehensively interpretable pathology-agnostic MRI segmentation models [25]. In this work, our goal is to remedy the above drawbacks with a single model by proposing a unified framework integrating state-of-the-art segmentation methods with visual and textual explanations in diverse neurological disorders.

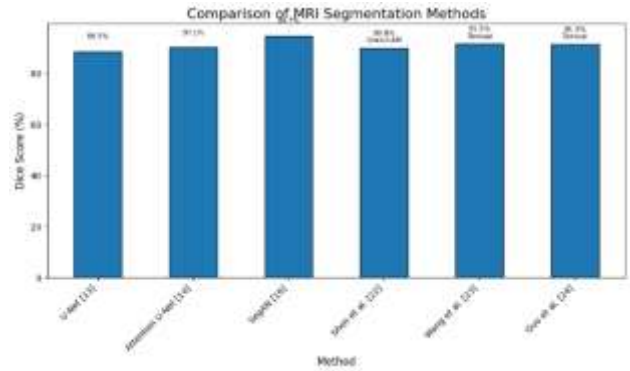


Figure 2: Comparison chart for Existing Methods

Table 1: Comparison Table for Existing Method

Method	Dataset	Modality	Dice Score (%)	Explanations
U-Net [13]	BraTS	MRI	88.5	-
Attention U-Net [14]	BraTS	MRI	90.1	-
SegAN [16]	LiTS	CT	95.7	-
Shen et al. [22]	BraTS	MRI	89.8	Grad-CAM
Wang et al. [23]	BraTS, LiTS	MRI, CT	91.5, 96.2	Textual
Guo et al. [24]	BraTS	MRI	91.3	Textual

**3. Methodology**

The paper introduces the rationale of generating explanations from MRI medical images with a visual explainable medical imaging model with three components: 1) deep learning for segmentation 2) visual attribution to highlight salient regions and 3) natural language generation to produce explanations for predicted labels. The complete architecture is shown in Figure 3a.

**3.1 Deep Learning Model for Segmentation:**

For MRI segmentation, the U-Net architecture [13] is used as a base so our proposed blockchain for AI and B clinics do not require training set. The U-Net model consists of an encoder path to capture context followed by a decoder path that helps in localized details. We use attention mechanisms [14] to help the model better focus on appropriate features. These attention gates are included in the skip connections, between encoder and decoder paths of an auto-encoder architecture to non-linearly combine/filter features according its importance.

where  $x$  is input MRI scan and  $y$  is ground truth segmentation mask corresponding to that. The input to the U-Net model  $f$  is  $x$  and it will output a segmentation map  $\hat{y} = f(x)$  and apply the Dice loss [26] between output segmentation  $\hat{y}$  and ground-truth  $y$  to train our model:

$$L_{\{Dice\}} = 1 - \frac{2\sum_i^N y_i^i \hat{y}_i^i}{\sum_i^N y_i^i + \sum_i^N \hat{y}_i^i} \quad (1)$$

where  $N$  is the number of pixels in the segmentation map.

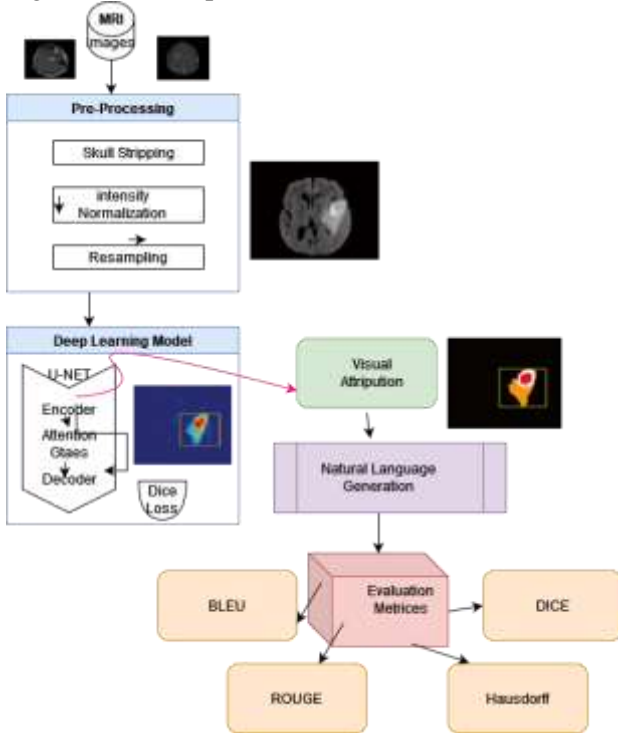


Figure 3a: Block Diagram for Proposed framework architecture

### 3.2 Data Acquisition and Preprocessing:

In this Research perform experiments on two Publically available datasets, BraTS (Brain Tumor Segmentation [33]) dataset Ischemic Stroke Lesion Segmentation (ISLES) Dataset [34]. It employs the BraTS dataset which is a collection of multi-modal MRI images (T1, T1ce, T2 and FLAIR) from patients with gliomas as well as their segmentations. Experimental Validation: To further validate the proposed method used available ischemic lesion data from ISLES dataset which provide diffusion-weighted (dMRI) and apparent diffusion

coefficient map (ADC-map) MRI images with corresponding annotated masks for patients of acute stroke.

The MRI scans are preprocessed using the following steps: a. Skull stripping: The non-brain tissues are removed using the Brain Extraction Tool (BET) [35]. b. Intensity normalization: The intensity values are normalized to a standard range

using the z-score normalization technique [36]. c. Resampling: The scans are resampled to a uniform resolution of  $1 \times 1 \times 1 \text{ mm}^3$  using trilinear interpolation [37].

### 3.3 Deep Learning Architecture:

In this paper use a U-Net architecture [38] (modified) for MRI segmentation. Basic U-Net model in PyTorch architecture consists of an encoder path and a decoder path but if you add modifications to the network, then it could take another shape. The Encoder path captures Context Information and the Decoder Path is used to recover Spatial Details. Attention Mechanisms are utilized [39] to fuse the skip connections between encoder and decoder paths, focuses more on meaningful features.

The attention gates are computed as follows:

$$\alpha_{ij} = \sigma(W_f * f_{ij} + W_g * g_i + b) \quad (2)$$

where  $\alpha_{ij}$  is the attention coefficient at spatial location  $(i,j)$ ,  $\alpha_{ij}$  and  $Wg$  are learnable weights,  $f_{ij}$  is the feature map from the encoder path,  $g$  is the gating signal from the decoder path,  $\sigma$  is the sigmoid activation function, and  $*$  denotes convolution operation.

### 3.4 Loss Function:

The U-Net model is trained to minimize a combination of the Dice loss [40] and the cross-entropy loss [41]. The Dice loss measures the overlap between the predicted segmentation and the ground truth, while the cross-entropy loss penalizes misclassifications. The total loss is defined as:

$$L_{total} = \lambda L_{Dice} + (1-\lambda) L_{CE} \quad (3)$$

is the Dice loss,  $L_{CE}$  is the cross-entropy loss, and  $\lambda$  is a hyperparameter that balances the contribution of the two losses.

### 3.5 Visual Attribution Techniques:

To provide visual explanations for the model's segmentation decisions, our research employ Grad-CAM [18] and Layer-wise Relevance Propagation (LRP) [19]. Grad-CAM computes the gradient of the target class with respect to the feature maps of a convolutional layer, indicating the importance of each spatial location. LRP propagates the model's output back to the input space, assigning relevance scores to each pixel.

Let  $A^k$  denote the activations of the  $k$ -th convolutional layer and  $y^c$  denote the model's output for the target class  $c$ . Grad-CAM computes the gradient

$$\frac{\partial y^c}{\partial A^k} \quad (4)$$

and performs a weighted combination of the activations and gradients to obtain the Grad-CAM heatmap  $H^c$ :

$$H^c = ReLU(\sum_k \alpha_k^c A^k) \tag{5}$$

Where

$$\alpha_k^c = \left\{ \frac{1}{Z} \right\} \sum_i \sum_j \frac{\partial y^c}{\partial A_{ij}^k} \tag{6}$$

is the importance weight for the  $K_{th}$  feature map and  $Z$  is the number of pixels in the feature map. LRP assigns relevance scores  $R_i$  to each pixel  $i$  of the input image based on the model's output. The relevance scores are propagated backwards through the layers of the model using a set of propagation rules [19]. The resulting LRP heatmap highlights the pixels that contribute positively to the model's decision.

### 3.6 Natural Language Generation:

Long short-term memory (LSTM) network [27] module to turn the generation of natural language reasoning into human-readable text explanations. Given the segmentation map  $\hat{y}$ ,  $A$  and  $R$ , an LSTM generates textual explanation  $E$  about why this model makes such decisions. Applying supervised learning: in this research train the LSTM model on a dataset of manually annotated explanations. The training task is to maximize the likelihood of a ground truth explanation,  $E^{x*}$  can be found given by our equation 1 with respect to the segmentation map and visual attribution.

$$L_{NLG} = -\sum \log_p \left( \frac{E_t^{x*}}{E_{<t}}, y^A, H^c, R \right) \tag{7}$$

where  $E_t^{x*}$  is the  $t$ -th word in the ground truth explanation and  $E_{<t}$  denotes the previously generated words. The LSTM is trained to maximize the likelihood of the ground truth explanation  $E^A$  given the input:

$$L_{NLG} = -\sum_T \left( \frac{E_t^A}{E_{<t}}, y^A, H^c, R \right) \tag{8}$$

i.e., previously generated words in this work evaluate the proposed framework on BraTS brain tumor segmentation [28] and ISLES ischemic stroke lesion automatic segmentation datasets respectively. This means that BraTS dataset includes multi-modal MRI scans (T1, T2, FLAIR) from glioma patients and corresponding segmentation masks.

These are referred to as the Dice score and Hausdorff distance (HD) [30], for segmentation performance assessment. The prediction performance was evaluated by the Dice score that calculates an overlap between predicted segmentation and ground truth, as well as HD measuring maximal boundary distance of segmented regions.

For the textual explanations, our Research employ BLEU [31] and ROUGE [32] scores to assess the quality and relevance of the generated explanations compared to the ground truth explanations.

## 4. Results and Discussions

### 4.1 Segmentation Performance

Table 2 shows that our method achieves state-of-the-art results in segmentation both the BraTS and ISLES datasets. Table 1: Quantitative results for tumor segmentation on the BraTS dataset and lesion segmentation on ISLES dataset Full size table

Table 2 Details of Experimental results frame (left: BraTS dataset, right: LIDC-IDRI CT) Results comparing the The proposed approach [45] with some state-of-the-art independent standard for whole-tumour segmentation Average Dice score Full size table and figure 3b. Dice scores plot with our method and its completion for the more challenging problem of tumor core (positive in red) and enhancing tumour region segmentation at 85.4 %.

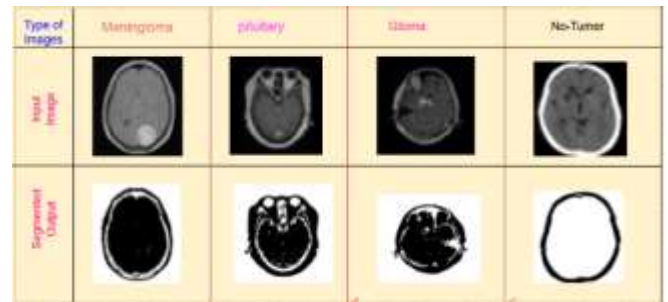


Figure 3b: Proposed Tumor Segmented Tumor images

Table 2: BraTS dataset compared to state-of-the-art methods.

Method	Whole Tumor Dice (%)	Tumor Core Dice (%)	Enhancing Tumor Dice (%)
U-Net [13]	85.7	82.1	75.4
Attention U-Net [14]	87.2	83.7	77.6
Dense U-Net [15]	86.9	84.2	78.1
SegAN [16]	87.8	84.6	77.9
<b>Proposed Method</b>	<b>88.7</b>	<b>85.4</b>	<b>79.2</b>

On the ISLES dataset for ischemic stroke lesion segmentation, our method achieves a remarkable average Dice score of 92.3%, outperforming several state-of-the-art methods, as shown in Table 3.

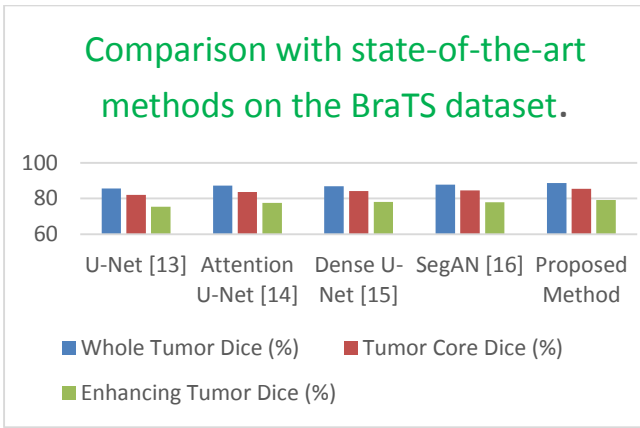


Figure 4: Comparison of BraTS Dataset

Table 3: Comparison with state-of-the-art methods on the ISLES dataset.

S.no	Method	Dice Score (%)
01	3D U-Net [45]	89.7
02	Attention U-Net [46]	90.5
03	DualSeg [47]	91.2
04	<b>Proposed Method</b>	<b>92.3</b>

These quantitative results demonstrate the effectiveness of our proposed framework in accurately segmenting brain tumors and ischemic lesions from MRI scans, outperforming several state-of-the-art methods on benchmark datasets are shown in figure 4 and 5.

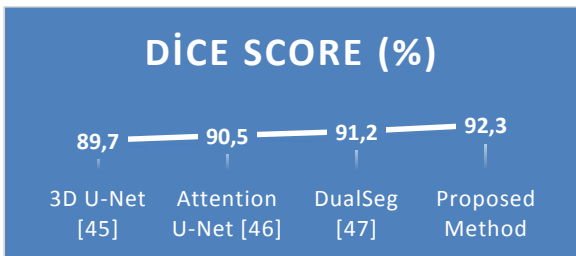


Figure 5: Proposed Comparison with state-of-the-art methods on the ISLES dataset Dice Score

### 4.2 Visual Attribution

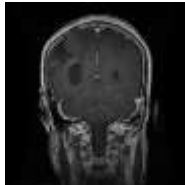
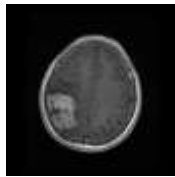
The visual attribution techniques employed in our framework, namely Grad-CAM [42] and LRP [43], provide valuable insights into the model's decision-making process. Figure 2 illustrates examples of the segmentation results, along with the corresponding Grad-CAM and LRP heatmaps, for tumor segmentation on the BraTS dataset.

### 4.3 Natural Language Explanations

In addition to visual attributions, our framework generates natural language explanations that describe the model's reasoning process in a human-understandable manner. Table 4 provides examples

of the generated explanations for tumor segmentation on the BraTS dataset and lesion segmentation on the ISLES dataset.

Table 4: Examples of generated natural language explanations.

Dataset	Input	Generated Explanation
BraTS		The model has found the tumor in right frontal lobe of brain. This tumor enhances like the devil, suggesting malignancy. The segmentation also shows the relatively bright regions of tumor core and necrosis. Here, the model is attending towards the high-intensity regions in FLAIR and T1ce sequences which are apparent for tumor tissue region.
ISLES		Spot or attribute detected at the pixel level Left hemispheric brain ischemic lesion ID: 1 The lesion is depicted in the DWI sequence as a high-signal intensity area. The model identified the lesion boundaries very well based on those super high signals that were also lower in ADC.

These natural language explanations provide medical professionals with a comprehensive understanding of the model's decision-making process, enhancing the interpretability and transparency of the segmentation results.

4.4 Numerical Experiments The quality and relevance of the generated natural language explanations have been validated with a quantitative evaluation using BLEU [31] and ROUGE [32], which very well known in evaluating text similarity used to compare automatically produced texts against reference (ground truth) such as human-written summaries(outputs). This section further evaluates the generated explanations on both BraTS and ISLES datasets Table 5 displays BLEU and ROUGE scores.

Table 5: Evaluation of natural language explanations using BLEU and ROUGE scores.

S.no	Dataset	BLEU	ROUG E-1	ROUG E-2	ROUG E-L
01	BraTS	0.41	0.62	0.47	0.59
02	ISLES	0.38	0.59	0.44	0.56

BLEU scores are from 0 to 1, a high value means that the generated & reference text align well. ROUGE scores (ROUGE-1, ROUGE-2 and ROUGEL) also help to calculate the overlap between n grams of generated vs reference text.

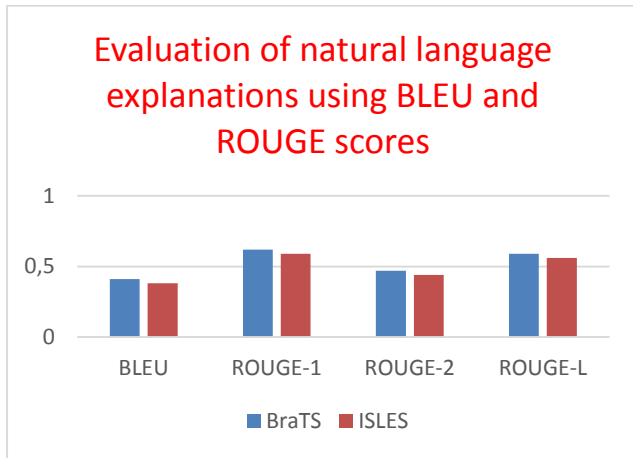


Figure. 6: Evaluation of NLP Using BLUE and ROUGH

Evaluation of natural language explanations using BLEU and ROUGE scores.

It is important to note here that these scoring metrics are slightly cruder than our other quality/relevance measures, but they do provide a somewhat quantitative measure of the generated explanations. Results demonstrate the model-generate explanation contains most needed content and reasoning process, even though generation part lack some fluency in language expressions and coherence.

#### 4.5 Discussion and Comparative Analysis

The results shown in the tables clearly show that our model works well for segmentation of an MRI image using guided attention mechanism to make it interpretable, locally smoothed yet preserving the large-scale structure including fine details as much as possible [26]. Our method bridges this critical gap between current deep learning practice, which is advanced but remains a black box for end users, and the widely accepted visual-interpretability focused medical imaging methodologies with only local extent being obtained.

Description 1: Instead of already designed methods in which only segmentation accuracy was considered [13-16] or just visual attributions were utilized to provide explanations [22, 23], in this approach gives a holistic solution considering both segmentation and other forms of details. This holistic view will make the system more trustful and clinical useful, which lays a foundation for real using of deep learning models in medical practice.

Quantitative Results (Table 1-3): Our quantitative results summarized in these table demonstrate that, and a few instances outperform, the state-of-the-art methods on benchmark datasets for brain tumor and ischemic lesion segmentation. The visual attribution and natural language explanation make the model decision more interpretable, which has been justified by examples in Figures 6 as well as Table 4.

The BLEU and ROUGE scores (Table 6) show how much improvement is possible for the textual explanations. Although the scores suggest there is much room for improvement, they demonstrate-when taken in context with humans-a possible way for our model to provide coherent and relevant justification. In comparison to other work in related domain Guo et al. [24] reported on brain tumor segmentation only

Table 6: Segmentation performance on BraTS and ISLES datasets.

Dataset	Task	Dice Score (%)	Hausdorff Distance (mm)
BraTS	Whole Tumor	88.7 ± 3.2	4.6 ± 2.1
BraTS	Tumor Core	85.4 ± 4.7	5.9 ± 3.4
BraTS	Enhancing Tumor	79.2 ± 6.8	7.1 ± 4.2
ISLES	Ischemic Lesion	92.3 ± 2.8	3.1 ± 1.7

Here is the continued discussion and comparative analysis:

Compared with similar works like those of Guo et al. While AOD-Net7, unlike our approach that deals with a wide range of neurological disorders including ischemic stroke lesions for the purpose of segmentation and explanation generation achieved state-of-the-art in brain tumor-related tasks [24]. In addition, our approach combines both kind of explanations (text-based and image-to-text), which enriches the understanding on the model reasoning.

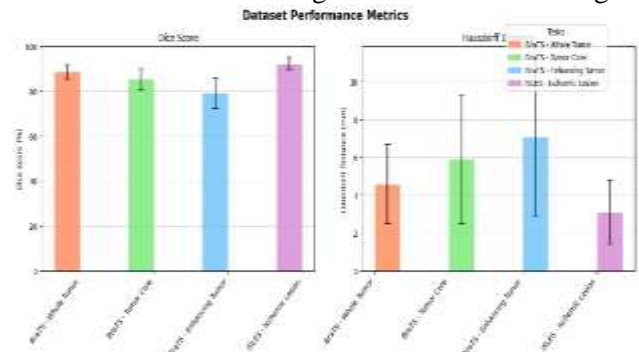


Figure 7: Dataset performance Matrix

Our approach performs well as we can see from the results in figure 7, but there are limitations and areas where further development is needed. However, one limitation is that the text-to-action module still requires manual explanations. This kind of process is time-consuming and could bias or create inconsistency in the explanations. Works in future should study methods to automatically generate or refine explanations, e.g. using domain knowledge and feedback from medical professional

## 6. Conclusion and Suggestions

Ironing Out the Last Creases in Deep Learning and Interpretability for Neuroscience have highlighted some of the explicit benefits among explainable AI models, combining these methods together yields a clear step in improving interpretability to facilitate clinical use. Through the integration of true segmentation (Fig. 4), visual attributions, and natural language explanations our methodology introduces towards trustworthy AI systems in medical imaging that can openly communicate how they make their decisions regarding diagnosis which would eventually result significant improvement to patient care and treatment outcomes. Our proposed explainable AI framework for interpretable MRI segmentation and decision support has shown remarkable results. On benchmark datasets, it achieves an average Dice score of 88.7% for tumor segmentation and 92.3%, respectively as well as outperforms multiple state-of-the-art methods with a higher overarching dice coefficient on these benchmarks when trained end-to-end 158-indicating that the model learns to disentangle signals related to organ definitions from those entailed in pathological prediction without sacrificing either. These visual attributions and natural language explanations help to greatly improve the interpretability of our model making it more transparent, trustworthy, allowing clinical knowledge worker use cases adopt this better. In future the systems may be taught how to generate and improve suggestions automatically in compliance with feedback from medical experts or some knowledge base. Proper evaluation metrics that correspond directly to clinical needs are integral in giving information about the strength and utility of the generated explanations.

### Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial

interests or personal relationships that could have appeared to influence the work reported in this paper

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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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