Explainable Transformer-Based Classification and Segmentation of Intracranial Hemorrhage

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1. Task

Intracranial Hemorrhage, also known as a brain bleed, is a life-threatening condition that occurs when blood pools in the skull. It accounts for 10-15% of all strokes. Normally, to detect this condition, radiologists or neurosurgeons must manually review the CT or MRI scan report by just looking at them, a process that is time-consuming and prone to human error. There are also 5 subtypes of hemorrhage - Intraparenchymal (IPH), Intraventricular (IVH), Subarachnoid (SAH), Subdural (SDH), and Epidural (EH), each is based on a different location in the brain. Our task is to develop a vision transformer-based classification model with explainability, using techniques like Grad-CAM to generate segmentation maps. The goal is to compare these segmentation results against those produced by an already accurate pretrained segmentation model.

2. Approach

We will begin by downloading and processing the competition data, which currently consists of over 400GB and 670,000 images. As part of preprocessing, we'll convert the images to NIFTI format, making them compatible with MONAI and significantly reduce the data size we are working with. To preprocess our dataset further,, we will prune the dataset down to the patient level, targeting a reduced dataset size of around ⅔ of the original size. To establish ground truth, we will run each image through a pre-trained segmentation model. This pre-trained model will be selected from a GitHub repo of multiple models, mainly looking for models that have 5 different classifications, and we will utilize whichever model has the best accuracy. Our main task will then involve developing a Vision Transformer (ViT) model for hemorrhage classification. To fine-tune the ViT, we will incorporate explainability methods such as Grad-CAM or attention maps, which will help guide the classification process. Finally, we will apply segmentation techniques to our ViT model and compare its segmentation performance with the output of the pre-trained segmentation model.

3. Dataset and Metric

The dataset being used will be the RSNA Intracranial Hemorrhage Detection. The dataset involves 399 volumetric CT scans with a resolution of 512x512x28 pixels per scan. The dataset is classified into 5 categories of different kinds of hemorrhages: EH, SAH, IPH, SDH, and IVH. A typical training-to-testing data set ratio of 80:20 will be used. The dataset will be split based on the original paper's split, which utilized 5,000 images from a collection of over 600,000 images. The data will be split in a 9:1 training and testing split, where the training data will be further divided into a 8:2 training and validation split. The metric for success will be based variably on the accuracy of the pre-trained segmentation model, and we will consider our project successful if our ViT model is 80% of the accuracy of the segmentation model.

4. Responsibilities

Task	Who
Preprocess dataset by converting images to NIFTI format and prune dataset to reduce size.	Albert Zhao
Utilize MONAI to train and classify hemorrhage samples from the dataset and proceed to choose the best pre trained segmentation model to run each image through.	Rupali Sinha
Begin to develop a ViT and incorporate Grad-CAM for explainability purposes.	Ishan Bhattacharje e
Apply segmentation techniques to the ViT model and compare the performance of the segmentation to the pre trained segmentation model.	Benjamin Axline

5. References

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