Intracranial Hemorrhage Segmentation Using Unet 3+ and Data Augmentation based on Clinical Knowledge

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Abstract. Intracranial Hemorrhages are one of the leading causes of mortality and disability. An accurate, fast and automated diagnosis is very crucial since these hemorrhages tend to develop secondary injuries if not treated in the first few hours of the accident. This is however a very challenging task because of various reasons that include the availability of limited annotated patient data, varying size, shape and location of these hemorrhages. This paper presents a deep learning framework which involves clinical knowledge. Firstly, a new data augmentation approach that leverages from the clinical knowledge that the two hemispheres of the human brain exhibit approximate symmetry is proposed. Secondly, this paper proposes to use UNet3+ network for the segmentation.The proposed method are evaluated on the validation dataset provided by the INSTANCE challenge and achieved about 67% in the leaderboard.

Keywords: Intacranial Hemorrhage · Deep Learning · Segmentation.

1 Introduction

Intracranial hemorrhage (ICH) is one of the common type of head injuries with highest mortality rate[1]. It is essential to develop an early and accurate diagnostic system for the detection of ICH for treating patients. In regular clinical practice, Non-Contrast Computed Tomography (NCCT) is the most widely used modality for diagnosing ICH due to its fast acquisition and availability in most of the emergency departments [2].

In clinical diagnosis procedures, accurately estimating the volume of intracranial hemorrhage is significant for predicting hematoma progression and early mortality [3]. The hematoma volume can be estimated by manually delineating the ICH region by radiologists, which is time-consuming and suffers from interrater variability . The ABC/2 method [4] is widely adopted in clinical practice to estimate hemorrhage volume for its ease of use. However, the ABC/2 method shows significant volume estimation error, especially for those hemorrhages with irregular shapes . Hence, it is necessary to establish a fully-automated segmentation method, which allows accurate and rapid volume quantification of the intracranial hemorrhage. However, it is still challenging to accurately segment the ICH for automatic methods because ICH exhibits large variations in shapes and locations, and has blurred boundaries. Recent advances of deep learning in computer vision tasks lead to explore its application in medical imaging and has been successful in many applications. There are quite a few attempts made to find the intracranial hemorrhages in CT scans. A lot of studies based on traditional image processing methods typically investigated only on few types of hemorrhages. Recently [7] proposed to use the popular CNN network and trained on a large datasets of around 32k CT scans For segmentation tasks, UNet like architectures are used for segmenting the brain lesions in CT scans [8–10]. A cascaded framework for detection and segmentation tasks is proposed in [11]. [12] used DeepMedic, a 3D CNN. The work was done on large datasets and have shown very high performance. A method to predict the segmentation as well as the prediction uncertainity has been proposed in [6] for intracranial hemorrhages. Most of the work is primarily concerned with detection or segmentation and the potential of incorporating clinical knowledge for TBI has not yet been explored.

In this paper, we propose to use UNet 3+ with data expansion method based on midsagittal plane extraction to obtain the optimal performance.

1.1 Data augmentation

The brain exhibits the inherent property called bilateral symmetry. The brain is approximately divided into two equal hemispheres by the midsagittal plane (MSP). The data augmentation methods where horizontal and vertical flipping methods are used for network generalisation and to improve the robustness of the model. But in case of the brain, we can actually use the MSP flipped versions of the CT scans as an extra data. We doubled the dataset by finding the midsagittal plane through the algorithm proposed in [5]. Then the MSP flipped versions are saved separately. We assume that the patients have intracranial hemorrhages and do not have large skull fractures for this problem. Also, most of the hemorrhages usually do not occur in the central part of the brain. To extract MSP, we first apply the sobel edge detection method followed by thresholding to obtain the outline of the skull. An inital plane of reference is chosen to be the exact middle slice in the sagittal direction. A similarity metric is computed between the two hemispheres that are divided with the plane of reference. The reference plane is rotated by an angle of $\pm$ 0.5 $^\circ$. The plane which yields maximum similarity is the required MSP. We flipped all the data over the MSP plane and thus doubled the dataset.

1.2 Network Architecture

We used a popular network UNet 3+ [8] which is a modification to the UNet model [9]. The UNet 3+ model consists of contracting and expanding path just as the Unet model. The main contribution in UNet 3+ compared to the UNet is the skip connections. UNet has plain and direct skip connection in every stage of the network from contracting layer to expanding layer whereas the UNet

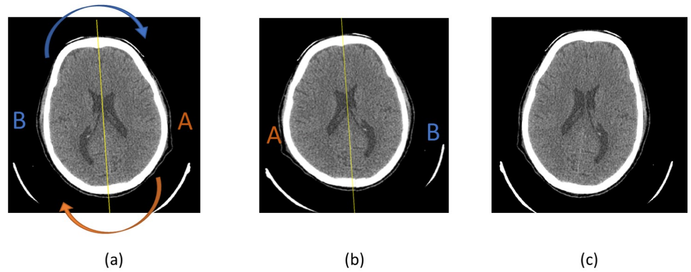

Fig. 1: An example for data augmentation through bilateral symmetry property of brain (a) Mid-sagittal plane (yellow line) is extracted by computing the similarity between the two hemispheres,(b) the image formed by flipping with respect to mid-sagittal plane and (c) the simple flip about vertical axis operation.

3+ consists of full scale skip connections. The full scale skip connections are the connections of every stage of contracting path to each stage of expanding path. Through this, the network can incorporate low-level details with high-level semantics from feature maps in different scales. This model also includes full-scale deep supervision by learning hierarchical representations from the full-scale aggregated feature maps. This mechanism is depicted in the Fig. 2 below.

2 Implementation details

The deep learning network considered for this work is UNet 3+ for performing the segmentation of TBI. This model are implemented using Tensorflow in NVIDIA Quadro RTX machine with 48 GB GPU. The sum of focal loss and Dice similarity loss is used as the loss function to minimize the loss between ground truth and model output. To improve the robustness of the model, the usual data augmentations such as shear, rotation,zoom, flip, elastic transform, noise etc are being used tec All the experiments are trained for 40 epochs with Adam optimizer with an initial learning rate of 0.0001. The learning rate is decayed by a factor of 0.1 if the validation loss does not change for 10 epochs and the taining stops if the validation loss doesn't change for 20epochs. The time taken for training each epoch with 5000 iterations is 5 minutes.

2.1 Preprocessing

The number of slices in each scan are around 30 in all the given patient data. However, the hemorrhages lies in very few slices and in certain cases the volume of the injury could be very small. Therefore, there exists a very high class imbalance between the hematoma and non-hematoma pixels. For this reason, only the slices which contain hemorrhages are used in the training process and all slices of each scan are tested in the testing phase. Also, to differentiate between the hemorrhage region and skull bone, which share similar intensities, we have

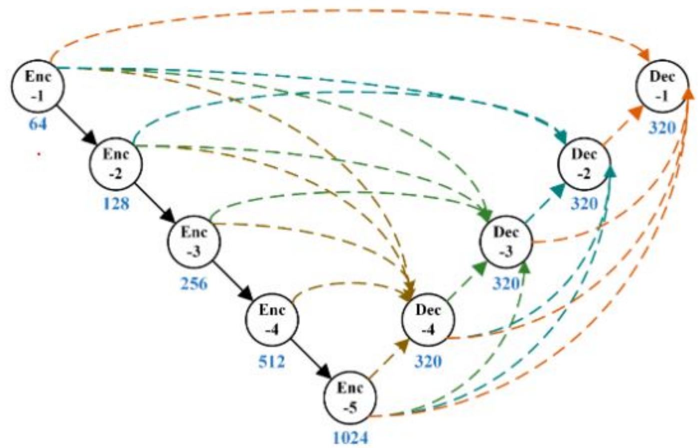

Fig. 2: The achitecture of the network UNet3+. Enc denotes encoder and Dec denotes decoder path. the number of filters are fixed at the skip connection of each stage

performed skull stripping on each scan for both training and testing process. Since the CT scans are of sizes of order 1GB, to faster the training process, we have saved the numpy file of each pre-processed CT scan in a separately.

3 Results on validation dataset

The proposed framework has achieved an average dice similarity score of 66.6%. With the use of MSP based data augmentation, we have observed an increment of 2% in the performance compared to the one without data augmentation.

Table 1: Performance comparison of UNEt3+

MSP based data expansion	Dice Similarity
Yes	66.66%
No	64%

4 Conclusion

The paper proposes to use UNet 3+ for segmentation along with the MSP based data expansion method. The model achieved a the validation score of 66% on the leaderboard. It is observed that the model has given significant improvement in performance compared to the baseline UNet architecture.

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