Dual-Path U-Transformer Network for Assessment of Brain Midline Shift in Hemorrhagic Stroke

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ABSTRACT

Midline shift is an important clinical indicator of the severity of hemorrhagic stroke and holds significance in a physician's clinical diagnosis. Segmentation-based methods for midline shift assessment are prevalent in the field, but the full utilization of global information within network remains a challenge. In addition, empirical integration with clinical knowledge is also essential. In this study, we developed a two-stage method for automatic midline shift assessment. Firstly, in the midline identification step, we proposed a Dual-Path U-Transformer to segment the brain midline. The Dual-Path U-Transformer can better capitalize on global information by integrating self-attention mechanism, while still retaining the characteristics of U-Net in making full use of local information and combining high and low dimensional features. In the second stage, according to clinical knowledge learned from clinical expert, we calculated the maximum shift distance for assessment of brain midline shift, determining whether each case has surgical indication. In the experiments process, we use 5-fold cross validation to train and validate the proposed model. Compared with traditional U-Net based method and transformer-based method, the proposed Dual-Path U-Transformer based method performed the best HD and Dice performance on our inhouse dataset. And the experiment results confirmed that the Dual-Path U-Transformer based exhibited excellent accuracy in the second stage of midline shift assessment.

Keywords: Brain Midline Shift, Assessment, Segmentation, Dual-Path U-Transformer, Hemorrhagic Stroke

1. INTRODUCTION

When a hemorrhagic stroke occurs, a hematoma may appear in various areas of the brain. Hematoma can induce compression of the surrounding areas, an increase in intracranial pressure, and a change in the relative position of structures within the brain. The midline of the brain, typically occurred near the symmetrical line where the two falxes are connected, can shift when such deformation occurs. Plenty of studies have demonstrated a close association between midline shift and hemorrhagic stroke, making the midline an important clinical diagnostic indicator of hemorrhagic stroke[1]–[8]. By assessing the severity of midline shift, the physician can quantify the severity of the hemorrhagic stroke and subsequently recommend treatment options.

Computed Tomography (CT) scans have the advantages of high resolution, fast imaging speed, high contrast and low cost. In the actual clinical diagnosis of hemorrhagic stroke, physicians usually choose CT scans for diagnosis. There are numerous datasets for brain midline shift composed of CTs[9]–[11]. Physicians manually estimates the midline shift based on their experience, and then determines whether a midline shift has occurred and its` severity. Manual diagnosis usually relies on the experience of specialists which is time-consuming. In the case of acute hemorrhagic strokes, diagnostic time is particularly valuable, and the imperative diagnosis needs to be made as quickly as possible, so that the patient can receive timely treatment. Automated methods, which utilize computers for diagnosis, are faster and provide more quantitative results than their manual counterparts.

Automated methods for assessing midline shift in the brain with hemorrhage continue to evolve. Automated midline shift assessment methods typically incorporate computer tools to optimize the use of midline-related features. Most current methods on this task can be broadly categorized into symmetry-based methods, landmark-based methods, and segmentation-based methods.

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Regarding the symmetry-based method, Liao et al.[12] developed a deformed midline model with quadratic Bezier curve based on genetic algorithm[13]. Chen et al.[14] incorporated an enhanced Voigt model and local symmetry to approximate midline. Symmetry-based approach hinges on local symmetry near the midline to achieve midline estimation. And symmetry-based methods do not work well when the hematoma is located near the midline, resulting in a loss of local symmetry. As for landmark-based methods, the approaches usually focus on detecting the landmarks to quantify the midline shift. Liu et al.[15] utilized six anatomical markers to define and gauge the distance of midline shift. Nguyen et al. [16] implemented a U-Net[17] based cascade network to locate landmarks in 2D and 3D for quantizing the midline shift. Yan et al.[18] used a modified key-point network to identify the key points of septum pellucidum and measure the midline shift while analyzing the clinical parameters connected with the results. Chen et al.[19] approximated midline shift by recognizing the ventricle shape feature points and matching the ventricle template. However, the landmark-based approaches fail when the landmarks are disrupted by a hematoma rupture. Moreover, landmarks, as discrete structures, fail to accurately represent the maximum offset in all situations.

Segmentation-based methods have been widely used recently to enhance the accuracy and robustness, with the booming development of deep learning. There are immense of existing segmentation-based methods for medical image segmentation based on improvements of U-Net[20]–[24]. To segment the midline, Pisov et al.[25] modified U-Net and combine structural features to segment the midline. Bukharaev et al. applied a probabilistic U-Net[26] to segment the dividing curve of the brain hemispheres. Wang et al.[27] proposed a U-Net based framework to accurately quantify the precise features. Due to the slender and continuous characteristics, global information is essential of detecting brain midline. Grasping the depth of this contextual information becomes paramount, underscoring the importance of capturing global features. Acknowledging this need for a broader perspective in brain midline segmentation, researchers like Wu et al.[28] have pioneered approaches that integrate specialized modules to expand the receptive field.

Benefiting from the self-attention mechanism, transformer can catch more global information and with a larger receptive field. In this paper, we deal with midline hift assessment in two stages including midline identification and shift assessment. We proposed a Dual-Path U-Transformer network (DP U-Transformer) inspired by the work[30]to better combine local and global characteristics. And the DP U-Transformer block overcome the problem of different weight assignment mechanisms for the self-attentive and convolutional layers, achieving better results. We adapted the DP U-Transformer in the midline identification part of the midline shift assessment process. After preprocessing, the images were input into the DP U-Transformer for detecting the midline. When getting predicted midline, we proceeded to measure the midline shift distance. The ideal midline is defined as the connected line that represents the connection between the two end points of brain midline, clinically defined as the line connecting the two brain falxes. Through discussions with physicians based on our clinical diagnostic experience, we established the threshold at 1 cm to ascertain whether each case has surgical indications. Finally, we calculated the accuracy of our assessment method by comparing the labels.

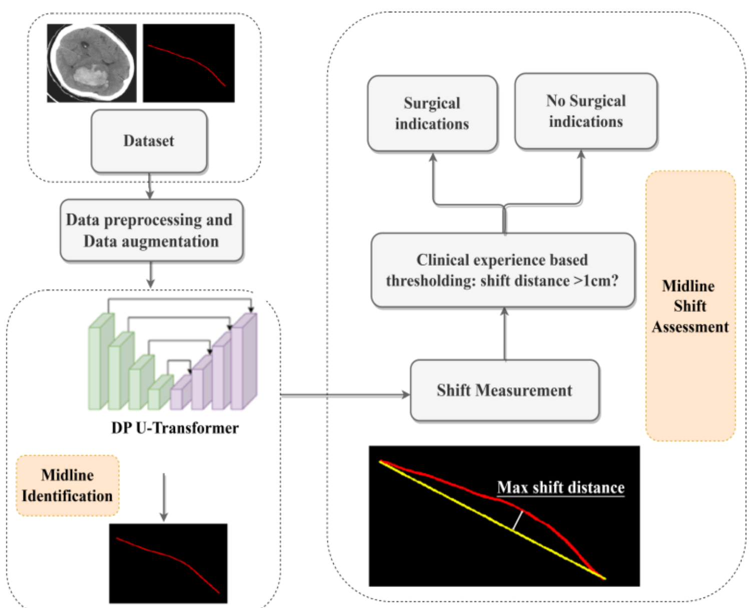

Figure 1. Flow chart of our midline shift assessment

2. METHOD

Figure 1 shows the overall flow chart. Our brain midline shift assessment method can be generally divided into two stages: midline identification and midline shift assessment.

2.1 Pre-Processing and data augmentation

Due to factors such as scanning equipment, parameter settings and scanning area, the pixel values of different CT images usually have different distributions and ranges. Therefore, we adapt a normalization operation to bring the pixel values to the same range. Normalized data can make the network training more stable and converge more rapidly. The data augmentation operations we use include random rotation, adding random noise, and random inversion. Random rotation is to randomly rotate the image by a random angle with a certain probability. Adding noise is adding random Gaussian noise to the image. Random inversion involves increasing the training dataset size by flipping the image. Data augmentation can enrich the diversity of data while increasing the amount of data, thereby making the trained model more robust and more generalized.

2.2 Midline identification

This stage performs the midline identification. In this stage, we proposed DP U-Transformer network to segment the midline, which combines different levels of scale features and has a larger perceptual field. DP U-Transformer network introduces a parallel Dual-Path module based on the combination of U-Net and transformer to better utilize global information and combine different levels features to achieve better segmentation.

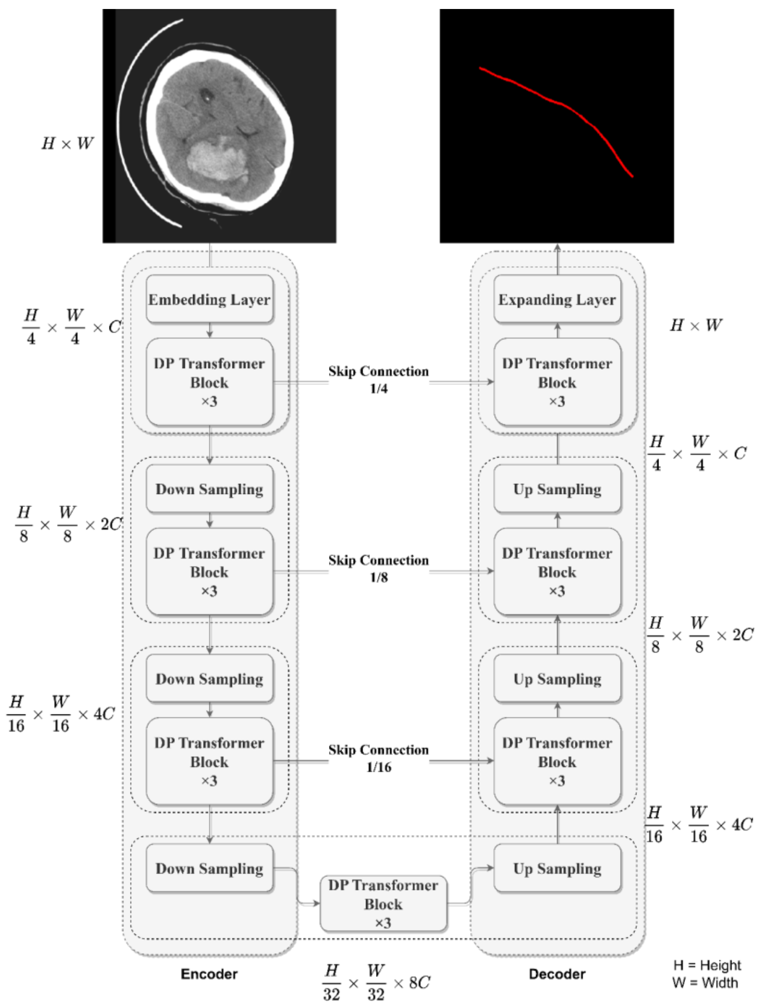

Figure 2. Network structure of DP U-Transformer

2.2.1 Dual-Path U-Transformer architecture

Figure 2 illustrates the structure of our proposed DP U-Transformer network. The proposed DP U-Transformer network is a network for medical image segmentation improved from the U-Transformer[29] we previously proposed, which uses a four-layer parallel structures of convolutional and self-attention, and introduces structures such as cross-scale connectivity and depth decoder. Skip connection and U-shape structure can combine feature information at different scales. In particular, the network introduces the DP U-Transformer block which can improve its ability to better handle local features and global feature.

The DP U-Transformer encoder consists of an embedding layer, parallel dual-path feature extraction module and a down sampling layer. The structure of the two conversion blocks in the Decoder is highly symmetric to that of the conversion blocks in the Encoder. In this paper, we use layered deconvolution to up-sample low-resolution feature maps into high-resolution feature maps. Convolution is used to upsample the low-resolution feature maps into high-resolution feature maps, which are also merged with the encoder through skip connection to merge with the encoder to capture semantic and fine-grained information. The embedding block consists mainly of four convolutional layers, each of which uses a 3 × 3 convolutional kernels for feature extraction. This embedding layer encodes precise pixel-level spatial information and provides low-level but high-resolution two-dimensional feature features. Each convolutional layer is followed by an additional GELU activation function and a layer normalization layer to enhance the model's expressiveness.

2.2.2 DP Transformer Block

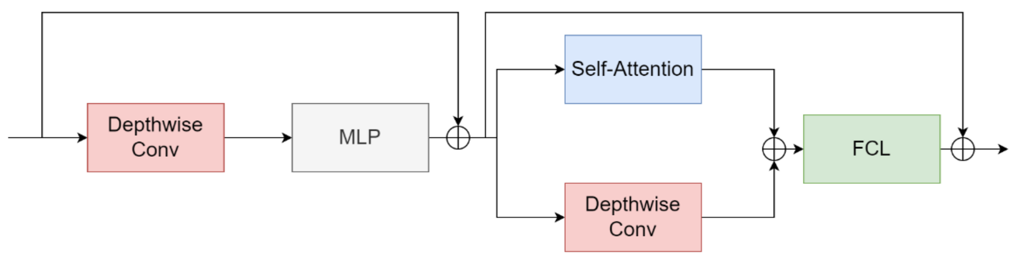

Figure 3. Structure of DP Transformer Block. FCL refers fully connected layer; MLP refers multilayer perceptron

In networks with mixed self-attentive and convolutional layers, the self-attentive and convolutional layers have weight assignment mechanisms. There are significant differences. The weight assignment mechanism of the self-attentive layer is dynamic, which adaptively assigns weights based on different parts of the input data. In contrast, the weight assignment mechanism of the convolutional layer is static, i.e., the weights are constant throughout the training period of the network. The weights are constant throughout the training period. This different weight assignment mechanism may result in the network not taking full advantage of the two different types of layers. To address the issue, this paper introduces a parallel DP U-Transformer Block by incorporating the self-attentive layer and the convolutional layer into separate different network blocks with different weight assignment mechanisms. Based on this, the block can better deal with the combination with global and local features.

Figure 3 illustrates the DP Transformer Block Structure. DP Transformer Block is a parallel dual path block. This block contains two branches, one is the depthwise convolution branch and the other is the self-attention branch. These two branches operate on the input feature map and then merge their results. The FCL represents the fully connected layer, where the self-attention layer and the depthwise convolution are parallelized and fused, and the fused output is passed to the fully connected layer. In this way, the network can more fully utilize the advantages of the two different types of layers. The model's performance is improved by leveraging the advantages of the two different types of layers. Also, since the self-attentive and convolutional layers are grouped into different network blocks, the dual-path network exhibits better parallelism and can use computational resources more efficiently.

2.3 Midline shift assessment

2.3.1 Midline shift measurement

In the midline shift measurement phase, we calculate the midline shift distance based on the segmentation results. The ideal midline is defined as a straight line which is clinically interpreted as two brain falx points connected, connecting the two endpoints of the brain midline. Therefore, we calculate the shift distance based on the identified brain midline and the ideal midline, with the maximum distance between the two lines is defined as the shift distance. Figure 4 shows the measurement.

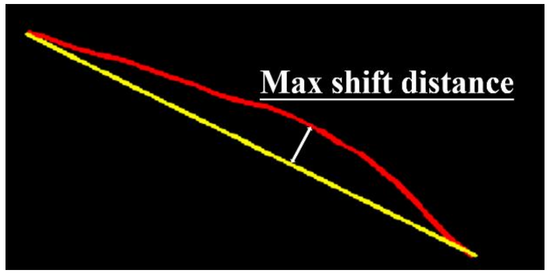

Figure 4. The measurement of max shift distance. Yellow line refers to ideal midline, and red refers to detected midline

2.3.2 Surgical indication assessment

The final step in our method is delivering the assessment results, which greatly aid the clinical diagnosis process. Following the calculation of the midline shift distance in the previous stage, we drew upon conversations with clinical experts and their clinical prior knowledge. Surgical indications can help screen out serious cases that are likely to require surgery. Experts suggest that the clinical diagnostic guideline for indicating surgical need based on midline shift is 1 cm. Therefore, we set the 1 cm threshold as indicative of the presence of surgical indications. Cases with a midline shift distance equal to or greater than 1 cm were categorized as having a surgical indication, whereas those with a shift of less than 1 cm not. Each case was evaluated based upon this criterion. The accuracy is calculated by cases. In each case, the largest value of the shift distance in all slices is taken to represent this case. The accuracy of our assessment was subsequently calculated by comparing our judgements with the ground truth.

3. EXPERIMENT

3.1 Dataset

The dataset used in our experiment consisted of 529 selected CT images of 99 patients with hemorrhagic stroke provided by Second Clinical Institute of Shantou University Medical College. The image reports of each case were used as ground truth values to determine the midline has shifted or not. The acquisition and management of these data were approved by the Ethics Committee of the Second Affiliated Hospital of Shantou University and complied with the relevant regulations. The ground truth of brain midline dataset was annotated by medical related students instructed and trained in annotation and were supervised and checked by clinical medical experts.

The experimental process will use a five-fold cross-validation method to evaluate the performance of the network and ensure that all cases are validated to make full use of all datasets, and avoid the overfitting phenomenon during the training process which might be caused by insufficient sample of the dataset. The training set & validation set accounts for 80% and the test set accounts for 20%.

In this experiment, the Hausdorff Distance (HD) and the Dice coefficient were initially adopted as evaluation metrics. The Dice coefficient is often used to measure the similarity between the predicted results and the true labels in image segmentation tasks. HD is a metric used to assess the similarity between two collections and is commonly used in medical image segmentation is used to evaluate the difference between the segmentation result and the true label. It is based on the idea of finding the maximum distance between two sets. In other words, HD is the distance from the real label in the distance from the farthest point to the nearest point in the segmentation result. HD is a more rigorous evaluation metric, which is sensitive to some details of the segmentation result. The brain midline shift assessment task pays particular attention to the of the midline shift, so HD is an important evaluation metric in brain midline segmentation. Accuracy is the result of dividing the number of correctly classified samples by the total number of samples.

3.2 Experiment settings

Our methods in the experiments are based on PyTorch, and our proposed network is trained and tested on a 4090 GPU with 24 GB of RAM. The batchsize was set to 12, the initial learning rate is set to 0.00042, and the number of training epochs is set to 1200.

The dataset is then divided 4:1 into training & validation sets and test sets, and input to the proposed network model in stages. During the training process, the model is evaluated using the validation set to avoid over-fitting the model. The best weights are automatically saved and used for testing.

The loss function we use is the combination of Dice Loss and Cross-Entropy Loss (CE Loss) as the combination of loss function. Dice Loss is a measure of the similarity between two sets, with values ranging from 0 to 1. The higher the values, the higher the similarity. CE Loss is another widely used loss function that measures the difference between the model prediction and the true label. CE has a smaller value for the CE Loss function when the model's prediction is close to the true label, and a larger value for the CE Loss function when the difference between them is large.

3.3 Results

We used U-Net and U-Transformer as the baseline for comparison, and trained and validated the network models of U-Net, U-Transformer and DP U-Transformer on our own dataset, respectively. The comparison of U-Net and U-Transformer proved that combining Transformer on top of U-Net has a positive effect. The comparison of DP U-Transformer with U-Transformer demonstrated that the proposed parallel dual-path module can improve the model performance.

3.3.1 Segmentation results

Figure 4 visualizes the segmentation results of the three networks. As the following tables show, Table 1 shows the results with 5-fold cross-validation of U-Net, Table 2 shows the results with 5-fold cross-validation of U-Transformer, and Table 3 shows the results with 5-fold cross-validation of DP U-Transformer. It is obvious that DP U-Transformer get the best segmentation performance in the dataset among the three networks. Especially, mean HD of DP U-Transformer values 4.5796, which is 1.11807 lower than U-Transformer, and 5.8886 lower than U-Net.

Table 1. The results with 5-fold cross-validation of U-Net on our dataset

5-Fold cross validation of U-Net						
Metrics	fold_0	fold_1	fold_2	fold_3	fold_4	Mean
Mean Dice	0.4779	0.4952	0.5148	0.4898	0.5113	0.4978
Mean HD	11.2778	10.3766	8.5425	16.8542	5.2900	10.4682

Table 2. The results with 5-fold cross-validation of U-Transformer on our dataset

5-Fold cross validation of U-Transformer						
Metrics	fold_0	fold_1	fold_2	fold_3	fold_4	Mean
Mean Dice	0.5675	0.5907	0.6175	0.6190	0.6070	0.6003
Mean HD	6.6476	6.8386	5.6409	6.4182	3.2565	5.7603

Table 3. The results with 5-fold cross-validation of DP U-Transformer on our dataset

5-Fold cross validation of DP U-Transformer						
Metrics	fold_0	fold_1	fold_2	fold_3	fold_4	Mean
Mean Dice	0.5592	0.5892	0.6208	0.6275	0.6101	0.6014
Mean HD	7.9765	5.0391	3.2768	3.8943	2.7113	4.5796

3.3.2 Surgical indication assessment

Upon acquiring the segmentation results for each patient, it's essential to assess the midline shift for each slice with surgical indication. This assessment involves determining the maximum distance between segmentation result and ideal midline, which is the straight line connecting the two brain falxes. From the slices obtained for each patient, the slice with the maximum midline shift distance is chosen. This maximum distance from the chosen slice serves as the definitive 1cm threshold to determine the surgical indications for the patient. The accuracy of this assessment method, when applied across different networks, is showcased in Table 4. The results indicate that the DP U-Transformer provides the highest accuracy in classifying midline shift assessments for surgical indications. The findings reveal disparities in performance among the individual network models for detecting midline and determining whether each case has surgical indications. Specifically, U-Net primarily employs convolutional blocks for processing, while U-Transformer utilises transformer blocks to better capture long distance dependencies. On the other hand, the most impressive attribute of DP U-Transformer is its hybrid structure, which expertly integrates the characteristics of convolutional and transformer blocks, both functioning in parallel. This design enables it to improve spatial understanding and context capturing abilities, highlighting greater accuracy in evaluating median offset.

Table 4. The accuracy of the classification on judgement of surgical indication based on the networks.

Network	Accuracy
U-Net	0.7677
U-Transformer	0.8485
DP U-Transformer	**0.8687**

4. CONCLUSION

In conclusion, we divide the task of midline shift assessment into two stages: segmentation of the midline and determination of midline shift in conjunction with clinical experience. We propose a DP U-Transformer to precisely segment the brain midline. The DP U-Transformer combines the advantages of the U-net in utilizing both high-level features and low-level features, and the advantages of the global perceptual field of the transformer based on the self-attentive mechanism. Specially, we propose a parallel dual-path block, which uses the self-attentive layer and the convolutional layer in different network blocks, effectively combining the advantages of both and saving computational resources. Experiments suggest that our proposed network DP U-Transformer shows excellent segmentation performance on our inhouse dataset. In the second stage, we assess midline shift based on the threshold of midline shift given by the clinical expert in conjunction with clinical experience. The experiment results showed that the DP U-Transformer based midline shift assessment demonstrate the best accuracy.

In the future endeavors on midline shift assessment, our primary methodological strategy will still focus on model improvement of DP U-Transformer and addressing the lack of dataset. To enhance the model, we will continuously refine the proposed model to incorporate more features applicable to the midline bias assessment task and explore the application of the latest state-of-the-art large models for midline assessment task. Confronted with the challenge of limited datasets, we would like to try to combine new data generation methods to supplement the data set, such as diffusion. Semi-supervised and unsupervised methods are also emerging for the problem of difficult to obtain labels for midline segmentation data, and further research is needed.

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