Identifying Sinus Invasion in Meningioma Patients before Surgery with Deep Learning

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ABSTRACT

Meningioma is the most common intracranial non-malignant tumor but is usually closely associated with the major venous sinuses. It has been recognized by neurosurgeons that meningioma should be treated with different surgical options depending on the status of sinus invasion. Therefore, it is necessary to accurately identify the venous sinus invasion status of meningioma patients before surgery; however, appropriate techniques are still lacking. Our study aimed to construct a deep learning model for accurate determination of sinus invasion before surgery.

In this study, we collected multi-modal imaging data and clinical information for a total of 1048 meningioma patients from two hospitals. ResNet-50 with a dual attention mechanism was used on the preprocessed T1c and T2WI data respectively, and the final model was generated by combining the two unimodal models. The classification performance was evaluated by the area under receiver operating characteristic (ROC) curve (AUC).

The results implied that the multimodal fusion classification model showed good performance in predicting meningioma sinus invasion. Further analysis on the patients with different WHO gradings indicated that our model has the best classification ability under WHO grading 1 in an independent validation cohort(0.84 AUC) . This study shows that deep learning is a reliable method for predicting sinus invasion in patients with meningioma before surgery.

Keywords: Deep learning; Meningioma; Sinus invasion; Multimodal fusion

1. DESCRIPTION OF PURPOSE

Meningioma is the most common intracranial non-malignant tumor, second only to gliomas.[1] At present, surgery for meningiomas that invade the sinuses remains a challenge for neurosurgeons.[2] For meningioma without sinus invasion, total resection of the tumor should be achieved, however, for meningioma with sinus invasion, forced total resection will result in a multiplication of the risk of sagittal sinus reconstruction and postoperative complications.[3,4] Therefore, accurate preoperative determination of sinus invasion is important to optimize surgical planning and help neurosurgeons prevent serious complications.[5]

Both intraductal ultrasound imaging and structural imaging are commonly used to determine whether a meningioma has invaded a sinus preoperatively.[6] Intraductal ultrasound imaging can't provide information about the venous wall[7]; structural imaging depicts the sinus wall but not clearly enough because of the lower resolution and contrast between the lumen and blood flow.[8] Therefore, it is essential to find a new technique to determine the sinus violation status.

Deep learning can automatically learn a large number of complex and useful features from images for various visual tasks, which shows great potential in medical image analysis.[9] In this study, we used multimodal images (T1c and T2) to establish a deep learning model for predicting the state of sinus invasion before surgery.

2. METHODS

2.1 Patient Database

This experiment collected the clinical information and imaging data of meningioma patients from two Hospital. After screening by inclusion and exclusion criteria, a total of 1048 meningioma patients (Hospital A: 288 positive +339 negative; Hospital B: 183 positive +238 negative) were included in this trial, each with imaging data from both T1c and T2 modalities.

2.2 Region-of-Interest Segmentation

Tumor segmentation of meningiomas was performed independently by two radiologists without prior knowledge of the surgical and pathological records. Two radiologists manually outlined regions of interest on T1c, T2 modalities and were examined by the third radiologists.[10]

2.3 Data Preprocessing and Enhancement

Some data pre-processing and augmentation were performed before training the model:

The final ROI was the smallest external cube of the patient's stereo outlined brain region, and the each layer was normalized and scaled to a luminance range of (0,255). Then, we used the histogram equalization technique to improve the visual effect of the pictures.

Since a model built with more samples could be more robust in general, we adopt the CycleGAN[11] to expand the original dataset. The patient slices from Hospital A were inputted into CycleGAN to obtain one-by-one corresponding pseudo slices. For the CycleGAN network building, 470 patients (215 positives and 255 negatives to sinus invasion) were selected randomly as the domain A, and the left 157 patients (73 positives and 84 negatives) were used as the domain B. The generated pseudo slices have the same labels as the corresponding input slices. Thus, the training set for model building was consisted of 6270 real slices and 6270 fake slices generated by CycleGAN. Further data enhancement operations were performed, including random rotation and flipping.

2.4 Classification Network

The model used in this experiment was ResNet50, which was pre-trained on the natural image dataset and started training after adding the attention module[12] (**Fig. 1**). The attention module was consisted of two parts: the spatial attention module and the channel attention module. The loss function used in this experiment was a binary cross-entropy loss, and the SGD optimizer was set as momentum=0.9, weight decay=1e-4. The initial learning rate was 0, after 5 epochs warmed up to 1e-3, and after 150 epochs the cosine decayed to 0.

The two unimodal models were built on slice level. Since one tumor could cover several slices in general, converting the predictions from slice level to case level for clinical application was necessary. In one image modal, the predicted probabilities of positive and negative on each slice in one tumor were summed separately. Then the predicted probabilities of positive and negative for the patient level were calculated according to the summed probabilities. The predicted probabilities calculated from two modals were summed to determine the predicted sinus invasion status based on the larger combined probability of positive or negative (**Fig. 1**).

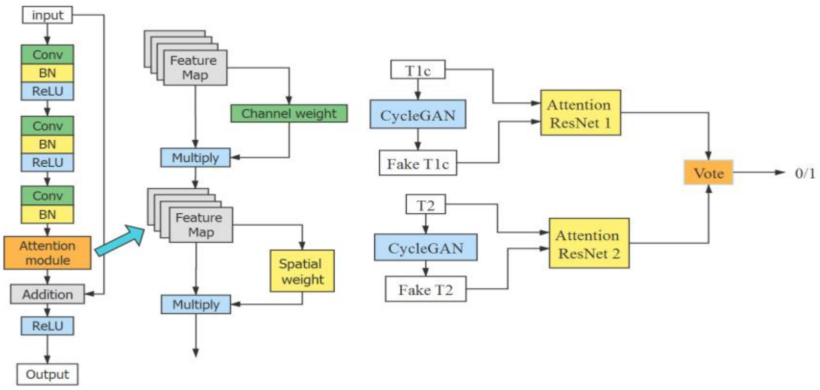


Fig 1 Left: Add the residual block of attention mechanism Right: Multimodal classification model

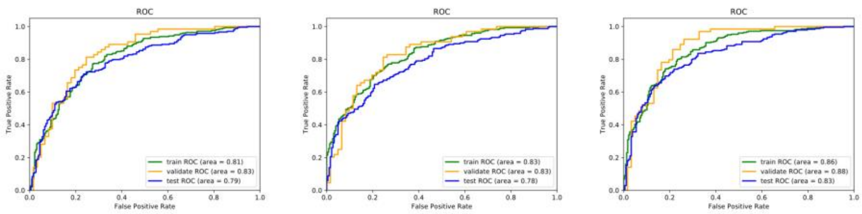
3. RESULTS

The training set and internal validation set were from Hospital A, and the test set was patients from Hospital B. There were 12540 slices (6270 real slices + 6270 fake slices) from Hospital A, after GAN enhancement, 1/5 of these slices were randomly selected as the internal validation set and 4/5 as the training set. **Table 1** shows the accuracy and AUC of the classification models in the training set, the internal validation set and the independent test set.

Table 1 Classification Performance

	Training set	internal verification set	independent test set
T1c			
Accuracy	0.74	0.75	0.73
AUC	0.80	0.83	0.78
T2WI			
Accuracy	0.78	0.75	0.72
AUC	0.83	0.82	0.79
T1c&T2 mixed modality			
Accuracy	0.78	0.82	0.76
AUC	**0.86**	**0.88**	**0.83**

The AUC in the internal verification set was 0.88, and the AUC in the independent test set was 0.83, which indicated that the multimodal classification model constructed in this experiment had the best classification performance (**Fig 2**). Further analysis of patients with different WHO gradings shows that the classification model constructed in this experiment has the best prediction effect for WHO grading 1 (test AUC:0.84).



(a) (b) (c)

Fig 2 ROC curves of the classification models (a)T1c mode (b)T2WI mode (c) T1C&T2 mixed modality

4. NEW OR BREAKTHROUGH WORK TO BE PRESENTED

There is a lack of preoperative techniques to accurately identify sinus invasion. In this study, we constructed a multimodal classification deep learning model with a dual attention mechanism to boost the weight of information favorable to prediction. The results show that the model we constructed is reliable in predicting the meningioma sinus invasion task.

5. CONCLUSIONS

In this paper, we constructed a multimodal deep learning model to predict meningioma sinus invasion. With the fusion of information from two modalities and the addition of an attention mechanism, the model could capture more intrinsic and important information. The experimental results demonstrated the potential of this model. Future work can focus more on the fusion mechanism of multimodal features and the enhancement of important information.

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