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Nasopharyngeal Carcinoma Lesion Recognition Based on Multi-Window Resampling Technology

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Abstract: Accurate deep learning-based detection of nasopharyngeal carcinoma (NPC) magnetic resonance (MR) images is conducive to diagnosis and treatment. These images are characterized by high dimensionality, complex noise interference, and blurred tissue structure boundaries. How to extract key pathological features from massive imaging information and provide quantitative basis for clinical diagnosis remains an important challenge in the current field of medical image processing. This paper uses multi-window fusion technology to map multiple key window information to the pseudo-color space, realizing the integration of multi-dimensional feature information and compensating for the information limitations of single-window imaging. Experiments show that this method can effectively improve model accuracy.

Keywords: Nasopharyngeal carcinoma; Multi-window resampling; Lesion recognition; Medical image processing; Pseudo-color fusion

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1. Introduction

As the core method for NPC diagnosis, medical imaging examination, especially magnetic resonance imaging (MRI), has become the preferred imaging modality for locating primary NPC lesions, evaluating invasion range, and monitoring therapeutic effects due to its advantages of high soft tissue resolution, strong multi-parameter imaging capability, and no radiation damage [1]. However, MRI data has characteristics such as high dimensionality, complex noise interference, and blurred tissue structure boundaries. How to extract key pathological features from massive imaging information and provide quantitative basis for clinical diagnosis remains an important challenge in the current field of medical image processing [2,3].

Clinical interpretation of MRI images usually relies on physicians' adjustment of different scanning sequences and window width/window level parameters to highlight specific tissue structures [4]. **Figure 1** shows NPC MRI images under different windows: T1-weighted imaging (T1WI) can clearly display anatomical structures, while T2-weighted imaging (T2WI) is sensitive to edema and inflammation. However, the traditional single-window imaging mode can only present local grayscale information, making it difficult to simultaneously balance the

contrast difference between tumor tissue and surrounding normal structures [5]. Studies have shown that primary NPC lesions often invade the parapharyngeal space, skull base bone, and intracranial structures, and their imaging manifestations are highly heterogeneous. Grayscale images under a single window are prone to boundary information loss or artifact interference, increasing the difficulty of lesion segmentation and quantitative analysis. Therefore, integrating the feature advantages of different windows to construct more distinguishable imaging representations has become the key to improving the accuracy of NPC MRI image analysis. Currently, many experts at home and abroad have applied computer technology in the medical field [6–8].

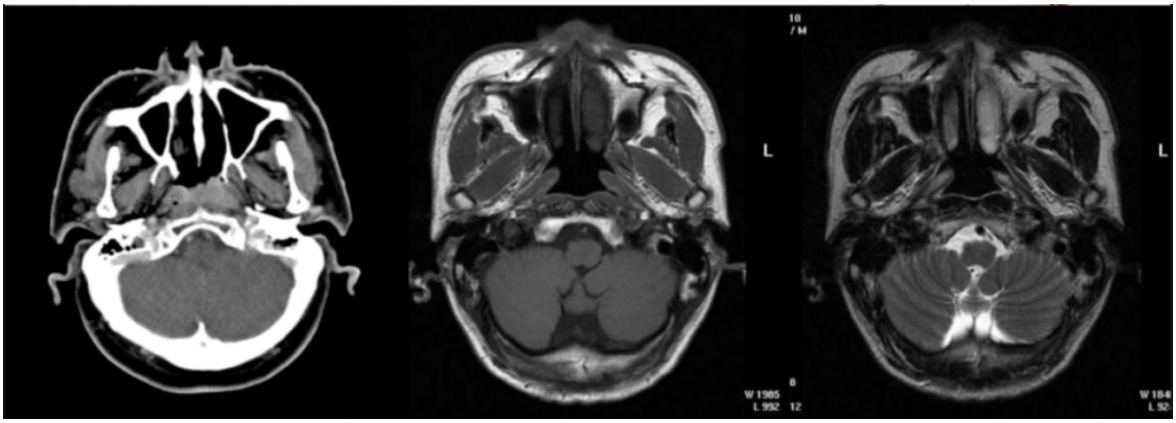

Figure 1. MRI images under different windows.

This paper maps key window information to the pseudo-color space through grayscale conversion and feature extraction of DICOM images under different window width/window level parameters, realizing the integration of multi-dimensional feature information [9]. Compared with traditional single-window imaging, multi-window fusion technology can effectively compensate for the information limitations of single-window imaging. The multi-window mechanism can adaptively cover heterogeneous image regions, avoid feature omission or redundancy of complex scenes by a single window, and enhance feature diversity and representation robustness. This paper used YOLOv8 as the base model to verify the effectiveness of the proposed method.

2. Related technologies

2.1. Window technology

Window width (WW) and window level (WL) jointly determine the contrast and brightness of medical images [10]. By collaboratively adjusting the grayscale mapping range and central threshold, they have a decisive impact on the visual presentation quality of digital medical images, directly affecting physicians' observation of lesions and tissue structures.

Window width refers to the range of CT values selected when displaying images. CT values outside this range will be displayed as pure white or pure black. Tissue structures within the specified range will be mapped to a series of grayscales from white to black (usually 16 levels or more) according to subtle differences in their density. A wide window width includes a broader range of CT values, allowing more tissues of different densities to be displayed simultaneously, thus reducing the overall contrast of the image, which is suitable for observing structures with large density differences; conversely, a narrow window width only displays a small range of CT values, amplifying subtle density differences of tissues within this range, significantly enhancing image contrast,

which is very suitable for observing soft tissues with similar densities.

Window level refers to the arithmetic mean of the upper and lower limits of CT values in the window width. It essentially determines which CT value will be displayed as intermediate gray. Since different tissues in the human body (such as bone, soft tissue, water, fat) have their typical CT value ranges, to observe the subtle structures of a specific tissue, it is necessary to select the CT value of that tissue as the center for window level setting. For example, a "lung window" with a low window level is needed to observe the lungs to highlight air-containing tissues and lung markings; while a "bone window" with a high window level was needed to observe bones to clearly display the cortex and medulla of bones.

For human MRI images, although the pixel values represent signal intensity rather than CT values, the same principle of window width and window level adjustment is fully applicable. Through precise adjustment of window width and window level, radiologists can effectively highlight the signal characteristics of specific tissues or lesions, thereby extracting more image details. This technology greatly optimizes the visual expression of images and is an extremely powerful tool for accurately distinguishing various tissues and organs in the human body, identifying early lesions, and conducting qualitative diagnosis.

2.2. YOLOv8

As a single-stage object detection algorithm, YOLOv8 consists of four parts: input layer, backbone network, neck network, and head network. Through architectural innovation, algorithm optimization, and training strategy improvement, YOLOv8 achieves a good balance between object detection accuracy, inference speed, and resource consumption.

The backbone network of YOLOv8 adopts an improved version of the CSPDarknet structure. By introducing the C2f module to replace the traditional C3 module, it improves computational efficiency while maintaining feature extraction capability. The C2f module divides the feature map into multiple branches for parallel convolution operations, combined with shortcut connections to realize feature reuse, effectively alleviating the gradient disappearance problem of deep networks. The neck network adopts the PAN-FPN structure, realizing multi-scale feature fusion through bottom-up feature pyramid and top-down path aggregation. The head network innovatively adopts an Anchor-Free design, directly predicting the center point coordinates, aspect ratio, and category probability of the target, avoiding the computational redundancy and hyperparameter dependence caused by the traditional anchor box mechanism.

3. MRI image resampling

3.1. Multi-window resampling

To effectively improve the utilization efficiency of original image data in the training and inference processes of deep learning models, this paper introduces an image resampling technology scheme based on multi-window settings. The core mechanism of this method was to input image data with more dimensional diversity into the deep learning model through fusion processing of multi-window image information, thereby helping the model capture richer image feature details and enhancing the model's ability to understand image content and extract features accurately.

By parsing the metadata information contained in DICOM format image files, the preset window parameters of this type of image were accurately obtained; subsequently, based on these preset window parameters, two other

representative window parameter combinations were adaptively selected within their neighborhood range, namely:

$$wwi = \mu * ww_0 \quad (1)$$

$$wi = \mu * w_0 \quad (2)$$

Where (ww_0, w_0) are the optimal window width and window level, *wwi* represents the new window width, *w0* represents the new window level, and represents the weight.

Set to 0.25, 1.75, 0.5, 1.5, 0.75, and 1.25 to obtain the corresponding window width and window level. Observe the image effect of the window corresponding to different weights. It is found that the image effect is optimal when mu is 0.5 and 1.5. Under these weights, images under two new windows were obtained, namely (ww_1, w_1) and (ww_2, w_2). The images under these two windows and the optimal window were used as data for the B, G, and R channels respectively to generate pseudo-color images. **Figure 2** is a schematic diagram of pseudo-color image generation.

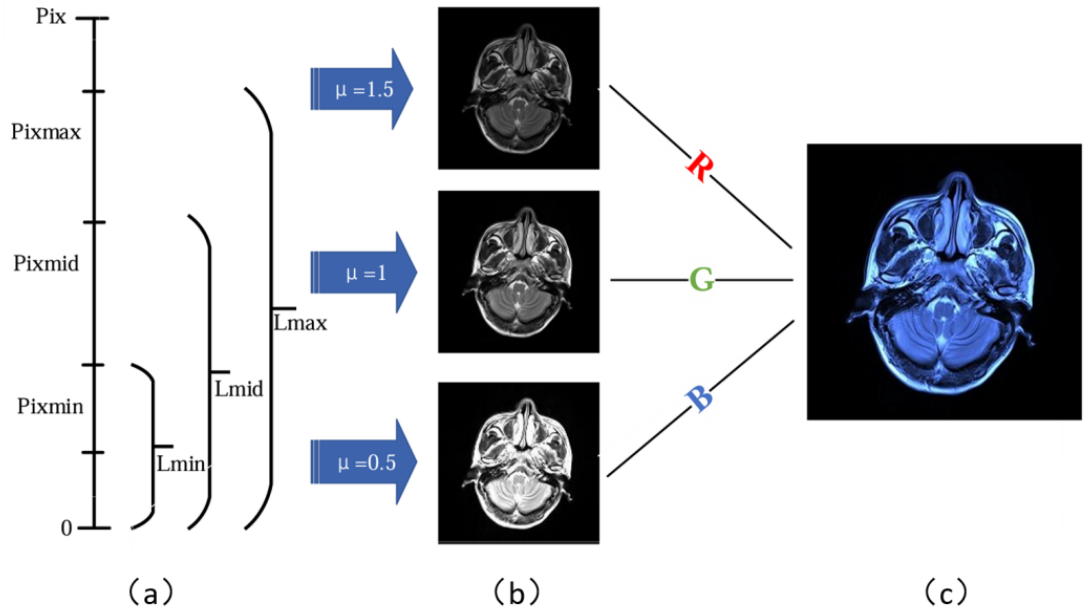

Figure 2. MRI image resampling schematic based on multi-window settings.

[0, Pix] in Figure 2 represents the entire grayscale level in the original MR image. According to the pixel range contained in the MRI image (a), images under different window widths and window levels were obtained respectively (b), which were used as R, G, and B channels to synthesize RGB pseudo-color images (c) according to their grayscale display.

The synthesized pseudo-color image (c) contains image information of three different parameter configurations including the preset window, which can highlight the lesion tissue structure and grayscale features in the image by combining multiple factors, provide more lesion feature information for model learning, and enable the model to have a stronger ability to locate NPC lesions. Subsequent NPC lesion detection will be carried out based on the synthesized pseudo-color images.

3.2. Image annotation

The medical image data in this experiment was stored in DICOM format. Combined with the input requirements of YOLOv8 for data, NPC lesions were accurately annotated using annotation tools under the guidance of experts, and the annotated lesion bounding box information was standardized and stored in accordance with the VOC data annotation format to ensure the format compatibility and usability of the annotated data.

A total of 7496 annotated NPC lesion images were finally obtained, which were divided into training set, validation set, and test set in a ratio of 3:1:1, namely 4498 as training data, 1499 as validation set, and 1499 as test set. The sample composition of the dataset fully considers age distribution, gender differences, and regional characteristics, which can objectively reflect the clinical imaging manifestations of NPC in different populations, and has good representativeness and clinical reference value.

4. Experimental results and analysis

4.1. Experimental settings

To ensure the comparability of experimental data, the experimental environment, model parameters, and other settings were kept consistent. The experiment was carried out based on the Pytorch deep learning framework, CUDA11.3, and other environments. The specific software and hardware configurations were shown in **Table 1**, and the model parameter settings were shown in **Table 2**.

Table 1. Experimental configuration

Parameter	Configuration
CPU	AMD Ryzen 7 5800H
GPU	NVIDIA GeForce RTX 3060
Memory	128G
Video memory	6G
Development tool	Pycharm2021.3
Programming language	Python3.9
Framework technology	Pytorch
Acceleration environment	CUDA11.3
System environment	Ubuntu 18.04.6

Table 2. Model parameter settings

Parameter	Value
Epochs	300
Batch size	2
Learning rate	0.001
Weight decay	0.0005
Optimizer	AdamW

4.2. Results and performance analysis

To verify the effectiveness of the resampling method based on multi-window settings, active object detection

experiments were performed on the single-window NPC image set and the multi-window resampled NPC image set respectively. The results were shown in **Table 3**. Among them, is mAP@0.5, the average value of AP when IOU was greater than 0.5; was mAP@50:5:95, referring to the average value of corresponding results when IOU ranges from 0.5 to 0.95 with a step size of 0.05.

Table 3. Experimental results of single window and multi window images

Data				
Single-window	76.6%	35.5%	77.1%	36.0%
Multi-window	77.4%	36.0%	78.3%	36.2%

It can be concluded from **Table 3** that the lesion localization effect of pseudo-color images resampled based on multi-window settings was better. The experimental results based on pseudo-color images under different conditions were higher than those of the single-window NPC image set. The accuracies of „ were were improved by 0.8%, 0.5%, 1.2%, and 0.2% respectively. Experiments were conducted on the NPC MRI image set with multi-window settings under different models, which effectively verifies the advantages of multi-window resampling of NPC MRI images, makes full use of data features, and improves the lesion detection performance of NPC. The detection effect of the NPC lesion detection model based on multi-window resampling was shown in **Figure 3.**

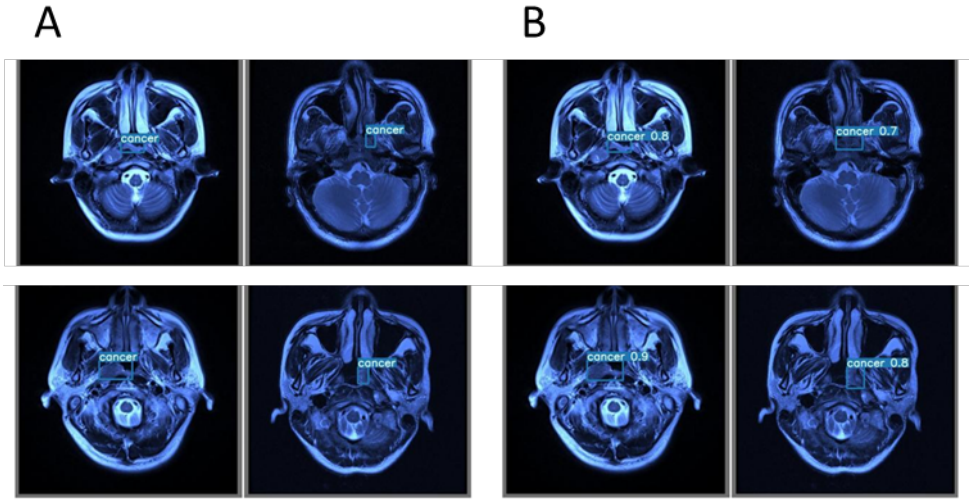

Figure 3. Nasopharyngeal carcinoma lesion detection results. A. Real lesion area; B. Detection result.

5. Summary

To fully utilize NPC lesion features, this paper proposes an NPC MRI image lesion recognition method based on multi-window resampling technology. This paper selects grayscale images of three windows with good effects, synthesizes them into NPC pseudo-color images, enhances lesion features, and compensates for the information limitations of single-window images. Experimental results show that this method can effectively improve the detection accuracy of the model for NPC lesions and has high clinical auxiliary diagnosis value.

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Disclosure statement

The authors declare no conflict of interest.

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