Automation of primary diagnostics of diseases of the human lumbar spine using intelligent analysis of CT images

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***Abstract*—This study aims to identify and detect vertebrae through CT image analysis, obtain the geometric dimensions of vertebrae, and assist in the diagnosis of degenerative spinal diseases in the human body. This study uses the YOLOv8-seg algorithm to segment vertebrae, extract geometric dimension parameters such as length and width of vertebrae, find the boundary lines between adjacent vertebrae, and calculate the corresponding angles. After verification, this study can provide strong support for clinical diagnosis in the early diagnosis of degenerative spinal diseases, help improve the diagnostic efficiency and accuracy of degenerative spinal diseases, and provide a scientific basis for early intervention and treatment of patients.**

***Keywords*—detect vertebrae, image analysis, YOLO, degenerative spinal diseases, clinical diagnosis**

I. Introduction

Lumbar degeneration is a physiological process that changes with age, manifested as low back pain, radiating pain in the lower limbs, numbness and inability to move, etc. It mainly includes diseases such as lumbar disc herniation, lumbar spinal stenosis, lumbar spondylolisthesis, degenerative lumbar scoliosis, etc. The proportion of adolescent patients is increasing, and adolescent patients are mostly related to unhealthy lifestyles (such as long-term sitting, lack of exercise), childbirth, trauma or genetics. Therefore, early detection and diagnosis can provide timely relief, delay lumbar degeneration, reduce obesity, and alleviate patients' pain [1] [2] [3] [4].At present, the diagnosis of spinal degenerative diseases mainly relies on imaging examinations. There are many technical means of medical imaging, including X-ray imaging, computed tomography (CT), ultrasound imaging, and magnetic resonance imaging (MRI). CT images have the characteristics of high resolution and high contrast, and can clearly display the anatomical structure of the spine [5] [6] [7]. Yang Qiaohui et al. conducted a comparative study on the diagnostic accuracy of spinal fractures between X-ray and CT, and verified that CT is better than X-ray [8].CT images can clearly show the overall picture and details of the fracture site, providing effective imaging data basis for clinical diagnosis and treatment.

With the application of artificial intelligence technology in the medical field, especially the advantages of deep learning in analyzing medical images, the diagnosis relies on the doctor's experience, is highly subjective, and has low efficiency, which effectively improves the diagnostic efficiency [9] [10].

Automatic diagnosis methods based on CT images have gradually become a research hotspot, such as vertebral segmentation, edge detection, and angle measurement.Kurochka et al. proposed a deep convolutional neural network as a classification method for an automatic detection model of vertebrae in X-ray images for osteoporosis diagnosis. In further research, an algorithm based on MaskR-CNN convolutional neural network was used to locate vertebrae on lumbar X-ray images and determine their geometric parameters to assist in the diagnosis of human spinal degenerative diseases [11] [12]. Hurtado-Aviles J et al. mathematically modeled the empirical data listed in the Raimondi table to use the Raimondi method in digital medical images more precisely and accurately, so as to use the axial vertebral rotation (AVR) parameters for the study of juvenile idiopathic scoliosis [13]. Based on the above research, this paper proposes a CT image analysis method based on the YOLO v8 model to determine the geometric dimensions and angles of the lumbar L1-L5 vertebrae, and then predict spinal degenerative diseases [14].

II. Materials and methods

The experimental environment is Windows 11 operating system, using Python 3.12 and PyTorch framework. The experimental tools include YOLOv8 model, OpenCV library, and the programming environment is PyCharm.

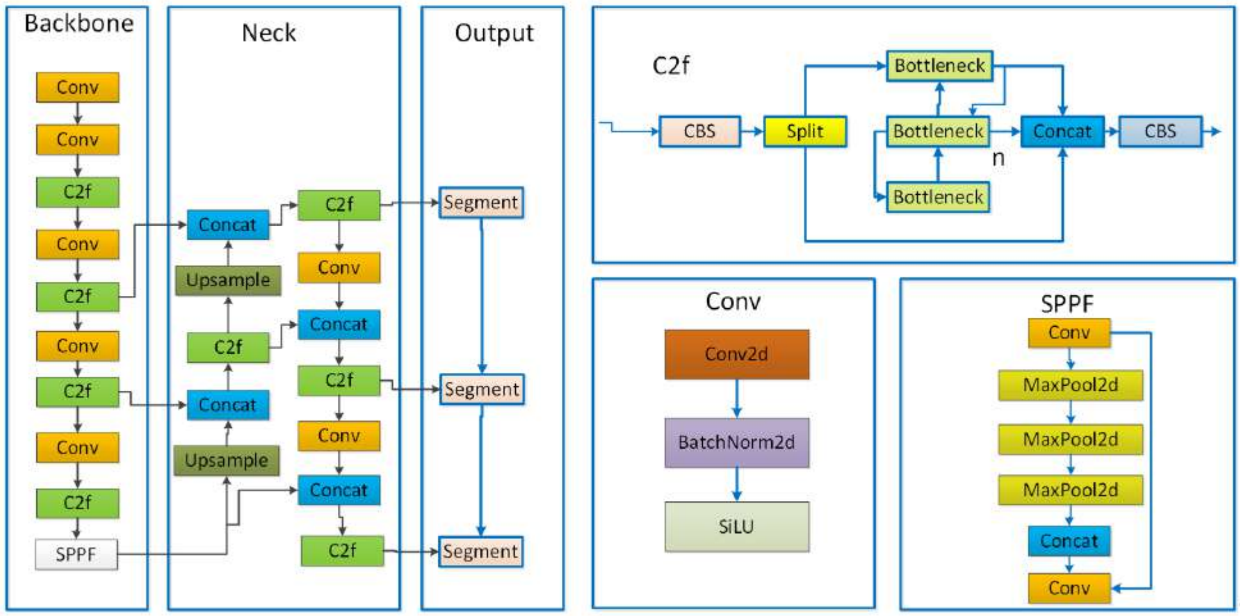

Figure 1. YOLOv8 network model structure diagram

A. Data collection and processing

- The experimental environment is Windows 11 operating system, using Python 3.12 and PyTorch framework. The experimental tools include YOLOv8 model, OpenCV library, and the programming environment is PyCharm.
- This dataset includes 99 lumbar CT images, each of which contains L1-L5 vertebrae. The data was annotated using the ImageMe tool, and the actual edge information of the vertebrae was annotated using the polygon tool.

B. Application of segmentation model

- YOLOv8 is a target detection model based on convolutional neural networks, which has the characteristics of fast detection speed and high accuracy. Compared with YOLOv5 and YOLOv7, YOLOv8 has significantly improved detection accuracy and speed. The backbone network (Backbone) of YOLOv8 usually adopts CSPDarknet, which reduces the amount of calculation and improves the feature extraction capability through cross-stage partial connections (CSP) [15]. "Fig. 1" is a diagram of the network model structure of YOLOv8.
- YOLOv8-Seg is an instance segmentation model based on YOLOv8, which increases the instance segmentation capability and can capture the detailed information of the target. It uses the target detection framework of YOLOv8 to detect the target in the image, and uses RoI (Region of Interest) alignment or RoI Pooling technology to extract the mask features of the target area from the feature map, which can segment the target more accurately and realize target detection and pixel-level segmentation at the same time. It is particularly suitable for small targets and complex edge structures such as lumbar vertebrae [16]. YOLOv8-Seg can not only identify and locate the target, but also process multiple targets in the image at the same time and generate independent masks for each target. The segmentation branch can generate high-quality pixel-level masks, which is suitable for tasks that require fine segmentation (such as organ or lesion area segmentation in medical images) and facilitate the acquisition of the features of each mask.

Therefore, in order to accurately and efficiently obtain the features of the vertebrae, this paper adopts the instance segmentation algorithm model YOLOv8-Seg to detect the vertebrae of the lumbar spine and obtain the features of the vertebrae [17].

C. Model training

To ensure the prediction performance of the model, the optimized dataset needs to be classified. There are 99 image datasets in total, of which the training set, validation set, and test set are 70, 10, and 19 images respectively.

In order to facilitate the comparison of post-processing effects, this dataset did not undergo image preprocessing and was directly used as the original image input. The input image size of the YOLOv8 instance segmentation model is 1024 pixels x 1024 pixels; the epoch iteration of each training cycle is set to 200 times. Tables 1 and 2 show the detection data of the yolov8-seg model for the lumbar vertebrae box and mask, with a recall rate of 88.5% and an accuracy rate of 89.8%. “Fig. 2” and “Fig. 3” show the parameter results of model training.

Table I
Model training data display-box

Class	Instances	P	R	mAP50
all	99	0.767	0.866	0.876
l5	17	0.802	0.882	0.926
l4	17	0.794	1	0.925
l3	17	0.857	0.882	0.917
l2	17	0.81	0.765	0.921
l1	17	0.66	0.916	0.825

Table II
Model training data display-mask

Class	Instances	Mask(P)	R	mAP50
all	99	0.767	0.866	0.876
l5	17	0.802	0.882	0.926
l4	17	0.794	1	0.925
l3	17	0.857	0.882	0.917
l2	17	0.81	0.765	0.921
l1	17	0.66	0.916	0.825

Experiments have shown that the YOLOv8-seg model can accurately detect and segment lumbar vertebrae, and the recall rate (Recall) and average precision (mAP) have reached a high level, which is suitable for medical image analysis tasks.

D. Acquisition of vertebral geometric parameters

The YOLOv8-Seg model detects lumbar vertebrae based on the input image and generates a bounding box and pixel-level mask for each vertebra. The mask is a binary image, where the pixel value of the target area is 1 and the pixel value of the background area is 0. Through segmentation, we can accurately locate the shape and coordinate information of the target, thereby obtaining the geometric parameters of the vertebrae.Regarding the acquisition of geometric parameters, this paper achieves it by calculating the minimum enclosing rectangle of the contour [18].

The minimum bounding rectangle is a geometric concept that refers to the smallest rectangle that can completely enclose a two-dimensional figure (such as a polygon or a curve set). It is to find the minimum rectangle that encloses a point set. The characteristic of this rectangle is that its edge passes through certain points on the point set. The rectangle obtained in this way is the minimum bounding rectangle (MBR).The minimum adjacent rectangle can be used to obtain the bounding box of the figure, determine its center point, aspect ratio and rotation angle, and thus obtain a minimum rectangle that can cover the entire figure. The length and width of the rectangle can vary depending on the figure, but the purpose is to fit all the edges of the figure as closely as possible. The basic process of its implementation:

- Find a simple circumscribed rectangle of a two-dimensional shape, whose sides are parallel to the x-axis and y-axis respectively.
- Algorithm for rotating any point on a plane around a fixed point to any angle.
- Rotate the original polygon. Calculate the simple circumscribed rectangle of the polygon after each rotation, save its area, vertex coordinates, and the rotation angle of the original polygon at this time.
- Calculate the simple circumscribed rectangle with the smallest area during the rotation process, and save the vertex coordinates and rotation angle of the smallest circumscribed rectangle.
- Rotate the simple circumscribed rectangle obtained in the previous step in the opposite direction by the same angle to obtain the minimum circumscribed rectangle.

The boundary of the minimum circumscribed rectangle is usually determined by the maximum horizontal coordinate, minimum horizontal coordinate, maximum vertical coordinate, and minimum vertical coordinate of each vertex of a given two-dimensional shape [19] [20]. It is often used in image processing, machine vision, target tracking, and other fields to determine the position and direction of the target object, which is the basis for target recognition and positioning. In the vertebra segmentation experiment, the minimum circumscribed rectangle of the segmented cone bone contour is calculated to obtain a rectangular contour with similar angles to the sides of the contour. Because the contour shape is mostly a quadrilateral, the calculated minimum circumscribed rectangle can restore the upper and lower boundary positions and inclination angles of the vertebra to a great extent, which plays an important role in the calculation of the size of each vertebra and the Cobb angle [21].

This article uses the OpenCV library function cv2.minAreaRect(points) to calculate the minimum enclosing rectangle. The parameter points of this function is the point set of the outline of the required minimum enclosing rectangle. The point set must be in the form of an array, for example, points=np.array([[x1,y1],[x2,y2],......,[xn,yn]]). To do this, make sure that the contour information of the mask is converted into array form.The cv2.minAreaRect() function returns a Box2D structure, which includes three pieces of information: (center point coordinates, (width, height), and rotation angle).

- Get height and width:The second parameter returned by cv2.BoxPoints(points). For example:
  rect = cv2.minAreaRect(contour); w, h = rect[1];
  At this time, the pixel value is obtained. If there is an actual size of the reference object, convert the pixel value to the actual size.The conversion rules are as follows:

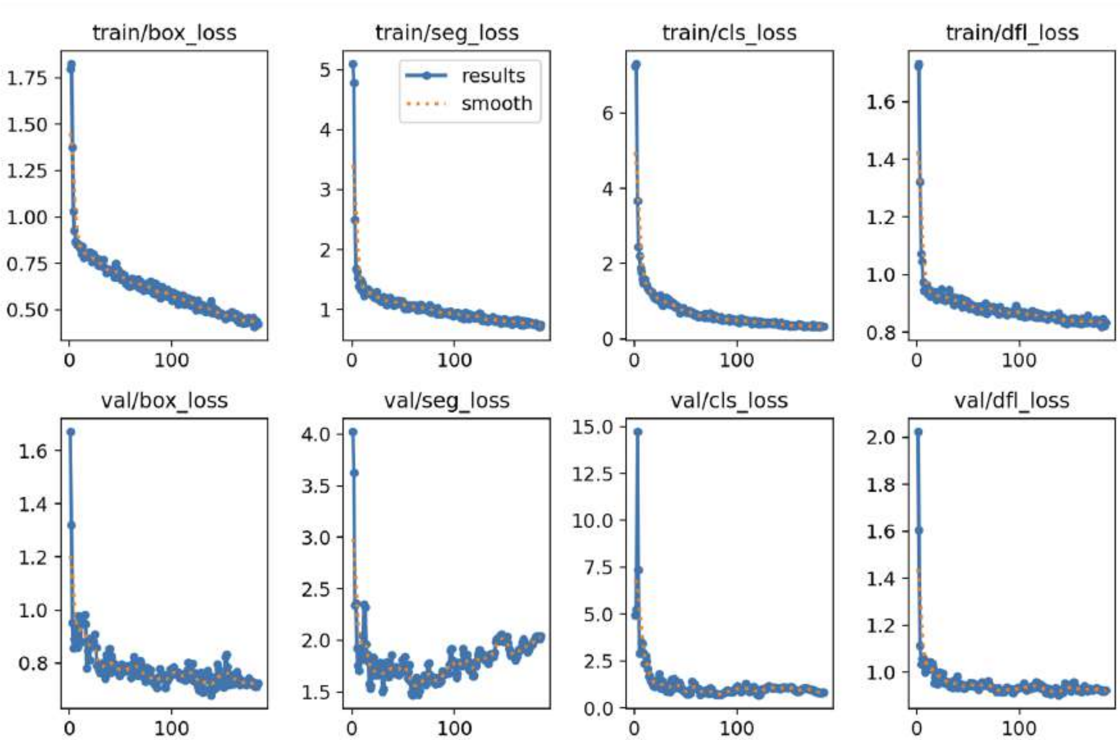

Figure 2. Model training results(a)

Calculate the scale_factor:

$$\text{scale\_factor} = \frac{\text{real\_size}}{\text{pixel\_size}}$$

Calculate the actual vertebra size based on the scale_factor:

$$\begin{cases} \text{actual\_width} = w \times \text{scale\_factor}, \\ \text{actual\_height} = h \times \text{scale\_factor}, \end{cases}$$

Among them:

- real_size is the actual size of the reference object.
- pixel_size is the pixel size of the reference object in the image.
- w is the pixel width of the vertebra.
- h is the pixel height of the vertebra.

- Get the angle between vertebrae:After segmenting the vertebrae image, the coordinate information in the bounding box and mask contour image cannot directly calculate the angle (such as Cobb angle) of the segmentation result. Therefore, we must first perform contour recognition on the segmentation result to obtain the contour coordinate information of all vertebrae, and then calculate the coordinates of the upper and lower boundaries based on the vertebrae contours, and finally calculate the angle between the vertebrae.

In this experiment, we get the minimum circumscribed rectangle rect based on the vertebral contour, obtain the four vertices of the contour circumscribed rectangle through cv2.boxPoints(rect), determine the inclination direction of the cone bone according to the relationship between the width and height of the vertebra, and then determine the vertex position by sorting the four vertices.

"Fig. 4" shows the use of the minimum adjacent rectangle method to determine the upper and lower boundary vertices of the vertebrae and connect them with two line segments to calculate the angle between the vertebrae. The upper left corner shows the angle between l5-l4.

It should be noted that when we draw the four sides of the adjacent rectangle, although we have obtained the four vertices of the adjacent rectangle, we cannot determine which vertex of the rectangle each of the four coordinate points corresponds to, so we still need to analyze according to the positions of the four coordinate points. The method used here is:

- Determine the arrangement structure of the vertebrae: Because the data set contains multiple different types of horizontal and vertical images, first determine whether the vertebrae are arranged horizontally or vertically. Different arrangements connect the vertices of the upper and lower boundary lines differently. Combine the position coordinates of l1 and l5, for example:

$$x_{\text{abs}} = |x_2 - x_1|$$

$$y_{\text{abs}} = |y_2 - y_1|$$

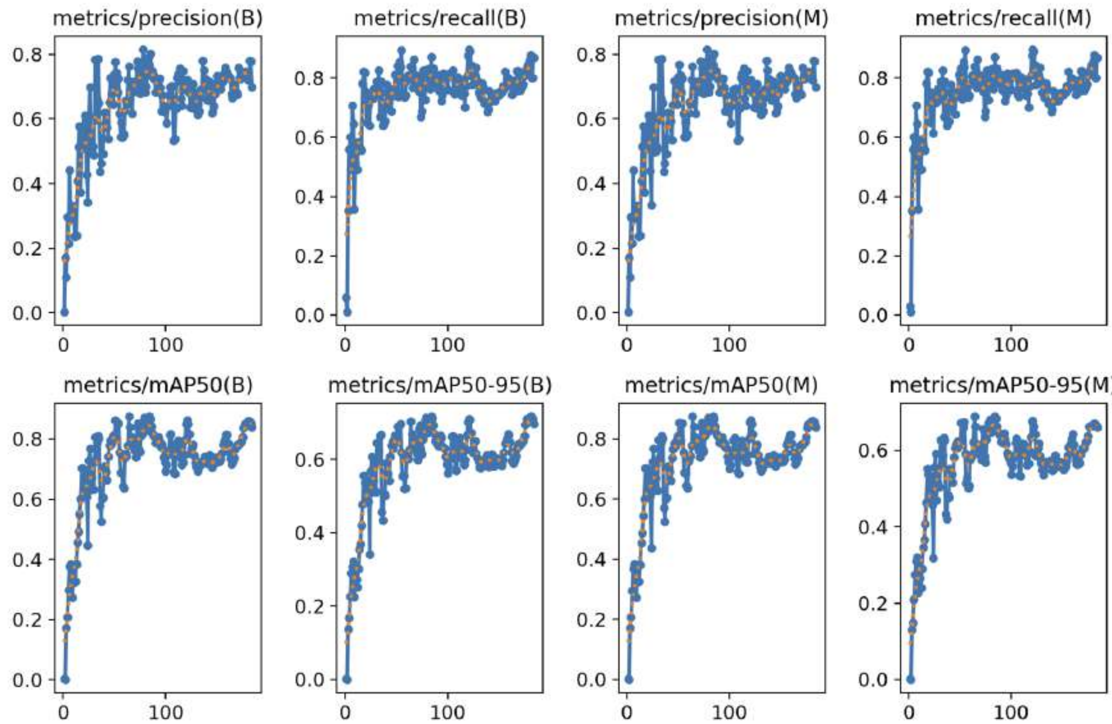

Figure 3. Model training results(b)

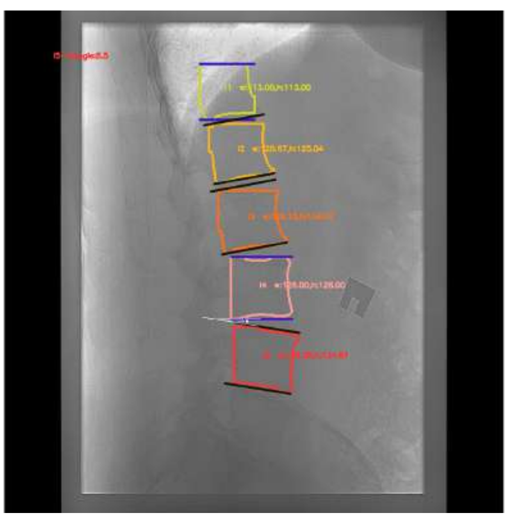

Figure 4. Geometric parameter display.

Among them:

- x_1 is the horizontal coordinate point of 11.
- x_2 is the horizontal coordinate point of 15.
- y_1 is the vertical coordinate point of 11.
- y_2 is the vertical coordinate point of 15.

Determine the size of x_{abs} and y_{abs}, determine the arrangement direction, and clarify the direction of the upper and lower boundary segments.

- Determine the tilt angle and width and height characteristics: Based on the comparison of the tilt angle and the width and height, sort the coordinates of the four vertices of the minimum adjacent rectangle according to the maximum horizontal coordinate, the minimum horizontal coordinate, the maximum vertical coordinate, and the minimum vertical coordinate.
- Determine the vertices of the upper and lower boundary segments: According to the sorting results of the previous step, the upper and lower boundary vertices of the corresponding rectangle of the vertebra are determined. In this experiment, the cv2.line() function is used to draw the line segments in combination with the boundary vertebrae. As can be seen from Figure 4, the upper and lower boundary vertex detection restores the upper and lower boundaries of the vertebrae well.
- Test the intervertebral angle: After the vertebral boundary segment is determined, the intervertebral angle can be calculated by finding the angle between the two line segments.

The above methods can be well verified for different lumbar CT image orientations, especially providing an important reference basis for the automated measurement of the lumbar Cobb angle, and playing a positive role in promoting the early diagnosis of lumbar degenerative diseases.

III. Summary

This study analyzed CT images and combined the YOLOv8-seg model to accurately detect and identify the lumbar vertebrae, and extracted the geometric parameters of the vertebrae based on the mask of the identified target, including the height and width of the vertebrae and the mask contour edge obtained by the minimum adjacency matrix, thereby obtaining the angle between the vertebrae. This provides a research idea for obtaining the Cobb angle and has important clinical application value in assisting the diagnosis of degenerative diseases of the lumbar spine.

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АВТОМАТИЗАЦИЯ ПЕРВИЧНОЙ ДИАГНОСТИКИ ЗАБОЛЕВАНИЙ ПОЯСНИЧНОГО ОТДЕЛА ПОЗВОНОЧНИКА ЧЕЛОВЕКА С ИСПОЛЬЗОВАНИЕМ ИНТЕЛЛЕКТУАЛЬНОГО АНАЛИЗА КТ-ИЗОБРАЖЕНИЙ

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Целью данного исследования является создание автоматизированной интеллектуальной системы для первичной диагностики заболеваний поясничного отдела позвоночника человека. Данная диагностика осуществляется посредством обнаружения и идентификации позвонков, а также получения геометрических размеров и взаимного их расположения относительно друг друга на цифровых КТ изображениях.

Ядром интеллектуальной системы является модель YOLOv8-seg, с помощью которой осуществляется локализация позвонков, после которой вычисляются углы между позвонками и осуществляется первичная диагностика. После валидации полученных результатов данное исследование может оказать хорошую поддержку медицинским сотрудникам при ранней диагностике дегенеративных заболеваний позвоночника, помочь повысить диагностическую эффективность и точность выявления дегенеративных заболеваний позвоночника и предоставить научную основу для раннего вмешательства и лечения пациентов.

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