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INTELLIGENT CT IMAGE ANALYSIS ALGORITHM FOR 3D MODEL CONSTRUCTION

KANSTANTSIN KURACHKA, XUEMEI WANG, HUANHAI REN

Sukhoi State Technical University of Gomel (Gomel, Republic of Belarus)

Abstract. This paper presents an algorithm and associated software implementing a comprehensive computational pipeline based on the YOLOv8n-seg model (Ultralytics) for automated analysis of human lumbar spine CT images, including localization of anatomical regions, segmentation and quantitative measurements of vertebrae, and 3D visualization. Geometric parameters (total lumbar spine height and segmental angles) are calculated directly from segmentation masks and converted into physical units using the image resolution. This generates an STL file that can be exported to third-party software (e.g., 3D Slicer) for 3D surface reconstruction. A critical aspect of the developed approach is its emphasis on quantitative accuracy and reproducibility of results, rather than solely on visualization: measurements obtained from masks translate the model output into clinically interpretable metrics. This opens up opportunities for subsequent applications such as screening, patient stratification, and longitudinal studies.

Keywords: computed tomography, YOLOv8, lumbar spine, deep learning, segmentation, geometric analysis, 3D visualization.

Conflict of interests. The authors declare that there is no conflict of interests.

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АЛГОРИТМ ИНТЕЛЛЕКТУАЛЬНОГО АНАЛИЗА КТ-ИЗОБРАЖЕНИЙ ДЛЯ ПОСТРОЕНИЯ 3D-МОДЕЛИ

К. С. КУРОЧКА, СЮЭМЭЙ ВАНГ, ХУАНХАЙ РЕН

Гомельский государственный технический университет имени П. О. Сухого
(Гомель, Республика Беларусь)

Аннотация. В статье представлены алгоритм и соответствующие программные средства, реализующие комплексный вычислительный конвейер на основе модели YOLOv8n-seg (компания Ultralytics) для автоматизированного анализа КТ-изображений поясничного отдела позвоночника человека, включая локализацию анатомических областей, сегментацию и количественные измерения позвонков, а также трехмерную визуализацию. При этом геометрические параметры (общая высота поясничного отдела и сегментарные углы) вычисляются непосредственно на основе сегментационных масок и конвертируются в физические единицы измерения с использованием разрешения изображения. В результате генерируется STL-файл, который может быть экспортирован в стороннее программное обеспечение (например, 3D Slicer) для реконструкции трехмерной поверхности. Критически важным аспектом разработанного подхода является акцент на количественной точности и воспроизводимости результатов, а не исключительно на визуализации: измерения, получаемые на основе масок, транслируют выходные данные модели в клинически интерпретируемые показатели. Это открывает возможности для последующих приложений, таких как скрининг, стратификация пациентов и лонгитюдное исследование.

Ключевые слова: компьютерная томография, YOLOv8, поясничный отдел позвоночника, глубокое обучение, сегментация, геометрический анализ, трехмерная визуализация.

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Introduction

Degenerative conditions of the lumbar spine, such as herniated discs, lumbar spinal stenosis, and vertebral compression fractures (VCFs), are leading causes of lower back pain and functional impairment worldwide, placing a heavy clinical burden on healthcare systems [1, 2]. The diagnosis, treatment planning, and prognostic assessment of these conditions rely heavily on the accurate interpretation of medical images such as computed tomography (CT) or magnetic resonance imaging (MRI) [3].

In clinical practice, the geometrical parameters of the spine, particularly lumbar lordosis (LL), vertebral height, and segmental angles, are crucial for maintaining sagittal balance [4–6]. Studies have shown that loss of LL angle is significantly associated with functional impairment and increased pain, and is a key indicator for assessing spinal health and the effectiveness of surgical correction [7, 8]. Similarly, accurate measurement of vertebral body height is crucial for the diagnosis and classification of VCFs, especially in patients with spinal trauma [8, 9]. However, traditional imaging assessment methods rely on radiologists or orthopaedic surgeons manually measuring these parameters on two-dimensional slices. This process is not only labor-intensive and time-consuming, but also suffers from significant between- and within-observer variability due to differences in operator experience and subjective judgment, thus affecting diagnostic consistency and the accuracy of surgical planning [3]. Therefore, developing an automated, repeatable, and efficient quantitative analysis tool is of significant clinical value for improving the diagnosis and treatment of spinal diseases.

To overcome the limitations of manual measurements, initial research explored automated methods based on classical computer vision, including threshold-based segmentation, watershed algorithms, and active contour models. While these approaches achieved some success under constrained conditions, they are generally sensitive to image noise and lack the robustness to accommodate the spine's complex anatomy, significant inter-individual morphological variation, and prevalent artifacts in CT imaging. Consequently, their generalization capability remains limited.

In recent years, deep learning (DL), particularly convolutional neural networks (CNNs), has driven revolutionary progress in medical image analysis [10]. Unlike traditional methods that rely on handcrafted features, DL models can autonomously learn hierarchical, task-relevant features directly from large-scale data. This has led to superior performance in key tasks such as image segmentation, classification, and object detection [11]. Within spinal image analysis, DL has been extensively applied across imaging modalities – including CT, MRI, and X-ray – achieving diagnostic accuracy that matches or even surpasses that of human experts in specific domains [1].

In medical image semantic segmentation, U-Net and its derivative networks (Attention U-Net, 3D U-Net, etc.) have long been considered benchmark methods, mainly due to their encoder-decoder structure and skip connections, which can simultaneously preserve high-resolution details and deep semantics, thus achieving stable and precise segmentation results on tasks with fine anatomical boundaries, such as the spine [1]. In contrast, instance segmentation models like Mask R-CNN are geared towards "multiple targets of the same type" scenarios, capable of distinguishing different vertebrae such as L1, L2, and L3 within the same image. They are more suitable for tasks requiring vertebral-by-vertebra measurement, ratio calculation, or lesion localization. In recent years, the two-stage strategy of "detection first, segmentation later" has been widely adopted in medical imaging. Its core idea is to first use an efficient detector to lock the region of interest (ROI), and then run a more computationally intensive segmentation network within a smaller area to simultaneously reduce background interference and computational overhead. Within this framework, YOLOv8, with its high speed, anchor-free architecture, and native support for segmentation branches, has become a suitable choice for building lightweight, locally reproducible automated spinal CT analysis workflows.

This study focuses on the design and validation of an ROI-guided lumbar CT analysis pipeline (LCAP) for lumbar spine CT analysis. The proposed LCAP integrates four linked stages: lumbar region localization, ROI-constrained vertebral segmentation, mask-derived geometric measurement, and 3D reconstruction. In contrast to studies that primarily emphasize algorithm benchmarking, the present work concentrates on process integration and practical translation, showing how routine CT data can be transformed into structured quantitative indicators and visually interpretable 3D outputs within a reproducible workflow. The main contribution of this study lies in the construction of a lightweight and transparent analytical pathway based on publicly available data and open-source tools. By combining YOLOv8-based localization, mask-based morphometric analysis, and 3D visualization in a single framework, the study provides a methodological template for lumbar CT quantification that is acces-

sible, modular, and extensible. This design is intended not only to support proof-of-concept validation, but also to facilitate future expansion toward larger cohorts, more advanced architectures, and clinically oriented validation studies.

Research methods

The data for this study came from the publicly available training dataset of the VerSe 2019 Challenge, a multi-center, multi-scanner benchmark dataset for vertebral segmentation and labelling. This dataset was established to provide a standardized platform for evaluating and comparing spinal image analysis algorithms. It contains multi-scanner CT (MDCT) scan images and segmentation masks for each vertebra accurate to the voxel level, generated by a "human–machine" hybrid algorithm, providing a high-quality gold standard for supervised learning. To validate this workflow, we randomly selected CT scan data from 30 patients from the VerSe 2019 training set as the research cohort. This sample size was considered sufficient for an exploratory study aiming to demonstrate the feasibility of the framework and conduct preliminary comparisons of models.

All raw data were in 3D DICOM or NIfTI format. In the preprocessing stage, we converted the 3D CT volume data of each patient into a series of 2D sagittal slices. To enhance the visibility of skeletal structures, intensity values of all images were normalized to the bone window through window width/window level adjustments (e. g., window width 1500 HU, window level 300 HU). The framework shown in Fig. 1 provides a schematic overview of the proposed ROI-guided LCAP. It summarizes the main stages of the workflow, including CT preprocessing, YOLOv8-based lumbar localization, vertebral segmentation within the detected ROI, and downstream quantitative and visualization tasks.

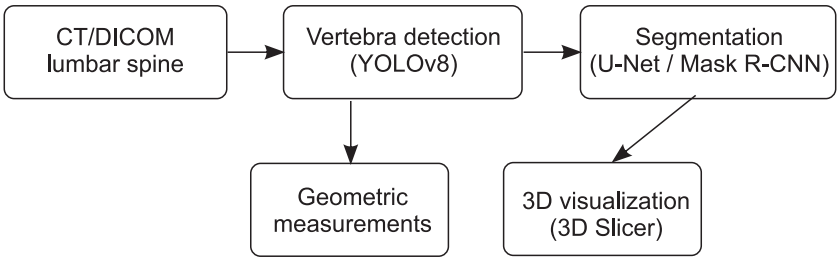


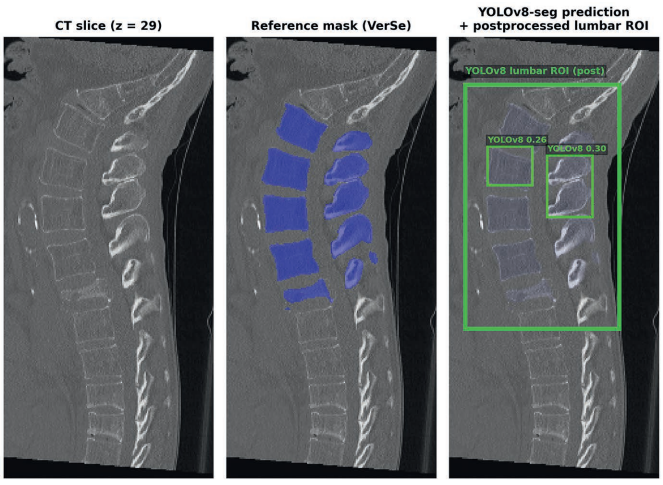
Fig. 1. Flow chart of lumbar spine through-the-body CT analysis

In the actual implementation, geometric measurements and 3D visualization are both derived from the segmentation masks obtained within the ROI. The role of YOLOv8 is therefore to provide robust anatomical localization and reduce irrelevant background before fine-grained analysis. This design improves processing efficiency and supports a practical 2D slice-based workflow that can be reproduced with open-source tools and extended in future studies.

In the first stage, the lumbar spine was examined using YOLOv8. Target detection is the initial step in this process, aiming to quickly locate the lumbar spine region on the entire CT slice. We used yolov8n-seg.pt provided by Ultralytics as the detection backbone. This model is small and fast, consistent with our research's vision of building a lightweight framework that can run locally. We fine-tuned the model for approximately 100 epochs to output single-class detection results sufficient to cover L1–L5 on sagittal lumbar spine slices. Considering that the model may generate multiple adjacent small boxes on individual slices, we merged all detection boxes in the same slice, calculated their minimum bounding rectangle as the final lumbar spine ROI, and then passed this ROI to the subsequent segmentation stage for fine vertebral delineation. The visualization of the results of the YOLOv8 detection stage is presented in Fig. 2.

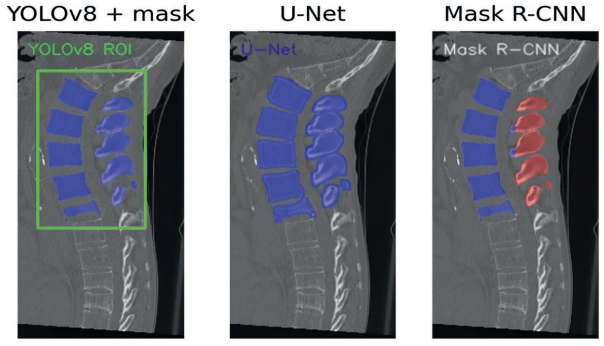
In the second stage, segmentation of the vertebrae within the lumbar ROI was performed. Within the lumbar ROI identified by YOLOv8, vertebral segmentation was performed to obtain masks suitable for subsequent quantitative analysis and visualization. At this stage, two representative segmentation paradigms were considered: semantic segmentation and instance segmentation. Representative results of vertebral segmentation within the detected ROI are shown in Fig. 3.

U-Net was adopted as a representative semantic segmentation architecture. Owing to its encoder-decoder design with skip connections, it effectively combines high-level semantic information with low-level spatial details, thereby producing continuous and well-defined foreground regions in medical images. In the present study, U-Net was trained as a binary segmentation model, in which all vertebral



a *b* *c*

Fig. 2. Visualization of YOLOv8 detection phase results: *a* – original sagittal CT slice; *b* – reference segmentation mask provided by the VerSe dataset; *c* – initial detection bounding box (small green rectangle) predicted by the YOLOv8 model and the final lumbar ROI (large green rectangle) generated by post-processing



a *b* *c*

Fig. 3. Results of vertebral segmentation within the detected ROI: *a* – YOLOv8 detection bounding box superimposed on the reference mask; *b* – semantic segmentation creating a continuous mask of vertebrae; *c* – segmentation of individual vertebral instances

pixels within the ROI were labelled as foreground to generate coherent masks for subsequent geometric analysis. Mask R-CNN was employed as a representative instance segmentation architecture. By extending the Faster R-CNN framework with an additional mask prediction branch, it enables pixel-level delineation of individual vertebral targets within the ROI. In the present workflow, this model provided vertebra-specific masks that were used for qualitative illustration and segmentation evaluation (Fig. 3).

In the third stage, after obtaining a two-dimensional segmentation mask of the lumbar spine, the segmentation results were transformed into a set of clinically significant quantitative indicators for an objective description of the spine morphology and potential pathological changes. Previous studies have shown that geometric parameters extracted based on automated segmentation can effectively reduce inter-observer variability and provide stable quantitative evidence for issues such as spinal degeneration and sagittal imbalance. This study first extracted vertebral body height: the vertical distance between the upper edge pixels of the mask for the uppermost lumbar vertebra (usually L1) and the lower edge pixels of the mask for the lowermost lumbar vertebra (usually L5) was considered an approximation of the overall height of the lumbar spine on the sagittal slice [10]. Furthermore, the vertical distances to the anterior, mid-high, and posterior edges of each vertebra within the mask of a single vertebra were measured to obtain three indicators – anterior/mid/posterior edge height, – used to identify compressive or wedge-shaped deformities, consistent with clinical quantitative fracture assessment practices [9]. At the implementation level, we first identify the top and bottom lumbar spine masks within the same slice, calculate their respective centroids, and connect them to form a lumbar spine principal

axis. The length of this principal axis in the pixel coordinate system is denoted as H_{px}. Combined with the image's pixel spacing S (mm/px), it can be converted to the actual scale

$$H_{mm} = H_{px}S. \tag{1}$$

Furthermore, to characterize the posture of the lumbar vertebrae in the sagittal plane, we select a representative anatomical boundary (such as the posterior margin of the superior vertebral body) near the principal axis, construct its direction vector $\mathbf{v}_2$, and calculate the angle between it and the lumbar vertebral principal axis direction $\mathbf{v}_1$ to obtain the approximate segmental lordosis angle of this section:

$$\theta = \arccos\left(\frac{\mathbf{v}_1\mathbf{v}_2}{\|\mathbf{v}_1\|\|\mathbf{v}_2\|}\right). \tag{2}$$

The above-mentioned automated extraction method can not only meet the clinical need for overall height and local edge height measurement, but also directly convert the segmentation results into structured features that can be used for subsequent classification or follow-up analysis. The total lumbar spine height H and the approximate LL angle were automatically calculated and marked on the segmentation mask. An example of automated extraction of geometric parameters is shown in Fig. 4.

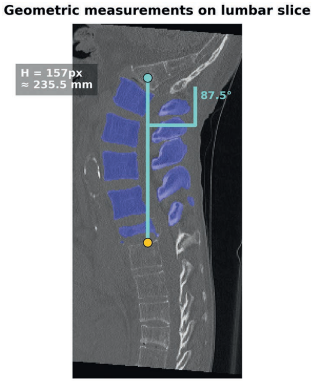


Fig. 4. Example of automated extraction of geometric parameters

In the fourth step, a 3D model of the lumbar spine surface was created by reconstructing the 2D segmented mask using 3D Slicer software, where different colors represent different vertebrae. To intuitively evaluate the segmentation quality and observe the overall 3D morphology of the lumbar spine, we reconstructed the 2D segmentation results into a 3D model. The process proceeds through the following steps: first, the 2D segmentation masks from all sagittal slices of a patient are sequentially stacked along the Z-axis to reconstruct a three-dimensional (3D) label volume. This volume is subsequently imported into 3D Slicer, an open-source and widely adopted platform for medical image computing. Leveraging the platform's dedicated "Segmentations" and "Model maker" modules, the 3D label data is converted into a surface mesh model (e. g., in STL format). The final output is an interactive, three-dimensional reconstruction of the lumbar spine, suitable for visualization and quantitative analysis (Fig. 5).

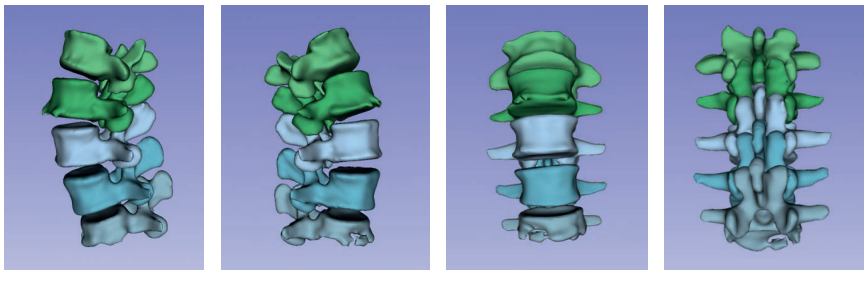


Fig. 5. 3D visualization results

This study primarily aimed at process validation; therefore, both qualitative visualization and typical segmentation metrics were employed in the evaluation phase. Qualitatively, by comparing the original CT slices, VerSe reference segmentation, and the lumbar spine ROI obtained through YOLOv8 post-

processing, the consistency of model localization and segmentation across different cases and vertebral levels could be visually assessed (Fig. 2–4).

Quantitatively, we used the intersection over union (IoU) and Dice similarity coefficient (DSC), commonly used in medical image segmentation, to measure the degree of overlap between the predicted mask and the reference mask. IoU, also known as the Jaccard index, is a metric that measures the degree of overlap between the predicted and ground truth regions and is widely used to evaluate the performance of object detection and image segmentation. Its calculation formula is as follows:

$$\mathrm{IoU}(A,B)=\frac{|A\cap B|}{|A\cup B|}=\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}+\mathrm{FN}}, \tag{3}$$

where A is the predicted region (boundary box or mask); B is the ground truth region; TP (true positives) is the number of correctly predicted pixels; FP (false positives) is the number of incorrectly predicted pixels; FN (false negatives) is the number of pixels that were not predicted.

DSC is the most commonly used evaluation metric in medical image segmentation. It also measures the overlap between the predicted and ground truth masks, but the weight for overlapping regions is twice that of IoU, making it more sensitive to the accuracy of segmentation boundaries. Its calculation formula is as follows:

$$\mathrm{DSC}(A,B)=\frac{2\cdot|A\cap B|}{|A|+|B|}=\frac{2\mathrm{TP}}{2\mathrm{TP}+\mathrm{FP}+\mathrm{FN}}. \tag{4}$$

This study primarily aims to validate the feasibility of the proposed LCAP rather than to establish state-of-the-art segmentation performance on a full 3D benchmark. Accordingly, IoU and DSC are reported here as reference indicators for process-level effectiveness within a lightweight exploratory setting based on sagittal lumbar slices from VerSe. In future work, when the framework is extended to larger datasets and more diverse imaging conditions, evaluation can be expanded to include finer-grained metrics such as mean surface distance, 95 % Hausdorff distance, and agreement analysis against expert manual measurements.

Research results and their discussion

The proposed ROI-guided LCAP demonstrated stable qualitative performance across the major stages of lumbar CT analysis. Accurate localization of the lumbar region of interest was achieved on sagittal CT slices (Fig. 2), followed by vertebral segmentation within the detected ROI (Fig. 3). On the basis of these segmentation results, the framework automatically extracted clinically relevant geometric parameters, including lumbar height and segmental angular information (Fig. 4), and further supported three-dimensional surface reconstruction in 3D Slicer for intuitive visualization of lumbar morphology (Fig. 5). Overall, the qualitative results confirm the technical feasibility of the integrated workflow summarized in Fig. 1. The main strength of the proposed LCAP lies not only in the performance of individual stages, but also in its ability to connect localization, segmentation, quantitative analysis, and visualization within one reproducible analytical process.

To objectively evaluate the performance of each stage of the system's operation, a quantitative analysis was conducted, the results of which are summarized in Tab. 1, which presents the results of YOLOv8's operation at the first stage of the lumbar spine ROI detection task.

Table 1. YOLOv8 detection efficiency

Index	Accuracy	Recall	mAP@0.5	mAP@0.5:0.95
Values	0.975	0.982	0.981	0.886

The results in Tab. 1 show that the model that the model performs excellently in locating the lumbar spine region, with both precision and recall exceeding 0.97, indicating that the model can accurately identify the target region with very few false negatives or missed detections. The mAP@0.5 (mean average precision at an IoU threshold of 0.5) reached 0.981, further confirming the model's high reliability in localization accuracy. These data strongly support the effectiveness of using YOLOv8 as a robust initial localization tool in this process.

Tab. 2 summarizes the segmentation performance obtained with two representative implementations used within the ROI segmentation stage (SD – standard deviation).

Table 2. Comparison of segmentation model performance

Model	DSC ± SD	IoU ± SD
U-Net	0.905 ± 0.05	0.826 ± 0.06
Mask R-CNN	0.923 ± 0.04	0.857 ± 0.05

Both approaches achieved high overlap with the reference masks. Mask R-CNN yielded slightly higher mean DSC and IoU values, whereas U-Net also demonstrated stable and satisfactory segmentation performance. In the context of the present study, these results are reported primarily to support the feasibility of the segmentation stage within the proposed LCAP rather than to establish an extensive benchmark comparison.

The present study demonstrates the feasibility of an ROI-guided LCAP for automated lumbar spine analysis based on open-source tools and public data. A key finding is that YOLOv8-based localization can reliably identify the lumbar region in sagittal CT slices, thereby restricting subsequent analysis to a focused anatomical area. This design reduces irrelevant background information and creates a more efficient basis for segmentation, quantitative measurement, and visualization. A second important result is that the proposed workflow does not stop at segmentation output. Instead, the segmentation masks are further converted into clinically meaningful geometric indicators, such as lumbar height and segmental angular measures, and then translated into 3D surface models. This step is methodologically important because it moves the analysis from image-level prediction toward structured quantitative description, which is more relevant to clinical interpretation and follow-up applications. Taken together, these findings suggest that the LCAP is not simply a visualization workflow, but a reproducible framework for lumbar CT quantification. Its value lies in connecting image processing, measurement, and 3D representation within one coherent analytical pathway, which may support future applications in screening, longitudinal monitoring, and computer-assisted diagnostic research.

The framework proposed in this study is consistent with current developments in DL-based spinal image analysis. Previous studies have demonstrated that modern segmentation methods can achieve high overlap with reference annotations, often with DSC values above 0.90. The results obtained in the present study fall within this range and therefore support the practical feasibility of the proposed workflow. Compared with studies based on fully three-dimensional CNN architectures, the present slice-wise 2D strategy combined with ROI-guided analysis offers a more lightweight and accessible implementation. Although full 3D models may better exploit inter-slice context, they usually require greater computational resources and more complex training procedures. In contrast, the present workflow emphasizes reproducibility, practical deployment, and the integration of localization, segmentation, quantitative analysis, and 3D visualization within one coherent process.

Several limitations of this study should be noted. First, the sample size remains relatively small and does not fully represent the anatomical variability, pathological complexity, and imaging heterogeneity encountered in routine clinical practice. Second, the present workflow is based on slice-wise 2D analysis and therefore does not explicitly exploit full 3D spatial continuity. As a result, segmentation consistency may still vary at superior and inferior vertebral margins or in anatomically complex regions. Third, although the extracted geometric parameters are clinically meaningful in principle, they have not yet been systematically validated against manual measurements performed by radiologists or spine surgeons.

Future work should therefore proceed in three directions. The first is data expansion, including validation on the full VerSe dataset and on additional multi-center CT cohorts. The second is methodological extension toward 2.5D or 3D architectures that can better capture inter-slice context while preserving the workflow logic of the current LCAP. The third is formal clinical validation, including agreement analysis between automated and expert-derived measurements and assessment of the framework in specific disease settings such as VCFs, lumbar spinal stenosis, or sagittal imbalance.

Conclusion

1. This study developed an ROI-guided lumbar computed tomography analysis pipeline for automated analysis of lumbar spine computed tomography images. Built on YOLOv8-based localization,

ROI-constrained segmentation, mask-derived geometric measurement, and 3D reconstruction, the proposed framework establishes a coherent workflow that transforms routine image data into structured quantitative and visual outputs.

2. The main significance of the study lies in workflow integration rather than in broad algorithm benchmarking. By linking localization, segmentation, morphometric extraction, and 3D visualization within a reproducible open-source framework, the lumbar computed tomography analysis pipeline demonstrates a practical route from pixel-level prediction to clinically interpretable information. This makes the framework suitable as a methodological basis for future expansion toward larger datasets, advanced architectures, and clinically validated decision-support applications.

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Authors' contribution

The authors contributed equally to the writing of the article.

Information about the authors

Kurachka K., Cand. Sci. (Tech.), Associate Professor, Head of the Department of Information Technology, Sukhoi State Technical University of Gomel (SSTUG)

Wang Xuemei, Postgraduate of the Department of Information Technology, SSTUG

Ren Huanhai, Postgraduate of the Department of Information Technology, SSTUG

Address for correspondence

246029, Republic of Belarus,
Gomel, Octiabria Ave., 48
Sukhoi State Technical University of Gomel
Tel.: +375 23 232-95-65
E-mail: wxm_doc@qq.com
Wang Xuemei