

ORIGINAL RESEARCH

Enhancing clinical efficiency and accuracy: automated segmentation for cervical cancer brachytherapy

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Abstract

Background: This study aims to develop an automatic segmentation model based on U-Net architecture. The model will delineate the high-risk clinical target volume (HR-CTV) and pelvic organs at risk (OARs) in brachytherapy for cervical cancer. The goal is to improve the consistency and clinical efficiency of segmentation results. **Methods:** The automatic segmentation model was developed by U-Net architecture, and the Computed Tomography (CT) images of 102 cervical cancer patients receiving Three-Dimensional image-guided brachytherapy (3D IGBT) were used for network training (63 cases in training set, 20 cases in test set, and 19 cases in validation set). The segmentation objects included HR-CTV, sigmoid colon, rectum, bladder and small intestine. The accuracy of the automatic segmentation model was evaluated by Dice similarity coefficient (DSC) and Hausdorff distance (HD). In addition, the time efficiency was evaluated by comparing the time of manual delineation and the time of artificial intelligence (AI) assisted automatic delineation. **Results:** The auto-segmentation performance of HR-CTV and OARs was good, with an average DSC of 0.90 ± 0.03 and 0.85 ± 0.04 , respectively. The DSC values of the rectum, sigmoid colon and bladder were 0.91 ± 0.04 , 0.88 ± 0.06 and 0.86 ± 0.04 , respectively. Among the organs at risk, the small intestine had the lowest segmentation data, with a DSC of only 0.77 ± 0.20 and a HD of 25.06 ± 16.24 mm. The automatic delineation took only 1.53 ± 0.03 minutes, while the manual delineation took the longest time. AI assisted manual delineation shortened the delineation time of HR-CTV and OARs by 5 minutes and 10 minutes, respectively. **Conclusions:** U-Net meets clinical expectations in the delineation of HR-CTV and OARs in brachytherapy for cervical cancer, and performs better than the traditional model in HR-CTV. However, the delineation results of small intestine and sigmoid colon need to be further verified by a larger sample size.

Keywords

Cervical cancer; Brachytherapy; Convolutional neural network; Automatic delineation; U-Net

1. Introduction

Cervical cancer is the fourth most common malignant tumor in women worldwide in terms of incidence and mortality. Data from the World Health Organization's International Agency for Research on Cancer indicate that there were an estimated 600,000 new cases and 340,000 deaths attributed to cervical cancer worldwide in 2020 [1]. In China, approximately 111,800 new cases and 61,600 deaths occurred in 2022, with both incidence and mortality rates showing increasing trends [2]. In recent years, surgery has remained the main treatment modality for early-stage cervical cancer, for locally advanced cervical cancer, treatment involves external beam radiation combined with brachytherapy, along with concurrent chemotherapy as the standard treatment [3]. Brachytherapy (BT) is an indispensable part of curative radiation therapy

for locally advanced cervical cancer and is irreplaceable with respect to external radiation [4]. It delivers high doses of radiation to tumor tissues while also minimizing damage to surrounding normal tissue due to the steep gradient dose fall off [5]. Compared with 2D image-guided brachytherapy (2D IGBT), 3D image-guided brachytherapy (3D IGBT) can more effectively increase the dose to cervical lesions and more accurately assess the dose received by nearby organs at risk. Research findings indicate that 3D IGBTs significantly outperform conventional brachytherapy in terms of disease control rates progression-free survival (PFS) and overall survival (OS) and significantly reduce complications [6, 7].

Despite advancements in brachytherapy techniques, implementing 3D IGBT requires physicians to reconstruct the source applicator and delineate the high-risk clinical target volume (HR-CTV) and organs at risk (OARs) each time, leading to

lengthy patient waiting times. This delay may lead to alterations in organ filling and displacement of the source applicator, affecting the accuracy of treatment delivery [8]. Additionally, accurate delineation of the clinical target volume and organs at risk is crucial for disease control and minimizing normal tissue toxicity. However, variations in physicians' delineation expertise lead to significant subjective differences, making standardization of evaluation criteria challenging [9]. To address these complexities, there is an urgent need for an efficient and consistent automated delineation model, which is critical for improving the quality of 3D IGBT implementation. In recent years, integrating the U-Net neural network into the treatment planning process has represented a significant advancement [10–12]. This complex tool can autonomously identify and delineate target volume and organs at risk, providing invaluable assistance in creating precise and personalized treatment plans [13, 14]. The ability of the U-Net neural network allows clinicians to achieve a higher level of accuracy in treatment planning, enhancing the therapeutic impact on target cancer tissues while minimizing unintended exposure to adjacent healthy structures. Advanced technology not only simplifies the treatment planning process, but also alleviates time burdens on medical staff and enhances treatment efficacy [15, 16].

In the field of radiation therapy, various convolutional neural network (CNN) models have successfully automated the delineation of clinical target volumes and organs at risk for brain tumors [17], head and neck cancers [18, 19], thoracic tumors [20], breast tumors [21, 22], and rectal tumors [23, 24], significantly enhancing the efficiency, repeatability, and quality assurance of radiation treatment plans. Research has also explored the segmentation effects of CNN models on automatic delineation in locally advanced cervical cancer, although most studies have focused on external beam radiation [25–27]. This study aims to develop an automated segmentation model based on the U-Net architecture for accurately delineating HR-CTVs and OARs in cervical cancer brachytherapy. By improving the consistency of the segmentation results and reducing the treatment time, the model aims to increase the clinical operational efficiency.

2. Materials & methods

2.1 Data collection

This study used CT image data from 102 IB–IVA stage patients with locally advanced cervical cancer treated with an 3D IGBT from December 2020 to December 2023. The exclusion criteria were: (1) patients who had undergone surgical treatment for cervical cancer and (2) patients who were treated with implant needles. The average age was 56.4 year (34–75 years), and the pathological type was squamous cell carcinoma or adenocarcinoma. According to the International Federation of Gynecology and Obstetrics (FIGO) staging (2018), 2 cases of IB3 stage, 3 cases of IIa1 stage, 8 cases of IIa2 stage, 44 cases of IIB stage, 4 cases of IIIB stage, 24 cases of IIIC1 stage, 12 cases of IIIC2 stage and 5 cases of IVA stage were taken into consideration. All patients were positioned in the lithotomy position and treated with Fletcher-type applicators.

CT scan is performed for each treatment and were performed with a PHILIPS Brilliance Big Bore 16-slice CT simulator (Haifa, Israel), with an image resolution of 1024×1024 and a slice thickness of 3.0 mm. The entire process adhered to confidentiality principles without involving any personal patient information.

All patients underwent simulation. The attending physician delineated the HR-CTV and OARs via the Oncentra Brachy treatment planning system (Elekta, Veenendaal, The Netherlands). The delineation standards adhere to Report No. 89 [28], details provided in Tables 1 and 2.

2.2 Network construction

The study employed a U-Net convolutional neural network model for the automatic segmentation and delineation of images. This model structure consists of multiple convolutional and pooling layers, which are used to progressively extract feature information from the input images and reduce spatial resolution. Through convolution operations, the model performs feature extraction and abstracts representations of the input feature maps. By stacking multiple convolutional layers, the model efficiently learns from complex data. The pooling layers reduce the dimensions of the feature maps by downsampling operations, enhancing the model's ability to learn translation invariance of objects, thus providing robustness against variations in object positioning within images.

In the decoder section of the U-Net, upsampling operations were employed to gradually restore the high-level semantic features obtained in the encoder to a segmentation result of the same size as the input image. The multiple convolutional layers in the decoder were used for feature reconstruction and the restoration of depth information. Additionally, the U-Net incorporated skip connections, which linked feature maps from corresponding levels in the encoder with those in the decoder. This helps to restore richer details and edge information, preventing information loss and vanishing gradients, thereby improving the network's convergence speed and segmentation performance.

The U-Net model constructed in this study is illustrated in Fig. 1 and consists of two main parts: a downsampling section (encoder) and an upsampling section (decoder). In the downsampling section of the encoder, image features are progressively extracted, while the spatial resolution is continuously reduced. The input image size is $512 \times 512 \times 3$ (RGB image), and after multiple convolution and pooling operations, the spatial dimensions are gradually diminished. The encoder contains 64, 128, 256 and 512 convolutional filters at each layer, with the Rectified Linear Unit (ReLU) activation function applied after each convolutional layer. The decoder section restores the spatial resolution of the image through deconvolution operations. Each layer utilizes a (2×2) deconvolutional kernel with a stride of 2, progressively recovering the image size from smaller feature maps to larger images. In the decoder, the number of convolutional filters at each layer is 512, 256, 128, 64 and 32. After each deconvolution operation, skip connections are established with the corresponding feature maps from the encoder layer, allowing for the retention of more spatial information via concatenation.

TABLE 1. Boundary and delineation of HR-CTV in cervical cancer brachytherapy.

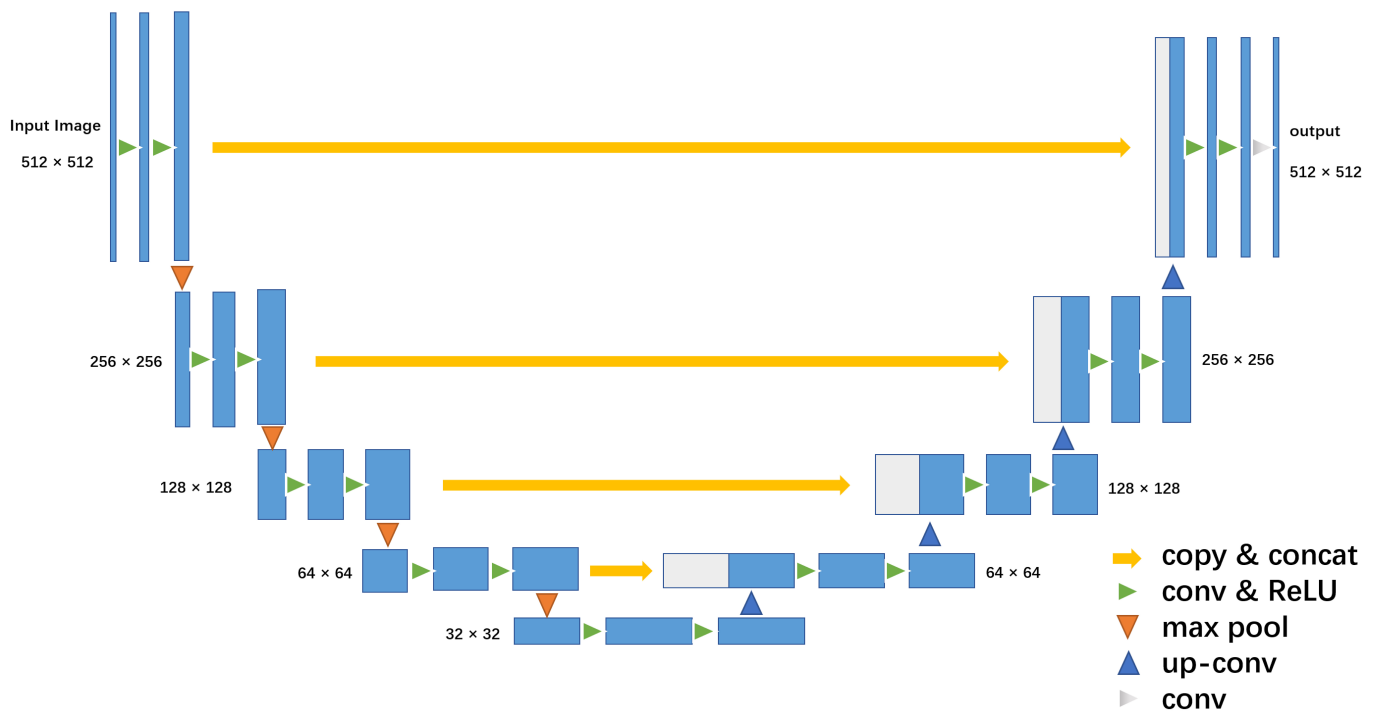
HR-CTV	Boundary Definition and Delineation Recommendations
Inferior Boundary	Superior Boundary of the Applicator
Superior Boundary	Two-thirds of the uterine height, gradually tapering from the contracted part of the uterus to a ring with a diameter of 1 cm to form a conical shape
Lateral Boundaries	Delineate the tissue on CT that appears gray–white and similar in density to the cervix. (Do not delineate when it is not apparent on CT)

HR-CTV: high-risk clinical target volumes; CT: Computed Tomography.

TABLE 2. Pelvic OAR delineation criteria.

OARs	Boundary Definition and Delineation Recommendations
Bladder	Lateral Wall of the Bladder, Including the Bladder Neck.
Rectum	Lateral Wall of the Rectum, from the Anal Sphincter to the Rectosigmoid Junction.
Sigmoid	Lateral Wall of the Rectum, from the Rectosigmoid Junction to the Left Iliac Fossa.
Small intestine	The outer contour of the small bowel loop (including the mesentery) within 3–4 cm.

OARs: organs at risk.

**FIGURE 1. U-Net model.** ReLU: Rectified Linear Unit.

The final output layer employs a (1×1) convolutional kernel to generate the segmented image, with output dimensions of $(512 \times 512 \times 1)$. A sigmoid activation function is applied for pixel-level binary classification.

2.3 Model training, testing and validation

CT images from 102 patients were used in the study, with 63 cases used for training, 20 cases used for testing, and 19 cases used for validation. The image resolution was uniformly cropped to 512×512 pixels and saved in GIF format. The segmentation targets included five regions: the HR-CTV, sigmoid colon, rectum, bladder and small intestine. The experiment utilized the PyTorch framework in Python for model con-

struction, training and evaluation. During data preprocessing, contrast-adaptive histogram equalization was applied for image enhancement across all segmentation targets. During the gradient descent process, each batch contained 16 samples, and the network was trained for 1000 iterations (epochs = 1000). The Adam algorithm was used as the optimizer for network training, with the learning rate set to $lr = 1 \times 10^{-4}$. The cross-entropy loss function (categorical_crossentropy) was selected as the loss function. The experiments were conducted on a computer with a 2.80 GHz CPU, 64 GB of memory, and an NVIDIA RTX A4000 GPU running Python 3.7 for computer simulation of the proposed algorithm.

2.4 Evaluation method

2.4.1 Performance evaluation index

To evaluate the precision of model segmentation on the test set, the Dice similarity coefficient (DSC) and the Hausdorff distance (HD) were used. The DSC can calculate the similarity or overlap between two contour regions, whereas the Hausdorff distance is the maximum value in the set of nearest distances between pixels in two regions. The formula for calculating the DSC is as follows:

$$DSC = \frac{2|A \cap B|}{|A| + |B|}$$

In the formula, A represents the manually delineated region, and B represents the automatically delineated region. The numerator is twice the intersection of the manual and automatic delineations, and the denominator is the union of the manual and automatic delineated regions. The larger the DSC value is, the greater the degree of overlap between the segmented image and the manual delineation. The DSC ranges between 0 and 1. The Hausdorff distance (HD) calculation formula for sets A and B is as follows:

$$HD(A, B) = \max(h(A, B), h(B, A))$$

$$h(A, B) = \max(\min\|a - b\|)$$

$$a \in A, b \in B$$

In this context, $h(A, B)$ denotes the maximum of the minimum distances from each point in set A to set B . The smaller the HD value is, the higher the degree of overlap between sets A and B , indicating better segmentation effectiveness.

2.4.2 Time consumption evaluation

CT images are selected from each patient's single-fraction brachytherapy for redelineation, using Report No. 89 as the delineation criteria. physicians complete manual delineations via the Oncentra Brachy planning system (Elekta, Veenendaal, Netherlands), whereas automatica and AI-assisted manual delineation are performed via the PV-iCurve intelligent delineation system (PerView Medical). The time taken for manual delineation and AI-assisted manual delineation of the HR-CTV and OARs (rectum, bladder, sigmoid colon, and small intestine) was recorded, as was the duration of AI automatic delineation.

3. Results

3.1 Segmentation performance evaluation

This study, which is based on the U-Net convolutional neural network, evaluated the segmentation results of high-risk

clinical target volume (HR-CTV) and organs at risk (OARs), including the sigmoid colon, rectum, bladder, and small intestine, during brachytherapy for cervical cancer. The average Dice similarity coefficient (DSC) values for the HR-CTV and OARs were 0.90 ± 0.03 and 0.85 ± 0.04 , respectively, with the HR-CTV showing the most favorable segmentation outcomes. The segmentation results for the OARs demonstrated that the rectum had the best performance, with a DSC of 0.91 ± 0.04 and a Hausdorff distance (HD) of 6.94 ± 4.02 mm. This is likely due to the rectum's distinct boundaries, which are easily recognizable by the model. The sigmoid colon and bladder also showed good segmentation performance, with DSC values of 0.88 ± 0.06 and 0.86 ± 0.04 , respectively. However, the sigmoid colon had a higher HD value, which may be attributed to its greater variability, variable position, and indistinct boundaries, making it more challenging for the model to identify. The small intestine exhibited the lowest segmentation data among the OARs, with a DSC of only 0.77 ± 0.20 and an HD of 25.06 ± 16.24 mm, due to its high mobility, which significantly increases the difficulty of delineation compared with other pelvic OARs. The detailed performance parameters of the model's segmentation results are presented in Table 3. Images illustrating the effects of U-Net automatic delineation for the HR-CTV and OARs can be found in Fig. 2.

TABLE 3. Quantification of the accuracy of automatic sketching (Mean $\pm$ SD).

	DSC	HD (mm)
HR-CTV	0.90 ± 0.03	4.41 ± 1.74
Bladder	0.86 ± 0.04	33.69 ± 27.23
Rectum	0.91 ± 0.04	6.94 ± 4.02
Sigmoid	0.88 ± 0.06	194.86 ± 8.83
Small intestine	0.77 ± 0.20	25.06 ± 16.24

DSC: Dice similarity coefficient; HD: Hausdorff distance (mm); HR-CTV: high-risk clinical target volume.

3.2 Time consumption evaluation

For the manual and AI automated delineation of the HR-CTV and OARs in cervical cancer brachytherapy, time taken were recorded along with the time taken by physicians with AI assistance to delineate the target areas. Manual delineation of the HR-CTV and OARs took 9.14 ± 0.08 minutes and 20.31 ± 0.08 minutes, respectively, whereas AI automated delineation of both the HR-CTV and OARs took a total of 1.53 ± 0.03 minutes. With AI assistance, the time required for manual delineation of the HR-CTV was reduced to 4.23 ± 0.07 minutes, and the time for delineating OARs was reduced to 10.24 ± 0.05 minutes, which is half of the manual time needed. The time statistics for manual and AI delineation of the HR-CTV and OARs are presented in Table 4.

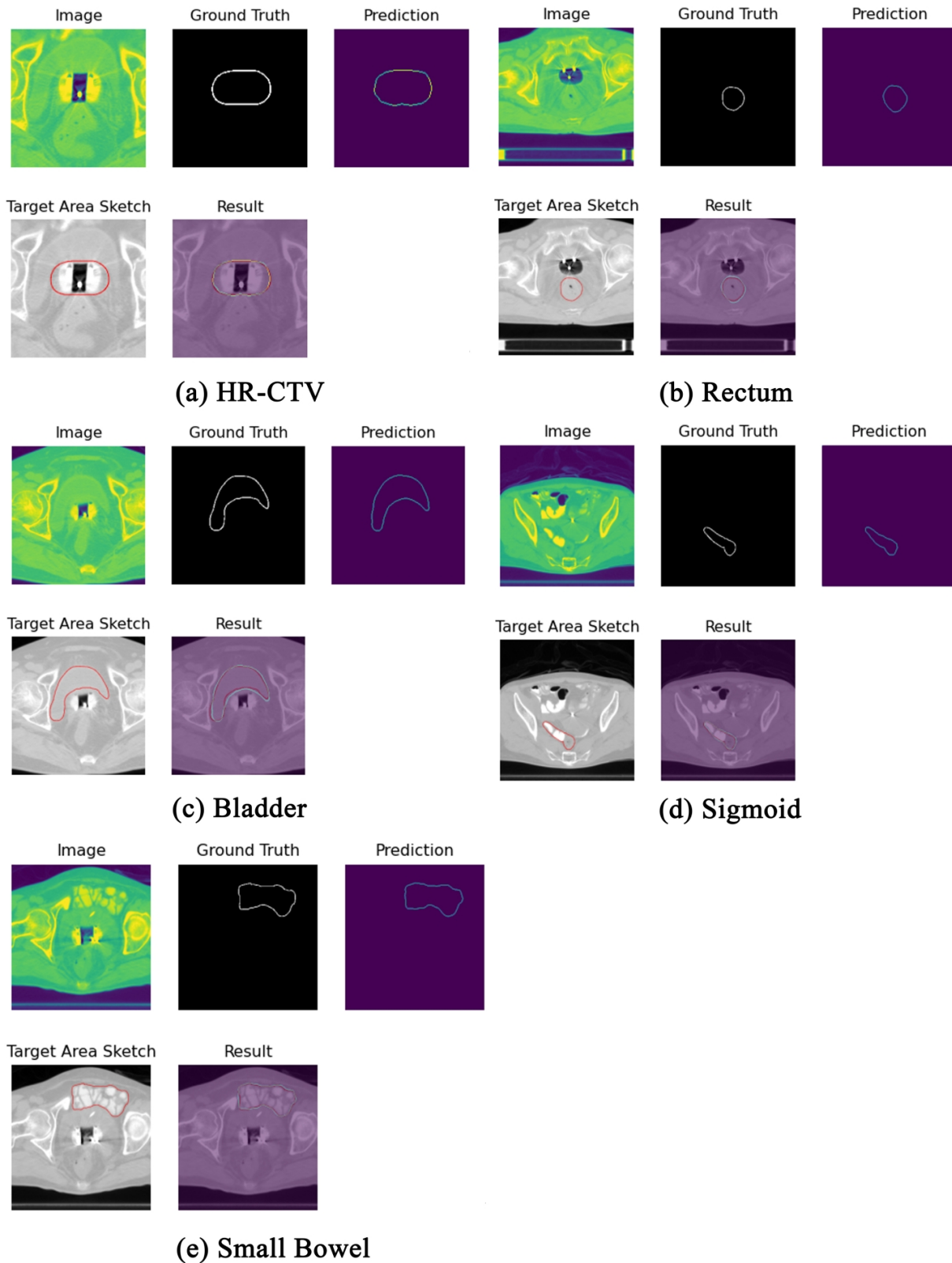


FIGURE 2. Effects of U-Net automatic delineation for HR-CTVs and OARs. (a) HR-CTV. (b) Rectum. (c) Bladder. (d) Sigmoid. (e) Small Bowel. Image: This refers to the result of contrast-adaptive histogram equalization enhancement applied to the image. Ground truth: This is the contour drawn by the physician. Prediction: This represents the contour predicted by the network. Target area sketch: This is the physician's initial contour on the image. Result: This is a comparison between the predicted contour and the physician's contour. In the resulting images, the red lines indicate the manually drawn contours of the HR-CTV and OARs (organs at risk), whereas the blue lines represent the contours automatically delineated by the model for the HR-CTV and OARs. HR-CTV: high-risk clinical target volumes.

TABLE 4. Time consumption of manual and AI automated delineation of the HR-CTV and OARs.

	HR-CTV (min)	OARs (min)
Manual/min	9.14 ± 0.08	20.31 ± 0.08
AI assisted/min	4.23 ± 0.07	10.24 ± 0.05
AI automated/min	1.53 ± 0.03	

HR-CTV: high-risk clinical target volume; OARs: organs at risk; AI: Artificial Intelligence.

4. Discussion

In image-guided brachytherapy, owing to the proximity of the treatment to critical structures, there is little margin for error, and the value of precision is self-evident. Manual delineation by doctors is time-consuming and subject to variability. Precise delineation by automatic delineation software not only improves the efficiency of clinical doctors but also reduces the impact of uncertainties associated with manual delineation [29]. U-Net, an improvement over fully convolutional networks, enhances the segmentation of medical imaging data by incorporating original detail information into deep features through upsampling [30]. Consequently, an automated segmentation model based on the U-Net architecture can reduce the time required for delineating tumor lesions and organs at risk, minimize the possibility of human errors, and improve clinical workflow efficiency. This allows doctors to focus more on patient treatment than on time-consuming manual processes.

This study utilizes the U-Net neural network to automate the delineation of high-risk clinical target volumes (HR-CTVs) and organs at risk (OARs) for cervical cancer brachytherapy. In terms of segmentation performance, the average Dice similarity coefficient (DSC) for HR-CTV was 0.90 ± 0.03 , and for OARs, it was 0.85 ± 0.04 , indicating that the model performed well. In particular, HR-CTV segmentation (DSC value of 0.90 ± 0.03) significantly outperforms traditional models, considering that the CTV has a certain degree of grayscale difference from the surrounding soft tissues and exhibits strong edge effects, the skip connections of the U-Net network are particularly adept at capturing these differences, thereby enabling accurate delineation of the CTV. In the delineation of OARs, the rectum had the best segmentation effect, with a DSC value of 0.91 ± 0.04 . Li and colleagues reported that [31] among three models—2D U-Net, 3D U-Net and 3D Cascade U-Net—the 3D Cascade U-Net performed best for HR-CTV, rectum and bladder, which corroborates the findings of this study. The automatic delineation of the bladder in this experiment has a DSC of 0.86 ± 0.03 , which also indicates good segmentation performance. Zhang and others [32] developed a U-Net model where the results for the bladder (DSC of 0.87) and rectum (DSC of 0.82) were similar to the bladder data obtained in this study, demonstrating comparable segmentation performance. The sigmoid colon also shows favorable delineation outcomes (DSC of 0.88 ± 0.06), but the bladder and sigmoid colon exhibit greater Hausdorff distances (HDs) than other OARs do, which may be related to volume changes and organ displacement due to

inconsistent bladder filling. There are experimental designs to explore the optimal bladder filling volume that minimizes the impact on surrounding normal organs in three-dimensional brachytherapy for locally advanced cervical cancer because hollow organs exhibit significant expansion variability [33]. The increased HD for the sigmoid colon is considered to be due to its propensity to overlap with the uterus, bilateral adnexa, and parts of the small intestine, which makes its boundaries difficult to distinguish and contributes to greater variability. However, these variations generally have minimal impact on clinical application. In this experiment, the delineation results for the small intestine were less satisfactory than those for other organs, with a DSC of only 0.77 ± 0.20 and an HD of 25.06 ± 16.24 . Studies have indicated [34–36] that pelvic OARs, which exhibit poor contrast and high variability in size, position, and shape, limit the application of atlas-based segmentation methods. The methods are more effective for relatively fixed head and neck OARs and perform poorly on tissues that are highly mobile, small in volume, and prone to deformation, requiring significant manual corrections [37]. In this study, the model's predictions for the small intestine are highly variable, are not fixed in position, have unclear boundaries, and perform poorly, with some instances even being unrecognizable. This may be due to the AI model's tendency to categorize structures such as ligaments and the sigmoid colon as part of the small intestine. Therefore, the accuracy of these delineations is strongly affected by changes in organ position, size and edge contrast.

This study also compared the time taken for manual delineation, AI-assisted manual delineation, and AI automatic delineation. According to the time consumption statistics, AI automatic delineation only took 1.53 ± 0.03 minutes, but on the basis of clinical experience, the results generally require manual correction. Compared with manual delineation, AI-assisted manual delineation of the HR-CTV and OAR significantly reduces the time, shortening it by 5 minutes and 10 minutes, respectively. This method is the most commonly used method in clinical settings, significantly reducing the workload of doctors and the waiting time for patients, allowing physicians more time to focus on patient treatment plans rather than the time-consuming manual process [9]. Pure manual delineation took the longest time, with HR-CTV taking 9.14 ± 0.08 minutes and OAR taking 20.31 ± 0.08 minutes, with the sigmoid colon taking the longest. This may be due to the uncertainty in the contours and the morphological variability of the sigmoid colon.

5. Conclusions

In summary, this study successfully developed an automatic delineation model for HR-CTVs and OARs in cervical cancer brachytherapy using the U-Net convolutional neural network. The model demonstrated good segmentation performance and potential clinical applicability for HR-CTV. For OARs, particularly the rectum, the model yielded excellent delineation results, which can effectively meet clinical needs, significantly shorten the delineation time, and improve consistency. The limitations of this study lie in the need for further improvement in the automatic delineation of the small intestine and sigmoid

colon; Secondly, the research findings require large-scale, multicenter clinical validation to ensure the reliability and safety of the model in practical applications.

AVAILABILITY OF DATA AND MATERIALS

The data cannot be shared due to ethical restrictions.

AUTHOR CONTRIBUTIONS

SFF—Conceptualization, methodology, funding acquisition, writing original draft. HXW—Methodology, data curation, formal analysis. YHY—Supervision, validation. SXC—Data curation, formal analysis. XYD—Supervision, validation. YXG—Supervision, validation. HYC—Conceptualization, supervision, funding acquisition. BQ—Conceptualization, supervision, funding acquisition. All authors reviewed and approved the final manuscript.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

The study was conducted in accordance with the Ethics Committee of Gansu Provincial People's Hospital (2021-275). All included patients voluntarily agreed to participate.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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