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Deep Learning–Based Needle Selection and Insertion Depth Determination for Venezia Applicator–Based Cervical Cancer Brachytherapy

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ABSTRACT

Purpose: Brachytherapy is a standard component in cervical cancer treatment. Venezia applicators allow addition of limited needle positions to tandem and ovoid procedures, but needle selection and insertion depth largely rely on physician judgement, requiring some level of estimation. This study proposes a deep learning-based approach for automated needle selection and depth determination guided by clinical target volume (CTV) geometry and patient anatomy.

Methods: The model includes (a) an encoder-decoder network for extracting CTV geometric features and (b) a regression network determining insertion depth. The encoder-decoder network adopts a U-Net backbone to encode CTV into geometric features, which are then modulated by an attention mask surrounding a specific needle to emphasize features relevant to the needle. These modulated features are used by the regression network to predict depth. Unused needle positions are defined as zero depths. The model was trained in a supervised manner with clinically recorded depths as the reference. 1,700 needle insertions from 220 Venezia cases were split into 1,324 training and 376 testing samples, each comprising a CTV and the corresponding insertion depth. The model predictions were evaluated against clinical records on a per-needle basis using the absolute difference (AD) from the CTV geometric depth, defined as the distance from the needle-ovoid intersection to the first dwell position.

Results: In 71.81% of cases, the model's AD from CTV geometric depth was within 3 mm of the clinical-record AD. Among these, 4.26% of all cases had model predictions closer to CTV than clinical records, with needle depths reduced relative to clinical use by 0.52–26.77 mm (median 8.40 mm).

Conclusion: The study demonstrated the feasibility of deep learning for predicting needle selection and depth. Prediction accuracy was limited by inter-physician variability in recorded depths. Future work will use dwell-position-derived depths as reference to better reflect true needle insertion requirements.

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INTRODUCTION

Brachytherapy is a standard component in cervical cancer treatment. Venezia applicators allow addition of limited needle positions to tandem and ovoid procedures, but needle selection and insertion depth largely rely on physician judgement, requiring some level of estimation.

This study proposes a deep learning-based approach for automated needle selection and depth determination guided by clinical target volume (CTV) geometry and patient anatomy.

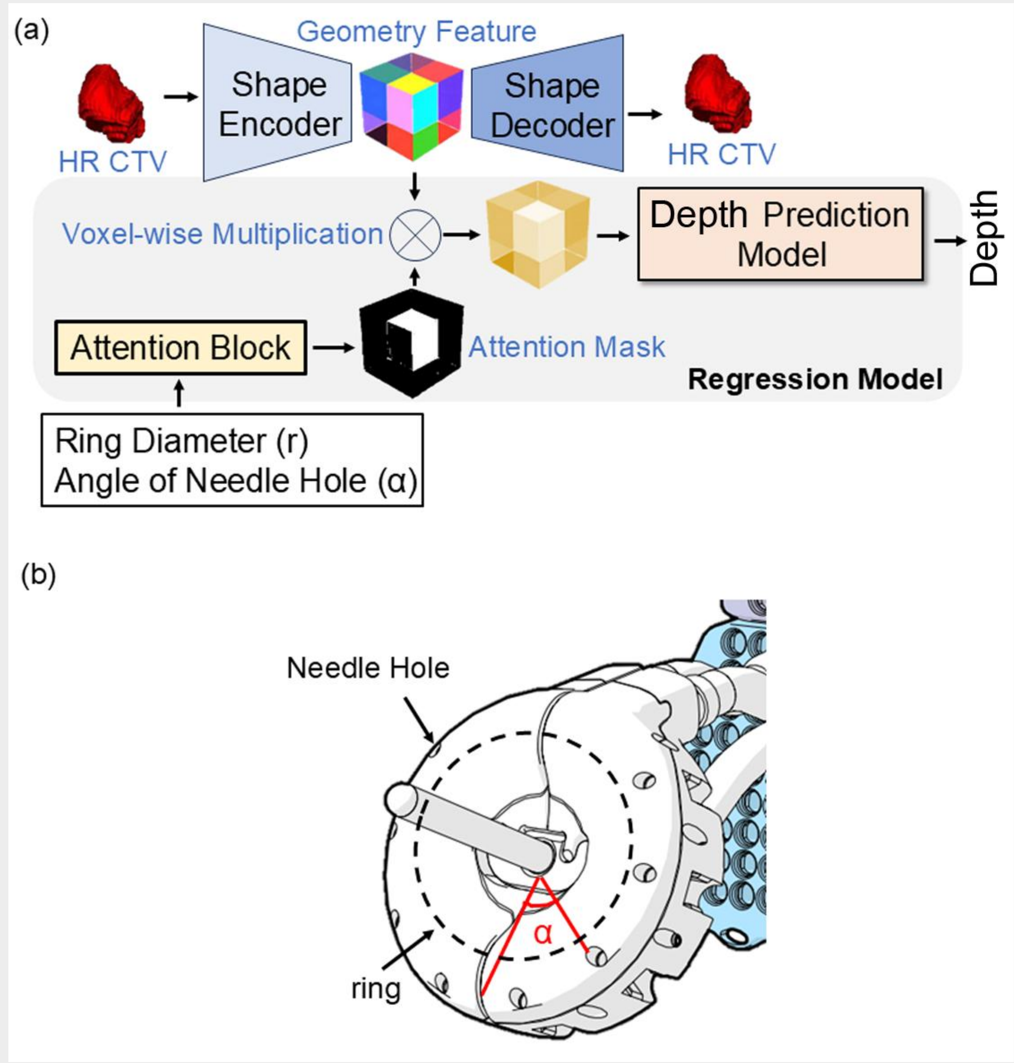

Figure 1. Illustration of (a) model structure and (b) Venezia applicator.

METHODS AND MATERIALS

■ **Model Overview**

As shown in Figure 1(a), the proposed model consists of two components: (a) an encoder–decoder network for extracting geometric features of CTV, and (b) a regression network for estimating the insertion depth of each needle.

The encoder-decoder network adopts a U-Net backbone to encode CTV into geometric features.

To associate the extracted CTV features with an individual needle, an attention mask centered around the target needle position is introduced. The attention mask selectively emphasizes the regions of the feature map that are most relevant to the corresponding needle while suppressing unrelated anatomical information, thereby improving the relevance of the extracted features for depth estimation.

The resulting attention-modulated features are subsequently fed into the regression network to predict depth. Unused needle positions are defined as zero depths.

■ **Training Strategy**

The model was trained in a supervised manner with clinically recorded depths as the reference.

1,700 needle insertions from 220 Venezia cases were split into 1,324 training and 376 testing samples, each comprising a CTV and the corresponding insertion depth.

RESULTS

■ **Evaluation Metric**

The performance of the model was evaluated against the corresponding clinical records on a per-needle basis using the absolute difference (AD) from the CTV geometric depth. The difference in AD between the model predictions and the clinical records (ΔAD) was then calculated as follows:

$$AD_{model} = |d_{model} - CTV\ geometric\ depth|$$

$$AD_{clinical} = |d_{clinical} - CTV\ geometric\ depth|$$

$$\Delta AD = AD_{model} - AD_{clinical}$$

where d_{model} denotes the insertion depth predicted by the model. $d_{clinical}$ represents the insertion depth recorded in the clinical records. The CTV geometric depth is defined as the distance from the needle-ovoid intersection to the first dwell position.

■ **Results**

As shown in Chart 1, in 71.81% of cases, the model's AD from CTV geometric depth was within 3 mm of the clinical-record AD. Among these, 4.26% of all cases had model predictions closer to CTV than clinical records, with needle depths reduced relative to clinical use by 0.52–26.77 mm (median 8.40 mm).

Chart 2 presents two representative cases, comparing the predicted needle insertion depths with the corresponding CTV geometric depths.

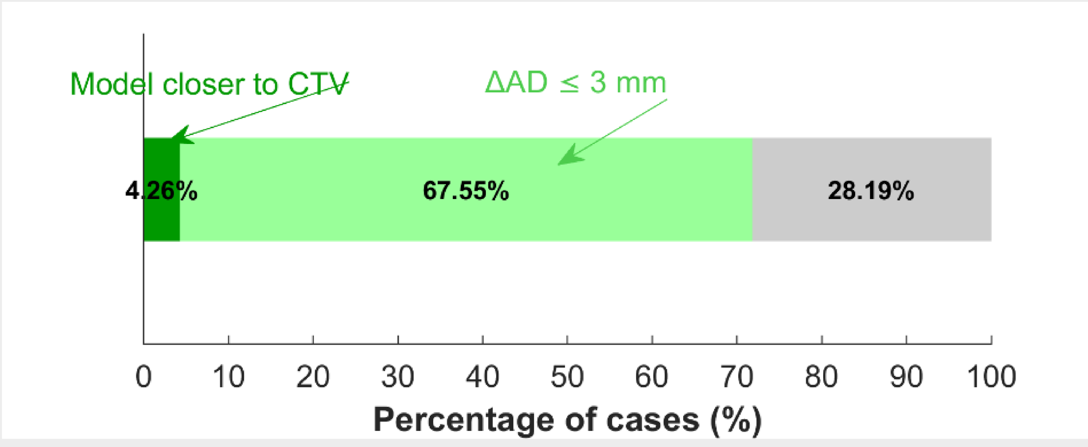

Chart 1. Distribution of cases by model accuracy relative to CTV geometric depth: ΔAD ≤ 3 mm and closer to CTV. ΔAD = model absolute difference from CTV − clinical absolute difference from CTV. The CTV geometric depth is defined as the distance from the needle-ring intersection to the first dwell position.

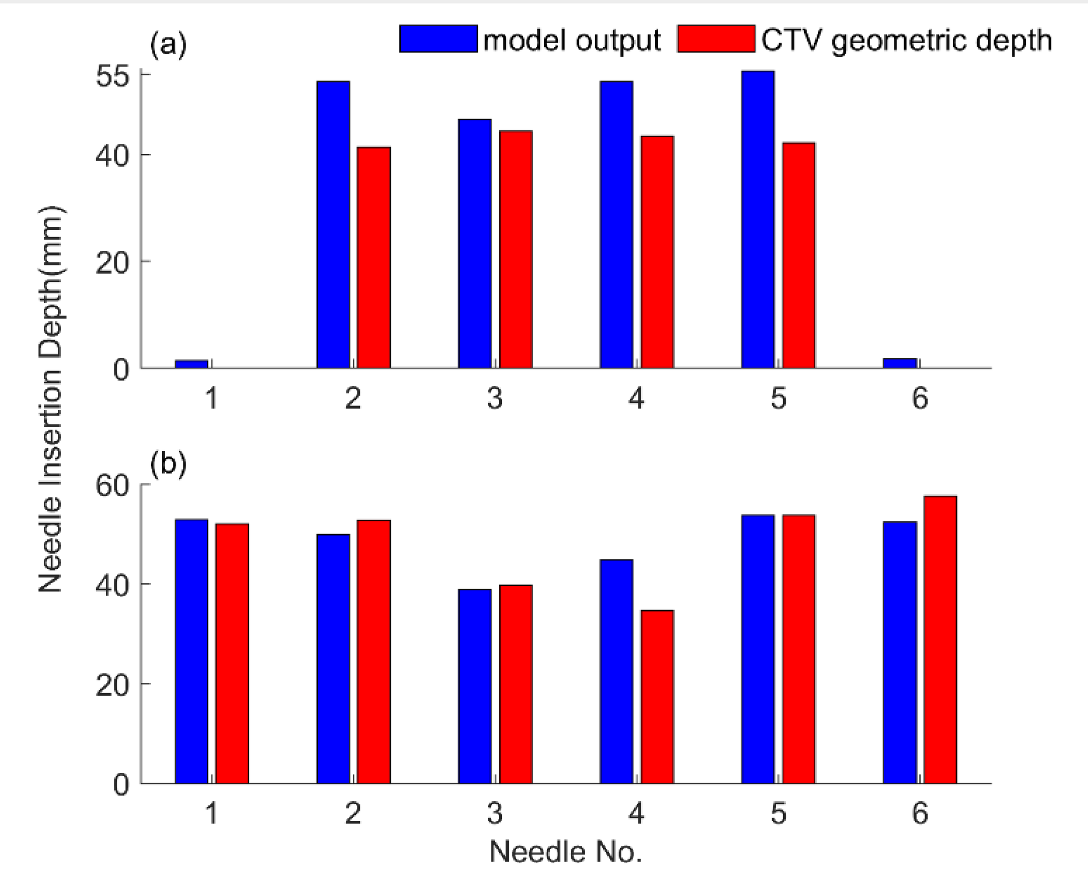

Chart 2. Comparison of predicted needle insertion depths and CTV geometric depths for two representative cases (a–b). The CTV geometric depth is defined as the distance from the needle-ovoid intersection to the first dwell position.

DISCUSSION

■ **Challenge**

(a) Complex anatomical variability

Tumor size, shape, and extent vary substantially across patients, leading to highly heterogeneous anatomy–needle placement relationships and challenging generalizable prediction.

(b) Needle-specific spatial dependencies

Optimal insertion depth is determined by patient anatomy as well as needle-specific geometry within the applicator, requiring joint modeling of anatomical and geometric constraints.

■ **Innovation**

(a) Regression-based prediction of needle insertion depth

Unlike prior classification-based methods that only assess needle usage, the proposed framework directly predicts needle insertion depth through regression, providing clinically relevant guidance for treatment planning by optimizing target coverage and organ-at-risk sparing.

(b) Geometry-aware attention for needle-specific prediction

The proposed model incorporates a needle-specific attention mechanism that guides feature extraction based on needle geometry. By focusing on trajectory-relevant image features, it better captures the spatial relationship between tumor anatomy and applicator configuration, yielding more interpretable predictions consistent with brachytherapy physics.

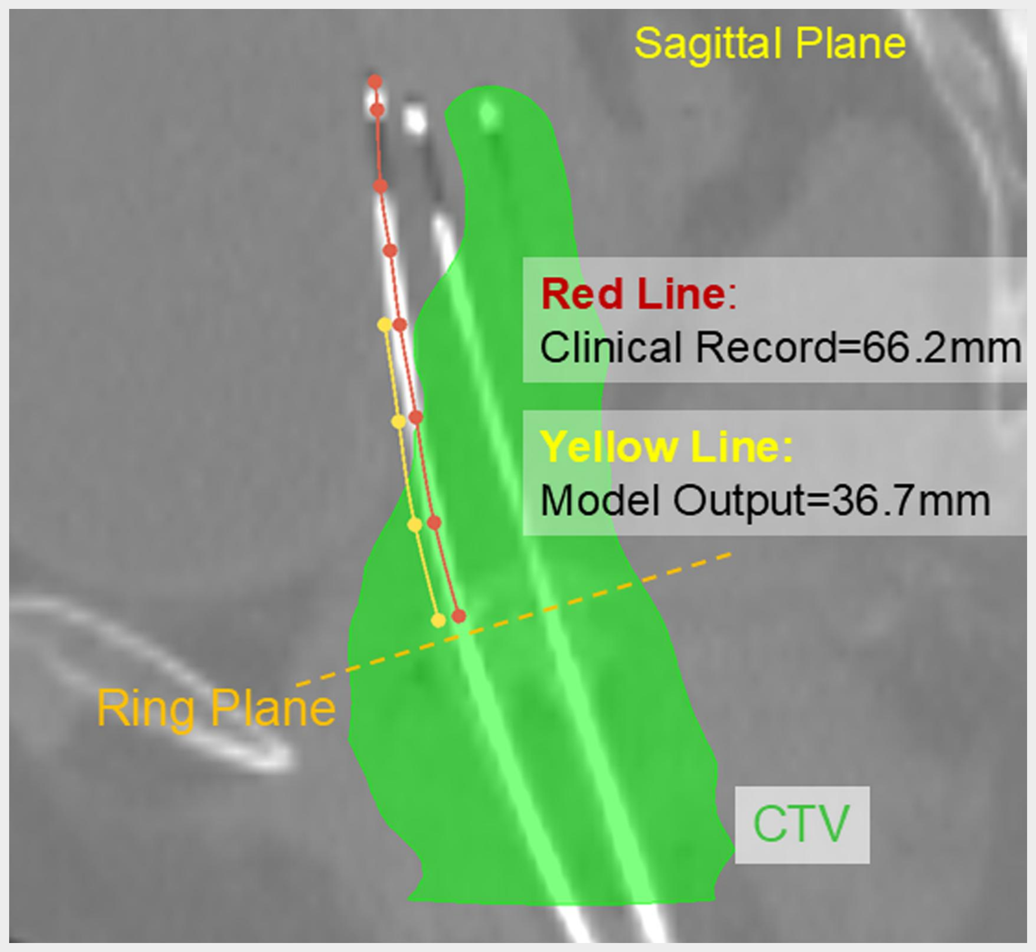

Figure 2. Sagittal-plane visualization of a representative case showing model-predicted (yellow) and clinically recorded (red) needle insertion depths. Green region represents CTV.

CONCLUSIONS

The study demonstrated the feasibility of using deep learning models to predict needle selection and insertion depth. However, prediction accuracy was limited by uncertainties arising from inter-physician variability in the clinically recorded needle depths used for model training. Future work will investigate the use of needle depths derived from dwell positions as ground truth, which more accurately reflect the true needle depths required for treatment.