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Deep Learning Applied to Ultrasonic Catheter Localization for HDR Prostate Brachytherapy: Evaluation of an Initial Model

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INTRODUCTION

Deep learning (DL) (1) represents a new paradigm in computer vision and provides an exciting opportunity for advancements in ultrasound (US)-guided high-dose-rate (HDR) prostate brachytherapy. Specifically, DL has the potential to detect and localize implanted flexible catheters on US images, which unlike other imaging modalities is uniquely challenging due to noise and artifacts (2).

Our team developed an initial DL model based on a proven segmentation architecture. The results presented here focus on the model's performance on detecting and localizing flexible catheters on 2D US images.

The eventual goal is to combine the collective results from a set of 2D images to reconstruct a catheter in 3D suitable for use in a clinical setting, with the potential to improve treatment quality assurance and reduce treatment time.

METHOD

Over 23,000 transverse US images from 178 retrospective prostate brachytherapy patients were available from a single institution. Associated with each image is a catheter binary label image generated from manual catheter localization during treatment planning. Images were consistently cropped to the area surrounding the prostate and resized to 256 x 256 pixels.

The U-NET deep learning convolution networks for biomedical image segmentation (3) was used to train and predict on 2D images independently. The drop-out rate was adjusted to 0.5.

A 5-fold cross-validation was deployed (4). Training required 6 hours (11 epochs) on an Intel Xeon E3-1245 3.7GHz CPU. No GPU was used. Reported evaluation results over the entire dataset are taken over the five testing folds.

A prediction is classified as a true positive if it is within 2 mm of a label, which represents typical user reconstruction variability (5).

REFERENCES

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RESULTS

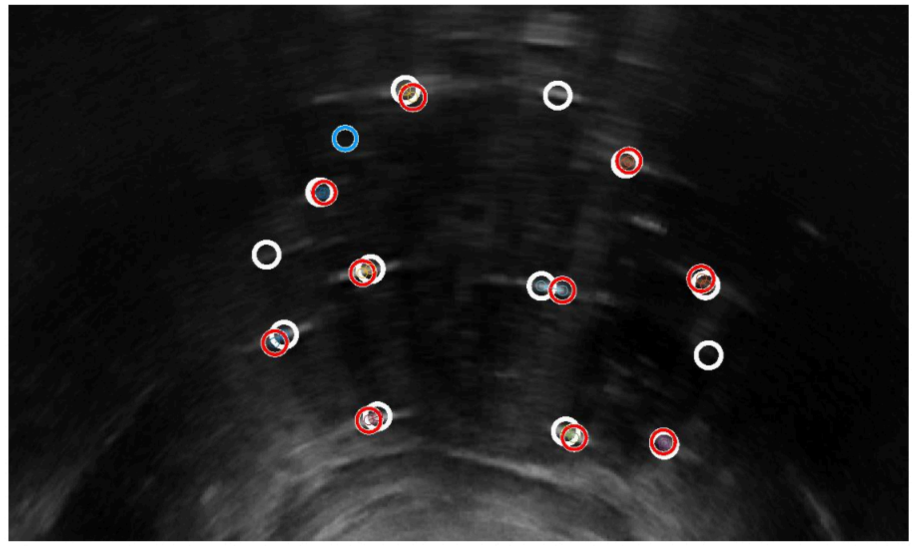

Figure 1: Transverse ultrasound image with user-localized catheter labels (white) and deep learning model predictions (red = high confidence, blue = low confidence).

	True	False
Positive	0.62	2.95
Negative	N/A	0.38

Table 1: Confusion matrix summarizing the binary classification performance of the model, summed across all patients and images. The true positive rate is the number of predictions accurate to within 2 mm of a catheter label, divided by the number of labels. The false negative rate is unity minus the true positive rate. The detection of true negatives is not applicable. The false position fraction is defined as the mean number of false-positives per image (6).

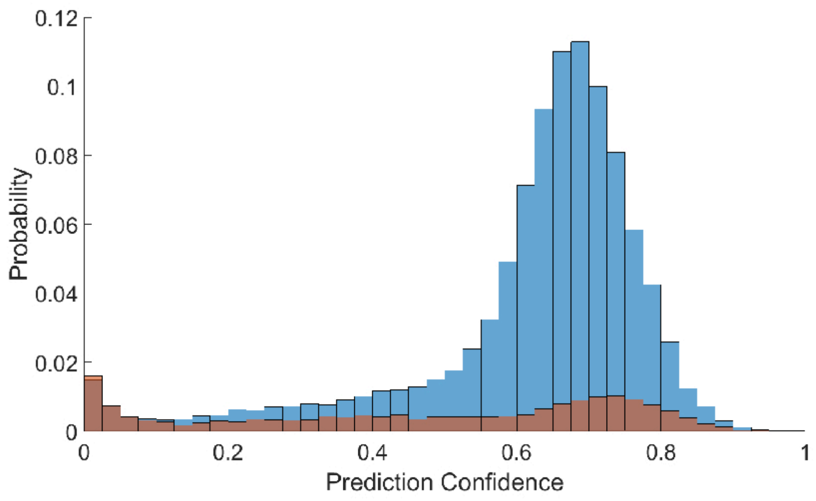

Figure 2: Probability distribution of true positive (blue) and false positive (red) predictions as a function of the prediction confidence.

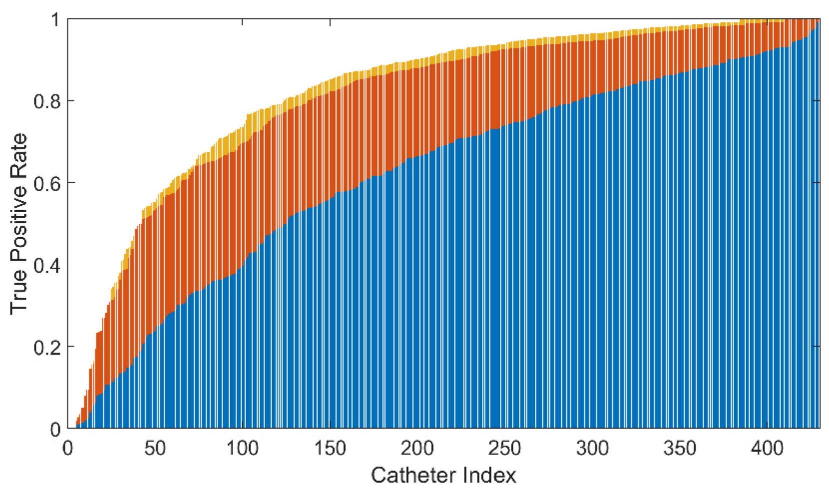

Figure 3: Waterfall plots showing the fraction of true positive predictions across image slices along an entire catheter (blue). Red: only consider slices where prediction is available. Yellow: exclude low confidence predictions. Catheter index is sorted separately for each plot. A random sample of catheters was considered for display purposes.

DISCUSSION

Figure 1 demonstrates the predictions on an example ultrasound image. Performance outcome includes correct catheter prediction (true positive), incorrect prediction (false positive), and undetected catheter (false negative). Small deviations between a correct prediction and the user-localized label are common. This is partially because the predictions are centered on the catheter signal on a single 2D image while the label represents a best-fit over consecutive slices in a 3D volume.

As shown in Table 1, each image has 2.95 false positive predictions on average. These mostly consist of false predictions beyond the prostate base and incorrect predictions due to US artifacts and echoes. We anticipate the majority of false positive predictions will be correctly excluded in a future 3D model, where adjacent slice predictions and a priori information (i.e. catheter insertion depth) are incorporated into the reconstruction.

Figure 2 shows the relationship between true and false positive predictions and its associated prediction confidence. An increased confidence value is associated with higher likelihood that the positive prediction is true, although there is a noticeable number of high confidence false positive predictions.

Figure 3 (blue curve) illustrates how much of each catheter is correctly predicted, in terms of its fractional length. The majority of catheters are not visible along their entire length, which is consistent with our clinical experience. As long as sufficient segments of the catheter are visible, 3D catheter reconstruction should be possible. In which case, if we consider only available predictions (red curve), then it appears the majority of predictions are reliable. Prioritizing high confidence predictions (yellow curve) should improve 3D reconstruction accuracy.

CONCLUSIONS

We demonstrated the feasibility of applying deep learning for ultrasonic catheter localization in HDR prostate brachytherapy. An initial segmentation model predicted implanted catheters with respectable performance, with a majority of predictions within 2 mm spatial accuracy.

The 2D image predictions from the deep learning model will enable the team to develop a 3D catheter reconstruction model suitable for clinical application. These results will guide us on how best to proceed with the 3D reconstruction.

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CONTACT INFORMATION

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