Deep Learning based Automatic Segmentation of the Levator Ani Muscle from 3D Endovaginal Ultrasound Images

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Abstract

The Levator Ani Muscle (LAM) deficit is a common side effect of vaginal childbirth and is linked to pelvic organ prolapse (POP) and other pelvic floor complications. Diagnosis and treatment of these complications require imaging and examining the pelvic floor, which is a time-consuming process subject to operator variability. We proposed using deep learning (DL) methods to automatically segment LAM from 3D endovaginal ultrasound images (EVUS) to improve diagnostic accuracy and efficiency. Over one thousand images extracted from 3D EVUS data consisting of healthy subjects and patients with pelvic floor disorders were utilized for the automated LAM segmentation. U-Net, FD-U-Net, Attention U-Net were implemented with Dice and Intersection over Union (IoU) used for model performance evaluation. The U-Net based models had 0.84-0.86 mean Dice score, which demonstrated efficacy compared to literature in LAM segmentation. Our study demonstrated the feasibility of DL-segmentation using U-Net and its variants for automated LAM segmentation from 3D EVUS images and has potential of being implemented in AI-based diagnostic tools for improved management of pelvic floor disorders, especially in low socioeconomic regions.

Keywords: pelvic floor muscle, ultrasound imaging, deep learning, image segmentation

1. Introduction

The Levator Ani Muscle (LAM) is a funnel-shaped structure responsible for supporting the pelvic floor, along with providing functionality, such as allowing structures to pass through it (Gowda and Bordoni, 2021). LAM avulsion, a common side effect of vaginal births, occurs in up to 35-36% of women after their first birth, causing pelvic organ prolapse (POP) and other pelvic floor disorders (Nygaard et al., 2008). Diagnosis of LAM avulsion and POP involves imaging the pelvic floor, usually through magnetic resonance imaging (MRI) or ultrasound (US) imaging, the latter of which is the more cost-effective option (Woodfield et al., 2010). The interpretation of the ultrasound is a challenging task, where the diagnosis can take weeks. To overcome the issues, we propose the use of deep learning (DL) segmentation methods, to automatically segment the LAM from 3D endovaginal ultrasound data – which is has yet to be performed on such images in literature – to improve diagnostic accuracy and reduce the diagnostic turnover time for patients.

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2. Methods

2.1. Dataset, Preprocessing and Preparation

The 3D UVUS images were obtained in previously conducted work approved by the Institutional Review Ethics Committee (IRB) of the INOVA Health System (Asif et al., 2023). The dataset consists of 1015 3D EVUS images and LAM traces in the axial plane of 512x512 size from both healthy subjects (n=14) and patients with different degrees of pelvic floor deficiency (n=13). Several preprocessing steps were performed on the images to prepare the data for DL-based segmentation as shown in Figure 1. The data was then allocated to 85% training (n=862) and 15% testing (n=153) for use with the DL models.

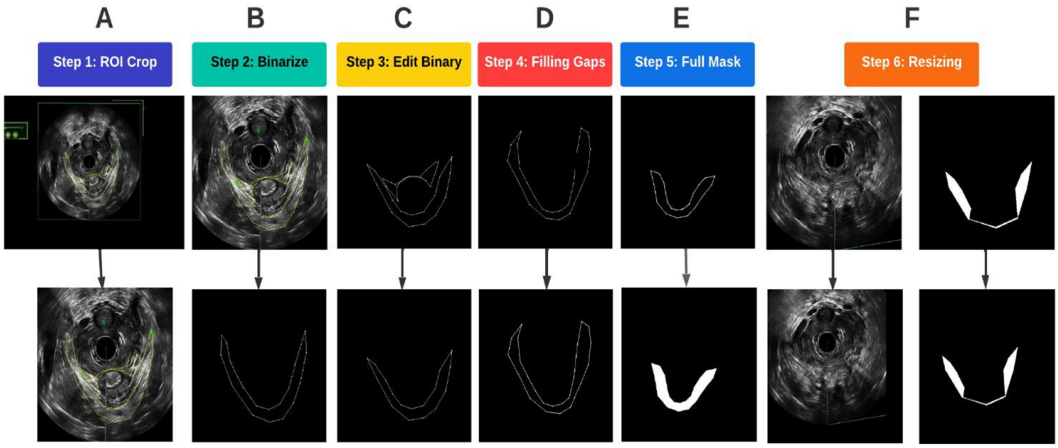

Figure 1: Flowchart of the 3D EVUS image pre-processing steps

2.2. DL Model Configuration

Our paper explores different DL-segmentation models: U-Net, FD-U-Net, and Attention U-Net. The U-Net is a convolutional neural network (CNN) which uses a contracting path to capture context of the data and symmetric expanding path to obtain precise localization (Ronneberger et al., 2015). FD-U-Net is an extension to the U-Net in which it uses dense connectivity into the contracting and expanding paths of network (Guan et al., 2020). Attention U-Net uses attention gates to the encoding path to focus on target features of image (Oktay et al., 2018). All models were implemented with TensorFlow on a Lambda workstation with a NVIDIA RTX A5000 GPU. Each model was trained in about 16min over 50 epochs with a batch size of 16. Predicted masks were subjected to Intersection over Union (IoU) and Dice accuracy metrics.

3. Results

Our proposed study utilized U-Net, FD-U-Net, and Attention U-Net models for segmenting LAM from EVUS images. The visual results (Figure 2) show that all three models were visually similar to the ground truth (Fig. 2B). Our U-Net model (Table 1) achieved Dice

score of 0.86 on the test data, with FD-U-Net and Attention U-Net achieving generally similar results. Furthermore, when compared to other published studies related to LAM segmentation, the U-Net variants that our study implemented, especially the standard U-Net had promising results. These comparative results are important, as this automatic segmentation procedure is one of the few that dealt with LAM segmentation, and one of the only, to our knowledge, performed on EVUS.

Table 1: Comparison of DL-based LAM segmentation

Study	**Imaging Modality**	**Segmentation Region**	**Number of Images**	**Segmentation Method(s)**	**Mean Dice**	**Mean IoU**
Proposed	EVUS	LAM	1015	U-Net FD-U-Net Attention U-Net	0.86 0.84 0.85	0.76 0.74 0.75
Noort, 2021	TPUS	LAM	100	Recurrent U-Net	0.65	-
Feng, 2020	MRI	LAM	528	CNN + MRFP	-0.61	-

(van den Noort et al., 2021) (Feng et al., 2020)

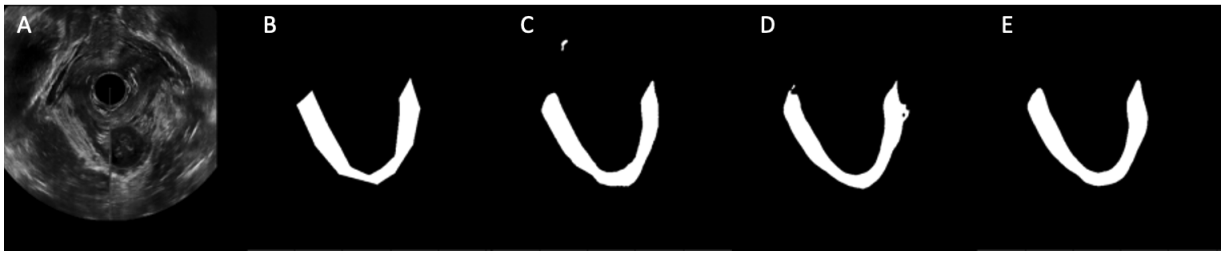

Figure 2: Example LAM segmentation results. (A) Raw EVUS image; (B) Expert traced LAM; (C) U-Net; (D) FD-U-Net; (E) Attention U-Net

4. Conclusion

We investigated the feasibility of using DL-based segmentation of LAM in EVUS images, a relatively unexplored imaging modality in this context. We processed the clinically acquired EVUS data and found that the U-Net based segmentation models outperform the models used in the literature to accurately segment the LAM. This study has highlighted the potential of using U-Net and its variants for the automatic segmentation of pelvic floor structures in EVUS and potentially other modalities. It also has the potential of being implemented in AI-based diagnostic tools for improved management of pelvic floor disorders, especially in low socioeconomic regions, where these conditions may be underdiagnosed or misdiagnosed.

Acknowledgments

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