Advanced Engineering Days

aed.mersin.edu.tr

Prostate lesion segmentation from MR images using deep learning methods

İrem Erkuş*[1], Bülent Bayram [1], Anime Melis Uzar [1], Tuna Çakar [2]

[1]Yildiz Technical University, Department of Geomatics Engineering, Türkiye, iremfm25@gmail.com; bayram@yildiz.edu.tr; auzar@yildiz.edu.tr
[2]MEF University, Big Data Analytics Program, Türkiye, tuna.cakar@tunasc.com

Cite this study: Erkuş, İ., Bayram, B., Uzar, A. M., & Çakar, T. (2023). Prostate lesion segmentation from MR images using deep learning methods. Advanced Engineering Days, 7, 41-43

Keywords
Deep Learning
Prostate MRI
DeepLabV3+
Lesion Detection

Abstract

Prostate cancer is a prevalent form of cancer in men, emphasizing the need for accurate and efficient methods for prostate lesion segmentation from magnetic resonance (MR) images. Manual segmentation of prostate lesions is time-consuming and subjective, highlighting the significance of automated approaches using deep learning methods. This study presents a comprehensive investigation into applying deep learning techniques for prostate lesion segmentation from MR images. The study explores state-of-the-art deep learning models, including U-Net, PAN, DeepLabV3, DeepLabV3+ for segmentation. A large PICAI dataset of prostate MR images, comprising multi-parametric MRI scans and expert annotations, is utilized for evaluating the developed methods. Performance metrics such as accuracy, precision, recall, specificity, accuracy, IOU, AP Score, PR curve, and AUC curve were employed to compare the proposed deep learning methods. In summary, this research contributes to the field of prostate lesion segmentation by investigating the effectiveness of deep learning methods applied to MR images. The DeepLabV3+ model achieves an IOU of 0.79 and an AP of 0.54 using Jaccard Loss.

Introduction

Prostate cancer is one of the most prevalent forms of cancer affecting men worldwide. Prostate cancer incidence increased by 3% annually from 2014 to 2019, resulting in 99,000 additional cases [1]. Magnetic Resonance Imaging (MRI) has emerged as a powerful imaging modality for the non-invasive evaluation of prostate cancer. However, the manual segmentation of prostate lesions from MRI scans is a time-consuming and subjective task, heavily reliant on the expertise of radiologists.

This study aims to present a comprehensive review of deep-learning methods for prostate lesion segmentation from MR images. The proposed study will investigate state-of-the-art deep learning architectures specifically tailored for prostate lesion segmentation. We will explore various models DeepLabV3+, DeepLabV3, and U-Net which have shown promising results in medical image segmentation.

Karagoz et al [2] state that their method achieves top results in the open-validation stage of the PI-CAI 2022 Challenge, with an AUROC (Area Under the Receiver Operating Characteristic curve) of 0.888 and AP (Average Precision) of 0.732. These evaluation metrics indicate the effectiveness of the proposed workflow in accurately detecting clinically significant prostate cancer using bi-parametric MRI.

Material and Method

The PI-CAI dataset [3] contains 1500 prostate bi-parametric MRI scans obtained between 2012-2021 from three medical centers in the Netherlands. The objective of the PI-CAI challenge is to assess the effectiveness of AI algorithms and radiologists in detecting and diagnosing clinically significant prostate cancer based on the provided imaging data.

To download the associated imaging data, visit [4]:

Table 1. Information About PI-CAI Dataset

Number of MRI scanners	5 Siemens Healthineers, 2 Philips Medical Systems Number
Number of patients	1476
Number of cases	1500
Benign or indolent PCa	1075
csPCa (ISUP ≥ 2)	425

Data Preparation

The PI-CAI dataset have 1500 prostate bi-parametric MRI scans data in total. 425 out of 1500 data are malignant. Among the 1075 data, there are indolent (with a tag value of 0) and benign ones. There are 391 indolent. We didn't use it. Those who have a 0 tag are of no use to us in training. 684 of them remained benign.

Table 2. Information About Our Dataset

Number of cases	1109
Number of malignant	425
Number of benign	684

T2, diffusion-weighted imaging (DWI) and apparent diffusion coefficient (ADC) images were used. As part of the preprocessing step for the lesion segmentation/detection models, all images were converted from MHA (.mha) format to numpy(.npy). By converting the images to the appropriate format, they could be seamlessly integrated and processed within the deep learning framework for effective lesion segmentation and detection.

Buslaev et al. [5], which is a library specifically designed for image augmentation. Image augmentation is a technique commonly used in machine learning and computer vision tasks to artificially increase the diversity of a dataset by applying various transformations to the images. These transformations can include rotations, translations, scaling, cropping, flipping, color adjustments, and many others. In this study, lambda transform is used for preprocessing the dataset.

The train image size is 809, test image size is 150, validation image size is 150.

Parameter

Lesion segmentation was carried out using different numbers of epochs, learning rates, and batch sizes. In addition, using loss functions such as BCEWithLogitsLoss, JaccardLoss, DiceLoss, and FocalLoss.

Metrics

The following metrics were calculated in order to compare the predictions of the model: F1 Score, Recall, Specificity, Accuracy, IOU (Intersection over Union), PR (Precision-recall) curve, AUC Curve, AP (Average Precision) Score.

Implementation Details

All experiments were conducted on a PC, which provides an NVIDIA GEOFORCE GTX 1650 GPU with 12GB memory.

Results

Metrics: Epoch: 200, Learning_rate: 0.001, Batch_size: 16 (Exception: Segformer batch size is 8), Image_size: 256, Metric: IoU, Seed: 42, Optimizer: Adam.

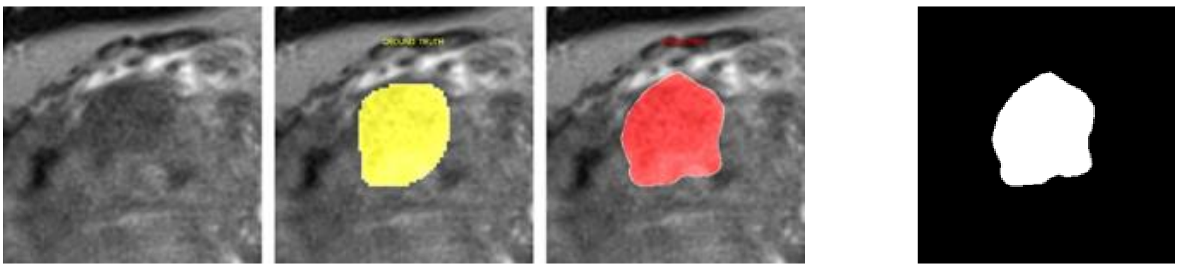

Figure 1. DeepLabV3 with BCEWithLogitLoss, IOU:0.7938

Table 3. The comparison of lesion segmentation results

No	Model	Loss	Best Epoch	Total Time	F1 Score	Precision	Recall	Specificity	Accuracy	IOU
1	DeepLabV3+	jaccard_loss	58	2 hours 138 minutes 13 seconds	0.8707	0.8893	0.8815	0.9817	0.9556	0.7911
2	DeepLabV3	BCEWithLogitLoss	67	4 hours 285 minutes 16 seconds	0.8727	0.8791	0.8942	0.9783	0.9557	0.7938
4	UNET	jaccard_loss	16	2 hours 144 minutes 12 seconds	0.8615	0.8900	0.8665	0.9827	0.9529	0.7807

The DeeplabV3+ model achieves an IOU of 0.79 and an AP of 0.54 using JaccardLoss. The Deeplab V3+ achieved the best score of AP (Average Precision) of 0.54.

Table 4. The comparison of lesion segmentation results (AP Score)

Model	**Loss Function**	**Average Precision (AP) Score**
DeeplabV3+	JaccardLoss	0.5430835551263445
DeeplabV3	BCEWithLogitsLoss	0.5363376783531771
UNET	JaccardLoss	0.531243452000525

Discussion

The study explores state-of-the-art deep learning models and evaluates their performance using a large dataset of prostate MR images. On the PICAI dataset, different three models were used to train. The DeepLabV3 model achieves an IOU of 0.79 and an AP of 0.53 using BCEWithLogitLoss and the prediction time is approximately 4 hours. DeepLabV3+ model achieves an IOU of 0.79 and an AP of 0.54 using JaccardLoss and the prediction time is approximately 2 hours.

Conclusion

The article contributes to the research for prostate lesion segmentation by comparing three different models and concluded that DeeplabV3+ deep learning method can be effective for prostate lesion segmentation from MR images.

References

1. Siegel, R. L., Miller, K. D., Wagle, N. S., & Jemal, A. (2023). Cancer statistics, 2023. CA: a cancer journal for clinicians, 73(1), 17-48.
2. Karagoz, A., Seker, M. E., Yergin, M., Kan, T. A., Kartal, M. S., Karaarslan, E., ... & Oksuz, I. (2023). Prostate Lesion Estimation using Prostate Masks from Biparametric MRI. arXiv preprint arXiv:2301.09673.
3. Saha, A., Bosma, J., Twilt, J., van Ginneken, B., Yakar, D., Elschot, M., ... & de Rooij, M. (2023, April). Artificial Intelligence and Radiologists at Prostate Cancer Detection in MRI—The PI-CAI Challenge. In Medical Imaging with Deep Learning, short paper track.
4. https://zenodo.org/record/6624726#.ZDvEiHZBxD8
5. Buslaev, A., Iglovikov, V. I., Khvedchenya, E., Parinov, A., Druzhinin, M., & Kalinin, A. A. (2020). Albumentations: fast and flexible image augmentations. Information, 11(2), 125.