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Prostate 3d Medical Image Segmentation

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Abstract: Prostate 3D medical image segmentation is a critical task in medical imaging, especially in the diagnosis and treatment planning for prostate cancer. Segmentation involves identifying and delineating the prostate gland and its surrounding structures from medical images. This paper shows segmentation process using MONAI..

Ключевые слова: MONAI, CNN, U-Net, Dice loss, pytorch, prostate 3D segmentation

INTRODUCTION.

Automated prostate 3D medical image segmentation has witnessed significant advancements in recent years, driven by developments in medical imaging technology and machine learning techniques, particularly deep learning. Convolutional Neural Networks (CNNs), in particular, have shown remarkable performance in various medical image segmentation tasks, including prostate segmentation.

This paper provides a comprehensive review of the state-of-the-art techniques, challenges, and future directions in prostate 3D medical image segmentation. We begin by discussing the importance of accurate segmentation in prostate cancer diagnosis, treatment planning, and monitoring. Subsequently, we delve into various segmentation methodologies, including traditional image processing techniques and modern machine learning approaches.

Furthermore, we explore MONAI framework for medical image segmentation process. Additionally, we discuss the importance of benchmark datasets, evaluation metrics, and clinical validation in assessing the performance and clinical utility of segmentation algorithms.

COMPREHENSIVE REVIEW OF THE STATE-OF-THE-ART TECHNIQUES, CHALLENGES, AND FUTURE DIRECTIONS IN PROSTATE 3D MEDICAL IMAGE SEGMENTATION AND IMPORTANCE OF ACCURATE PROSTATE SEGMENTATION.

State-of-the-art techniques for 3D medical image segmentation:

a) Traditional Methods:

- Intensity-Based Segmentation: Thresholding, region growing, and morphological operations are commonly used for prostate segmentation based on intensity differences.

- Atlas-Based Segmentation: Registration of patient images to a pre-segmented atlas to transfer the segmentation labels.

b) Machine Learning Approaches:

- Convolutional Neural Networks (CNNs): CNN architectures like U-Net, V-Net, and 3D variants have shown promising results in prostate segmentation tasks.

- Deep Learning Architectures: Architectures with attention mechanisms, dense connections, or spatial context aggregation modules have been proposed for improved segmentation accuracy.

- Generative Adversarial Networks (GANs): GAN-based models facilitate data augmentation, domain adaptation, and uncertainty estimation for robust segmentation.

Challenges for 3D medical image segmentation:

a) Anatomical Variability:

- The shape and appearance of the prostate gland can vary significantly among individuals, challenging the generalization ability of segmentation models.

b) Image Artifacts and Noise:

- MRI and CT images often contain artifacts and noise that can degrade segmentation accuracy, especially in regions with low contrast.

c) Computational Complexity:

- Processing 3D medical images requires significant computational resources, limiting the real-time applicability of segmentation algorithms.

d) Lack of Standardization:

- The absence of standardized protocols, datasets, and evaluation metrics hinders the comparison and reproducibility of segmentation algorithms.

e) Clinical Translation:

- Segmentation algorithms need to be validated clinically to ensure their reliability and usability in real-world medical settings.

Future Directions for 3D medical image segmentation:

a) Multi-Modal Fusion:

- Integration of information from multiple imaging modalities (e.g., MRI, CT, ultrasound) can enhance segmentation accuracy by capturing complementary features.

b) Uncertainty Estimation:

- Incorporating uncertainty estimation techniques in segmentation models can provide confidence measures and improve the robustness of predictions.

c) Domain Adaptation:

- Techniques for adapting segmentation models to different imaging protocols, scanners, and patient populations can enhance generalization across diverse datasets.

d) Clinical Decision Support Systems (CDSS):

- Integration of segmentation algorithms into CDSS can assist clinicians in treatment planning, disease monitoring, and predicting patient outcomes.

e) Patient-Specific Modeling:

- Personalized segmentation models considering individual patient characteristics, such as age, prostate volume, and disease stage, can tailor treatment strategies for better clinical outcomes.

f) Explainable AI:

- Development of interpretable segmentation models that provide insights into the decision-making process can enhance trust and acceptance among clinicians.

g) Real-Time Segmentation:

- Optimization of segmentation algorithms for real-time processing to enable intraoperative guidance and immediate feedback during interventions.

h) Data Sharing and Collaboration:

- Establishment of large-scale annotated datasets, open-source software frameworks, and collaborative platforms can foster research reproducibility and accelerate algorithm development.

i) Integration with Advanced Imaging Techniques:

- Integration of advanced imaging techniques such as diffusion-weighted imaging (DWI), dynamic contrast-enhanced MRI (DCE-MRI), and spectroscopy can provide additional functional information for more accurate segmentation and characterization of prostate lesions.

Accurate segmentation of the prostate gland plays a pivotal role in various aspects of prostate cancer diagnosis, treatment planning, and monitoring.

Diagnosis:

- Lesion Detection: Accurate segmentation helps in detecting suspicious lesions within the prostate gland. These lesions can be indicative of prostate cancer and require further investigation through biopsy or other diagnostic procedures.

- Quantitative Analysis: Precise segmentation allows for the quantification of various parameters such as prostate volume, tumor volume, and tumor location. This quantitative analysis aids in assessing disease severity, determining the stage of cancer, and guiding treatment decisions.

- Image Fusion: Segmentation facilitates the fusion of different imaging modalities (e.g., MRI, CT, PET) for comprehensive evaluation. Multi-modal fusion provides complementary information about tumor morphology, metabolism, and microenvironment, improving diagnostic accuracy.

Treatment Planning:

- Radiation Therapy: In radiation therapy, accurate delineation of the prostate gland and surrounding organs at risk (OARs) is essential for optimizing treatment plans. Precise segmentation ensures that therapeutic doses are delivered to the tumor while minimizing radiation exposure to healthy tissues.

- Surgical Guidance: For prostate cancer surgery (e.g., radical prostatectomy), precise knowledge of the prostate's location, size, and shape is critical for surgical planning and intraoperative navigation. Accurate segmentation assists surgeons in preserving critical structures and achieving optimal oncological outcomes.

- Targeted Therapies: Segmentation aids in identifying specific regions of interest, such as tumor foci or aggressive cancerous areas, for targeted therapies such as focal therapy or brachytherapy. This personalized approach minimizes treatment-related side effects while maximizing therapeutic efficacy.

Monitoring:

- Disease Progression: Serial segmentation of the prostate over time enables monitoring of disease progression or response to treatment. Changes in tumor volume, shape, or location can provide valuable insights into disease dynamics and guide adjustments in treatment strategies.

- Assessment of Treatment Response: Accurate segmentation allows for objective assessment of treatment response, such as tumor regression or recurrence, based on changes in tumor size and morphology. This information helps clinicians evaluate the effectiveness of therapeutic interventions and make informed decisions regarding further treatment.

- Follow-up Care: Segmentation assists in long-term surveillance of patients post-treatment, facilitating early detection of recurrence or metastasis. Regular monitoring ensures timely intervention and improves overall patient outcomes.

In summary, accurate segmentation of the prostate gland is indispensable for every stage of prostate cancer management, from initial diagnosis to treatment planning and long-term monitoring. It provides crucial information for clinicians to make informed decisions, tailor treatment strategies, and optimize patient care.

TRAINING AUTOMATED 3D PROSTATE SEGMENTATION NEURAL NETWORK USING MONAI.

In this chapter, first we give some information about MONAI and metrics systemMedical open network for AI (MONAI) is an open-source, community-supported framework for Deep learning (DL) in healthcare imaging. MONAI provides a collection of domain-optimized implementations of various DL algorithms and utilities specifically designed for medical imaging tasks. MONAI is used in research and industry, aiding the development of various medical imaging applications, including image segmentation, image classification, image registration, and image generation.[1]

MONAI was first introduced in 2019 by a collaborative effort of engineers from Nvidia, the National Institutes of Health, and the King's College London academic community. The framework was developed to address the specific challenges and requirements of DL applied to medical imaging.

Built on top of PyTorch, a popular DL library, MONAI offers a high-level interface for performing everyday medical imaging tasks, including image preprocessing, augmentation, DL model training, evaluation, and inference for diverse medical imaging applications. MONAI simplifies the development of DL models for medical image analysis by providing a range of pre-built components and modules.[2]

As a loss metrics we used Dice loss, below we give some explanation about it:

Dice loss, also known as the Sørensen-Dice coefficient or Dice similarity coefficient (DSC), is a widely used loss function in medical image segmentation tasks. It measures the similarity between two sets, such as predicted segmentation masks and ground truth masks. The Dice coefficient is defined as:

$$Dice\ loss = 1 - \frac{2 \times |A \cap B|}{|A| + |B|}$$

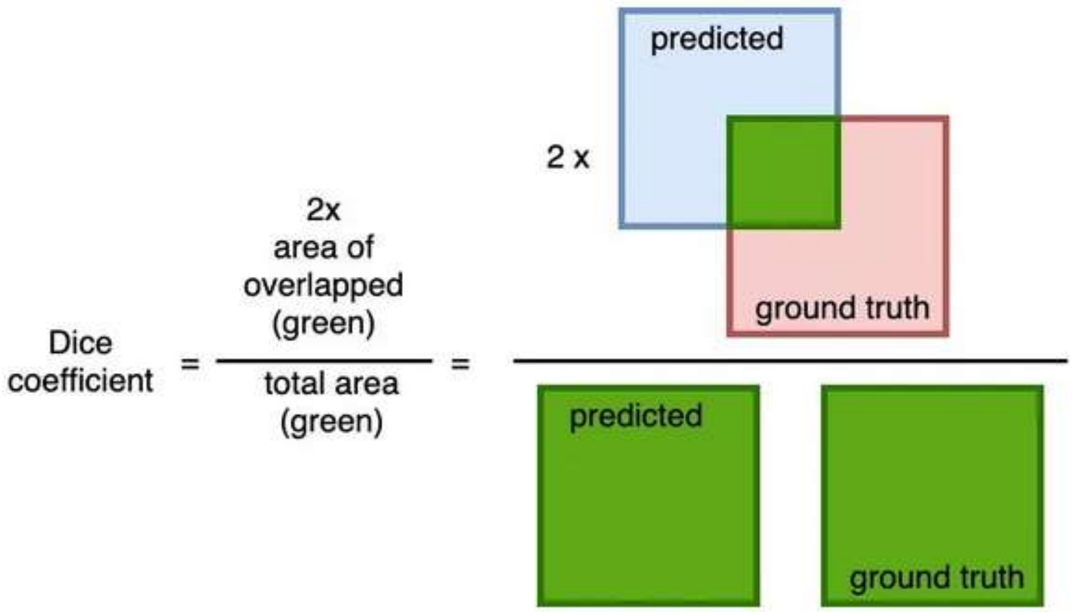
Where:

A is the set of pixels in the predicted segmentation mask.

B is the set of pixels in the ground truth mask.

|A∩B| represents the number of overlapping pixels between the predicted and ground truth masks.

|A| and |B| are the total number of pixels in the predicted and ground truth masks, respectively.



Dice loss is defined accordingly as 1 — Dice_Coefficient.

From the definition, we notice that dice coefficient enlarges the weight of overlap both in the denominator and numerator, based on Sugar water inequality, if the overlap rises, the dice loss will response with greater gradient flow information which encourages more precise segmentation.[3]

In our previous paper [4], we gave information about how to download and prepare data, tools for manual segmentation and gave some fragment of code for first preprocessing. We need further preprocessing for training and testing datasets.

For both training and testing dataset, we should download data, check to ensure the channel dimension is the first dimension, rescale the voxel spacings of both volume and segmentation. For this we use bilinear interpolation for the volume and nearest neighbor interpolation for the segmentation mask. Then, Scale the intensity values of the volume image to the specified range. This normalization helps standardize the input data for the neural network. After that, we have to crop the foreground region of both volume and segmentation mask based on the non-zero elements in the source key ("vol"). This removes empty space around the volume. Furthermore, Resize both volume and segmentation mask to the specified spatial size. Last but not least is convert both volume and segmentation mask to PyTorch tensors for further processing.

To do all of the above steps, MONAI transform function can help us:

```
from monai.transforms import (
    Compose,
    EnsureChannelFirstD,
    LoadImaged,
    Resized,
    ToTensord,
    Spacingd,
    Orientationd,
    ScaleIntensityRanged,
    CropForegroundd,
)
```

As we can see, all preprocessing can we made as showed above. One can add more transforms to work with their data, but for simplicity we used just these.

After that, we take the number of the background and the foreground pixels to return the `weights` for the cross-entropy loss values:

Let val1 and val2 be background and foreground pixels and create numpy array with val1 and val2, as count =np.array([val1, val2]).

1. Calculate sum of values:

$$summ = val1 + val2$$

2. Calculate the weights:

$$weights = \frac{count}{summ}$$

3. Invert the weights:

$$weights = \frac{1}{weights}$$

4. Recalculate the sum of inverted weights:

$$summ = \sum weights$$

5. Normalize the weights:

$$weights = \frac{weights}{summ}$$

After that, we initialized 3D UNet model using MONAI`s Unet class as follows:

```
model = UNet(
    spatial_dims=3,
    in_channels=1,
    out_channels=2,
    channels=(16, 32, 64, 128, 256),
    strides=(2, 2, 2, 2),
    num_res_units=2,
    norm=Norm.BATCH,
).to(device)
```

Where,

- spatial_dims: Specifies the dimensionality of the input data, which is 3 for 3D medical images.
- in_channels: Specifies the number of input channels, typically 1 for grayscale images or 3 for RGB images.
- out_channels: Specifies the number of output channels, which is usually the number of segmentation classes. Here, it's set to 2, indicating binary segmentation.
- channels: Specifies the number of channels in each layer of the encoder and decoder. It defines the model's capacity and complexity.
- strides: Specifies the strides for downsampling in each dimension. It controls the spatial resolution reduction in the encoder path.
- num_res_units: Specifies the number of residual units in each block of the UNet architecture. Residual units help in learning complex features.
- norm: Specifies the normalization type used in the model. Here, Norm.BATCH indicates batch normalization, which helps stabilize and accelerate the training process.
- The .to(device) moves the model to the specified device (e.g., GPU or CPU) for computation.

Then, we chose Adam optimizer (Adaptive Moment Estimation is an algorithm for optimization technique for gradient descent. The method is really efficient when working with large problem involving a lot of data or parameters. It requires less memory and is efficient) as our optimizer. With learning rate and weight decay 0.000001 and used AMSGrad, this is an adaptive learning rate method that modifies the Adam algorithm to prevent the learning rate from decreasing too aggressively.

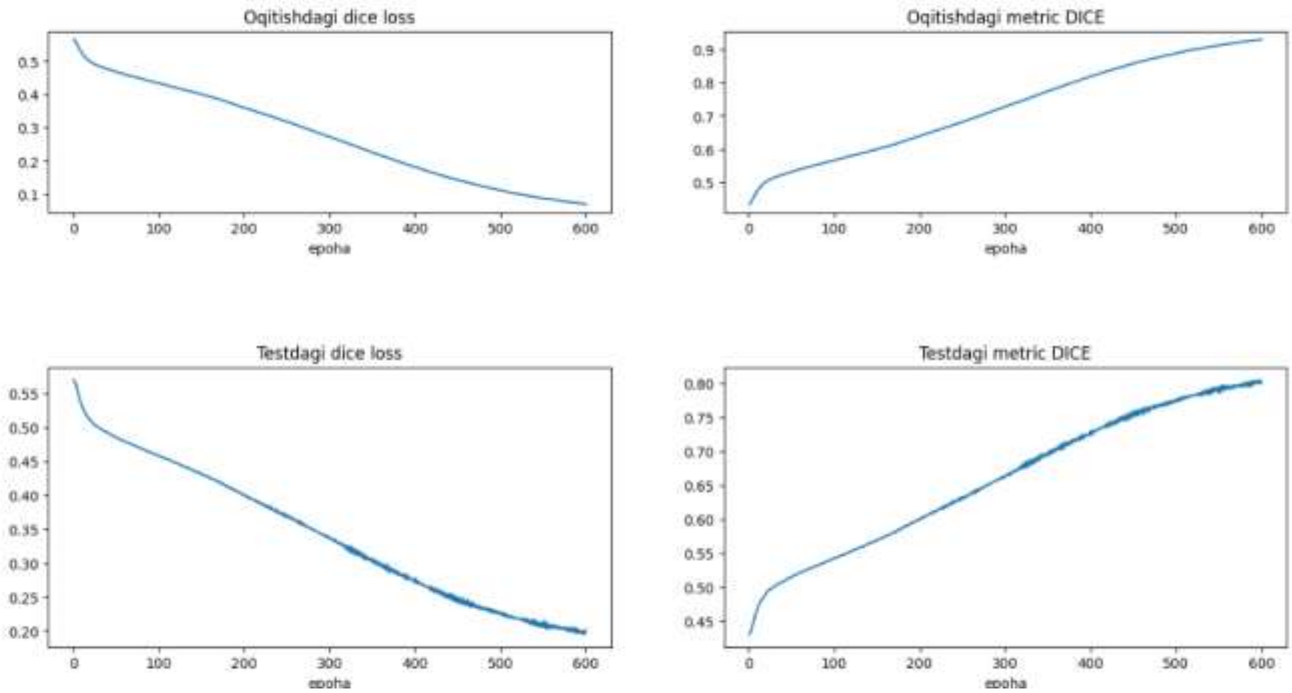
For our case we trained about 600 epochs.

RESULT AND DISCUSSION.

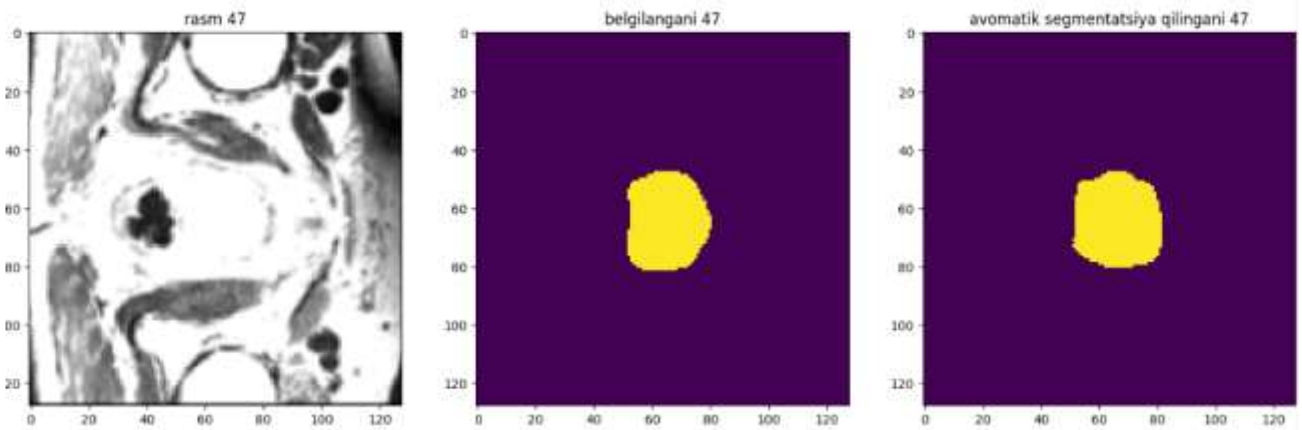
As mentioned in our previous paper [4], labelled 3D prostate image datasets are hard to find among open-source resources. For this reason, we used Decathlon`s dataset and labelled them manually. Overall, 32 patients prostate 3D medical images are labelled and 25 of them used as training dataset and 7 as testing dataset.

```
Epoch_loss: 0.0706
Epoch_metric: 0.9294
test_loss_epoch: 0.2005
test_dice_epoch: 0.7995
current epoch: 600 current mean dice: 0.8078
best mean dice: 0.8053 at epoch: 598
train completed, best_metric: 0.8053 at epoch: 598
```

After training and testing, best mean dice was 0.8053 at epoch 593, and we save this model.



Above photo shows best dice loss for training is about 0.08 and for testing is about 0.2.



Here, we can see results of a random patient`s prostate 3D image`s slice. On the left is slice of 3D prostate medical image, on middle is ground truth, on the right we can see our automated segmentation model`s result.

Because of lack of patient dataset and computational power this result is satisfying. If there are big resources of datasets for prostate 3D image and enough computational power for this, results can be about 95%-99%. Moreover, this is first our work for this difficult task and it is satisfying, because it saves about 99% time for labelling of 3D prostate image.

CONCLUSION

Theories, mathematics and some code implantations of 3D medical image automatic segmentation and data processing shown above. The task from this paper is to show the steps for training neural network for medical image automatic segmentation and using MONAI.

This is the 2nd part of our main project which is creating automatic medical image segmentation and prostate cancer detection neural network, which is mainly focused for medical image segmentation. Furthermore, for next steps we publish prostate cancer detection using neural network.

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