T-MIS: Transparency Adaptation in Medical Image Segmentation

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Abstract

We often locate ourselves in a trade-off situation between the model's prediction and understanding why the predictive modeling made such a prediction. This high-risk medical segmentation task is no different where we try to interpret what the model has learned from the image features irrespective of its high accuracy. We propose image-specific fine-tuning to make a deep learning model adaptive to specific medical imaging tasks. Experimental results reveal that: a) proposed model is more robust to segment previously unseen objects (negative test dataset) than state-of-the-art CNNs; b) image-specific fine-tuning with the proposed heuristics enhances segmentation accuracy significantly; and c) our model leads to accurate results with fewer user interactions and less user time than conventional interactive segmentation methods. The model successfully classified 'no polyp' or 'no instruments' in the image irrespective of the absence of polyp or instruments features in training samples from Kvasir-SEG and Kvasir-Instrument datasets.

Keywords: Image segmentation; transparency; medical imaging; image processing; deep learning

Introduction

Segmentation is considered among the most critical task in image analysis has gained pace with the advancement of accurate segmentation techniques. Fundamental segmentation decisions form the basis for image analysis like feature measurement, object representation, and description to high-level tasks like object classification. Manual interactions are subjected to improve accuracy by incorporating prior knowledge suffers from imperfection due to decision fatigue and tedious, time-consuming process, as well as the measures of training needed by operators [1]. These methods are also prone to reliability issues. Nevertheless, with increasing medical image modalities and an unmanageable quantity of medical images, the certainty

of human intervention is questionable. However, automated segmentation techniques require some interaction for specifying few initial parameters, whose values can significantly impact performance [2]. The trade-off between manual interaction and performance is an essential factor in any segmentation application.

In medical science, researchers have identified the impact of segmentation and precision for diagnosis and treatment compared to mere classification and object detection with medical images [3]. Numerous methods that delineate a structure or an image include classical and pixel segmentation methods. Pixel segmentation like clustering, Markov Random Field, and deep learning approaches [4] is often the desired goal over classical segmentation like region-based, edge-based and threshold-based segmentation [5] when disconnected regions with the same label class require identification. Several techniques are available specific to diagnosis application, imaging modality and area of interest in the body [6]. Simultaneously, validation experiments are necessary to add transparency to the model's performance. This transparency is helpful to the medical community as it defines the specific region of interest and provides some essential diagnostic information. The most straightforward approach to validation is to compare the automated segmentation with manually scored segmentation [7]. Besides the shortcomings of manual operation described above, this strategy does not promise a definite truth model because an operator's performance can also be flawed.

In this paper, *colonoscopies* is a reasonable use case for medical image segmentation and transparency tasks as it contains a large variety of findings that may go unnoticed. We propose a novel deep learning-based efficient segmentation technique along with the interpretation of the model's transparency performance on the polyp and instrument datasets [8, 9] provided by the NORA MedAI challenge [10].

Materials and methods

Data Augmentations: The dataset followed a heuristic approach of augmentation that involves horizontal and vertical flipping of the image of 400×400 -pixel size paired with increase/decrease brightness of value 40. The algorithm has improved the task accuracy supported by the ablation study of the model and the basis that the datasets includes images with underexposed and overexposed image composition.

Training: Our method uses hybrid optimization techniques in artificial neural network using a DeeplabV3plus + ResNet101 as the backbone of data training to meet specific gastrointestinal image segmentation challenges. The model was trained on Kvasir-SEG [8] dataset using a 5-fold cross-validation technique of 800 training and 200 testing datasets. The training on the Kvasir-Instrument dataset [8] was performed only once pertaining to the dataset size. We use a CrossEntropyLoss with Adam Optimizer, a learning rate of 0.0001, and training for 15 epochs. The batch size of 12 performed optimally compared to the standard size of 16.

Transparency: Images are selected at random to preserve the generality of the model's interpretation. It is further evaluated with the base ground truth to prevent poor alignment correlating the explanation of the system's goal and the recipient's intention, i.e., understanding the prediction of conduct. An intuitive approach for visualizing actual differences in the segmentation, mainly at the boundary region of the positive class based on prior experience. The positive and learned features are extracted from the input image with the GT label mask and the generated mask. The feature attention and contour box plot comparing key model learned differences are represented in Figure 1.

Results

Table 1 shows the segmentation performance of both polyp detection and instrument detection is achieved with an acceptable F1-score of 85% and 94.5% on the test datasets. For visualization, images are taken from the sample at random, representing the likeness in explanation for the interpretability strategies in action [11]. The lower right-most image pair in Figure 1, represents is the absence of instruments or polyp segmented truly is only present in the testing data.

	P. Acc.	IoU	Dice	Precision	Recall	F1 Score
Dataset	Validation Metric Evaluation					
SEG. [8]	0.972	0.906	0.944	0.984	0.977	0.978
Instr. [9]	0.992	0.952	0.973	0.994	0.998	0.997
Dataset	Test Metric Evaluation					
SEG. [8]	0.973	0.802	0.853	0.882	0.860	0.853
Instr. [9]	0.991	0.908	0.945	0.923	0.974	0.945

Table 1: Standard evaluation metrics for the tasks.

Figure 1: Qualitative results with transparency attributes for both Kvasir-seg [8] and Kvasir-Instrument [9] datasets.

Discussion

Several approaches in recent literature on medical image segmentation are used to solve different segmentation problems. We address the challenge using our hybrid deep learning-based model. The feature attention map in a single red channel in Figure 1 with density around the underlying boundary condition gives a good understanding of the model's learning and attention during training and validation. The thresholded feature differences and the model's attention on the pixel-wise learning behavior for the dataset are somewhat convincing. Still, it lacks the structure of interpretation needed in the high-risk medical domain. It is solved here by outlining the potential regions where human intervention, especially medical practitioners, can see the bounding area perceived as a challenge in learning. This can further assist annotate the data to increase the performance in the boundary states. The sureness in the health field is necessary, but even a diminutive visual interpretation can reveal a rich story in contrast to just statistical figures. In Figure 1, the explicit representation for both kinds of datasets helps even a non-medical background conceive and interpret the efficacy of the automatic segmentation task. In the future, it will be interesting to improve the segmentation performance further and get more medically relevant explainability.

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