Attention U-Net ensemble for interpretable polyp and instrument segmentation

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Abstract

The difficulty associated with screening and treating colorectal polyps alongside other gastrointestinal pathology presents an opportunity to incorporate computer-aided systems. This paper develops a deep learning pipeline that accurately segments colorectal polyps and various instruments used during endoscopic procedures. To improve transparency, we leverage the Attention U-Net architecture, enabling visualisation of the attention coefficients to identify salient regions. Moreover, we improve performance by incorporating transfer learning using a pre-trained encoder, together with test-time augmentation, softmax averaging, softmax thresholding and connected component labelling to further refine predictions.

Keywords: artificial intelligence; machine learning; segmentation; transparency; medicine

Introduction

The Norwegian Artificial Intelligence Research Consortium (NORA) MedAI challenge aims to encourage the development of automatic medical image segmentation systems that are both accurate and explainable [1]. The challenge involves developing a pipeline to perform colorectal polyp and endoscopic instrument segmentation, favouring transparent and explainable solutions. To achieve both aims, we develop a deep learning pipeline that leverages the Attention U-Net for transparency, together with several post-processing stages to refine predictions: test-time augmentation, softmax averaging, softmax thresholding and connected component labelling.

Methods

Attention U-Net

Currently, the most widely used convolutional neural network (CNN) for medical image segmentation is U-Net [2]. The Attention U-Net incorporates Attention Gates (AGs)

into U-Net, which uses a gating signal that aggregates multiscale spatial information to highlight salient features present in skip connections [3]. Importantly, attention coefficients provide interpretable intermediate outputs at each depth, and it has been observed that the AGs learn during training to localise target regions. We leverage the interpretable nature of the Attention U-Net, with the performance benefits of transfer learning, combining a ResNet152 encoder pre-trained on ImageNet with an Attention U-Net decoder network [4]. The network architecture is shown in Figure 1.

Prediction pipeline

To further improve accuracy, we perform a series of post-processing steps on the network predictions. The full prediction pipeline is shown in Figure 2.

Firstly, we perform test-time augmentation using a series of 90° rotations and reflections to generate 8 variants for each input image, and average the resulting predictions [5]. Next, we incorporate ensemble learning by averaging the softmax outputs generated by each network [6]. To control the recall-precision bias, the ensembled predictions for the segmentation target are compared to a threshold, assigning the segmentation target class to a pixel if above the threshold.

Finally, after resizing the segmentation labels to the original resolution, we use connected component labelling to identify and remove any regions assigned to the segmentation target occupying < 1% of the image, reducing the false positive predictions and generating the final prediction.

Dataset descriptions and evaluation metrics

Two training datasets were provided for this challenge: the Kvasir-SEG dataset for polyp segmentation and the Kvasir-Instrument dataset for endoscopic instrument segmentation [7, 8]. For evaluation, the Dice Similarity

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