GAN-enhanced Echocardiogram Segmentation

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1 Background

Two-dimensional echocardiography (echo) is a common modality for assessing cardiac structure and function. The process of evaluating an echocardiogram typically involves the measurement of multiple clinical indices, which quantify various aspects of the hearts structure and function.

These clinical indices typically rely on manual image processing tasks performed by the reading clinician. An example of one the most important and general measurements is left ventricular ejection fraction (LVEF). The measurement of LVEF requires the manual segmentation of the left ventricle at both end-systole (ES) and end-diastole (ED). Semi-automated solutions for this do already exist, but have limited performance in the clinical workflow.

Recent work has shown that an automated pipeline using convolutional neural networks (CNNs) are able to extract standard clinical indices to near human level accuracy. Almost all the prior work in the space is reliant on encoder-decoder architecture CNNs to automate the segmentation of cardiac structures from echocardiography images. Subsequently the entire analysis pipeline is sensitive to the performance of the underlying encoder-decoder neural network.

Encoder-decoder neural networks for semantic segmentation maps an input image to a segmentation mask, labelling each pixel within the image to one of any number of pre-defined segmentation classes. The encoder half of the neural network maps the high-dimension input image, to a lower-dimension latent representation of the image, similar to a convolutional neural network being used for classification. Rather than using fully-connected layers to then arrive at an end classification, the decoder half of the neural network maps the latent representation of the image, to a segmentation map labelling each pixel to a segmentation class.

Since their introduction in 2014 by Goodfellow et al., Generative Adversarial Networks (GANs) have made significant advances in a wide variety of deep learning problem domains. GANs are made up of two seperate neural networks - the generator, and the discriminator. The generator takes a random variable "seed" and generates a fake sample. The disciminator classifies the input sample (coming from either the generator, or the ground truth dataset) into either "real" or "fake."

During training, the weights of both the generator and the discriminator are updated simultaneously until the generator is generating samples that the discriminator can no longer distinguish from real and fake. In this way, the generator of a GAN learns to model a probability distribution - a more obvious example coming from the field of image generation. If one imagines there is a probability distribution over the set of all labrador images, then the discriminator would be learning to discriminate between the real labrador images from the training dataset, and the fake ones being synthesised by the generator. In early iterations the synthesised images from the generator would have little resemblance to an image of a labrador, but in later epochs the generator would produce highly realistc images of a labrador.

A subfield of GANs known as Conditional Generative Adversarial Networks (C-GANs) have more direct utility in the field of image segmentations. C-GANs are largely similar to a base GAN model, except the input of the generator is a specific condition or parameter rather than a random variable seed input.

In this body of work, we first establish a baseline for the segmentation of echo frames using the well known encoder-decoder neural network U-Net. We also validate previous work that a C-GAN can be used to generate photorealistic ultrasound images from a groud truth segmentation map. Finally, we then compare the effect on segmentation accuracy by using either image-processing data augmentation or C-GAN synthesised images as a form of data augmentation, on the original encoder-decoder segmentation neural network.

2 Literature Review

3 Methods

4 Results and Discussion

5 Conclusion

6 Ethics