MOOD Abstract - Kaspressknedl

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Abstract

Since the goal of this challenge is to create an algorithm that processes a single sample and returns probabilities for anomalies on sample and pixel level, first attention should be paid to the training data. As there are no out-of-distribution examples in the two provided datasets, in a first step we generate a wide range of synthetic anomalies for the training process. To this end, we randomly create binary masks of different shapes in each training epoch, including cuboids, ellipsoids, and even more complex non-convex objects of different sizes and random positions. Using these masks we then change the input data by applying different kinds of perturbations in the corresponding areas. This includes changing the pixels to a constant random value, rescaling intensities by different factors, adding Gaussian noise, as well as applying a sobel filter. Neural networks are then trained on these corrupted images using the binary masks as ground truth. In order to be able to also make reasonable predictions at sample level, we leave about 20% of the training images unprocessed and pass them with corresponding zero masks.

To circumvent the problem of high dimensional input data, we present a supervised global-local approach. In the global part, the volume as well as the created masks are downsampled to $64 \times 64 \times 64$ pixels. On these low-resolution volumes, we train a state-of-the-art 3D U-Net to roughly estimate the positions of the synthetically generated anomalies. Based on the global prediction of the anomalies we train a local two-channel 3D U-Net on $64 \times 64 \times 64$ patches of the original resolution volume with the upsampled global network prediction as additional input. To combine these two networks for the final results, we divide the volume into overlapping patches and use the local network to locate anomalies even more precisely. However, this is only done in areas where the global network has exceeded a threshold of predicted out-of-distribution pixels. To

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further stabilize the results we use an ensemble of two local networks to predict on the high resolution patches.

To conclude, by combining versatile data synthetics with a global-local segmentation approach we present an effective, computationally tractable approach for identifying naturally occurring anomalies in MR and CT scans.

Checklist

- **Team Name**: Kaspressknedl
- **Team Members**: 4
- **Synapse.org username**: Kaspressknedl@synapse.org
- **I want to officially take part in the Challenge and be eligible for prizes**: Yes
- **Code Repository**: `https://github.com/anger-man/mood-challenge`
- **I want to appear**
  - **On the MICCAI presentation**: Yes
  - **On the leaderboard**: Yes if in Top 10
  - **On the challenge paper**: Yes if in Top 10
- **I want to participate 100% anonymously**: No
- **I would be willing to make a presentation for MICCAI**: Yes
- **Method Name**: Global-Local Segmentation
- **Built on which methods/ prior work**: U-Net