Deep Learning Final Project Assignment

Theme: <u>Bi-Directional ConvLSTM U-Net with Densely Connected Convolutions</u>

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Project Proposal

Problem Statement

In recent years, deep learning-based networks have achieved state-of-the-art performance in medical image segmentation. Among the existing networks, U-Net has been successfully applied on medical image segmentation. In this paper, we propose an extension of U-Net, Bi-directional ConvLSTM U-Net with Densely connected convolutions (BCDU-Net), for medical image segmentation, in which we take full advantages of U-Net, bi-directional ConvLSTM (BConvLSTM) and the mechanism of dense convolutions. Instead of a simple concatenation in the skip connection of U-Net, we employ BConvLSTM to combine the feature maps extracted from the corresponding encoding path and the previous decoding up-convolutional layer in a non-linear way. To strengthen feature propagation and encourage feature reuse, we use densely connected convolutional in the last convolutional layer of the encoding path. Finally, we can accelerate the convergence speed of the proposed network by employing batch normalization (BN). The proposed model is evaluated on three datasets of: retinal blood vessel segmentation, skin lesion segmentation, and lung nodule segmentation, achieving state-of-the-art performance.

Medical images play a key role in medical treatment and diagnosis. The goal of Computer-Aided Diagnosis (CAD) systems is providing doctors with precise interpretation of medical images to have better treatment of a large number of people. Moreover, automatic processing of medical images results in reducing the time, cost, and error of human based processing. One of the main research areas in this field is medical image segmentation, being a critical step in numerous medical imaging studies. Like other fields of research in computer vision, deep learning networks achieve outstanding results and use to outperform non-deep stateof-the-art methods in medical imaging. Deep neural networks are mostly utilized in classification tasks, where the output of the network is a single label or probability values associated with labels to a given input image. These networks work fine thanks to some structural features such as: activation function, different efficient optimization algorithms, and dropout as a regularizer for the network.

Dataset Selection

DRIVE is a dataset for blood vessel segmentation from retina images. It includes 40 color retina images, from which 20 samples are used for training and the remaining 20 samples for testing. The original size of images is 565 × 584 pixels. It is clear that a dataset with this number of samples is not sufficient for training a deep neural network. Therefore, we use the same strategy as for training our network. The input images are first randomly divided into a number of patches. In total, around 190, 000 patches are produced from 20 training images, from which 171, 000 patches are used for training, and the remaining 19, 000 patches are used for validation. The size of batches utilized as the input data to the network is 64 × 64. Some precise and promising segmentation results of the experimental output of the proposed network are shown. The first column is the original color image, the second one is the ground truth mask and the third column is the output of the proposed BCDU-Net. Table 1 lists the quantitative results obtained by different methods and the proposed network on DRIVE dataset. We evaluate the network with d = 1 and d = 3 as the number of dense blocks in the network. With d = 1 we have one convolutional block without any dense connection in that layer, i.e., like the last encoding layer of the standard U-Net. With d = 3 We have three convolutional blocks and two dense connections in that layer. It is shown that the BCDU-Net (with both d = 1 and d = 3) outperforms w.r.t. the state-of-the-art alternatives for most of the evaluation metrics.

ISIC 2018 Dataset

The ISIC dataset was published by the International Skin Imaging Collaboration (ISIC) as a large-scale dataset of dermoscopy images. This dataset is taken from a challenge on lesion segmentation, dermoscopic feature detection, and disease classification. It includes 2594 images

Convolutional Neural Network (CNN)

CNN for automatic segmentation of brain MRI images. Firstly, we divided the input images into some patches and then utilized these patches for training CNN. To handle an arbitrary number of modalities as the input data.
CNN for brain lesion segmentation. To process MRI data, the network consists of four channels: non-enhanced and contrast-enhanced T1w, T2w and FLAIR contrasts.

Fully Convolutional Network (FCN)

One of the main problems of the CNN models for segmentation tasks is that the spatial information of the image is lost when the convolutional features are fed into the fc layers. To overcome this problem the fully convolutional network (FCN) was proposed. This network is trained end-to-end and pixels-to-pixels for semantic segmentation.

Results
For evaluating the performance of the proposed method, Two challenging tasks in medical image segmentation have been considered. In bellow, results of the proposed approach illustrated.