DENSEUNET-K: A SIMPLIFIED DENSELY CONNECTED FULLY CONVOLUTIONAL NETWORK FOR IMAGE-TO-IMAGE TRANSLATION

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ABSTRACT

Fully Convolutional Neural Networks have been highly successful in image-to-image translation tasks. Dense connectivity between the convolutional feature maps have shown to further improve the network performance. Here we propose a simplified densely connected network architecture with a fixed number (K) of convolutional feature maps throughout the network, dubbed DenseUNet-K. Hence, the network capacity is a function of the number of feature maps — K, and the network depth. Proposed architecture has fewer number of trainable parameters, while being competitive with other existing state-of-the art models. PyTorch implementation of the model is publicly available at https://github.com/ShusilDangi/DenseUNet-K.

Keywords Convolutional Neural Network · Dense Connectivity · Image-to-Image Translation · Image Segmentation · Image Enhancement

1 Description

Convolutional Neural Networks (CNNs) [1] are parameter-efficient neural network architectures able to learn spatially invariant hierarchical image features important for image classification or regression in an end-to-end manner. A Fully Convolutional Network (FCN) [2] is a type of CNN that can produce an output image with same spatial resolution as the input image. FCNs have been extensively used for image segmentation, image enhancement, image super-resolution, and other various image-to-image translation tasks.

The U-Net architecture [3] proposed skip connections from the encoding to the decoding part of the FCN network at various resolutions to improve the flow of information and retain high-frequency high-resolution information important for image-to-image translation tasks. The DenseNet architecture [4] introduced dense connections of convolutional feature maps from all the previous layers to the current layer, allowing the features to be reused and further improve the information flow through the network, ultimately resulting in improved network performance. However, DenseNet was primarily designed for image classification tasks; as such, the number of convolutional feature maps in the DenseNet architecture increased by a growth-factor (K) along the forward direction, resulting in high number of network parameters.

Here, we propose an image-to-image translation network inspired by both the U-Net and DenseNet architectures. Our proposed network has densely connected feature maps with skip connections from the encoding to the decoding layers at multiple resolutions. We further simplify the dense connectivity by introducing 1×1 convolutions to homogenize the network, such that each network layer consists of a fixed number of K feature maps (we label the network as

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DenseUNet-K). Hence, we reduce the number of network parameters by preventing the network from growing, as in the original DenseNet architecture. Finally, the capacity of our network architecture can be changed by changing the number of feature maps, K, and/or the network depth.

Several preliminary studies using our proposed DenseUNet-K network have shown competitive segmentation performance for highly variable and otherwise challenging to segment 4D MR images of the heart, using a network architecture featuring a significantly lower number of network parameters. More details of the model can be found in the PyTorch implementation we made available open-sourced at `https://github.com/ShusilDangi/DenseUNet-K`.

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