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A Review On Image Segmentation Using Neural Architecture Search

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Abstract: Neural Architecture Search (NAS) is one of the most significant tool for automatically constructing deep neural networks. The generated neural networks are mostly applied for image segmentation ,image classification and natural language processing. However, there are increasing need for image segmentation in different areas, such as medical image processing, satellite image object location, and autopilot technology

***Index Terms* - Neural architecture search, Image segmentation, Deep neural network.**

I. Introduction

Neural Architecture Search (NAS) leads to search for the best neural network architecture by learning the dataset. Frequently, it has been successfully applied for image classification and language modeling.NAS consists of two sections : a controller and a validation neural network .Controller is used for generating architecture parameters of the neural network and a validation neural network for validating the given architecture parameters by constructing, training, and testing the network. The optimization of controller and validation network is based on reinforcement learning [1][2] .The accuracy of the trained network will be fed back to the controller as a reward and guide the controller to optimize frequently. This process will continue for fixed epochs or stop while a specific parameter turn to a particular value. Categorization of NAS depends on three dimensions: search space, search strategy, and performance estimation strategy [3]. It is illustrated in Figure 1.

Fig 1. Illustration of NAS

1)Search Space-The search space defines which architectures can be represented in principle. Incorporating prior knowledge about typical properties of architectures well-suited for a task can cut down the size of the search space and shorten the search. On the other hand, this also introduces a human bias, which may prevent finding novel architectural building blocks that go beyond the current human knowledge

2)Search Strategy -The search strategy details how to look at the search space (which is often exponentially large or even unbounded). It encompasses the classical exploration-exploitation trade-off since, on the one hand, it is desirable to find well-performing architectures rapidly, while on the other hand, premature convergence to a region of suboptimal architectures should be avoided.

3)Performance Estimation Strategy-The purpose of NAS is typically to find architectures that attain high predictive performance on invisible data. Performance Estimation refers to the process of estimating this performance: the simplest choice is to perform a standard training and validation of the architecture on data, but this is unfortunately computationally very expensive and restricts the number of architectures that can be look at. So the recent research therefore focuses on developing methods that decrease the cost of these performance estimations.

II. RELATED WORKS

Neural architecture search (NAS) has significant progress in improving the accuracy of image classification. Recently, some works attempt to extend NAS to image segmentation which shows preliminary feasibility. However, all of them focus on searching architecture for semantic segmentation in natural scenes.

2.1 V-NAS : Neural Architecture Search for Volumetric Medical Image Segmentation

One of the main methodology used for volumetric medical image segmentation is 2D and 3D fully convolutional neural network. However, 2D convolutions cannot fully control the rich spatial information along the third axis, while 3D convolutions suffer from the demanding computation and high GPU memory consumption.[4]It propose a method to automatically search the network architecture tailoring to volumetric medical image segmentation problem. Concretely, it formulate the structure learning as differentiable neural architecture search[5], and the network itself choose between 2D, 3D or Pseudo-3D (P3D) convolutions at each layer. It evaluate method on 3 public datasets, i.e., the NIH Pancreas dataset, the Lung and Pancreas dataset from the Medical Segmentation Decathlon (MSD) Challenge .V-NAS, consistently outperforms other state-of-the-arts on the segmentation tasks of both normal organ (NIH Pancreas) and abnormal organs (MSD Lung tumors and MSD Pancreas tumors), which shows the power of chosen architecture. In addition, the searched architecture on one dataset can be well generalized to other datasets, which demonstrates the robustness and practical use of V-NAS method. It define a cell to be a fully convolutional module, typically composed of several convolutional (Conv+BN+ReLU) layers, which is then repeated multiple times to construct the entire neural network. V-NAS segmentation network follows the encoder-decoder structure while the architecture for each cell, i.e., 2D, 3D, or P3D, is learned in a differentiable way. The search process is computationally efficient and effective. By searching in the relaxed continuous space, this method outperforms state-of-the-arts on both normal and abnormal organ segmentation tasks. Moreover, the searched architecture on one dataset can be well generalized to another one.

2.2 AutoSegNet : Automated Neural Network for Image Segmentation

Efficient Neural Architecture Search (ENAS) [6], targeting on image classification, generates the best neural network architecture with a fixed structure. The fixed structure is a traditional convolutional network with pooling layers. The ENAS generates the optimized neural network in two ways: figuring out the best component of each layer and searching the best combination of a layer, and generating the architecture by stacking layers. To increase efficiency and decrease the amount of calculation, build the best architecture differently .As AutoSegNet for image segmentation. AutoSegNet [7] has a fixed encoder-decoder structure, which is considered one of the most classic network structures for image segmentation .The structure includes three types of layers: the downsampling layer, the bridge layer, and the upsampling layer. The downsampling layer decrease the input size so that the network can learn from the more significant receptive field. The upsampling layer works oppositely. Based on the features from the downsampling layer,the upsampling layer rebuild the input image. A bridge layer connects the upsampling and downsampling layers and it lies in the middle of the whole network. Each layer includes several cells, and the number of cells can vary. The components of the cells are the parameters that need to be searched .It includes five operations for searching, AutoSegNet has a smaller search space, which significantly improves efficiency. As we have a fixed encoder-decoder network structure [8],[9] with the downsampling layers reducing the input size, the pooling operation is removed from the search space. Instead, a new hybrid dilated convolution operation [10],[11] is added to the search space. The hybrid dilated convolution is a kind of dilated convolution without the gridding effect. It processes the input with several convolution rates at the same time, a group of rates is set to 1, 2, and 3. By doing so, the network can learn the input features from previous layers in a different receptive field without resolution reduction as well as grill effect. skip connection plays a significant role in image segmentation. However, instead of manually adding the skip connection empirically the proposed method searches both intra-cell skip connections and inter-cell skip connections, resulting in a more automated search.

2.3 Unet

UNet architecture [12] adapted to tackle medical image analysis problems in 2D, which is based on an encoder-decoder framework: the encoder is designed to learn higher and higher level representations while the decoder decompresses compact features into finer and finer resolution to obtain dense prediction. It change and widen this architecture such that it works with very few training images and yields more accurate segmentations. UNet design three types of primitive operation set on search space to automatically find two cell architecture DownSC and UpSC for semantic image segmentation especially medical image segmentation.

2.4 NAS-Unet: Medical image segmentation using NAS

NAS-Unet is another structure stacked by the same number of DownSC and UpSC on a U-like backbone network. The architectures of DownSC and UpSC updated simultaneously by a differential architecture strategy during each search stage. It choose U-like backbone (search space includes U-net and lots of its variants) to search on and introduce a memory-saving search algorithm (Binary gate) [14] to accelerate the search process. The results of the search, NAS-Unet, is evaluvated by training on medical image segmentation datasets from scratch.

2.5 Scalable Neural Architecture Search for 3D

In [15], a neural architecture search (NAS) framework is proposed for 3D medical image segmentation, to automatically optimize a neural architecture from a large design space. NAS framework searches the structure of each layer including neural connectivities and operation types in both of the encoder and decoder. A novel stochastic sampling algorithm based on a continuous relaxation is also proposed for scalable gradient based optimization, Because optimizing over a large discrete architecture space is difficult due to high-resolution 3D medical images.. On the 3D medical image segmentation tasks with a benchmark dataset ,an automatically designed architecture by the proposed NAS framework outperforms the human-designed 3D U-Net, and moreover this optimized architecture is well suited to be transferred for different tasks.

III .CONCLUSION

NAS is one of the recent technology which reduce human effort to generate neural networks. Most popular and successful model architectures designed by human experts and it requires hundreds of hours of arbitrary training and testing and hyper parameter tuning. However ,it doesn't mean we explored the entire network architecture space or that found an optimal solution. The generated neural networks by NAS is used for Image classification and segmentation .This paper discussing five types of medical image segmentation using NAS. V-NAS, AutoSegNet, UNet, NAS-Unet and Scalable NAS. These methods give accurate segmentation output compare to traditional segmentation methods.

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