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AUTOMATIC SEGMENTATION OF MEDICAL IMAGES BY DEEP NEURAL NETWORK TECHNIQUES: A REVIEW

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Deep learning techniques; medical image segmentation; neural network; CNN

ABSTRACT
Image segmentation with some popular deep learning techniques shown to be a reliable approach for image segmentation. Segmentation is basically division of an image or patches into homogenous partitions as it is the first and most important step in the diagnosis and treatment process. We give a critical assessment of prominent algorithms for medical image segmentation that have used deep-learning techniques in this work. We also provide a summary of the most frequent issues encountered and potential answers.

Introduction

One of the most difficult problems in medical image processing is recognizing pixels that make up various organs or lesions in an image of the background medical modalities for example CT scans and MRI. Using accessible technology, a number of researchers have developed several automatic segmentation methods. Traditional technologies like edge detection filters and mathematical algorithms were used to construct earlier systems. Then, for a long time, machine learning techniques for extracting hand-crafted characteristics were the dominating strategy. The key challenge for establishing such a system has always been designing and extracting these traits, and the intricacies of these techniques have been seen as a substantial barrier to deployment. Deep learning algorithms approaches have been applied to medical images in the 2000s as hardware improved, and they began to demonstrate their significant capabilities in image processing applications. Deep learning architectures and models have emerged as the key alternative in segmenting images tasks, particularly for medical image segmentation, due to their promising capabilities. Segmentation of an image based on the deep learning algorithms has received much interest recently, which emphasizes the need for a thorough evaluation. To the best of our knowledge, a comprehensive study on biomedical image segmentation employing deep learning approaches has not been published. [1] and [2], for example, are two recent survey publications on medical picture segmentation. Shen et al. covered many types of medical image analysis in [2], however they paid little attention to the technical elements to segment medical images. Many other aspects related to medical image analysis are included in [1], such as classification, detection, and registration.

Many techniques based on deep learning that are used in medical image segmentation have been developed for: the brain [3][4][5], lung [6], pancreatic [7] [8], and prostate [9] all motivated with the success of deep learning. Segmentation of medical images is a crucial aspect in analyzing the medical image for the diagnosis purpose, monitoring the treatment, and therapy. The purpose is to give a label to each pixel in an image. There are two steps to this process: first, discover diseased/tumorous regions of interest, and second, variations in various anatomical shapes. In performing the task of medical image segmentation, our deep learning-based algorithms performed better than standard methods. Using multi-modal medical images to gain more precise segmentation for improved diagnosis has been a popular method.

Segmentation

It is the division of one image into distinct non-overlapping sections based on the set of requirements and filters passed by, such as pixels or inherent properties like colour, contrast, and texture [10]. Segmentation is an interesting feature that allows you to reduce the search area of an image by breaking it into two categories, such as foreground and background. As we understand, the most crucial aspect of image segmentation is to represent the image in a meaningful fashion that can be readily utilized and examined [11] [12]. Contour detection [13] and object identification [14] benefit from segmentation. The literature has described several image segmentation approaches based on the thresholding [15], growth of region [16], clusters forming [17], and detection of edges [18] etc. In recent research, segmentation applied on a variety of image formats [19-21] for different purposes and applications, including satellite images [22, 23], tomographic volumes [24], and some other medical imaging [25, 26]. Shape, size, and relative location of organs, with anomalies identification are all examples of useful information derived from medical images employing segmentation [27, 28]. [29] describes an iterative 3D multi-scale thresholding method to segment medical images. In order to eliminate multiple effects of noise and rough edges/outliers, images contain many layers and filters. [30] presents a hybrid technique for automatic ultrasound image segmentation that combines edge characteristics based on the distance regularized level set (DRLS) function with features of different spatial constraint based kernel fuzzy clustering. Various investigations on synthetic and actual ultrasound images are used to assess performance. [31] describes a 3D medical image segmentation approach that allows the system to analyze and compare segmentation quality. Some statistical methods are based on statistical shape characteristics and an enhanced hierarchical clustering technique, with three separate datasets of 3D medical images being utilized for testing. The provided technique was tested and assessed using datasets, BRATS 2013 and BRATS 2015. [32] describes a recent brain tumor segmentation algorithm based on cascaded deep CNN, whereas [33] describes another deep CNN-based approach for glioma tumor segmentation.

Deep Learning Networks

A neural network containing numerous layers and various nonlinear processing units is known as deep learning [34]. The output of the preceding layer is used as input for each subsequent layer. Using these layers, the network can extract complicated hierarchical characteristics from the vast size of data. Deep learning achieved huge advancement in the field of image classification, detection of objects, and also analysis of medical images in recent years, producing great results that are equivalent to or somehow better in many cases when compared to the human experts of its field. Among the most popular deep learning approaches, which includes stacked auto-encoders [35], deep Boltzmann machines [36], and convolutional neural networks (CNNs) [37] are the most successful for image segmentation.

It was initially suggested by LeCun in 1989, and Hand-written digit recognition was the first project that got successful real-world application [38], which LeCun demonstrated in 1998 using the fully-adaptive architecture consisting of 5 layers. Because of their great accuracy findings, networks might be applied in a real-world setting. However, until Krizhevsky et al entry submission in the ImageNet competition in 2012, it received less attention. AlexNet [39], which is similar to LeNet but more sophisticated, outperformed all rivals and also won the challenge by dropping the top-5 error (the proportion of test samples in which the correct class was not among the top 5 predicted classes) from 26% to 15.33%. Other CNN networks have been developed in the recent years since, including VGGNet [40], GoogleNet [41], Residual Net [42], and DenseNet [43]. Convolution filters, some pooling layers, activation functions, and fully connected layers make up a CNN network. CNNs are built on convolution layers, which are used to extract features. Depending on the filters employed, the convolution procedure might create distinct feature maps. To lower the spatial size of each feature map, the various pooling layers conduct down sampling operations by taking the maximum or average of the designated neighborhood as value. A non-linear rectified layer (ReLU) activation function and its variants, for example Leaky ReLU, are among the most widely used [44], that convert data by dropping the negative input values to zero and passing positive input values as output. All activation functions applied to the preceding layer are fully connected to the neurons in fully connected layer and those are used to flatten the data before making a prediction using linear classifiers and are inserted before the final output classification. The model predicts some class scores for the training images, computes loss using the chosen loss function, and then back-propagates to optimize the weights with the help of gradient descent plot. Cross-entropy loss is considered as one of the most often used and better performance loss functions, and stochastic gradient descent (SGD) is the most prevalent gradient descent method.

Deep learning algorithms uses big data [45] for training purpose. The application of deep learning varies. Two different examples of deep learning are Tomato Leaf Disease Detection [46] and in Fake News Detection [47].

Conclusion

In this research, we first described the most used network topologies for medical image segmentation and discussed their benefits over their predecessors. Then we went through the primary training strategies for medical image segmentation, as well as their benefits and limitations. Finally, we concentrated on major issues associated with deep learning-based medical image segmentation solutions. We have also discussed the best ways to deal with a variety of problems. We think that this article will assist researchers in selecting the appropriate network topology for their topic as well as being aware of potential obstacles and solutions. Deep learning algorithms appear to be playing an increasingly important role in medical image segmentation.

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