JOURNAL OF ALGEBRAIC STATISTICS
Volume 14, No. 1, 2023, p.162-167
https://publishoa.com
ISSN: 1309-3452

Review on Medical Image Segmentation Methods

G. Arunalatha
Assistant Professor, Department of Computer Science and Engineering,
PerunthalaivarKamarajar Institute of Engineering and Technology (PKIET), Karaikal.
Puducherry.
Email: vigneshgayu1121@gmail.com

Abstract

Medical images, such as Ultrasound, X-Ray, Computed Axial Tomography (CAT) and Magnetic Resonance Imaging (MRI) are often stored in Picture Archiving and Communication Systems (PACS) and linked with other clinical information. Medical image segmentation aims to extract meaningful information such as shape, volume and motion of organs to detect abnormalities from the medical images by processing and analyzing. This paper provides a review on various medical image segmentation techniques. U-Net is a popular deep learning based semantic image segmentation technique. The medical image segmentation methods based on U-Net strategy were discussed.

Keywords: CNN. U-Net, DC-UNet, Half_UNet, UNet++.

1. Introduction:

Medical imaging refers to the system of obtaining pictures of inner organs for therapeutic purposes. The goal of medical image processing is to enhance the efficiency of medical research and remedy alternatives. Deep learning has made medical image analysis, with excellent outcomes in image registration, segmentation, feature extraction, and image classification. Deep learning techniques are well to extract at hidden patterns in images. It has proven to be the simplest technique for organ segmentation, disease analysis, cancer detection and computer-assisted diagnosis.Deep learning is a subset of machine learning, which is a neural network with three or more layers. These neural networks work to simulate the behavior of the human brain. Deep learning models can recognize complex patterns in text, sounds, pictures, and other data to produce accurate predictions. Deep learning has been used in several fields such as manufacturing, automotive, aerospace, medical research, electronics, and other fields. Deep learning eliminates some of data pre-processing that is typically involved with machine learning. These algorithms can ingest and process unstructured data, like text and images, and it automates feature extraction, removing some of the dependency on human experts. Machine learning and deep learning are both types of AI. In short, machine learning is AI that can automatically adapt with minimal human interference. Deep learning simulates the human brain using multiple layers of neural networks. It works on large data sets while machine learning uses small data sets. Deep learning uses artificial intelligence technique to teach computers to process data similar to the human being brain. Since we are adding more layers in deep learning, it is called as deep learning. Deep learning uses neural networks with 3 layers namely input layer, hidden layer and output layer. Neural network is a layer structure consisting of several neurons that simulates the human brain.

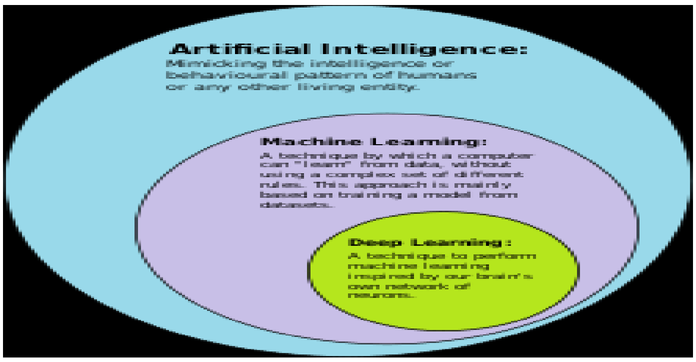

Figure1: Deep learning

Deep neural networks consist of multiple layers of interconnected nodes, each constructing upon the previous layer to refine and optimize the prediction or categorization. This progression of computations through the network is referred to as forward propagation. The input and output layers of a deep neural network are called as visible layers. An artificial neural network has several nodes that input information into it. Those nodes make up the input layer of the machine. The input layer is used for information processing, and the output layer is for the final prediction. The output layer consists of the nodes that output the information. Deep learning models that output as "yes" or "no" answers with only two nodes in the output layer. Another layer is the Hidden layer. The input layer processes the data and passes it to the successive layer in the neural network. The hidden layers process fate at special levels, as they receive new information. Deep uses hidden layers to investigate a problem from several angles.

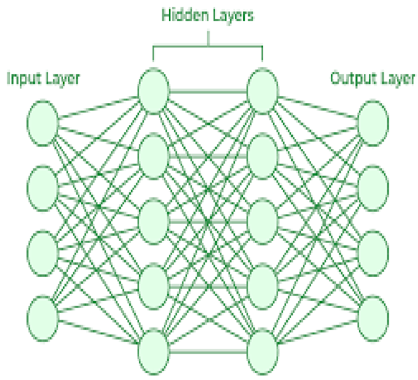

Figure 2: Deep Neural Networks

2. Convolution Neural Networks(CNN):

A Convolution Neural Network (CNN) or ConvNet is a type of neural networks that makes a specialty of processing information that has a grid-like topology. A digital image is a binary representation containing a chain of pixels arranged in a grid-like structure that carries pixel values to denote the brightness and the color of each pixel.

CNN based classification is performed in small x-ray dataset and the performance is evaluated. A convolution neural network (CNN or convnet) is a subset of machine learning. It is one of the various types of artificial neural networks which are used for different applications and data types. A CNN is a kind of network architecture for deep learning algorithms and is specifically used for image recognition and tasks that involve the processing of pixel data. A CNN typically has three layers: a convolutional layer, a pooling layer, and a fully connected(FC) layer. The convolution layer is the core building block of the CNN. It carries the main portion of the network's computational load. This layer performs a dot product between two matrices, where one matrix is the set of learnable parameters otherwise known as a kernel, and the other matrix is the restricted portion of the receptive field. The kernel is spatially smaller than an image but is more in-depth. This means that, if the image is composed of three (RGB) channels, the kernel height and width will be spatially small, but the depth extends up to all three channels. The pooling layer replaces the output of the network at certain locations by deriving a summary statistic of the nearby outputs. This helps in reducing the spatial size of the representation, which decreases the required amount of computation and weights. The pooling operation is processed on every slice of the representation individually. Neurons in this Fully Connected Layer have full connectivity with all neurons in the preceding and succeeding layer as seen in regular FCNN. This is why it can be computed as usual by a matrix multiplication followed by a bias effect. The FC layer helps to map the representation between the input and the output.

JOURNAL OF ALGEBRAIC STATISTICS
Volume 14, No. 1, 2023, p.162-167
https://publishoa.com
ISSN: 1309-3452

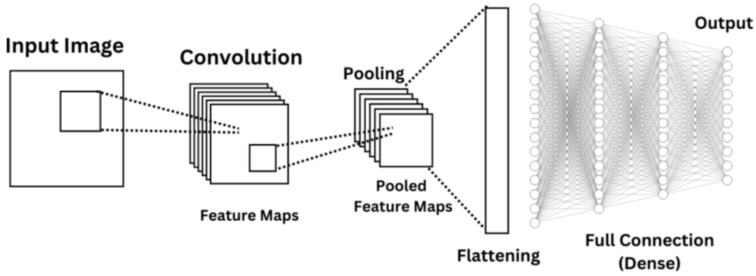

Figure 3: CNN Architecture

Medical Image Segmentation is a computer vision task that involves dividing a medical image into multiple segments, where each segment represents a different object or structure of interest in the image. The goal of medical image segmentation is to provide a precise and accurate representation of the objects of interest within the image, typically for the purpose of diagnosis, treatment planning, and quantitative analysis.

3. Literature Survey

A medical image segmentation method based on multi-dimensional statistical features [1] consisting of a hybrid feature extraction network and a multi-dimensional statistical feature extraction module is proposed. The hybrid feature extraction network is designed by CNNs and Transformer, and the lightweight processing is utilized to adapt to practical application scenarios. The purpose of the multi-dimensional statistical feature extraction module is to strengthen low-dimensional image texture features and to enhance medical image segmentation performance. Experimental results show that the proposed method provides excellent results on heart and brain tumor segmentations. In [2], the various widely used medical image datasets, the different metrics used for evaluating the segmentation tasks, and performances of different CNN based networks were analyzed.

a) U-Net:

U-Net is a U-shaped architecture consists of a specific encoder-decoder scheme [3]. The encoder reduces the spatial dimensions in every layer and increases the channels. On the contrary, the decoder enhances the spatial dimensions while reducing the number of channels. The tensor that is passed through the decoder is commonly referred to as the bottleneck. Ultimately, the spatial dimensions are restored in order to generate predictions for each pixel in the input image. These types of models are extensively utilized in practical applications. U-Net, a well-known deep-learning framework for semantic segmentation, initially gained recognition in the field of medical imaging and achieved remarkable success. However, this was just the beginning! The architecture has since demonstrated improved performance across various data types, ranging from satellite images to handwritten characters. In order to showcase the versatility of the U-Net, three distinct segmentation tasks are presented. The first task involves segmenting neuronal structures in electron microscopic recordings. The training dataset consists of 30 images (512x512 pixels) obtained from serial section transmission electron microscopy of the Drosophila first instars larva Ventral Nerve Cord (VNC). Each image is accompanied by a fully annotated ground truth segmentation map, indicating cells (white) and membranes (black). Although the test set is publicly available, the segmentation maps remain undisclosed. To evaluate the performance, participants can submit their predicted membrane probability map to the organizers. The evaluation process involves thresholding the map at 10 different levels and calculating the "warping error," "Rand error," and "pixel error." The U-Net architecture has consistently demonstrated exceptional performance across a wide range of biomedical segmentation applications.

JOURNAL OF ALGEBRAIC STATISTICS
Volume 14, No. 1, 2023, p.162-167
https://publishoa.com
ISSN: 1309-3452

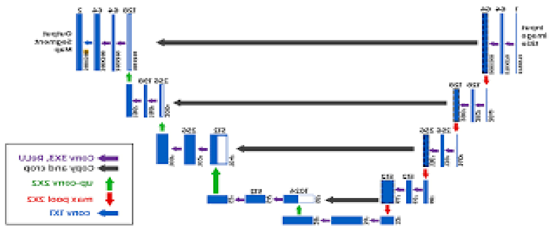

Figure 4: U-Net

b) DC-UNet:

Multimodal medical picture segmentation holds great promise with the use of DC-UNet [4]. The CVC-ClinicDB dataset has shown that DC-UNet performs exceptionally well. DC-UNet is known for its reliability and robustness, as it can identify ambiguous boundaries and reduce noise interference. Even in challenging situations, DC-UNet has a superior ability to capture small details. Therefore, DC-UNet architecture can serve as a valuable medical model for picture segmentation. This repository contains the implementation of a new version of U-Net called DC-UNet, which is used to segment various types of biomedical images such as X-rays, CT scans, and MRIs. Medical imaging tools can provide non-destructive information on illnesses, abnormalities, and anatomical structures inside the human body. Medical images contain a vast amount of data and are susceptible to noise interference, making it crucial to analyze them and extract the most useful information. The most effective deep learning-based segmentation of biological images to date is the Dual Channel U-Net (DC-UNet), an improved version of the traditional U-Net model. DC-UNet's contribution to medical image segmentation is significant, and several medical images have been used to evaluate its performance. The results show that DC-UNet consistently outperforms the traditional U-Net model, making it more reliable and durable. DC-UNet can detect unclear boundaries and minimize noise interference, making it an excellent tool for medical image segmentation.

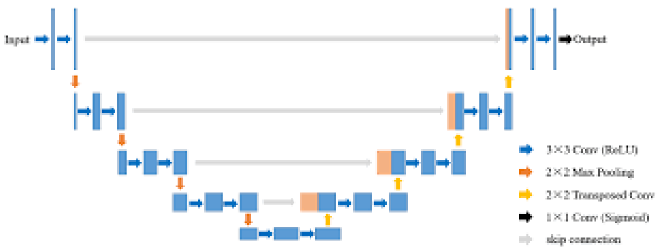

Figure 5: DC-U-Net

c) Half-UNet

U-Net is widely used in medical image segmentation. Many variants of U-Net have been proposed, which attempt to improve the network performance while keeping the U-shaped structure unchanged. However, this U-shaped structure is not necessarily optimal. In this article, the effects of different parts of the U-Net on the segmentation ability are experimentally analyzed. Then a more efficient architecture, Half-UNet [5], is proposed. The proposed architecture is essentially an encoder-decoder network based on the U-Net structure, in which both the encoder and decoder are simplified. The re-designed architecture takes advantage of the unification of channel numbers, full-scale feature fusion, and Ghost modules. We compared Half-UNet with U-Net and its variants across multiple medical image segmentation tasks: mammography segmentation, lung nodule segmentation in the CT images, and left ventricular MRI image segmentation. Experiments demonstrate that Half-UNet has similar segmentation accuracy compared U-Net and its variants,

JOURNAL OF ALGEBRAIC STATISTICS
Volume 14, No. 1, 2023, p.162-167
https://publishoa.com
ISSN: 1309-3452

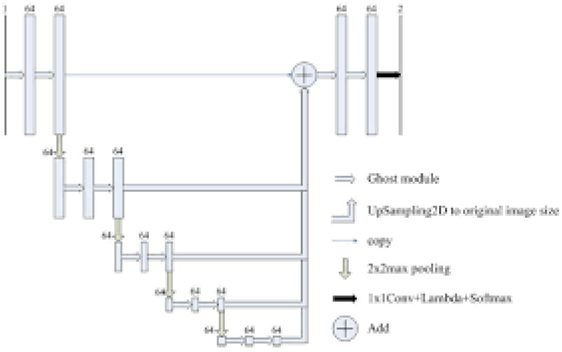

Figure 6: Half U-Net

d) UNet++: A Nested U-Net Architecture:

To improve the image segmentation accuracy, a new, powerful and versatile image segmentation technique called UNet++ [6] has been introduced. UNet++ contains U-Nets of varying depths at the same resolution via revised skip routes, with decoders densely linked. The medical image it contains convolution layers and dense block between decoder and encoder. The connectivity of the encoder and decoder sub-networks undergoes a transformation with the implementation of re-designed skip pathways. For model Evaluation, four medical image datasets such as cell nuclei, colon polyp, liver, and lung were tested. Enhanced supervision allows for improved segmentation accuracy, especially for lesions that manifest at various scales, such as colon polyps in endoscopic videos.

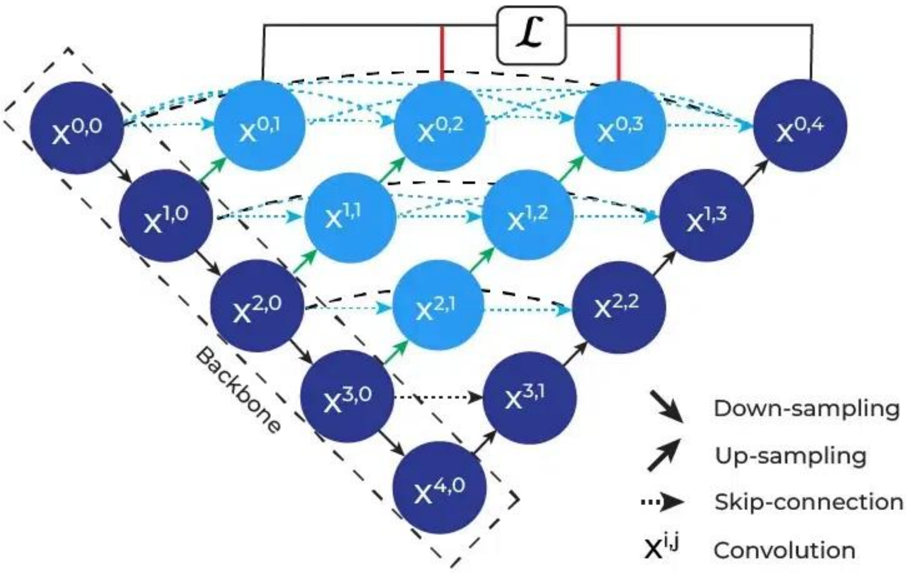

Figure 7: U-Net++ Architecture

4. Conclusion:

Image segmentation plays an important role in medical image segmentation. Medial image segmentation involves extracting Region of Interest from the medical images for further processing of medical image. U-Net is a semantic segmentation method proposed for medical images. U-Net is a Convolution Neural Network based image segmentation method. In this study, the various medical image segmentation methods based on U-Net were discussed.

References:

[1] Xu, Yang & He, Xianyu& Xu, Guofeng& Qi, Guanqiu& Yu, Kun & Yin, Li & Yang, Pan & Yin, Yuehui& Chen, Hao. (2022). A medical image segmentation method based on multi-dimensional statistical features. Frontiers in Neuroscience. 16. 10.3389/fnins.2022.1009581.

[2] Malhotra, Priyanka & Gupta, Shieldlike, Deep &Zaguia, Atef&Enbeyle, Wegayehu. (2022). Deep Neural Networks for Medical Image Segmentation. Journal of Healthcare Engineering. 2022. 1-15. 10.1155/2022/9580991.

[3] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18. Springer International Publishing, 2015.

[4] Lou, Ange et al. DC-UNet: Rethinking the U-Net architecture with dual channel efficient CNN for medical image segmentation. Medical Imaging (2020).

[5] Lu H, She Y, Tie J, Xu S. Half-UNet: A Simplified U-Net Architecture for Medical Image Segmentation. Front Neuroinform. 2022 Jun 9;16:911679. doi: 10.3389/fninf.2022.911679. PMID: 35756960; PMCID: PMC9218935.

[6] Zhou, Zongwei& Rahman Siddiquee, MdMahfuzur&Tajbakhsh, Nima& Liang, Jianming. (2018). UNet++: A Nested U-Net Architecture for Medical Image Segmentation: 4th International Workshop, DLMIA 2018, and 8th International Workshop, ML-CDS 2018, Held in Conjunction with MICCAI 2018, Granada, Spain, September 20, 2018, Proceedings. 10.1007/978-3-030-00889-51.