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A Systematic Literature Review on Deep Learning Based Medical Image Segmentation

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Abstract: Medical imaging becoming an essential life supporting aspect in the current world. It having various types of modalities and each one serves for specific applications. Lot of applications and necessities are there to figure out the various life-threatening diseases. But the identification of abnormalities is not so easy doing manually. It is error prone and time consuming. And also requires lot of proficiency and experience. Deep learning is a state of art methodology which having a huge span of applications especially in medical field. Particularly, in medical imaging the deep learning methods can be applied and can make huge differences in the accuracy of findings. They can be used for synthesis, segmentation, and classification. This study is aimed to focus on the different types of medical imaging modalities and the various deep learning algorithms on medical imaging. The performances of different methods were compared by means of various evaluation metrics.

Keywords*: Medical imaging, deep learning, Segmentation*

1. Introduction

As the world evolves the darken side of the development is the increase of deadly deceases. The medical practitioners and researchers together fighting for the welfare of human kind to safeguard from the evil of them. The curation from any ailment is not only based on the medication but the earlier detection plays a vital role. For the detection of abnormalities, the medical imaging techniques can be used to figure out. There are lot of imaging techniques are available like ultrasound scan, MRI scan, CT scan etc. The accuracy is majorly depending on the expertise of the professional since manual measurements. And it takes much time to get an accurate result. To overcome this struggle automation can be utilized. In that perspective the researchers from other fields also trying to sort out the difficulties encountering while diagnosis.

In computer science the emergence of artificial intelligence plays a crucial role to make the betterment and reducing difficulties in various applications. In such a way medical field also take the advantage of utilizing the benefits artificial intelligence. At the initial stage the back-office tasks from doing the routine tasks like nursing to digitizing the healthcare data the field of artificial intelligence make great variance. Later it has been expanded to emerge as a lifesaving support. Machine learning is an advancement of artificial intelligence. And deep learning is a sub category of machine learning. There are numerous methodologies are available in deep learning to automate the finding of anomalies with medical imaging. They are range from Convolutional Neural Network based methods, Recurrent Neural Network based methods, attention-based methods, Encoder-Decoder based methods, multi scale-based methods, Generative Adversarial Network based methods and Atlas based methods [1]. This review is aimed to focus on the classification of various medical imaging modalities and the deep learning-based segmentation techniques. The organization of the paper is as follows: section II elucidates the jargons related to the review. Section III deals with the classification of medical imaging modalities and the comparison of different methods are given. Section IV discusses the various deep learning-based segmentation techniques and comparing the pros and cons of each method. The performance is evaluated using the loss functions in Section V. Conclusions are given in the Section VI.

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2. Terminologies

a. Artificial intelligence

It is defined as the intelligence shown by the machine. The machine can be programmed as to get intelligence by learning and attain expertise through experience. A learnt machine can mimic human actions by decision making capabilities and it can able to learn things from its environment. Artificial Intelligence having a wide span of applications which includes Healthcare, Natural Language Processing, Speech Recognition, Vision Systems, Gaming, and Automotive, can be used in risky areas, can be used as a public utility and it can act as a digital assistance. Artificial intelligence is a method of teaching a machine to think like a person. It is the study of how the human brain thinks, learns, makes decisions, and works to solve issues.

Artificial intelligence aims to develop computer intelligence in areas such as reasoning, learning, decision-making, and problem-solving that are related to human understanding. It has numerous benefits, including excellent precision, speed, and reliability.

b. Machine learning

Machine learning is a subclass of Artificial intelligence. It aimed to design models which can learn through experience. It is used to gain that experience from the environment itself. The prediction of a new case is based on the past cases handled.

c. Deep learning

Deep learning is a subclass of machine learning. it utilizes the concept of neural network which mimics the human brain neurons. Normally the deep learning models have neural networks with three or more number of layers. These layers are categorized into three groups namely input layer which used to give input values to the network, hidden layer where actually the processing has been done and finally the output layer which is producing the output. Depending upon the requirement of application the number of hidden layers can be increased.

d. Medical imaging

Medical imaging is a class of technologies which are used to visualize the inner organs of the body to aid the medical practitioners to investigate clearly. These technologies collectively termed as radiology. They provide the information regarding the functioning of organs, current state of any disease, data about anomalies if any and etc. This information will help the doctors to get a clear intervention and accurate conclusion in a short span of time. So, the medication can be started soon will lead a better output. There are a number of imaging modalities are available namely X-Rays, Ultrasound scan, Magnetic Resonance Imaging scan and Computed Tomography scan and cross-sectional radiotracer like PET scan. Depending upon the requirement of application of the patient any modality can be selected and utilized. In some cases, the hybrid modality can also be used. It means two or more imaging modalities can be combined and used like CT-PET, MRI-PET etc.

e. Segmentation

Image segmentation is a process of splitting an image into segments that will leads to a better understanding of parts of that image. Segmentation is treated as the basis for image processing-based tasks like object detection and classification. The segments are group of pixels that are represented by a labelled image. The image segmentation can be classified based on some parameters like based on the approach selected for segmentation and technique used.

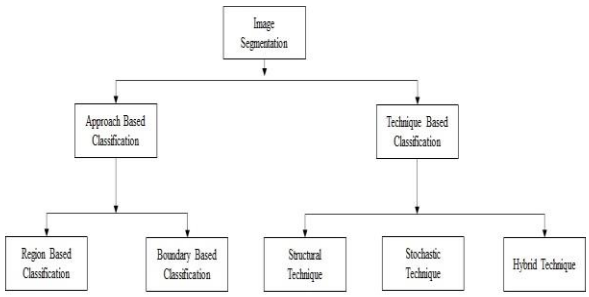

Fig. 1: Classification of Image Segmentation using parameters.

In region-based classification the objects present in a particular image is separated based on the similarity of pixels into different regions. This method uses very simple calculations. It works very well if the contrast of object and the background is. If the difference is less than it is difficult to figure out the object from the image. And in case if overlapping regions, it faces lot of difficulties to work with. In boundary-based classification by defining the boundaries of an image the objects are segmented. When the segmentation methods are classifying with based on technique it can be grouped into structural, stochastic and hybrid techniques. The structural techniques are working based on the structure related information like specific region of interest. Whereas the stochastic techniques using the pixel values. In hybrid techniques relevant features from both techniques can be utilized.

There are some primary types of image segmentation are given.

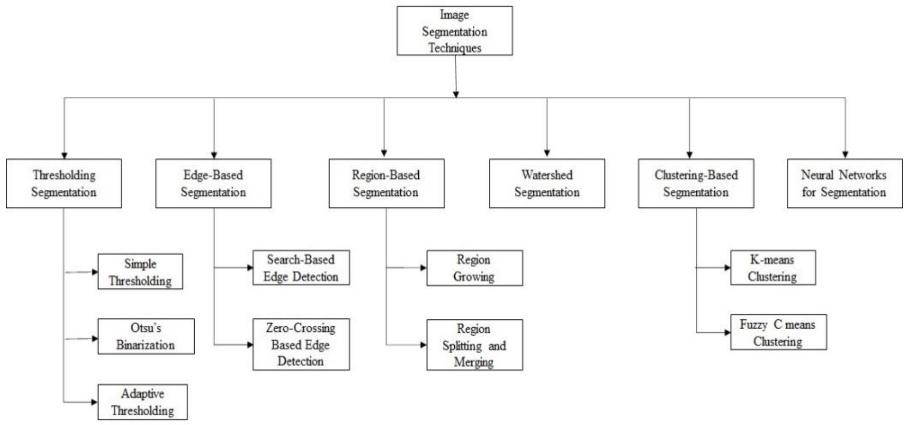

Fig. 2: Primary Types of Image Segmentation Techniques

The three types segmentation are instance segmentation, semantic segmentation and panoptic segmentation. If the application needs to group the objects as collection like human, buildings, vehicles then the semantic segmentation can be used. Else if it needs to identify every element in any group like every person in the human category or every vehicle in the vehicle category then instance segmentation will be the option. The panoptic segmentation is the combination of semantic and instance segmentation.

3. Medical Imaging Modalities

They are a broad span of techniques used to visualize the inner parts of the human body for the purpose of diagnosing, monitoring and treating from the various ailments. They are being an essential tool for the physicians to identify the possible disease, malfunction, abnormalities or injuries etc. There are different modalities and each one is used for specific application and providing different kind of information. "*Medical imaging deals with the interaction of all forms of radiation with tissue and the design of technical systems to extract clinically relevant information, which is then represented in image format"* [2].

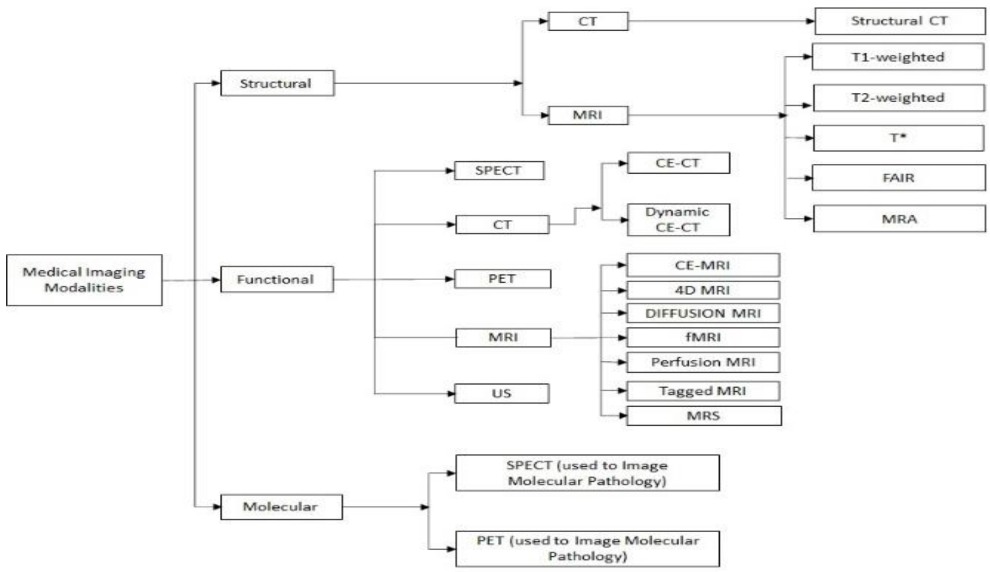

Fig. 3: Various Medical Imaging Modalities

Structural imaging used to visualize the structure of the organs mainly used to diagnosis tumors and injuries. Functional imaging shows the information process happening in the organ and used to diagnosis metabolic diseases like Alzheimer. Molecular imaging technique includes the visualization of biological processes at the molecular level and used for molecular diagnosis like tumour localization.

4. Deep Learning Approaches to medical Image Segmentation

Generally, there are three image tasks are image classification, object localization and segmentation.

U-Net

It is a type of convolutional neural network mainly focused to work with biomedical applications. The shape of the architecture looks like an English alphabet U. so it is named as U-Net architecture. It is an expanded concept from fully convolution network. Since it is based on the convolutional neural network, it consists of number of convolution layers with ReLu activation functions. Apart from the convolution layers there are encoder in the left side of the architecture to reduce the image size with the help of max-pooling layers with striding 2. In the same way on the right side of the architecture the decoder is there. Martin *et al*. [15] trained a Convolution Neural Network with U-Net architecture and added a dropout layer with 0.5 as p value.

ResU-Net-C

It is a deep Convolutional Neural Network-based semantic segmentation model for automatic segmentation of the cerebellum in ultrasound images. It employs the U-Net architecture and contains residual blocks with dilated convolution units in the final two layers to improve and maintain image resolution. According to Singh et al. [10], the employment of highly efficient features has been encouraged since the use of residual block. It causes a high learning curve acceleration and gives correct robustness and reliability. Even if the processing time is faster than the U-Net, it is slower than the U-Net attenuation. The attention gates and residual modules, according to Zhang et al. [11], are combined with the U-Net design, which can extract dense features and store spatial and temporal information.

Random Decision Forest Framework

The Random Decision Forest consist of multiple decision trees which are used for the various image analysis tasks like classification, segmentation, localization etc. It is an automatic segmentation method to segment fetal brain structures in 3D ultrasound scan images. Priorly preprocessing has been done to put the image in a common coordinate space. First the images are preprocessed to identify the head orientation and head center then the novel features are developed. Once preprocessing is over the RDF classifiers are trained to figure out the important regions. Three VOIs (volume of interest) are identified and the RDF classifiers are trained to classify the voxels in the regions. Yaqub *et al.* [16] built a RDF framework to segment the four fetal brain structures and in the preprocessing the three regions which contain the structure of interest were identified. The RDF classifiers are used to train on the voxels from each region. Yaqub *et al.* [17] proposed a 3D segmentation technique based on the Random Decision Forest with two improvements. Voxel classification has been improved by selecting strong features and during testing phase each tree has been weighted.

Active Shape Model

It is a semi-automated segmentation model which uses the hermit features. It uses an image texture model based on Hermite transform which belongs to polynomial transforms that uses the Gaussian derivatives for the segmentation task. The edges cerebellum has been located with high probability values. The active form mode developed by Reyes López et al. [18] contains the profiles of Hermite features. Vargas-Quintero et al. [19] developed a multi-texture active appearance model (AAM) based on the Hermite transform (HT), with the steered coefficients of the Hermite transform utilised to code the texture patterns of the multi-texture AAM.

Automated Atlas based Segmentation Pipeline

For segmenting 3-dimensional ultrasound pictures, a completely automated atlas-based segmentation process was built. The phase congruency map, multi-atlas initialised technique, an atlas selection strategy, and a multi-phase geodesic level set were used by Qiu et al. [4]. To speed up the computation the proposed segmentation pipeline has been parallelized and implemented on a GPU. Qiu *et al.* [5] followed by a manual segmentation the segmented ventricles are rigidly registered through six selected landmarks. Qiu *et al.* [6] initialized the segmentation by sampling the foreground and background voxels and the edges are indicated by a phase congruency map. To overcome the optimization problem a novel convex relaxation approach was utilized. Boucher *et al.* [7] used a multi atlas registration initially followed with a label fusion which converts the output into a mesh then a deformed mesh-based segmentation taken place.

Confidence-guided brain Anatomy Segmentation

Jose Valanarasu et al. [24] introduced a Confidence-Guided Brain Anatomy Segmentation Network, which learns weights based on a confidence measure and outputs a segmentation map at various scales.Reddy et al. [25] proposed a segmentation method which used the confidence surface to do segmentation and uses both the intensity and texture information.

Fully Convolutional networks

It just has convolution layers, which are used to extract features from an image using kernel values and provide a segmentation map as an output. It is not necessary to be fully connected. The output feature map from the given input image is created using a number of convolution layers of the same size. Nie et al. [9] created a 3-D architecture for MR pictures that consisted of groups of convolutional and de-convolutional layers, with only three pooling layers and relatively small convolution filters. Long *et al.* [12] adapted the classification networks AlexNet, VGGNet and GoogleNet into fully convolutional network and the learned features are transferred for segmentation by fine tuning. Skip architecture is defined to get the accurate result.

Convolutional Encoder-Decoder Based Models

A fully connected conditional random field is combined with the last layer of Fully connected convolutional network to minimise the insufficient localization in deep convolution models. Teng et al. [30] introduced a deep multiscale convolutional neural network-based segmentation model that includes encoders, decoders, and the U-Net Jha et al. [31] proposed a two U-Net architecture called DoubleU-Net which combines modified U-Net and VGGNet-19. The encoder-decoder based models are used for both general image segmentation and medical and bio medical image segmentation. Wang et al. [14] present a CNN encoder decoder structure that incorporates the desirable properties of SegNet and U-Net, with two key components: deep feature extractor (i.e. encoder) and multi-scale decoder.

Multi-Scale and Pyramid Network Based Models

Khan et al. [21] proposed PMED-Net which is a pyramid based multi-scale encoder-decoder network having six pyramid levels which are working in a pyramid fashion for medical image segmentation. They are extracting the complex lesions and biomarkers by multi-scale feature representation. MNPNet is an unique multi-level nested pyramid network with encoder decoder proposed by Wang et al. [22] for dealing with bulk segmentation. Roth et al. [23] introduced a novel method for doing semantic segmentation at greater resolutions in a multi-scale pyramid of stacked 3D FCNs using auto-context

Recurrent Neural Network Based Models

The Cascade R-CNN, proposed by Cai et al. [27], is a multi-stage object detection architecture consisting of a chain of detectors trained successively with rising IoU thresholds. Visin et al. [28] presented ReSeg, a structured prediction architecture based on the ReNet model, which incorporates both CNN and RNN.

Attention-Based Models

A new synthesis network was developed to provide a steady high-resolution image. Jia et al. [20] proposed a multi path encoder and decoder deep network with self-attention weight fusion of multi model features to control the fusion weights. Gu et al. [26] proposed CA-Net, which adds convolution blocks to comprehensive attentions and uses U-Net as the backbone.

Active Contour Models

Sciolla *et al.* [8] proposed an active contour segmentation was proposed to parametrize the contours using a level-set function. The 3D complex wavelets were used for denoising the images. The feature maps were utilised to improve the accuracy in limited regions. Xiang et al. [29] introduced a new edge-based active contour approach that maintains edge fidelity while using a long-range and orientation-dependent interaction between picture boundaries and moving curves.

5. Performance Comparison

The assessment metrics Mean Dice Similarity Coefficient DSC, Mean Absolute Surface Distance MAD, and Maximum Absolute Surface Distance or Hausdroff Distance MAXD are used to compare the performance of different approaches used for medical picture segmentation.

i. Mean Dice Similarity Coefficient

It is a statistical too which calculates the similarity between two data sets. It can be defined as

$$DSC(A,B) = 2(A \cap B)/(A+B)$$

ii. Mean Absolute Surface Distance

It calculates the average minimum distance between two boundaries [32].

It can be defined as

$$dmin(x, B_j) = \min \{d_E(x, y) | y \in B_j\}$$

where $d_E(x, y)$ denotes the Euclidean distance between points x and y, B_j denotes set of boundary points.

iii. Maximum Absolute Surface Distance

It measures the largest minimum distance between two boundaries [32]. T can be defined as

$$HAUSD = \max \{h(BI, BGT), h(BGT, BI)\}$$

where I stand for the segmented picture for which the quality index is calculated, and GT stands for the ground truth

	Technique used	Mean DSC	MAD	MAXD
Qiu et al. [4]	Phase Congruency map, multi-atlas initialization technique	76.7 ± 6.2 %	1.0 ± 0.3 mm	5.4 ± 1.6 mm
Qiu et al. [5]	Convex optimization	72.4 ±2.5 %	0.7 ± 0.1 mm	3.5 ± 1.5 mm

Oiu et al. [6]	Convex optimization-based user guided segmentation	78.2 ± 4.4 %	0.7 ± 0.3 mm	3.2 ± 1.0 mm
Boucher et al. [7]	multi-atlas deformable registration	70.8 ± 3.6 %	0.88 ± 0.20 mm	6.84 ± 3.15 mm
Fuerst et al. [13]	similarity measure Linear Correlation of Linear Combination	-	2.7 mm	-
Singh et al. [10]	ResU-Net-C with residual block	0.749	-	3.74 mm
Zhang et al. [11]	U-Net architecture with attention gates and residual blocks	86.70 %	-	-
Martin et al. [15]	CNN with U-Net architecture	0.816 ± 0.04 %	0.62 ± 0.2 mm	13.6 ± 4.7 mm
Fuerst et al. [13]	Atlas-based with LC^2	57.4 ± 7.8	1.33 ± 0.44 mm	8.55 ± 3.42 mm
Fuerst et al. [13]	Atlas-based with area weights	60.4 ± 7.5	1.14 ± 0.30 mm	7.52 ± 2.81mm
Fuerst et al. [13]	Atlas-based with LC^2 + Mesh	65.1 ± 4.1	1.08 ± 0.33 mm	8.46 ± 2.98 mm

Table 1: Segmentation based on various deep learning methods compared regarding Evaluation metrics

6. Conclusion

We have surveyed the various segmentation methods used in medical imaging based on deep learning models. The performance was compared with the help of various evaluation metrics. It is tough to conclude any of the model as a good one. In accordance with the application and requirements the significant model can be selected.

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