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Research paper

A survey on applications of machine learning techniques for medical image segmentation

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Abstract

With development of science and technology in this digital era, the digital imaging is increasing expeditiously in every field. This digital image processing converts the image into its digital form to perform some operations on it to get either improved version of image or to get informational features from it. Different image processing techniques are available and image segmentation has a prime role in it. Segmentation of image is done principally to separate objects of interests from backgrounds. Ample of techniques are available for image segmentation. But, sometimes many techniques fail sporadically to yield the desired outcome. To fill up the requirement, the machine learning techniques come into play and perform well with satisfactory results. Here, is a fleeting review of machine learning techniques, mainly focusing on the artificial neural network with highlight of its improvements towards deep learning and convolution neural network along with some light on other machine learning techniques. It also includes brief descriptions of some neural networks used for segmenting different medical images and focus is given on convolution neural network which is developed primarily to work with images. The review will provide researchers a visualization and ideas to further use these techniques in improved ways for better performance for image segmentation.

Keywords: *Image Segmentation; Machine Learning; Deep Learning; Convolution Neural Network.*

1. Introduction

Sight or vision is probably the most developed sense in human beings, so image plays an important role everywhere. With the advancing technologies capturing an image is very easy today. Day by day generating and storing of these image data is increasing even more in numerous fields like education, medical, agriculture, military etc. These data need to be identified and sorted in a proper way so as to access, use and interpret them easily for which image processing is required [1-2]. One of the fundamental steps in image processing is image segmentation.

Breaking down or partitioning of the image into possible separate homogenous regions is called segmentation. It is done to make the image more meaningful and easy to analyse for identifying objects. Basically the object and the background are separated during this activity. Generally, the segmentation technique is followed by classification where those separated objects are assigned to particular classes and wholly this process is taken as the elementary part of computer vision. Not only for classification, segmentation is a pre-requisite step for other image analysis techniques like image registration, image fusion etc [2-4]. Though segmentation comes under different fundamental techniques of image processing, it is itself a huge field in image processing. Accuracies of many image analysis techniques depend upon the accuracies of image segmentation [5]. Segmentation is a mid-level image processing step out of low, mid and high level image processing where inputs are generally images but the outputs are attributes extracted from the images, further to be scrutinized. Sometimes, it requires pre-processing and post-processing and sometimes not.

In a non-mathematical way the word image segmentation means division of images into different regions having similar properties. In medical terms, separation of image data to flawless expressive portions by assigning limits is segmentation i.e. separate regions that distinguish itself from back ground or from other regions. Mathematically, segmentation can be described as a decomposition of an image to dissimilar regions or categories that restrict the overlap of image regions. It can be expressed as following [6]

Let A be the collection of all pixels in an image, so the segmentation is dividing the set A to set of linked subsets ($\mathbf{Sub_1}, \mathbf{Sub_2}, \mathbf{Sub_3}, \ldots, \mathbf{Sub_n}$) as represented in (1) and (2).

Here,

$$\bigcup_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{S_i} = \mathbf{A} \quad (1).$$

And

$$\mathbf{S_i} \cap \mathbf{S_j} = \emptyset \ \textbf{where i} \neq \mathbf{j} \quad (2)$$

A wide range of segmentation techniques are available, mainly edge based, region based and threshold based. Edge based segmentations depend on edges that are the local changes in the image intensity. But, these could not be applied on images having smooth edges or many edges. Similarly region based image segmentation rely on seed point, based on which the region grows by checking the neighbouring pixel's intensity to add or not, thus separating the regions. It is also called as pixel based segmentation. This technique is computationally expensive and different seed points may generate different segmentation results, which is a detriment to segmentation. The combination of edge based and region based techniques overcome their individual lacunas and develop a good segmentation technique [7-8]. The thresholding based segmentation is one of the simplest and widely used segmentation techniques [9-10]. Here, optimum threshold is calculated which separates the two classes, minimizing the intra-class variance and maximizing inter-class variance. This method exhibits good performance if the histogram of the image have bimodal distributions, but it cannot process the images having uni-modal intensity distributions [11-13]. To overcome all these, we can go for machine learning techniques, a branch of Artificial Intelligence developed on basic idea that it should be able to learn and adapt through experience. In machine-learning there are different approaches like clustering, decision tree, support vector machine, artificial neural networks, deep learning etc. Here, we have mainly knuckle down to artificial neural networks (ANN) and its implementations on medical image field for segmentation.

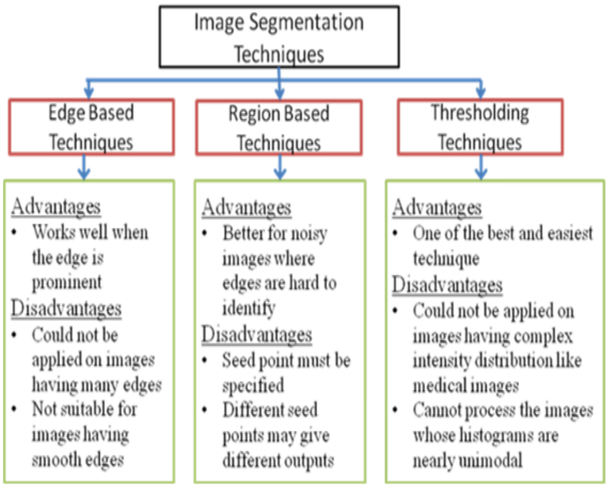

Fig. 1: Classical Image Segmentation Techniques with Their Advantages and Disadvantages.

When we are considering biological image or medical image specifically, morphological operations like dilation, erosion or interpolations operations may not be applied but for these high content images, segmentation is often required as the first step before analysis. Due to its high intensity distribution techniques like thresholding may not be applicable for best results. We can apply machine learning techniques like ANN which has a very wide range of applications in almost every field [14-22]. Here is an introductory analysis between different ANNs, Deep Neural Network(DNN) and Convolution Neural Network (CNN) which are on high dictate technically in almost every field. The analytical study of these individual methods gives a clear picture about their usage with advantages and disadvantages, so that they can be suitably used in specific domains of image segmentation.

2. Literature review

ANN are the networking algorithm techniques developed in resemblance with human brain that learns with experience and increases its performance accordingly. Different types of ANN have been applied in many fields for image segmentation. Here mainly we have focused on segmentation techniques used for medical images.

Self Organizing Map is a type of unsupervised ANN introduced by Kohonen. Hence called as Kohonen network or map. Its working principle can be parted as two steps: in the first step it is trained to build the map using examples and in the second step it classifies new inputs by mapping.

Figure 1. Classical image segmentation techniques with their advantages and disadvantages

In a paper by Torbati N. et al. [23] a neural network based method for medical image segmentation is proposed where a modified Self-Organizing Map (SOM) network known as Moving Average SOM (MA-SOM) is used to segment medical images and is compared with normal SOM network. A dataset of 30 Breast Ultrasound(BUS) Images, 10 Magnetic Resonance Images (MRI) of brain images and one Computerized Tomography (CT) head image is used for the evaluation. A two-dimensional Discrete Wavelet Transform (DWT) is used to build the input feature space for the network. The filtering property of the network reduces the image noise to many extents. Accuracy of the proposed method in comparisons with SOM based network method is proved by Jaccard index, Rogers index and Tanimoto index.

Ailing D. and Chengan G. [24] have used SOM for the image segmentation of real brain MRIs collected from Internet Brain Segmentation Repository (IBSR). In their work Vector Quantization (VQ) is used for the segmentation task and SOM network adaptively performs the codebook learning for VQ-based image segmentation as codebook learning is an essential for VQ approach. Ortiz A. et al. [25] have also used the data from IBSR and performed segmentation using SOM network. A Growing Hierarchical SOM (GHSOM) is used which has the ability to build a SOM hierarchy. The depth and breadth created by the hierarchy and map are adapted to the input data to control the quantization error. The discovery of hierarchical relationship between the data by GHSOM enhances the performance. Taneja A. et.al. have used SOM network and Expectation-maximization (EM) approach for image segmentation [26] followed by feature extraction and classification methods showing a good result. SOM

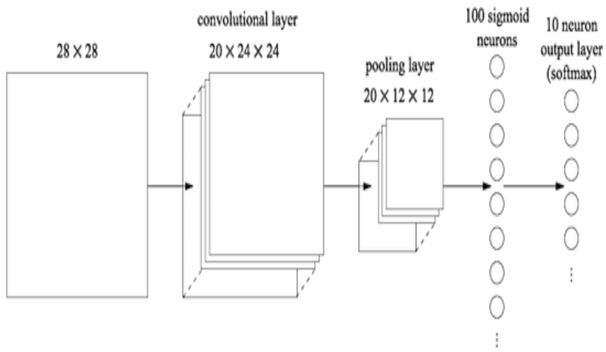

Fig. 2: Architecture of Convolutional Neural Network.

is also used for the segmentation of data apart from medical data [27-29].

Another type of neural network called Pulse Coupled Neural Network (PCNN) is also used in many fields of image processing. PCNN is a single layered, two-dimensional artificial neural network developed by Johnson et al developed on the basis of cat's visual cortex. In this network each neuron corresponds to one pixel of the input image. It has three parts mainly i.e. input part, linking part and the pulse generator. PCNN receives the input stimulus through both feeding and linking connections which are combined in an internal activation system, and accumulates the stimuli until it exceeds a dynamic threshold, resulting in a pulse output. Through iterative computation, PCNN neurons produce temporal series of pulse outputs that contain information of input images to be utilized for various image processing applications. Determining the values of parameter is an insignificant and unavoidable task in all neural networks and the performance of the model is affected in a great way by this[30-33].

Gao C. et al. [34] have taken a modified PCNN, where a new neural threshold is considered in spite of general dynamic threshold to get an improved segmentation result. Comparing with simplified PCNN, the proposed model gives better segmentation performance. Yao C. and Chen H.J. have used simplified PCNN with 2D-Otsu Algorithm for retina image segmentation [35] that works well specifically for low contrast images and small vessels. In another work by Jiang W. et al. [36] PCNN is used along with

Canny operator edge detection method by simplifying the parameters of the network for multichannel image segmentation. A parameter adaptive PCNN is designed by Lian J et al. [37] and applied on ultrasound images, MRIs and mammograms providing a improved segmentation precision. Chou N. et al. have taken a 3D-PCNN [38] based on the 2D PCNN for brain MRIs. Though it has some computational complexity, it is robust to noise and gives a very low accuracy reduction for highly noisy data. A modified network is proposed by Guo et al. [39] by combining the theory of saliency detection with simplified PCNN for object segmentation and termed as saliency motivated improved simplified pulse coupled neural network (SM-ISPCNN). The network is used for segmenting mammographic images for the diagnosis of breast cancer proving excellent segmentation capabilities with strong robustness.
Deep Neural Network (DNN) is simply a stack of neural networks or we can say a feed forward ANN having multiple hidden layers. The term 'deep' signifies more than three layers in the network including input and output layers. Here, deep is strictly defined technical term, representing more than one hidden layer. Depth of layers is the distinction between normal NN and Deep NN. Each layer of nodes work on different sets of features as the output of previous layer, capable of handling more complex, large and high dimensional datasets with billions of parameters that pass through nonlinear functions[40-43].
Convolutional Neural Network (CNN) is a class of deep feed forward ANN which uses a special multilayer architecture particularly adapted to classify images. It can also be describes as a deep multi layer perception network[44]. It basically uses local perceptive field, shared weight, bias and pooling. In fully connected neural networks the input is represented as a vertical line of neurons, but in CNN the input is taken as a square matrix corresponding to the pixel values of the input image i.e. the original image is directly taken. These neurons are connected to every neuron of the hidden layer i.e. each neuron in the hidden layer is connected to a small, localized region of the input image. That region in the input image is called the local receptive field for the connected hidden neuron. Then the local receptive field is slided across the entire input image starting from the top-left corner by one pixel at the right which creates the total matrix of hidden layer. Each connection from hidden layer neuron to input neurons bears a weight and each node in the hidden layer has a bias. The same weight and bias is used by total hidden neuron matrix, so called as shared weight and bias.
The convolutional layers generate feature maps by the local connectivity and weight sharing i.e. the local features in all locations of the input image. All the neurons in the first hidden layer detect exactly the same feature. The numbers of parameters are significantly reduced by the weight sharing rule which increases the efficiency and prevents over-fitting. A CNN may have many feature maps. At last, pooling is applied to each feature map separately to reduce the number of features so as to reduce dimensionality in the network. The convolution and the pooling layers are considered as 2-D layers whereas the output layer is a 1-D layer. Here, each 2-D layer has several planes and the planes consist of neurons arranged in 2-D array. Then from the reduced pooling layers required output comes with one label per node. Now, this 1-dimensional data is fed to a simple neural network to get the required output [45], [46].
Following are some advantages of CNN along with NN which make it more suitable for image analysis -

1) The deep architecture of neural network i.e. with more hidden layers gives more efficient result behaving in a more intelligent way. Adaptive learning, parallelism, fault tolerance and generalization - are some characteristics of neural network which makes neural network more suitable for many fields of applications.[47]
2) In CNN the spatial arrangement of units is the primary characteristics that make it suitable for processing visual information [48].
3) The local connectivity, parameter sharing and pooling of hidden units are advantageous for prediction.
4) In CNN, feature extraction and classification are integrated into one structure within a fully adaptive network.
5) The network extracts 2-dimensional image features at increasing dyadic scales.
6) It is relatively invariant to image noise and local geometric distortions.
7) The non linear classification boundaries obtained during the training of neural network helps in the medical image data segmentation[49].

Tumors are a disorder which that they can appear anywhere in any size and shape. The flexibility of machine learning gives a platform to solve many complexities like this. The Deep Neural Network (DNN) is used by Havaei M. et al. [50] for the segmentation of brain MRIs. The convolution nature of the network along with an efficient graphic processing unit results in a fast segmentation system exploiting both local and global features of the image. A two phase training procedure is used to handle the difficulties regarding the imbalance of tumor labels. A hybrid or cascaded architecture of CNN is designed where the output of first network is an additional source for the subsequent network. CNN is used for the glioma segmentation from MRI of brain by P.Sergio et al. [51] BRATS 2013 and BRATS 2015 datasets are taken with preprocessing for intensity normalization followed by some post-processing after segmentation. For the evaluation of the segmentation technique metrics like Dice Similarity Coefficient (DSC), Positive Predictive Value (PSV) and Sensitivity are considered. Likewise in another work by Yu L. et al. [52] a novel dynamic CNN approach is considered for the segmentation of fetal left ventricle in echocardiographic sequences. Semantic segmentation of medical image is done for disease diagnosis and clinical research. Jiang F. et al. [53] have considered CNN with some modifications. A Hybrid recurrent neural network with some alternation in deep learning framework is taken for the segmentation of chest radiograph images from Japan Society of Radiological Technology (JSRT). Li. R. et al. [54] have used CNN for the tracing or digital reconstruction of three dimensional neuron structures from microscopy images. The high computational complexity property of the neural network is appraised here and voxel-wise segmentation of the microscopic images is performed. For automatic characterization of Plaque composition in carotid ultrasound images Lekadir K. et al. [55] have taken CNN. The network is designed to extract optimal information from the image to identify different plaque constituents. Though the procedure is little time consuming the output comes out well with satisfactory validation results.

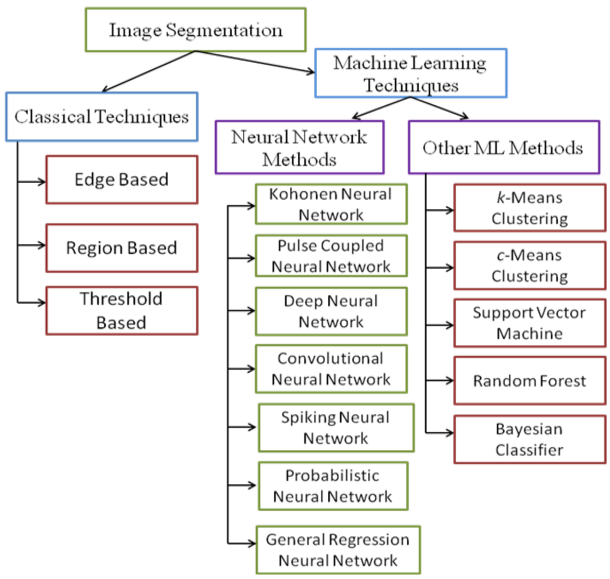

Fig. 3: A Taxonomy of Image Segmentation Techniques.

For segmentation of retinal blood vessels Liskowski P. et al. [47] have employed CNN proving that deep neural networks are really suitable for medical imaging and many more. Xavier initialization is used for network initialization with rectification non-linearity

and stochastic gradient descent used for optimization. Simple feed-forward neural network is also used for biometric retina identification by Sadikolu F. and Uzelaltinbulat S.[56] with back propagation algorithm for training. Advanced pre-processing and feature extraction is done to extract the features and fed them to the network for recognition of retinal images. Tan J.H. et al. [57] have taken a 7-layer CNN for the segmentation of optic disc, fovea and retinal vasculature from fundus images. Though, this method has lower specificity it gives good accuracy and works well in terms of sensitivity. In another article by Zeng Z. et al. [58] a Multi-Target Deep Neural Network (MT-DNN) is proposed where the network is used for different targets i.e. one for classification, one for regression and one for masks. A single model is designed for multiple purposes here. The study exhibits huge capability and usability of the DNN.
A spiking neural network clustering based approach is used for image segmentation and edge detection by Meftah B. et al. [59] Parameter selection and network architecture are taken as key features here and it has to be setup for each specific image problems. The experiment concludes that a careful parameter setting is required to get an efficient result. For breast cancer diagnosis and screening Probabilistic Neural Network (PNN) and General Regression Neural Network (GRNN) are used [60,61] showing that these statistical neural networks increases the accuracy and objective of the diagnosis. A modified PNN called as Weighted PNN (WPNN) is used by Song T. et al. [62] for brain MRI segmentation. So, different types of neural networks are used for the medical image segmentation sucessfully. Other machine learning techniques apart from neural network are also used for many purposes of image analysis. Some of them are mentioned below :
Visualization of different brain anatomical structures and measures from MRI can be done successfully through segmentation by clustering algorithms. Hung C. L. et al. [63] have used Fuzzy C-Means clustering (FCM) with Genetic Algorithms (GA) as GAFCM. The problem i.e. sensitivity towards selection of initial cluster by FCM is solved by using GAFCM and it works well on multiple embedded graphic processing unit systems.
An adaptive k-means approach is used by Moftah H.M. et al. [64], where k-means clustering algorithm is taken along with concept of adaption. The adaption here is an assessment process. An assessment is done after each phase of clustering to compare between the current phase and previously processed phase, so as to proceed accordingly to maintain best results. After the comparison either the current clusters are stored or re-clustering is done. Some texture-based methods, shape-based methods and accuracy are taken as evaluation measures. Their proposed method improves the efficiency of work better than the conventional k-means algorithm. Baracho S.F. et al. [65] have also taken k-means clustering for segmentation along with another segmentation technique called Grabcut method. Rat heart and Human heart photos are taken for myocardial ischemia/infarction detection. The iterative version of the Grabcut method is first applied on acquired image to separate the heart image from background, and then fuzzy k-means clustering is used to segment the ischemia region of the heart. This is then followed by a sequence of image processing techniques including some morphological operations to get the final segmented image. For the purpose of validation of the results accuracy, sensitivity, positive predictivity, Dice coefficient and tracing error were calculated and compared which concludes that an accurate combination of techniques can give an improved result. M.A. Balafar [66] have shed light on many segmentation methods based on fuzzy C-mean for the segmentation of brain MRIs. Comparative evaluations are made on their reported results of experiments. Many more approaches are available using k-means and c-means for the image segmentation[67-74] and in some articles it is mentioned as mostly used technique for segmentation. Apart from FCM another techniques for brain MRI segmentation are discussed by M.A. Balafar et al. [75]. Fusion of different techniques works quite well in many cases though not always in all cases, proving the concept of machine learning ‘no free lunch’. In a proposed work by Cabira I. et al. [76] they have used a fusion of segmentation techniques for detection of brain tumor. Potential Field Segmentation (PFS), Force clustering for seed initialization (FOR) and Potential Field Clustering (PFS) are used for segmentation of image. After that the segmented images from these three techniques are fused by fusion methods. Two fusion techniques are adapted i.e. Fusion through intersection (FSI) and Fusion through Union (UNI) for fusing the segmented results. The comparison results concludes though for many images the fused segmentation is better but in some images a single techniques outperforms better than both the fusion techniques.
Another machine learning technique called Random Forest (RF) is used as a classifier by Zhao B. et al. [77] for Lung vessel segmentation of Computed Tomography (CT) images. Gaussian pyramids and Sparse auto-encoder are used to extract the features of the image, followed by RF for which the extracted features are inputs to perform the segmentation. With these methods segmentation results show better performance as compared to the classical segmentation techniques. Machine Learning techniques like Bayesian Classifier [78-79] and Support Vector Machines [80], [81] are also used for segmentation of different medical images. Juan et al. [82] have proposed a novel Bayesian technique for longitudinal segmentation of hippocampal sub-regions in MRIs of brain. The advantages like robustness and computational efficiency of Bayesian classifier develops a proficient segmentation algorithm.

3. Insights of the review

These following observations can be highlighted from the study:

a) Though thresholding is one of the best methods for image segmentation in many fields, it is not suitable for medical images. Thresholding combined with other methods might give good results.
b) Neural network based methods can be used to achieve robustness towards noise by its huge connection architecture, but the drawback is that sometimes they need prior information about the image to give qualitative performance.
c) Segmentation performance can also be improved by using prior knowledge. Prior information like intensity distribution, information about shape etc can be taken as prior information for the enhancement of the performance.
d) An accurate and appropriate combination of techniques can give improved results in many cases, though sometimes the single technique works well for specific images of concerned domain.

4. Discussion

Different techniques for segmentation of medical images, mainly machine learning techniques highlighting the role of NN are elaborated in this study. Following inferences can draw attention for discussion:
As it is observed from the results that though thresholding is one of the most appropriate technique for image segmentation, it may not be acceptable for complicated medical images. Medical images having a complex image distribution and intensity similarity making themselves unsuitable for segmentation through thresholding. To get rid of this problem soft computing techniques like neural networks, that also comes under machine learning techniques can be used. The non-linear classification boundaries of NN helps better for segmentation of medical images. Specifically the deep architecture of NN behaves more intelligently with adaptive learning, parallelism and robustness towards noise. The spatial arrangement of units of CNN are prime features designed to work with images. The requirement of prior knowledge or additional human effort for feature extraction is not required for classification or segmentation using CNN, as this NN works for both feature extraction and prediction in an integrated way.
When two techniques have different advantages, by combining the techniques a more productive technique can be evolved to get better results. Techniques hybridized together in a perfect way can

give rise to a high performance model that can provide improved outcomes.

5. Conclusions

Applications of different machine learning techniques emphasizing the role of neural network are concisely discussed in this paper. Taking segmentation as a prerequisite for image processing, many techniques are developed. To get improved performance, use of prior knowledge, use of super-pixels, combination of specified techniques or making a hybridized technique may give satisfactory results. The techniques discussed are the mostly used ones for medical image segmentation. Proficiency of ANN is proved to be significant in multiple fields showing its robustness towards noise due to its high complex architecture. Mainly, the CNN works in an amazing way for images having the capacity of simultaneously performing as a feature extractor and classifier. Many advantages of CNN is making it more suitable in this field and further more effective methods could be designed. Lastly, it can be presumed that no one algorithm or technique works well for every data, we have to study and analyze the characteristic of the data and perform experimentation accordingly with techniques to obtain closer to perfect results.

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