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AN OVERVIEW OF THE USE OF MACHINE LEARNING METHODS FOR SEGMENTING MEDICAL IMAGES

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Abstract
As science and technology advance in this digital age, digital imaging is growing quickly across all domains. Through digital image processing, the image is transformed into its digital form and subjected to various procedures that yield either an enhanced version of the image or informational characteristics. Image segmentation plays a key part in the various image processing techniques that are accessible. The main purpose of image segmentation is to distinguish interesting items from backgrounds. There are numerous methods for segmenting images. However, a lot of methods occasionally fall short of producing the intended result. Machine learning techniques are used to meet the need, and they work well and produce satisfactory results. This is a brief overview of machine learning methods, with a particular emphasis on artificial neural networks and their advancements in deep learning and convolution neural networks, as well as some information on other methods. Additionally, it provides brief explanations of a few neural networks that are used to segment various medical images, with an emphasis on convolution neural networks, which were created primarily to work with images. The review will give researchers a visual representation and suggestions for how to use these methods further for improved results for segmenting images.

Keywords: Convolution Neural Network, Deep Learning, Machine Learning, and Image Segmentation

1. Introduction

Since human sight or vision is arguably the most developed sense, images are significant everywhere. These days, taking pictures is quite simple thanks to developing technologies. These picture data are being generated and stored at an ever-increasing rate in a variety of industries, including education, medicine, agriculture, the military, and more. Image processing is necessary to properly identify and sort these data so that they may be readily accessed, used, and interpreted. Image segmentation is one of the core processes in image processing.Segmentation is the process of dividing an image into potentially distinct, homogeneous areas. This is done to make the image easier to analyze and more meaningful for item identification.
In essence, this activity separates the object from the background. Typically, classification

follows the segmentation technique, assigning the separated objects to specific classes. This procedure is considered to be the fundamental component of computer vision. Segmentation is a prerequisite for other image analysis methods, such as image fusion and registration, in addition to classification. Segmentation is a vast area of image processing even though it falls under several basic image processing techniques. Many images' accuracy The accuracy of image segmentation is a prerequisite for analytic methods A mid-level stage in image processing, segmentation takes inputs, which are often images, and outputs, which are attributes taken from the images and subjected to more scrutiny. Preprocessing and post processing are sometimes necessary, while other times they are not. Image segmentation, to use a non-mathematical definition, is the split of images into several sections with comparable characteristics. In the context of medicine, picture data separation to perfect expressive Segmentation, or separating areas that set themselves apart from the background or from other regions, is the process of defining boundaries for sections. Segmentation, as defined mathematically, is the decomposition of a picture into distinct sections or categories that limit the overlap of image portions. The following is one way to state it

As shown in (1) and (2), segmentation is the process of splitting a set A into a set of connected subsets (Sub1, Sub2, Sub3,...,Subn). Let A be the collection of all pixels in a picture.

$$U_{i=1}^{n} S_i = A \qquad (1).$$

And

$$S_i \cap S_j = \emptyset \text{ where } i \neq j \qquad (2)$$

There are several different segmentation methods available, primarily region-, edge-, and threshold-based. Edges that represent local variations in image intensity are the basis for edge-based segmentations. However, these could not be used on pictures with a lot of edges or smooth edges. In the same way, region-based picture segmentation depends on the seed point, from which the region expands by determining whether to add the neighboring pixel's intensity in order to divide the sections. Another name for it is pixel-based segmentation. This method is computationally costly and uses distinct seeds. Points could produce disparate segmentation outcomes, which would be detrimental to segmentation. The combination of edge based and region based approaches transcend their separate lacunas and build a good segmentation approach. The thresholding based segmentation is one of the simplest and extensively used segmentation algorithms Here, the ideal threshold that divides the two classes while increasing inter-class variation and minimizing intra-class variance is calculated. This approach performs well when the image's histogram shows bimodal distributions, but it is unable to handle images with unimodal intensity distributions We may use machine learning techniques, a subfield of

artificial intelligence founded on the notion that it should be able to learn and adapt, to get past all of these. by way of experience. There are several methods used in machine learning, including deep learning, support vector machines, decision trees, clustering, and artificial neural networks. Artificial neural networks (ANN) and its applications in the segmentation of medical images are the primary focus of this discussion.

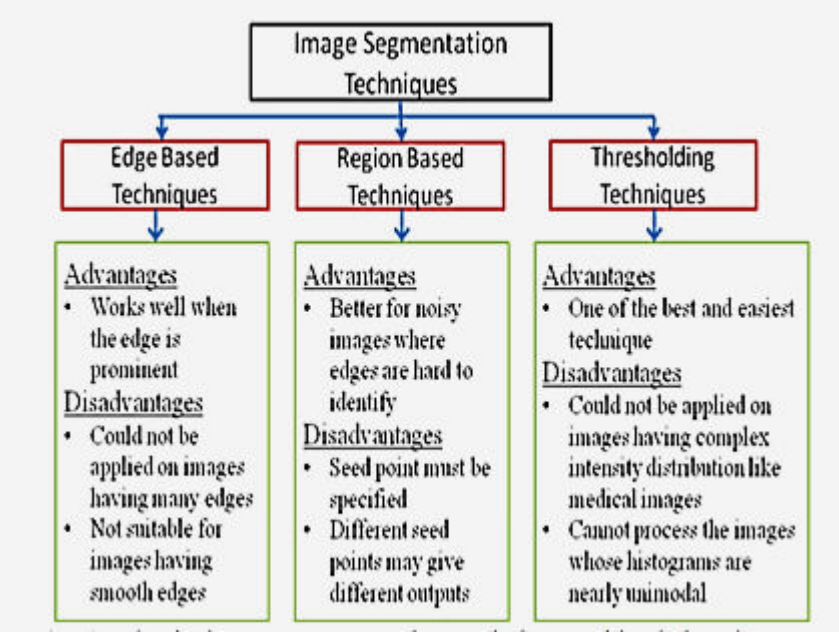

Fig. 1: Benefits and Drawbacks of Traditional Image Segmentation Techniques.

Morphological processes like dilatation, erosion, or interpolation may not be used when looking at biological or medical images specifically, although segmentation is frequently necessary as the initial step prior to analysis for these high content images. Its high intensity distribution methods, such as For optimal outcomes, thresholding might not be appropriate. We can use machine learning methods like artificial neural networks (ANNs), which have numerous uses in practically every industry This is a basic comparison of two ANNs that are highly influential in practically every field: Convolution Neural Networks (CNN) and Deep Neural Networks (DNN). The analytical An analysis of these distinct approaches provides a clear picture of their use, including pros and cons, allowing them to be appropriately applied in particular image segmentation domains.

2. Literature review

The networking algorithm techniques known as NN were created with the idea that the human brain learns from experience and improves performance in proportion. ANNs of many kinds have been used for picture segmentation in numerous applications. Here, we have mostly concentrated on segmentation methods for medical pictures. Kohonen introduced the Self Organizing Map, a kind of unsupervised ANN. Thus, the term "Kohonen network" or "map." Its

operation can be divided into two stages: first, it is taught to create the map using examples, and then it uses mapping to classify fresh inputs. figure 1. Classical image segmentation techniques with their advantages and disadvantages A neural network-based approach for medical image segmentation is presented in [1],

where a modified Self-Organizing Map (SOM) network called Moving Average Medical image segmentation is done using SOM (MA-SOM), which is compared to a standard SOM network. The study makes use of a dataset that includes 30 breast ultrasound (BUS) images, 10 brain magnetic resonance imaging (MRI) images, and one computerized tomography (CT) head image. To construct the input feature space for the network, a two-dimensional Discrete Wavelet Transform (DWT) is employed. The network's filtering feature significantly lowers image noise. The Tanimoto, Rogers, and Jaccard indices demonstrate the accuracy of the suggested approach when compared to the SOM-based network method.

SOM was utilized [2] to segment real brain MRI images that were gathered from the Internet Brain Segmentation Repository (IBSR). They employ Vector Quantization (VQ) for the SOM network and segmentation job in their work. Adaptively carries out codebook learning for VQ-based picture segmentation since the VQ approach requires codebook learning. Additionally, employed the IBSR data and used the SOM network for segmentation. A Growing Hierarchical SOM (GHSOM), which may create a SOM hierarchy, is employed. To regulate the quantization, the hierarchy and map's depth and breadth are adjusted to the input data mistake. Performance is improved by GHSOM's finding of a hierarchical relationship between the data. have segmented images using SOM networks and expectation-maximization (EM) techniques [3], which were followed by feature extraction and classification techniques that produced positive results. SOM

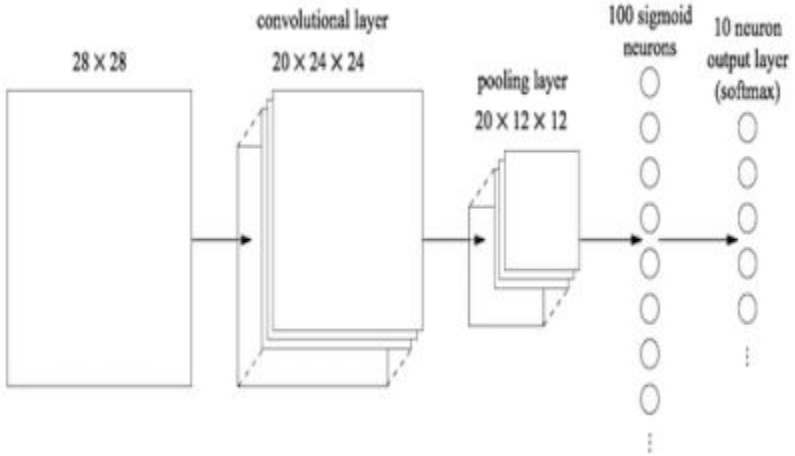

Figure 2: Convolutional Neural Network Architecture.

is employed for data segmentation other than medical data Numerous image processing domains also make use of a different kind of neural network known as the Pulse Coupled Neural Network (PCNN). Johnson et al. created PCNN, a single-layered, two-dimensional artificial neural network, based on the visual brain of cats. Each neuron in this network represents one the input image's pixel. It is primarily composed of three parts: the pulse generator, the connection portion, and the input part. Through feeding and linking connections that work together to create an internal activation system, PCNN takes input stimuli. It then accumulates these stimuli until they surpass a dynamic threshold, producing a pulse output. PCNN neurons generate a temporal series of pulse outputs through iterative computation that contain input image information for use in a variety of image processing applications. In all neural networks, determining the parameter values is a trivial and inevitable process that has a major impact on the model's performance [4-5].

In order to improve the segmentation outcome,[6] used a modified PCNN in which a new neural threshold is taken into consideration despite the general dynamic threshold. Better segmentation performance is provided by the suggested model when compared to a simplified PCNN. [7] have employed simplified PCNN with The 2D-Otsu Algorithm for retinal image segmentation is particularly effective for images with low contrast and tiny vasculature. Another study by [8] PCNN is used along with by streamlining the network parameters for multichannel picture segmentation, the Canny operator edge detection approach is achieved. [9] developed a parameter adaptable PCNN that is used on mammograms, MRIs, and ultrasound pictures to increase segmentation accuracy. For brain MRIs, [10]. have developed a 3D PCNN based on the 2D PCNN. Despite its computational complexity, it is noise-resistant and provides a extremely little loss of accuracy for extremely noisy data, motivated improved simplified pulse clustered neural network (SM-ISPCNN) is a simplified PCNN for object segmentation that combines the principle of saliency detection. The network is employed to segment mammograms in order to diagnose breast cancer demonstrating tremendous robustness and outstanding segmentation capabilities. Simply put, a deep neural network (DNN) is a stack of neural networks, or alternatively, a feed forward artificial neural network (ANN) with several hidden layers. 'Deep' refers to a network that has more than three layers, including input and output layers. In this context, "deep" is a carefully defined technical term that denotes multiple buried layers. The difference between standard NN and Deep NN is the depth of layers.Each layer of nodes processes distinct feature sets as the output of the layer before it, enabling it to handle increasingly intricate, substantial, and high dimensional datasets that go through nonlinear functions with billions of parameters [11-13].

A type of deep feedforward artificial neural network (ANN) called a convolutional neural network (CNN) has a unique multilayer design that is specifically tailored for image classification. Another way to characterize it is as a deep multilayer perception network [14]. In essence, it makes use of pooling, shared weight, bias, and local perception field. CNN interprets the input as a square matrix that corresponds to the pixel values of the input image, whereas fully

connected neural networks represent the input as a vertical line of neurons. taken straight away. Each neuron in the hidden layer is linked to a small, specific area of the input image, meaning that these neurons are connected to every other neuron in the hidden layer.The local receptive field for the linked hidden neuron is that area of the input image. The local receptive field is then moved over the whole input image that generates the entire hidden layer matrix, beginning in the upper-left corner and ending with one pixel at the right. Every node in the hidden layer has a bias, and every connection between hidden layer neurons and input neurons has a weight. The complete hidden neuron matrix uses the same weight and bias, which is referred to as shared weight and bias.

By using local connectivity and weight sharing, or the local features in every area of the input image, the convolutional layers produce feature maps. The identical feature is detected by every neuron in the first hidden layer. The weight sharing rule significantly lowers the number of parameters, which raises the efficiency and keeps over-fitting from happening. There could be numerous feature maps on a CNN. Finally, to decrease the amount of features and hence the network's dimensionality, pooling is applied independently to each feature map.While the output layer is a 1-D layer, the convolution and pooling layers are thought of as 2-D layers. Each 2-D layer in this case comprises many planes, each of which is made up of neurons arranged in a 2-D array. One label per node is then produced from the decreased pooling layers. To obtain the desired output, this one-dimensional input is now fed into a basic neural network
Following are some advantages of CNN along with NN which make it more suitable for image analysis -

1)Neural networks with a deep architecture—that is, with more hidden layers—produce more intelligent and efficient results. Neural networks are better suited for a wide range of applications because to their adaptive learning, parallelism, fault tolerance, and generalization features.

2)The main feature of CNN that makes it appropriate for processing visual information is the spatial arrangement of its elements
3)Prediction benefits from local connectivity, parameter sharing, and hidden unit pooling.
4) CNN is a fully adaptable network that combines feature extraction and classification into a single structure.
5) At increasing dyadic scales, the network collects information from 2-dimensional images.
6) It is comparatively unaffected by local geometric imperfections and picture noise.
7) Medical image data segmentation is aided by the nonlinear classification boundaries that are acquired during neural network training [15].

A condition known as a tumor can develop anywhere and in any shape or size. Machine learning's adaptability provides a platform to address several challenges like this one. In order to segment brain MRIs, [16] employ the Deep Neural Network (DNN). An effective graphic

processing unit and the network's convolutional architecture produce a quick segmentation system that takes advantage of the image's local and global properties. To address the challenges posed by the imbalance of tumor labeling, a two-phase training process is employed. CNN is constructed with a hybrid or cascaded architecture, in which the output of the first network serves as an additional source for the network that follows.CNN is utilized by P. Sergio et al. to segregate gliomas from brain MRIs. [17] following segmentation, the BRATS 2013 and BRATS 2015 datasets undergo some post processing following preprocessing for intensity normalization. For the assessment of measures such as the Dice Similarity Coefficient (DSC) for segmentation techniques, Sensitivity and Positive Predictive Value (PSV) are taken into account. Similarly, a novel dynamic CNN approach is taken into consideration for the segmentation of the fetal left ventricle in echocardiographic sequences in another study. Clinical research and disease diagnostics use semantic segmentation of medical images.

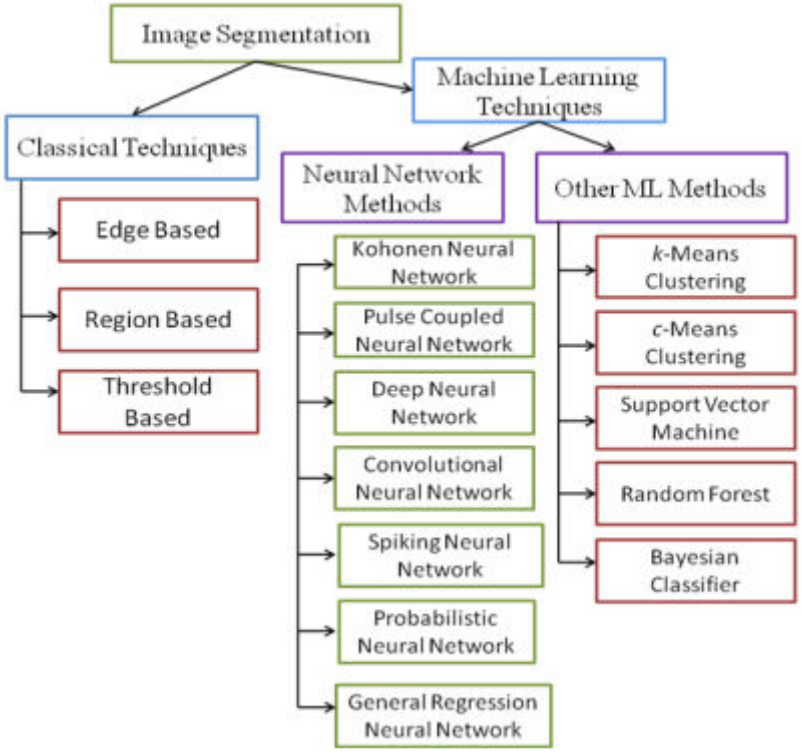

Figure 3: A Taxonomy of Image Segmentation Methods

For retinal blood vessel segmentation CNN was used by Liskowski P. et al. [47], demonstrating that deep neural networks are indeed appropriate for medical imaging and a variety of other applications. Initialization of Xavier is employed for rectification non-linearity network initialization.and optimization by stochastic gradient descent. Sadikolu F. and Uzelaltinbulat S. [56] also employ a simple feed-forward neural network with a backpropagation algorithm for training in biometric retinal identification. To extract the features and provide them to the

network for retinal image recognition, sophisticated pre-processing and feature extraction are carried out. Tan J.H. and associates [57] have segmented the optic disc, fovea, and retinal vasculature from fundus pictures using a 7-layer CNN. Despite having a lower specificity, this approach provides good accuracy and sensitivity. In a different paper by Zeng Z. and colleagues [58]A MultiTarget Deep Neural Network (MT-DNN) is suggested, in which the network is used to three distinct targets: masks, regression, and classification. There is only one model made for This serves several uses. The study demonstrates the DNN's enormous potential and usefulness.

Thus, a variety of neural network types are employed to successfully segment medical images. For many image analysis applications, machine learning methods other than neural networks are also employed. A few of these are listed below:

Through segmentation using clustering algorithms, various brain anatomical structures and MRI measurements can be properly visualized. Fuzzy C-Means clustering (FCM) using Genetic Algorithms (GA) was employed by Hung C. L. et al. [63]. as GAFCM. GAFCM solves the issue of sensitivity to FCM's initial cluster selection, and it functions effectively on a variety of embedded graphics processing unit platforms.Moftah H.M. et al. [64] employ an adaptive k-means technique, in which the idea of adaptation is combined with the k-means clustering algorithm. This adaptation is an evaluation procedure. Following each clustering process, an evaluation is conducted to compare between the present phase and the phase that has already been processed, in order to go on appropriately and preserve the best outcomes. Following the comparison, either re-clustering or the storage of the existing clusters are carried out. Accuracy, shape-based techniques, and some texture-based techniques are used as evaluation metrics. Their suggested approach outperforms the traditional k-means algorithm in terms of work efficiency. Additionally, Baracho S.F. et al. [65] used k-means clustering for segmentation in conjunction with another segmentation method known as Grabcut technique. Photographs of the human and rat hearts are taken in order to detect myocardial ischemia or infarction. The heart image is initially separated from the backdrop using the iterative Grabcut method, and the ischemic zone of the heart is then segmented using fuzzy k-means clustering. The final segmented image is then obtained by a series of image processing methods, including certain morphological procedures.Accuracy, sensitivity, positive predictivity, Dice coefficient, and tracing error were computed and compared for the goal of validating the results. The results indicate that a precise combination of procedures can produce a better outcome. There are numerous other methods for segmenting images that use k-means and c-means [67–74], and in certain sources, they are mentioned as the most popular segmentation technique. M.A. Balafar et al. discuss several methods for brain MRI segmentation in addition to FCM. [75] Combining many approaches often yields good results, but not always, demonstrating that machine learning is a "no free lunch" idea. In their proposed work, Cabira I. et al. [76] have combined segmentation methods for brain tumor identification. Images are segmented using Potential Field Segmentation (PFS), Force Clustering for Seed Initialization (FOR), and Potential Field Segmentation (PFS). The

segmented photos from these three were then Fusion methods combine several techniques. To fuse the segmented findings, two fusion techniques—Fusion through intersection (FSI) and Fusion through Union (UNI)—are modified. The comparison results show that while fused segmentation performs better for many photos, in some images, one strategy performs better than both fusion strategies.

3. Discussion

This paper explains many methods for medical image segmentation, mostly machine learning methods emphasizing the function of NN. The following conclusions may spark conversation:

As can be seen from the findings, thresholding is one of the best methods for segmenting photos, however it might not work well for complex medical images. Complex picture distribution and intensity similarity in medical images rendering them inappropriate for thresholding-based segmentation. Neural networks, which fall under the category of machine learning techniques, are one example of a soft computing technology that can be utilized to solve this issue. Medical picture segmentation is improved by the non-linear classification bounds of NN. In particular, the deep architecture of NN exhibits more intelligent behavior with parallelism, adaptive learning, and noise resilience. One of CNN's key advantages for working with images is the spatial organization of its units. Classification or segmentation with CNN eliminates the need for prior knowledge or additional human labor for feature extraction because this neural network (NN) integrates feature extraction and prediction.

When two methods have distinct benefits, they might be combined to create a more effective method that produces superior outcomes. Methods that have been perfectly hybridized can create a high-performance model capable of producing better results.

4. Conclusions

In this paper, applications of several machine learning approaches that highlight the function of neural networks are succinctly discussed. Numerous methods are created with segmentation as a requirement for image processing. To achieve better results, make use of Using super-pixels, combining specific techniques, existing knowledge, or creating a hybridized methodology can all produce outcomes that are suitable. The methods covered are the most used ones for segmenting medical images. Because of its extremely complicated architecture, ANN proficiency has been demonstrated to be significant in a variety of disciplines, demonstrating its resilience to noise. In general, CNN performs remarkably well on images that can function as both a feature extractor and a classifier at the same time. Numerous benefits of CNN is making it more appropriate for this industry, and more efficient techniques may be developed in the future. Last but not least, it may be assumed that no single algorithm or approach works well for all data; in order to get

closer to ideal outcomes, we must examine and assess the characteristics of the data and conduct experiments with techniques appropriately.

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