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A Survey on Various Segmentation methods for Medical Image Processing

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***Abstract*— With extensive research on image segmentation, there is always opportunity for improvement. Digital image processing's subfield of medical image segmentation contains many medical image analysis and diagnosis approaches. A technique named image segmentation partitions an image into distinct components. The quality of the image (brightness, contrast, and texture) needs to be enhanced in order to improve on the segmented image of the tumour. The region of interest of an image is highlighted in segmentation. Present study observes the performance of several algorithms for diverse images and categorizes different medical image segmentation techniques, along with their subfields and submethods. In this paper very recent existing segmentation strategies are reviewed, and compared.**

Keywords*— Classifiers, Clustering, Modalities, Deep learning, Bayesian approach and Thresholding.

1. Introduction

Segmentation divides an image into smaller segments depending on a given attribute. It allows you to search for a particular section of the image. Segmentation is a method that has several applications in the medical profession. Much effort has been made to overcome the challenges that develop during the segmentation process. As part of the segmentation process, the information required to do so depends on how the issue will be employed in the current world. The purpose of segmentation is to make it simpler for individuals to find what they are searching for, allowing them to do it more quickly and efficiently. As seen in Fig.1, there are other reasons why medical images must be separated. Analyzing the functions of anatomical issues is accomplished by breaking them down. It considers all factors that might influence how an illness is studied. Segmentation is a method of looking at, diagnosing, counting, monitoring, and planning how to avoid disease.

Making alterations in anatomical or pathological features more evident in images is known as segmentation. Because it enhances diagnostic speed and accuracy, it is often employed in computer-aided diagnostics and intelligent medicine. Some of the most popular medical image segmentation jobs are as follows: Segmentation of the brain and brain tumours, the optic disc, the cell, and so forth. It is due to the increased availability and use of imaging technologies in medicine. In medical facilities, X-rays, computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound are the four primary image-assisted procedures. to assist physicians in diagnosing and planning procedures [1-3]. Because these imaging modalities have both advantages and disadvantages, they may be employed to examine various human body regions for medical purposes.

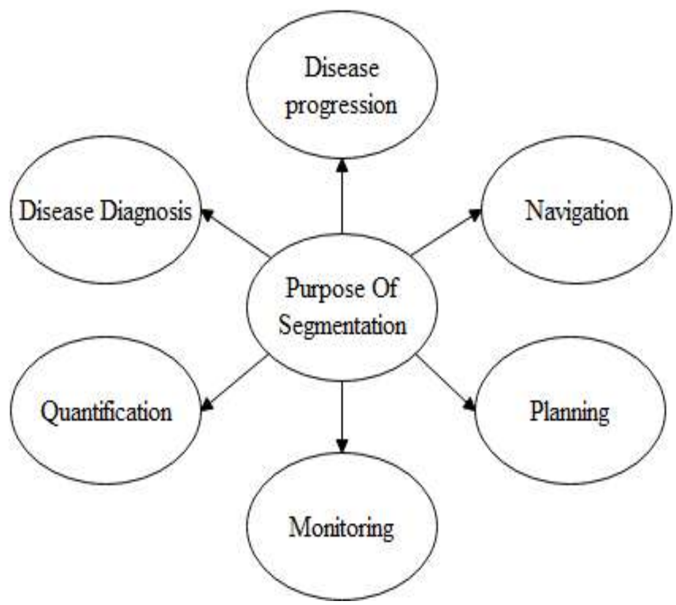

Fig. 1 A typical diagram demonstrating the goal of segmentation

A. Modalities for Medical Image Segmentation

Segmentation is implemented in the medical sector in a number of distinct scenarios. The segmentation procedure manages a wide range of medical conditions. Figure 2 depicts these modes. This section will summarize medical modalities and discuss these modalities in the context of reconstruction. While provides a complete examination of these modalities. Similarly, we discuss how to improve these modalities [4].

1) MRI

The majority of medical research is based on MRI brain imaging. Because these images must be enhanced and segmented o discover the area of interest. The fact that these images have such a wide range of resolutions is another problem, making it difficult to separate the image with the appropriate amount of contrast [4]. The primary uses in this field include determining the size of the brain, distinguishing distinct substances in grey and white matters, cerebrospinal fluid, and determining particular brain structures.

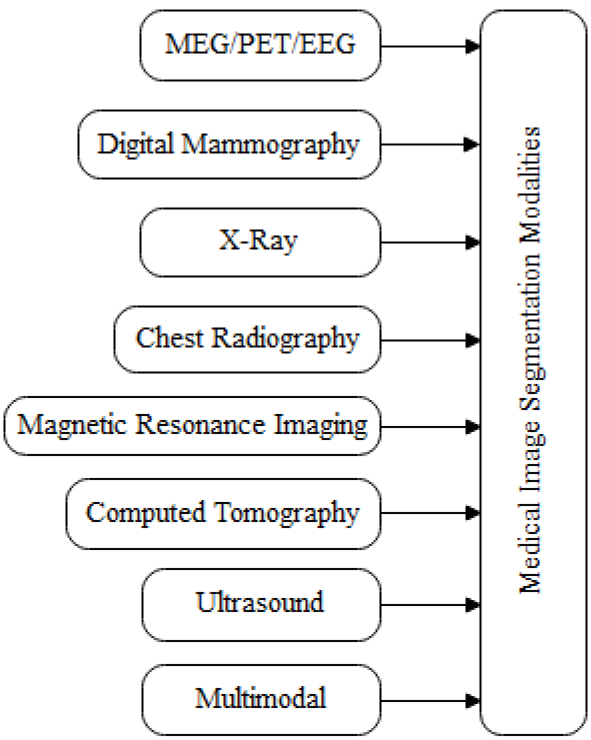

Fig. 2 Medical Image Segmentation Modalities

2) CT Scan

The segmentation method has several uses in computed tomography image processing. The segmentation procedure is mainly used in this instance to review images of the liver, brain, stomach, bones, and hearts [4]. They lack the MRI pictures' contrast and resolution, although they are superior to these images. There are several methods for segmenting CT scans.

3) Ultrasound

Ultrasound scans often feature many defects, making it difficult to determine where the region of interest is. As a result, numerous strategies for breaking apart ultrasound images failed miserably. It is not the first time something like this has been done. Manual segmentation is used the majority of the time. These images are also utilized to determine the amount of mobility and to search for disease using textural classifiers [4].

4) Multimodal

In this situation, many procedures are used concurrently to determine what is wrong. The information obtained from various sources narrows down a particular area of interest. Some individuals struggle with this mode since getting data from many sources might be difficult. Another issue is that they must typically be aligned [4].

5) Digital Mammography

The basic approach to discovering various tumors in digital mammography is to break the images into pieces. Methods for dividing a mammogram into sections are often based on several means of creating a threshold [5].

6) Chest Radiography

A radiograph is obtained in chest radiography to examine or determine what is wrong with the chest region and its structure [5].

This is way the paper is laid out: Section-II outlines the different strategies. for improvement of medical images. Sections-III shows the analysis and discussion of various medical image segmentation methods. Lastly Conclusions are shown in Section-IV.

2. METHODOLOGIES

Various approaches for the improvement of medical images are discussed in this section. Segmentation methods are classified into six types: methods based on thresholding, regions, edges, clusters, classifiers, and other techniques. There are additional ways for image segmentation as well. Fig. 3, depicts the various image segmentation methods.

A. Thresholding based

1) Gray-level thresholding: An excellent a demonstration of a method that employs a component of thresholding-based picture segmentation is grey-level thresholding. An input image in their paper may be grayscale or coloured, and it can be either. After that, the image is separated into segments that are all the same size and position. histogram of intensity is created for every section of the image. It is used in the creation of local segmentations. Information from its neighbours may assist in discovering clusters that may not have adequate local support since the image was divided into pieces [6].

2) Otsus method: Otsu discovered that this thresholding approach is based on a reasonably basic idea: determining which threshold is least likely to cause the weighted within-class variance to change. Ostu employed a method that automatically converted a grayscale image into a binary image by adjusting the threshold to make things simpler for threshold-based approaches [6].

3) Gaussian Mixture method: A technique is called Gaussian mixture image segmentation. for calculating the quantity of components in an image without starting from scratch[6]. The method starts with a single mixing component that encompasses the entire data set.. As the expectation maximisation processes are completed, they are divided into smaller pieces. This Gaussian mixing approach is accurate after several experiments.

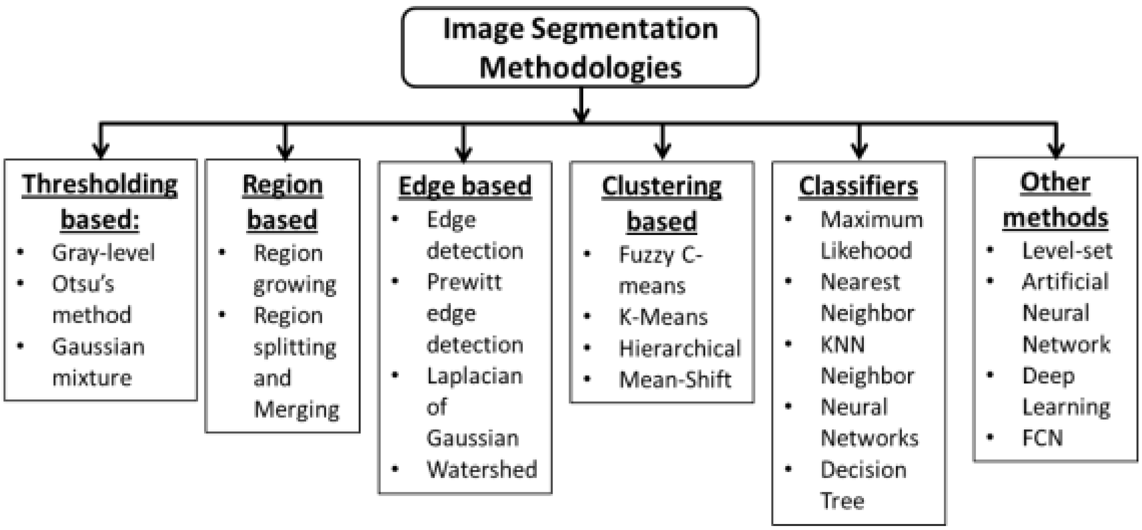

Fig. 3 Various Image Segmentation Methodologies

B. Region based

1) Region growing: Cootes and Taylor demonstrated that the region growth approach might be used by adding an offset and scaling to ensure that all grey values have the same mean and variance. Instead of dealing with intensities, Cootes and Taylor devised a method for storing the gradients' direction and strength, projected non-linearly. This approach was proven to be superior to the normalised intensity method, which was previously utilised. The second technique was particularly beneficial when the images had a non-Gaussian distribution, such as ultrasound scans [7].

2) Region Splitting and Merging: The region-based approach has widely recognised the process of area splitting and merging. This approach combines splitting and combining. This experiment showed that split-and-merge techniques could be applied to 2D and 3D MRI with similar outcomes in different orientations. Simulated annealing and boundary removal may also improve 3D or 2D MRI, and it takes less time to execute the segmentation process.

C. Edge based

1) Edge detection: Edge detection is the technique of locating and detecting sharp edges in an image. Edge detection is critical for recognising human organs in medical imaging since it aids in their identification. The edge of the lung CT picture with salt-and-pepper noise is suggested to be identified using a special mathematical morphological edge detection.The suggested approach is more efficient than the current method in both cases

2) Prewitt Edge detection: According to the Prewitt, edge detector is an excellent approach to determining the size and direction of an edge. Compass edge detection rapidly exposes the kernel with the most potent reaction because differential gradient edge detection takes a long time to identify the orientation from magnitudes in the x and y axes. The Prewitt operator can only choose from eight different orientations. However, experiments show that the majority of direct orientation computations are not accurate. The (3x3) neighbourhood edges are estimated in this gradient-based edge detector in eight different orientations. Convolution masks have been created for all eight. The most extensive module of one of the convolution masks is then

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selected. In this experiment, the Prewitt detector performs well in determining where the edges are [8].

3) Laplacian of Gaussian: First, in 1980, Marr and Hildreth utilised Gaussian filtering with the Laplacian approach to creating a Gaussian Laplacian. When it comes to machine vision, this algorithm is seldom employed.

4) Watershed: Watershed is an image segmentation technique developed.It aids in the separation of items that are close together. They claimed to be able to split apart images using mathematical morphology. The paper's purpose is to prevent having too many separate pieces. This strategy used two tools: watershed transformation and homotopy modification. Several experiments and favourable findings were appended to a paper authored by the author [9].

D. Clusteringbased

For medical image segmentation, two basic clustering techniques are often used.

1) Fuzzy C-means clustering method: Bezdek developed the fuzzy c-means method. It is the image segmentation technique that has been studied and used the most since it is straightforward to use and can extract more data from photos. Both spatial and grey-level local information can be used with the fuzzy local information c-means (FLICM) technique, and none of the parameters need to be altered. (except for the number of clusters) [10].

2) K-means clustering method: K-means is a method for determining how many members in a group have the same number of friends. The Clustering Method divides a given collection of data into a fixed number of groupings known as "K-clusters." When the k-means method is used to divide all features into n groups, each point is assigned to the cluster with the most features from that spot [10]. There is just one cluster to compare the characteristics obtained at each study milestone with..

3) Hierarchial clustering: It is one of the edge-based approaches. Hierarchical clustering to determine the degree of connection in a functional MRI. This approach can explore patterns in low-frequency oscillations, and the findings demonstrate that functional connectivity patterns may be identified using hierarchical clustering that looks like neural connections [10].

4) Mean-Shift: This mean-shift method to split an image is to discover the sites in feature space with the highest local density. Grayscale or color information and each pixel's coordinates are contained in feature vectors for each pixel.

E. Classifiers

This technique for classifying images involves extracting features from the image. Depending on the purpose stated in the feature space, this feature space is then partitioned into numerous parts. It implies that a feature space may be named since it encompasses the whole range of a classification function. Classifiers operate based on pattern recognition. The data in this instance has been trained, which means it's been manually broken apart and then utilized for the automated process [7]. Fig. 4 shows the division of classifiers.

1) Maximum Like Hood: Because of its low error rate, ML is the least risk approach and may provide the most significant outcomes. The approach states that the probability of features must be precisely known for the range of features in the feature space. The approach is not particularly helpful because reliable information is hard to get.

2) Nearest Neighbor:It is not a numerically based approach. The method operates by categorising items using all of the data that has been trained. The most important drawback of this approach is how long it takes to identify items.

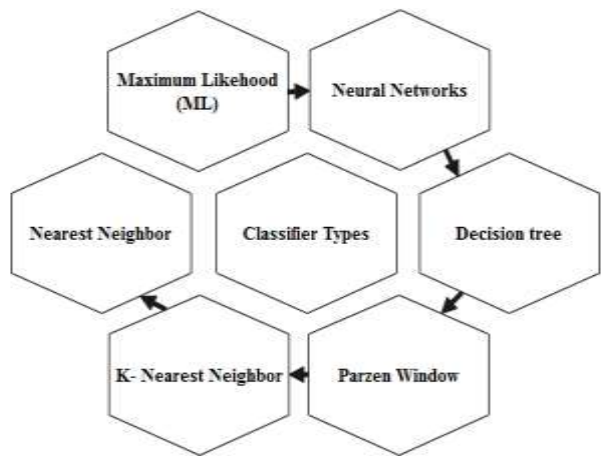

Fig. 4 Types of Classifiers

3) K Nearest Neighbor: It is not a numerically based approach. The method involves arranging k points in a feature space that is jam-packed with objects in clusters.. These are essentially the centres of the first groupings. After the points are established, each item is placed in the cluster with the same centre point. Once the groups are assigned, each k-point moves again. Until the centroids stop moving, this technique is repeated. Repeating this creates a measure that may determine how many distinct groupings of items exist. The fundamental advantage of this strategy is that it does not need any training or trust in the outcome [11-12].

4) Neural Networks: Several kinds of neural networks exist for learning a multilayer perceptron, a kind of supervised network [13]. But classifying may be done fast.

5) Decision Tree: The Decision Tree Classifier is a simple approach to categorise objects. It is also widely used. The decision tree classifier may be shown laying out a sequence of questions and answers in the form of a tree. The decision tree's root and nodes are areas where you may distinguish evidence that is distinct from other evidence.

F. Other Methods

Level-Set method: Here a shape representation is used with regional characteristics or on the edges. They added a term to the original energy calculation that modifies the contour's shape to fit a previously known shape model. The signed distance maps used in the shape model, according to some, do not create a linear space. which may cause the shapes to be incorrect if the training samples do not match up properly. Method for converting signed distance maps into linear Log Odds space, which might help in modeling. The conceptual contrasts between the discrete models they meant to focus on and the implicit representation would have required more work in the following sections. [10].

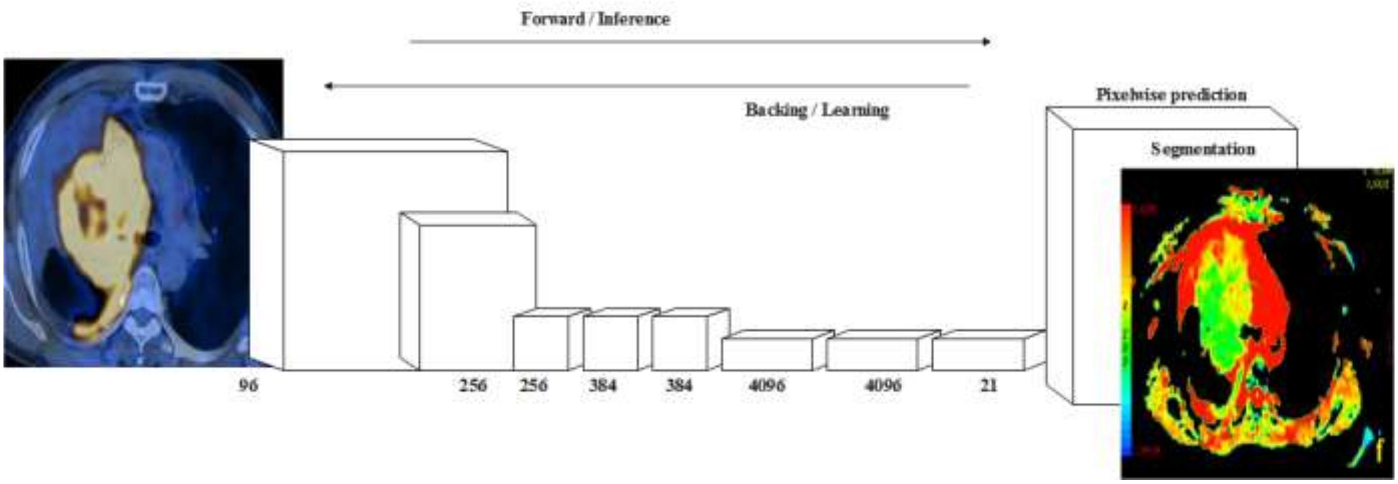

Fig. 5 Basic Structures of Fully Convolutional Networks (FCN)

1) Artificial Neural Network: Veeramuthu [13] researched how ANNs may be used to split things up. ANN is widely utilised in image processing. To determine the crucial portions of an image, Kohonen's Self-Organizing Maps (SOM) from an ANN and a GA (Genetic Algorithm) were used.. People are interested in how SOM interacts with GA, such as Variable Structure SOM (VSSOM) and Parameter-Free SOM (PLSOM) function. VSSOM and PLSOM are merged to provide a novel unsupervised approach with no parameters. The improved PLSOM turns out to be more efficient than previous approaches. It also takes less time than other approaches to segmenting data.

2) Deep Learning: Convolutional neural networks are excellent at extracting and expressing features while doing image segmentation. It doesn't require you to manually choose image characteristics or conduct a lot of image editing. In recent years, CNN has been used for medical image segmentation. With the aid of diagnostics, it has had a great deal of success in the field. [13-14]. In this section, existing deep-learning-based medical image segmentation algorithms are categorised into three groups: FCN, U-Net, and GAN. This section also covers prior classic research findings. These three groupings are as follows: Each category is presented individually.

3) Fully Convolutional Neural Networks: For semantic segmentation, the most effective and complex deep learning technique FCN, is the result of a pioneering effort. The benefits and drawbacks of FCN networks are discussed in this section. The versions of FCN and their uses are discussed.

4) Fully Convolutional Networks: There are fully connected layers after general-purpose CNNs like VGG and ResNet. After the softmax layer, the probability data for each category can be obtained. However, this probability data is just 1-D. It indicates that only the category of the entire image may be determined, not the category of each individual pixel. As a result, this completely linked technique is ineffective for dividing a image into sections. Lei et al. [14] devised the fully convolutional network to address the abovementioned issues. Convolutional layers normally make up the first five layers of a CNN, but not the final layers. Each of the sixth and seventh levels is 4096 pixels long (one-dimensional vector). There is a completely linked layer with a length of 1000 in the eighth layer, which corresponds to the likelihood of 1000 distinct occurrences happening. FCN creates convolution layers using kernel sizes of 7 x 7, 1 x 1, and 1 x 1 out of the three layers from layer 5 to layer 7, allowing each pixel to be shown in two dimensions. The information about each pixel is then obtained by sending the data via a softmax layer. There is no longer an issue with segmentation. Given its ability to accept images of any size, the fully convolutional network can assess images of any size. The deconvolution layer is used for upsampling the feature map of the previous convolution layer and returning it to the same size as the image it came from, allowing it to be reused. Given its ability to accept images of any size, the fully convolutional network can assess images of any size.Since the spatial information from the original image is preserved, a forecast may be generated for each pixel, allowing each pixel to be expected. Finally, the image segmentation is completed by classifying the upsampled feature map pixel by pixel. Upsampling kinds include FCN-32s, FCN-16s, and FCN-8s. Fig. 5 depicts how the FCN operates.

3. ANALYSIS AND DISCUSSIONS

As the search and development process for medical image segmentation progresses, more effective and efficient methods were discovered and implemented.
This notion may be understood by looking at how methods are categorised by generation. Approaches that are used in this way are broken down into three generations, 1st, 2nd, and 3rd, as shown in Figure 6.

Methods for segmenting medical images may be divided into categories to see how the field has developed and progressed. This grouping will demonstrate how much research and development has been conducted in this field. Because the initial generation of approaches does not need much information to process the image, they are referred to as low-level techniques. It took some time for new and improved ways to emerge. The methodologies of the second generation include optimization, imaging, and uncertainty models. Third-generation approaches rely heavily on prior knowledge about the image and need professionals to create models and criteria for image classification.

Table I, presents the comparison of various medical image segmentation methods and will assist better in determining the best course of action in a given situation.

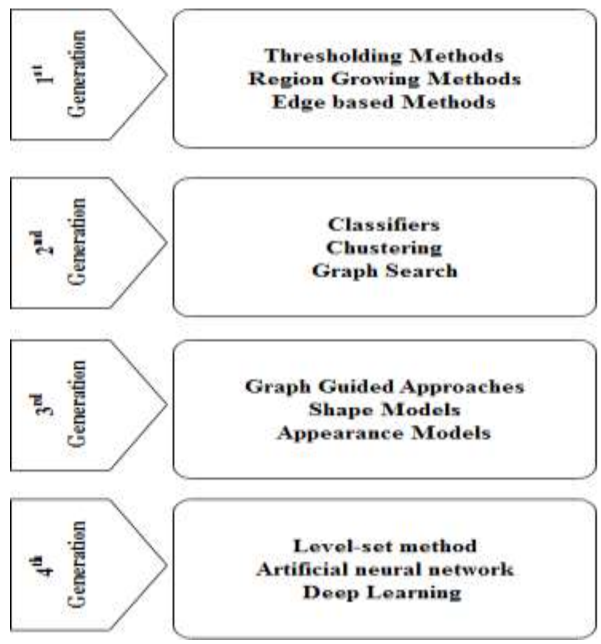

Fig. 6 Generations of medical segmentation approaches

TABLE I. COMPARISON OF VARIOUS MEDICAL IMGAE SEGMENTAION METHODS

S.No.	Method	Pros	Cons	Application	Memory
1	Thresholding	These approaches are the quickest, simplest, and most straightforward to apply.	Some of these strategies effectively pay attention to details, but they do not ensure piecewise continuity.	They are most often employed in structures with varying intensity allocations.	Fastest
2	Region Growing	These approaches provide piecewise continuity while being less susceptible to noise.	These approaches have a few flaws, the most notable being the start point and blurring effects.	They work well with structures that have much contrast between them.	Fastest
3	Clustering	These solutions are simple to adopt and may also serve	They need a specific amount of room to function properly.	They mainly deal with MR images and cannot handle CT scans.	Medium

		as a springboard for further approaches.			
4	Classifiers	Approaches are most often employed in the segmentation process.	They are quite intricate and require a long time to complete.	These tools work nicely with images from MRI and CT scans.	Slow
5	Bayesian method	It helps to merge previously known knowledge with the provided data and provides a suitable scenario for various models.	It does not provide adequate methods for determining a prior, and it uses posterior distributions that are very reliant on the prior.	These are often used to solve verification difficulties.	Fastest
6	Deformable Methods	They provide piecewise continuity and are adept at handling topological changes. These methods offer sub-pixel precision and are noise-free.	It is necessary to specify settings, which may slow down the system's pace.	It works best if the image has statistical information about its origin.	Medium
7	Atlas guided Approaches	These methods work as indicated and offer the finest solution for two-class segmentation.	It is difficult to partition a complicated composition precisely on your own.	They are primarily used to examine MRI.	Slow
8	Edge-based techniques	They offer an effective computational component and are easy to deploy.	Trying to tackle all types of issues is a bad concept.	It can be used to split medical images in a variety of ways.	Fastest
9	Compression based methods	They have the benefit of requiring less storage space.	These approaches are time-consuming.	These techniques are typically used to examine MR and CT images.	Medium
10	Deep learning Networks	Deep learning provides several benefits in terms of segmentation accuracy and speed.	Design Complexity is much high	These techniques are typically used to examine MR and CT images.	Fastest

TABLE II. INFORMATION REGARDING VARIOUS MEDICAL IMAGE DATA SETS FOR SEGMENTATION

S.No.	Data Set	Modalities	Objects	URL
1	MSD	MRI,CT	Various	http://medicaldecathlon.com/
2	BRAgfTS	MRI	Brain	https://www.med.upenn.edu/sbia/brats2018/data.html
3	DDSM	Mammography	Breast	http://www.eng.usf.edu/cvprg/Mammography/Database.html
4	ISLES	MRI	Brain	http://www.isles-challenge.org/
5	LiTS	CT	Liver	https://competitions.codalab.org/competitions/17094
6	PROMISE12	MRI	Prostate	https://promise12.grand-challenge.org/
7	LIDC-IDRI	CT	Lung	https://wiki.cancerimagingarchive.net/display/Public/LIDC-IDRI
8	OASIS	MRI,PET	Brain	https://www.oasis-brains.org/
9	DRIVE	Funduscopy	Eye	https://drive.grand-challenge.org/

10	STARE	Funduscopy	Eye	http://homes.esat.kuleuven.be/~mblaschk/projects/retina/
11	CHASEDB1	Funduscopy	Eye	https://blogs.kingston.ac.uk/retinal/chasedb1/
12	MIAS	X-ray	Breast	https://www.repository.cam.ac.uk/handle/1810/250394?show=full
13	SCD	MRI	Cardiac	http://www.cardiacatlas.org/studies/
14	SKI10	MRI	Knee	http://www.ski10.org/
15	HVSMR2018	CMR	Heart	http://segchd.csail.mit.edu/

Table II, gives a short explanation and a list of publicly accessible datasets for medical image segmentation. Images of benchmark datasets are also available.

4. CONCLUSION

This work presented in this article investigated the current image segmentation algorithms and its importance. The scope of this work is to include digital watermarking in medical images. It is not feasible to employ all image segmentation algorithms simultaneously. This document may be used as a reference. However, image segmentation has significant limitations in digital watermarking for medical photographs. When it comes to essential things like recognizing tumors in medical imaging, the segmentation quality is still the most critical factor to consider. To improve the accuracy and speed of picture segmentation for digital watermarking in medical imaging, work on these topics must be done in the future.

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