Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606

Volume 05 Issue 01
2023

*Review Article*
https://doi.org/10.56979/501/2023

# A Methodical Review on the Segmentation Types and Techniques of Medical Images

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**Received:** February 17, 2023 **Accepted:** May 30, 2023 **Published:** June 05, 2023.

**Abstract:** Medical specialty records and imaging knowledge are two types of medical expertise combined in medical image processing. Imaging modalities generate pixels that depict an entity's surroundings to comprehend medical images. Determining the value of medical image knowledge approaches for analyzing and diagnosing a specific ailment can be challenging. Image segmentation is critical in computer-aided diagnosis and poses considerable difficulty for image analysis techniques. Using image processing, pattern recognition, classification outcomes, and the verification of picture segmentation allows for extracting valuable clinical information. Identifying the human body sections affected by the disease is the primary objective of medical picture segmentation, in addition to being entirely accurate. This study examined the most contemporary imaging techniques and picture segmentation strategies to diagnose disorders in the human body.

**Keywords:** Image Modalities; OCT Images; X-Ray; Medical Image Segmentation; Segmentation Techniques; Disease Diagnosing.

## 1. Introduction

An IP, or image processing, is a field that deals with input and output images, such as still images or video frames. Traditional signal processing methods are commonly used for handling images as secondary signals using typical image processing techniques. Image processing can be broadly categorized into digital and medical image processing. In the medical field, medical imaging and processing tools play a crucial role in various applications. These applications are particularly important in diagnostic settings and play a significant role in the planning, assessment, and analysis stages before surgical procedures [1]. It is worth noting that the advantages and disadvantages of medical images directly impact a doctor's ability to make accurate patient diagnoses. Furthermore, medical imaging poses challenges due to factors such as turbulence and diffraction, similar to those encountered in ultrasound imaging, thus adding complexity to clinical decision-making.

Among the different imaging techniques, magnetic resonance imaging (MRI) [40] is a highly effective method for producing high-contrast images of soft tissues in the human body. It can provide detailed visualization of organs and tissues in the brain, abdomen, legs, vertebrae, and other areas. Various MRI modalities, including T1-weighted, contrast-enhanced T1-weighted (T1c-weighted), T2-weighted, Magnetization Prepared-RApid Gradient Echo (MP-RAGE), Fluid Attenuation Inversion Recovery (FLAIR), and Proton density (PD-weighted) sequences, are commonly used in clinical practice and are the focus of this study. Each of these sequences offers unique insights into different characteristics of human tissues [56]. The information these sequences provide is essential for medical practitioners, as it enables precise diagnoses and facilitates the development of effective treatment plans [41].

This study aims to compile and analyze various medical image processing tools available. The aim is to identify open-source tools and determine their compatibility with different software systems, ensuring they are suitable for specific applications.

Image segmentation reveals a crucial role in the computer-aided identification of medical images. The goal of image breakdown is to separate a picture into distinct, non-overlapping elements having implications for the size and volume of that medical image.

The primary phase in segmenting a small number of images is de-noising; during this stage, the image can use an appropriate filter that approximates a low pass, high pass, and vector median filter. It is crucial to convert a photo into a binary image for de-noising, computing threshold values that extract the items from the data. For this alteration, the Otsu threshold is used, which leads to the bar graph threshold dependent on the bar graph's form properties. The image bar graph has a wide range of highs and lows, with each high corresponding to a distinct area and the lows acting as the threshold values to smooth out these areas [42].

In image segmentation, the choice of methods and strategies for utilizing the findings of image processing, classification methods, pattern recognition, and finally, the verification of the image classification leads toward the rise in professionals understanding. It can be challenging when doing image analysis [2]. The primary goal of medical image classification is to identify the parts of the human body affected by the disease and achieve high accuracy [3]. Future clinical treatment will involve the development of an automatic identification method with imaging knowledge [2].

The paper continues in the following sequence: Section 2 discusses the state-of-art work relevant to the image modalities and segmentation techniques of medical images. Section 3 discusses the adopted research methodology for this systematic literature review. Section 4 describes the conclusion and future work.

## 2. State-of-the-Art

This section presents the published research studies in the medical image field. The author divides the section into two parts which are: Imaging modalities and Segmentation.

### 2.1. Imaging Modalities

#### *2.1.1. Related Work*

Imaging technologies are essential for diagnosing anomalies and treatments because they allow medical professionals to more accurately visualize their patients' conditions [3, 4]. The recording and measurement techniques electroencephalography (EEG), magnetoencephalography (MEG), and electrocardiography (ECG) do not provide visuals. Still, they depict the data as a parameter graph instead of time or maps, which less accurately reveal sensitive information. Hence, on a narrow scale, these modalities can create medical imaging. Up until 2010, there were roughly 5 billion medical imaging studies conducted worldwide [5].

Around 50% of all ionizing radiation exposure in the United States [6] is made up of radiation exposure from medical imaging. Illnesses are diagnosed, managed, treated, and prevented by technologies for medical imaging. A critical diagnostic tool for most primary forms of medical abnormalities and illnesses, including trauma disease, numerous cancer diseases, cardiovascular diseases, neurological disorders, and a more comprehensive range of other ailments, has evolved into imaging techniques in the modern era. Highly skilled professionals use medical imaging techniques, including medical experts like primary care doctors and oncologists [1].

Medical diagnoses rely heavily on imaging technologies, enabling healthcare professionals to identify illnesses and their associated symptoms. The process of medical diagnosis involves determining the patient's ailment and collecting relevant data about the disease or condition, which is crucial for effective treatment. This information is obtained from the patient's medical history, physical examinations, or surveys. However, the diagnostic process can be challenging due to the lack of specificity in numerous indications and symptoms. For example, erythema, which is characterized by skin redness, can be an indication of various disorders. Therefore, multiple diagnostic techniques are necessary to identify specific diseases' underlying causes and provide appropriate treatment or preventive measures [7].

A model for orbital organ segmentation in CT images, called OrbitNet, uses a transformer and CNN architectures [61]. OrbitNet uses a FocusTrans encoder to extract global features and a squeeze-attention block to capture boundary features. OrbitNet achieves high accuracy and robustness on orbital organ segmentation.

When Wilhelm Conrad Röntgen discovered the X-ray in 1895, radiography was born. When Rontgen viewed a photo of his wife's hand on an X-ray-created photographic plate, he realized it could be used in medicine [49]. In 1963, Cormack first described the CT imaging method. Hounsfield unveiled the first clinical CT scanner in 1972. Since that time, the clinical X-ray CT has completely changed the field of medical imaging and is arguably the most significant development in radiology since the discovery of X-rays. The early 1970s saw the beginning of MRI research, and the first MRI prototypes were tested in 1980. Sonography was initially utilized as a diagnostic technique in 1942 to locate brain tumors. In 1965, it was introduced as a real-time imaging method. Now, there are numerous applications for medical sonography. Elastography was created in 1991 to find tissue irregularities [50, 51].

Deep learning for lung image segmentation can help diagnose tuberculosis (TB) and other lung diseases from X-ray images [57]. The authors compare four segmentation architectures: U-Net, SegNet, FCN, and U-Net + +. They claim that U-Net + + is the best model for lung segmentation, achieving more than 98% accuracy and 0.95 mean_iou. They also discuss the benefits of segmentation before classification for TB detection and provide a detailed U-Net + + results analysis.

### *2.1.2. Background Knowledge*

Biomedical devices employ imaging techniques such as mammography, magnetic resonance imaging (MRI), and computed tomography (CT) to generate data for medical images [4]. Various medical imaging modalities encompass ionizing radiation, ultrasound, magnetic resonance, nuclear medicine, and optical techniques, each with distinct characteristics and responses to different human body parts and organ tissues [5]. There are four imaging techniques available [4]:

#### *2.1.2.1. Projectional Imaging*

Projectional imaging, commonly called conventional radiography, is a type of medical imaging that uses X-ray radiation to create two-dimensional images. Radiographers typically acquire the images, and radiologists frequently evaluate the images afterward. The process and any resulting images are commonly called "X-rays." Projectional imaging is sometimes known as plain radiography or roentgenography. The electromagnetic energy (EM) that produces X-rays has a wavelength range of 0.1 to 10 nm. They are converted into photons that have energies between 12 and 125 keV. Laboratory testing is required as a medical diagnostic tool almost simultaneously with the adoption of X-ray scanning projection. The image generation process has three basic steps: Processing, preliminary reading, and rereading [4]. Figure 1 represents the Acquisition of projectional radiography with an X-ray generator and a detector [52].

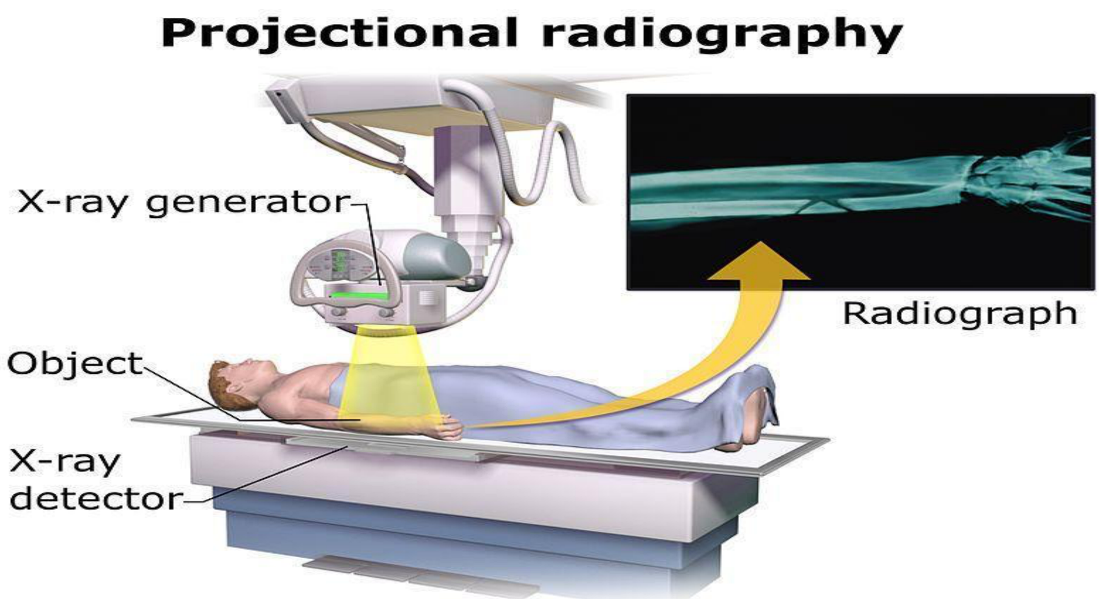


**Figure 1.** Acquisition of projectional radiography with an X-ray generator and a detector [52]

*2.1.2.2. Computed Tomography (CT)*

Computed tomography, usually a CT scan, is a technique medical experts use to analyze inside body structures. A CT scan creates images of a cross-section of your body using X-rays and technology. Due to minute changes in absorbance (less than 5%), the typical X-ray imaging projection occasionally fails to produce satisfactory results. CT enhances subject to contrast with less than 1% discrimination. CT is frequently used in applications for cancer screening, including virtual colonoscopies and lung exams. Positron emission tomography (PET)/CT, Dual source and dual-energy CT, CT angiography, and CT perfusion are a few of the different types of CT imaging [48]. Figure 2 shows the image of computed tomography.

**Figure 2.** Computed Tomography [53]

*2.1.2.3. Magnetic Resonance (MR)*

Radiologists utilize magnetic resonance imaging (MRI) as a medical imaging technique to create images of the body's structures and functions. Unlike CT and PET scans, MRI scanners employ powerful magnetic fields, magnetic field gradients, and radio waves to produce detailed images of organs without using X-rays or ionizing radiation. The MRI technique involves aligning the nuclear magnetization of hydrogen atoms in water molecules using a strong magnetic field. It has become the standard method for cross-sectional imaging, particularly effective in visualizing soft tissues (such as the brain and muscles), fat, and even bone, including bone marrow. Figure 3 presents an illustration of the patient's positioning for head and abdominal MRI examinations [54].

**Figure 3.** Image of patient positioning for head and abdominal MR studies [54]

*2.1.2.4. Ultrasound Imaging*

Ultrasound imaging, or sonography, utilizes high-frequency sound waves to visualize the body. It enables real-time display of blood flow through blood vessels and the movement of internal organs. Unlike X-ray imaging, ultrasound imaging does not expose patients to ionizing radiation. The high-frequency sound waves for creating cross-sectional human body images range from 1 to 20 MHz. The intensity of the echo ultrasound rebound is determined by the properties of the biological tissue through which the sound waves pass [55].

2.2. Medical Image Segmentation

*2.2.1. Related Work*

Medical image segmentation approaches often rely on modern techniques to achieve accurate results. Traditional segmentation methods, including threshold and region growth segmentation, are commonly employed. In addition, various classification and clustering methods, such as fuzzy C-means (FCM), K-nearest neighbors (KNN), dataset-based guided segmentation, Monte Carlo random field model (MRF), convolutional neural networks, random forest methods, expectation maximization (EM), support vector machines (SVM), Bayesian methods, and artificial neural networks (ANNs), are utilized for segmentation purposes [39].

Image segmentation serves as the foundation of image processing [24]. It encompasses a range of techniques categorized into two primary groups: layer-based segmentation techniques and block-based segmentation techniques. Picture segmentation, often called labeling, involves grouping the components of an image based on shared characteristics [25]. The flowchart in Figure 1 illustrates the process.

Recently, convolutional neural network-based models for medical image segmentation have emerged as powerful tools capable of performing on par with radiologists [10, 17]. However, these models are typically stand-alone programs with customized architectures, preprocessing steps, data augmentations, and metrics specific to the segmentation problem and dataset [14]. Moreover, these optimized pipelines exhibit varying performance across different medical scenarios. The diverse sizes, shapes, localizations, and distinct features of multiple datasets make evaluating and comparing these models challenging, even when addressing the same medical condition.

CNNs have been the primary foundation for many computer vision tasks over the past few years, particularly in semantic segmentation. The encoder-decoder-oriented FCN and U-Net are the two commonly used techniques for segmenting medical images. Based on U-Net, U-Net++ creates more dense skip connections. ResNet, a residual module, is added by Res-UNet, creating a deeper system for extracting the features [43-47].

ResViT is a newly introduced generative adversarial model utilized to synthesize medical images. It incorporates vision transformers and convolutional neural networks [58]. The generator of ResViT employs aggregated residual transformer (ART) blocks as a bottleneck. These blocks combine residual convolutional and transformer modules to capture contextual and local features effectively. ResViT also offers a unified implementation capable of handling various combinations of source-target modalities. ResViT demonstrates superior performance in synthesizing missing sequences within multi-contrast MRI and CT images using MRI data, surpassing current CNN and transformer-based methods, as showcased by the authors.

CTCNet, on the other hand, is a network model designed for medical image segmentation. It combines CNN and Transformer encoders to produce complementary features [59]. The architecture of CTCNet includes a cross-domain fusion block, which blends features from different domains, and a complementary feature module, facilitating the capture of cross-domain correlation and dual attention. CTCNet incorporates a Swin Transformer decoder with multi-level skip connections to extract spatial details, contextual semantics, and long-range information. The authors show that CTCNet outperforms existing methods on several medical image segmentation tasks.

*2.2.2. Background Knowledge*

Image segmentation in computer vision splits digital images into various pieces (sets of pixels conjointly stated as super-pixels). Segmentation aims to change and transform a picture's design into something significantly more significant and straightforward to analyze. Image segmentation is a technique of tagging each picture component in a picture; quantifiable pixels with perpetual label share certain qualities; image segmentation captures objects and limits (lines, curves, etc.) in photos very precisely.

Image segmentation results can manifest as organized components encompassing the entire image or as a set of shapes extracted from the visual data (edge detection). Each pixel within a region is associated with a specific characteristic or visual attribute, such as a similar hue, intensity, or texture. Adjacent regions exhibit significant differences in size units due to their distinct characteristics [6]. In medical imaging, the resulting contours become distinguishable when picture segmentation is employed to construct 3D reconstructions using interpolation methods like walk dice. There are various methods for segmenting an image, each with the characteristics listed below:

*2.2.3. Types of Segmentation*

The following list of picture segmentation types and their characteristics includes:

*2.2.3.1. Edge Detection-Based Segmentation*

The image segmentation technique aims to identify the edges or pixels associated with regions exhibiting rapid intensity changes [7-11]. These pixels or edges are subsequently connected to establish closed object boundaries, resulting in a binary image [8]. Two fundamental methods for edge-based segmentation are commonly employed: the gray histogram approach and the gradient-based methodology [10]. The area of edge detection in image processing has been developed well. Although region limits and boundaries are closely related, there is frequently a substantial difference in concentration at these limits. Therefore, further segmentation procedures have been built on the foundation of edge detection approaches. The edges that may be identified by edge location frequently need to be connected. Even so, one requires tight local restrictions to separate a query from a picture. The boundaries between these protests are the sought-after edges.

Additionally, division algorithms can be linked to edges obtained from edge identifiers. Lindeberg and Li [12] developed a coordinated technique for parts-based inquiry acknowledgment that divides edges into straight and bowed edge fragments. This division is centered on a base depiction length (MDL) foundation enhanced by a part and consolidation approach using rival breakpoints from correlating intersection indications to acquire more likely spots to contemplate allocations into various portions.

*2.2.3.2. Thresholding Method*

This method can be customized manually based on existing information or automatically using image data. Additionally, these estimates excluded half-breed, district-based, and edge-based models. The edge data is coupled to edge-based calculations. Edge focuses are capable of depicting the protest's structural elements. Such locations can be ordered for standard edge locating algorithms, such as vigilant edge finder and Laplacian edge locator. Such techniques are employed to modify the edge pixels without introducing noise. For instance, a clever edge locator found probable edge pixels using the edge of inclination greatness and crushed them using non-maximal hiding and masking techniques. The detected edges are made up of discrete pixels since the calculations used to make them rely on pixels; as a result, they may be insufficient or spasmodic. As a result, it is necessary to use post-preparing techniques like structural tasks to associate breaks or do away with openings. This methodology's flaw is the discomfort of processing the images of finished blob objects, even if it can be used to piece together 3D images with great precision. In Thresholding, Picture splitting is a quick and effective method to divide apart pictures with light questions on darker surroundings [7]. The thresholding method is dependent on the picture space areas or the picture's properties [10].

Thresholding action converts a multilayered figure/picture into a paired image by selecting a genuine edge T, which divides the pixel information into distinct sections and separates content from the base. Any pixel (x, y) is regarded as a piece of evidence if its strength is greater than or equal to the edge value, i.e., f(x, y) T; otherwise, the pixel belongs to the foundation [9, 13]. There are two types of thresholding procedures [14], global and local thresholding, as determined by threshold esteem. Local Thresholding refers to when T is variable, while if T is constant, the method is global Thresholding. Global Thresholding tactics may only be successful if the foundation brightness is balanced. Different limitations are used in adjacent Thresholding to account for variable illumination [12]. Limit selection is often carried out intuitively. However, it is theoretically possible to deduce programmed edge determination algorithms.

The thresholding approach is limited because it only produces two classes and cannot be linked to multichannel images. Additionally, Thresholding does not consider a picture's spatial characteristics, rendering it susceptible to disturbance [10] since both artifacts degrade the picture's histogram, making division more difficult.

*2.2.3.3. Region-Based Segmentation Methods*

Division calculations based on the area are more straightforward and less noise-resistant than edge identification strategies [10, 15]. While locale-based approaches divide an image into equal parts following established criteria, edge-based techniques divide a visual based on rapid alterations in force close edges [7, 16]. A region-based hybrid watermarking scheme by [60] for medical images and electronic patient records (EPR) in IoMT. The scheme uses adaptive Least Significant Bit (LSB) substitution and DWT-SVD hybrid transforms to embed tamper detection and recovery bits, encrypted EPR, and hospital logo in the medical image. The scheme ensures high imperceptibility, robustness, security, payload, and recovery accuracy. Calculations of division concerning area typically include techniques such as:

- Region Growing

A district development procedure [8, 9] divides the pixels in the complete image into smaller areas or more significant localities following a specified paradigm [17]. Four steps can be taken to prepare a locale.:-

(i) Choose a group of initial pixels for a unique image [18].

(ii) Choose a set of comparative criteria, such as dark-level force or color, and establish a guiding principle.

(iii) To expand domains, annex nearby pixels to each seed with predetermined features, such as seed pixels.

(iv) When no more pixels in that district satisfy the criteria for consideration (i.e., the measure, proximity between a rival pixel and the pixels created up to that point, and the area's state getting developed), stop growing there.

- Merging and Splitting the Region

Instead of selecting seed points, a client can divide a picture into several independent, self-contained regions and then merge the regions [8, 10] while attempting to adhere to the rules of logical picture division. Area splitting and merging are often carried out under the assumption of quad-tree data. Allow R to address the entire picture before choosing a predicate Q.

(i) Start with the big picture; if Q(R) = FALSE [7], divide the image into quadrants. Divide the quadrants into sub-quadrants if Q(Ri) = FALSE until no subdivision is possible.

(ii) If only a portion is used, the final piece can include neighboring districts with similar qualities. This drawback can be avoided by allowing convergence and blending any adjoining sections. Rj and Rk for which Q(Rj U Rk) = TRUE

(iii) Cease the process while no more consolidation is possible.

*2.2.3.4. Segmentation Based on Clustering*

To group pixels, one must discriminate between a small group of categories known as bunches in an unsupervised learning task [19]. Bunching uses preparation organizers instead of preparation organizers; they get ready independently using readily available knowledge. Most often, grouping is used when categories are already established. After establishing a similitude criterion between pixels [8]. The criteria for expanding subject py and rising bury class comparability depend on collecting pixels into bunches. The similitude measure that the method uses and how it is applied determines the type of grouping outcome. K-implies bunching, hard determines, fluffy grouping, and other bunching calculations are assigned.

*2.2.3.5. Hybrid Watershed and Quick Region Image Segmentation*

The issue of how to split a picture into homogeneous parts that, when combined, generate a heterogeneous part is a prevalent one. As histogram-based speaks to the uncomplicated likelihood dispersion capacity of power estimations of every picture, several approaches exist for error-free picture parts. Several methods were used to identify and sort by image angle or Laplacian and then grouped into forms. In the district-based division process, divide the scene into a collection of uniform localities and combine them by predetermined criteria [18]. The Markov random field-based segmentation approach employs a Markov or Gibbs random field with a distribution task to identify the actual image. It utilizes hybrid division methods that combine edge-based and region-based techniques. Initially, the image is segmented into sections, followed by the split-and-consolidate process for combining them. The shapes are subsequently identified through edge-based processing. Table 1 provides an overview of the advantages and disadvantages of the various discussed approaches for segmenting medical images.

**Table 1:** Pros and Cons of Segmentation Types

| Segmentation Types | Description | Advantages | Disadvantages |
|---|---|---|---|
| Thresholding method | Multiple peaks in an image's histogram correspond to different regions as required. | It does not require knowledge of the image beforehand.<br><br>This technique performs admirably with minimal computational complexity for a large class of photos that meet the criteria. | It could function better for images with large, flat valleys or no discernible peaks.<br><br>Due to the absence of spatial considerations, ensuring contiguous segmented pieces becomes impossible. |
| Clustering Approach | The possibility that each section of the image corresponds to a separate cluster in the feature space is considered. The typical process involves two steps: firstly, aggregating the objects in the feature space, and secondly, establishing unique regions and mapping the clusters to the spatial domain yet to be determined. | Simple to classify and straightforward to implement. | Lacks calculating cluster validity, often known as the number of clusters.<br><br>Features frequently depend on images, and how to choose features to produce effective segmentation results is yet to be determined.<br><br>Lacks the use of geographical information |
| Region-based Approaches | Pixels are organized into similar segments through region expansion, division, fusion, or combination. | The region homogeneity criterion exhibits optimal performance when its specification is straightforward. Moreover, it demonstrates excellent resistance to noise compared to edge-detection techniques. | It operates sequentially, producing relatively long computational time and memory demands.<br>The choice of the initial seed region and the sequence in which pixels and regions are significantly analyzed influence the expansion of a region.<br>The adopted splitting strategy often leads to segmented regions with a square-like shape. |

| | | | |
|---|---|---|---|
| Edge Detection Approaches | Regular efforts are made to detect discontinuities to identify points with varying degrees of rapid fluctuations in the gray level.<br>Typically divided into two groups, i.e., parallel and sequential. | The edge-detecting technique mimics how humans see objects and effectively uses photos with a solid regional contrast. | Does not perform well with photos with too many or poorly defined edges.<br><br>The creation of a closed curve or boundary is a difficult task. |

*2.2.4. Techniques Used for Segmentation*

The segmentation methods utilized in the previously mentioned medical image segmentation types are briefly explained in the following paragraphs.

- Principal Component Analysis (PCA)

It is a cost-effective method of reducing the spatial properties of a knowledge set that contains a wide variety of reticulated variables. However, the PCA technique could not provide the optimum choice of possibilities for evidence with thin distribution and noise [20].

- Active Contour Model:

Systems in PC vision depicting alliance degree questions classify from a likely barefaced second image, including dynamic form shows, also called snakes. In computer vision, the snakes' model is widely employed in tasks like protest trailing, frame acquirement, division, edge recognition, and stereo coordinating.

- Euclidean Distance:

The "conventional" straight-line distance between two points is the geometer separation or geometer metric in Euclidean space. This division transforms Euclidean space into a scientific space. The Geometer Standard is the corresponding standard's name.

- PHOW

In this study, the utilization of the PHOW technique is implemented. The bag-of-words method is a specific approach for representing highlights [21]. Within the PHOW approach, images are considered words. The colored fundus images are divided into meaningful grids, usually ranging in size from 4 to 10. Following that, SIFT descriptors are extracted at various scales. The SIFT descriptors capture the local orientation and presentation of the region by applying conditions (1) and (2) individually.

- Fisher vector

Utilizing the Fisher kernel, Fisher vector encoding is based on the core concept of aggregating a dense set of neighboring highlights into a high-dimensional representation, effectively capturing the highlights at the image level [22]. The evaluation of these descriptors involves assessing the logarithmic probability of neighboring highlights using slope and likelihood thickness capabilities. The modeling of the slope is achieved through a Gaussian Mixture Model (GMM) that characterizes the Fisher data. When determining weights in the Fisher vector, considerations are given to factors such as the mean and edge detection [21]. This approach enables the storage of event counts linked to each visual word and provides supplementary information regarding the distribution of descriptors for a meaningful vocabulary measurement.

The Fisher vector is encoded by considering the discrepancies between the descriptors of the images and utilizing 500 GMM cluster centers. Specific highlights extracted from the four classes (DR, AMD, glaucoma, and typical) are incorporated into the Fisher vector to facilitate grouping.

- Absolute gradient

The spatial variation of light level values across an image can be assessed by examining the tilt of a picture. A high tilt value is observed when the brightness level abruptly transitions from dark to white. On the other hand, if the transition is from dark to slightly lighter dark, a low tilt value is observed.

The tilt may be positive or negative, depending on whether there is a transition from dark to light or light to dark in the brightness level.

- Run-length matrix

The image is scanned consistently over a set guideline for clusters of pixels with comparable dark-level values by the run-length framework, a technique for this purpose. The frequency of runs of, say, two consecutive pixels with a similar value for each permissible dim level is calculated by the run-length grid, given a direction (such as the flat heading). Then the process is repeated for the next 3, 4, and 5 pixels. One run-length grid for each selected course may be processed for a single image. In the future, usually, four grids are processed, along with a vertical grid and two corner-to-corner heads.

- Co-occurrence matrix

The technique known as the co-event grid focuses on retrieving factual information concerning the movement of sets of pixels within an image. It involves the definition of a heading and a separation, followed by the analysis of isolated groups of pixels based on the specified separation and processing according to the defined heading. The count of groups of pixels exhibiting a specific distribution of dark-level values is then calculated. This approach facilitates the comparison of each grid cell with a distribution that shares a similar dark level.

To illustrate, let us consider a vertical heading of 3 pixels, denoted as sg, and determine the corresponding co-event framework for an 8-bit image. The allowable dark level values range from 0 to 255 in this case. Consequently, the grid will have a size of 256, indicating that the element (0, 10) corresponds to the count of pixel combinations found in the image. These combinations are defined by intensity values of 0 and 10, respectively, with a vertical distance of 3 pixels.

- Auto-regressive model

The next-regressive model proposes that image pixels interact locally since each pixel's grayscale value of each pixel is calculated as the weighted sum of the grayscale values of its neighbors. Table 2 displays the disease diagnosis segmentation methods and the data set.

**Table 2.** Shows the Medical Image Segmentation Techniques

| Author Name | Year | Segmentation Technique | Problem | Dataset |
|---|---|---|---|---|
| Nicolas Lermé et al. [23] | 2016 | ACM | Segmenting artery walls | Drive |
| M. Srinivas et al. [24] | 2015 | OMP | Grouping Similar images | IRMA |
| Fan Zhang et al. [25] | 2014 | Euclidean Distance | Similarity b/w images | VISCAR |
| Joel E.W. Koh et al. [26] | 2018 | PHOW and Fisher vectors | Untreated age-related macular degeneration (AMD), diabetic retinopathy (DR), and glaucoma | Fundus images |
| Sukhpreet Kaur et al. [27] | 2017 | PCA | Diabetic Retinopathy | Drive |
| Nicolas Lermé et al. [28] | 2015 | ACM | Automatically segmenting the walls of retinal arteries | Twenty images from healthy and pathological subjects |

| | | | | |
|---|---|---|---|---|
| Radu Dobrescu et al. [29] | 2010 | Co-occurrence matrices | benign and malignant tumors | set of medical images obtained with a dermoscopy and a digital camera |
| G. Castellano et al. [30] | 2004 | Absolute gradient, Run-length matrix, Co-occurrence matrix, Auto-regressive model | Clarify the principles of texture analysis | Image applications |

**3. Materials and Methods**

One of the most crucial aspects of any systematic literature review is research methodology (SLR). Many scholars do systematic literature reviews, including those in [31-33, 62]. [31,32] uses a comprehensive literature evaluation to identify the research already done in requirements engineering education. Whereas performing the SLR, [31,32] carry out the two steps, while [34] carry out the four steps. Formulating the research topic was the first step in the SLR, which was then done by [31-34]. Finding research papers from various computing data sources is the second phase in the SLR process, carried out by [34, 62]. The selection and screening of the pertinent papers was the third SLR phase, carried out by [31–34]. Figure 4 represents the steps of the methodology followed in this paper.

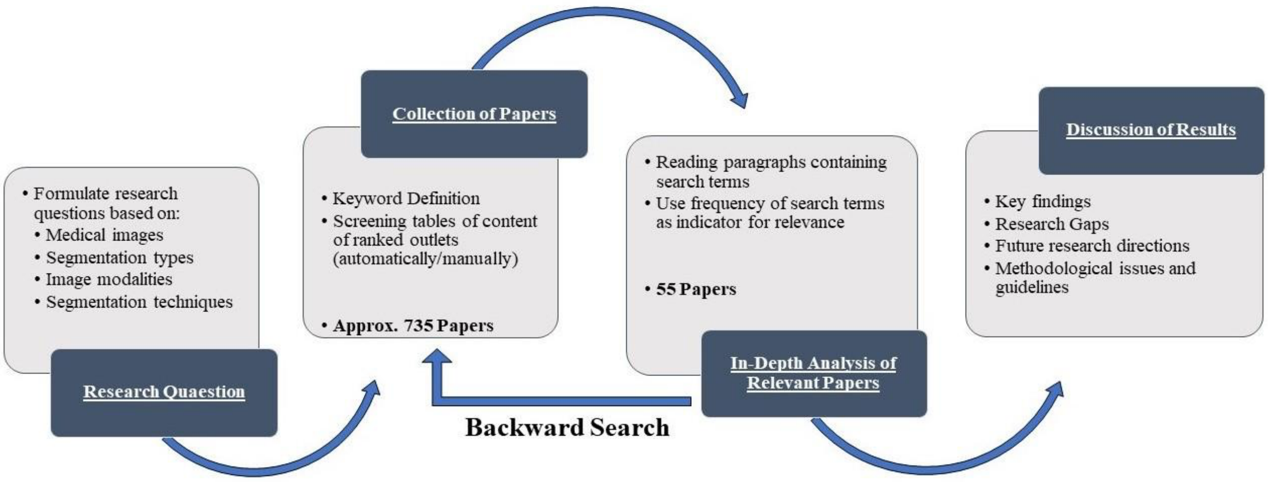


**Figure 4.** Steps of the methodology followed in this paper.

3.1. Research Questions

To close the research gap in a systematic literature review. The subsequent research inquiries were developed:
1. What various picture modalities are applied to medical images?
2. What kinds of segmentation are there?
3. For what kind of segmentation is the appropriate segmentation approach used?

3.2. Data Sources

This study was prepared using data from a survey of several papers compared to the abovementioned topics from various databases.

- ACM
- IEEE
- Springer
- Google Scholar.

Using search phrases or a search query makes it easy to look for papers. We conduct searches using the following phrases or queries on the data sources mentioned above.

("Image" OR "Modalities" OR "Segmentation")

("Imaging" OR "Image" OR "modalities" OR "types of images") AND ("types of segmentation" OR "techniques of segmentation" OR "segmentation").

Both Query 1 and Query 2 form the components of the final query. Once the databases retrieve the papers, the subsequent step entails examining and selecting relevant papers that align with the research domain.

3.2. Screening Process

The screening process in the systematic literature review holds crucial importance. The articles are read, and the papers are chosen by the researchers in this step based on the research questions.

3.3. Evaluation of Results

The computer encounters several challenges when trying to comprehend an image. Firstly, there is constant growth in the diversity and quantity of image data. Secondly, there is the potential utilization of mathematical and statistical approaches in the field of medicine [35]. Lastly, computational power poses a significant hurdle. Analysis models present their own set of problems. Firstly, the complexity of image data makes it difficult to consistently enhance the quality of medical imaging modalities. The information gathered from these modalities is only sometimes comprehensive or clear [36]. An additional aspect to consider is the model's or prototype's intricacy. The field of medical imaging analysis encompasses a wide range of human body structures and characteristics applicable in various scenarios. These include fundamental structures like the spine, retina, brain cortex, and coronary arteries and pathological tissue such as tumors, myocardial infarctions, inflammation, and edema. Furthermore, it encompasses functional regions like the motor cortex and glucose metabolism and artificial objects like implants, electrodes, and catheter tips. Each of these elements demonstrates substantial biological variability in subjects. Drawing from prior knowledge [37], a medical imaging model or prototype needs to account for and recognize the various visual representations of the human body. Lastly, validation is a recurring issue in medical imaging analysis. Human measurements could be more precise [38]. To validate their output, medical imaging algorithms require a ground truth standard.

## 4. Conclusion

Medical image segmentation combines the roles of medical analysis and diagnosis, making it an exciting research area. The comprehensive overview of image segmentation types and segmentation techniques for identifying chassis disease in this work includes imaging modalities and all datasets used for each methodology. Many reliable methods are being created, and for long-term work, the development of picture segmentation techniques can boost the accuracy rate and make it viable for computer-aided diagnosis.

## 5. Future Work

Medical image processing is a field that combines medical specialty records and imaging knowledge to analyze and diagnose various diseases from pixels. Image segmentation is a key step in computer-aided diagnosis to identify the affected body parts accurately. This field constantly evolves with new imaging modalities, segmentation techniques, and datasets, enabling more reliable and efficient diagnosis. In the future, medical image processing will be integrated with other technologies such as artificial intelligence, cloud computing, and big data to provide personalized and precise healthcare solutions. Medical image processing will also adhere to ethical standards and data-sharing policies to ensure the quality and validity of the research outcomes. Medical image processing will improve human health and well-being in the 21st century.

**References**


1. Lee, L. K., Liew, S. C., & Thong, W. J. (**2015**). A review of image segmentation methodologies in a medical image. In Advanced Computer and Communication Engineering Technology: Proceedings of the 1st International Conference on Communication and Computer Engineering (pp. 1069-1080). Springer International Publishing.
2. Hosseini, M. S., & Zekri, M. (**2012**). Review of medical image classification using the adaptive neuro-fuzzy inference system. Journal of medical signals and sensors, 2(1), 49.
3. Lashari, S. A., & Ibrahim, R. (**2013**). A framework for medical image classification using soft set. Procedia Technology, 11, 548-556.
4. Othman, M. F. B., Abdullah, N., & Rusli, N. A. B. A. (**2010**). An overview of MRI brain classification using FPGA implementation. In 2010 IEEE Symposium on Industrial Electronics and Applications (ISIEA) (pp. 623-628). IEEE.
5. Aberle, D., El-saden, S., Abbona, P., Gomez, A., Motamedi, K., Ragavendra, N., ... & Kangarloo, H. (**2010**). A primer on imaging anatomy and physiology. Medical imaging informatics, 15-90.
6. Tripathi, S., Kumar, K., Singh, B. K., & Singh, R. P. (**2012**). Image segmentation: a review. International Journal of Computer Science and Management Research, 1(4), 838-843.
7. Rastgarpour, M., & Shanbehzadeh, J. (**2011**). Application of AI techniques in medical image segmentation and novel categorization of available methods and tools. In Proceedings of the international multiconference of engineers and computer scientists (Vol. 1, pp. 16-18).
8. Zhang, Y. J. (2006). An overview of image and video segmentation in the last 40 years. Advances in Image and Video Segmentation, 1-16.
9. Wahba, M. (**2009**). An automated modified region growing technique for prostate segmentation in trans-rectal ultrasound images (Master's thesis, University of Waterloo).
10. Kang, W. X., Yang, Q. Q., & Liang, R. P. (**2009**). The comparative research on image segmentation algorithms. In 2009 First international workshop on education technology and computer science (Vol. 2, pp. 703-707). IEEE.
11. Pal, N. R., & Pal, S. K. (**1993**). A review on image segmentation techniques. Pattern recognition, 26(9), 1277-1294.
12. Lindeberg, T., & Li, M. X. (**1997**). Segmentation and classification of edges using minimum description length approximation and complementary junction cues. Computer Vision and Image Understanding, 67(1), 88-98.
13. Aurdal, L. (**2006**). Image Segmentation beyond thresholding. Norsk Regnescentral.
14. Zhang, Y., Qu, H., & Wang, Y. (**2006**). Adaptive image segmentation based on fast thresholding and image merging. In 16th International Conference on Artificial Reality and Telexistence--Workshops (ICAT'06) (pp. 308-311). IEEE.
15. Zhang, H., Fritts, J. E., & Goldman, S. A. (**2008**). Image segmentation evaluation: A survey of unsupervised methods. computer vision and image understanding, 110(2), 260-280.
16. Kaganami, H. G., & Beiji, Z. (**2009**). Region-based segmentation versus edge detection. In 2009 Fifth International Conference on Intelligent Information Hiding and Multimedia Signal Processing (pp. 1217-1221). IEEE.
17. Chang, Y. L., & Li, X. (**1994**). Adaptive image region-growing. IEEE Transactions on image processing, 3(6), 868-872.
18. Singh, K. K., & Singh, A. (**2010**). A study of image segmentation algorithms for different types of images. International Journal of Computer Science Issues (IJCSI), 7(5), 414.
19. Dehariya, V. K., Shrivastava, S. K., & Jain, R. C. (**2010**). Clustering of image data set using k-means and fuzzy k-means algorithms. In 2010 International conference on computational intelligence and communication networks (pp. 386-391). IEEE.
20. Miranda, E., Aryuni, M., & Irwansyah, E. (**2016**). A survey of medical image classification techniques. In 2016 international conference on information management and technology (ICIMTech) (pp. 56-61). IEEE.
21. Ciompi, F., de Hoop, B., van Riel, S. J., Chung, K., Scholten, E. T., Oudkerk, M., ... & van Ginneken, B. (**2015**). Automatic classification of pulmonary peri-fissural nodules in computed tomography using an ensemble of 2D views and a convolutional neural network out-of-the-box. Medical image analysis, 26(1), 195-202.
22. Manju, B., Meenakshy, K., & Gopikakumari, R. (**2015**). Prostate Disease Diagnosis from CT images using GA optimized SMRT based Texture Features. Procedia Computer Science, 46, 1692-1699.
23. Lermé, N., Rossant, F., Bloch, I., Paques, M., Koch, E., & Benesty, J. (**2016**). A fully automatic method for segmenting retinal artery walls in adaptive optics images. Pattern Recognition Letters, 72, 72-81.
24. Srinivas, M., Naidu, R. R., Sastry, C. S., & Mohan, C. K. (**2015**). Content-based medical image retrieval using dictionary learning. Neurocomputing, 168, 880-895.
25. Zhang, F., Song, Y., Cai, W., Depeursinge, A., & Müller, H. (**2017**). Text-and Content-Based Medical Image Retrieval in the VISCERAL Retrieval Benchmark.
26. Koh, J. E., Ng, E. Y., Bhandary, S. V., Hagiwara, Y., Laude, A., & Acharya, U. R. (**2018**). Automated retinal health diagnosis using pyramid histogram of visual words and Fisher vector techniques. Computers in biology and medicine, 92, 204-209.
27. Kaur, S., & Mann, K. S. (**2017**). Optimized retinal blood vessel segmentation technique for detection of diabetic retinopathy. International Journal of Advanced Research in Computer Science, 8(9).
28. Lermé, N., Rossant, F., Bloch, I., Paques, M., Koch, E., & Benesty, J. (**2015**). A Fully Automatic Method For Segmenting Retinal Arteries in Adaptive Optics Images.

29. Dobrescu, R., Dobrescu, M., Mocanu, S., & Popescu, D. (**2010**). Medical image classification for skin cancer diagnosis based on combined texture and fractal analysis. WISEAS Transactions on Biology and Biomedicine, 7(3), 223-232.
30. Castellano, G., Bonilha, L., Li, L. M., & Cendes, F. (**2004**). Texture analysis of medical images. Clinical radiology, 59(12), 1061-1069.
31. Ouhbi, S., Idri, A., Fernández-Alemán, J. L., & Toval, A. (**2015**). Requirements engineering education: a systematic mapping study. Requirements Engineering, 20, 119-138.
32. Zakari, A., Lee, S. P., Alam, K. A., & Ahmad, R. (**2019**). Software fault localisation: a systematic mapping study. IET Software, 13(1), 60-74.
33. Petersen, K., Feldt, R., Mujtaba, S., & Mattsson, M. (**2008**). Systematic mapping studies in software engineering. In 12th International Conference on Evaluation and Assessment in Software Engineering (EASE) 12 (pp. 1-10).
34. Dar, H., Lali, M. I., Ashraf, H., Ramzan, M., Amjad, T., & Shahzad, B. (**2018**). A systematic study on software requirements elicitation techniques and their challenges in mobile application development. IEEE Access, 6, 63859-63867.
35. Lehmann, T. M., Güld, M. O., Deselaers, T., Keysers, D., Schubert, H., Spitzer, K., ... & Wein, B. B. (**2005**). Automatic categorization of medical images for content-based retrieval and data mining. Computerized Medical Imaging and Graphics, 29(2-3), 143-155.
36. Miranda, E., Aryuni, M., & Irwansyah, E. (**2016**). A survey of medical image classification techniques. In 2016 international conference on information management and technology (ICIMTech) (pp. 56-61). IEEE.
37. Suetens, P. (**2017**). Fundamentals of medical imaging. Cambridge university press.
38. Dhawan, A. P. (**2011**). Medical image analysis. John Wiley & Sons.
39. Ashour, A. S., Guo, Y., & Mohamed, W. S. (**2021**). Thermal Ablation Therapy: Theory and Simulation. Academic Press.
40. Aggarwal, P., Vig, R., Bhadoria, S., & Dethe, C. G. (**2011**). Role of segmentation in medical imaging: A comparative study. International Journal of Computer Applications, 29(1), 54-61.
41. Müller, D., & Kramer, F. (**2021**). MIScnn: a framework for medical image segmentation with convolutional neural networks and deep learning. BMC medical imaging, 21(1), 1-11.
42. Mustafa, W. A., Salleh, N. M., Idrus, S. Z. S., Jamlos, M. A., & Rohani, M. N. K. H. (**2020**). Overview of segmentation X-Ray medical images using image processing technique. In Journal of Physics: Conference Series (Vol. 1529, No. 4, p. 042017). IOP Publishing.
43. Zhou, Z., Rahman Siddiquee, M. M., Tajbakhsh, N., & Liang, J. (**2018**). Unet++: A nested u-net architecture for medical image segmentation. In Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support: 4th International Workshop, DLMIA 2018, and 8th International Workshop, ML-CDS 2018, Held in Conjunction with MICCAI 2018, Granada, Spain, September 20, 2018, Proceedings 4 (pp. 3-11). Springer International Publishing.
44. Xiao, X., Lian, S., Luo, Z., & Li, S. (**2018**). Weighted res-unet for high-quality retina vessel segmentation. In 2018 9th international conference on information technology in medicine and education (ITME) (pp. 327-331). IEEE.
45. Li, Y., Wang, Z., Yin, L., Zhu, Z., Qi, G., & Liu, Y. (**2021**). X-Net: a dual encoding–decoding method in medical image segmentation. The Visual Computer, 1-11.
46. Moeskops, P., Wolterink, J. M., Van Der Velden, B. H., Gilhuijs, K. G., Leiner, T., Viergever, M. A., & Išgum, I. (**2016**). Deep learning for multi-task medical image segmentation in multiple modalities. In Medical Image Computing and Computer-Assisted Intervention–MICCAI 2016: 19th International Conference, Athens, Greece, October 17-21, 2016, Proceedings, Part II 19 (pp. 478-486). Springer International Publishing.
47. Xu, Y., He, X., Xu, G., Qi, G., Yu, K., Yin, L., ... & Chen, H. (**2022**). A medical image segmentation method based on multi-dimensional statistical features. Frontiers in Neuroscience, 16.
48. Hussain, S., Mubeen, I., Ullah, N., Shah, S. S. U. D., Khan, B. A., Zahoor, M., ... & Sultan, M. A. (**2022**). Modern Diagnostic Imaging Technique Applications and Risk Factors in the Medical Field: A Review. BioMed Research International, 2022.
49. Hounsfield, G. N. (**1973**). Computerized transverse axial scanning (tomography): Part 1. Description of system. The British Journal of Radiology, 46(552), 1016-1022.
50. Ophir, J., Cespedes, I., Ponnekanti, H., Yazdi, Y., & Li, X. (**1991**). Elastography: a quantitative method for imaging the elasticity of biological tissues. Ultrasonic imaging, 13(2), 111-134.
51. Kasban, H., El-Bendary, M. A. M., & Salama, D. H. (**2015**). A comparative study of medical imaging techniques. International Journal of Information Science and Intelligent System, 4(2), 37-58.
52. https://en.wikipedia.org/wiki/Projectional_radiography
53. https://my.clevelandclinic.org/health/diagnostics/4808-ct-computed-tomography-scan
54. https://en.wikipedia.org/wiki/Magnetic_resonance_imaging
55. https://www.fda.gov/radiation-emitting-products/medical-imaging/ultrasound-imaging.
56. Azad, R., Khosravi, N., Dehghanmanshadi, M., Cohen-Adad, J., & Merhof, D. (**2022**). Medical image segmentation on mri images with missing modalities: A review. arXiv preprint arXiv:2203.06217.
57. Gite, S., Mishra, A., & Kotecha, K. (**2022**). Enhanced lung image segmentation using deep learning. Neural Computing and Applications, 1-15.
58. Dalmaz, O., Yurt, M., & Çukur, T. (**2022**). ResViT: residual vision transformers for multimodal medical image synthesis. IEEE Transactions on Medical Imaging, 41(10), 2598-2614.

59. Yuan, F., Zhang, Z., & Fang, Z. (**2023**). An effective CNN and Transformer complementary network for medical image segmentation. Pattern Recognition, 136, 109228.
60. Singh, P., Devi, K. J., Thakkar, H. K., & Kotecha, K. (**2022**). Region-based hybrid medical image watermarking scheme for robust and secured transmission in IoMT. IEEE Access, 10, 8974-8993.
61. Li, W., Song, H., Li, Z., Lin, Y., Shi, J., Yang, J., & Wu, W. (**2023**). OrbitNet—A fully automated orbit multi-organ segmentation model based on the transformer in CT images. Computers in Biology and Medicine, 155, 106628.
62. Tahir, A., Chen, F., Khan, H. U., Ming, Z., Ahmad, A., Nazir, S., & Shafiq, M. (**2020**). A systematic review on cloud storage mechanisms concerning e-healthcare systems. Sensors, 20(18), 5392.