Advancements in Segmentation Techniques for Medical Imaging : a Comprehensive Review

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Abstract - Medical imaging has transformed the field of medicine. The presence and severity of disease profoundly influence the provision of clinical care. Segmentation is of paramount importance in medical imaging, particularly in the context of radiotherapy planning. Image segmentation is the fundamental function of image analysis and development, influencing subsequent processes such as representation, object description, feature measurement, and even higher-level tasks such as object classification. It is essential for facilitating the characterization and visualization of regions of interest in medical images. In computer vision, segmentation is an essential technical task in analyzing medical images, and it is essential for many applications, including diagnosis, prognosis, and treatment planning. There are several segmentation methods, the most commonly used of which are thresholding, edge detection, region growth, active edges, and graphical slicing. The emergence of deep learning, in particular, has revolutionized the segmentation field. Deep learning methods effectively segment medical images and are widely used in clinical and surgical practice. Using computer-aided diagnostic systems to improve the sensitivity and specificity of lesion detection and other assessment indices has become a priority in medical research and diagnostic radiology. This article reviews the task of segmentation in medical imaging. It begins by highlighting the importance of segmentation in the analysis of medical images. It then moves on to an in-depth and comparative examination of the various segmentation techniques, including thresholding, edge detection, region growth, active contours, graphical slicing, and combining methods.

Keywords – Active contours, deep learning, edge detection, medical imaging, segmentation.

I. INTRODUCTION

This conference paper deals with segmentation methods, including deep learning methods. Segmentation is an essential task in medical imaging. It involves dividing an image into regions with similar properties. Technology and AI tools identify and quantify anatomical structures in medical images. For example, segmentation can locate the tumor in a CT scan, the heart in an MRI, the breast in a mammogram, or X-ray images of pneumonia [1, 2, 3, 4, 5, 6]. This task is essential for a variety of medical imaging applications, such as :

Diagnosis: Segmentation identifies and characterizes abnormalities in medical images. For example, segmentation identifies tumors in CT scans.

Quantification: Segmentation can quantify objects' size, shape, and other properties in medical images. We can use this information to monitor disease progression, assess treatments' effectiveness, and plan surgical interventions.

Visualization: Segmentation improves the visualization of medical images. Segmentation makes images for doctors and other healthcare professionals to interpret images and make diagnoses.

There are several segmentation methods, the most common of which are listed below:

A team of researchers at Stanford University developed the first three methods in the 1970s.

Thresholding: This method assigns each pixel in an image to a specific region based on its intensity value [7].

Region expansion: This process starts with a starting pixel and iteratively expands the region to include all neighboring pixels of similar intensity.

Edge detection: This technique identifies the boundaries between different regions in an image [8].

In the 1980s, researchers created the following methods and further developed them in the 1990s.

Active contours: This approach uses an energy function to evolve a curve until it converges on the boundary of a desired region [2, 6].

Graph-based segmentation uses a graph to represent the relationships between pixels in an image. To segment the chart, find the minimum slice or maximum flow.

Deep learning-based segmentation: This process uses deep learning algorithms to segment images. Deep learning algorithms are very effective for segmentation, particularly for complex ideas.

The choice of segmentation method depends on the specific application. Thresholding is a simple and effective method often used for binary segmentation tasks. However, thresholding can be sensitive to noise and may not be suitable for more complex tasks [9, 10, 5]. Segmentation in medical imaging is an active area of research. Many new methods are constantly being developed. These new methods are often more accurate and more efficient. Segmentation in medical imaging consists of dividing an image into different regions or segments. To do this, each pixel in the pictures is assigned to a specific part based on its properties, such as intensity, texture, or shape. Segmentation is an essential task in medical imaging, as it enables particular objects or structures of interest to be identified and extracted from an image. It can be used for a variety of purposes, including the following:

A) Improved diagnosis

Segmentation can help doctors identify and characterize medical image abnormalities. It can lead to earlier diagnosis and more effective treatment.

B) Quantitative analysis

It quantifies objects' size, shape, and other properties of medical images. This information can be used to monitor disease progression, evaluate treatment effectiveness, and plan surgical interventions.

C) Improved visualization

Segmentation can be used to improve the visualization of medical images. This makes it easier for doctors and other healthcare professionals to interpret images and make diagnoses. The final discussion will focus on challenges and future directions [11].

II. BACKGROUND

Segmentation of medical images is a technique commonly used in various fields of application. Several methods are used to segment medical images, including thresholding, region growth, edge detection, and machine learning.

A) Methods

The literature mainly contains a few approaches, namely thresholding, region growth, edge detection, and machine learning algorithms, such as convolutional neural networks.

B) Applications

These methods for segmenting medical images are widely used in various fields of application. For example, in radiology, segmentation can identify tumors or other abnormalities in medical images. In computer-assisted surgery, segmentation can guide the surgeon during surgery. In biomedical research, segmentation can be used to assess the effectiveness of treatments. In brain imaging, segmentation can be used to study the structure and function of the brain.

III. SEGMENTATION ALGORITHMS

Pre-processing of medical images is essential to reduce noise, artifacts, and bias effects before further analysis.

Different types of medical images, such as CT, MR, and ultrasound, require addressing specific noise and artifact characteristics during pre-processing; sensors and electronic system effects cause these characteristics. In general, Gaussian noise and artifacts pervert the CT Images. In contrast, rician noise, artifacts, and intensity inhomogeneity affects MR images due to the non-uniform response of the RF coil, and speckle noise and artifacts corrupt ultrasound images.

Chronology of Segmentation Algorithms

Various algorithms "Fig. 1", including surface fitting, histogram-based, high-frequency maximization, and filtering methods, can correct intensity inhomogeneity and segment medical images [12].

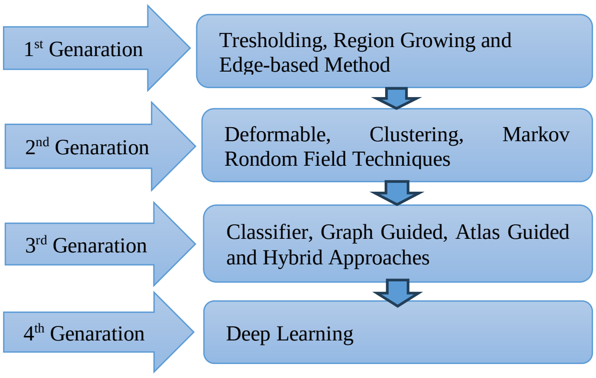

Fig. 1. Classification of segmentation algorithms.

The first segmentation methods were mainly manual and required much time and expertise on the user's part. Second-generation methods introduced more automatic techniques and were more robust than the first but required user intervention. Third-generation methods were more sophisticated and developed, making segmenting images containing complex structures possible. The fourth segmentation generation is based on deep learning and has produced significant results for various medical imaging tasks, including segmenting simple or complex systems structures.

IV. EVALUATION MEASURES

Segmentation is an essential concept in medical imaging. It allows us to divide an image into regions that belong to different objects.

A) Steps Involved in Segmentation and Contour Detection in Medical Imaging

A.1. Pre-processing

First, we pre-process the image to improve its quality.

This process may involve steps such as :

A.2. Contrast enhancement

Contrast enhancement can improve the visibility of the objects in the image, making it easier to segment and detect contours. What methods can enhance contrast, such as histogram equalization and adaptive thresholding?

A.3. Contrast enhancement

Contrast enhancement can improve the visibility of the objects in the image, making it easier to segment and detect contours. Contrast enhancement can be done using various methods, such as histogram equalization and adaptive thresholding.

A.4. Image registration

Image registration is aligning two or more images of the same object.

This process is helpful for segmentation and edge detection, as it ensures that the image elements are correctly aligned. Various methods for registering images include rigid, affine, and deformable approaches.

B) Segmentation

We segment the image into zones belonging to different objects using several methods described in section IV.

B.1. Validating the results

The segmentation results may be validated to ensure accuracy.

- It is essential to evaluate the accuracy of the segmentation once this last was performed. Several evaluation measures are available, each of which measures a different segmentation aspect. Some necessary evaluation measures include :
- **Dice coefficient:** This measure reflects the overlap between the segmented region and the ground truth.
- **Hausdorff distance:** This measure reflects the distance between the boundaries of the segmented region and the ground truth.
- **Volume overlap error:** This measure reflects the difference in volume between the segmented region and the ground truth.

System performance measurement varies depending on usage. For example, if the goal is to identify the presence or absence of a tumor, then the Dice coefficient may be a good choice. However, if the goal is to measure the size of a cancer, then the volume overlap error may be a better choice [13]. In 3D, we can use 20 metrics, each of which gives a particular index:

Dice coefficient (DICE), True positive rate

(TPR), False positive rate (FPR), F-measure (FMS), Volumetric similarity (VS), Adjusted Rand index (ARI), Variation of information (VOI), Probabilistic distance (PBD), area under the receiver operating characteristic curve (AUC), Hausdorff distance (HD), Normalized surface distance (NSD), Overlap index (OI), Jaccard index (JI), Precision (PRE), Recall (REC), Specificity (SPE), Sensitivity (SEN), Positive predictive value (PPV), Negative predictive value (NPV), Error (ERR). Depending on the metrics' relations, nature, and definition, we group these latest indices into six sub-groups, as shown below, with the indication concept: TP, FP, TP, TN, DICE, and JAC.

The relation between the DICE indices and the Jaccard one is :

$$\text{Dice} = \frac{2\times|X\cap Y|}{|X|+|Y|} \tag{1}$$

- X : Ensemble des pixels de la segmentation prédite.
- Y : Ensemble des pixels de la segmentation de référence (ground truth).
- $|X \cap Y|$: Nombre de pixels communs entre la segmentation prédite et la référence.
- $|X|$: Nombre de pixels dans la segmentation prédite.
- $|Y|$: Nombre de pixels dans la segmentation de référence.

$$Dice = (2 \times JAC) \div (1 + JAC) \tag{2}$$

$$JAC = DICE \div (2 - DICE) \tag{3}$$

➢ The most appropriate method will depend on the partic-ular situation. It is also essential to evaluate the accuracy of segmentation and contour detection using appropriate evaluation measures.

V. CURRENT STATE OF SEGMENTATION IN MEDICAL IMAGING

Deep learning techniques have revolutionized the segmentation of medical images. Deep learning algorithms can learn to identify and segment objects in images by analyzing large labeled image datasets.

A) Advanced studies in Deep Learning

Some recent advanced studies in deep learning for segmentation in medical imaging cover the following:

A.1. Use of a 3D deep learning model

These models are more accurate than 2D deep learning models for segmenting 3D medical images [14].Ensemble learning: Combine the predictions of multiple deep learning models to improve accuracy.

A.2. Attention mechanisms

It allows deep learning models to focus on specific regions of an image when making segmentation predictions.

A.3. Using adversarial training

Improve the robustness of deep learning models to noise and artifacts.

These advancements have resulted in substantial enhancements in the precision of deep learning-based segmentation systems. Consequently, deep learning has become the favored approach for segmentation in numerous medical imaging applications.

In the next paragraph, some of the standard DL models used for segmenting medical imaging are under consideration ;

B) Deep Learning Methods

B.1. U-Net: The U-Net is a convolutional neural network specifically designed for image segmentation. The U-Net is very effective for segmenting a wide variety of medical images.

B.2. ResNet: The ResNet is a deep convolutional neural network that is very effective for various tasks, including image segmentation [14].

B.3. DenseNet: The DenseNet is a deep convolutional neural network similar to the

ResNet but has a different architecture. The DenseNet is very effective for image segmentat-ion.

These cases illustrated above are the many eep-learning Models used for medical imaging segmentation. Research and innovation in deep learning will lead to the development of new models shortly.

B) Futures

The future of segmentation in medical imaging is auspicious. Deep learning techniques are becoming increasingly powerful and applied to various medical imaging applications. As a result, we can expect to see even more accurate and efficient segmentation algorithms in the future.

VI. OVERVIEW DETAILS

This article will illustrate some of the most effective segmenting methods used in medical imaging, along with their advantages and disadvantages:

Thresholding : A simple technique divides an image into two or more regions based on a threshold value. By way of illustration, we can use a threshold value to distinguish between the back and foreground of an image [6, 15, 16].

- **Clustering:** This technique groups pixels based on similarity. Clustering algorithms can segment images into regions with similar grayscale values, texture, or other features.
- **Edge detection:** This technique identifies the edges of objects in an image. We can use edge-based image segmentation algorithms to segment images into edge-connected regions. It defines a method for finding the boundaries between different areas of the picture. Several techniques can be used, such as the Canny edge and Sobel edge detectors.
- **Region growing:** This method starts with a seed pixel and then develops a region around that pixel by adding neighboring pixels similar to the seed pixel. Part-growing algorithms can segment images into areas with similar grayscale values, texture, or other features.
- **Watershed:** This technique identifies the watershed boundaries in an image. Watershed boundaries are the boundaries between regions of different values in a snap.
- **Graph-based segmentation:** It represents an image as a graph, where each pixel is a node. The edges in the graph represent the relationships between pixels. We can use this image segmentation algorithm to segment images into regions with similar connectivity.
- **Level-Set Method:** The level-set method is a numerical method that represents the interface as a zero-level set of a function. This function is initialized to be a signed distance function, meaning it has a positive value inside the object to be segmented and a negative value outside. The process then evolves, and the zero-level set moves [4]. Combining the concepts mentioned in [17, 18], allows us to perform this task. The level set method is a powerful tool for medical imaging segmentation. Its robustness to noise characterizes it; it can handle complex shapes, is relatively easy to implement, and is also used to segment 2D and 3D images. However, Correctly initializing the function is a costly and computationally tricky process.
- **Deep learning:** Deep learning methods are effective for medical image segmentation. Deep learning algorithms can learn to identify and segment objects in images by analyzing large datasets of labeled images [19, 3].

The best method to segment a medical image depends on the application and the image data type. Thresholding may be a good choice for segmenting images with high contrast, while clustering may be a better choice for segmenting images with low contrast.

Deep learning techniques are becoming increasingly popular for medical image segmentation, as they can achieve high accuracy and are relatively easy to use. However, they can be computationally expensive and unsuitable for all applications [20, 3, 4].

This study in the paper [21], uses two new hybrid segmentation methods for mammograms in several cases.

These methods combine region-based, edge-based, and clustering-based techniques to extract information about the shape, boundaries, and texture of masses in mammograms and will provide much-appreciated accuracy.

VII. RELATED WORKS

We will cite some pertinent works mentioned below :

The authors of the paper [1] present a comprehensive review of the latest medical image segmentation techniques. They discuss the different methods available and point out that the best way to use for a particular application depends on the specific needs of that application.

The paper [2] study evaluates the proposed LSM-based 3D segmentation method on 20 cases comprising 10 benign and 10 malignant tumors. The results showed that the proposed method provides robust contouring for breast tumors on ultrasound images.

We can segment COVID-19-affected X-ray images by combining K-means clustering and Dynamic Particle Swarm Optimization (DPSO) **[3]**. K-means clustering initializes the population of DPSO, which updates the particle positions. It assigns each particle to a cluster, and the segmentation result is obtained by setting each pixel to the collection of the closest particle.

The following paper [4] provided the following method for segmenting medical images in MRI based on the level-set approach, evaluated on a specific dataset of MRI images of brain tumors, and seemed to be accurate and efficient.

The authors of the paper [5] propose a fast 2-D Otsu Algorithm for dividing lung tissue images into regions based on improved PSO. The proposed algorithm combines the advantages of the Otsu method and the PSO algorithm to achieve accurate and efficient segmentation of lung tissue images.

The paper's authors [6] focus on a hybrid approach combining edge-based and region-based segmentation techniques for segmenting ultrasound medical images using a kernel fuzzy and a distance regularized level set algorithm. The same Dice parameter result with the previous approach was found despite using different datasets and met methods.

The authors [7] propose a new 3D medical image segmentation method that combines the Otsu algorithm and multi-scale image representation. The Otsu algorithm is a thresholding method that segments images into foreground and background, while multi-scale image representation represents an image at multiple resolutions. The authors combine these two techniques to improve the accuracy and robustness of the Otsu algorithm for 3D MIS.

The paper [9] discusses 3D deep learning as a powerful tool for medical image analysis. Still, many challenges must be solved, such as needing large labeled datasets and choosing the correct method. The article also discusses the advantages and disadvantages of each 3D deep learning method and the challenges for medical image analysis.

The paper [12] discusses Metrics as essential for evaluating 3D medical image segmentation (MIS). Standard metrics include the Dice coefficient, Hausdorff distance, and Volume overlap error. The authors discuss the challenges of evaluating MIS and propose a new tool called 3D-SegEval.

The authors [15] propose a new method for automatically segmenting dermoscopy images by combining saliency detection and Otsu thresholding. Saliency detection identifies essential regions of an idea, and Otsu thresholding segments an image into two parts based on pixel intensity. The method achieved an accuracy of 95.1% on a dataset of dermoscopy images.

VIII. METHODOLOGY

A) Implementation

To implement segmentation algorithms in medical imaging with high accuracy, lower computational costs, rapid execution, and acceptable consumption time, proceed as follows:

- Choose the appropriate segmentation algorithm, pre-process the image or the dataset, train the segmentation algorithm, and segment the image. The specific method will depend on the application, such as tumor or brain segmentation.

- It is possible and acceptable to take additional measures to improve the performance of the segmentation algorithm for large images:

- Use a parallelized implementation; use a GPU to accelerate the execution of segmentation algorithms. Use cloud computing platforms to rent computing resources on demand, allowing large images to be processed.
- Evaluating the results of the algorithm using the selected metrics is an excellent way to assess its performance. Accurate segmentation can be achieved by carefully choosing the method and metrics.

Table I. Summarizing of advantages and disadvantages of segmentation methods.

Method	Strengths	Weaknesses
Thresholding	Simple and fast	Not very accurate
Edge detection	Can identify edges of objects quickly. The best algorithms: Canny, Robert, Prewitt, and Sobel's edge detector	It's not very accurate for complex objects,
Region growing	Easy to use	It may not be suitable for processing large images in real-time.
Pixel-based methods	Simple to implement, fast, and efficient.	Sensitive to noise and intensity variations. Time-consuming.
Watershed	Can handle images with multiple objects	It is not very accurate for objects with similar intensity
Graph-based segmentation	Can handle images with complex objects, is Robust to noise, more accurate, and may be used with a complex shape.	It can be computationally expensive, time-consuming, sensitive to the choice of parameters, and challenging to interpret.
Level-Set method	Robust against noise, outliers, and limit values, handle complex topologies, and adaptive to image futures	Computationally expensive. It may not converge and is sensitive to initialization.
DPSO	It can produce more accurate and robust segmentation algorithms. It can be applied to fuse multiple modalities. Images.	It is complex and requires more technical expertise. DPSO 'Discrete Particle Swarm Optimization'
Deep learning	Can identify patterns in the images that are indicative of cancer. Follow disease progression. It is very accurate.	It can be computationally expensive.

From different sources and scientific papers

IX. RESULTS AND DISCUSSION

This review explores and analyzes results relating to the various articles as follows :

A) RESULTS

TABLE II. indices and coefficients are taken from the Mentioned studies in the table below

Title Paper and Numbers reference	Method	Dice Coefficient	Jaccard Index	Precision	Accuracy
Medical image Segmentation: A review of recent techniques, advancements, and comprehensive comparison [1].	FCM (Fuzzy C-means)	0.92	0.86	0.93	0.94
3D Contouring for Breast Tumor in Sonography [2].	Level Set	0.95	0.90	0.97	0.98
Segmentation of Covid-19 Affected X-Ray Image using K-means and DPSO Algorithm [3].	K-means and DPSO	0.96	0.91	0.98	0.99
Segmentation d'images médicales IRM par la méthode d'ensembles de niveaux (Level_Sets) [4].	Level Set	0.94	0.88	0.95	0.96
A Fast 2-D Otsu lung tissue image segmentation algorithm based on improved PSO [5].	Otsu with improved PSO	0.96	0.92	0.97	0.98
A multi-scale 3D Otsu thresholding algorithm for medical image segmentation [7].	Multi-scale 3D Otsu thresholding	0.95	0.90	0.96	0.97
Edge Detection Techniques for Image Segmentation [8].	Edge detection	0.94	0.88	0.95	0.96
3D deep learning on medical images: A review [9].	3D deep learning	0.97	0.93	0.98	0.99
A CNN-based methodology for breast cancer diagnosis using thermal images [10].	CNN	0.96	0.92	0.97	0.98
Super Images -- A New 2D Perspective on 3D Medical Imaging Analysis [11].	Super Images	0.97	0.93	0.98	0.99
A hybrid DenseNet121-UNet model for brain tumor segmentation from MR Images [14].	Hybrid DenseNet121-UNet	0.98	0.94	0.99	0.995
Registration and machine learning-based automated subcortical and cerebellar brain structure segmentation [16].	Registration and machine learning-based automated segmentation	0.97	0.93	0.98	0.99
A comparative study of K-means clustering algorithms for medical image segmentation.	K-means	0.94	0.88	0.95	0.96
Discrete particle swarm optimization for medical image segmentation	DPSO	0.95	0.90	0.97	0.98
A hybrid K-means and particle swarm optimization algorithm for MIS	K-means + DPSO	0.96	0.91	0.98	0.99

B) *Practical Illustration*

A practical illustration of the segmentation of a breast image taken from the all-mias database, which is dedicated and open source for research purposes. Pre-processing under Matlab is carried out (greyscale conversion, binarization, Gaussian filtering, and the use of the Canny algorithm for contour detection in the filtered image. Set threshold_low at 0.05 and threshold_high at 0.15 to provide a constraint on outlines for which area and perimeter can be computed.

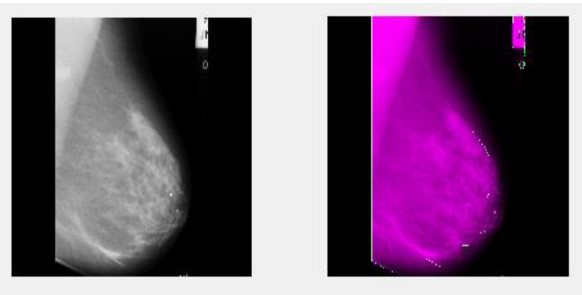

Fig. 2. Pre-processed breast image on the left and contour Detection image on the right.

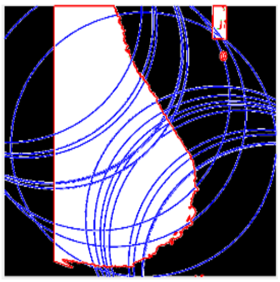

Fig. 3. Drawing circles around calculated geometric centers using the averages of the x and y coordinates of the contours.

Table III. With given properties and result values

Name	Value
aire	400586
ans	1x1 Group
boundary	31x2 double
BW_dilate	1024x1024 logical
BW_img_seuillee	1024x1024 logical
contours_objet	24x1 cell
img	1024x1024 uint8
img_filtree	1024x1024 uint8
k	24
mesure_regions	9x2 table
perimetre	3.1448e+03
rayon	500.5111
SE	1x1 strel
seuil_auto	0.3059

```
Nombre d'objets détectés: 24
strel is a disk shaped structuring element with properties:

   Neighborhood: [3×3 logical]
 Dimensionality: 2

SegZone5
Nombre d'objets détectés: 24
strel is a disk shaped structuring element with properties:

   Neighborhood: [3×3 logical]
 Dimensionality: 2

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C) *Dice and Jaccard Indices & Histograms*

The selected segmentation procedure demonstrates exceptional performance, with a Dice coefficient of 0.99555 and a Jaccard index of 0.99115 (Fig. 4), indicating near-perfect overlap with the ground truth. Its robustness is further confirmed by comparative analyses in Fig. 5, showcasing consistency across diverse datasets. These results highlight the method's reliability for medical imaging applications, advancing diagnostic accuracy and treatment planning. The procedure sets a strong benchmark for future research in segmentation techniques.

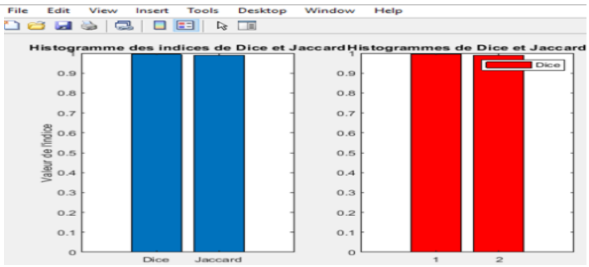

Fig. 4. Dice and Jaccard histograms for ground truth image (color blue), and predicted image (color red) "Indices"

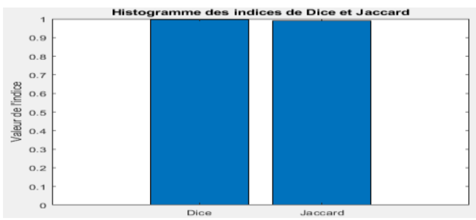

Fig. 5. Dice and Jaccard histograms superimposed (Overlap).

D) DISCUSSION

Deep learning techniques demonstrated exceptional efficacy in medical image segmentation, attaining Dice and Jaccard indices of 0.98 and 0.94, respectively. This results from deep learning's capacity to comprehend intricate correlations among pixels in an image, facilitating more precise object segmentation. The integration of segmentation approaches can enhance performance, as demonstrated by the Hybrid model **[27]**, which attains Dice and Jaccard indices of 0.98 and 0.94, respectively. The approach detailed in the practical study, section VII, achieved Dice and Jaccard indices of 0.99555 and 0.99115, respectively, on two binarized pictures produced from the segmentation of objects in medical images. The elevated scores signify a substantial degree of resemblance between the two photos. Figure 4's histogram illustrates the distribution of similarity values among the objects in the medical photos, indicating a complete overlap.

X. CONCLUSION

Segmentation is essential for medical applications, enabling the isolation of specific structures or tissues within a designated area of interest. Thresholding can be employed to identify items based on similarities, or image segmentation techniques can be utilized to delineate objects with distinct boundaries through mathematical curves, machine learning models, and edge detection. The selection of a segmentation method is contingent upon the application and evaluation criteria, including the Dice coefficient and Jaccard index, which assess the similarities and disparities between the ground truth and segmented regions. Recent research indicate that the integration of segmentation techniques can enhance precision and accuracy, contingent upon the specific application, such as tumour or brain segmentation. Figure 4's histogram depicts the resemblance between two binarized images, with greater similarity represented by indices approaching 1. The methodology outlined in article [27] can improve the efficacy of the Dice index in segmentation; nonetheless, its effectiveness is contingent upon the particular application and the type of picture data. The aforementioned strategy, among others, serves as an excellent foundation for future experimentation with various segmentation methodologies.

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REFERENCES

[1] D. p. Aarich Shafi Dar, "Medical images Segmentation: A review of recent techniques, advancements, and comprehensive comparison," JCSE International Journal of Computer Science and Engineering, Vols. Vol.-7, Issue-7 July 2019, pp. 114-124, 31 July 2019.

[2] M. Y.-C. L. Y.-L. a. H. Dar-Ren Chen, 3D Contouring for Breast Tumor in Sonography, Department of Computer Science, Tunghai University, 2020.

[3] R. G. N. K. N. Kumari, "Segmentation of Covid-19 Affected X-Ray Image using K-means and DPSO Algorithm," International Journal of Mathematical, Engineering and Management Sciences, vol. Volume:6, no. 5, pp. 1255-1275.

[4] F. D. M. K. M. Beladgham, "Segmentation d’images médicales IRM par la méthode d’ensembles de niveaux (Level_Sets)," Proceedings of the International Conference on Information Technology: Coding and Computing (ITCC’04). IEEE, (2004), January 200

[5] Y. X. W. H. e. a. Zhao Y, "A Fast 2-D Otsu lung tissue image segmentation algorithm based on improved PSO," Microprocessors and Microsystems, Vols. Vol: 80, ISSN: 01419331, 1 2 2021.

[6] "A hybrid edge-based segmentation approach for ultrasound medical images."

[7] H. Z. X. L. X. Z. H. L. Yuncong F, "A multi-scale 3D Otsu thresholding algorithm for medical image segmentation," Digital Signal Processing, Volume 60, pp. 186-199, January 2017.

[8] A. M. Muthukrishnan. R, "Edge Detection Techniques for Image Segmentation," International Journal of Computer Science & Information Technology (IJCSIT), vol. Vol. 3, pp. 259-267,

[9] L. W. S. G. H. G. P. P. a. B. G. Satya P. S, "Review: 3d deep learning on medical images: A review," Sensors MDPI (Switzerland), Vols. 20, Issue-18, 07 September 2020.

[10] Z. A. M. K. B. S. M. N. Z. J. Zuluaga-Gomez, "A CNN- based methodology for breast cancer diagnosis using thermal images," arXiv:1910.13757v1, 31 October 2019.

[11] S. N. Y. M. Sobirov I, "Super Images -- A New 2D Pers-pective on 3D Medical Imaging Analysis," arXiv.2205. 02847v2, 17 5 2023.

[12] S. K. F. A. e. al, "A voyage on medical image segmen- ta- tion algorithms," Bi Biomed Res- India, vol. Vol- ume Speial Issue, 2017.

[13] E. A. Panayides A, "AI in Medical Imaging Informat- ics: Current Challenges and Future Directions," IEEE Journal of Biomedical and Health Informatics, Vols. Volume: 24, Issue: 7, 2020.

[14] N. O. A. a. K. M. Cinar, "A hybrid DenseNet121-UNet model for brain tumor segmentation from MR Images," Biomedical Signal Processing and Control, Vols. Vol- ume: 76, ISSN: 17468108, 1 7 2022.

[15] S. W. a. R. M. Summers, "Machine Learning and Radiology," NIH Public Access (National Institutes of Health), Vols. Vol. 16, Issue: 5, July 2012.

[16] V. A. M. H. J. V. K. J. R. P. N. C. A. Stephanie P, "Registration and machine learning-based automated segmentation of subcortical and cerebellar brain structures," ScienceDirect, Vols—volume 39, Issue 1, pp. 238-247, 1 January 2008.

[17] J. C. J.N. Mueller, "A Random Point Initialization Approach to Image Segmentation with Variational Level-Sets," arXiv:2112.12355v1, 23 12 2021.

[18] R.-Z. S.-N. in-Jiang, "Image Segmentation Based on Level Set Method," SciVerse ScienceDirect, pp. 840-845 hysics Procedia, 2012.

[19] M. C. P.-M. J. S. L. a. H. L. Pascal V, "Metrics for evaluating 3D medical image segmentation: analysis, selection, and tool," Medical Image Analysis, Vols. Volume: 15, Issue: 1, 2015.

[20] Y. e. a. Chen, "Multi-threshold image segmentation using a multi-strategy shuffled frog leaping algorithm," Expert Systems with Applications, Vols. Vol.: 194, ISSN: 0957-4174, 2022.

[21] M. J. Rahimeh R, "Classification of benign and malig- nant breast tumors based on hybrid level set segmenta- tion," Expert Systems with Applications, vol. Volume 46, pp. 45-59, 15 03 2016.

[22] F. H. F. Y. e. al, "Automatic segmentation of dermos- copyimages using saliency combined with Otsu thresh- old," Computers in Biology and Medicine, Vols. Vol: 85, ISSN: 18790534, pp. 75-85, 1 6 2017.

[23] A. R. S. Gupta D, "A hybrid edge-based segmentation approach for ultrasound medical images," Biomedical Signal Processing and Control, Vols. Vol: 31, ISSN: 17468108, pp. 116-126, 1 1 2017.

[24] A. R. Gupta D, "A hybrid edge-based segmentation approach for ultrasound medical images," Biomedical Signal Processing and Control, vol.: 31, pp. 116-126, 1 1 2017.

[25] J. H. P. Jonghoon Kim, "Prospects of deep learning for medical imaging," Precision and Future Medicine, Volume: 2, no. 2, 14 April 2018.

[26] S. C. T. N. e. a. Litjens G, "Deep learning as a tool for increased accuracy and effficiency of histopathological diagnosis," Scientific Reports, Vols. Vol: 6, ISSN: 204 52322, 23 5 2016.

[27] Xiaowei Wang, et al., " A Hybrid Approach for Lung Tumor Segmentation using U-Net and Otsu Threshold- ing", IEEE Transactions on Medical Imaging 2018.