Journal of Kerbala University, Vol. 22, Issue 2, June , 2025

IRAQI Academic Scientific Journals

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Iraqi Academic Scientific Journals

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Review Article

MRI Image Segmentation Using Machine Learning Methods: A Survey

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Article Info

Article history:

Received 15 -4-2025

Received in revised form 18-5-2025

Accepted 8-7-2025

Available online 30 -6 -2025

Keywords: Magnetic resonance imaging (MRI), image segmentation, Region-based segmentation, Clustering-based segmentation

Abstract:

Magnetic resonance imaging (MRI) has been utilized as a non-invasive imaging technique to detect and diagnose central nervous system disorders, as well as to monitor their treatment course. Neurologists can more accurately detect abnormalities from brain imaging because of the three-dimensional images that MRI creates. The machine learning techniques such as K-Means, naive Bayesian, logistic, Decision tree, or random forest. Furthermore, deep learning used CNN to segment images into specific regions, such as “UNet”, “ResNet”, “GoogleNet”, etc. A computer-aided method for analyzing MRI images and precisely identifying abnormalities has been made possible by advancements in machine learning and rapid processing. Image segmentation has become more popular and a focal point of research in medical image analysis. The ability to rapidly classify the disease for early treatment is made possible by the computer-aided technique for identifying brain abnormalities. The research articles on brain tumor segmentation from MRI images are reviewed in this article. The comparison of segmentation methods in accuracy is in thresholding is about 0.75, in k-means clustering is about 0.8, in a U-Net is about 0.9, and in V-Net is about 0.92, respectively.

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Peer review under responsibility of Iraqi Academic Scientific Journal and University of Kerbala.

1. Introduction

A surge of new machine learning methods has recently made their impact on the medical imaging domain, most importantly in the MRI image segmentation task [1]. These anatomical structures on MRI scans are complex, and robust analytical methods are essential to segment and classify the regions of interest accurately. Emphasizing the importance of deep learning approaches, this study aims to provide a broad perspective on techniques emerging in MRI picture segmentation. As an example, recent research demonstrated the effectiveness of convolutional networks on medical imaging and provided an overview of over 300 works of segmentation and closely related tasks [2]. New techniques have also emerged from 3D image volume annotation, including Active Learning with geometric priors, which has outperformed previous methods [3]. It has an important role in medical data analysis & enables the identification of their normal anatomical structures as well as pathological conditions. This enhances not only diagnosis precision but also indicates potential treatment pathways and monitors disease progression [4]. Also, deep learning methods, which are a type of machine learning, have been applied with increasing interest to MRI segmentation in recent years, showing great promise. Conventional networks have emerged as the dominant modality used for image analysis during recent times, manifesting in their strong performance on both segmentation and classification tasks [5]. Moreover, novel methodologies that leverage active artificial learning techniques can enhance data usage, leading to remarkable increases in segmentation performance [6]. In conclusion, the fusion of sophisticated algorithms and magnetic resonance imaging (MRI) segmentation highlights the significance of incorporating machine learning methods, paving the way for a transformation in the realm of medical diagnostics and tailored treatment approaches.

To advance MRI segmentation algorithms and increase their practicality in clinical settings, these problem statements must be addressed [7]. Developing more resilient algorithms, improving data annotation procedures, and utilizing cutting-edge machine learning techniques are the main goals of ongoing research to address these issues. An example of an MRI is shown in Figure 1 of a brain image.

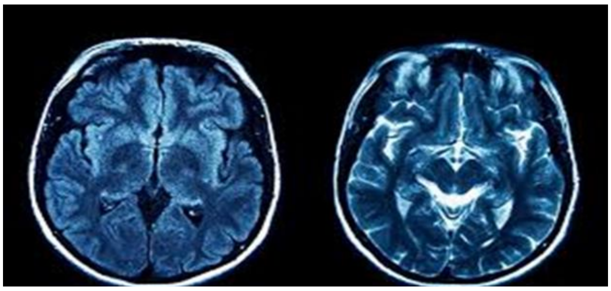

Figure 1: Brain MRI image

2.Challenges in MRI Segmentation

The challenges of magnetic resonance imaging (MRI) segmentation, some points can be noted, such as data scarcity, obtaining large and diverse datasets, leading to a lack of training for machine learning models, model generalization, which struggles to generalize to new or unfamiliar data, and evaluation inconsistency in which the criteria vary between studies, making it difficult to compare results. The lack of a standardized metric can weaken the significance of the results and make it difficult to determine the effectiveness of different methods [8].

3.Segmentation types

Segmentation refers to partitioning MRI images into meaningful regions to facilitate analysis and interpretation. Several types of segmentation techniques are used in MRI imaging, each with its strengths and applications.

•Manual Segmentation

Involves a radiologist or medical expert manually outlining the regions of interest (ROIs) on the MRI images. The accuracy is when done by an expert and is useful for complex cases, but it is subjective, time-consuming, and likely to exhibit variability amongst observers [9]. Drawing in slices of radiological data by hand is the most straightforward and universal technique for picture segmentation; the user uses a pointing device to indicate the pertinent components. It is frequently possible to change the contour by redrawing a specific area that takes the place of the previously drawn area [10]. Other pointing devices, like a pen, are more suitable for drawing jobs, even if the mouse is commonly used for manual segmentation. Manual segmentation is always necessary. However, it is time-consuming and neither precise nor reproducible because the user often deviates slightly from the desired contour. Manual segmentation is nevertheless frequently used despite these problems, particularly when objects are complicated to identify. ITK-Snap is an example of manual segmentation [11]. A sample of manual segmentation is explained in Figure 2.

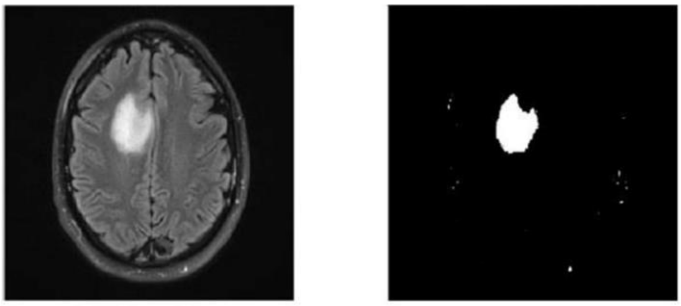

Figure 2: Manual Segmentation of the Brain MRI

•Threshold-based segmentation

Utilizes intensity values of pixels to segment the image; regions are classified according to whether their intensity values fall above or below a certain threshold [12]. The method is simple, fast, and effective for images with apparent differences in intensity, but it has poor performance in images that contain intensity distributions that overlap. The threshold-based method may be local threshold-based segmentation [13], global threshold-based segmentation [14], and adaptive threshold-based segmentation [15]. A sample of segmentation-based thresholding is explained in Figure 3.

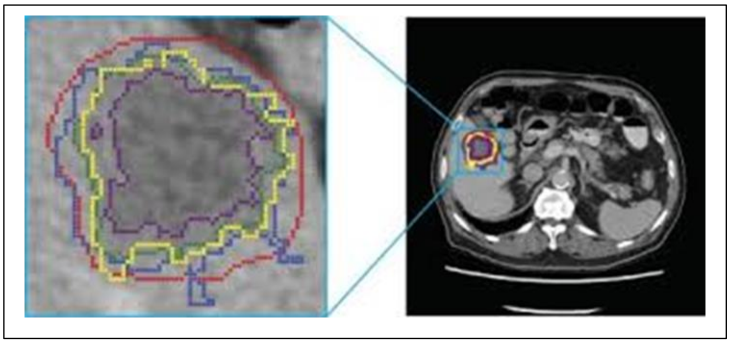

Figure 3: Threshold-based segmentation of the Brain MRI

•Region-based segmentation

Segment images based on predefined criteria for pixel connectivity. The common methods include region growing and region splitting/merging [16]. It captures the spatial continuity of structures and can handle noise better than thresholding, but it's sensitive to initial seed points and may struggle with complex structures. Clustering-based segmentation contains two types: clustering by merging (agglomerative clustering, the bottom-up approach) [17] and clustering by division (divisive splitting, the top-down approach) [18]. An example of region-based explanation is shown in Figure 4.

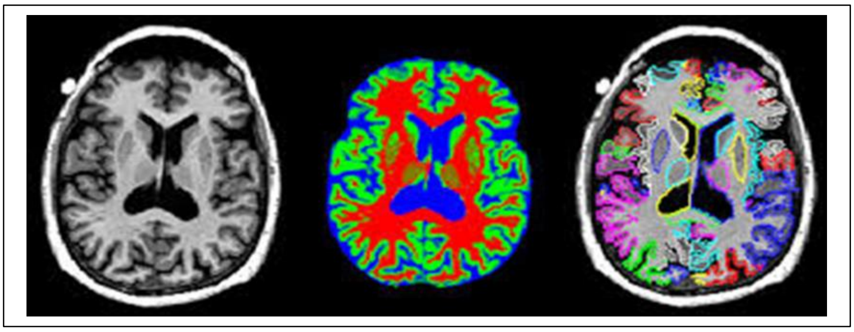

Figure 4: Region-based segmentation of the Brain MRI

•Edge-based segmentation

It emphasizes identifying boundaries within the image using edge detection methods, such as the Sobel operator and Canny edge detector [19]. It is effective for images with clear boundaries, but it may miss weak edges and is sensitive to noise. There are several types of edge detection of MRI images, such as Canny, Sobel, and Prewitt edge detection [20].

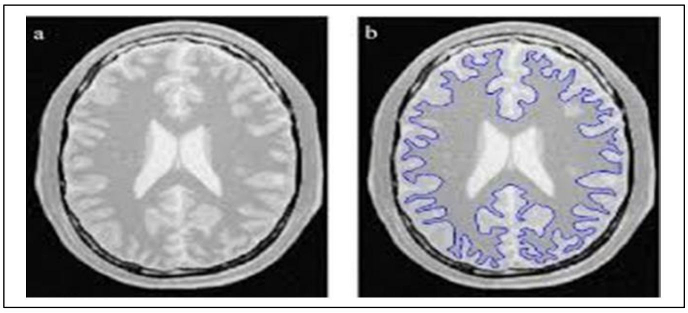

Figure 4: Edge-based segmentation of the Brain MRI

•Clustering-based segmentation

The method represented by grouping pixels into clusters based on feature similarity, with K-means and GMM, standing for Gaussian Mixture Models, being common approaches [21]. It is useful for segmenting images with varying intensity distributions. Requires selecting the number of clusters and can be affected by initialization. A sample of clustering-based explanation is shown in Figure 5.

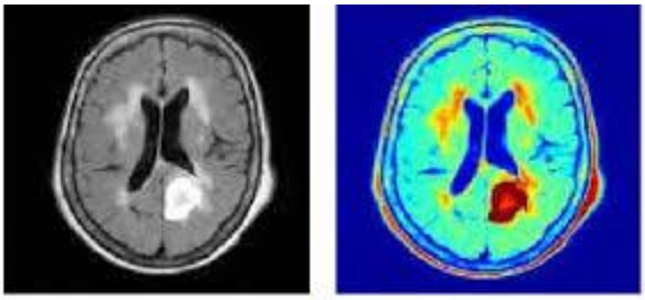

Figure 5: Clustering-based segmentation of the Brain MRI

•Model-based segmentation

The predefined models (e.g., active contours, level sets) are used to fit the anatomical structures in the images, incorporating prior knowledge about the shape and appearance of structures, but they are computationally intensive and may require fine-tuning of parameters [22]. An explanation of model-based segmentation is shown in Figure 6.

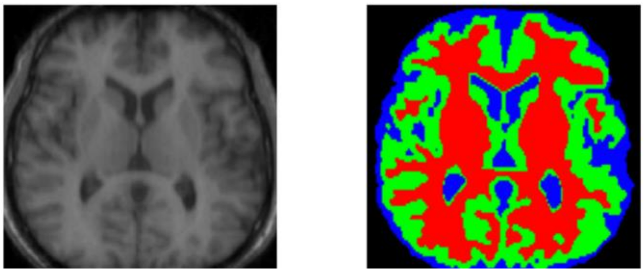

Figure 6: Model-based segmentation of the Brain MRI

•Deep Learning-Based Segmentation

Utilizes deep learning architectures, particularly Convolutional Neural Networks (CNNs), to perform automatic segmentation [23]. It has robustness and high accuracy to variations in data and can learn complex patterns. Nonetheless, it requires large annotated datasets for training and can be computationally expensive. A sample of deep learning based segmentation is explained in Figure 7.

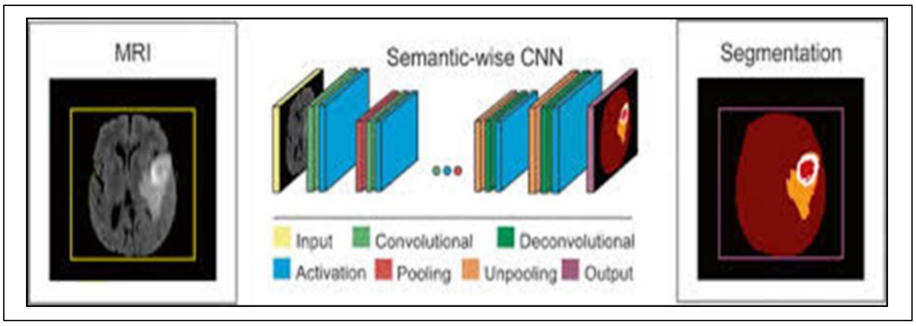

Figure 7: Deep-learning segmentation of Brain MRI

•Hybrid Methods

Because of the high-dimensional nature of medical data, such as the Magnetic Resonance Imaging (MRI), novel approaches use advanced machine learning methods to get appropriate segmentation of the data. In recent years, deep learning methods have emerged explosively, and CNNs, standing for convolutional neural networks, are one of the most common methods because of their capacity to acquire traits from the original image data automatically, which greatly reduces the difficulty of the segmentation task. Recent studies have shown that these deep learning approaches have substantially exceeded contemporary performance benchmarks on several segmentation tasks through their ability to be tailored towards the diverse anatomical structures and pathologies present in MRI images [24], as explained in Figures 8 and 9.

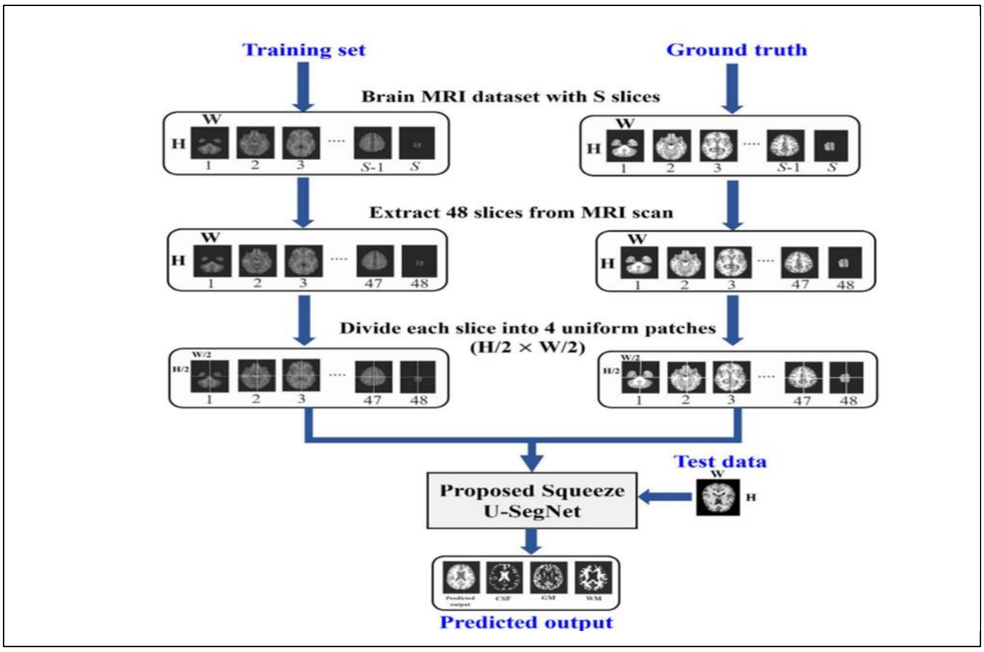

Figure 8: U-SegNet Architecture Based on Residual Conv. (Brain MRI Segmentation) [16]

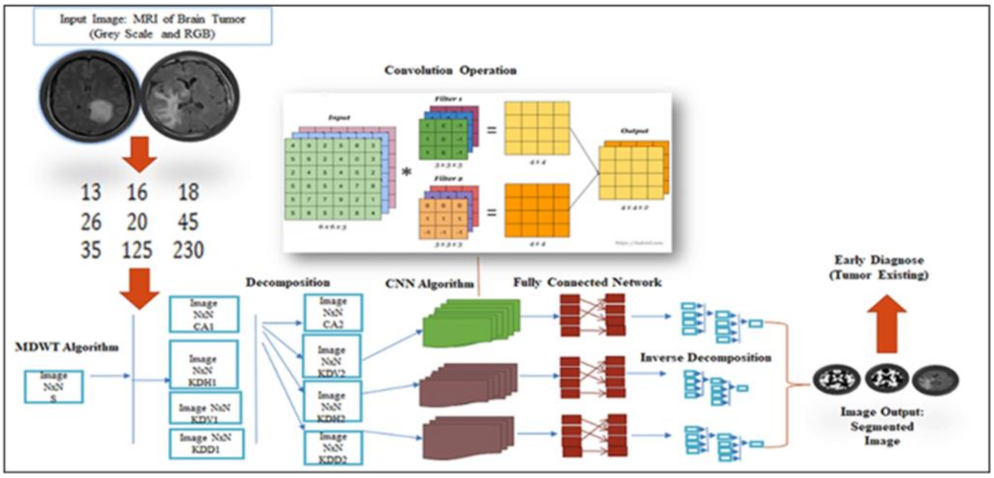

Figure 9: Hybrid architecture design of the MRI brain image segmentation[17]

Moreover, several novel approaches have emerged addressing training efficiency through the application of geometric priors, e.g, Active Learning. This method reduces the annotation workload, concentrating only on important locations within the 3D volumes

4.Comparison of Traditional vs. Machine Learning Approaches

Conventional and machine learning techniques for MRI image segmentation have become widely used, and advanced algorithms have several advantages over conventional techniques. Due to variations in image quality and natural non-homogeneity of anatomical structures, traditional algorithms for segmentation are often based on ad hoc features and rule-based methods of segmentation. Machine learning approaches, particularly deep learning approaches, have shown comparatively more flexibility and accuracy. Deep Learning algorithms are, for instance, Convolutional neural networks, which are central to how MRI images are interpreted [26], as they acquire distinct representations of the data they receive, thus promoting end-to-end learning without manual feature engineering. After that, Active Learning methods employing the geometric priors improved the segmentation pipelines and accelerated segmentation annotation with efficiency and accuracy. Machine learning remains a dominant paradigm in the field of medical imaging as it is flexible and performant enough to continue to respond to a changing landscape that generates the need for new paradigms.

5.Applications of Machine Learning in MRI Image Segmentation

Machine learning, particularly deep learning, has revolutionized and is considered a significant advancement for health organizations and AI applications like MRI image segmentation. The use of more recent architectures like CNN and other shows tremendous progress on segmentation tasks over traditional methods. This technology is capable of automatic abnormality detection, which helps in better and timely interventions. This is important as large amounts of data are being generated via medical imaging, and it so that segmentation classifiers can be effectively built with a small amount of data input [25]. All of this gives a very hopeful outlook in the context of the usage of machine learning in picturing in the medical environment.

poses a challenge to extract meaningful insights from this collection of enormous data [27]. Additionally, recent surveys highlight that deep learning methods are evolving rapidly and are gaining traction for numerous segmentation goals, paving the way for a clinical practice future where these solutions become standard [28]. This area of research shows significant promise, as it not only improves diagnostic capabilities but also has potential applications to both hold and improve patient outcomes.

6.Case Studies Highlighting Successful Implementations

Several recent studies of successful applications of machine learning in MRI image segmentation demonstrate the extent to which this technology could impact the medical imaging landscape. Convolutional neural networks have become the focus of deep learning algorithms as they can address some challenges related to medical image analysis. To this end, various works in the literature show that application of these models for segmentation of cardiac MRI images leads to a notable increase in accuracy as compared to classical methods, hence improving diagnostics. These implementations showcase the ability of these advanced models to discern and classify anatomical structures from MRI modalities, echoing current literature to inform their use as automated assistants to complicated health outcomes [29]. Moreover, the introduction of machine learning methods into cardiovascular MRI analysis has yielded a new dimension in clinical practice that has led to correlations between aortic properties and cardiovascular diseases [30].

We have also discussed the traditional methods and their limitations, and how the automated techniques covered in this survey have the potential to improve precision and speed. In particular, a new adaptive thresholding for stroke segmentation gained a high Dice coefficient of 0.96 from the area of interest to help clinicians in providing decisions for them [31]. Likewise, the evaluation of the marker-controlled watershed segmentation (MCWS) algorithm displayed enhanced performance metrics [32], further highlighting the substantial need for reliable image segmentation in the treatment planning of different brain tumors. These developments provide a pathway for the more extensive application of machine learning to the field of medical imaging, but also point to a need for continuous iteration of such techniques to refine them for real-world use and improve patient care and outcomes.

7.Semi-supervised in DICOM Image Segmentation

Model predictions on unlabeled images are used as labeled data to reinforce learning, such as Pseudo-Labeling. Furthermore, the recent developments, such as the MixMatch method, which combines labeled and unlabeled data using optimization techniques, enhance segmentation accuracy in DICOM images, and FixMatch, which uses uncertain labels with performance optimization techniques, improve segmentation results. The data used are labeled and unlabeled data, and unlabeled data only. The applications of segmenting tumors and lesions in DICOM images, and clustering regions with similar features [33].

8.Challenges in MRI Image Segmentation Using Machine Learning

As the field of MRI image segmentation using machine learning continues to evolve, numerous potential future directions and challenges deserve attention. The reliance on massive annotated datasets, which can be extremely expensive and time-consuming to compile, is a major obstacle. Addressing this, researchers are exploring semi-supervised and unsupervised learning techniques to reduce annotation burdens while maintaining segmentation accuracy. Furthermore, while CNNs, convolutional neural networks, have shown remarkable performance, the need for models that balance efficiency and precision is becoming increasingly apparent, especially in clinical settings. Recent studies highlight those innovations in semantic segmentation, particularly through advanced architectures, and provide pathways to overcome challenges related to fine-grained localization and scale invariance [34]. Additionally, expanding the focus to a three-dimensional context may enhance segmentation outcomes, paving the way for integrating richer datasets that reflect complex anatomical variations [35].

9.Evaluation and Validation

Nowadays, the most popular method for quantitatively assessing segmentation outcomes is to compute the overlap with the ground truth. The most often utilized evaluation criteria in the field of brain tumor segmentation are the Dice Similarity Coefficient (DSC) and the Jaccard coefficient [36]. They can have a value between 0 and 1, where 0 denotes no overlap and 1 denotes perfect overlap. For the probabilistic brain tumor segmentation, three distinct validation criteria were compared, such as Mutual Information (MI), DSC, and area under the Receiver Operating Characteristic (ROC) curve [37].

They came to the following conclusions: the Dice coefficient is the optimal metric for evaluating spatial alignment, MI is the preferred metric when interested in sensitivity to changes in tumor size, and the area under the ROC curve should be utilized for overall classification accuracy. Because there isn't a brain tumor database with ground-truth segmentations that is accessible to a large community of academics and physicians, most researchers verified their algorithms on a small number of cases from their data a few years ago. This makes it challenging to conduct a standard comparison of the performance of various approaches. Because multiple metrics were employed, it is impossible to evaluate the accuracy, validity, and robustness of the various approaches. They came to the following conclusions: the Dice coefficient is the best metric for evaluating spatial alignment, MI is the preferred metric when interested in sensitivity to changes in tumor size, and the area under the ROC curve should be used for overall classification accuracy. Because there isn't a brain tumor database with ground-truth segmentations that is accessible to a large community of researchers and clinicians, most researchers validated their algorithms on a small number of cases. A comparison of performance is explained in Table 1.

Table 1: Comparison criteria of different MRI segmentation methods

Method	Accuracy (DSC)	Processing time	Robustness	Data Requirements
Thresholding	0.75	Low	low	low
k-means clustering	0.8	Medium	medium	Medium
U-Net	0.9	High	high	high
V-Net	0.92	Very high	high	high
Fuzzy C-means	0.85	Medium	medium	medium

The different metrics were utilized, but it is not possible to directly compare the methods' accuracy, validity, and robustness. Only a small number of groups have conducted tests on these images, even though synthetic data has been available for consistent comparison up until recently [30]. At present, the BraTS is the most widely used open MRI database for unbiased comparisons of algorithms used to segment brain tumors [37].

10.Available brain MRI dataset

There are several public datasets for segmentation available for the application, as explained in Table 2. These datasets are essential for developing and improving image segmentation techniques using machine learning and contribute to enhancing the accuracy and efficiency of models used in medical applications.

Table 2: Public dataset for segmentation

Dataset	Modalities	Number of brain Images	Resolution	URL
BRATS	MRI	30,000	512*512	http://www.med.upenn.edu/sbia/brats2018/rigistration.html
ISLES	CT/MRI	1,000	240*240	http://www.isles-challenge.org/
mTOP	MRI	2,000	256*256	https://www.smir.ch/MTOP/Start2016
MSSEG	MRI	1,200	256*256	https://portal.fli-iam.irisa.fr/msseg-challenge/data.
NeoBrainS 12	MRI	1,200	128*128	Http://neobrains12.isi.uu.nl/
MRBrainS	MRI	1,000	256*256	http://mrbrains13.isi.uu.nl/

These datasets in the previous table are essential for developing and improving image segmentation techniques using machine learning, and contribute to enhancing the accuracy and efficiency of models used in medical applications.

11.Conclusion

Each type of MRI segmentation has its applications depending on the specific clinical context, the structures of interest, and the quality of the MRI data. The choice of segmentation technique often depends on the desired accuracy, computational resources, and the specific characteristics of the images being analyzed. In summary, the integration of machine learning methods into MRI image segmentation has demonstrated significant advancements in medical imaging, particularly in diagnosing complex conditions such as brain strokes and glioblastoma multiforme. The objectives of this paper are to analyze and categorize various machine learning methods used for MRI image segmentation, including traditional algorithms (e.g., K-means, Random Forest) and modern deep learning approaches (e.g., Convolutional Neural Networks, U-Net). Compare the performance of different segmentation procedures according to metrics such as accuracy. Examine how segmentation accuracy can be improved and a more thorough analysis can be obtained by combining MRI data with other imaging modalities (such as CT or PET). The advances in neural networks could be used model such as Transformers and attention mechanisms to improve segmentation accuracy.

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