Medical Image Segmentation Using Soft Computing Techniques

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ABSTRACT

Purpose: In this research, soft computing technique for medical image segmentation is proposed that integrates with geographical information. Segmentation separates an image into discrete provinces, each containing pixels with similar properties. The regions should have a strong connection to the portrayed objects or aspects of interest in order to be expressive and effective for picture analysis and interpretation. For efficient accuracy, many soft computing and hard computing algorithms are employed for medical image segmentation. Soft computing is a recent method based on the concepts of approximation, uncertainty, and flexibility.

Design/Methodology/Approach: For image segmentation, the suggested method is soft computing techniqueThis study discusses a variety of image segmentation approaches for medical image analysis. We have detailed the most recent segmentation algorithms used in medical image analysis in this study. Each method's benefits and drawbacks are discussed, as well as an evaluation of each algorithm's use in Magnetic Resonance Imaging.

Findings/Result: The efficiency of the fuzzy logical information C-means clustering algorithm for identifying tissues in brain MR images is significantly higher than that of the FCM and fuzzy local information C-means clustering algorithm segmentation approaches.

Paper Type: Conceptual Research

Keywords: Medical Image Segmentation, Hard computing, Soft computing, Medical imaging

1. INTRODUCTION

The procedure of subdividing a picture into subsequent pieces or objects is known as image segmentation. These objects are used in image processing and analysis as well. Each of these components consists of a collection of pixels. Image segmentation is very reliant on the application. When an object or part of interest is found during automatic image recognition and analysis difficulties, segmentation should be stopped [1]. A good image analysis relies heavily on an efficient image segmentation procedure. Researchers have been working on creating an automatic state-of-the-art picture segmentation procedure that can be used in conjunction with high-level machine-based image analysis. For different types of picture analysis, different image segmentation processes are used [2]. Manual annotations are frequently employed to carry out image segmentations, however they are time-consuming, inefficient, and labour-intensive. As a result, the field of automating the image segmentation process is drawing a large number of academics, and several notable breakthroughs have occurred as a result [3]. However, various studies based on medical picture segmentation are currently underway. There is yet no accurate way to apply segmentation to various datasets. This study gives a quick overview of some of the current soft and hard computing algorithms for medical image segmentation. Furthermore, this study is arranged so that Sect. 3 provides an

overview of soft and hard computing strategies, and Sect. 4 provides a brief introduction to some current soft and hard computing methodologies for medical image segmentation. Sect. 5 contains the conclusion. Finally, in Section 6, the references are listed.
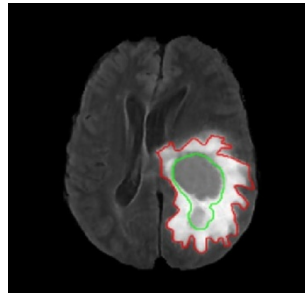
Fig. 1 Brain tumour image segmentation

1.1 Medical image segmentation

Deep learning algorithms entered the picture in the 2000s as hardware improved, and they began to demonstrate their significant capabilities in image processing applications. Deep learning algorithms have emerged as a key alternative for image segmentation, particularly for medical image segmentation, due to their promising capabilities. Image segmentation based on deep learning algorithms has gotten a lot of attention recently, which underscores the need for a thorough review. To the best of our knowledge, no comprehensive study of medical image segmentation utilising deep learning approaches has been published. For example, are two recent survey publications on medical picture segmentation. Shen et al. covered many types of medical image analysis in [5], however they paid little attention to the technical aspects of medical picture segmentation. Many other aspects of medical image analysis are included in [4], such as classification, detection, and registration, making it a medical image analysis review rather than a specialised medical image segmentation survey. The details of networks, capacities, and flaws are absent due to the large scope of this article.The practise of segmenting photos into many objects based on homogeneous properties such as intensity or hue is known as image segmentation. This simplifies image analysis by displaying only the characteristics of the entire image that are required for analysis. Image attributes such as pixels can be used to assess the degree of uniformity of these features [6]. On all levels, segmentation is the most important and fundamental aspect of both image processing and image analysis. Image segmentation is demonstrated in Figure 1. Image segmentation is also a subprocess in the subtask image analysis. In medical imaging processes such as brain tumour locators and breast cancer detectors, picture segmentation is a major benefit [7]. It's in charge of reducing the amount of work that the image processor has to accomplish. As a result, a lot of research is being done to define and dedicate new approaches for picture segmentation that are faster, more user-friendly, and more accurate. There is currently no standard method for segmentation, and various approaches exist, each with its own set of advantages and disadvantages, and are used in image processors appropriately.
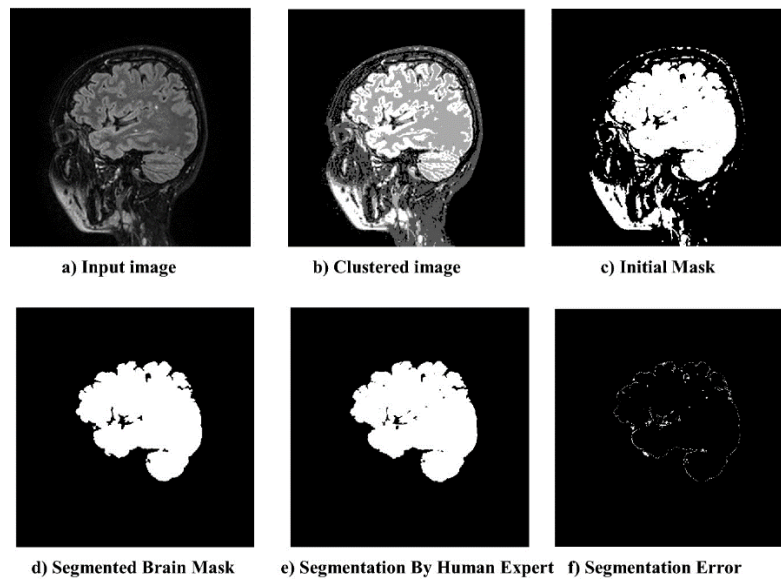
Fig. 2 Medical image processing using soft computing techniques

1.2 Soft computing techniques

Soft computing allows us to address problems in a more realistic manner; for example, we may simulate the workings of a human mind and generate outputs using neural networks and fuzzy logics. It can be thought of as a combination of biological structures with computational processes, with the ability to develop more competent and dependable solutions as a result of this combination. Genetic algorithms, fuzzy logics, and artificial neural networks are thought to function together to predict unpredictable events and work on incomplete truth [8]. The neural network is divided into feedforward neural network, feedback neural network, Hopfield neural network (HNN), recurrent neural network (RNN), and radial basis network, while fuzzy logic is divided into propositional logic and predictive logic. Figure 3 shows a flowchart of the major picture segmentation approaches that have been discussed in this work. Using binary and Boolean logics, hard computing techniques, in contrast to soft computing techniques, allow us to extract precise results. Rather than relying on approximation modelling, they use analytical methodologies. They always give us precise results and are always consistent. They have a proclivity for sequential computation [9]. Figure 4 shows a simple FCN (fully convolutional neural network) that can be used to segment brain data images (Fig. 4).
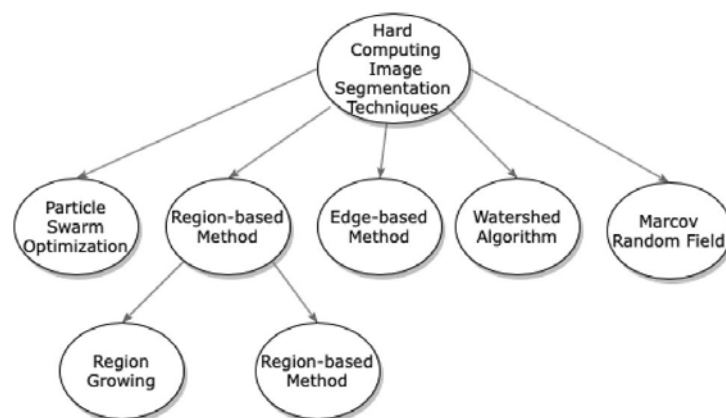
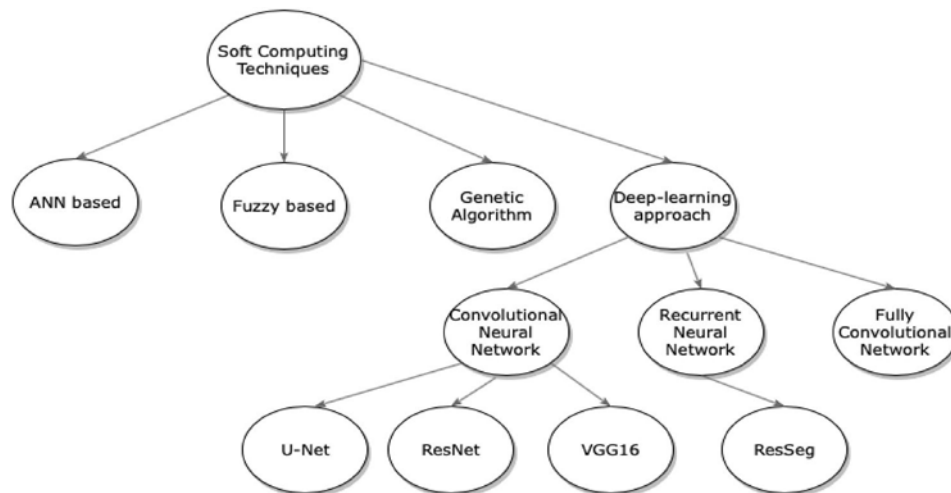
Fig. 3 Hard computing techniques

Fig. 4 Soft computing techniques

1.3 Description of different hard computing methods

Thresholding: The grey level of the pixels of the topic to be segmented out is commonly different from the background, and thresholding is a common segmentation tool in these situations. Threshold techniques are divided into two categories based on their state and location of action: local and global procedures. In global techniques, a single threshold is applied to the entire image, but in local techniques, a series of thresholds are applied to various portions of the image locally. Global thresholding, adaptive thresholding, optimal thresholding, and local thresholding are examples of several forms of thresholding.

Edge-based method: For picture segmentation, the edge detection approach is a critical and extensively used technique. Object detection, which is an important aspect of medical image processing, is the most common use. The original image is turned into edge images using this method, which is based on variations in the grey tones in the image. It is highly recommended for locating specific geometric and physical characteristics of an image. It draws a line around the object and separates it from the background for additional examination.

K-means clustering: The goal of this method is to construct clusters of comparable elements; pixels of images are clustered on three separate axes based on RGB. Clustering is done using a function that minimises the distance between data points and the cluster's centroid or any central tendency.

Markov random field: Images are usually homogeneous in nature, meaning they have comparable properties in all of their surrounding locations. In these circumstances, Markov random field performs well by distinguishing between comparable attributes such as texture, intensity, and hue. It's a probabilistic model that takes into account context limitations. Labelling fields, nearby pixels, Gibbs distribution, energy function, and cliques are some of the major components of this concept.

1.4 Description of different soft computing methods

Fuzzy-based image segmentation: It is based on the degree of truth or falsehood principle. It's a probabilistic segmentation method based on a fuzzy logic framework. The input image is first fuzzified, then passed on for membership modification based on expert knowledge and a set of fuzzy logics and set theory. After passing the modified image through image defuzzification, the final output is produced. Fuzzy thresholding, fuzzy integral-based decision making, and fuzzy c-means clustering are examples of fuzzy-based approaches.

Artificial neural network (ANN)-based image segmentation: The architecture of neural networks is entirely based on the human nervous system. The building and learning blocks of neural networks are perceptron's. They are self-teaching models that learn through repeated iterations and adjustments in the weights of various features. Hopfield neural network (HNN), constraint satisfaction neural

network (CSNN), back-propagation neural networks (BPNN), feedforward neural network (FFNN), and pulse-coupled neural network are examples of neural networks (PCNN).

2. PROBLEM STATEMENT

One of the most difficult challenges in medical image analysis is recognising the pixels of organs or lesions from background medical pictures such as CT or MRI scans in order to offer essential information on the shapes and sizes of these organs. Using available technologies, many researchers have proposed numerous automated segmentation systems. Traditional methods such as edge detection filters and mathematical methods were used in previous systems. Then, for a long time, machine learning approaches to extracting hand-crafted characteristics became the dominating strategy. The complexity of these systems has been deemed a significant barrier for their deployment, and designing and extracting these elements has always been the primary focus for establishing such a system.

3. RESEARCH OBJECTIVE

To develop an intelligent system for detecting brain tumours based on time-consuming MRI image-processing clustering methodologies like Fuzzy-C Means and optimization intelligence algorithms like PSO and GA.

4. METHODOLOGY

4.1 Current Approaches for Medical Image Segmentation: Soft and Hard Computing Approaches

a. Deep learning with image specific fine-tuning: The dataset that was used was (B) (2-D segmentation of multiple organs) Stacks of T2-weighted MRIs are acquired using single-shot fast spin echo (SSFSE).(3-D segmentation of T1c and FLAIR brain tumours) The training set for the 2015 Brain Tumor Segmentation Challenge (BRATS) is used (B). Obtainable outcomes the suggested model outperforms traditional CNNs in terms of segmenting previously undetected items.

Observations: For interactive 2-D/3-D picture segmentation, a deep learning-based framework with a bounding box-based CNN is used. They're good at segmenting objects that haven't been seen before. For both supervised and unsupervised modifications of initial segmentations, image-specific fine-tuning based on a weighted loss function is presented.

b. DeepIGeoS: a deep Interactive Geodesic for Medical Image Segmentation: The Placenta dataset was created from 2-D foetal MRI scans, and the Brain Tumors dataset was created from 3-D FLAIR images.

Observations: The use of a deep learning approach to create an interactive framework is advocated. The framework is divided into two stages, the first of which is P-Net, which is used to generate an initial automatic segmentation. After translation into geodesic distance maps, the second stage includes an R-Net to further process the output based on user involvement, which is integrated into the input of the R-Net.

c. Brain tumour segmentation using fuzzy c-means-based particle swarm optimization initialization and outlier rejection with level-set methods

Dataset used Brain MRI images are used. Two synthetic grey images with different level of noise are used. The dataset that was used was Images from MRI scans of the brain are used. Two synthetic grey images are employed, each with a different level of noise.

Observations: The suggested approach is a modified version of the KPCM method that takes into account the pixel's spatial information as well as the fuzzy partition matrix. The proposed model is described in the steps below:

(A) PSO algorithms for cluster centre and membership initialization.

(B) Outlier rejection is taken into account while altering the KPCM's membership function.

a. Fuzzy clustering

The dataset that was used was Using a high-resolution T1-weighted phantom with a slice thickness of 1 mm resolution, a dataset from brain web pictures is employed using traditional acquisition conditions.

Observations: The efficiency of the reformulated fuzzy logical information c-means clustering algorithm (RFLICM) for identifying tissues in brain MR images is significantly higher than that of the FCM and fuzzy local information c-means clustering algorithm (FLICM) segmentation approaches.

4.2 Segmentation Algorithms for Medical Images

Several studies have looked into segmenting different organs for the purpose of extracting questionable regions from medical pictures [10]. Active appearance models (AAMs), supervised support vector machines (SVMs), and artificial neural networks (ANNs) are common supervised methods used in medical image processing that require a training set. Nonlinear statistical data showing approaches for modelling complex relationships between inputs and outcomes are ANNs and SVMs. The weights of the classifiers are set by optimising the energy function distinct by organs, structures, cells, and other features. By handling each sample in the training set, these weights are restructured. As a result, metaheuristics can be used to determine the best weights. The extracted information from the training set provides crucial structural cues, such as shape, location, and intensity, which can be valued as corresponding information for the test image segmentation. The AAM, on the other hand, are statistical models of the structure's shape, with the ranges, mean appearance, and mean shape extracted from the training samples. Restrictions on shape parameters are essential to ensure similarity between the segmentation result and the training samples, where the segmentation technique is to locate the superior placements of the shape points based on appearance information. As a result, in medical imaging, the classifier-based algorithms can be used to segment organs such as the brain and cardiac images.

4.2.1 Meta heuristics-Based Segmentation of Magnetic Resonance Images

When infrequent cells shape appears inside the cerebrum, it is called a brain tumour. There are two types of brain tumours: benign tumours and malignant tumours [11]. Basic tumours and secondary tumours that have spread elsewhere are two types of malignant tumours [12]. MRI is currently one of the most effective tools for detecting brain tumours. Segmentation is also useful for extracting questionable areas from complex medical imaging of the brain. Automated brain tumour diagnosis by MRI can provide a positive perspective and allow for earlier and more accurate detection of the tumour. Gopal and Karnan [13] developed an intelligent system for brain tumour identification based on MRI image-processing clustering approaches that were time-consuming, such as Fuzzy-C Means, and optimization intelligence algorithms such as PSO and GA. Enhancement, segmentation, and classification are three stages in the tumour detection process [14-16].

### 4.3 Use of Soft Computing Technique in Image Processing

Image processing is any type of signal processing in which the input is an image, such as a photograph or video frame, and the output is an image or a set of characteristics or parameters connected to the image in imaging science. The majority of image processing approaches treat the image as a two-dimensional signal that is then processed using traditional signal processing techniques [17].

5. RELATED WORK

Nookala Venu, et al., (2016) [30] studied on several segmentation strategies based on hard and soft computing approaches is presented, along with a description of the observed work, dataset used, and findings produced.

Nookala Venu, et al. (2013) [24] used the FCM algorithm to build an MRI segmentation technique for brain tumour images based on entropy maximisation. For a better knowledge of the pathological history as well as for natural/modified therapy, quantitative measurement of MRI lesion load in individuals with multiple sclerosis is critical. Multiple approaches for segmenting MS lesions in MR images have been tested.

Nookala Venu, et al. (2015) [27] developed the Gaussian mixture approach for image segmentation, which is a method for estimating the number of components, their means, and covariance sequentially without requiring any setup. During the expectation maximisation steps, the experiment technique starts with a single mixed component that covers the entire data set and splits incrementally. After numerous tests, the Gaussian mixing approach has proven to be beneficial.
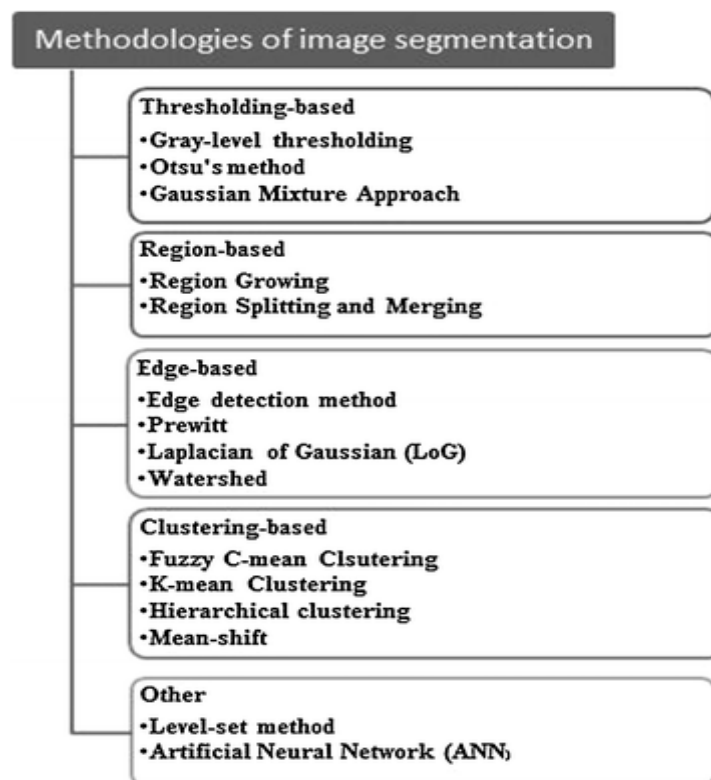
Fig. 5 Methodologies of image segmentation

6. RESULTS AND DISCUSSIONS

Using the deep learning with image-specific fine-tuning,weighted loss function, image-specific fine-tuning produces more accurate results (B). When compared to CNNs, user interaction efficiency is higher (C).When compared to automatic CNNs, better results were obtained. The segmentation of 3-D brain tumours was shown to be more accurate. In comparison to traditional CNNs, it resulted in a shorter user interface time.On the same picture dataset, improved kernel possibilistic c-means (IKPCM), fuzzy c-means (FCM), robust FCM, and kernel possibilistic c-means (KPCM) were examined, with IKPCM outperforming the others. For 1 percent, 5 percent, and 9 percent Gaussian noise, the partition coefficient for the IKPCM model is 0.9834, 0.9721, and 0.9752, respectively, compared to 0.9324, 0.9222, and 0.9126 for the KPCM model for 1 percent, 5 percent, and 9 percent Gaussian noise, respectively. For Gaussian noise of 1%, 5%, and 9%, the experimentally measured partition entropy values are 0.0369, 0.0741, and 0.0826, respectively, in comparison to 0.1605, 0.1835, and 0.1943 partition entropy values for the KPMC model for 1%, 5%, and 9% Gaussian noise, respectively. The fuzzy clustering technique is used in the segmentation of medical images and it has 99.86 percent efficiency with salt pepper noise.

7. CONCLUSION

MRI used in the medical field to distinguish pathological tissues from normal tissues and to obtain images of various body sections for subsequent analysis and processing. In several computer-aided medical imaging applications, image segmentation is the most important task. Tumor segmentation is regarded an essential operation based on MRI data; however, it is time demanding if done manually. As a result, automated image analysis becomes critical for picture-based diagnosis. Medical image analysis can be done using a variety of techniques that have been used in a variety of applications. The analysed computer-based images are utilised in computer-aided systems to assist radiologists and clinicians in making speedier diagnoses. The current paper discussed many techniques used in the segmentation of MRI images. These optimization techniques are used to acquire the optimal parameters needed during the segmentation process, which includes an explanation of several segmentation methodologies.

8. FUTURE WORK

Despite significant advances in medical image segmentation research, the effect of segmentation still does not satisfy the needs of practical applications. The fundamental reason for this is that current medical image segmentation research is still beset by obstacles and challenges:

1. Between these two areas, medical image segmentation is a cross-disciplinary field. Medical pathology issues in clinical practise are complex and varied. Artificial intelligence researchers, on the other hand, are unfamiliar with therapeutic requirements. Clinicians are unfamiliar with artificial intelligence's unique technologies. As a result, artificial intelligence is unable to match the unique clinical requirements. It may also assist machine learning researchers in better aligning deep learning algorithms with clinical needs and applying them to computer-aided diagnosis equipment, resulting in increased diagnosis efficiency and accuracy.

2. Medical images differ from natural images in several ways. Various medical images have different characteristics. This discrepancy has an impact on the deep learning model's adaptability during segmentation. Medical picture noise and artefacts are also a key issue in data preparation.

3. Existing medical picture data sets have limitations. The scale of existing medical picture data sets is limited. Deep learning algorithms require a huge quantity of data set support for training, which contributes to the problem of overfitting in the deep learning model training process. Data augmentation, such as geometric transformation and colour space enhancement, is one technique to address the lack of training data.GAN synthesises new data from original data. Another strategy for studying medical picture segmentation under small sample settings is based on a Meta learning model.

4. There are weaknesses in the deep learning model. Network structure design, 3D data segmentation model design, and loss function design are the three primary areas covered. It's worth looking into the network structure's architecture. Modifying the network structure has a major impact that can be easily transferred to other jobs. When 3D medical data is cut slice by slice, it can more effectively capture the geometric information of the target, which can be lost. As a result, designing 3D convolution models to process 3D medical picture data is a researchable direction. Loss function design has long been a challenge in deep learning research.

Deep learning has done admirably in the segmentation of medical images. To increase the accuracy and robustness of segmentation, more and more novel methods are being applied. Artificial intelligence-assisted diagnosis of various diseases realises the concept of long-term medical treatment. For clinicians, it becomes a useful tool. However, because it is still an open subject, we can expect a slew of new technologies and study findings in the next years [21].

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