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AN ANALYTICAL STUDY ON USE OF SOFT COMPUTING IN MEDICAL IMAGE WATERMARKING

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ABSTRACT

Purpose: This study suggests a soft computing method that combines geographical data with medical image segmentation. When an image is segmented, it's broken up into regions that share similar characteristics across their pixels. In order to be expressive and effective for picture analysis and interpretation, the regions should have a strong connection to the depicted objects or aspects of interest. Several different kinds of algorithms, both soft and hard, are used for medical image segmentation in order to achieve high levels of efficiency and accuracy. Soft computing is a relatively new approach to computing that takes into account approximation, uncertainty, and pliability.

Design/Methodology/Approach:

Soft computing technique is recommended for image segmentation. Multiple methods of image segmentation for clinical image analysis are discussed in this article. In this research, we describe the state-of-the-art segmentation algorithms employed in diagnostic imaging analysis. The strengths and weaknesses of each technique are exposed, and their applicability to MRI algorithm comparisons are provided.

Findings/Result

When compared to the FCM and the fuzzy local information C-means clustering algorithm, the fuzzy logical information C-means clustering algorithm is much more effective at segmenting brain MR images so that different tissues can be identified.

Keywords: ***Medical Image Segmentation, Hard Computing, Soft Computing, Medical Imaging***

1. INTRODUCTION

Segmenting an image into its component parts or individual objects is a process known as image segmentation. Also, these things are employed in image processing and analysis. A set of pixels constitutes each of these elements. The success of an image segmentation process is highly dependent on the program being used. During times of trouble with automatic image recognition and analysis, segmentation should be halted whenever an object or part of interest is found. Effective image segmentation is crucial for accurate image analysis. Automated, state-of-the-art picture segmentation that can be used with sophisticated machine-based image analysis has been the subject of extensive study. Different image segmentation procedures are used for various kinds of picture analysis. Manual annotating images is a common method for performing image segmentations, but it is labour-intensive, inefficient, and takes a lot of time. Consequently, many researchers are focusing on the problem of automating the segmentation of images, leading to some significant advances in the field. On the other hand, there are a number of ongoing studies that use segmentation techniques applied to medical images. Currently, there is no reliable method for applying segmentation to a wide variety of datasets. In this article, we take a high-level look at the current state of the art in soft and hard computing algorithms for medical image segmentation. Section 3 gives an overview of soft and hard computing strategies, and Section 4 gives a brief introduction to some current soft and hard computing methodologies for medical image segmentation. The final section, 5, contains the summary. Section 6 contains the bibliography and is the final section.

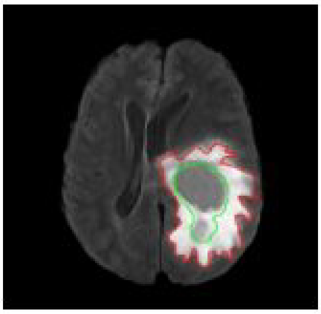

Figure 1: Classification of Brain Tumor Image

1.1 Classification of Medical Images

In the 2000s, with the advent of more powerful hardware, deep learning algorithms emerged and quickly proved their worth in various image processing tasks. Since the advent of deep learning algorithms, they have become a viable alternative for image segmentation, especially in the field of medical image segmentation. Recent interest in deep learning-based image segmentation algorithms highlights the importance of conducting a comprehensive review of the state of the art in this area. There has not been a published study of deep learning methods

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for medical image segmentation, to the best of our knowledge. For instance, look at these two recently published review articles on segmenting medical images. Shen et al. discussed a wide range of medical image analysis methods, but they gave only cursory coverage to the specifics of segmenting medical images. Rather than being a specialized medical image segmentation survey, is a medical image analysis review, covering topics such as classification, detection, and registration. Because of its breadth, this article avoids specifics about networks, capacities, and vulnerabilities. Image segmentation is the process of breaking up a picture into smaller, more manageable pieces based on shared characteristics like colour or brightness. This streamlines the process of analysing images by exposing only the attributes of the image that are actually being analysed. The uniformity of these features can be evaluated with the help of image attributes like pixels. The process of segmentation is the backbone of both image processing and analysis. In Figure 1 we can see an example of image segmentation. Segmenting images is a type of image analysis that is performed as part of the task. Detectors for breast cancer and brain tumour localizers rely heavily on image segmentation. The job of this component is to ease the burden on the image processor. Much effort is being put into defining and committing to new methods for image segmentation that are quicker, friendlier to users, and more precise. Different segmentation methods, each with their own merits and drawbacks, are used appropriately in image processors because there is currently no unified method.

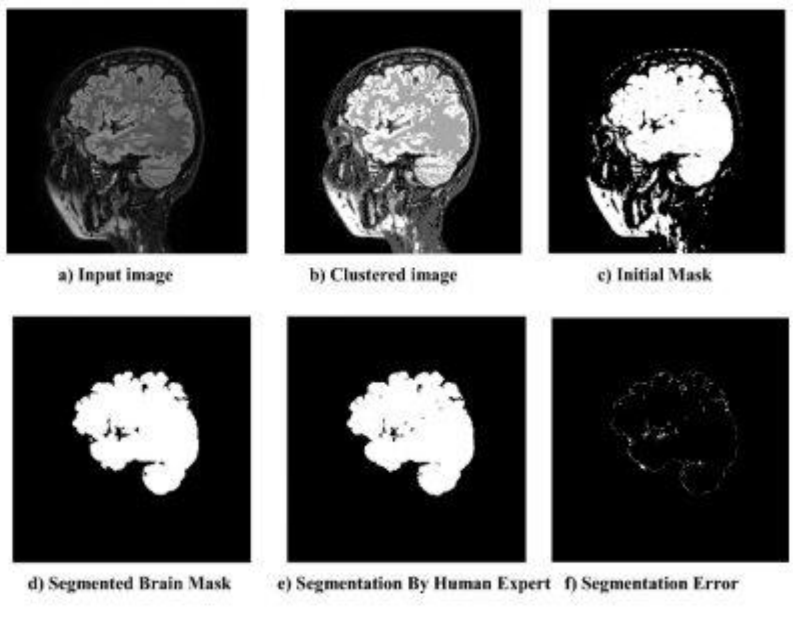

Figure 2: Soft Computing Methods for Medical Image Processing

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1.2 Methods of 'Soft Computing'

Through the use of neural networks and fuzzy logics, for instance, we can use soft computing to model the functioning of the human brain and generate solutions to problems. This can be understood as the integration of biological components with computational methods, leading to the creation of more expert and dependable solutions. Some researchers believe that genetic algorithms, fuzzy logic, and artificial neural networks can all work together to predict random events and handle partial information. Both neural networks and fuzzy logic can be further subdivided into distinct types; for example, a feedforward neural network, a feedback neural network, a Hopfield neural network (HNN), a recurrent neural network (RNN), and a radial basis network. A flowchart summarizing the various methods of image segmentation discussed in this work is presented in Figure 3. In contrast to the less precise results that can be obtained with soft computing methods, hard computing methods can be used to extract results using binary and Boolean logics. Analytical methods are used instead of approximation models. They have consistently reliable results and provide us with pinpoint information. They tend to perform calculations in order. A basic fully convolutional neural network (FCN) for use in segmenting brain data images is shown in Figure 4. (Fig. 4).

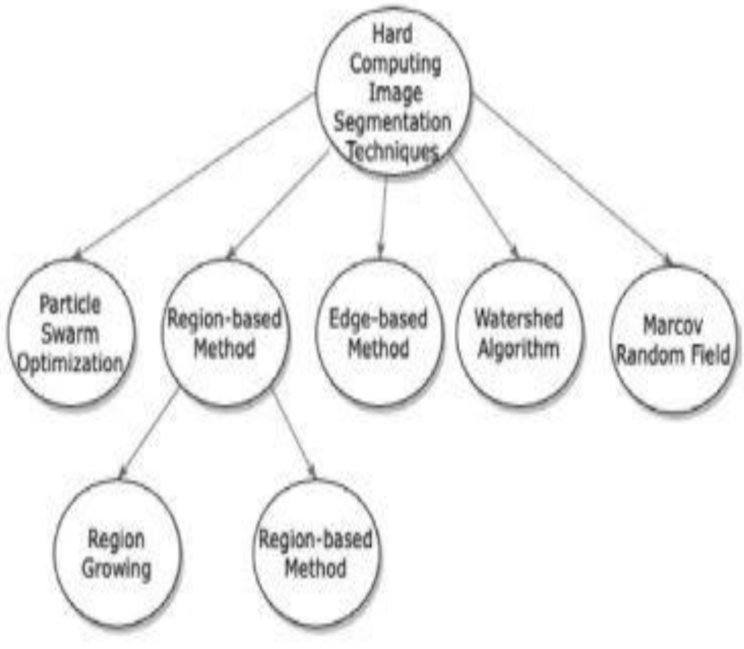

Figure 3: Methods of "Hard Computing"

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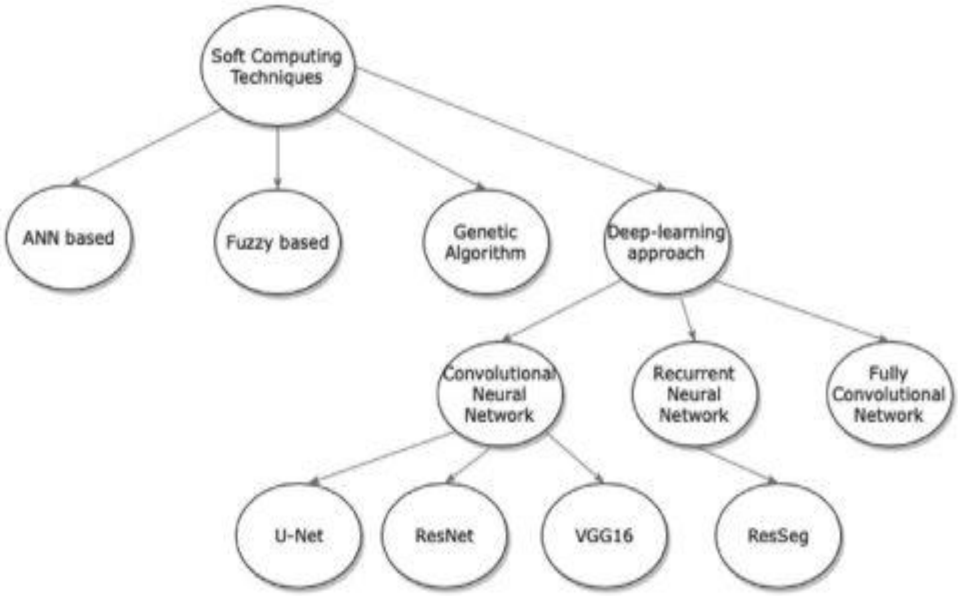

Figure 4: Methods of 'Soft Computing'

1.3 Details on Various Forms of Intensive Computation

Thresholding: Thresholding is a common segmentation tool in situations where the grey level of the topic to be segmented out is different from the background. Based on the scope and scale of their effects, threshold techniques can be broken down into "local" and "global" methods. Instead of applying a single threshold to the entire image, as is done in global techniques, local techniques apply a series of thresholds to different parts of the image. There are a few distinct types of thresholding, including global thresholding, adaptive thresholding, optimal thresholding, and local thresholding.

The Edge-Based Method: The edge detection method is essential and widely employed for image segmentation. The most prevalent application is object detection, a crucial part of medical image processing. This technique, which uses differences in the image's grey tones, converts the original image into edge images. If you need to zero in on certain geometric and physical features of an image, this method comes highly recommended. A boundary is established between the foreground and background so that the object can be more closely studied.

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Clustering By Arithmetic Mean Distance, or K-Means: The pixels of images are clustered along three different axes based on RGB, and the goal is to create clusters of similar elements. It is possible to cluster data by employing a function that minimizes the distance between each data point and the cluster's centroid or any central tendency.

The Markov Random Field: Images are typically of a uniform nature, with consistent features across all of their spatial extents. By differentiating between otherwise similar characteristics like texture, intensity, and hue, Markov random field excels under these conditions. It's a probabilistic model that considers contextual restrictions. There are many parts to this idea, but some of the most important ones are labelling fields, neighbouring pixels, the Gibbs distribution, the energy function, and cliques.

1.4. Methods in Soft Computing Are Described

Using Fuzzy Logic for Image Segmentation: It's founded on the concept of relative truth or falsehood. It is a fuzzy logic-based probabilistic segmentation technique. As a first step, the input image is fuzzy-ed, and then it's forwarded on to be modified in terms of membership using prior knowledge, fuzzy logic, and set theory. The final result is achieved by running the altered image through a defuzzification process. Some examples of methods that use fuzzy logic are fuzzy thresholding, fuzzy integral-based decision making, and fuzzy c-means clustering.

Segregating Images Using An ANN: Neural networks are completely modelled after the human nervous system in terms of their structure. Perceptron's are the neurons that make up neural networks and are the basis for their learning. These models are self-learning in that they improve with practice by reweighing features and iterating on the results. Neuronal networks include the Hopfield network (HNN), constraint satisfaction network (CSNN), back-propagation network (BPNN), feedforward network (FFNN), and pulse-coupled network (PCNN).

2. DEFINITION OF THE PROBLEM

Recognizing organ or lesion pixels from background medical pictures like CT or MRI scans to provide crucial information on organ shapes and sizes is one of the most difficult challenges in medical image analysis. To this end, many researchers have proposed various automated segmentation systems using the currently available technologies. In earlier

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systems, engineers relied on tried-and-true techniques like edge detection filters and mathematical calculations. Then, for a considerable amount of time, machine learning techniques for extracting human-created traits were the go-to method. Designing and extracting these elements has always been the primary focus for establishing such a system, and their complexity has long been seen as a major barrier for their deployment.

3. THE GOAL OF THE STUDY

Using labour-intensive MRI image processing clustering methodologies like Fuzzy-C Means and optimization intelligence algorithms like PSO and GA, we aim to create a system capable of detecting brain tumours.

4. METHODOLOGY

4.1 Methods Currently Used for Segmenting Medical Images, Including Both Soft and Hard Computing Techniques

a) Training A Deep Neural Network with Pixel-Level Detail from An Image: Dataset (B) (2-D segmentation of multiple organs) was used. Single-shot fast spin echo imaging is used to acquire multiple T2-weighted MRI scans in a stack (SSFSE). (Three-dimensional T1c and FLAIR brain tumour segmentation) For this task, we leverage data from the Brain Tumor Segmentation Challenge (BRATS) 2015 training set (B). The results that can be obtained show that the proposed model performs better than conventional CNNs at detecting previously undetected items.

Observations: A deep learning framework employing a bounding box-based CNN is used for interactive 2-D/3-D picture segmentation. They excel at recognizing and separating novel shapes. Image-based fine-tuning based on a weighted loss function is presented, and it can be used for both supervised and unsupervised alterations of original segmentations.

b) A Deep Interactive Geodesic for Segmenting Medical Images (DeepIGeoS): Two-dimensional foetal MRI scans were used to create the placenta dataset, while three-dimensional FLAIR images were used to create the brain tumours dataset.

Observations: It is suggested that a deep learning method be used to build the interactive framework. P-Net is used to create an initial automatic segmentation in the first stage of the framework. The second stage incorporates an R-Net to process the output based on user

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involvement, which is integrated into the R-input Net's after it has been translated into geodesic distance maps.

c) Initiating Particle Swarm Optimization on The Basis of Fuzzy C-Means and Then Excluding Outliers Using Level-Set Techniques for The Segmentation of Brain Tumours.

Utilized Dataset There is a reliance on magnetic resonance imaging (MRI) scans of the brain. Uses two noise-modified greyscale synthetic images. Our data source was Brain MRI scan images are used. We use two artificial greyscale images, one with low noise and one with high.

Observations: To account for both the spatial information of the pixel and the fuzzy partition matrix, the KPCM method is proposed in a modified form. The steps of the proposed model are as follows:

a. Cluster membership and centre establishment utilizing PSO algorithms
b. The membership function of the KPCM is adjusted with outlier rejection in mind.

Clustering with Fuzzy Logic: The dataset used was obtained from the brain web and was acquired using standard conditions (high-resolution T1-weighted phantom, slice thickness of 1 mm resolution).

Observations: When compared to the conventional fuzzy clustering method (FCM) and the fuzzy local clustering method (FLICM), the reformulated fuzzy logical information c-means clustering algorithm's (RFLICM) efficiency in identifying tissues in brain MR images is dramatically improved.

4.2 Methods for Segmenting Medical Images

Extraction of suspicious areas from medical images via segmentation is the subject of multiple research projects. Common supervised methods used in medical image processing that necessitate a training set include active appearance models (AAMs), supervised support vector machines (SVMs), and artificial neural networks (ANNs). Artificial neural networks (ANNs) and support vector machines (SVMs) are two methods for modelling complex relationships between inputs and outputs that are supported by nonlinear statistical data. Classifier weights are determined by optimizing an energy function that is feature-specific across organs, structures, cells, and more. These weights are reorganized through the

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treatment of each training set sample. So, we can use metaheuristics to find the optimal weights. Important structural cues like shape, location, and intensity are extracted from the training set and used as corresponding information in the test image segmentation. In contrast, the AAM are statistical models of the shape of the structure, where the ranges, mean appearance, and mean shape are all extracted from the training samples. The goal of the segmentation technique is to identify the best possible locations for the shape points based on appearance information, so it is crucial to impose constraints on the shape parameters to guarantee that the resulting segmentation is consistent with the training samples. Thus, the classifier-based algorithms can be used to segment images of the brain and heart in medical imaging.

4.2.1 Magnetic Resonance Image Segmentation Using Meta Heuristics

A brain tumour is what doctors call an abnormal growth of cells in the brain. In the brain, tumours can be either benign or malignant. The two main categories of malignant tumours are primary tumours and metastatic tumours. One of the best methods for identifying brain tumours is magnetic resonance imaging (MRI). Additionally, segmentation can be used to remove suspect regions from brain imaging studies. In a positive light, automated MRI diagnosis of brain tumours can lead to earlier and more accurate detection of the tumour. Based on laborious MRI image-processing clustering methods like Fuzzy-C Means and optimization intelligence algorithms like PSO and GA, Gopal and Karnan designed an intelligent system for brain tumour identification. There are three steps involved in detecting tumours: enhancement, segmentation, and classification.

4.3 Utilization of a Soft Computing Method for Image Processing

In imaging science, "image processing" refers to any signal-processing technique where an image (such as a photograph or video frame) is used as input and another image (or associated characteristics or parameters) is produced as output. Common image processing methods reduce the image to a two-dimensional signal and apply conventional signal processing algorithms.

5. RELATED PAPERS

The research conducted by Nookala Venu et al. (2016) on various segmentation strategies utilizing hard and soft computing approaches is presented, along with a summary of the work that was observed, the dataset that was used, and the results that were obtained.

The FCM algorithm was used to develop an entropy-optimized method of MRI segmentation for images of brain tumours by Nookala Venu et al. (2013). Quantitative measurement of MRI lesion load in people with multiple sclerosis is crucial for a better understanding of the pathological history and for natural/modified therapy. MS lesion segmentation in MR images has been tested using a variety of methods.

The Gaussian mixture approach for image segmentation was created by Nookala Venu et al. in 2015. This method sequentially estimates the number of components, their means, and their covariance with no prior setup. The experiment method begins with a single mixed component that encompasses the whole data set and splits incrementally throughout the expectation maximization steps. The Gaussian mixing method has been shown to be effective in a number of experiments.

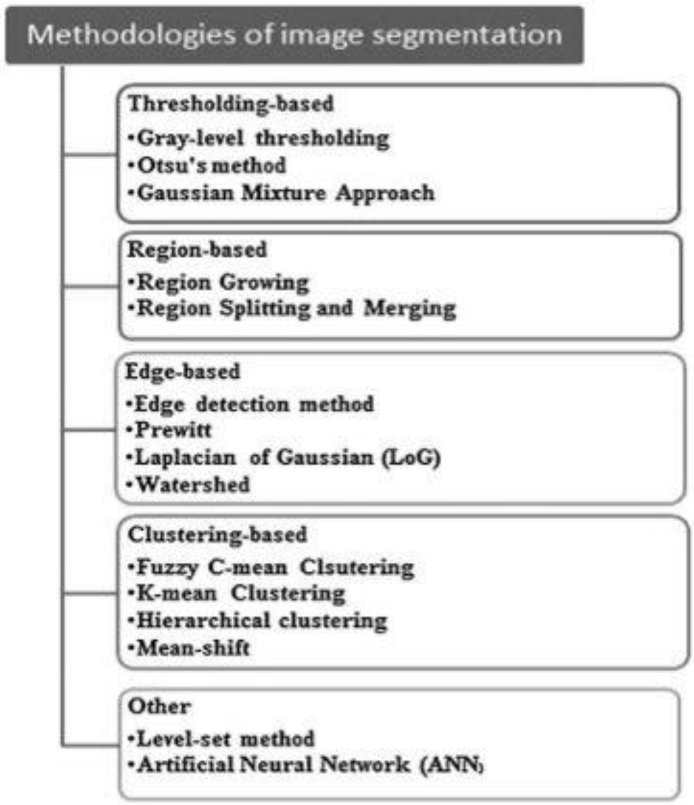

Figure 5: Strategies for Segmenting Images

6. RESULTS AND DISCUSSIONS

Results are improved when deep learning is combined with image-specific fine-tuning and a weighted loss function (B). The effectiveness of user interaction is higher than that of CNNs (C). The outcomes improved over those obtained by automatic CNNs. It was demonstrated

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that 3-dimensional brain tumour segmentation was more accurate. The result was a faster learning curve and an easier-to-use interface than with conventional CNNs. In a head-to-head comparison using the same image dataset, improved kernel possibilistic c-means (IKPCM) was found to be superior to fuzzy c-means (FCM), robust c-means, and kernel possibilistic c-means (KPCM). The partition coefficient for the IKPCM model is 0.9834, 0.9721, and 0.9752 for 1, 5, and 9 percent Gaussian noise, respectively, while it is 0.9324, 0.9222, and 0.9126 for the KPCM model in the same noise levels. Compared to the KPMC model's partition entropy values of 0.1605, 0.1835, and 0.1943 for 1%, 5%, and 9% Gaussian noise, respectively, the experimentally measured values are 0.0369, 0.0741, and 0.0826. When it comes to segmenting medical images, the fuzzy clustering technique is used, and it has a 99.86% success rate when dealing with salt pepper noise.

7. CONCLUSION

MRI is used in the medical field to detect abnormal tissues, obtain images of different parts of the body, and then analyse and process the data. Image segmentation is the primary focus of many computer-assisted medical imaging programs. The manual process of tumour segmentation from MRI data, while considered an essential operation, is labour-intensive. This makes the use of automated image analysis vital for image-based diagnosis. Numerous methods have been implemented successfully in various settings for medical image analysis. Computer-aided systems use the analysed images to speed up the diagnostic process for clinicians and radiologists. Several methods for segmenting MRI images were discussed in the present paper. Several segmentation methods are explained, and each is optimized using the aforementioned techniques in order to acquire the optimal parameters required for the segmentation process.

8. FUTURE WORK

Research into medical image segmentation has come a long way, but the results of segmentation still don't meet the requirements of real-world applications. The primary explanation for this is the continued presence of difficulties in the field of medical image segmentation research.

1) Medical image segmentation bridges the gap between these two fields. Clinical pathology issues come in many forms and are often difficult to diagnose. On the other hand, scientists working on AI have little experience with medical protocols. Most doctors haven't had much experience with the cutting-edge tools of artificial

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intelligence. Thus, AI falls short of fulfilling the specific needs of the medical field. It may also help researchers in machine learning better tailor deep learning algorithms to clinical requirements and integrate them into CAD systems for more precise and effective diagnoses.

2) There are a number of ways in which medical pictures diverge from their natural counterparts. Distinct features distinguish one medical image type from another. The versatility of the deep learning model used for segmentation is influenced by this difference. In addition, noise and artifacts in medical images are a major problem when cleaning up the data.
3) There are gaps in the existing medical image databases. Existing medical image data sets are small in size. Overfitting is an issue when training deep learning models, and the need for a large training dataset is a contributing factor. One approach to dealing with a dearth of training data is data augmentation, which can take the form of geometric transformation or colour space enhancement. To put it simply, GAN creates new data from existing data. A Meta learning model-based approach is another method for investigating medical image segmentation in low-sample settings.
4) The deep learning model has some flaws. Three main topics are discussed: network structure design, 3D data segmentation model design, and loss function design. Taking a look at the architecture of the network is a good idea. Changing the framework of the network has far-reaching effects that can be readily applied to other contexts. It is possible to better capture the geometric information of the target when 3D medical data is sliced slice by slice. Therefore, developing 3D convolution models for handling data from 3D medical images is a viable area of study. For a long time, the design of loss functions has been a stumbling block for deep learning studies.

When it comes to medical image segmentation, deep learning has performed exceptionally well. More and more cutting-edge strategies are being utilized to enhance segmentation's precision and durability. The concept of long-term medical treatment is made possible by artificial intelligence-assisted diagnosis of various diseases. It can be a helpful resource for doctors and nurses. Since this is still a developing field of inquiry, however, many exciting innovations and scientific breakthroughs are likely to occur in the coming years.

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