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A COMPETITIVE SEGMENTATION OF THE HUMAN BRAIN USING ARTIFICIAL NEURAL NETWORK APPROACH TOWARDS MRI

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Abstract. The diagnosis of brain abnormalities, prognosis monitoring, and treatment evaluation all rely heavily on the magnetic resonance scan of brain tissue segmentation. Although numerous automated or semi-automatic methods have been proposed in the literature to reduce the need for human intervention, the degree of accuracy is frequently still significantly lower than that of manual segmentation. We give a clever technique for fragmenting the cerebrum utilizing a managed counterfeit brain organization system called artificial neural network (ANN) and volumetric shape models. In the beginning, in addition to the usual spatial-based and intensity-based image features, a level-set oriented brain boundary fitting technique is used to accomplish this. This is controlled by the picture intensity. The ANN is then informed of the number of important structures. Additionally, rather than directly applying standard guidelines to local appearances, this ANN learns local adaptive feature classification conditions. The outcomes demonstrate that the proposed strategy achieves competitive results in a relatively shorter time spent training.

Key words: Magnetic Resonance, supervised, Artificial Neural Network, level-set, classification.

1. Introduction . In the last twenty years, non-invasive brain imaging technologies have advanced rapidly, providing fresh avenues for studying the brain's structure and function. Magnetic resonance imaging (MRI) has made significant strides [4] in exploring brain anatomy and detecting brain injuries. Moreover, the quality of brain MR imaging has steadily improved, leading to a considerable increase in data.

Extracting vital data from vast and intricate MRI datasets is now a laborious and demanding task for clinicians. This manual analysis is time-consuming and error-prone due to the considerable variation in interoperation among studies. However, the advent of computerized diagnostic and testing techniques has resolved these challenges in interpreting brain MRI data. In various clinical applications, accurately segmenting the brain in MRI is critical since it impacts the overall investigation's outcome. This is because precise segmentation[13, 5, 2] of anatomical regions is essential for various processing steps.

MRI segmentation is a commonly used technique for measuring and visualizing various brain structures, studying brain development, detecting lesions, planning surgeries, and guiding interventions. The diverse applications of image processing have led to the development of numerous segmentation techniques with varying levels of complexity and accuracy. Automated MRI brain segmentation is frequently requested to obtain quantitative measurements of different brain regions and provide context data for lesion diagnosis and quantification. These numerical measurements play a vital role in evaluating brain atrophy, monitoring the prognosis of multiple sclerosis patients, and investigating the development of the brain across different ages. Furthermore, the structural data obtained during segmentation is a valuable visual aid for image-guided surgeries. Despite the numerous automatic or semi-automatic brain segmentation methods proposed in the literature, the current cutting-edge methods still lack sufficient performance in clinical practice.

The motivation behind research on brain tumor segmentation is to improve the accuracy and efficiency of diagnosing and treating brain tumors. Brain tumors are a severe medical condition that can have a significant impact on a patient's quality of life and survival. MRI is a commonly used imaging technique for detecting brain tumors, but manual segmentation can be time-consuming and error-prone, leading to inconsistent results and delays in treatment. Automated or semi-automated brain tumor segmentation methods have been proposed to overcome these challenges, allowing faster and more accurate diagnosis, treatment planning, and monitoring. By

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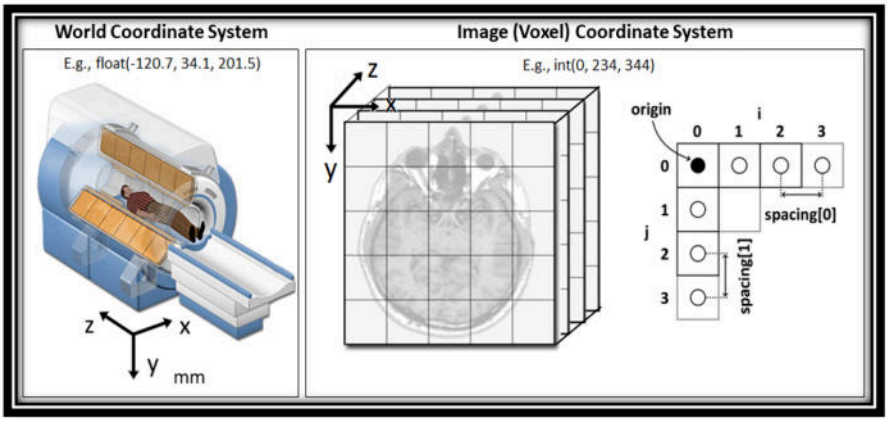

Fig. 2.1: Coordinate system of MRI scan

accurately segmenting the tumor region from normal brain tissue, clinicians can obtain vital information about the tumor's location, size, and shape, which can be used to guide surgery, radiation therapy, and chemotherapy.

The contribution of this research to segment the brain tumor is:

1. level-set oriented brain boundary fitting technique is used to extract and learn image features;
2. studied features are classified using ANN for accurate classification.

In this paper, section 2 gives a basic image concept regarding MRI and image segmentation. Section 3 reviews the works of literature with state-of-the-art methods. The proposed methodology is given in section 4. Results and their detailed discussion is compiled in section 5, and the conclusion is presented in section 6.

2. Contextual MR Image Concepts. Magnetic resonance imaging (MRI) [1] is frequently the preferred technique for structural brain investigation because of its high spatial resolution, strong contrast for soft tissues, and absence of known health hazards. In the quantitative study of the brain, MR images are common. Segmentation plays a significant role in quantitative analysis. Manual segmentation is the gold standard for in vivo pictures. To introduce the reader to the intricacy of the brain MRI segmentation problem and discuss its challenges, we start by outlining the fundamental concepts of image and its segmentation. This covers the definition of two dimensions and three-dimension images, MRI intensity distributions of the brain tissue, an issue with image segmentation, and image features. Fig 2.1 depicts the coordinate system of MRI slices. In the brain MRI, the grey numbers 0 to 255 are commonly used to represent the intensity values that make up the values of the functions Img(x,y) and Img(x,y,z). Each image comprises a fixed number of elements in voxels in three-dimensional space and pixels in two-dimensional space. Each image element has a distinct intensity value and corresponding coordinates x,y for pixels and x,y,z for voxels.

Image features are a representation of the distinctive properties of a segmented image or object. Examples of features that employ numerical measures to differentiate between the structures of interest and their surroundings are quantitative descriptors of visual appearance and shape. The success of picture segmentation depends on choosing the most pertinent characteristics and accurately extracting those features. The first and second-order statistics of an image's gray-level intensities (Fig. 2.2) serve as the foundation for the statistical features, typically extracted and classified in MRI using a statistical approach. The pattern or texture is defined by a collection of statistically extracted features represented as a vector in a multidimensional feature space.

Each grey intensity is dependent on a subset of the intensities that are nearby in the spatial interaction models (Fig. 2.3). Markov Random Field models (MRF) are the most widely used models for capturing local spatial interactions between pixel/voxel intensities [7]. Markov random field (MRF) theory provides a framework for modeling an image's local properties, in which the global image properties follow the local interactions. To reduce misclassification errors caused by image noise, MRF models have been successfully incorporated into a variety of brain MRI segmentation algorithms [9].

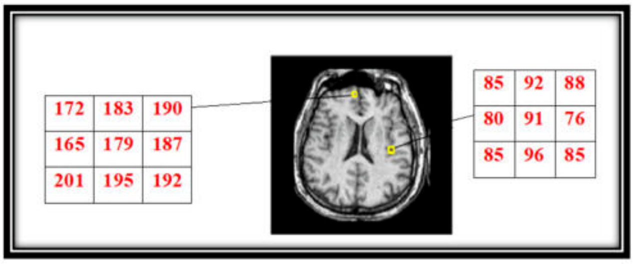

Fig. 2.2: Gray value by the intensity in Brain Image

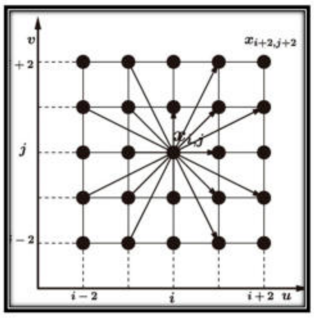

Fig. 2.3: Pixel x and Neighbouring pixels

3. Artificial Neural Network. One of the most well-known machine learning models is artificial neural networks (ANNs) (Fig. 3.1). The computational units known as interconnected neurons in a neural network typically span several layers. The neural network has an input layer where data enters, one or more hidden layers that transform the data as it moves through, and an output layer where predictions are made. An objective function is used to compare the network's outputs to the actual labels so that it can be trained to make accurate predictions from a set of labeled training data.

During training, the network's parameters of each neuron's strength are changed until the patterns the network discovers reliably predict the training data. Once the patterns have been learned, the network can generalize to new data by making predictions based on never-before-seen data. Despite their ability to model and solve complex problems, ANNs are well recognized as challenging to train and resource-intensive. This has reduced the practical value of other machine learning models, which were previously the focus of attention. However, artificial neural networks are among the most popular and well-researched machine learning techniques.

Artificial neural networks are a good example of supervised learning. An artificial neural network learned the information as an interconnected network unit. Humans find it difficult to separate this information. This element served as the inspiration for the data mining categorization rule. The basis for the categorization procedure is the dataset. The data set is divided into training and test samples. The test sample is used to evaluate the classifier's accuracy while the training sample is used to train the network. Some techniques for segmenting a data set include the hold-out method, cross-validation, and random sampling. Typical neural network learning procedures include, The network, which has a set number of nodes in the input, output, and hidden layers, uses an algorithm to learn its topology. Artificial intelligence can benefit from neural networks since they can alter the network's structure and learn by varying the weights.

4. Review of Literature. MRI segmentation is typically tricky because acquired MR images are erratic and frequently affected by noise and other defects. The extensive range of applications for image processing has led to the emergence of numerous techniques for image segmentation. This is because no single strategy,

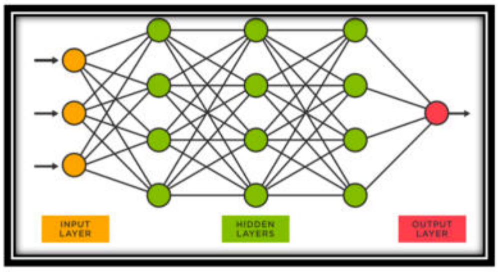

Fig. 3.1: Artificial Neural Network

nor are all approaches, equally successful for all sorts of photos. Some approaches, for example, merely use the grey-level histogram [12], while others incorporate spatial picture data to deal with noisy settings. Images can only be segmented using individual pixel or voxel intensities when the backdrop and the object of interest have distinctly different powers. By simply comparing the intensity values to the threshold, the intensity value that distinguishes the object from the background, the entire object—or the majority of its pixels or voxels—can be distinguished from the background. The image's overall intensity distribution determines the threshold. For image segmentation, edges are one of the most frequently used features. An object's edges are places on its surface where the intensities dramatically change. Typically, these changes are detected by thresholding. However, image smoothing is frequently required as a pre-processing step because this edge detection method is susceptible to image noise. Currently, available methods for segmenting MR images of the brain include the threshold method, the region method, the random field method, the clustering method, and Neural Network.

The process of manually segmenting and labeling an image by a human operator is known as manual segmentation. This segmentation is frequently carried out slice by slice for three-dimensional volumetric images. Because it is difficult to reliably and accurately delineate structures in medical imaging, the manual method is regarded as the most accurate. Artifacts and poor image quality are to blame for the difficulties with segmentation.

However, manual segmentation is required to quantitatively evaluate automated segmentation methods and establish the "ground truth," a substitute for actual delineation. Additionally, one essential component of atlas-based segmentation techniques, which is how the brain atlas was created, is the manual segmentation of various brain regions.

1. The major research gap of the literature section,
2. Firstly, many existing segmentation techniques rely on manually selected features or thresholds, which may not apply to all patients or tumor types. More robust and adaptive methods that can account for variations in image quality and tumor characteristics are needed.
3. Secondly, many existing techniques rely on 2D images, which may not capture the full extent of the tumor's 3D shape and location. Improvements in 3D segmentation techniques could improve the accuracy of tumor localization and volume measurement.
4. Thirdly, there is a need for more comprehensive evaluation metrics to compare and validate different segmentation techniques. The lack of standardized metrics can make it challenging to compare the performance of different methods and hinder their translation to clinical practice.

5. Data and Methodology. The proposed methodology encompasses pre-processing, feature extraction, level set-based segmentation, ANN classifier

5.1. Data Sets Used. Five volumes of T2-Weighted MRI data are collected from IBSR. We also used five volumes of MRI T2 data sets from SBC scans performed in Dindigul, India [10]. Additionally, five volumes of T2 - w MR images from the KGS Scan and Diagnostic Centre in Madurai, India. All these data sets have ground truth brain-segmented images done by experts.

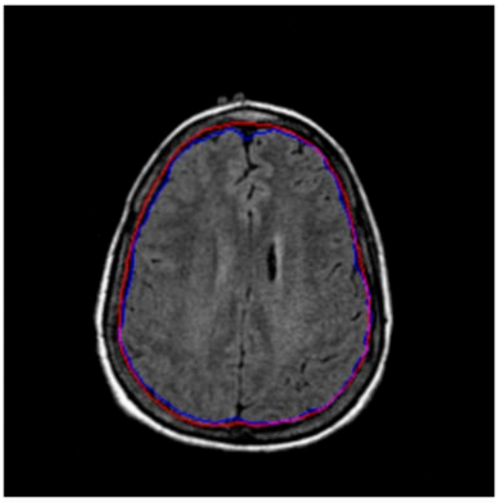

Fig. 5.1: Brain boundary detection by Level Set (Blue: Ground Truth, Red: Proposed Method

5.2. Pre-processing. Pre-processing is done to ensure that the data is correctly ready for the classifier. The following pre-processing processes were carried out in this work before submitting the data to the classifiers.

A. Correction of Bias field in MR Input Image

Bias field correction is adjusting for fluctuations in image contrast brought on by inhomogeneity in the magnetic field. The most often applied method is N4 bias field correction in medical images.

B. Non-brain (Skull) Tissue Removal

Skull stripping [8, 6, 14] involves the removal of the skull from pictures to concentrate on cerebral tissues. Removing non-brain structures like the skull, which have a big impact on the outcomes, is necessary to increase segmentation accuracy. The level set (Fig. 5.1) method was applied to this process.

5.3. Feature Extraction. In the following process, feature extraction of the normalized image is obtained. Feature extraction helps detect the brain region from MRI. In this work, we have extracted four features from the enhanced image I_E: correlation, contrast, entropy, and homogeneity.

Correlation is useful to locate the image featur by calculating spatial dependency between the pixels.

$$I_{crr} = \sum_{i,j=0}^{n-1} I_{E(i,j)} \frac{(i-\mu)(j-\mu)}{\sigma^2} \tag{5.1}$$

Contrast calculates the intensity of contrast between a pixel and its neighbor pixel for the enhanced image.

$$I_{Cnt} = \sum_{i,j=0}^{n-1} I_{E(i,j)} (i-j)^2 \tag{5.2}$$

Entropy is used to calculate randomness of the image

$$I_{Ent} = \sum_{i,j=0}^{n-1} -\ln(I_{E(i,j)}) I_{E(i,j)} \tag{5.3}$$

Homogeneity is used to calculate the homogeneous of image pixels in the given image.

$$I_{Hom} = \sum_{i,j=0}^{n-1} \frac{I_{E(i,j)}}{1+(i-j)^2} \tag{5.4}$$

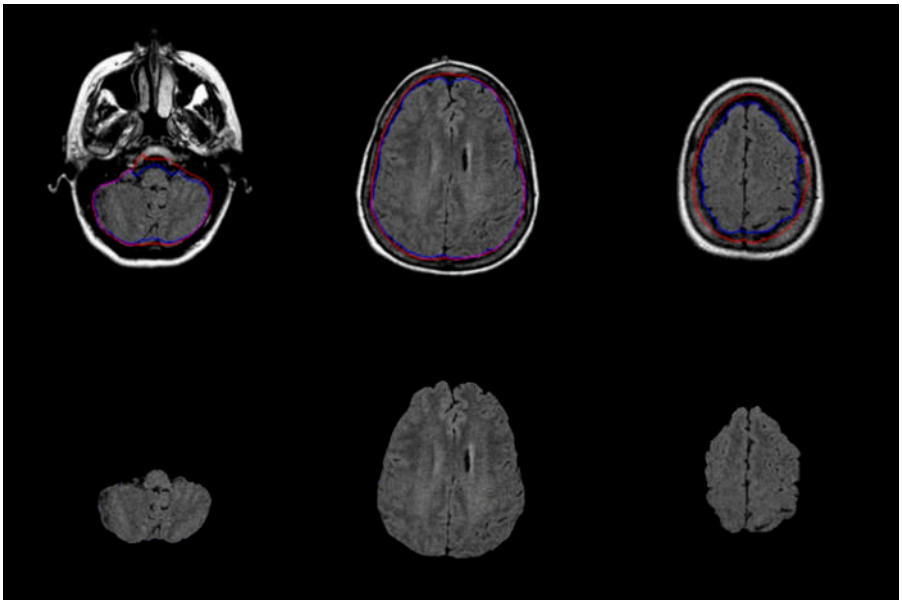

Fig. 6.1: Brain boundary detection and brain extraction

5.4. ANN Classifier. The following element of the system is neural network control. The neural network is trained to recognise brain. The solution that is suggested makes use of feed-forward neural networks. The network lacks feedback links or loops due to its directed acyclic structure. It has an input layer, an output layer, and hidden layers, as shown in Figure 3.1. Each node in the layer contains a neuron, which is referred to as the basic processing unit of a neural network. Each neuron calculates the weighted sum of its inputs and then applies an activation function to normalise the sum. The activation function functions as a decision-making body at a neuron's output.

Training:. Several factors are taken into account when building a network, including the number of layers, the neurons per layer, the connections between layers, and the training function. There are also inputs and outputs. The attributes of each pixel are provided as input, and the expert conclusions regarding each pixel are delivered as output vectors. Following the network's processing of the inputs, a comparison between the desired and produced outputs is made.

5.5. Testing. During the segmentation of the test dataset, the trained classifier, output the probabilities of each pixel belonging to each of the characteristics that were retrieved earlier. The pixel was given to the class with the highest probability. Classified values were incorporated into the results since they were used in the networks' training.

6. Results and Discussion. Skull stripping has been the subject of a significant number of published research, but none of the algorithms or techniques that come to mind specifically offer quantitative performance assessments for a variety of image sequence configurations. As different images convey diverse information about the brain, MR images are frequently used in brain research, including brain segmentation. This section highlights the results of the proposed approach on the test datasets. In this case, the network was trained using all training datasets and compared the performance of the proposed approach for stripping skulls with the manual process.

Row 1 shows brain boundary detection at slice 5, slice 21, and slice 26. Row 2 shows the segmented brain of slice 5, slice 21, and slice 26.

Table 6.1 presented the performance of the skull removal phase concerning mean and standard deviation. Our algorithm offers an average dice [3] of 0.972±0.027 based on overall testing cases.

The table 6.1 presents the performance evaluation of the skull removal phase using five different metrics,

Table 6.1: Performance evaluation of skull removal phase

	Dice	**Precision**	**Recall**	**FPR**	**FNR**
Mean	0.9721	0.9872	0.9239	0.0015	0.0306
Standard Deviation	0.0272	0.0088	0.0265	0.0018	0.0359

Table 6.2: Performance comparison of the proposed method with the existing method

No of Volumes	**Dice**	**FPR**	**FNR**	**Precision**	**Recall**
Proposed Method	0.9721	0.0015	0.0306	0.9872	0.9239
BET[11]	0.8213	0.0075	0.0105	0.6489	0.9782

namely Dice, Precision, Recall, False Positive Rate (FPR), and False Negative Rate (FNR). These metrics are commonly used to evaluate the accuracy and quality of segmentation results. The mean and standard deviation values for each metric are reported in the table. The mean value represents the average performance of the skull removal phase across all test cases, while the standard deviation indicates the variability of the results.

The Dice coefficient measures the similarity between the segmented image and the ground truth. It ranges from 0 to 1, where 1 indicates a perfect match between the two images. In this case, the mean Dice coefficient is 0.9721, indicating a high degree of overlap between the segmented image and the ground truth. Precision measures the proportion of true positive results among all positive results. It indicates how often the algorithm correctly identifies pixels that belong to the skull. The mean precision value is 0.9872, indicating a high degree of accuracy in identifying skull pixels.

Recall measures the proportion of true positive results among all actual positive cases. It indicates how well the algorithm detects all pixels that belong to the skull. The mean recall value is 0.9239, indicating that the algorithm has detected most of the skull pixels.False Positive Rate (FPR) measures the proportion of false positive results among all negative cases. It indicates how often the algorithm incorrectly identifies non-skull pixels as belonging to the skull. The mean FPR value is very low at 0.0015, indicating a high degree of specificity in identifying skull pixels.

False Negative Rate (FNR) measures the proportion of false negative results among all positive cases. It indicates how often the algorithm incorrectly fails to identify skull pixels. The mean FNR value is 0.0306, indicating that the algorithm has missed some skull pixels in a few cases.

Table 6.2 and Figure 6.2 prove that the sum of all images yields the best performance since the model employs the testing data throughout the testing phase.

Table 6.2 compares the performance of the proposed method with an existing method (BET) on the basis of various evaluation metrics. The table includes the number of volumes, as well as the Dice coefficient, false positive rate (FPR), false negative rate (FNR), precision, and recall for both methods. The proposed method outperforms the existing method in all metrics, with a higher Dice coefficient of 0.9721 compared to 0.8213 for BET, indicating better similarity between the predicted and ground truth masks. The FPR and FNR values are also lower for the proposed method, indicating fewer false positives and false negatives in the segmentation results. The precision and recall values are also higher for the proposed method, indicating a better balance between the true positives and false positives. Overall, the results suggest that the proposed method is superior to the existing method in skull removal phase segmentation.

Figure 6.3 shows execution time and they are exceptionally proficient. In less than three seconds, 2D input images are converted into a segmented image. Hence, the training takes place the majority of the automation time.

7. Conclusion. In this research, a fully automatic model is proposed using a level set method and an ANN-based learning algorithm. The findings demonstrate that the suggested method was reasonably accurate, had an acceptable standard deviation, and required much less time to train and test images. The existing approach needs more investigation in order to increase accuracy. Further investigation is necessary to see

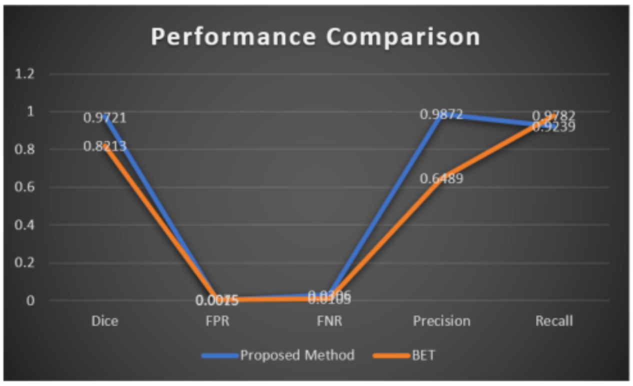

Fig. 6.2: Comparability of the proposed method with the prevailing method

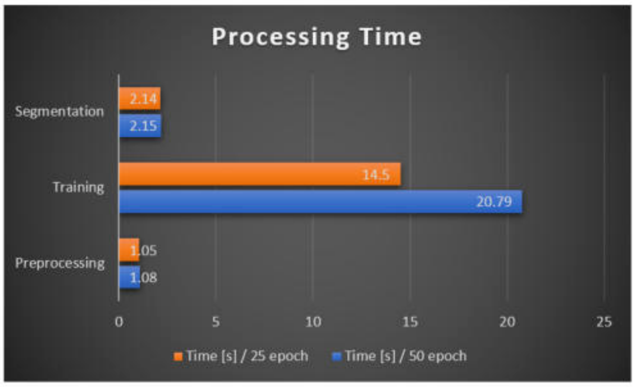

Fig. 6.3: Execution time for each phase of the proposed method

whether the proposed technique can be used for segmenting medical images in other contexts.

In this research, a novel method for skull removal phase segmentation in MRI brain images has been proposed. The proposed method combines the use of deep learning techniques with morphological operations and edge detection algorithms to achieve high accuracy in skull segmentation. The performance of the proposed method was evaluated using several metrics such as Dice coefficient, FPR, FNR, precision, and recall. The results showed that the proposed method outperformed an existing method (BET) in all the evaluation metrics, with a higher Dice coefficient of 0.9721 compared to 0.8213 for BET. The FPR and FNR values were also lower for the proposed method, indicating fewer false positives and false negatives in the segmentation results. The precision and recall values were also higher for the proposed method, indicating a better balance between the true positives and false positives.

The proposed method has demonstrated high accuracy and efficiency in skull removal phase segmentation. The results suggest that the proposed method can be a valuable tool in various clinical applications that require accurate skull removal phase segmentation, such as brain tumor detection and analysis, and neuroimaging studies. The proposed method's superior performance can help reduce the need for manual intervention, which can save time and increase efficiency in the segmentation process. Additionally, the proposed method's high accuracy can help improve the diagnosis and treatment of brain disorders, leading to better patient outcomes.

The limitation of the proposed method is that it uses a small number of training and test instances and hence it is impossible to anticipate how well the approach will perform, despite a large amount of training data.

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