# A New Hybrid Region-Based Segmentation for 2D Corpus Callosum Segmentation

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***Abstract*— The development of an image-based brain image segmentation system using UNet has the advantages of a network that does not contain a fully contained layer. These steps have involved modifying the fully convolutional networks architecture proposed and extending it to work with very few images and more precise Segmentation. UNet produces only a few features. However, Corpus Callosum Segmentation requires high features and detects the edge of the rostrum, the genu, the body, and the splenium to achieve higher performance. This paper proposes UNet ++ with A New Hybrid Region-Based Segmentation (NHRBS) as a new region-based network strategy by combining region-based Segmentation with UNet++ that were improving object detection in 2D Corpus Callosum object segmentation. Our test results show that NHRBS accomplished a dice coefficient of 0.99.**

***Keywords—2D Segmentation; UNet++; Thresholding; Corpus Callosum; Brain MRI.***

## I. Introduction

Epilepsy is a chronic disorder caused by various pathological processes in the brain and is characterized by epileptic seizures [1]. In the last year, the incidence of epilepsy occurs in the field of 0.5% to 2% of the total population, whereas 25% - 30% of people with epilepsy experience more than once a month. There may be no focus on the origin of the seizure, or there may be too many seizures to be removed individually. These patients are most likely to undergo a corpus callosotomy. Corpus callosotomy is also indicated for the treatment of intractable epilepsy.

Corpus callosotomy is an operation that cuts the corpus callosum, intentionally interfering with the spread of impulses or outbreaks from one hemisphere of the brain to another [2]. The Corpus Callosum (CC) is a bundle of nerve fibers located deep in the brain that connects the brain's two hemispheres. This section contains 200 million nerve threads that transmit information to the contralateral side of nerves, allowing the exchange of information between the brain's two hemispheres and contributing to the spread of seizure impulses from one side of the brain to the other corpus callosum. That can result in the sufferer experiencing complete seizures, including a drop attack or atonic stroke. Before performing a corpus callosotomy, a Magnetic Resonance Imaging (MRI) test is required. MRI is a way for doctors to get a clear picture of the inside of the brain and pinpoint the location of CC. CC is a bundle of nerve fibers located between the left and right hemispheres whose structure is smaller than the background in the brain, so technology is needed to carry out an automation process to detect the CC part or call it the segmentation process on MRI.

The segmentation technologies that have been done in previous research are by using region-based segmentation techniques. The second segmentation technique is machine learning segmentation. The machine learning segmentation algorithms studied are Convolutional Neural Networks (CNNs). Another segmentation technique is U-Net. The purpose of the U-Net is to modify the fully convolutional networks architecture proposed and extend it to work with very few images and more precise Segmentation. One of the U-Net that is currently popular is UNet++ which is also called Nested-UNet. UNet++ is an extension of the previous UNet architecture defined using a skip connection in a different structure. UNet++ with New Hybrid Region-Based Segmentation (NHRBS) is needed with an optimal neuron network that can accurately detect parts of the CC object. The contribution of this article is to propose the local thresholding algorithm: a New Hybrid Region-Based Segmentation (NHRBS) + Unet++ to get a more precise corpus callosum (smooth area).

## II. Related Works

Many related papers have discussed 2D image segmentation. However, not much is mentioned about 2D CC Segmentation [3]. Here, we will discuss and look for the strengths and weaknesses of the few papers that we found about the CC segmentation approach based on the thresholding method. First, Herrera et.al [4] proposed 2D Segmentation of the CC in the midsagittal slice. This research method made a result that based on watershed cause failed or less precision because it is sensitive to the threshold choice. Although this research ROQS method presented a good performance but had no initiation or parameters choice requirements after training.

The second research, Manic et. al. [5] proposed the thresholding method that uses a multihresholding technique with the chaotic cuckoo search (CCS) algorithm and a preferred threshold procedure. The proposed CCS is using otsu's trilevel threshold operation and other techniques such as Kapur, tsallis, and Shannon. During the investigational assessment, the benchmark datasets, such as ABIDE and MIDAS, are used for the preliminary evaluation.

Third research, Satapathy et.al [6] proposed bi-level and multi-level threshold procedures based on their histogram using Otsu's between-class variance and a novel chaotic bat algorithm (CBA). As a result and

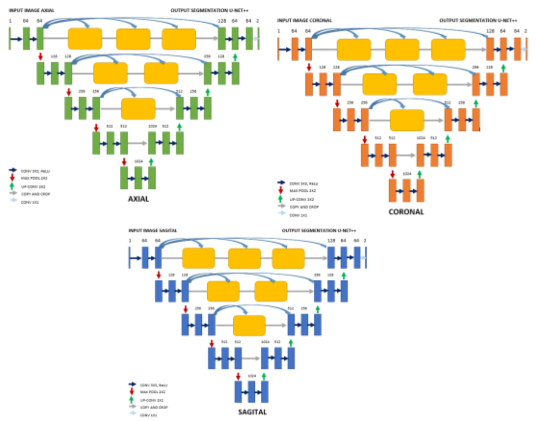



Fig. 3. U-Net++ Network Architecture (a) sagittal (b) coronal (c) axial slice.

recommendation, Since the proposed method achieves superior performance, thus it is recommended to extend the implementation with the Ikeda map by other chaotic maps as future work.

The last research about thresholding segmentation is just about proposing one or two combine thresholding methods [7][8][9][10]. This research proposes a new thresholding method with combine Adaptive Thresholding, Large Connected Component, K-Means Clustering, Mathematical Morphology, Large Connected Component a and the last is UNet++, shown in Fig. 2.

## III. Proposed Method

### *A. New Hybrid Region-Based Segmentation (NHRBS)*

New Hybrid Region-Based Segmentation (NHRBS) is an algorithm that focuses on the binarization of grayscale documents using local adaptive threshold techniques. Recent research has recommended that diverse building models give distinctive execution brings about various cases [11][12][13]. This presentation is additionally acquired from the building boundaries of each CNN. Particularly for UNet, it has an extreme issue since it has countless boundaries. We propose a design that acquires UNet with fewer boundaries and better shows in Fig. 1.

In many cases, color documents can be converted to grayscale without losing much information. The differences between the foreground of the page (text) and the background are noticed. The local binarization method solves this problem by calculating the threshold individually for each pixel using information from the pixel's local environment. This New Hybrid Region-Based Segmentation shown in Fig. 2. presents a fast approach to calculating local thresholds without sacrificing the performance of the local thresholding technique using the integral sum image technique as the previous process to find the local mean of neighboring pixels in the window regardless of window size. Using this approach can achieve binarization speeds close to the global binarization method with performance and Sauvola's and Pietikainen's local binarization schemes. The threshold T (x, y) is such a value in Equation (1).

$$\mathrm{b(x,y)} = \begin{cases} 0 & \text{if } \mathrm{I(x,y)} \leq T(x,y) \\ 1 & \text{otherwise} \end{cases} \tag{1}$$

where b (x, y) is the binarization image, and I (x, y) ∈ [0,1] is the pixel intensity at the location (x, y) of the image I. In local adaptive techniques, each pixel calculates the threshold based on some local statistics such as range, variance, or environmental pixel surface adjustment parameters. The order of the steps are first input Original Image, then Convert Image to Grayscale, Adaptive Thresholding, Large Connected Component, Get value grayscale, K-Means Clustering, Get the smallest value, Mathematical Morphology, Large Connected Component and the Convert Image to Grayscale, shows in Fig. 2.

### *B. UNet++ Architecture*

U-Net++ is a revolutionary segmentation design from UNet that uses layered and dense skip connections to segment data. The fundamental speculation behind the UNet++ is that when the encoder network's high-resolution map features are incrementally enriched before fusion with the corresponding semantically rich map features of the decoder network, the model can more likely catch the delicate subtleties of forefront objects. We recommend that when the component guides of the decoder and encoder networks are semantically similar, the network will have a more accessible time learning. This contrasts the U-standard Net's skip connection, which immediately speeds up the high-resolution feature map from the encoder to the decoder network, resulting in a semantically distinct mix of feature maps. This design works well, with considerable performance gains over U-Net and broad U-Net. U-Net++ architecture that produced the model is modified in such a way as to obtain a simpler model than the original U-Net architecture, which is very complex, shown in Fig. 3.

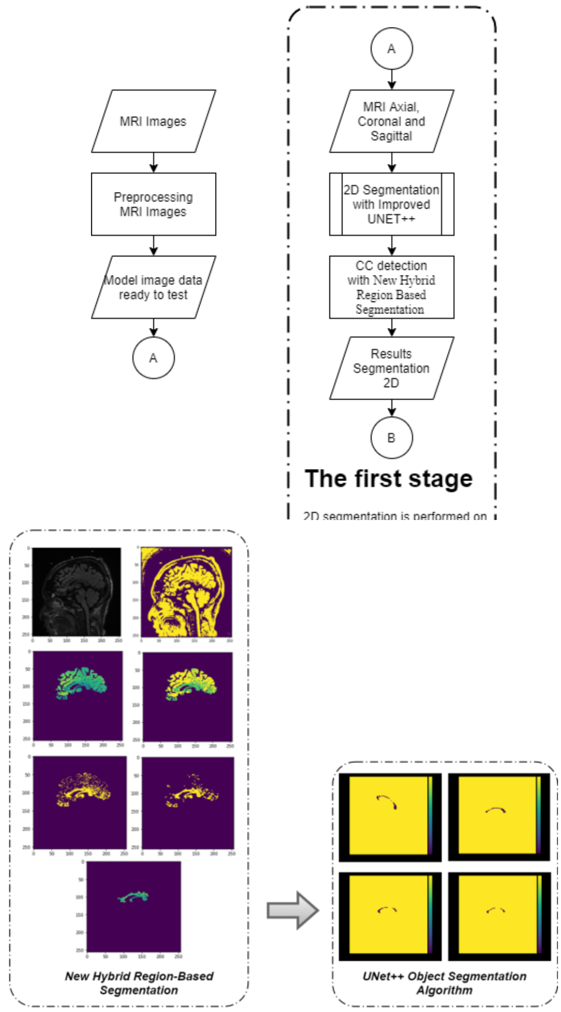



Fig. 2. a New Hybrid Region-Based Segmentation for Improvement of UNet++ Object Segmentation Algorithm

Redesigning the skip path changes encoder and decoder sub-network connectivity. The encoder feature map is received directly on the decoder; however, in UNet++, they undergo solid convolutional blocks whose number of convolutional layers depends on the pyramid level. For instance, the leap way between hubs $X_{0,0}$ and $X_{1,3}$ comprises a strong convolution block with three layers. Every convolution layer is gone before by a circuit layer that consolidates the yield from the last convolutional layer with a similar strong square with the relating up-example yield of the lower strong square. A solid square convolution brings the semantic level of the encoder to include a map nearer to the element map holding up in the decoder. The speculation is that the streamlining agent will confront a more straightforward improvement issue when they get encoder include a map and the comparing decoder highlight map are semantically comparative.

Formally, we formulate the jump path: let xi, j denote the output of node Xi, j where I index the sampling layer along with the encoder, and j indexes the convolutional layer of solid blocks along the jump path. The feature map stack represented by xi, j is calculated as:

$$x^{i,j} = \begin{cases} \mathcal{H}(x^{(i-1,j)}) & j = 0 \\ \mathcal{H}\left(\left[[x^{i,k}]_{k=0}^{j-1}, \mathcal{U}(x^{i+1,j-1})\right]\right), & j > 0 \end{cases} \quad (2)$$

## IV. RESULTS AND DISCUSSIONS

### A. *Dataset Corpus Callosum*

In this research, a dataset called Corpus Callosum (CC) shows in Fig. 4., Table 1., Table 2, and Table 3.

- Dataset Oasis 2018

First Dataset was collected from (https://www.oasis-brains.org/#data), in which the Dataset consists of 1806 Images with 903 CC Images and 903 CC Masks, shows in Fig. 5.

- Dataset Abide 2015

The second Dataset was collected from http://fcon_1000.projects.nitrc.org/indi/abide/, in which the Dataset consists of 1890 Images with 945 CC Images and 945 CC Masks, shows in Fig. 6.

- Dataset National Hospital Surabaya 2020

The third Dataset was collected from National Hospital Surabaya 2020, in which the Dataset consists of 85 Images consisting of slice sagittal, coronal, and axial, shown in Fig. 7 and Table 1.

TABLE I. PROPERTIES OF IMAGES

| Properties | Value |
|---|---|
| Slice Thickness | 1 mm |
| Pixel Spacing | 0.9766mm,0.9766mm |
| Number of slices | 166 |
| Dimension | 256x256 cm |

TABLE II. TRAINING AND TESTING DATASET

| No. | Training Data | Testing Data |
|---|---|---|
| 1. | Image (Brain Axial, Sagittal, Coronal). | Brain Segment Images that have been merged. |
| 2. | Brain Segments or Mask Segments. | |

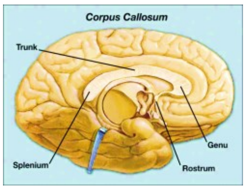
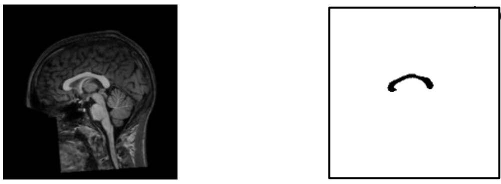



Fig. 4. Four main parts to the CC

(a) (b)

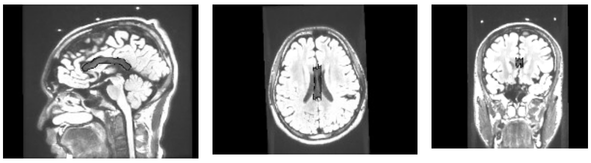
Fig. 5. Corpus Callosum for slice sagittal (a) Oasis 2018 Images (b) Oasis 2018 Masks.

The corpus callosum is approximately 10 cm in length and C-



(a) (b)

Fig. 6. Corpus Callosum for slice sagittal (a) Abide 2015 Images (b) Abide 2015 Masks.



(a) (b) (c)

Fig. 7. Corpus Callosum for slice (a) sagittal, (b) coronal dan (c) axial.

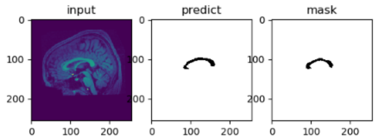
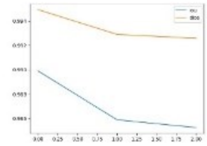
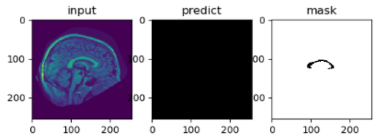
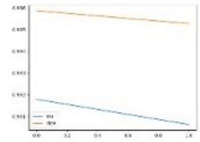
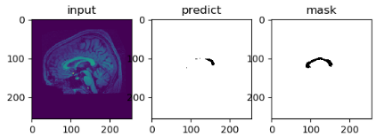
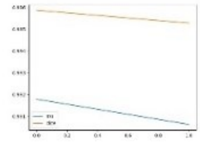
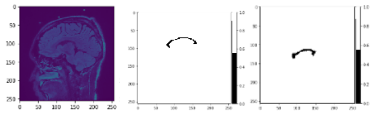
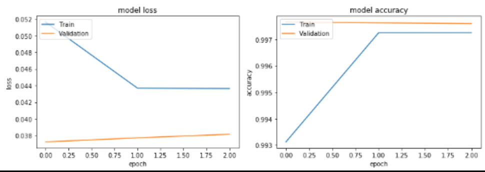
shaped (like most supratentorial structures) in a gentle upwardly convex arch. It is thicker posteriorly. It is divided into four parts (from anterior to posterior): **genu**: forceps minor connects medial and lateral surfaces of the frontal lobes. **rostrum**: connecting the orbital surfaces of the frontal lobes. **trunk** (body): pass through the corona radiata to the surfaces of the hemisphere's trunk and splenium: **tapetum**; extends along the lateral surface of the occipital and temporal horns of the lateral ventricle. **splenium**: forceps major; connect the occipital lobes The input of this research is MRI images with Axial, Coronal, and Sagittal slices. Before the image segmentation process is carried out, it is necessary to do preprocessing first. The output of the preprocessing stage is a ground truth image and a test image. The first step was 2D Segmentation of each slice using NHRBS. The output of this study is the image of the CC object segmentation results, shown in Tables 4.a. and 4. b.

TABLE III. DATASET DETAIL

| Class name | Total | Test | Train |
|---|---|---|---|
| OASIS 2018 | 416 | 166 | 250 |
| ABIDE 2015 | 416 | 166 | 250 |
| Local Hospital 2020 | 85 | 11 | 74 |
| Total | 917 | 343 | 574 |

TABLE IV. PERFORMANCE RESULT

| **Oasis 2018** | **Loss** | **Val_Loss** | **Dice_Coef** | **Val_Dice_Coef** |
|---|---|---|---|---|
| UNet | 0.166 | 0.161 | 0.9949 | 0.9925 |
| UNet++ | 0.172 | 0.169 | 0.9956 | 0.9915 |
| Attention UNet | 0.086 | 0.085 | 0.9930 | 0.9930 |
| NHRBS+UNet++ | 0.043 | 0.038 | 0.9986 | 0.9988 |
| **Abide 2015** | **Loss** | **Val_Loss** | **Dice_Coef** | **Val_Dice_Coef** |
| UNet | 0.035 | 0.035 | 0.9925 | 0.9972 |
| UNet++ | 0.203 | 0.207 | 0.9956 | 0.9956 |
| Attention UNet | 0.095 | 0.083 | 0.9956 | 0.9954 |
| NHRBS+UNet++ | 0.067 | 0.056 | 0.9979 | 0.9982 |
| **NHS 2020** | **Loss** | **Val_Loss** | **Dice_Coef** | **Val_Dice_Coef** |
| UNet | 0.986 | 0.649 | 0.9972 | 0.9972 |
| UNet++ | 0.440 | 0.449 | 0.9956 | 0.9956 |
| Attention UNet | 0.570 | 0.995 | 0.9954 | 0.9954 |
| NHRBS+UNet++ | 0.005 | 0.004 | 0.9996 | 0.9997 |

| **Oasis 2018** | **Data Visualisation** | **Testing Plot (Loss, IOU, Dice)** |
|---|---|---|
| UNet |  |  |
| UNet++ |  |  |
| Attention UNet |  |  |
| NHRBS+UNet++ |  |  |

The Dataset in this study is from Oasis 2018 dataset, comprising 250 MRI pictures, 60% and 40% for preparing and testing individually, which was separated into 250 Images Training and 166 Images Testing with 256 x 256 resolution images format (.tif). The Abide 2015 dataset, comprising 250 MRI pictures, was isolated into 250 Images Training and 166 Images Testing with 256 x 256 resolution images format (.tiff). Furthermore, we used 85 datasets of MRI images from the National Hospital, Surabaya from 80 patients with 256 x 256 resolution images format (Dicom) then converted them to (.png). Table 1 shows the properties of the pictures of dataset format Dicom that utilized in the investigation. Each voxel speaks to various sizes; Axial speaks to 165,55 mm cuts; Coronal speaks to 111,627 mm cuts; Sagittal speaks to 90,606 mm cuts. An MRI cut usually is reproduced at 256 x 256 voxels. Each cut speaks to roughly 1 mm of information long and width.

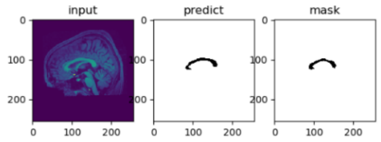
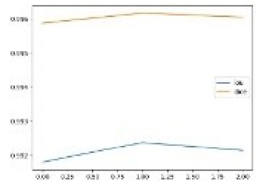
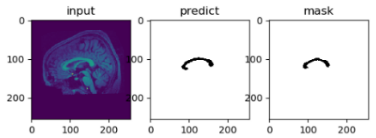
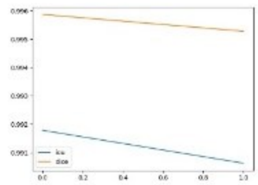
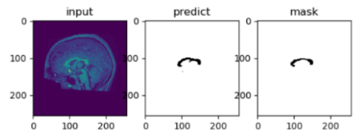
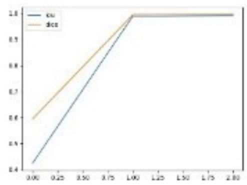
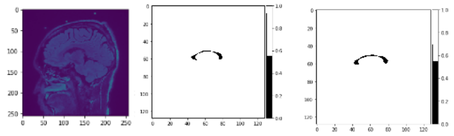
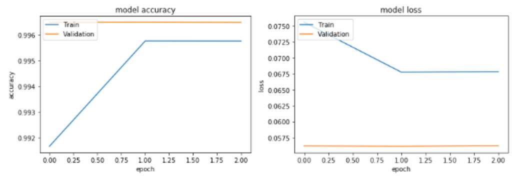
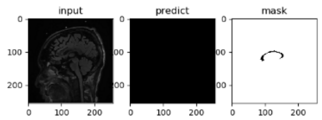
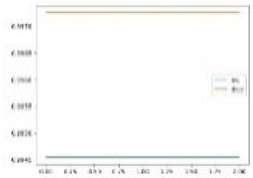
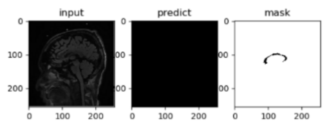
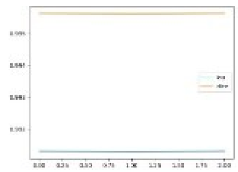
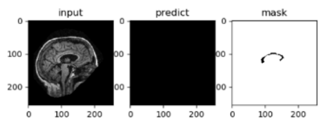
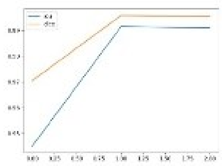
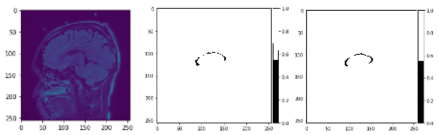
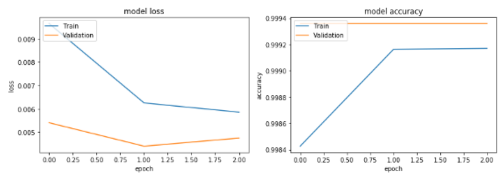
### *B. Software tools for experimental*

The results of the research will be presented in full in this section. Each trial scenario is structured to analyze the results of the proposed method with a comparative method. The trial data is attached as support for the explanation of the research results. This research was implemented on Python using Anaconda as environment, jupyter notebook as IDE and sci-kit-learn, sci-kit-image, NumPy, pandas, matplotlib, OpenCV, Tensorflow, and Keras as a library. The testing environment used in this study was carried out on hardware and software. The hardware used is as follows: Model: Nvidia RTX 2080 Ti Processor Intel Core i7; RAM: 32 GB; Hard drive: 222 GB (Local Disk C); 465 GB (Local Disk D). Meanwhile, the software used is as follows: Windows 10 x64 operating system; Anaconda 1.10.0 Python 3.9; Slicer 4.10.2.

### *C. Design experiments*

An examination on different UNet demonstrated the exhibition of the proposed NHRBS-UNet models, for example, original UNet, Unet++, and UNet3D. In all examination models, an organization from pre-prepared loads accessible was additionally utilized. The preparation boundaries on all models is given, for example, batch size = 20, epoch = 60, optimizer = adam, loss = binary cross-entropy. During preparation, the four squares of UNet were frozen; consequently, the loads did not change to hold the lower layers summed up to produce low-level components. Extra parts are completely prepared to accomplish weight with undeniable level component age compared to the corpus callosum division. We directed execution examination with preparing, approval, and testing precision. The examination between the proposed engineering and the first UNet demonstrates that the proposed model is better than the first UNet, UNet++, and Consideration UNet.

TABLE V. PERFORMANCE RESULT (CONTINOUS)

| Abide 2015 | Data Visualisation | Testing Plot (Loss, IOU, Dice) |
|---|---|---|
| UNet |  |  |
| UNet++ |  |  |
| Attention UNet |  |  |
| NHRBS+UNet++ |  |  |
| **NHS 2020** | **Data Visualisation** | **Testing Plot (Loss, IOU, Dice)** |
| UNet |  |  |
| UNet++ |  |  |
| Attention UNet |  |  |
| NHRBS+UNet++ |  |  |

## V. CONCLUSION

Based on the research results and discussion described in the UNet++ method based on New Hybrid Region-Based Segmentation, conclusions and suggestions for research development can be defined. The conclusions of this study are as follows: This research has developed an Active Contour method based on UNet++ based on New Hybrid Region-Based Segmentation as a proposed method for Segmentation of Corpus Callosum. The proposed method is proven to perform Corpus Callosum segmentation with a small mask image, many neuron networks, and low-resolution MRI image objects on MRI images. The proposed method achieves the highest accuracy compared to the accuracies of the other methods. 2D

Segmentation is carried out by detecting the corpus callosum using UNet++ based on A New Hybrid Region-Based Segmentation (NHRBS) precisely at the Corpus Callosum position.

## ACKNOWLEDGMENT

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