

Corpus Callosum Segmentation Using Enhanced Hyperparameters in the U-Net Model

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ABSTRACT

This study presents a deep learning segmentation technique for effectively segmenting the brain anatomy, particularly the corpus callosum, using magnetic resonance imaging. The approach employed in this study involves utilizing U-Net with Hyperparameter Optimization. Following the training of the program, the model is evaluated using a test set sourced from the same dataset. The evaluation compares the Ground Truth and Predicted Images using the dice coefficient (DC). The method was tested four times with different hyperparameters, yielding the highest accuracy F1-Score of 92.16% with 150 epochs and the lowest accuracy of 89.4% with 50 epochs. These outcomes indicate the effectiveness of the method used in producing favorable results.

Keywords: *Corpus callosum, Deep learning, Image processing, Magnetic resonance imaging, Reconstruction image, Segmentation, U-Net.*

1. INTRODUCTION

Brain is one of most complex anatomy systems consisting of millions of interconnected neurons. Approximately 100 billion neurons are in the average brain and every one of them, on average, connects with a thousand others. It's likely to lead to trillions of connections in total. There are important structures inside the brain. Corpus callosum is one of them, it is a vast assembly of nerve fibers that links the brain's left and right hemispheres.

Many image segmentation methods have been tried in the literature to accurately segment the corpus callosum in the brain [1]. First method using K-Means for unsupervised clustering to categorize every pixel in an image into distinct clusters was proposed. The results of this study show a weakness in the output of the segmentation results, which loses some of the corpus callosum structure because K-Means does not take into account the spatial information between pixels in the image. This means these algorithms can produce segmentation that is not smooth or does not pay attention to the context.

In [2], the initially extracted regions should meet the statistical criteria for the distribution of gray-level intensity values in the corpus callosum. Anatomy regions typically have relatively high intensity values. The outcome is then merged with a quest for an area with the structure of the corpus callosum. These results suffer from noise which is considered to be part of the structure of the corpus callosum itself, because of that, this study research uses data augmentation techniques so that the method is more tolerant of small variations or noise in image and use hyperparameter to optimization training, that is the development and contribution to this research study



Figure. 1. Visualization result segmentation from previous work (a) and ground truth (b)

The previous research using the improved Spatial Fuzzy Clustering Algorithm approach to, and produced high accuracy result. The segmentation problem is still exist, which are the area not the

corpus callosum are segmented. As seen in Fig. 1, the part marked in the red box is an area that is not part of the corpus callosum, because, according to the ground truth image made by medical experts, that is the image of the corpus callosum in the human brain. This error is very critical in the world of health considering that the corpus callosum organ is an important part of the human brain structure [3].

This study aims to produce accurate segmentation of the corpus callosum, good results can help medical experts to diagnose diseases. Finally, deep learning using U-Net based on fully connected network is proposed. This method also introduced performs hyperparameter tuning to optimize parameter values that are not determined automatically during training but affect model performance. Lastly, augmentation is used, such as rotation, enlargement, cropping, or small shifts in the image to make the data more varied, U-Net model can be trained to be more tolerant of small noise to produce accurate segmentation.

The paper is divided into key sections. Introduction (Section 1) provides background, problem statement, and objectives. (Section 2) outlines the approach, including the use of Image Processing, Segmentation and U-Net Method. (Section 3) detailing datasets, (Section 4) methodology. Experiment and Results (Section 5) discusses practical application, results, and (Section 6) future work and conclusion.

2. LITERATURE REVIEW

Related research, previous paper was segmenting 3D MRI Brain Data using the U-Net. Approach to segment the entire brain or brain tissue (outside the skull) with good and accurate results. In another paper proposed unsupervised learning method to segment the corpus callosum and produce smooth segmentation with the highest accuracy was 87,53% [4] [5]. Another paper is resulted that segmentation corpus callosum with level set method, it is a computational approach in image processing and computer graphics for the segmentation of objects or areas of an image based on their contours or boundaries. The main idea of this method is to represent object boundaries as level sets of continuous functions defined in the image space. That results is comparison with K-Means and Fuzzy Cluster and the highest is the method proposed with 85,14 % accuracy [6]. The corpus callosum of male autism patients was manually segmented by another paper was performed to identify and chart the spatial patterns of corpus callosum irregularities in autism patients using conventional morphometric techniques. The findings of this study suggest that the study approach successfully identified a noteworthy decrease in both the overall area of the callosal as well as one-third of the anterior corpus callosum in autism patients [7].

On the other hand, the method was utilized semi-automatic methods for corpus callosum segmentation. Their study incorporated a hybrid approach involving a restricted affine transform (RAT) constrained snake and an unconstrained snake optimization. The RAT formulation optimized the geometry of snakes restricted using local contrast-based energy, while the unconstrained snake deformation optimized snake geometry using integrated energy formulations. This hybrid approach resulted in enhanced resilience to initial segmentation, along with improved speed and accuracy [8].

2.1 3D Model from Medical Images

Creating a 3D model begins with the initial step of image acquisition, which involves the use of computed tomography (CT) or magnetic resonance imaging (MRI). In the case of constructing bone models, CT is often preferred due to its high tissue-to-bone contrast, making it the standard choice and producing images with clear bone delineation [3]. MRI provides more detailed information about tissue structure and texture, especially in T1-weighted, and similar images. This information can be exploited by segmentation algorithms to better identify the boundaries between various anatomical structures and MRI has higher spatial resolution for soft tissue compared to CT. This enables more accurate and detailed segmentation of complex or small anatomical structures in medical images [9] [10].

DICOM data (Digital Imaging and Communications in Medicine) is an international standard for exchanging, storing, and retrieving medical image information. Each file contains image data in a structured format, allowing the storage of various types of medical images, such as radiology images (X-ray, CT, MRI). It also provides additional information such as patient data, imaging technical information (e.g., imaging device setting parameters), and other information related to the medical study referred to as metadata [11] [12].

2.2 U-Net Method

U-Net has a symmetric structure and consists of two main parts, the encoder and decoder. The encoder is responsible for extracting features from the input image, while the decoder returns an image segmented to the same resolution as the input image. U-Net's methods goal is to extend and modify. That network architecture it can operate with fewer images and more accurate segmentations. [13] [14]. In the Fig. 2, The contraction path uses pooling and downsampling in the same manner as conventional Convolutional Neural Networks (CNNs). As mentioned in the preceding sections, the expansion path employs upsampling operators, umpsampling is image enlargement process relies on various algorithms to minimize quality loss through interpolation [15].

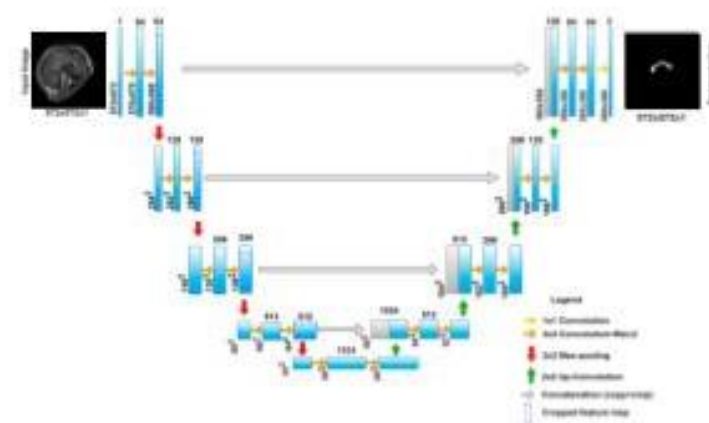


Figure. 2. U-Net Method [13]

2.3 Image Processing

The processing of images can involve the removal of artifacts and noise as well as the selection of specific areas of interest within images. For this particular study, filters for eliminating noise and artifacts were not utilized. The following explanation of image processing concentrates on various methods for segmenting the brain structure of the corpus callosum from MRI images. Shaping or blurring involves using kernels. When sharpening, there is a balance between enhancing edges and increasing noise, while smoothing reduces sharp edges and decreases noise are challenging to eliminate noise while preserving image features, as it may result in loss of structure and constrain MRI analysis [16]. Delineation of pixels or voxels within an area of interest is called segmentation. This process is important for generating 3D models of specific imaging modality areas. Several manual segmentation techniques such as thresholding, edge detection, also exist using clustering or deep learning methods like this work [17].

2.3 Stacking DICOM

The MRI medical image obtained is in the form of per-slice data stored in DICOM files. In order to produce a three-dimensional image, the data needs to be organized in a stacked format. The DICOM stacking process carried out in this study is guided by a previous study which dictates that the stacking must align with the slice order indicated in the DICOM metadata [9]. High resolution characteristics from the contracting path are mixed with the output that has been upsampled in order to localize. One significant change made by U-Net is the addition of numerous feature channels to the upsampling portion, which enables the network to transport context information to higher resolution layers [18].

3. DATASETS

This dataset was obtained from various hospitals in Surabaya, and the total data used in this study was 280 data. Understanding the image dataset that was utilized to train the deep neural network is crucial. The upcoming sections will provide detailed information about its organization and methods for improving the trained model through additional input, such as data augmentation.

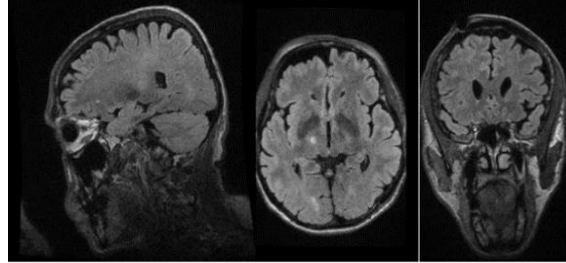


Figure 3. Visualization of dataset from coronal, sagittal and axial

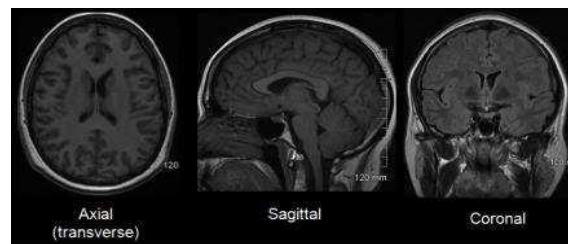


Figure 4. Visualization of dataset from left axial, coronal and sagittal

As seen in Fig. 3 and Fig. 4 MRI produces three types of images, axial images, which represent "slices" of the body in the transverse plane, sagittal images, which are taken perpendicular to the axial plane and separate the left and right sides, and coronal images, which are taken perpendicular to the sagittal plane and separate the front from the back. The corpus callosum is entirely visible in the sagittal plan, while some of it can also be seen in the other view planes. This study are solely using sagittal pictures for model training and evaluation in this work. The MRI pixel size from when it came into use was 256x256. This data will be scaled down to 128x128 during data preprocessing for more affordable computing. The aim of this study is to segment the corpus callosum [19] [20].

4. METHODS

The primary method in this work is U-Net. Two method developments in this paper are carried out, namely data augmentation and hyperparameter optimization, as explained previously. Augmentation to enrich small amounts of data, and hyperparameter optimization to find combinations to produce the best segmentation of corpus callosum. In this study, four experiments were carried out for this matter evaluation uses dice coefficient, which has the advantage of considering the ratio of true positives and false positives, the steps of this method are depicted in the Fig. 5.

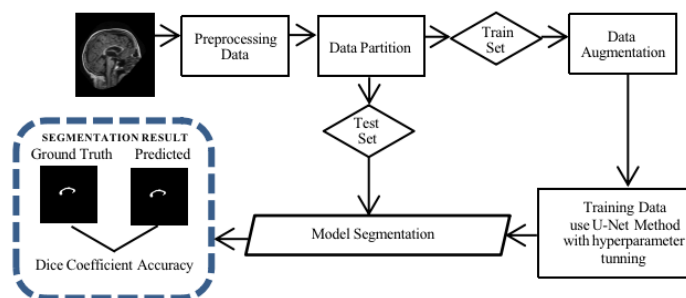


Figure 5. Proposed method

The corpus callosum is entirely visible in the sagittal plan, as can be shown in Fig. 6 and Fig. 7, while some of it can also be seen in the other view planes. This study are solely using sagittal pictures for model training and evaluation in this work. The DICOM datasets from multiple hospitals are utilized. A set of magnetic resonance imaging datasets is provided for research and analysis. An initial cross-sectional sample of 45 participants, ranging in many age , makes up the data set. Each patient scan with T1-weighted magnetic resonance imaging. The high contrast-to-noise ratio of many captures within a session enables the application of various analysis techniques [21].

4.1 Preprocessing Data

The dataset is normalized using statistical parameters like the mean and standard deviation of the entire batch. Achieved by subtracting the mean and dividing the image by the standard deviation. Since the parameters remain constant within the batch, the process is linear and results in the same histogram alignment.

4.2 Data Partition

In order to achieve generalization of your machine learning algorithm, split the dataset into three parts, training set, validation set, and test set. This will enable to accurately assess model performance by ensuring that the dataset used for training the model is distinct from the dataset used for evaluating it. Out of the original 280 image pairs, 70% will be allocated for training, 10% for validation, and 20% for testing.

4.3 Data Augmentation

Data augmentation were performed using two types of affine transformations, translations and rotations. An affine transformation refers to a function between two affine spaces that maintains the integrity of points, straight lines, and planes. This implies that the rotations and translations applied to the original images do not alter the image structure. For instance, a brain MRI will continue to display an image of a brain, albeit slightly displaced and/or rotated. Table 1 provides an overview of the rotations and translations utilized in this study.

4.4 Training Data

The network is trained with a different set of hyperparameters to obtain each one. This study change the dropout rate, which helps reduce overfitting in artificial neural networks, for each test essentially. Batch normalization, a technique used to speed up training and increase model stability by normalizing the input of each batch of data entering the network, number of epochs, the right number is needed to allow the model to learn complex patterns from the data without taking too long to cause overfitting, batch size is the number of samples used in one training iteration [22].

Batch size controls how many samples are processed at once before updating the model weights and kernel size is the size of the convolution filter applied to the input image. This filter is used to extract features from images by looking at local areas in the image. A larger kernel size can capture larger global features, while a smaller kernel size is better for capturing fine details in the image [23].

The U-Net approach is trained using the Adam optimizer and mini-batch gradient descent with an initial batch size of 32. The training data's presentation order is randomized for each training epoch to prevent bias from affecting the final result. Parameters were declared manually with four experiments to assess which results were the best, the number of epochs in this study was 50 then 100 and 150. Table 2 provides an overview of the various hyperparameters utilized in this study.

Table 1. Augmentation Factor

Train	Translations	Rotation	Factor
140	$[(-1, -1), (-1, 0), (0, -1), (0, 0)]$	$[-1, 0]$	8

Table 2. Diferent Parameters on Test Set

Epochs	BatchSize	FilterSize	Dropout	BN
150	32	3x3	x	x
50	32	3x3	x	x
100	32	5x5	√	√
50	32	5x5	√	√
150	32	3x3	x	x

4.4 Dice Coefficient Accuracy

Dice coefficient is one of the commonly used evaluation metrics to measure the similarity between two data sets. In the context of image or data segmentation. Therefore, the use of the dice coefficient needs to be considered by taking into account the context and special characteristics of the segmentation problem being faced [24]. The pixel predictions are categorized using the dice coefficient loss function, also known as the F1-Score. Understanding important statistical concepts such as the 2x2 contingency table. True positive (TP), true negative (TN), false positive (FP), and false negative (FN) is essential for clear comprehension [25]. After this understanding, statistical measures such as Precision, Recall, and ultimately F1 Score can be demonstrated, the accuracy can be calculated using the following equations Eq. (1), Eq. (2), Eq. (3).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

5. EXPERIMENTAL RESULTS

All original dataset are in dcm format, 280 sagittal photos, 100 original photographs, and 100 ground truth images were created using a python application that converted the original format into tiff files. The results are measured using the dice coefficient with four test trials. This study will see which results are the best from various tests. The first experiment uses a baseline, while the second experiment uses data augmentation, then the third experiment adds dropout and batch normalization, then the final experiment uses a larger filter size. The average F1Score can be seen in the Table 3

Table 3. Result for Precision, Recall, F1Score

Test	Precision	Recall	F1 Score	Test
1	93,63 %	90,74 %	92,16 %	1
2	88,94 %	89,91 %	89,42 %	2
3	88,83 %	91,38 %	90,08 %	3
4	93,65 %	95,16 %	94,4 %	4

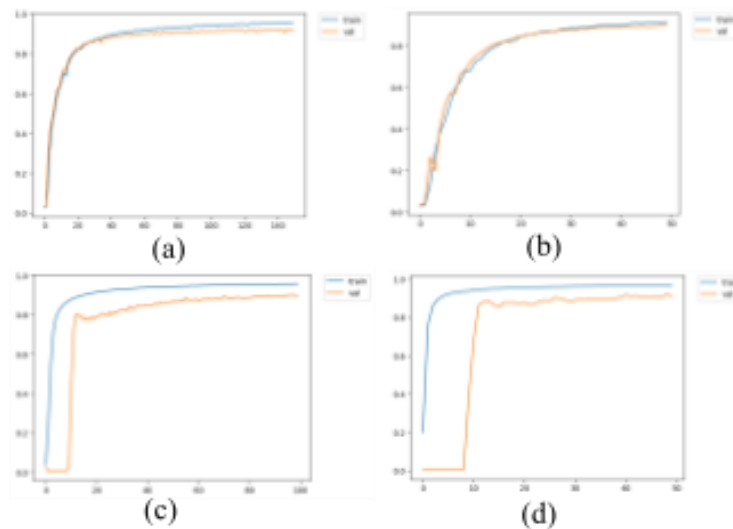


Figure. 7. Graph loss for each result with different set hyperparameter

Refers to Fig. 7, each graph the explanation is, first test (a) is getting a baseline nor are any additional data from the training set added. Upon setting the initial parameters, this study want to explore the influence of data augmentation, for this purpose, this study employ the identical setup as described in the first experiment, but with as decreased number of epochs and the introduction of data augmentation. The loss results for this specific trial are shown in the second test (b).

Despite this study efforts, this study did observe significant improvement compared to first test (a) it is worth nothing that this study only trained for 50 epochs due to substantial increase in the dataset size compared to first test - training for 150 epochs would be computationally expensive. Furthermore, the loss curve clearly indicates that this study achieve satisfactory convergence even before reaching 50 epochs. However, the introduction of augmentation resulted in an enhanced model, as demonstrated by the validation loss cover maintaining closer proximity to the training loss curve. Next, this study carried out a test by incorporating dropout and batch normalization, third test (c) illustrates the loss curve indicates that the overall validation loss does not decrease compared into previous test.

The proximity of the validation loss curve to the training curve, implies that the model does not exhibit improved performance on the validation set within the same epoch. It is possible that conducting more epoch could yield better outcomes. Fourth test (d), the last experiment aims to observe the model's behavior with increased capacity, meaning more parameters, this study begin with 64 filters of size 5x5 instead of 32. Similarly to the explanation in second test, the number of epochs is fifty in this experiment due to the increased computational expense of training a model with more parameters. The graphic illustrates the loss trend in this experiment. The experiment is evident that with greater capacity and model becomes slightly less stable compared to others, although this instability does not lead to a significant impact and not overfitting happen. The results of the four experiments show the best results in terms of accuracy, but the model looks unstable, this may be due to the small number of epochs. On the other hand augmentation plays an important role in making validation results better. The addition of dropout and batch normalization did not have a major impact on this study, the biggest impact when data augmentation was added, that is makes test results even better.

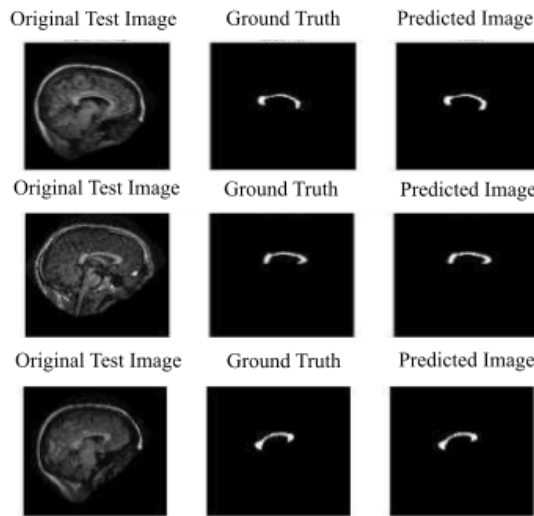


Figure. 8. Result segmentation for corpus callosum

As can be seen in Fig. 8, this method succeeded in answering the problem raised, namely segmenting the corpus callosum which is really part of it, the existing noise can be recognized with deep learning so that it can be classified as not part of the corpus callosum and not segmented. Apart from that the results are also smooth without there is a loss of structure that makes the form different from the ground truth. The success of this method is due to optimizing each hyperparameter and using data augmentation techniques to recognize noise better.

5.1 Visualization with Point Cloud

The 2D segmented image per slice is organized into a segmented data structure, which can be stacked into a 3D array and easily converted to a point cloud. Combining a pair of depth and color images of matching resolution creates a data structure that can be visualized using the matplotlib package to arrange point clouds as shown in Fig. 9 and Fig. 10. This method uses a stack array from 2D to 3D from the python package, the array will be combined into 3 dimensions in this study the initial array is 256x256 and combined with all the slices of each array it becomes 256x256xn slices [12].

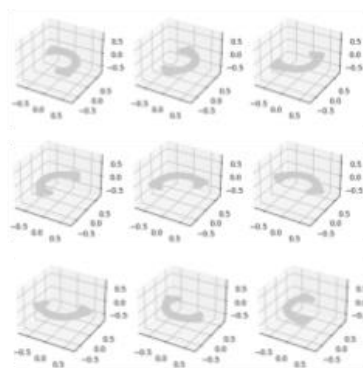


Figure. 9. Visualization for Point Cloud in matplotlib



Figure. 10. Point Cloud for Corpus Callosum

The results of the 3D numpy array with point cloud provide more realistic results to the human eye. The image can be rotated, enlarged, and reduced to see the shape of the corpus callosum segmentation results. This visualization is helpful to reconstruct the surface for more realistic results in the 3D plane.

6. CONCLUSION

This study developed succeeded in segmenting the corpus callosum well without noise, achieved an impressive overall accuracy core of 91.5% using just 280 annotated images in the dataset, This data can be trained well because augmentation was previously carried out for variations in the data, this study also shows that large epoch results without dropout and batch normalization produce a greater accuracy score, then with augmented data and fewer epochs the results decrease slightly, additional kernels size and batch size have an increasing effect on training time but results increase, this shows that training works better with these additions. This also shows that accuracy in hyperparameter declaration has a big influence on segmentation results.

Future work, there could be improvements made to achieve better results. It would be advantageous to compare with other deep learning method networks for evaluation, additionally, it would be valuable to assess how the system compares to traditional techniques. Moreover, exploring new data augmentation methods such as shear, zoom, and elastic deformation may contribute to the network's ability to handle unforeseen data with greater resilience. The lack of this study is that hyperparameter adjustments are manual and waste time.

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