# Corpus Callosum Segmentation from Brain MRI and its Possible Application in Detection of Diseases

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***Abstract*: The corpus callosum is a standout amongst utmost vital structures in the human brain. A large portion of neurological disorder consider explicitly or in a roundabout way to morphological highlights of the Corpus Callosum. The mid-sagittal cerebrum of the Magnetic Resonance Imaging completely portray the anatomical structure of the corpus callosum. Frequently thought to be testing errand for segmenting the Corpus Callosum from the Magnetic Resonance Imaging has demonstrated the significance of the Corpus Callosum segmentation. This paper proposed a deep learning approach for segmentation of the Corpus Callosum. Aftereffects of segmentation maybe utilized later on feature extraction and classification arrangement in the therapeuticanalysis.**

**Keywords --- Corpus callosum, Magnetic Resonance Imaging, Segmentation , deep learning, MidSaggital.**

## I.INTRODUCTION

It was just in the 1950's that the corpus callosum, in the spearheading work of Myers and Sperry, was attributed the capacity of transferal of data between the two sides of the hemisphere. This was trailed by the improvement, in themid 1960's, of a careful intercession went for lessening the interhemispherictransmissionofstrangeelectricalreleasesin epileptic patients. It is the biggest connective pathway, comprising of 200 milion nerve fibers. It interfaces the left and right half of the hemispheres.Its function is communication and transfers thefollowing:

- Motorinformation
- Sensoryinformation
- Cognitiveinformation

"All through left and right hemispheres"

The presentation of the Magnetic Resonance (MRI) imaging has allowed an assessment of the corpus callosum variations from the norms in vivo. Inherent inclusion, for example, corpus callosum dygenesis, agenesis, and the hypoplasia are the most successive callosal anomalies, and these abnormalities has been recorded broadly with utilization of the Magnetic Resonance imaging [2]. Different disorders, for example the schizophrenia, Dyslexia [1, 3], Alzheimer's disorder [4].NumerousSclerosisassertedthecorpuscallosumirregularity as an unfortunate casualty. The corpus callosum has been broke down in investigations of the sexual deformorphism, schizophrenia, chemical imbalance [5] and numerous others. Contrasts in size and region of the corpus callosum are assessed to identify with contrasts in bury hemispheric availability. On the off chance that the region of corpus callosum can be fragmented effectively, anatomical and auxiliary highlights, for example, the shape and size ,is to be utilized to decide the various ailment of the neurological infections[6].

The segmentation of corpus callosum out from the Magnetic Resonance Imaging is a testing assignment. A few investigations have demonstrated that the majority of the neurological disorder, for example, the Alzheimer's,Dyslexia, [7-8], the Multiple Sclerosis ponder exceedingly the anatomical structure of corpus callosum. As it is a casualty of numerous neurological disorders, any exact extraction of corpus callosum is very critical. The examination is to be done for segmentation of the corpus callosum from mid sagittal Magnetic Resonance imaging [1, 4] [6, 9-11]. The past experimental works have shown that the 2D and the 3D mechanized division of corpus callosum is conceivable [1]. Division strategy utilizing versatile mean move grouping and geometric dynamic form mode had been applied which give relatively 92% precision [6]. One of the work has suggested for a mechanized methodology for corpus callosum segmentation utilizing an anatomical map book VoxelBased Morphometric examination [9]. A calculation which utilizes the learning of intensities and the earlier data about the corpus callosum shape had been proposed, with very little client connection, the corpus callosum area was removed from the information MR images[10]. A semiautomatic method had been suggested to bifurcate (segment) the corpus callosum utilizing the snake formulation in two stage [11].The exploration has been done to look at typical furthermore, strange corpus callosum qualities for different disorders [2].

The main difference between the conventional machine learning and the deep learning algorithm is the part of FeatureEngineering. In conventional machine learning algorithm there we have to handcraft the feature. But in dissimilarity with a deep learning algorithm, feature engineering is done automatically by the algorithm.

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The Feature Engineering isvery tedious and time consuming, and it requires area aptitude. The deep learning is moreprecisealgorithms of machinelearningwhenit is comparedwith the machine learning that is traditional with almost no or very less feature engineering.

Because of the irregular pixel intensity dissemination in Magnetic Resonance images, the machine learning method fails to give excellence image .Therefore deep learning approach have been used for corpus callosum segmentation.The algorithm have promising accuracy which makes it popular for implementation of segmentation and classification problem.

## II.SEGMENTATION IN MEDICALIMAGING

### A. *Segmentation in Imageprocessing.*

The Image segmentation is a procedure of consequently or semi-naturally subdividing any relevant image into critical sections. Its point is to find the voxels which produces either the outskirts or the inside of the articles examined. A name is then doled out to all voxel which are normally alluded as the semantic segmentation and thus the outcome is a picture where the voxels with a similar mark sharing certain characteristics [16]. Hence picture division give a more significant portrayal of the information and it is a critical advance for completely understanding the substance of medicinal pictures and doing analysis. In restorative picture preparing ,this assignment by and large concentrates fundamental data for a quantitative examination of the clinical parameters[12]. The segmentation of the bones, body organs or any other substructure is in reality ofa basic advance for byfarmostof the PCsupportedrecognition(CAD)frameworks.

### B. *Deep Learning as being applied to MedicalImages*

In the previous two years, there have been an extraordinary expansion in the use of the deep learning algorithms for the Medical Images Analysis. Much papers is being published on this topic and many of them have reached human master level execution. The most investigated task until now is the image classification, the object detection, the segmentation and the registration. Still much more are tobeexamined.Contrastedtotheothercomputeralgorithms, the deep learning has the vital upper hand in finding the informative representations of theconcerned data by itself. In this manner the complex and tedious advance of the manual highlights designing can be kept awayfrom.

Convolutional neural network have drawn an immense interest on the topic of deep learning becauseofitselementarycapabilityofacceptingimagesas the input. It may perform a segmentation and classification task and have turn out to be the most accomplishing type of an Artificial Neural Network for the image analysisproblems[14].

### C. *Unet Architecture*

The important idea behind U-Net architecture is that it is made up of contracting path and expanding path. A contracting path follow normal architecture of a convolutional networkas shown in figure 1. It is made up of continuous function of the two 3x3 convolution,each of them is followed by a rectified linear unit and a max pooling operation with a stride of 2 for the downsampling operation.

We double the number of channel at each down sampling step. In each step of expansive path an upsampling operation of the feature map is performed which is being followed by a 2x2 convolution, also called upconvolution and thus the number feature channels is halves. A series of Convolution operations is performed and the final downsample layer has 1024 feature maps.The feature maps are then upsampled and

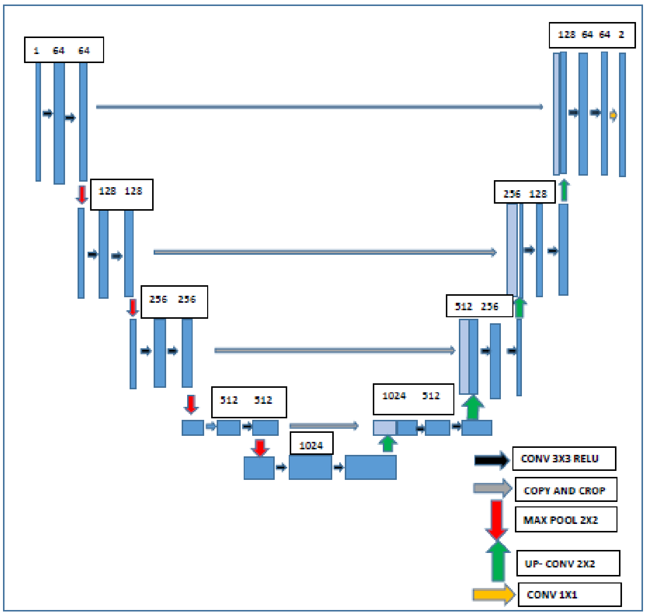


Fig.1 U-net architecture

concatenated with previous feature maps till we get the segmented image of the same dimension as the original image. The loss function being used for initial proof of concept was different from the one used in original paper. We used a dice coefficient plus binary cross entropy loss for the training purpose. Unet outputs high resolution segmentation map.

## III.METHODOLOGY

The data used for training the UNet Model for Corpus Callosum Segmentation is the open source data acquired by Austim Brain Imaging Data Exchange(ABIDE) initiative. The original data file contains brain MRI scans in .nii format. A python script was used to take the Sagittal view slice from the scans and these slices are converted to jpg format.
Flipping(Horizontal and Vertical) and the Rotation by (90, 180, 270 degrees) of the images was applied as Data Augmentation techniques which gave us a master dataset of 7700 Sagittal view images with their corresponding masks. Data Augmentation was necessary to make sure that the model is generalised and is able to work under varied circumstances. Out of 7700 datapoints; 6300 was used forthe training, 700 for the validation and 700 forthetesting.The original Unet model proposed by Philipp et. al. in the original paper was used to train the model. The loss function used was dice loss coefficient which makes use of the confusion matrix and hence, observed to give better results.TheUNet model was created to perform biological image segmentation when the amount of data available is relatively low, and thus suited for our task.

## IV.RESULT

Originalimage groundtruth predicted

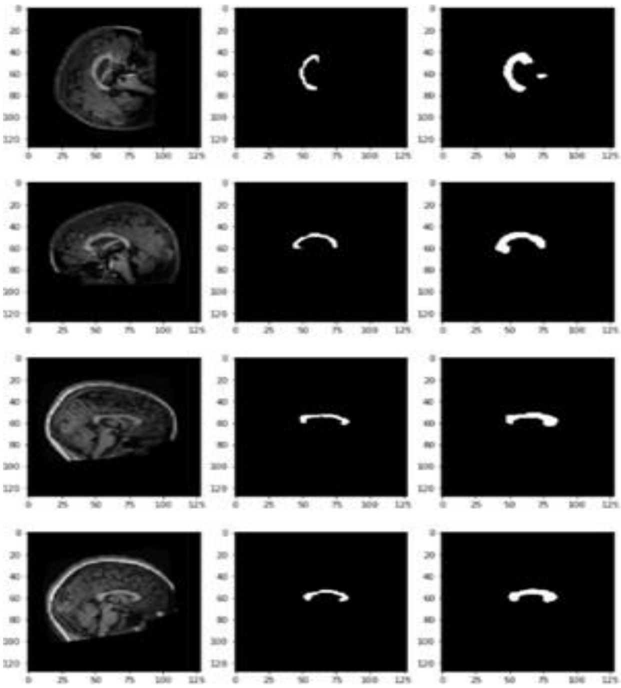

Fig.2 Final Result of test images 1

Originalimage groundtruth predicted

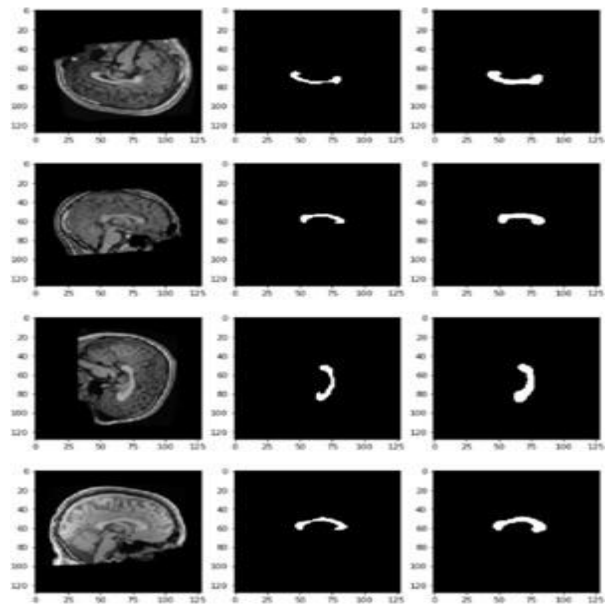

Fig .3 Final result of test images 2

The results obtained were as shown in the figure 2 and 3.The training was done only for 10 epochs and with limited number of augmentation. The training and validation loss values improved after every epoch. The images shows prediction on test data and randomly selected images from internet. Training was done on an Apple MacBook Air with 8GBRAMand1.8GHzdual-coreIntelCorei5processor(No GPU). The results are expected to improve with increase in number of epochs, varied augmentation and use of multiple loss functions.

## CONCLUSION

This paper marks the first attempt (to the best of our knowledge) for Corpus Callosum Segmentation using Deep Learning. The applications of Deep Learning in Biomedical imaging is immense and Corpus Callosum segmentation is one such important task.It has been planned to use different Augmentation techniques to increase our dataset size and use different available models as base structure to create our own model. The purpose is to create a generalizedreal-time system for corpus callosum segmentation which can be used reliably by medicalprofessionals.

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