CONVOLUTIONAL NEURAL NETWORK APPROACH FOR MR HUMAN BRAIN SEGMENTATION WITH U-NET ARCHITECTURE

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Abstract

Brain segmentation is a potential and essential task for early prediction of diseases. This will further help in treatment planning. The conventional hand segmented brain images are validated unsatisfactory and they are time consuming as well. A substitute methodology is convolutional neural network (CNN) approach with U-Net architecture. 38 volumes of MRI slices were used and validated the performance of this methodology with Dice, Precision, recall and F1-score. The results show that the model CNNbased U-Net has performed well to predict the data.

Keywords: MRI, Brain Segmentation, Conventional Neural Network, UNet.

I INTRODUCTION

Human brain segmentation assumes a key part in disease analysis, treatment arranging, and treatment assessment. In view of the fact that the expert's hand segmented process is difficult, the supervised and fully automatic approaches [1],[2] even for a fetus brain [3],[4], hippocampus [5],[6] then again makes a huge need by the specialists [7]. Ultrasound, Computed tomography (CT) and Magentic Resonance Imaging (MRI) conventions are benchmarkimaging methodologies that are utilized for various medical diagnoses. Numerous past investigations have exposed that the various MRI conventions can be utilized to detect and segment human brain portion to medically treat the patient. The various MRI conventions incorporate T2- T1-weighted (T1-w), T2-weighted (T2-w), T2-weighted fluid attenuated inversion recovery (FLAIR) etc.Automatic segmentation approaches has been effectively implemented to extract human brain region from MRI.On the other hand, semi-automatic strategies request a couple of training information and its mark to prepare a classifier that would subsequentlycapable in segmenting original information by not including training the model.

Recently, a great deal of scientists have utilized the convolution neural networks (CNNs) to characterize images which provides image features which helps to conceivable for preparing deep neural networks from initialising weight values randomly. The deep neural network approaches are developed by joining numerous convolutional layers,which convolve a picture with kernal for feature extraction that are more powerful and versatile for differential trained models. Deep Neural Network have shown huge accomplishment in the recent years [8,9,10] in different fields especially in neuroimaging.Phellanet al. [11] investigated a generally superficial neural net in MRI. While showing potential outcomes, shallow net prompted restricted performance. Here, U-Net is the most encouraging deep learning systems in the case of segmentation[12]. It is a particular convolutional neural net (CNN), similar to auto encoder approach, incorporating downsampling(encoding) and upsampling(decoding) paths.This approach was intended for bio medical image segmentations. Table 1 exemplifies the summary of literature review on U-Net based approaches.

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Table 1 Summary of Literature review on U-Net architecture

References	Database	Methodology	Explanation	Evaluation Metric	Performance
Rehman et al.[13]	BraTS Data sets (2017,2018)	Bu-Net	U-Net modified with residual extended skip (RES) and wide context (WC).	Dice	Dice similarity obtained are 0.901, 0.837, 0.788 for whole, core and enhancing brain tumor.
Ibtehaz et al.[14]	Five different data sets including Fluorescence microscopy,Electronmicroscopy,Dermoscopy,Endoscopy and MRI	MultiResUNet	MultiRes blocks by introducing residual connections to the convetional layers	5-fold cross-validation	10.15%, 5.07%, 2.63%, 1.41%, and 0.62% for five different data sets used.
Livne et al.[15]	66 Data sets from Charité Universitätsmedizin Berlin	U-Net Deep Learning	energy function is calculated by pixelwisesigmoid over the final feature channel.	Dice , 95% Hausdorff distance (95HD), average Hausdorff distance (AVD)	0.88, 47 voxels, 0.4 voxels, for dice,95HD and AVD respectively
Le at al.[16]	BraTS (2013)	U-Net based fully CNN and extremely randomized trees	Brain image features are extracted from multimodal MRI training dataset and applied to Extremely randomized trees classifier , in order to segmenttumor	Dice	0.85, 0.81 and 0.72 for whole, core, and enhancing brain tumor
Li et al.[17]	30 data sets collected from University Medical Center Utrecht (Netherlands)	Deep residual dilated u-net	Segmentation was done by averaged probability maps with the ensemble model.	Dice ,95% Hausdorff distance (95HD HD, Volumetic Similarity(VS)	80.9% averaged Dice score, 4.35mm averaged Hausdorff distance

II DATA SETS

Internet Brain Segmentation Repository (IBSR) [18] is a publically available data source where two T1-W MRI data sets were collected and used to train and test this methodology. Data set 1 contains 20 volumes of MRI and each volume contains approximately 50 to 60 slices. Similiarly, Data set 2 contains 18 volumes and each volume hold approximately 120 to 128 slices. These coronal oriented slices are of size 256 x 256. All MRI volumes come with ground truth images. Table 2 and Table 3 provides the details of two data sets.

Table 2 Data set 1

Volume Index	Volume Label	Gender	Patient's Age
1	1_24	F	35
2	2_4	F	34
3	4_8	F	29
4	5_8	F	20
5	6_10	M	22
6	7_8	M	29
7	8_4	M	27
8	11_3	M	28
9	12_3	M	38
10	13_3	M	32
11	15_3	M	31
12	16_3	F	36
13	17_3	F	29
14	100_23	M	23
15	110_3	M	25
16	111_2	M	27
17	112_2	M	32
18	191_3	M	32
19	202_3	F	28
20	205_3	F	24

Table 3 Data set 2

Volume Index	Gender	Patient's Age
1	M	37
2	M	41
3	F	Adolescent
4	M	Adolescent
5	M	41
6	M	46
7	F	70
8	M	60
9	M	41
10	F	35
11	F	59
12	M	71
13	M	Adolescent
14	M	Adolescent
15	M	8
16	M	7
17	M	8
18	M	13

III METHODOLOGY

Segmentation procedure generates decision function (DF) to facilitate the information vectors and allocates every vector to a class. DF intends to construct the required instructive connection dependent on the training samples. Also, the quality of the image segmentation process relies upon the nature of the given data and the quality of segmented features. Automatic segmentation procedures make such relational points dependent on the input image intensity to manual segmented image.

Basic ideologies used in this brain image segmentation

This section will explain the basic ideologies incorporated in segmenting the brain mask from the input image.

Pre-processing by Image Enhancement

Image enhancement is the essential pre-processing step to discriminate the brain region from the surrounding non brain regions. For that, Median based Bi-Histogram equalization technique [19] was utilized to deal with intensity heterogeneity in the input image which brought about MRI scanner during image acquisition. The MBHE first and foremost disintegrates the input image into two subimages based on the median. One of the subimages is the arrangement of tests not exactly or equivalent to the median though the other one is the arrangement of tests more noteworthy than the median. Finally, the sub images are equalized separately.

IV CONVOLUTIONAL NEURAL NETWORK

Convolutional Neural Network (CNN) is an emerging technology and the essential idea of CNN[20],[21] is to include convolutional and pooling layers (Fig.1) prior to connect into successive completely connected network.The process of convolutional layerdepends onevery neuron whichinterfaces with parts of neurons in the previous neighbouring layer. Such neurons that are coordinated in a network structure involve a few feature maps, and the neurons distribute similar weight value in each map. Subsequently, the pooling layer groups theneurons from the feature maps to get meanor maximum value. In this manner, the boundaries are considerably diminished prior to utilizing the completely connected network.

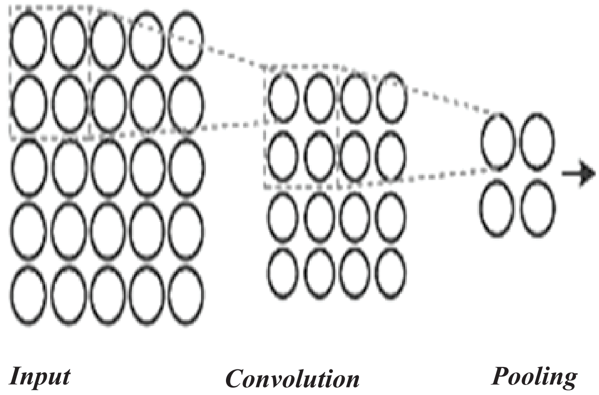

Fig.1 Convolution layer and Pooling layer [22]

V U-NET ARCHITECTURE

The U-net architecture (Fig.2) espoused from the model proposed in [22]. This model depends on a convolutional neural network (CNN) and comprises of downsampling (encoding) andupsampling (decoding) element. The left side of this network is referred as the contracting path(encoding part), the right side is known as expansive path (decoding part) and both are connected from side to sidewith skip connections. All padded 3 × 3 convolutional layers are followed by a rectified linear activation unit (ReLU). In encoding and decoding part, each includes with 3 convolutional blocks.A block in the encoding part comprises of two convolutional layers abide by a 2 x 2 maxpool layer. On the other side, in decoding part , a block comprises of a 2x2 decoding part, connecting the parallel block from the peer layer of encoding part, a dropout layer [23] and 2 convolutional layers. Ultimately, the last layer is a 1 × 1 convolution layer with sigmoid activation function for comparing feature vector to the predict binary value such as brain or non brain. The enhanced image of size 256 x 256, is passed through this architecture. For every predicted output, a binary value is applied bycomparing each pixel intensity, whether they are above the threshold (1) or below the threshold (0). Hence, a 256 x 256 segmented mask is obtained.

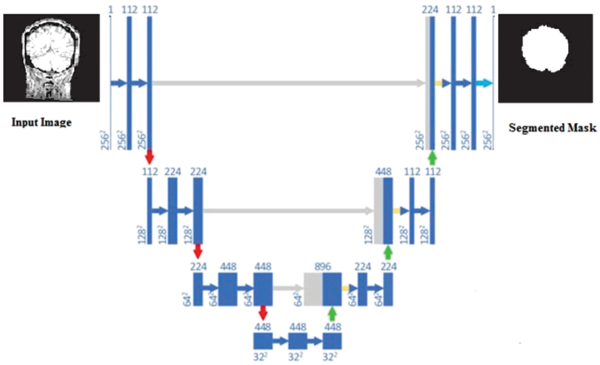

Fig. 2 U-Net approach for segmenting brain image from MRI

VI Training

The purpose of semantic segmentation [24]isto anticipate the individual pixels whether they address with a corresponding class or not.Then, this issue leads to binary classification approach to decrease classification process. Therefore, in this work, a binary cross entropy is applied and mimimized the loss function (L). Let, G be the gold standard image for the input image I and the predicted segmentation mask be P then the binary cross entropy is computed as

$$Bin\_Cross\_Entropy(I,G,P) = \sum -(Glog(P) + (1-G)log(1-P)) \quad (1)$$

and

$$Loss\_Function\ L\ = {}^{1}/_{N} \sum_{i=1}^{N} Bin\_Cross\_Entropy(I,G,P) \quad (2)$$

where N = number of images in the group, thus minimized the L value.

Subsequently, Adam optimizer is used to train the model, since it manages the deterioration of first and second moments of the gradients. In this work, the optimal epochs used by Adam optimizer was 150 (Table 4), for the reason that there were no chances in the added epochs and the learning rate was 0.001 were achieved. In this work, 80% of data set (both 1&2) was used for training the model and 20% was used for testing the model.

VII PERFORMANCE ANALYSIS

The performance of the methodology is evaluated by dice similarity [25] between predicted mask (PM) and ground truth mask (GM) as

$$Dice\ (D) = \frac{2x|PM \cap GM|}{|PM|+|GM|} \quad (3)$$

To show the performance of CNN based U-Net model, the dice value produced by popular BSE and BET methods are compared in figure 3.

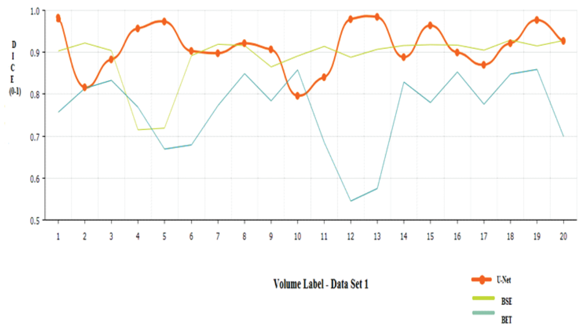

Fig.3 Performance analysis using Dice of U-Net, BSE and BET for Data Set1

From the figure 3, dice score shows that U-Net methodology performed well than other two methods. Visual comparison and validation has given in figure 4. It can be observed that the performance of U-Net methodology has outperformed and it is much similar to the ground truth mask as well.

(a) (b) (c)

Fig.4 Comparison of segmented mask of ground truth (a), CNN based U-Net (b) and segmented brain region (c)

Data Set	Epochs	Learning Rate
1	150	0.001
2	150	0.001

Table 4 Performance Validation Parameters

Minimum training loss, Minimum validation loss and maximum validation accuracy were recorded in Table 5. The values indicates that the model accurately predict the data as the ground truth.

Data Set	Minimum Training Loss	Minimum Validation Loss	Maximum Validation Accuracy
1	0.074523	0.143726	94.12%
2	0.073154	0.148125	94.25%

Table 5 Parameters for validating the model

To measure the accuracy, precision and recall were calculated for the data sets. The highest precision (92.62) and the highest recall (93.24) are shown in Table 6. The F1 score denotes the accuracy of the results predicted by the model, using precision and recall. The highest F1-score (91.85) indicates the performance over the ground truth and signifies the model's better performance.

Data Set	Precision	Recall	F1 - Score
1	92.62	80.11	85.91
2	90.52	93.24	91.85

Table 6 Accuracy metrics obtained for the data sets

VIII CONCLUSION

A CNN based U-Net model has applied on IBSR data sets to segment the brain data. The segmented results are further trained and tested by the model. The segmented masks are compared with ground truth images for visual validation and for quantitative validation as well. All the recorded results are shown that CNN based U-Net model outperforms for the data sets.

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