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A Civilized Method to Fetal Brain Segmentation with U-Net Architecture using Optimal Semantic Blend Algorithm

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ABSTRACT: The Fetal Brain is one of the significant organs that need to be focused precisely and periodically by anobstetrician to observe the growth of the child. There are more than 76 abnormalities can be identified in the first tri-semester during the pregnancy. The main objective is to locate and segment the fetal brain and identify the abnormalities earlier to diagnose it. Early prediction is the ultimate challenge to save a life. The Magnetic Resonance Imaging (MRI) technique was adopted to obtain the fetal images and analyze the image for any abnormalities manually which consumes more time. The automatic semantic segmentation is performed using U-Net architecture with deep learning techniquewill epitomize solution to address this issue. The model is trained with 47 sets of MRI images with various abnormalities. The input image of T2-MRI images isfeed to the model as input. The physician will be provided with assisting enhanced segmented fetal brain image with mask, structure and different enhanced imagesas an output out of the model. The interpretation can be made handy for the physician to diagnose fetal abnormalities in the early stage.

Keywords: Precise Slice Enhancement Algorithm, Optimal Semantic Blend Algorithm, Fetal Brain Segmentation, Fetal Brain Semantic Segmentation, U-Net Architecture, OSB Algorithm, PSE Algorithm.

Abbreviations: PSE, Precise Slice Enhancement;OSB, Optimal Semantic Blend; ROI, Region of Interest; MRI, Magnetic Resonance Imaging; CSF, Cerebro Spinal Fluid; COG, center of gravity; CNN, Convolutional Neural Networks; ReLU, Rectified Linear Unit; EI, Enhanced Image; SI, Segmented Image; TPF, True Positive Fraction; TNF, True Negative Fraction; OH, OneHot; WM, Weight Map; GPU, Graphic Processing Unit; CPU, Central Processing Unit.

I. INTRODUCTION

The human fetus growth will be varying in every week and it is closely monitored periodically. A Perception decides all the decisions. A subject with abnormalities is unknown from one slice and vice versa from another slice. It varies from human and machine learning algorithms. The decisive goal is to handle the fetal brain and segment in such a way to aid the physician to analyze the fetus's growth, to diagnose the abnormality if any. Around 7.9 million infants (6% of worldwide births) are born with severe birth defects [8, 15] and a further 3.2 million birth leads to dead pregnancy each year [16]. However, in approximately half of all birth defect cases, the causes are unknown, 70% of birth defects [1] can be prevented from the early analysis [16]. The health care [11] industry after adopting the machine learning into the picture, will result in a great step towards predicting the disease before the occurrence and taking necessary and preventive steps accordingly to reduce the impact.

An Image experiences different phases of the examination. At first, it is begun with an order, which predicts whether the Region of Interest (ROI) is accessible in the picture will be recognized. Further, the work is stretched out to identify [12] all the different items i.e., multiple or more locale of intrigue is recognized utilizing the characterization model [18]. The following dimension is Object identification, which can find the article with a dissimilar color embossment, frequently noted with a rectangular box. The ultimate process is to exactly segment the Region of Interest from an image [21] and extract various features in detail for further analysis and guide the physician with cutting edge deep learning model.

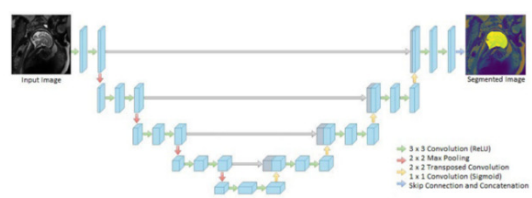

Fig. 1. Fetal Brain Segmentation using U-Net Architecture.

Fetal brain Magnetic Imagining Resonance (MRI) is taken as the Region of Interest (ROI). The Dataset of 47 subject/volumes difference dicom images were used. All the objects will have unique features and parameters. The fetal brain MRI [10] has very different and unique features. The image is very small in size which is the most crucial and hard way to segment the image [22]. The fetal brain images are subject to continuous movements due to which the image quality will be affected. The challenges are identified in the aspect and exact features of the fetal brain have to be segmented using the novel algorithm.

The proposed model will be a creamy method to localize and perform automatic segmentation of the fetal brain [4] [17] comparatively to the existing techniques. The results obtained through this algorithm was better

II. RELATED WORK

Michael Ebner *et.al.* [2] used the bottom up strategy for localization of the fetal brain using a coarse segmentation method [13] with pixel-level prediction. The P-Net model is used to perform the automatic segmentation [7] [9] from the localized region and finally build the super-resolution reconstructed fetal brain. A Bayesian network model [4] composed of a mathematical ground method, which is computationally expensive. A come in handy multiple models for uncertainty estimation method.

The template to slice block matching [20] is adopted on fetal brain segmentation to obtained better results. But it was computational time expensive and will not fit all the orientation of the input image. Distributed weak supervision Fully CNN technique [5] was adopted by on the fetal brain. However, all the above methods failed in the challenging cases of an input image.

Table 1: Comparative study between various techniques and its limitations.

S.No.	Authors	Proposed Techniques	Limitation
1.	Taimouri *et al.*, [20]	Block Matching Approach	Success rate of 73%
2.	Khalili *et al.*, [1]	Separate network branches and combined in the last layer and applied CNN	Respect to Image Orientation
3.	Salehi *et al.,* [17]	2D U-net and a voxelwise fully convolutional network	Motion Detection
4.	Somasundaram *et al.*, [7,10]	2D MRI slices using center of gravity (COG)	Time Consuming
5.	Caldairou *et al.*, [19]	Intensity-based features for the application Cerebro Spinal Fluid (CSF)	Manual anatomical knowledge Assistance
6.	Gayathri *et al.*, [4]	Computes the Area and Volume of the Fetal Brain.	Manual Segmentation
7.	Ebner *et al.*, [2]	Bottom up Strategy for Localization and CNN with Pixel Level Prediction	Template Space Alignment, Heavy Motion
8.	Ye *et al.*, [14]	Dilated convolution segmentation model	Elliptical shape segmentation of ROI

III. METHODS

Network Architecture. The U-Net architecture is a benchmark in the medical image segmentation [19]. The dataset contains 47 subject of MRI images with 884 features are used. An input of 227 × 227 images entered in the U-Net architecture [5] and resulted in the segmented mask of size, 227 × 227 sources [3].

In the following Eqn. [1]. Let K_i be the output of the K^{th} layer. In U-Net design, this vector is regularly acquired from the yield of the past layer K_{i-1} by a mapping A_i made out of a convolution pursued by a non-linear activation function:

$$K_i = A_i\ (K_i\text{-}1) \qquad (1)$$

In U-net Architecture, connectivity pursues an example that iteratively links all element yields in a feed-forward way. U-Net architecture is specially built for biomedical image segmentation [14]. U-Net is composed of convolutional [6], no recurrent or dense layer is added in the architecture, so it is called a fully convolutional network. The shape of the architecture is appeared to be 'U' in structure so it is termed as U-Net architecture. The architecture is build based on the concept of encoder and decoder approach which contains 3 parts, first a contracting/down sampling path, second a bottle necklace layer, third expanding/up sampling path. The down sampling path contains two 3 × 3 unpadded convolutions and each followed by Rectified Linear Unit (ReLU) and 2 × 2 max pooling operation with the stride of 2. At every step in the down sampling we square the number of the feature channels. All the way in the up sampling path consist of 2 × 2 convolution, and it is concatenated by the feature map. Finally it is ended up with two 3 × 3 convolutions and each layer is followed by a ReLU. The significant part of the U-Net architecture is the Skip connection, which acts as a bridge in between the down sampling and up sampling path. The feature map from the down sampling path is performed to acquire the local information. In the up sampling path, it draws the big picture with the help of the local information to global information.

In the final layer of the architecture, a 1 × 1 convolution matches the feature vector to the desired classes. The merit of using the U-net architecture is to obtain the localizationinformation in the down sampling path. The localization and context are used to predict the feasible segmentation of the fetal brain MRI.

Proposed Method. The raw data of MRI images are collected in the .nii format. Dicom volume (.nii images) are loaded by the itkpython package from the file path using itk reader,it is stored in an array. Each slice in the NIfTI-1 Data Format is converted into hdf5 file format using nibabel library. The dataset is imported from the folders and defines the path for hdf5 file.

The Precise Slice Enhancement (PSE) algorithm consist of 3 sections as follows:

(a) **Input Section:** The dataset is feed into the algorithm as an input, it labels all the input images from the dataset by reading sequentially from the specified path and constituted in an array.

(b) **Processing Section:** Initially, Normalization (x) which will define the minimum (min_val) and maximum value (max_val) to obtain cumulative value (C) in the Eqn. [2].

$$\text{Cumulative Value } C = \frac{(x - min\_val)}{(x - max\_val)} \quad (2)$$

Using the obtained Cumulative values, the Histogram Equalization tread is adopted to flatten the input image. The Z_Min and Z_Max values are identified from the min_val and Max_val to obtain the appropriate slice for the interpretation. The OneHot (OH) function will expand the dimension to localize the fetal brain, the expansion will be performed all the 3 axes. The Weight Map (WM) function is used to map the ROI in the given input image.

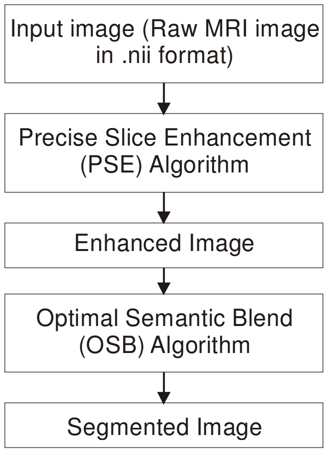

Fig. 2. Fetal Brain Segmentation using U-Net Architecture.

 # Pseudocode: Precise Slice Enhancement (PSE) Algorithm.
Start
Input Section
Volume V = "/Dataset/Test_Images/"
Read Image (I) and Mask (M) in an Array
I = down_sample (I)
Read Features from Image Array
Processing Section - Precise Slice Enhancement Algorithm (Step 1)
Normalize (N) the Image and obtain Cumulative Image
Find Z_Min and Z_Max
One Hot and WM function is applied to localize the fetal brain
Apply Machine Learning Model to enhance the localized fetal Brain
Post Processing Section - Precise Slice Enhancement Algorithm (Step 2)
Enhanced Image EI = Histogram(Image)
Display Output Section
Display Enhanced Output Image
End

Initially, the weight map is evaluated and collected 3 different variables. (a) The argmax function is used on the axis=3 which composes the label of the image. (b) The canny edge detection algorithm is deployed on the given image to morph the segment of the image using binary dilation method. (c) Weight map is calculated for the shape of the given image. Finally, perform the down sampling of the image with softmax function.

The softmax is given by,

$$p_c(x) = \exp \frac{(a_c(x))}{\sum_{c'=1}^{K} (a_{c'}(x))}$$

where, ac(x) denotes the activation in feature channel c, at the pixel position x. K is the number of classes and pc(x) is the approximated maximum-function. i.e., pc(x) ≈ 1 for the c that has the maximum activation ac(x) and pc(x)) ≈ 0 for all other k.

(c) **Display Output:** Weight Map will apply the label and perform semantic segmentation on the given input image by demonstrating in a different color. The Enhanced Image (EI) is obtained as the output of the PSE Algorithm.

The Optimal Semantic Blend (OSB) Algorithm, which finally applied to the enhanced image (EI) obtained from the PSE algorithm. The enhanced fetal brain image is feed in as input to the OSB algorithm, which will segment the region of the fetal brain with dissimilar color.

 # Pseudocode: Optimal Semantic Blend (OSB) Algorithm
Start
Input Section
Read Enhanced Image (EI) and Image Mask (IM)
Processing Section
Verify the dimension of EI and IM
SI = Blend EI and IM
# Display Output Section
Display Segmented Image (SI)
End

IV. RESULTS AND INTERPRETATION

Initially, the location of the fetal brain is identified by using the PSE algorithm and the mask is obtained from the given test image, Fig. 3 Segmented Results from the raw input file (.nii format) which interprets the shape and structure of the given fetal brain MRI. The image is enhanced with histogram function which will spotlight the intense tissues in the ROI. OneHot (OH) function and Weight Map (WM) applied to enhance and highlight the abnormalities if any on the test sample. The shape and size of the ROI are measured which assist the physician for better diagnosis. The OSB algorithm will produce the fetal brain image with dissimilar (yellow) color, which helps to interpret and expose the fetal brain abnormalities in detail, by ignoring the rest of the ROI image space. The collection of 17 test images in .nii format can be automatically segmented within 19.23 seconds.

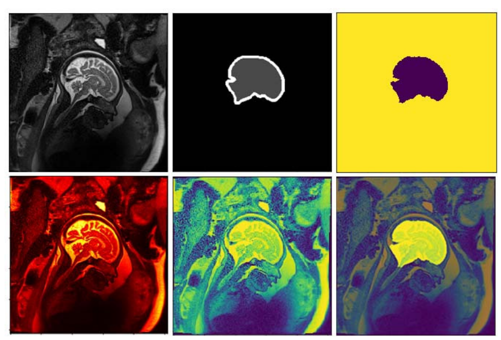

Fig. 3. Fetal (a) Raw Input (b) Boundary of the Fetal Brain (c) Shape of the brain (d) Enhanced Image (e) Enhanced Image with Histogram (f) Segmented Results.

In Fig. 3 (a) The Raw Input (.nii) format was sliced with appropriate axis which helps to interpret the abnormalities was feed into the model. (b) The Shape of the fetal brain was segmented using edge detection algorithm. (c) Dissimilar color of the fetal brain helps the structure and size of the ROI. The following two images incorporated the OneHot encoding (d) technique and WM Map (e) technique to enhance the result. The next enhanced and segmented results (f) helps to physician to detect and diagnose the abnormalities in the ROI.
The appropriate ROI mask computed by True Positive Fraction (TPF) as sensitivity using Eqn. (3) and theremaining area apart from ROI in the input image was calculated as specificity True Negative Fraction (TNF) using Eqn. (4). The Dice (D) and Jaccard (J) Coefficient was computed using the Eqns. (5) and (6) respectively. Using the equations the segmentation accuracy is computed in the following Table 2.
Eqn. (3) True Positive Fraction TPF is given by,

$$\frac{\text{True Positive}}{\text{True Positive+False Negative}} \tag{3}$$

Eqn. (4) True Negative Fraction TNF is given by,

$$\frac{\text{True Negative}}{\text{True Negative+False Positive}} \tag{4}$$

Eqn. (5) Dice Coefficient D is given by,

$$\frac{2\,|\text{True Positive}|}{2|\text{True Positive}|+2|\text{False Negative}|+2|\text{True Negative}|} \tag{5}$$

Eqn. 6 Jaccard J is given by,

$$\frac{2\,|\text{True Positive}|}{2\,|\text{True Positive}|+2|\text{False Positive}|+2\,|\text{False Negative}|} \tag{6}$$

Table 2: Consolidated report after segmentation.

Computational Paradigm	Achieved Results
Architecture	U-Net
Dice	98.58 %
Jaccard Index	96.42 %
Sensitivity	98.63 %
Specificity	99.40 %
Time	4.45 seconds / Iteration

The Dice score increased by more than 7% compared with other architectures. The computational performance of accuracy and mean squared error during the Training was measured and listed below in Table 3. To increase the efficiency and to reduce the training time the model is trained using Graphic Processing Unit (GPU) NVIDIA 1050 was employed in this process which saves approximately 3 hours comparatively with CPU.

Table 3: Accuracy and Mean Squared Error.

Computational Results during Training			
Computational Paradigm	**Min**	**Max**	**Cur**
Accuracy for Training	0.882	0.929	0.929
Accuracy for Validation	0.918	0.925	0.928
Mean Squared Error for Training	0.011	0.019	0.011
Mean Squared Error for Validation	0.011	0.013	0.011

Dataset. First Tri-semester MRI images of Volume of 47 fetal brains with 52 slices each is used as atraining set and 15 volume is used as a test set. The model is trained with 823 features and able to segment the various challenging fetal brain structure with all 3 axes.

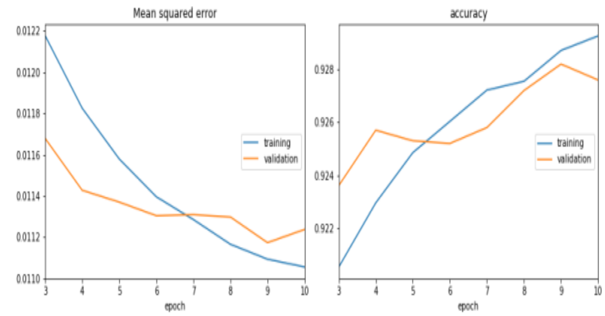

Fig. 4. Mean Squared Error b) Accuracy.

V. CONCLUSION

The fetal brain segmentation is performed and achieved the expected results with the dice coefficient of 98.58% and the Jaccard index as 96.42%. The accuracy is comparatively higher than the existing techniques. The physician needs to provide the scanned MRI images as the input to the algorithm and the model will perform the automatic segmentation and assist them with handy interpretation results. The test image of 3.2% get failed in some challenging cases (includes motion) with our algorithm.

VI. FUTURE SCOPE

In the future, segmentation is performed with various tissues in the fetal MRI images and CT imageswhich helps to diagnose any abnormalities in detail and interpreted easily using deep learning techniques. The Challenging cases with motion affected MRI images have to be addressed in the preprocessing to increase the efficiency of the model accuracy.

Conflict of Interest. The Author(s) declare that there is no conflict of interest

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