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Fetal ultrasound image segmentation using dilated multi-scale-LinkNet

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***Abstract*---**Ultrasound imaging is routinely conducted for prenatal care in many countries to determine the health of the fetus, the pregnancy's progress, as well as the baby's due date. The intrinsic property of fetal images during different stages of pregnancy creates difficulty in automatic extraction of fetal head from ultrasound image data. The proposed work develops a deep learning model called Dilated Multi-scale-LinkNet for segmenting fetal skulls automatically from two dimensional ultrasound image data. The network is modeled to work with Link-Net since it offers better interpretation in biomedicine applications. Convolutional layers with dilations are added following the encoders. The Dilated convolution is used to expand the size of an image to prevent data loss. Training and evaluating the model is done using the HC18 grand challenge dataset. It contains 2D ultrasound images at different pregnancy stages. The results of experiments performed on an ultrasound images of women in different pregnancy stages. It reveals that we achieved 94.82% Dice score, 1.9 mm ADF, 0.72 DF and 2.02 HD when segmenting the fetal skull. Employing Dilated Multi-Scale-LinkNet improves the accuracy as well as all the evaluation parameters of the segmentation compared with the existing methods.

***Keywords*---**Fetal ultrasound image segmentation, Deep learning, Dilated convolution, Encoder-decoder, Link-Net.

Introduction

Ultrasound is a useful tool to monitor fetus and mother during pregnancy due to its non-invasiveness and less expenses for imaging while

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comparing with modalities like CT or MRI. Ultrasound-based fetal diagnosis can also be used for a variety of clinical applications [1]. During pregnancy, it is a widely used method to assess the fetal development and also to calculate fetal biometric measurements such as biparietal diameter (BPD), head circumference (HC), and abdominal circumference (AC). An accurate measurement of the fetal head can be used to calculate gestational age and to examine fetal development [2]. The ultrasound captured data are examined by experts for calculating the dimensions of fetal head, fetal body and fetal moves, which allows them to accurately determine abnormalities in fetal growth [3]. In many clinical ultrasound diagnoses, it is crucial to precisely quantify anatomical structure to improve efficiency and avoid data heterogeneity during data capturing. Calculating the head circumference (HC), biparietal diameter, abdominal circumference, femur length, and humerus length are crucial in evaluating fetal development [4]. Ultrasound fetal biometric measurements are generally done manually, and the accuracy of the measurement depends on two factors: (1) The image should be obtained at proper angle by radiologist, and (2) Positioning the caliper properly. A specialist can calculate the period of gestation and fetal weight using special mathematical functions [5]. All of these factors require a lot of time and are operator-dependent. Therefore, automated image segmentation and measurement techniques are necessary to facilitate such a process and aid in its result analysis [6]. The reduced transmission capacity of ultrasound may present varying intensities. In addition, it typically comprises speckle noise, acoustic shadows, discontinuous anatomical boundaries, and low contrast, can complicate the process of border recognition [7].

The HC is assessed in the standard plane, which can be specified as perimeter of the fetal skull boundary, and calculated in cross sectional view of fetal head as shown in Fig.1. Using ultrasound equipment, physicians segment fetal HC manually. The segmented HC is fitted with ellipse, which calculates the longitudinal measurement of the HC in an automated manner. However, the scarcity in experienced sonographers for using with low resource settings is a major issue.

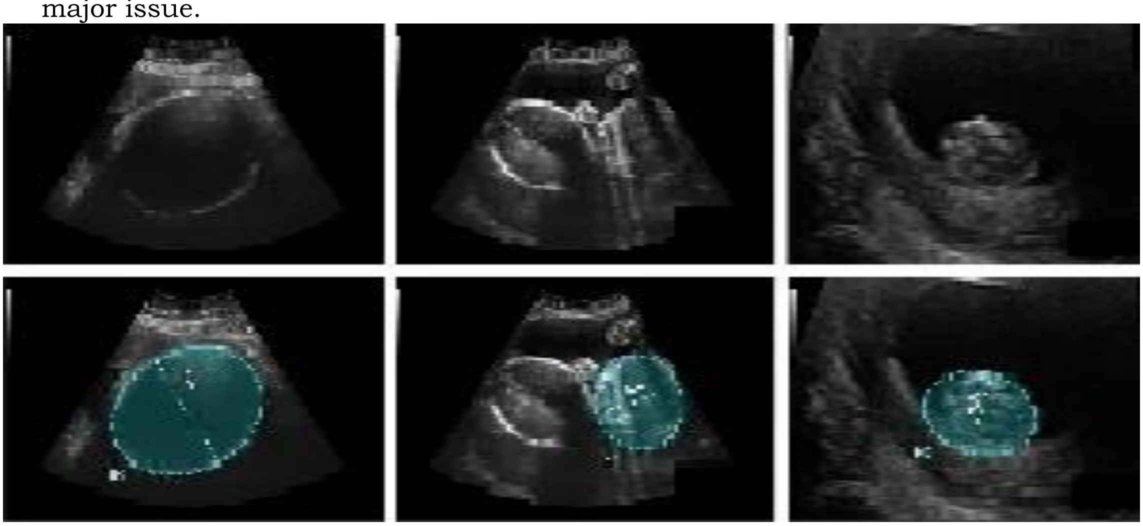


Fig.1. Sample images of 2D ultrasound fetal head area

An automatic model could help untrained manual experts to acquire accurate measures. Recent research in the estimation of fetal biometric characteristics has focused on deep learning algorithms as it utilizes high performance of convolutional neural networks (CNN) on numerous image interpretation problems. This increase the requirement of computerized determination of fetal biometric attributes in order to enhance working procedures without considering the effect of data variance in acquisition process.

Development of advanced algorithms focuses on reducing the diagnostic steps and time while improving the performance accuracy [8]. This proposed work introduces an automated fetus skull segmentation using 2D ultrasound imaging technique. A Dilated Multi-Scale LinkNet is developed to recognize the fetal skull. An analytical study with related work demonstrates that the proposed model yields better results than competing strategies.

Related works

Many recent studies have focused on improving the fetal organ extraction from2D ultrasound image data due to the importance of the measurements in evaluating fetal development difficulties. In this paper [9] they use a Fully Convolutional Neural Network (FCN) with an Encoder-Decoder structure for automatic segmentation of 2Dultrasound images with various perceptive angles and random locations. In this paper [10] they use shape based thresholds for initial segmentation. Locating fetal head from this preliminary segmented output is done using two methods, 1. Chamfer Matching based ellipse detection and 2. Hough Transform for Ellipse detection. In [11], it is observed that HC can be calculated using OSP. A deep learning network was used to detect the frames in the obstetric sweep protocol (OSP). Using simple network architecture, it achieves frame-based accuracy of 0.97 in an independent test datasets. It measures HC values by using the frames to identify the fetal head circumference automatically. In [12, 30] a V-net architecture named Fully Convolutional Neural Network-Combination (VNet-c) is proposed for extraction of fetal skulls in 2D ultrasound images. It adopts 3D V-Net for preprocessing. It is identified that the fetal skull extraction and HC values touches 97.91% correct and outperform the conventional methods. In this study [13] they suggested a deep-learning-based segmentation strategy for automatic fetal head biometry assessment from 2D ultrasound fetal images. They highlight the variations of boundary pixels around head from others based on transformation operations. It concludes that the proposed model works efficiently for segmentation using U-Net. In this paper [14,29], A network named MFP-Unet is jointly adopting U-Net and Feature Pyramid Network (FPN) is used .To segment the femur, MFP-U-net learns features from pre-processed images. In this work [15], the deep learning model employs feature pyramids and attention modules. It is named SAPNet in which the features of fetal head are segmented and BPD, OFD values are measured. Using these values, circumference of fetal head is obtained by performing Ellipse fitting in the least square method. In this paper [16] they developed a method called Multi-Task deep network model adapting Link-Net architecture. The inputs with multiple scales are given to the network for segmenting and estimating fetal head circumference in 2D ultrasound images. It results a smooth segmented output in elliptical shape and it offers efficient results without implementing Ellipse Tuner. In paper [17] they use an encoder-decoder based structure called Link-Net for segmenting 2D ultrasound fetal image and this network preserves deep information. Link-Net is designed for semantic segmentation, but it also performs well for segmenting medical images. However, there are some limitations in existing convolutional neural network techniques like minimal accuracy in noise degraded and low resolution images. Appreciating the advantage of dilated convolutions [27] and to overcome the drawbacks of the existing approaches we proposed a novel automatic framework for fetal skull segmentation in 2D ultrasound fetal images that uses simple Deep Learning network to accurately identify fetus' head portion.

Methodology

In this paper, we describe a novel deep learning model based on CNN for identification of fetal head region in 2D Ultrasound Fetal Image [28]. The architecture of our suggested technique is depicted in Fig.2.

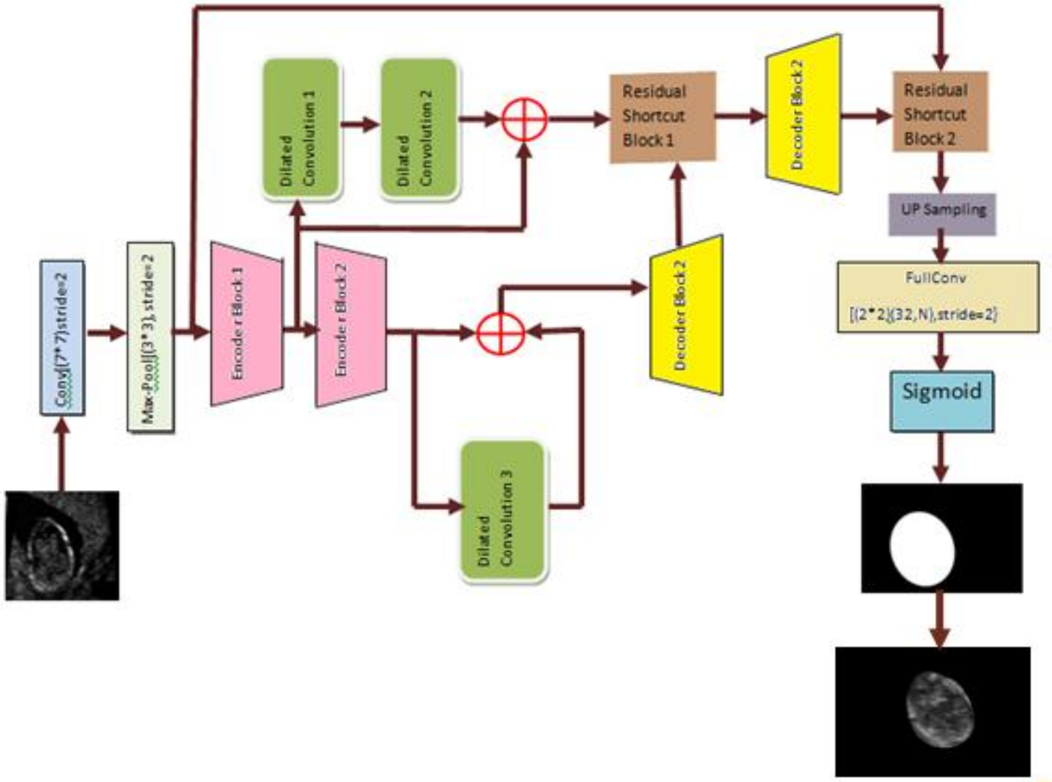


Fig. 2. Dilated Multi-Scale-LinkNet Architecture

The network includes Max-Pooling layer, encoders, decoders, Residual block and dilated convolution modules to improve identification of fetal skull boundary and its segmentation on 2D ultrasound images [24]. Dilated convolution can extract features like edges, colors, texture, and gradient orientation from larger spatial information, and it is efficient in finding the edges with limited model complexity for fetal HC measurement. The encoder-decoder structure protects detailed information; it has been employed for medical image segmentation [25].

Pre-Processing

To get the accurate results with a 2D convolution, it is necessary to pre-process the image into grayscale image. Pre-processing comprises two operations. Initially, rescaling the pixel values from 0-255 and floating point values from 0-1. It includes a resizing from 800x540 pixels to 240x240, and normalizing the values (by subtracting the mean and divided by standard deviation). The second experiment was carried out on ground truth images, and to display them as solid ellipses, an algorithm was defined for filling the image. There is no method for delimitating the missing area, which makes it impossible to calculate the ellipse accurately. Finally, the dataset is divided into 70% training and 30% testing randomly.

Proposed segmentation network structure

We apply an encoder-decoder architecture based on convolutional neural network (CNN) for segmenting fetal head on the 2D US fetal images [18]. The 2D prenatal ultrasound images from various pregnancy trimester are used as input. The model was trained using two types of labelled images: annotations of fetal HC image data (depicted in Fig.7(b)) and fetal skull segmented image data (depicted in Fig.7(c)).

Encoders

The encoder-decoder [19] model preserves deep information and it is efficient for medical image segmentation and extraction. For segmentation, the proposed network employs higher-level and lower-level feature representations. There are two encoders and two decoders are employed in this architecture. The symmetric design permits every decoder to get data from the previous layers. First the convolution is applied on the input image using 64 convolution filter with the kernel size of 7x7 and stride=2, then we create a maxpooling layer with kernel size 3x3 and stride length 2**.** Then the output is given to the encoder block1**.** This encoder block starts with convolution operation on input image with 64 filters, the kernel size 3×3 and a stride of 2.

Dilated convolution module

Dilated convolution method increases the receptive field and extracts high resolution feature maps of multiple scales. The dilation factor is set as 1using the information of each convolution output for different dilation factors. This technique is utilized to obtain more information without changing the kernel values. When convolving the kernel with input, the value of l is set as 2 and skip 1 pixel i.e., l-1 pixels. This helps to get more detailed representations from each step. Let $F: Z^2 \rightarrow R$ is consider as discrete function. Let $\Omega_r = [-r, r]^2 \cap Z^2$ and let $k: \Omega_r \rightarrow R$ be referred as discrete filter with the size $(2r + 1)^2$. The discrete convolution operator $*$ can be denoted as,

$$(F * k)(p) = \sum F(s)\, k(t) \qquad (1)$$

$s+t=p$

This operator is now generalized. Let l refers dilation factor and define $*_l$ as,

$$(F *_l k)(p) = \sum_{s+lt=p} F(s)\, k(t) \tag{2}$$

*l denotes a dilated convolution or an l-dilated convolution. It is known as standard convolution when setting l value to 1.

Where,
F(s) = Input
k(t) = Applied Filter
$*l$ = l-dilated convolution
$(F_{*lk})(p)$ = Output

For the output of the first encoder block we have add two dilated convolution layers with 192 filters, the kernel size 3x3, strides=(1,1) and dilation factors equal to 2, 4 respectively. The concatenation of the above output and encoder1 (yf) is calculated. Then the output of the first encoder block is fed into the second encoder block to process input image with convolution of 128 filters, the kernel size 3×3 and a stride=2. We have added one dilated convolution for the encoder block2 output with 448 filters with the kernel size 3x3, strides=(1,1) and dilation factors equal to 2. Then it performs concatenation operation for the above output and the encoder block2 (zf).

Decoders

The network consists of two decoder blocks in the upsampling portion. The concatenated output is fed into the decoder block2 which executes convolutions on input using 64 filters, the kernel size 3×3 and a stride of 2. This output is concatenated with the residual shortcut block. The shortcut operation of two convolutions is added to form residual units [26]. Then the output of the residual shortcut block is fed into decoder block1. The output of the decoder block1 and max pooling layer is concatenated with the residual shortcut block2. Its structure includes some down sampling steps in the encoder which can be further utilized for upsampling in the decoder. The technique of upsampling is employed to increase the resolution of feature map representations. In the up sampling module, the up-sampling operations and the transpose convolution operations are used. Finally, the sigmoid activation function is applied, which maps the extracted feature vector into the desired channel to generate the segmentation output.

Loss function

The Dice loss function is common for medical image segmentation [20] which can be highly correlated and characterized by,

$$\text{Dice} = \frac{2 \times TP}{(TP + FP) + (TP + FN)} \tag{3}$$

Where, TP stands for true positive, FN stands for false negative, and FP stands for false positive. However, for difficult US images, another loss function should be considered for training. The loss function employed here is represented as,

L_{LN}=$(x)*(Bce)+Dice$ (4)

Where, w refers weighting representation [21]. By using the value of (x), gradient loss value for fetal head boundary region is increased, (x) represents the similarities between the ground truth boundaries and pixels. ω_0 and σ are set as 30 and 10, respectively.
Binary cross-entropy (Bce) is used to calculate the loss value on the basis of pixels. It can be defined as,

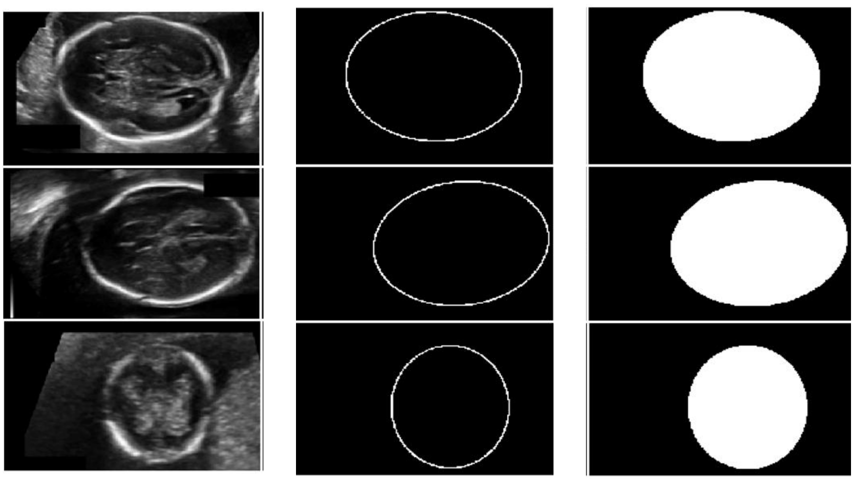
$Bce(G,I)= -(G\times\log(P)+(1-G)\times\log(1-\mathrm{P}))$ (5)

Where, G refers ground truth, P refers predicted map which is the output.

Experiments and Results
The HC18 dataset

We use the HC18 training dataset which was provided by Heuvel and collaborators [22] that contain 999 two dimensional ultrasound images and its equivalent annotations were acquired at varying times during the pregnancy, along with the corresponding head circumference. This dataset has a main issue that all the images were collected from all three pregnancy stages.

We used the same model to train and test it for two operations 1.boundary segmentation and the whole fetal skull segmentation. Two different annotations are considered: 1) The ground truth of fetal skull borders and it is represented as thin elliptic line (fig.3(b)). It is sparse and narrow with limited amount of annotated pixels; 2) the ground truth of whole skull extraction is a solid ellipse with pixel annotations, which should be a mask image (fig.3(c)).



(a) Original image (b) ground truth (c) Mask image
Fig.3. HC18 challenge Dataset

Evaluation metrics

For evaluating our system's performance, we use DSC (Dice Similarity Coefficient), DF (Difference), ADF (Absolute Difference), and HD (Hausdorff Distance) [23].

$$DSC = 2' \frac{(Area_S \text{Ç})}{|Area_S| + |Area_R|} \quad (6)$$

$$DF = HC_P - HC_{GT} \quad (7)$$

$$ADF = |HC_P - HC_{GT}| \quad (8)$$

Where, $Area_S$ refers ground truth area and $Area_R$ is the area extraction by the proposed network. HC_P defines the computed perimeter of segmented output and the ground truth (for head circumference) is denoted asHC_G. The Hausdorff Distance (HD) is calculated as follows,

$$(S, R) = \max(h(S, R) , h(R, S)) \quad (9)$$

$$h(S, R) = \max \min || s - r|| \quad (10)$$

$$s \in S r \in R \quad (11)$$

Where S = $\{s_1, . . . , s_q\}$ represents pixels of segmented output and $R = \{r_1 , . . . , r_q\}$ represents the pixels of ground truth.

The outcomes of applying our suggested network to the test dataset are detailed in Table 1. All of the evaluation parameters have improved, as demonstrated.

Table 1
Evaluation Results of Proposed Net in Comparison with Other Net

Method	Dice Score %	DF (mm)	ADF (mm)	HD (mm)
LinkNet	91.6	1.92	4.95	4.81
mini-LinkNet	92.65	0.94	2.39	2.39
MultiScale mini-LinkNet	92.46	1.19	2.22	3.4
Dilated Multi-Scale-LinkNet	94.82	0.72	1.99	2.02

In this work, we compare three networks. The model is executed in Python and TensorFlow, and they have been training is carried for 200 epochs with stochastic gradient descent with momentum (learning rate of =0.001). It took approximately 15 hours to train our system on NVIDIA GeForce GTX 1080 Ti. The proposed results are competed against three models which applied for extracting fetal skulls in 2D ultrasound images. In Table 1, we compare the proposed model with others described in the related works. Since the proposed model outperforms the competing models in terms of HD, ADF, and DSC, the final result shows more improvements in all evaluation parameters. Visual evidence of head region localization by the proposed architecture is shown in Fig.4.

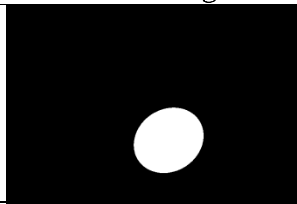
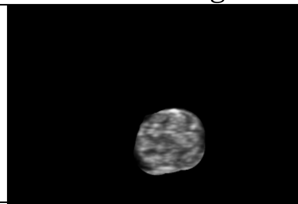
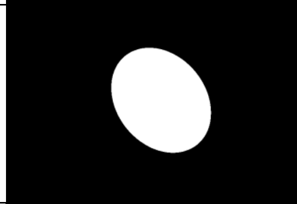
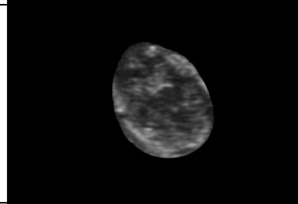
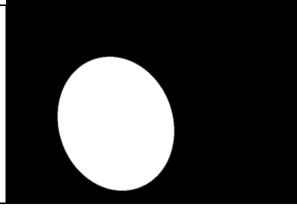
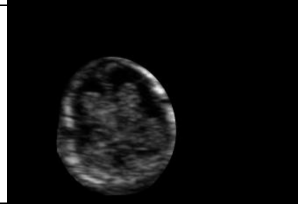
Image_name	Original Image	Mask Image	Result Image
007_HC.png			
017_HC.png			
029_HC.png			

Fig.4. Segmentation results of the fetal head

Column (a) displays the original ultrasound images, column (b) depicts the mask image from the fetal skull annotations, and column (c) displays the predicted segmentation as determined by our model.

Comparative analysis

The comparison of proposed model with competing models is presented in this section. Fig.3 illustrates the improvement in network performance corresponding to each changes of the proposed architecture. Our results were compared with those obtained by three models for segmenting fetal skulls from two-dimensional ultrasound images. Our proposal has shown promising results when evaluating with state-of-the-art systems. The proposed system offers better results than the other techniques in terms of dice metric. HD, DF and ADF all performed better.

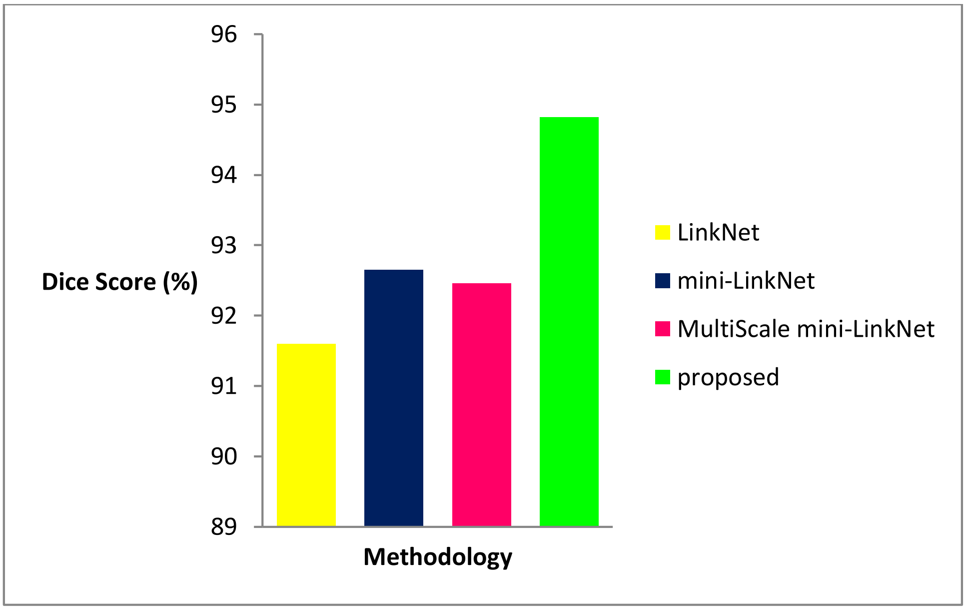


Fig.5. Comparison of the dice score of the proposed method with other methods

Fig.5 represents the results of Enhanced Multi-Scale Link Net on fetal skull segmentation. The results shows that our method achieved the best Dice score 94.82 which is higher than other methods.

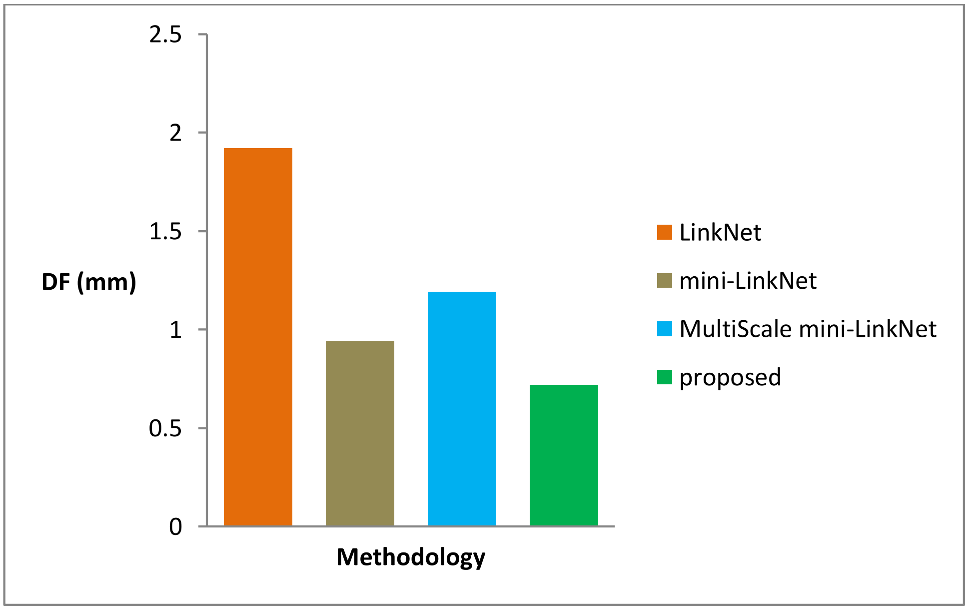


Fig.6. Comparison of the DF of the proposed method with other methods

The Result shown in fig.6 shows that the lowest DF =0.72 mm was achieved with the proposed network comparing the other methods.

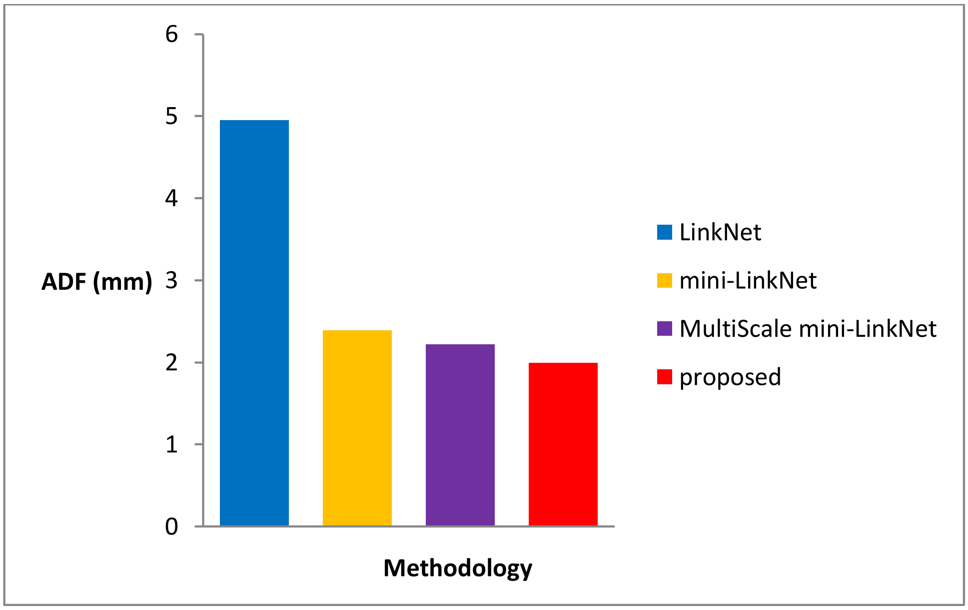


Fig.7. Comparison of the ADF of the proposed method with other methods

The Result shown in fig.7 shows that the lowest mean ADF =1.99 mm was achieved with the proposed one compared with other methods.

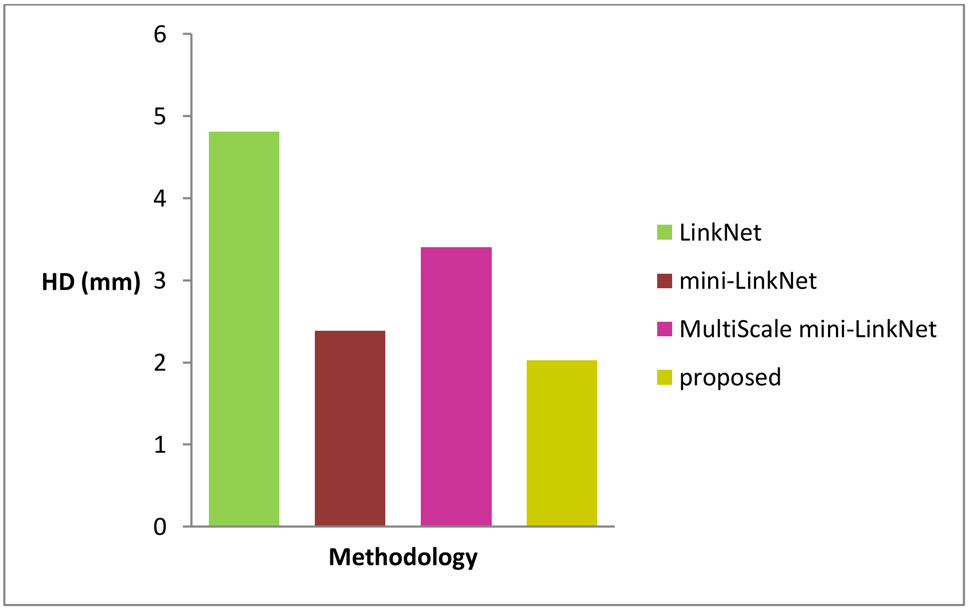


Fig.8. Comparison of the HD of the proposed method with other methods

The performance comparison for the different networks in terms of HD is presented in fig.8. It shows that the proposed method provides better results in terms of HD (2.02).

Conclusion

The proposed research introduced a novel deep learning based method named Dilated Multi-Scale-LinkNet for automated segmentation of fetal head in 2D prenatal ultrasound fetal images. In this methodology, a fully convolutional neural network is adapted to enhance the network performance. Using the segmented results, fetal HC length can be estimated. The fetal HC is essential for the calculation of gestational age time and maternity date, as well as observing the fetal development throughout the three trimesters. As a result of modifying and extending the Link-Net architecture to include dilated convolution layers, we compared its performance to that of a LinkNet, mini-LinkNet network and a multi-scale mini-LinkNet. We achieved better results with our approach than others in terms of dice scores, ADF, DF, HD even when the ultrasound images had uncompleted and blurry skull regions, our model was able to find the whole fetal skull boundaries and skull. According to experimental results, the proposed model outperformed the existing segmentation methods. In the future, medical specialists will be able to use the segmentation results as an effective tool. Moreover, if the datasets are large enough, further analysis will be done with efficient computer capacities.

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