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Automated Fetal Head Segmentation and Head Circumference Measurement Using A Hybrid Ca-Unet Deep Learning Model for Ultrasound Imaging

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The intrinsic properties of fetal ultrasound images at different semesters of pregnancy provide challenges to the automatic computerized segmentation of the fetal head from ultrasound images and head circumference (HC) biometric assessment. In this paper a novel deep learning technique which is a hybrid combination of CA and UNET is proposed for automated segmentation.This research proposes a novel method to automate the biometry of the fetal head utilizing live ultrasound feed, which can even handle low abdominal contrast against the surrounding environment.Accurate and efficient measurement of HC and the ability to make subsequent predictions can be facilitated by precisely segmenting fetal ultrasound images.A produced dataset for the head circumference and belly circumference segmentation tasks, as well as a publicly available dataset (the HC18-Grand Challenge dataset) for the measurement of the fetal head circumference, were used to assess the performance of our suggested architecture. When compared to alternative approaches, the processing time was greatly reduced by the suggested fast network.

1. Introduction

The primary function of medical image segmentation, which is characterized by the labeling of every pixel in medical images, is to support clinical applications and equipment. The early learning-based techniques for medical image segmentation rely on hand-crafted elements including texture, color, look, and form among other aspects. In these methods, the target item is distinguished from its surrounding using a classifier. These approaches have several drawbacks, including a high miss-detection rate, due to the significant intra-class variability of medical pictures and the restricted representation capacity of hand-crafted features.

One of the most common and important prenatal testing is prenatal ultrasonography. It is a quick, safe, and non-invasive treatment that provides clear visual images of the developing fetus. Normal fetal ultrasonography care may check for structural abnormalities and track the health of the developing fetus. The measurement of the fetal head circumference (HC) from ultrasound pictures is essential for tracking the size of the embryo, determining the gestational age, and determining the dimensions, weight, and due date of the baby. Experts in medicine can quickly identify the uterus and the fetal skull from the prenatal ultrasound picture, as seen in Figure 1.

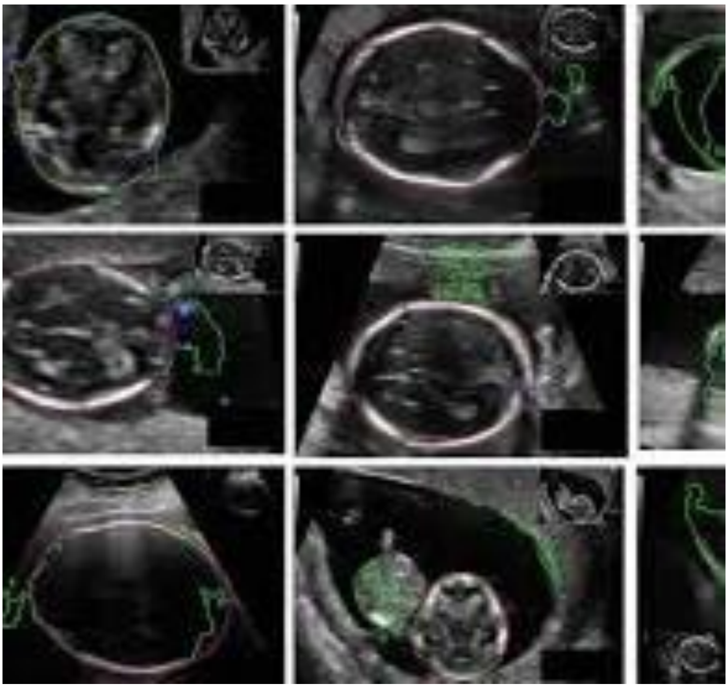


Fig 1. Fetal Ultrasound Image segmentation

Because it can extract the Region of Interest (ROI) through an automated method with good prediction outcomes, medical image segmentation is crucial to medical image processing. To assess fetal HC more accurately and easily, researchers are trying to segregate and measure HC automatically using computer vision algorithms. Machine learning classifiers were primarily trained to locate the fetal skull using Haar-like features, i.e., digital image features used in object recognition [1], such as edge features, line features, center-surround features, and rectangle features [2]. Several techniques, like the Hough transform [3] and Elli-Fit [4], can be used to fit the elliptic skull border for further HC measurement after the skull characteristics have been extracted.

Numerous segmentation algorithms based on deep learning have been created to extract meaningful information from medical photos. [5] used regression convolutional neural networks to predict HC, allowing for the direct calculation of HC's perimeter from the segmented data. U-Net [6] is a common architecture that has shown promising results for automated medical picture segmentation among various models. Due of their exceptional identification and automated segmentation capabilities, which have improved workflow efficiency in clinics, they have become quite popular.

Fetal biometry assessments have been conducted using ultrasound scans, one of the many forms of medical imaging. [7] used dilated convolutional layers applied as a U-Net model to estimate the fetal HC. A novel U-Net model for fetal biometry analysis on the ultrasound pictures was proposed by [8]. Nevertheless, there are certain significant drawbacks to the U-Net based structures for medical image segmentation in clinical devices that were previously discussed. The ultrasound instruments will be equipped with a prepared model. This ready-made model is trained on training data using a variety of convolutional neural network (CNN) architectural weights and biases. While it is clear that the prediction period is shorter than the training phase, it depending on the network's design.

The structure of the paper is as follows. In Section II, we introduce a few relevant papers regarding fetal HC measurement and biomedical image segmentation. A detailed discussion of our model structure and enhancements is provided in Section III. The dataset, implementation specifics, segmentation outcomes, and comparison with alternative approaches are all covered in Section IV. Section V concludes with a succinct analysis and discussion of our study.

2. LITERATURE SURVEY:

In this work [9], we use the deep learning encode-decode architecture to assess fetal HC by segmenting the fetal skull and fetal skull border. Four adjusted 2D-convolutional, 2D-transposed convolutional, and batch normalization layers make up the primary layers of the suggested quick and accurate U-Net model[10].A fully convolutional neural network (FCNN) was created by Li and et.al., [11] for the purpose of segmenting ultrasound HC, OFD, and BPD measurements. To decrease noise and choose the most useful scales, a new attention layer was applied to the feature filtering process. In order to extract the elliptic feature maps and estimate the BPD and OFD measures, a new pooling layer was also added during the regression phase. Metrics like DSC, mPA, and mIoU show that the new FCNN outperforms earlier segmentation techniques. Nevertheless, the computational cost is high.

After that, Zeng and et al., [12] developed a deeply supervised attention-gated (DAG) V-Net model to outperform the most advanced models currently in use for segmentation. Unfortunately, the training dataset was very small—this is the predominant form of failure in the domain. A pretrained convolutional neural network (CNN) was employed by Sridar and colleagues [13] to categorize 14 prenatal features from 2D ultrasound pictures. In a similar vein, Burgos-Artizzu et al. [14] classified six fetal ultrasonography planes using a deep CNN model. However, as a direct result of inadequate training data, the model exhibits overfitting, an inflating gradient, and class imbalance.

Recent Image segmentation research has mostly relied on deep learning (DL) techniques, which use numerous processing layers to simulate how the human brain works and extract representations from data [15]. Convolutional neural networks (CNNs) have become the standard networks in this application, and they are often tweaked to achieve superior segmentation performance [16], especially the U-Net [17] architecture. On the other hand, new developments in deep learning, including transformers [18] and especially their integration into CNN-based networks [19], have demonstrated their potential in computer vision by increasing segmentation efficiency and lowering computational complexity. This integrated technique makes it possible to extract dependencies from images that are both local and long-range, which makes it easier to understand intricate connections between signals [20]. This is how the task of segmentation is completed in a few seconds because to graphics processing units' parallel calculation capabilities, which can accelerate computation performance and enable nearly real-time task execution. Because DL approaches learn to accomplish tasks directly from training data, they are essentially model-free. As they receive more training data, their performance can be improved in a methodical manner. In order to segment fetal brain tissue from fake "noisy" annotations, which are generated by a semi-automatic technique based on multi-atlas segmentation, Karimi et al. (2023) [21] developed a unique training approach of the nnU-Net (i.e., 3D U-Net) .

In order to segment the fetal brain image into its seven components—intracranial space and extra-axial cerebrospinal fluid spaces, gray matter, white matter, ventricles, cerebellum, deep gray matter, brainstem, and spinal cord—we developed the 2-way Ensemble U-Net model in this paper[22]. This is a convolutional neural network architecture. Our work is presented as an extension of the previously published segmentation efforts. The fetal brain picture can be created by segmenting it from the fetal magnetic resonance images using any of the prior works on fetal brain segmentation. The improved FCN with multi-scale dilated convolution method[23] for ultrasound image segmentation is a suggested approach that begins with preprocessing medical ultrasound images through image filtering, normalization, and enhancement. Next, it builds four-dilated convolutions with varying dilation rates to improve the fully convolutional neural network. These convolutions are capable of capturing multi-scale context feature information. Lastly, the Laplace correction operator is used to post process the segmentation results of the medical ultrasound image. Our tests show that, when applied to the breast ultrasound dataset, the suggested method outperforms state-of-the-art techniques in terms of segmentation outcomes. In this work[24], we offer Attention Deeplabv3+, an enhanced version of Deeplabv3+ that uses a two-stage attention method to segment skin lesions.To close the gap and find more supervision, we present a self-supervised equivariant attention mechanism (SEAM) in this study[25].

3. METHODOLOGY:

3.1 U-NET ARCHITECTURE:

The UNET architecture is mainly designed for segmentation technique .The main goal of this architecture is to solve the issue of the scarcity of annotated data in the medical domain. This architecture consists of two paths and they are contracting and expanding path. The contracting path deals with the encoder layers that decrease the input's spatial resolution and gather contextual information and expanding path deals with decoder layers that use skip connections to obtain information from the contracting path in order to decode the encoded data and create a segmentation map. Fig 2 shows the architecture for UNET .

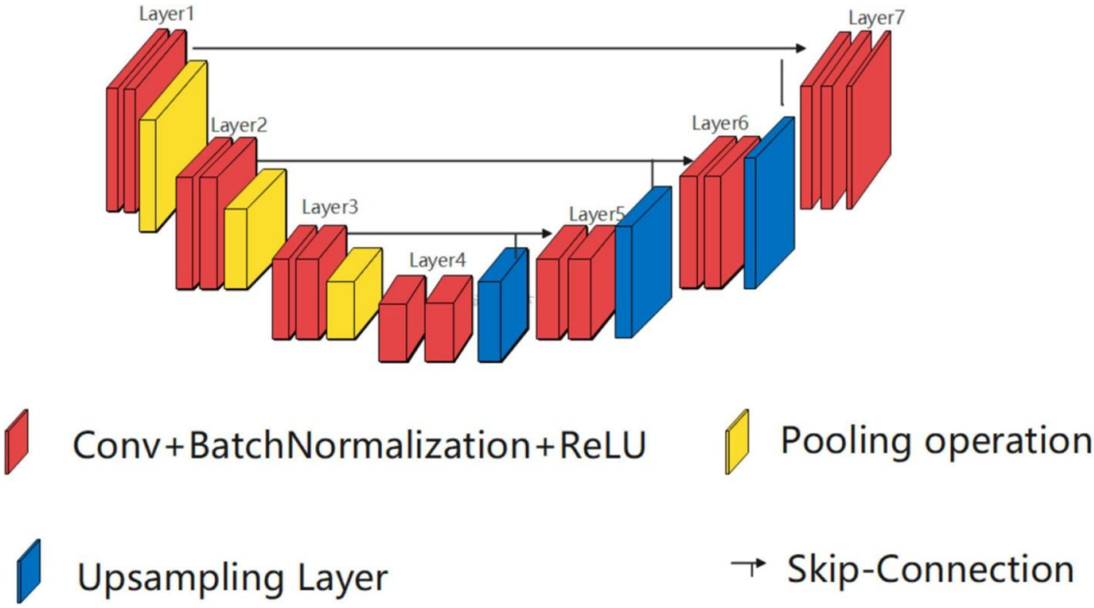


Fig 2 UNET ARCHITECTURE

U-Net's contracting path is in charge of locating the pertinent features[26] in the input image. In order to capture increasingly abstract representations of the input, the encoder layers conduct convolutional operations that decrease the spatial resolution of the feature maps while increasing their depth. The feed forward layers of various convolutional neural networks resemble this contracting pattern. Conversely, the expansive path preserves the input's spatial resolution while identifying the features and decoding the encoded data. Along with upsampling the feature maps, the decoder layers in the expanding route also carry out convolutional processes. In order to help the decoder layers identify the features, the skip connections from the contracting path aid to maintain the spatial information lost in the contracting path

The U-Net model is easy to use and effective for some small-scale medical picture segmentation; nevertheless, it has an average segmentation effect on natural images and generic items due to its limited feature extraction capabilities.

3.2 ATTENTION MECHANISM:

Attention mechanisms improve the precision and computing efficiency of deep learning models by concentrating on crucial input components. Among the different attention mechanism, channel attention is used.

In convolutional neural networks, a Channel Attention Module is a module for channel-based attention as shown in Fig 3. By utilizing the inter-channel relationship of characteristics, we generate a channel attention map. Given an input image, "what" is meaningful is the emphasis of each channel in a feature map, which functions as a feature detector. We squeeze the spatial dimension of the input feature map in order to compute the channel attention efficiently.

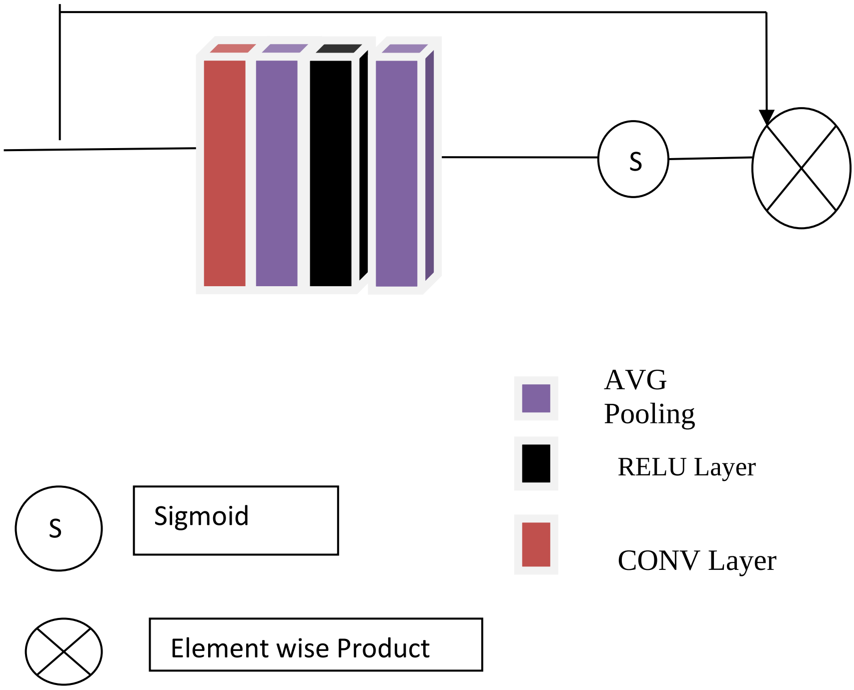


Fig 3 Channel Attention

The Spatial Information from the feature map is aggregated by using the pooling technique such as Average and Max Pooling. The output from the pooling technique is passed to shared network to produce Channel Attention Module. The shared network comprises of Multi Layer Perception (MLP) with one hidden Layer. Following the application of the shared network to every descriptor, we use element-wise summing to combine the resultant feature vectors.

3.3 Proposed Methodology:

The Proposed methodology for our technique is a hybrid combination of CA and UNET (Channel Attention and UNET). UNET is also called as “ENCODER-DECODER” . Our Proposed technique consists of three parts as shown in Fig 4. The First part contains encoding and second part deals with the combination of skip connection and third part deals with decoder part.

The Encoding Part contains the contracting path and it contains convolutional layers followed by Max-pooling to downsample the feature maps. The Input Image is decreased to its Spatial dimension.Its main objective is to efficiently capture pertinent information for segmentation by compressing and abstracting the input image. The second and Decoding deals with the expanding part. It constructs the final segmentation map and recovers spatial information by upsampling the feature maps from the contracting path.

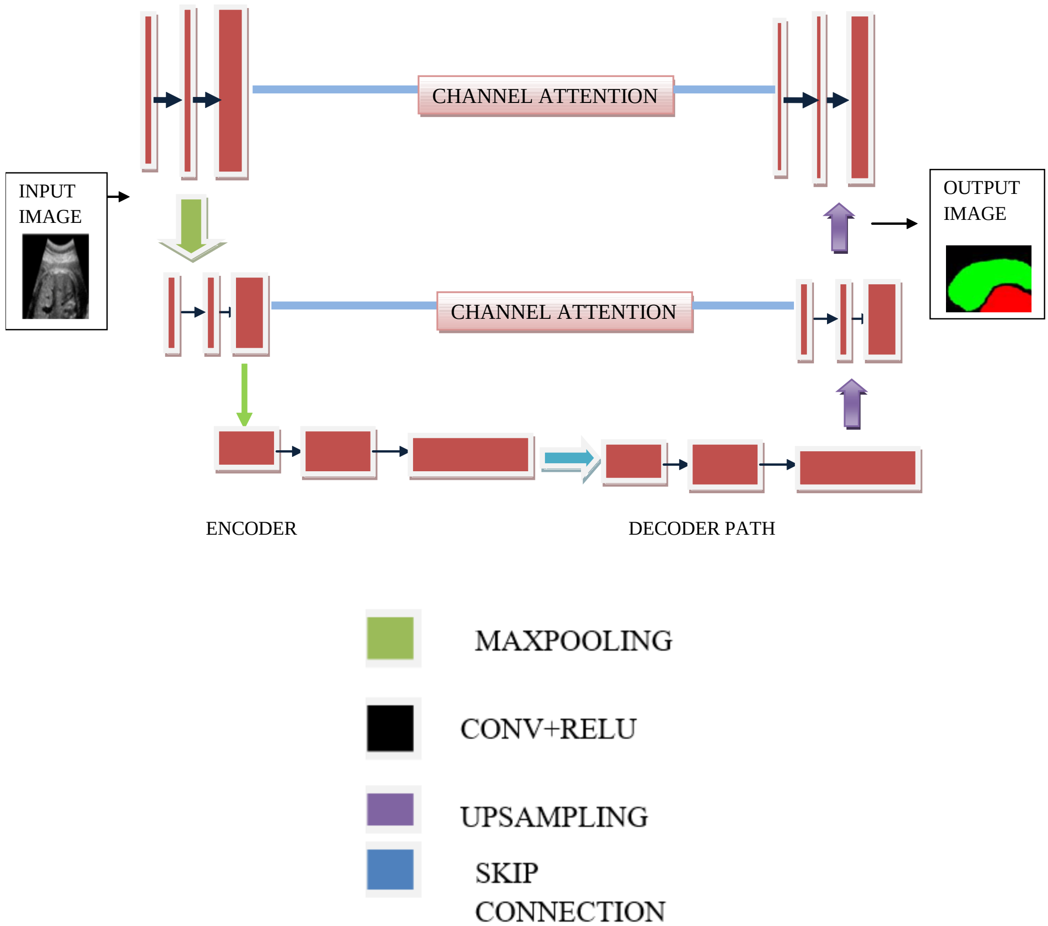


Fig 4 MULTITIERHCAUNET

The Third Part deals with skip connection that combine both encoder and decoder part. They enable data to move between the contracting (encoding) and expanding (decoding) channels, skip links are crucial to the UNET concept. They are essential for preserving spatial information and raising the precision of segmentation. Important spatial information that would otherwise be lost during downsampling is protected by skip connections. By using these links, data from the encoding stream can be sent straight to the decoding pipeline, avoiding downsampling. The CA technique is incorporated with the skip connection in the UNET. In CA technique the global average pooling is used to transform the channel-wise global spatial information into a channel descriptor.

$$g_c = H_p(F_c) = 1/H \times W \sum_{i=1}^{H} \sum_{j=1}^{W} X(i, j) \qquad (1)$$

$X(i,j)$ = Value of channel at (i,j) position.

H_p = Global Pooling function

The shape of the feature map changes from C × H × W to C × 1 × 1.

The Channel Attention is given by

$$CAc = \sigma(Conv(\delta(Conv(g_c)))) \tag{2}$$

$$\sigma = SigmoidFunction$$

Where $\delta = \mathrm{Re}\,luFunction$

Finally the output is obtained by the multiplying the input F_C and CA_C

$$Fc = CA_c \otimes F_c \tag{3}$$

Finally CA technique is used to choose the selected features among all the features that comes from the encoder part of the UNET and only meaningful feature are taken through skip connection that is needed for the segmentation. And then Extracted features are sent to decoder part of UNET. The features are upsampled to produce the segmented output.

4. Performance Matrix:

The evaluation criteria selected aim to evaluate both the segmentation and measurement quality. Three distinct standards were taken into account. Initially, the Dice similarity, accuracy, specificity, and sensitivity were evaluated using measures based on regions.

4.1 Dice Similarity:

The dice similarity coefficient is a measure of reproducibility validation and a geographical overlap index.

$$DiceCoefficient = \frac{2*(AnB)}{(AuB)}$$

4.2 Accuracy:

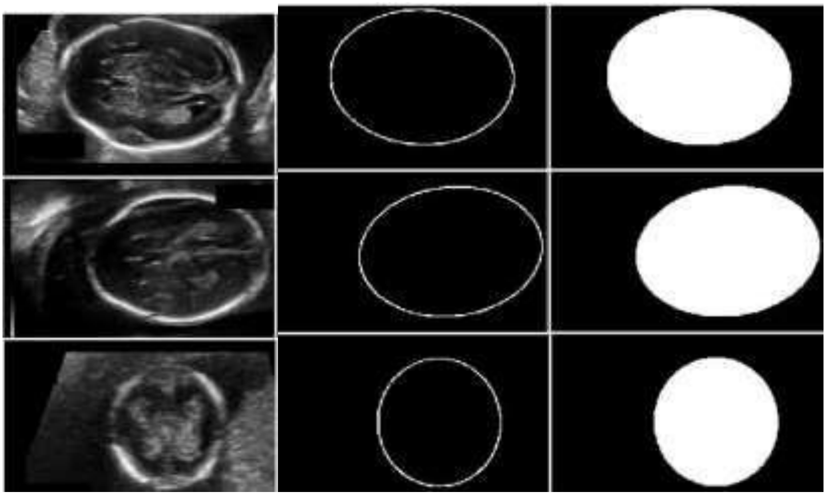
It is the ratio of True positives and Negatives to all positive and negative observations.

$$Accuracy = \frac{Truepositives + TrueNegatives}{AllDatas}$$

5. Experimental Analysis:

5.1 HC18 dataset:

We make use of the HC18 training dataset, which was made available by Heuvel and associates [22]. It comprises 999 two-dimensional ultrasound pictures, the accompanying head circumference, and its corresponding annotations that were obtained at various points throughout the pregnancy. The primary problem with this dataset is that all of the photos were taken during the three stages of pregnancy. The two operations—boundary segmentation and complete fetal skull segmentation—were trained and tested using the same model. Two distinct annotations are taken into account: 1) Figure 4(b) shows the ground truth of the fetal skull margins as a narrow elliptic line. It is narrow and sparse, with few annotated pixels; 2) the full skull extraction ground truth is a stable



(a) Original image (b) Ground truth (c) Mask image

Fig.4. HC18 challenge Dataset

The following are the various methods compared with our proposed methods for Dice-Coefficient and Accuracy.

Table 1 Comparative Analysis of Dice Coefficient with our proposed Technique to various methods

Methods	Accuracy	Dice Coefficient
Fast Proposed methods[27]	90	95
MFP UNET[28]	89	96.39
UNET[29]	83	96.25
Dilated U-Net[30]	87	96.81
R2U-Net[31]	93	74.5
Attention U-Net[32]	94	96.57

Fast and accurate method[33]	95	96.19
HCAUNET	99	98

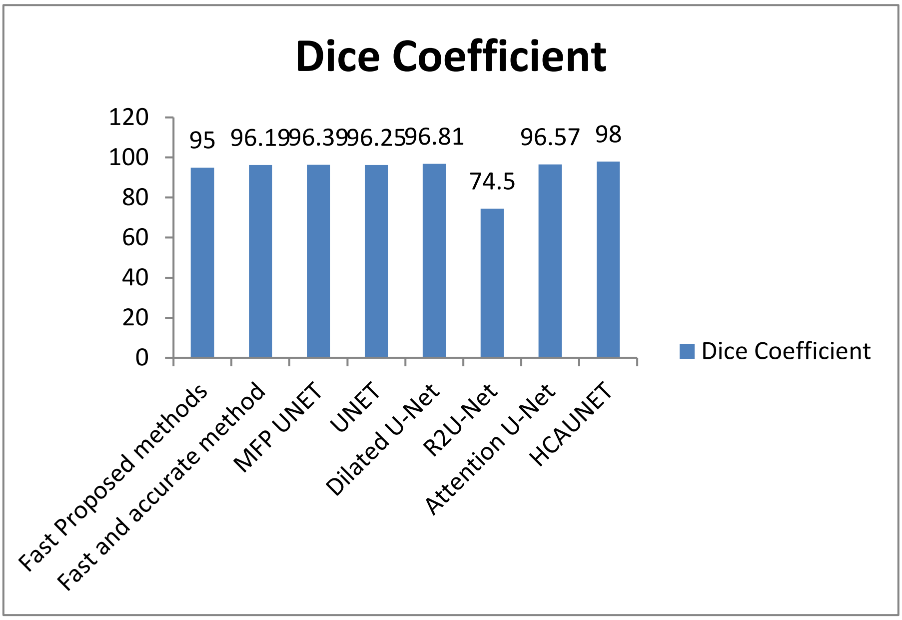


Fig 5 Performance graph for Dice Coefficient

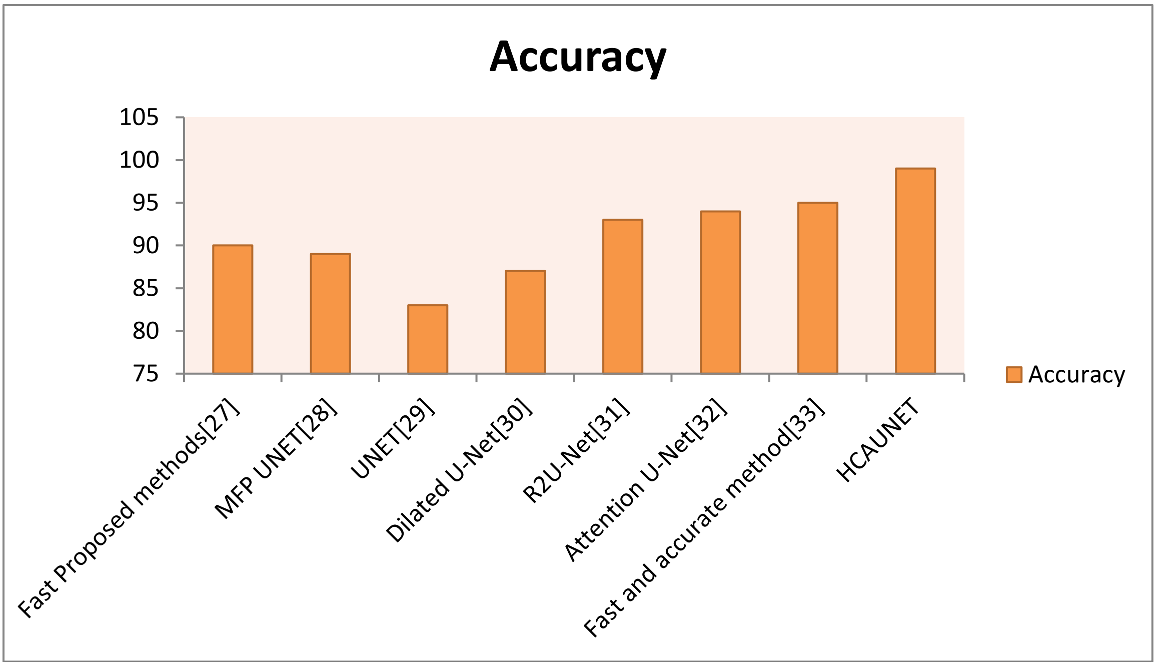


Fig 6 Performance Graph for Accuracy

We have used a test sample of AC for 1, 10, 100, and 200 iterations in order to provide a reliable comparison between the models in terms of computing speed. The suggested model has a good processing time and becomes substantially faster as the number of consecutive segmentations grows, as seen by the findings shown in Table 2. However, when the number of iterations increased in consecutive segmentations, other models showed noticeably longer computation times.

Table 2 Time Complexity for our proposed method with various methods

Iteration/Test time (Second)	HCAUNET	MFPUNET	ATTENTION UNET	Dilated UNET	R2UNET	UNET
1	0.47	1.49	1.02	0.82	2.39	0.49
10	1.33	5.64	4.15	3.44	7.67	4.12
100	8.7	51.08	42.39	33.76	57.97	36.85
200	18.58	98.9	79.36	72.02	117.24	73.17

The visual demonstration of the head area localization by the suggested architecture HCAUNET is displayed in the following table 3

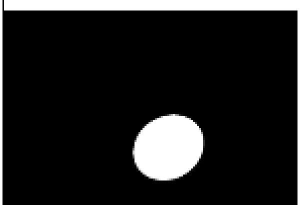
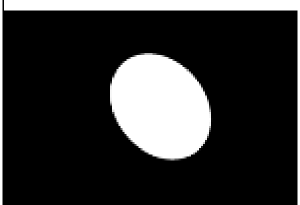
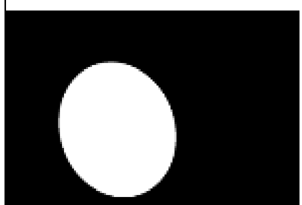
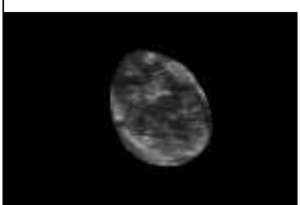
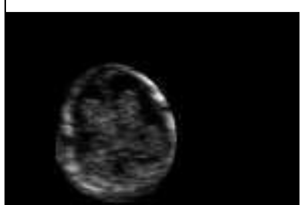
Images	009_HC	010_HC	030_HC
Original Image			
Mask Image			
HCAUNET			

Table 3 Segmentation results of the fetal head

Table 3 presents the results of using our proposed network on the test dataset. It is evident that every evaluation parameter has improved.

6. Conclusion:

In this study, we presented a revolutionary HCAUNET for medical picture segmentation, taking into account the intricate calculations of U-Net based models for clinical equipment. We tested the suggested model on two distinct segmentation datasets in medical images in order to validate our methodology. In addition, we evaluated our model against the current approaches that have been suggested recently for the segmentation of medical images. Our experiment's results demonstrated competitive outcomes when compared to alternative methods for target segmentation. Additionally, the suggested model has a minimal computing complexity, making it extremely quick when compared to existing U-Net based models. We've determined, based on the results, that the suggested model is adequate for usage in clinical devices since it is well-structured and refined.

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