Adaptive feature fusion network for fetal head segmentation in ultrasound images

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ABSTRACT

The measurement of fetal biometrics from ultrasound images plays a vital role in assessing potential development during pregnancy. However, existing fetal segmentation methods failed to accurately segment and asses the head circumference that gives inaccurate segmentation results. To overcome this limitation, a feature feedback and global feature with adaptive feature fusion network (FGA–Net) model is proposed to enhance fetal head segmentation (FHS). It involves four key components for feature extraction, fusion, and correction, respectively. The adaptive feature fusion module (AFFM) and correction map integrate the local features and global features and refine the features to enhance accurate FHS from the ultrasound images efficiently. Initially, ultrasound images are obtained from the two publicly available datasets and preprocessed using normalization and data augmentation techniques. Finally, preprocessed images are fed to FHS by proposed FGA-Net utilizing EfficientNet-B0 as the backbone network for efficient feature extraction. Experimental results of proposed FGA-Net are evaluated using the dice coefficient (DC) of 95.78% and 98.95% for FH-PS-AoP and HC-18 datasets, which shows better results than the existing segmentation approaches like inverted bottleneck patch expanding (IBPE) method.

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1. INTRODUCTION

In medical diagnostics for fetal growth analysis and monitoring, the biometric measurement of fetal head circumference (HC) plays an important role. This HC from ultrasound images efficiently assists to measure the due date, gestational age, and fetal weight during pregnancy, which are majorly dependent on this HC measurement [1]. For assessing the neurological development and abnormalities in fetus growth in clinical practice, prenatal ultrasound plays a crucial role in this assessment. Generally, this assessment involves three stages: initially, an ultrasound probe scans the fetal brain and acquires the 3D data directly during the scanning process. After that, an ultrasound specialist recognizes the 2D fetal brain mid sagittal plane image manually according to anatomical knowledge and acquires a 3D ultrasound image. At last, the physician manually identifies and segments the target regions in the 2D image [2], [3]. In recent decades, diffusion-weighted magnetic resonance imaging (DMRI) has been more used for evaluating fetal brain development in utero. However, the process of data acquisition from DMRI is difficult to segment and analyze [4], [5]. Additionally, transvaginal ultrasonography (TVS) is a commonly used technique by doctors and physicians to monitor the development of the embryo [6]. Biological indicators like crown-rump length (CRL), gestational sac area (GSA), and yolk sac diameter (YSD) from TVS images are used by the doctors to assess the growth and development of the fetus. However, the assessment of HC and evaluation of the aforementioned indicators by TVS technique are obtained manually by the physicians, which consumes more time.

To address these issues, fast magnetic resonance imaging (MRI) acquisition methods are used to acquire 2D slices for fetal head segmentation (FHS) [7]. In various applications, brain extraction from MRI slices is the primary step, which includes slice-level motion correction, slice-to-volume reconstruction, and monitoring the motions of the fetal head [8]. However, automated fetal brain segmentation faces limitations due to various brain shapes, structure, and size across gestational age, as well as image distortions and intensity non-uniformity. Also, contrast of the image varies for distinct fetal MRI sequences, such as DMRI-based data [9]. Thus, automatic segmentation is required in medical images analysis for personalized medicine and to study anatomical development in healthy populations as well as pathology [10]. Hence, artificial intelligence (AI) algorithms are used in medical image segmentation due to their ability to segment or process data efficiently without any manual intervention. Deep learning (DL) models significantly enhanced the image processing in the medical domain that involves analysis of ultrasound fetal images segmentation to assess fetal growth [11]. Recently, DL-based segmentation approaches like convolutional neural network (CNN) [12], transformers, and other deep neural network (DNN) achieved better performance in segmentation related tasks, which has the ability to handle large datasets with pixel annotations effectively [13]–[15]. However, these DL models also have drawbacks such as time complexity, labor intensive, and expensive to acquire large scale pixel annotated dataset [16], [17]. Moreover, the generalization performance of existing FHS methods is limited due to variations in quantity and quality of distinct dataset. Qiu *et al.* [18] developed a segmentation method to identify the pubic symphysis-fetal head standard plane (PSFHSP) from intrapartum ultrasound images based on an efficient lightweight network. Relevant features were extracted using ResNet-18, which use residual blocks to improve feature extraction by preventing vanishing gradient issues. Task specific layers were used for accurate classification and to identify the correct ultrasound plane.

Cai *et al.* [19] presented a segmentation model for fetal head and pubic symphysis using ultrasound images. The presented segmentation model utilized a U-Net-like approach with an inverted bottleneck patch expanding (IBPE) module to efficiently capture both local and global semantic features. Dubey *et al.* [20] developed a fetal ultrasound segmentation model based on hierarchical density regression (HDR) with deep convolutional neural network (DCNN). An advantage of the developed FHS model was its use of ellipse fitting to evaluate fetal head circumference, which helps the segmentation process efficiently. Chen *et al*. [21] suggested a segmentation model based on the fetal head-pubic symphysis segmentation network (FH-PSSNet) for the estimation of automatic angle of progression (AoP) with direction guidance. An advantage of the FH-PSSNet model with direction strategy was that it helped identify fetal head and focus on the position of the pubic symphysis effectively. Chen *et al.* [22] designed a dual path boundary guided residual network (DBRN)-based segmentation model for automated fetal head-pubic symphysis (FH-PS) segmentation. The designed DBRN model involves a multi-scale weighted module to collect global context information and enhanced boundary module to acquire precise boundary information about the fetal head.

Although various DL based models have been utilized for FHS, they face several challenges such as poor generalization across datasets, sensitivity to noise, and due to variations in fetal head shape, size, and orientation. Moreover, most of segmentation models rely on fixed anatomical assumptions and ellipse fitting, which are ineffective for different fetal positions and low-quality ultrasound images. Thus, to overcome these limitations, proposed segmentation model is used for FHS from ultrasound images efficiently.

The major contributions of this research are:

i) Integration of EfficientNet-B0 as a backbone: the proposed feature feedback and global feature with adaptive feature fusion network (FGA–Net) based segmentation model introduces the use of EfficientNet-B0 model in FHS, which enable the effective extraction of both low-level and high-level features across multiple scales in the ultrasound images.
ii) Multi-scale context-aware segmentation: the multi-scale feature feedback (MSFF) module in the proposed FGA-Net model is proposed to capture both global semantic context and fine-grained structural details of fetal head efficiently. The high to low level feature fusion (HLF) module in FGA-Net helps to segment the fetal heads of various sizes and shapes in ultrasound images precisely.
iii) Adaptive feature fusion module (AFFM): an AFFM within FGA-Net is used to iteratively refine and fuse the both low level and high-level features. This module enhanced accurate segmentation by effectively eliminating noise and highlighting the relevant structures in complex ultrasound images.

The remaining part of this manuscript is organized as follows: section 2 discusses the methodology. Section 3 explains the proposed feature feedback and global feature with adaptive feature fusion (AFF) network-based segmentation method. Section 4 presents experimental results and discussions. Section 5 concludes the paper.

2. METHOD

The aim of this research is to develop an effective segmentation method for FHS, which involves three phases: data acquisition, preprocessing, and proposed segmentation. Figure 1 represents the proposed FHS framework using a DL-based segmentation method. The process of FHS is: initially, the ultrasound images of fetal are obtained from two benchmark datasets. Then, the acquired images are preprocessed by technique like normalization, resizing, and data augmentation to enhance the segmentation process. After preprocessing, the enhanced images are used for FHS by the proposed DL approach. The overall process is briefly explained in this section.

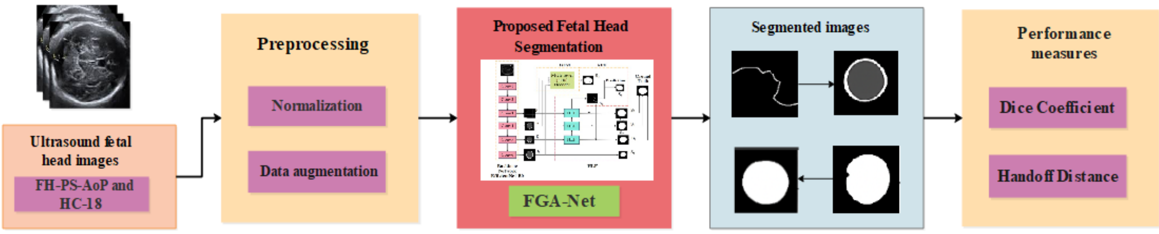

Figure 1. The proposed FHS framework using a DL feature fusion-based segmentation method

2.1. Datasets

In this research, the ultrasound feat head images used for segmentation are acquired from two benchmark datasets: the FH-PS-AoP [22] and HC-18 [23] datasets respectively. These two datasets provide a wide range of fetal head ultrasound images, which ensure robustness in training and evaluation for segmentation tasks. Moreover, they include annotations from the experts that ensure high-quality ground truth for accurate segmentation of fetal head structures which is crucial for prenatal diagnostics. Table 1 represents detail description of two benchmark datasets.

Table 1. Dataset description

Features	FH-PS-AoP dataset	HC-18 dataset
Source/institution	Perinatal transperineal ultrasound videos	Radboud university medical center, Netherlands
Total samples	5100 images	1354 images
Subjects/patients	Multiple pregnant women (gestational age varies)	551 pregnant women
Training samples	4000	999
Validation samples	400	Not specified
Testing samples	700	355
Image resolution range	800×600 to 1024×768 pixels (approx.)	640×480 to 800×600 pixels (approx.)
Ultrasound machine types	High-frequency transperineal probes; GE Voluson E8	Philips and GE ultrasound machines
Annotation quality	Verified by two senior radiologists	Gold-standard annotations by medical experts
Format	PNG/JPEG ultrasound frames extracted from video	DICOM or converted grayscale PNG

2.1.1. FH-PS-AoP dataset

This FH-PS-AoP dataset is an open-access dataset widely used in FHS and HC measurement. This dataset includes 5,100 data samples, which are extracted from perinatal transperineal ultrasound videos. These videos are carefully acquired by a proficient sonographer and confirmed by 2 experienced radiologists. At last, the acquires images from the videos are categorized into 3 sets such as training (4,000), testing (700), and validation (400), respectively.

2.1.2. HC-18 dataset

The HC-18 dataset at https://www.kaggle.com/datasets/thanhbnhphan/hc18-grand-challenge is a publicly available dataset that is generally used to validate the segmentation process of models. This HC-18 dataset involves 1354 ultrasound images acquired from 551 pregnant women, which are further divided into training (999) and testing (355). These images are passed to the next phase, the pre-processing stage.

2.2. Pre-processing

Raw fetal images acquired for this study are processed in a pre-processing stage to ensure the data is in a useful format for effective segmentation. The segmentation techniques, such as normalization and data augmentation, are used in this research to enhance the images. The processes of these techniques are discussed as follows:

2.2.1. Normalization
Generally, ultrasound images have a pixel intensity range of 0 to 255. However, in the acquired ultrasound image, pixels vary between images, which affects the accuracy of the segmentation process. Thus, a min-max normalization [24] is applied to rescale the pixel intensities in the ultrasound images within the range of 0 and 1.

2.2.2. Data augmentation
Data augmentation techniques are employed following the normalization of ultrasound images to generate additional training data from the existing dataset. This data augmentation technique generates new data by modifying the existing data conditions and fetal positions. Horizontal flipping [25], center flipping, rotation, and adjustments to contrast and brightness are the data augmentation techniques used in the normalized images to increase the data samples. Additionally, brightness and contrast adjustments are utilized to handle various lighting conditions in the normalized images, which help improve the FHS performance. Table 2 represents the data augmentation technique used for the proposed FHS framework. These preprocessed images are then passed to the proposed segmentation model.

Table 2. Augmentation techniques used in pre-processing for ultrasound images

Augmentation technique	Values
Flipping	Center flip=-10° to $+10^{\circ}$
	Horizontal flip=-20° to $+20^{\circ}$
Rotating	Randomly rotated up to 10° to 15°
Brightness	-20% to$+20\%$
Contrast	$\pm10\%$ to$\pm20\%$

3. THE PROPOSED FGA-NET ARCHITECTURE
The proposed FGA-Net architecture provides a robust framework for FHS by effectively processing pre-processed ultrasound images. The main objective of the proposed FGA-Net is to utilize multiple features at various scales by combining both low- and high-level features with the modification of the feedback module. Then, a global feature map is generated along with a modification map to detect fine grained details. Figure 2 represents the proposed FGA-Net model for FHS using ultrasound images. The proposed FGA-Net architecture comprises of four components such as Backbone network, MSFF module, global feature module (GFM), and AFFM. These components and their processes are explained briefly as Figure 2.

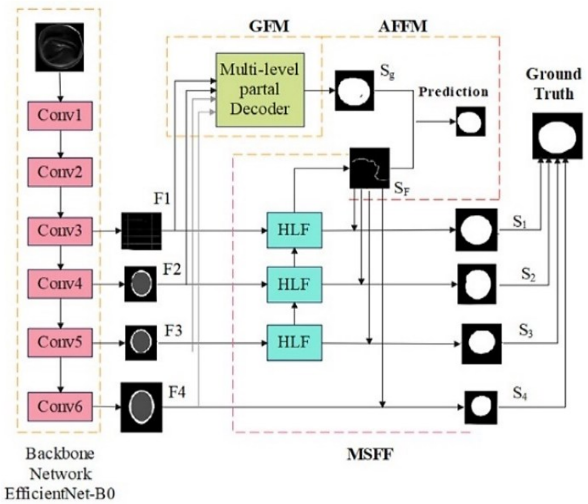

Figure 2. Architecture of proposed FGA-Net model for FHS using ultrasound images

3.1. Backbone network/feature extraction network
In the pre-processed ultrasound images, the appearance of fine-grained details is difficult extract, which helps in accurate FHS. Thus, a DCNN is utilized to capture deep features like both low-level features and high-level features, for learning fine-grained details to segment the fetal head precisely. However, the

proposed FGA-Net have the ResNET-50 as a backbone network, due to its deep and heavy architecture, that lead to overfit on limited fetal ultrasound data. Also, the ResNet-50 model failed to capture subtle variations in fetal head boundaries, which make the FGA-Net struggle to segment the fetal heads with varying sizes and shapes. Thus, in this research, the EfficientNet-B0 model is used as the backbone network for extracting features in the proposed FGA-Net. The EfficientNet-B0 overcomes these limitations with its lightweight and balanced scaling strategy, enabling better generalization, finer boundary localization, and improved segmentation of fetal heads in diverse ultrasound settings This backbone network in the proposed FGA-Net scales the depth, width, and resolution of the preprocessed ultrasound images using the compound scaling method for efficient feature extraction. The scaling technique in EfficientNet-B0 extracts both global and local features to improve fetal head boundary detection. Unlike residual network (ResNet), visual graph geometry (VGG), and DenseNet models, the EfficientNet-B0 model extracts the features efficiently with fewer parameters. Also, this network efficiently handles the specific noise in ultrasound images, known as speckle noise that makes the model more robust for feature extraction.

3.2. MSFF module (HLF module)

Then, the features extracted from the EfficientNet-B0 model are fed to the MSFF module, which primarily involves of 2 components such as the correction map feedback module and HLF module. In this module, there are three HLF modules utilized for generating four different scale of features, which are represented as F1, F2, F3, and F4, respectively. These features are used as inputs to generate a final feature modification map, which is denoted as SF, then it compensates and generates four scales of output maps, which are indicated as S1, S2, S3, and S4. Besides its multi-semantic information features and high resolution, MSFF module provides precise segmentation results.

In MSFF, the HLF module is a cross-feature module, which combines features extracted from various scales to mitigate background noise between the features. This feature fusion module compensates for missing parts in the features to enhance the segmentation of the fetal head efficiently. At first, the deep features derived from the backbone model are fed into the HLF module, and a matrix multiplication operation is performed to remove the background noise present in the features. These fused features are further used to correct the actual extracted features by the correction map feedback module. The output of the HLF contains both FH and FL, which are mathematically expressed in (1) and (2).

$$F_H = CB\big(UP(f_H)\big) + CB\Big(CB\big(UP(f_H)\big)\Big) \times CB\big(UP(f_L)\big) \tag{1}$$

$$F_L = CB\big(UP(f_L)\big) + CB\Big(CB\big(UP(f_H)\big)\Big) \times CB\big(UP(f_L)\big) \tag{2}$$

Where CB denotes the convolutional block; UP represents the upsampling convolutional block. High-level feature f_H is upsampled and combined by matrix multiplication. After a convolution operation, the convolutional block, which comprises of convolutional layers, batch normalization, and the rectified linear unit (ReLU) activation function. Similarly, the low-level feature f_L is combined through the matrix multiplication in the convolutional block. Both UP and CB in the HLF module contains a similar number of convolutional layers, pooling layers, and activation layers. This HLF module utilizes the f_L features to provide rich information from low level features to the f_H and less background noise from f_H to the f_L features, respectively. This MSFF module utilizes several HLF modules to gradually improve the optimal features at various levels to make the final feature modification map. Correction map feedback in the MSFF module is mathematically formulated as in (3). Where S_i denotes the output corrected and refine feature map; F_i represents extracted features from EfficientNet-B0 where $i = 1,2,3 \; and \; 4$; S_F indicates the final feature modification map. $DP\,(.)$ represents downsampling of S_F to the same size; $+$ indicates matrix addition operator.

$$S_i = F_i + DP\,(S_F) \tag{3}$$

3.3. Global feature module

In the GFM, two operators are utilized to focus on fetal head boundary information by integrating global features from the generated multi-scale feature maps. Operators like element-by-element multiplication and concatenation function of matrix spatial dimensional splicing are the fusion operators used to fuse global features. Initially, in the GFM, the extracted features, such as F1, F2, F3, and F4 at various scales, are upsampled to a uniform size, and then these resized features are fused by the multiplication operator. Since the network layers in the backbone network (EfficientNet-B0) increases at last for extracting high level features, the extraction is gradually changes from low-level to high level semantic information. Simultaneously, element-by-element multiplication operator makes the low-level features to focus on high level features with semantic information as the target, efficiently mitigating background interference. The final global information graph S_g is obtained by upsampling the fused features, which are then spliced in spatial channel dimension that helps to avoid loss of fine-grained details after the element-by-element multiplication operator.

3.4. Adaptive feature fusion module

An AFFM is used to combine global and refined feature maps adaptively to produce the final segmentation detection results. Global feature map S_g and final refined feature map S_F from MSFF module are fed into the AFFM for feature fusion. The AFF module utilizes learnable weights, such as ω_g and ω_F, to fuse the two feature maps, generating an accurate segmentation map. This dynamic fusion adjusts the weight of each map according to their relevance to the segmentation task. The segmentation of the fetal head is performed in this AFF module after fusing the two different set of features. The mathematical expression for the final segmentation prediction is given in (4).

$$Prediction = \omega_g \times S_g + \omega_F \times S_F \quad (4)$$

After performing feature extraction using EfficientNet-B0, feature fusion of low level and high-level features in the MSFF module, and global features fusion in the AFF, the model provides a refined feature map at various scales. The final segmentation prediction is made by combining $S_g$and S_F through adaptive fusion. This combined map represents the segmented regions corresponding to the fetal head. The weights ωg and ωF are dynamically studied to optimize the contribution of each map towards the final segmentation result.

4. RESULTS AND DISCUSSION

Experimental results of the proposed FGA-Net-based FHS method utilizing two benchmark datasets are illustrated in this section. The proposed segmentation model is simulated using Python 3.9 software with the system configuration tool on Windows 10, 16 GB RAM, and an i5 processor. Performance evaluation of the FGA-Net model is evaluated against state-of-the-art approaches, as represented in section 4.1. The comparative analysis of the proposed segmentation method with existing FHS methods is illustrated in section 4.2. Table 3 illustrates the parameter settings of FGA-Net model and EfficientNet based backbone network.

Table 3. Parameter settings of the proposed FGA-Net model

Methods	Parameters	Values
EfficientNet-B0	Batch size	32
	Epochs	100
	Initial learning rate	0.001
	Optimizer	Adam
	Loss function	Binary cross-entropy
FGA-Net	Learning rate	0.0001
	Optimizer	Adam
	Step Size	30
	Gamma	0.1
	Loss function	Weighted binary cross entropy

Evaluation metrics such as dice coefficient (DC), handoff distance (HD), and mean intersection of union (mIoU) are used for evaluating effectiveness of FGA-Net approach, which are mathematically represented by (5) and (6). Where I_P represents predicted result, I_L denotes ground truth; $|\cdot|$ indicates number of pixels. Where X denotes subset of I_P or I_L, and $d(x, y)$ indicates distance between point x and point y.

$$DC = \frac{2 \times |I_P \cap I_L|}{|I_P| + |I_L|} \quad (5)$$

$$HD = MAX \begin{pmatrix} MAX_{XCI_P}\ MIN_{XCI_L} d(x, y), \\ MAX_{XCI_L}, MIN_{XCI_P} d(x, y) \end{pmatrix} \quad (6)$$

The mIoU evaluates the average IoU across several segmented areas, such as the fetal head and background measurements. This produces an overall estimation for segmentation performed by the automated segmentation algorithms that aligns with the ground truth annotations. A higher mIoU value represents better segmentation performance.

4.1. Performance analysis

Quantitative and qualitative analysis of FGA-Net segmentation method, using two publicly available datasets such as the FH-PS-AoP and the HC-18 datasets, are depicted in this section. State-of-the-art methods such as UNet-based segmentation models, Transformer based models, encoder-decoder-based models, threshold-based models, region-based segmentation models, and cluster-based models are used for evaluation. In this section, the recent transformer-based segmentation models are also considered for performance evaluation with proposed method such as segmentation transformer (SegFormer), bidirectional token transformer (Bi-Former) and mobile vision transformer (MobileViT) respectively. The above-mentioned performance measures are used for the evaluation of the proposed method against various segmentation methods. Table 4 represents the performance of the FGA-Net method using the FH-PS-AoP dataset. The proposed FGA-Net-based segmentation model achieved a DC of 95.78 % and an HD of 2.54 mm, which represents accurate segmentation of the fetal head using ultrasound images.

Performance analysis of the proposed FGA-Net-based FHS using HC-18 dataset is represented in Table 5. The existing DL methods used for segmentation, which are DL-based approaches such as 2D-UNet, 3D-UNet, and V-Net. The proposed FGA-Net-based segmentation model achieved a DC of 98.95 % and an HD of 1.19 mm, which represents accurate segmentation of the fetal head using ultrasound images.

Performance analysis of the proposed FGA-Net-based FHS using the FH-PS-AoP dataset is represented in Table 6. State of the art methods used for segmentation such as cluster-based methods, threshold-based methods, and region-based approaches. The proposed FGA-Net-based segmentation model achieved a DC of 95.78 % and an HD of 2.54 mm, which represents accurate segmentation of the fetal head using ultrasound images.

Performance analysis of proposed FGA-Net-based FHS using HC-18 dataset is represented in Table 7. State of the art approaches used for segmentation like cluster-based methods, threshold-based approaches, and region-based methods. The proposed FGA-Net-based segmentation model achieved a DC of 98.95 % and an HD of 1.19 mm, which represents accurate segmentation of fetal head using ultrasound images.

Table 4. Performance comparison of proposed segmentation with DL-based methods on FH-PS-AoP dataset

Methods	Metrices		
	DC (%)	HD (mm)	MIoU (%)
2D-UNet	91.75	3.56	92.80
3D-UNet	92.46	3.18	93.91
V-Net	93.24	2.89	95.56
SegFormer	94.32	2.73	96.01
Bi-Former	94.68	2.63	96.28
Mobile ViT	93.85	2.78	95.34
Proposed FGA-Net method	95.78	2.54	96.72

Table 5. Performance comparison of proposed segmentation with DL-based methods on HC-18 dataset

Methods	Metrices		
	DC (%)	HD (mm)	MIoU (%)
2D-UNet	95.44	2.11	94.19
3D-UNet	95.86	1.82	96.63
V-Net	96.92	1.57	97.24
SegFormer	97.45	1.43	97.68
Bi-Fomrer	97.83	1.32	98.12
MobileViT	96.54	1.61	96.94
Proposed FGA-Net method	98.95	1.19	98.96

Table 6. Performance comparison of proposed segmentation with traditional methods on FH-PS-AoP dataset

Methods	Metrices		
	DC (%)	HD (mm)	MIoU (%)
Clustering methods	89.75	3.15	91.29
Threshold methods	90.94	2.96	92.64
Region methods	91.85	2.73	93.76
Proposed FGA-Net method	95.78	2.54	96.72

Table 7. Performance comparison of proposed segmentation with traditional methods on HC-18 dataset

Methods	Metrices		
	DC (%)	HD (mm)	MIoU (%)
Clustering methods	89.78	2.03	92.63
Threshold methods	93.37	1.91	93.71
Region methods	96.51	1.64	94.59
Proposed FGA-Net method	98.95	1.19	98.96

Cross-validation is performed to evaluate the performance of a proposed segmentation model to ensure generalization ability for unseen data. Table 8 represents the cross-validation results of proposed method using various k-folds. From the results, the k=5 folds configuration of proposed method achieved better results because it provides a balanced trade-off between training data and validation reliability. When the data is splitted into k=2 and k=3 folds lead to underfitting due to limited training data, while higher folds such as k=7 and k=9 splits reduce the validation set size and results in overfitting. Hence, k=5 yields more robust performance which reflects higher DC and MIoU and lower HD that ensure the generalization ability for unseen data using the proposed segmentation model.

The performance of proposed FGA-Net model in fetal segmentation method is evaluated based on the computational complexity and statistical tests which is represented in Table 9. From computational and statistical analysis in FHS, the FGA-Net model achieved less time because of its efficient feature fusion by AFFM that reduced redundant processing and enhanced faster convergence. Moreover, the proposed segmentation model achieved p-value <0.05 based on the DC parameter because it directly reflects how well the predicted segmentation aligns with the ground truth. The obtained p-value indicates the performance improvement over existing methods is statistically significant. The optimized architecture improves both speed and consistency, leading to narrow confidence intervals and reliable segmentation performance in FHS.

Table 8. Cross validation of proposed FGA-Net model using different k-folds

K-folds	Dataset	DC (%)	HD (mm)	MIoU (%)
k=2	FH-PS-AoP dataset	94.83	2.68	95.89
k=3		95.16	2.61	96.21
k=5		95.78	2.54	96.72
k=7		95.43	2.58	96.48
k=9		95.34	2.59	96.33
k=2	HC-18 dataset	97.91	1.34	98.12
k=3		98.17	1.28	98.35
k=5		98.95	1.19	98.96
k=7		98.62	1.23	98.71
k=9		98.45	1.26	98.52

Table 9. Computational complexity and statistical analysis of proposed FGA-Net model

Methods	Computational time (s)	p-value	Confidence interval (CI)
2D-UNet	2.38	0.041	±0.132
3D-UNet	2.85	0.034	±0.128
V-Net	3.12	0.029	±0.117
SegFormer	2.74	0.025	±0.109
BiFormer	2.56	0.019	±0.103
MobileViT	2.63	0.021	±0.107
Proposed FGA-Net	2.12	0.012	±0.095

4.2. Comparative analysis

Comparative evaluation of FGA-Net based FHS method with existing various segmentation approaches by using two publicly available datasets such as FH-PS-AoP and HC-18, is depicted in this section. The existing fetal segmentation models, such as IBPE [17] and HDR-DCNN [18], are used for comparative analysis with the proposed FHS method. The above-mentioned performance measures are used for evaluation the proposed method against various segmentation methods. Tables 10 and 11 represents comparative analysis of FGA-Net method with existing segmentation models using FH-PS-AoP and HC-18 datasets respectively.

Table 10. Comparative analysis of proposed FGA-Net based fetal segmentation method in FH-PS-AoP dataset

Methods	Metrices		
	DC (%)	HD (mm)	MIoU (%)
IBPE [17]	90.20	10.81	-
Proposed FGA-Net method	95.78	2.54	96.72

Table 11. Comparative analysis of proposed FGA-Net based fetal segmentation method in HC-18 dataset

Methods	Metrices		
	DC (%)	HD (mm)	MIoU (%)
IBPE [17]	94.18	8.12	-
HDR-DCNN [18]	98.86	1.22	98.87
Proposed FGA-Net method	98.95	1.19	98.96

4.3. Discussion

The proposed FGA-Net-based segmentation model achieved better results in FHS using ultrasound images. The EfficiNet-B0 as the backbone of the proposed segmentation model extracts multi-scale features at various scales using the compound scaling technique. The AFF module in FGA-Net fuses the global context from global features and fine details from the MSFF module, which helps to segment the fetal head accurately, which varies in shape, positions, and sizes across distinct image resolutions. The proposed FGA-Net-based segmentation model refines and optimizes the features iteratively that improved the accuracy of segmentation process, especially in noisy and partially occluded fetal head images. Existing models such as IBPE [17] and HDR-DCNN [18] achieved less and inefficient results in FHS due to limitations such as variations of shapes and size of the fetal head, occlusion, noise, and poor image quality that affect in accurate segmentation results. However, the proposed FGA-Net is a feature fusion-based segmentation model that integrates both low-level features and high-level features from ultrasound images, which helps it adapt to various sizes and shapes of the fetal head, which results in accurate segmentation. Also, the brightness and contrast enhancement in the data augmentation technique improves the quality of ultrasound images efficiently, which helps in precise FHS.

5. CONCLUSION

An accurate FHS model is essential to assess and monitor the development of fetal from the ultrasound images. However, the existing segmentation methods are failed to accurately segment the fetal head due to variations in fetal head shape, orientation, gestational age, and image quality. To overcome these challenges, FGA-Net based segmentation model is proposed in this research for FHS using ultrasound images. The proposed FGA-Net model involves a feature feedback mechanism to improve the boundary refinement of fetal head by reusing the extracted high-level contextual information which enhanced the segmentation accuracy for different anatomical variations. Specifically, the AFF module in the proposed segmentation model dynamically integrates the multi-scale features, to ensure fine grained details to the FHS. Hence, the reliability of proposed FGA-Net model, which contributes for effective and accurate FHS. Experimental results of the proposed FGA-Net are evaluated using DC and HD metrics, which show better results than existing segmentation approaches like IBPE. However, the EfficientNet-B0 based backbone network with downsampling layers reduce the size of the feature maps, which helps the model capture high-level information but also causes a loss of certain fine details. Though the upsampling is used later to recover the original image size, some of the detailed boundary information are lost in the process, that leads to imprecise segmentation edges. In the future, advanced DL-based backbone network and improved segmentation method will be used to enhance FHS.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from:

- The corresponding author [VN].
- Openly available in [Kaggle] at https://www.kaggle.com/datasets/thanhbnhphan/hc18-grand-challenge], reference [23]

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