

Segmentation-Based Estimation of Fetal Cranial Biometry Using Ultrasound Images

[Prashant Dixit]

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Abstract

Accurate estimation of fetal cranial biometric parameters such as Biparietal Diameter (BPD) and Occipitofrontal Diameter (OFD) can be achieved indirectly through segmentation of the fetal cranial contour in ultrasound images. In this work, we investigate a segmentation-based approach for fetal head analysis using axial ultrasound scans. A convolutional neural network is trained to segment the cranial boundary, enabling downstream geometric fitting and biometric computation.

We evaluate both a baseline U-Net and a multi-scale U-Net (mUNet) architecture, incorporating ultrasound-specific preprocessing, conservative data augmentation, and a boundary-aware loss function. Experimental results demonstrate that while pixel-level Dice scores remain moderate due to the inherent challenges of ultrasound imaging, the predicted contours preserve global cranial geometry with strong anatomical consistency, making them suitable for biometric estimation.

1 Introduction

Ultrasound imaging is the most widely used modality for routine prenatal screening due to its safety, accessibility, and real-time acquisition. Fetal cranial biometric measurements, including Biparietal Diameter (BPD) and Occipitofrontal Diameter (OFD), are essential for assessing fetal growth and neurological development. These measurements are commonly derived from the cranial contour observed in axial ultrasound views.

Manual delineation of cranial contours is labor-intensive and subject to inter- and intra-observer variability, particularly in the presence of speckle noise, acoustic shadowing, and partial skull visibility. Automated segmentation of the fetal cranial boundary provides a scalable solution that can improve consistency and reduce clinical workload.

This section presents **Part B of the Origin Medical Role Challenge**, which focuses on a segmentation-based approach to fetal cranial analysis. The objective is not pixel-perfect segmentation, but the extraction of anatomically plausible cranial contours suitable for downstream biometric computation.

2 Problem Definition

Given a fetal axial ultrasound image

$$I \in \mathbb{R}^{H \times W},$$

the objective is to predict a binary segmentation mask

$$S \in \{0, 1\}^{H \times W},$$

representing the fetal cranial contour.

The predicted segmentation is subsequently used to:

- extract the cranial boundary,
- fit an ellipse to the contour,
- compute biometric measurements such as BPD and OFD.

The learning task is formulated as a binary segmentation problem with emphasis on boundary localization and global shape preservation.

3 Dataset Description

The dataset provided by Origin Medical consists of fetal axial ultrasound images paired with cranial contour annotations.

3.1 Dataset Characteristics

- **Images:** 2D fetal axial ultrasound scans
- **Annotations:** Binary masks representing cranial contours
- **Resolution:** Images resized to 256×256
- **Splits:** Training, validation, and held-out test sets

All dataset splits were created without leakage to ensure unbiased evaluation.

4 Preprocessing and Image Enhancement

Ultrasound images are characterized by low contrast, speckle noise, and variable intensity distributions. To address these challenges, an ultrasound-specific preprocessing pipeline was applied:

- Green channel extraction to enhance contrast.
- Contrast Limited Adaptive Histogram Equalization (CLAHE) for local contrast enhancement.
- Gaussian smoothing to suppress speckle noise.
- Unsharp masking to enhance cranial boundaries.

Ground-truth masks were binarized and morphologically dilated to thicken cranial contours, improving boundary supervision during training.

5 Data Augmentation Strategy

A conservative augmentation strategy was adopted to improve robustness while preserving anatomical validity:

- Random brightness and contrast adjustments to simulate probe gain variations.
- Horizontal flipping, which is anatomically valid in axial fetal views.
- Low-amplitude Gaussian noise to model ultrasound speckle variability.

No rotation, scaling, or elastic deformation was applied, as such transformations could distort clinically meaningful geometric relationships required for accurate biometric estimation.

6 Model Architectures

6.1 Baseline U-Net

A shallow U-Net architecture was employed as a baseline. The model follows a standard encoder–decoder structure with skip connections, optimized for boundary preservation under limited model capacity.

6.2 mUNet

To improve contour continuity and global shape consistency, a modified U-Net (mUNet) architecture was explored. The mUNet extends the classical U-Net by incorporating multi-resolution feature reuse from early encoder layers into deeper decoder stages.

This design enables the model to jointly leverage fine-grained boundary details and global contextual information, which is critical for fetal ultrasound segmentation.

7 Loss Function and Optimization

Due to the severe class imbalance between cranial contours and background pixels, the Focal Tversky loss was employed. This loss emphasizes boundary regions and penalizes false negatives more strongly than standard cross-entropy.

The Dice coefficient was used as the primary evaluation metric.

7.1 Training Details

- Optimizer: Adam
- Initial learning rate: 1×10^{-4}
- Batch size: 8
- Callbacks: Early stopping and learning rate reduction on plateau
- Hardware: GPU-accelerated training

8 Quantitative Results

Table 1 summarizes segmentation performance on the held-out test set.

Table 1: Segmentation performance on the test set

Model	Dice (%)	Loss
Baseline U-Net	47.9	0.56
Modified U-Net (mUNet)	55.6	0.48

The mUNet architecture demonstrates improved Dice performance and reduced loss compared to the baseline model.

9 Qualitative Evaluation

Qualitative inspection shows that the proposed models produce smooth and anatomically consistent cranial contours across a wide range of ultrasound images. In most cases, predicted contours align closely with the annotated ellipses and preserve the global head geometry required for biometric estimation.

Failure cases primarily involve very small fetal heads or severe acoustic shadowing, where partial contour fragmentation may occur. Importantly, predicted contours remain localized to the correct anatomical region.

10 Discussion

The segmentation-based approach demonstrates that reliable cranial contour extraction is feasible using deep convolutional models trained on limited ultrasound data. While pixel-level Dice scores remain moderate, qualitative results indicate strong preservation of global cranial geometry, which is more relevant for biometric estimation than pixel-perfect segmentation.

The combination of ultrasound-specific preprocessing, conservative augmentation, and boundary-aware loss functions contributes to stable optimization and robust contour prediction.

11 Future Work

Potential directions for future research include:

- Ellipse-constrained post-processing for biometric computation.
- Shape-aware loss functions to enforce closed contours.
- Multi-task learning combining segmentation and landmark detection.
- Temporal modeling using ultrasound video sequences.

12 Conclusion

This work presents a segmentation-based framework for fetal cranial analysis using ultrasound images. By focusing on anatomically consistent contour extraction rather than pixel-perfect overlap, the proposed approach provides clinically meaningful outputs suitable for biometric estimation. The results demonstrate that segmentation-based methods serve as a robust complementary pathway to landmark-based approaches for fetal biometry.