A Study of Automated Measurement of Fetal Head Circumference Using 2D Ultrasound Images

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1 Introduction

The fetal head circumference (HC) is an important indicator of fetal growth and development. Traditional approaches rely on manual measurement, which is time-consuming and subject to inter- and intraobserver variability. The goal of this research is to automate the assessment of fetal head circumference using deep learning techniques, namely by developing U-Net models with varied loss functions.

2 Data Analysis

The HC18 dataset, consisting of 999 training images and 335 test images of fetal head ultrasound scans, was utilized in this study. We split the training dataset into 80% for training, 10% for validation, and 10% for testing. The dataset includes ground truth masks for segmentation, facilitating the training and evaluation of our models.

3 Model

3.1 U-Net Architecture

The U-Net model, a convolutional neural network optimized for quick and precise picture segmentation, was used. The model's design consists of an encoder path to collect context and a symmetric expanding path for exact localization.

3.2 Loss Functions

In our study, we investigated the impact of three distinct loss functions on the performance of our U-Net model for fetal head circumference measurement: Mean Squared Error (MSE), Binary Cross-Entropy (BCE), and a novel combination of BCE and Intersection over Union (IoU). The rationale behind selecting these functions stems from their diverse approaches to penalizing the difference between predicted and actual segmentation masks.

- **Mean Squared Error (MSE)**: MSE loss computes the average of the squares of the errors between the predicted and the ground truth masks. This loss function is primarily used to ensure that our model minimizes the variance between the predicted values and the actual values.

- **Binary Cross-Entropy (BCE)**: BCE loss measures the difference between two probability distributions - the predicted mask and the ground truth mask, making it suitable for binary classification problems like ours.

- **BCE + IoU**: The combination of BCE and IoU aims to leverage the strengths of both - BCE's ability to handle binary classification and IoU's effectiveness in evaluating the overlap between the predicted and actual masks. The combination loss is formulated as $\text{MSE} + \text{IoU} = \alpha \cdot \text{BCE} + (1 - \alpha) \cdot \text{IoU}$, where α is a weighting factor that balances the two loss components.

These loss functions were carefully selected to explore their individual and combined impacts on the model's ability to accurately segment the fetal head boundary in ultrasound images.

4 Results

Our evaluation criteria for model performance included both qualitative and quantitative analyses. We particularly focused on the model's ability to detect the fetal head boundary and the accuracy of its circumference measurements.

4.1 Evaluation

We observed the performance of the U-Net model trained with different loss functions over 20 epochs. The model utilizing the MSE loss function demonstrated a consistent decrease in the loss value, indicating steady improvement. In contrast, models trained with other loss functions did not exhibit significant changes in loss values over time.

The effectiveness of the loss functions was also evaluated using two metrics: Mean Absolute Error (MAE) and Intersection over Union (IoU). Our findings are summarized in the table below:

Loss Function	**MAE**	**IoU**
MSE	0.0108	0.0226
BCE	38.0359	0.2237
BCE + IoU	11.6979	0.0224

Table 1: MAE and IoU values of the U-Net model with different loss functions

5 Conclusion

This study demonstrates the feasibility of using U-Net models with different loss functions for the automated measurement of fetal head circumference in 2D ultrasound images. Future work will focus on further optimizing these models and exploring additional metrics for evaluating their performance.