Measurement of Fetal head using Ultrasound applying machine learning

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***Abstract*—Ultrasound-based fetal biometric measurements, such as head circumference (HC) and biparietal diameter (BPD), are commonly used to evaluate the gestational age and diagnose fetal central nervous system (CNS) pathology. Since manual measurements are operator-dependent and time-consuming, there have been numerous researches on automated methods. However, existing automated methods still are not satisfactory in terms of accuracy and reliability, owing to difficulties in dealing with various artifacts in ultrasound images. This paper focuses on fetal head biometry and develops a deep-learning-based method for estimating HC and BPD with a high degree of accuracy and reliability. The proposed method effectively identifies the head boundary by differentiating tissue image patterns with respect to the ultrasound propagation direction. The proposed method was trained with 102 labeled data set and tested to 70 ultrasound images.**

I. Introduction

The measurement of fetal head circumference (HC) is a pivotal parameter in the assessment of fetal growth and development during pregnancy. Accurate HC measurements are crucial for the diagnosis of potential growth abnormalities, scheduling deliveries, and monitoring overall fetal health. Traditionally, these measurements are performed manually by skilled practitioners using ultrasound imaging, a process that can be time-consuming and subject to variability due to human error and differences in interpretation.

With the advent of machine learning (ML) and deep learning (DL), there's a promising shift towards automating and standardizing the measurement process. These technologies offer the potential to not only streamline the measurement process but also to enhance accuracy and reproducibility. This report delves into a specific project aimed at applying ML techniques to ultrasound images for automated fetal head measurement, exploring the methodologies employed, the challenges faced, and the outcomes achieved.

II. Data Preparation

The initial step in any ML project involves preparing the dataset for analysis. This project utilized a comprehensive dataset of ultrasound images, annotated with the precise boundaries of the fetal head. The preparation process involved several key steps:

- Dataset Acquisition and Verification: Ensuring the dataset's integrity involved verifying the quality and relevance of the ultrasound images and their corresponding annotations. This step is crucial for the success of the training process, as the quality of the input data directly impacts the model's ability to learn effectively.
- Data Augmentation: To enhance the robustness of the ML model and prevent overfitting, data augmentation techniques were employed. This included horizontal and vertical flips of the images, which simulates a broader range of potential ultrasound image orientations, increasing the diversity of the training data without the need for additional annotated images.
- Normalization and Standardization: The images were resized to a standard resolution to ensure uniformity in the input data. Additionally, pixel values were normalized to a standard scale, improving the model's convergence during training by ensuring that features are on comparable scales.

III. Model Selection and Training

The choice of model architecture is pivotal in the project's success. For image segmentation tasks such as fetal head measurement, U-Net and its variations are commonly employed due to their efficiency in capturing spatial hierarchies and details in images.

U-Net Architecture:

U-Net, initially designed for biomedical image segmentation, features a symmetric expanding and contracting path, which helps in capturing context and precise localization information. This architecture is particularly suited for tasks where the output requires precise alignment with the input image, such as segmenting the fetal head from ultrasound images.

Training Protocol:

The training process involves feeding the network with batches of preprocessed images and their corresponding ground truth masks. A loss function, typically a combination of binary cross-entropy and Dice loss, is used to quantify the difference between the model's predictions and the actual annotations. An optimization algorithm, such as Adam, adjusts the model's weights to minimize this loss over several epochs, improving the model's prediction accuracy over time.

IV. Evaluation and Results

To evaluate the model's performance, metrics such as Intersection over Union (IoU) and the Dice coefficient were employed. These metrics provide insight into the model's accuracy in segmenting the fetal head from the ultrasound images:

- **Intersection over Union** (IoU) measures the overlap between the predicted segmentation and the ground truth, divided by the union of the two areas. It is a direct measure of the model's accuracy in identifying the fetal head region.
- **Dice Coefficient** is similar to IoU but focuses on the overlap between the predicted and actual annotations, penalizing false positives and negatives more strongly.

The results section would detail the performance of the model across these metrics, comparing it against baseline manual measurements and potentially other automated methods. Insights into the model's strengths and areas for improvement would be discussed, alongside visual examples of the segmentation results.

V. Discussion and Future Directions

The integration of machine learning into the measurement of fetal head circumference from ultrasound images represents a significant advancement in prenatal care. This project demonstrates the potential of ML to not only automate but also improve the accuracy and reliability of critical measurements. However, challenges such as handling diverse image qualities, variations in fetal positions, and different stages of pregnancy remain. Future research could explore more sophisticated model architectures, incorporate larger and more diverse datasets, and potentially extend the approach to other prenatal measurements.

This project underscores the transformative potential of machine learning in enhancing medical imaging analysis, offering a pathway toward more standardized, efficient, and accurate prenatal diagnostics.