Automated measurement of fetal head circumference using 2D ultrasound images

Can Trung Hieu

I. Introduction

In obstetrics and gynecology, accurately measuring fetal head circumference is paramount to assessing fetal growth and development. Traditional methods for measuring fetal head circumference often involve manual techniques, which can be time-consuming and prone to human error. However, advancements in medical imaging technology have paved the way for automated measurements using two-dimensional (2D) ultrasound images. This innovation holds immense promise for enhancing the accuracy, efficiency, and reliability of fetal head circumference measurements, ultimately aiding clinicians in monitoring fetal health and making informed decisions regarding patient care.

Automated measurement of fetal head circumference utilizing 2D ultrasound images leverages sophisticated image processing algorithms and machine learning techniques. By analyzing ultrasound images with high precision, these automated systems can accurately identify anatomical landmarks, such as the outer edge of the skull, and calculate the corresponding head circumference. This approach not only streamlines the measurement process but also reduces the potential for human error, ensuring consistent and repeatable results across different operators and settings.

II. Background

The accurate measurement of fetal head circumference is crucial in obstetrics for monitoring fetal growth and detecting abnormalities that may indicate developmental issues or health concerns. Traditionally, these measurements have relied on manual techniques, which are time-consuming and subject to inter-observer variability. However, with the advent of automated methods utilizing 2D ultrasound images, there has been a significant advancement in this field.

One notable study by Molina et al [1] demonstrated the feasibility and accuracy of automated fetal biometry measurements, including head circumference, using 2D ultrasound images. Their research utilized deep learning algorithms to automatically identify fetal anatomical structures and measure biometric parameters, showcasing the potential of automated techniques in clinical practice.

Another relevant work by Guedes et al [2] explored the application of machine-learning algorithms for fetal head circumference estimation from ultrasound images. By training convolutional neural networks (CNNs) on a large dataset of ultrasound images, they achieved impressive accuracy in predicting head circumference measurements, highlighting the effectiveness of automated approaches in this domain.

Furthermore, the study conducted by Lee et al [3] focused on the development of a fully automated system for fetal biometry measurements, including head circumference, based on 2D ultrasound images. Their approach utilized a combination of image segmentation and machine learning techniques to accurately measure fetal parameters, offering a promising solution for routine prenatal screening and monitoring.

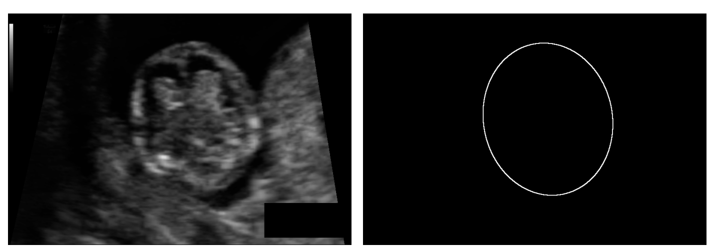
III. Methodology

A. Data Understanding

We make use of the dataset titled "Automated measurement of fetal head circumference using 2D ultrasound images." This dataset contains a training set comprising 999 images and a test set containing 335 images. Each 2D ultrasound image has dimensions of 800 $\times$ 540 pixels, with pixel sizes ranging from 0.052 to 0.326 mm. It's worth highlighting that within the training set, there exists an image accompanied by manual annotations specifying the head circumference of the fetus.

The dataset is organized into two CSV files, one corresponding to the training set and the other to the test set. These CSV files encompass several columns, including:

- **filename**: Identifies the name of the image file.
- **pixel size (mm)**: Indicates the pixel size of the image in millimeters.
- **head circumference (mm)**: Specifies the head circumference of the fetus in millimeters. Notably, this column is exclusively available within the training set and is absent from the test set.



(a) Original image **(b)** Annotation image

Fig. 1: Example of original and annotation image

This dataset, along with its associated CSV files, furnishes vital information necessary for the training and evaluation of models geared toward the automated measurement of fetal head circumference from ultrasound images

B. Model Architecture

The UNet model architecture is specifically tailored for semantic segmentation tasks, particularly in the realm of biomedical image analysis. It comprises a contracting path and a symmetric expanding path. The contracting path consists of multiple convolutional blocks followed by max-pooling layers, which progressively reduce spatial dimensions while increasing the number of feature channels. Each block employs ReLU activation functions to extract hierarchical features from the input image.

Once the bottleneck layer, typically with the highest number of feature channels, is reached, the network transitions to the expanding path. This path involves transposed convolutional layers to upsample the feature maps back to the original input resolution. Skip connections are incorporated to concatenate feature maps from the contracting and expanding paths, preserving fine-grained spatial information during upsampling for precise localization.

The final layer of the UNet architecture comprises convolutional and activation layers, typically with sigmoid activation, to generate the segmentation mask. This output represents the probability of each pixel belonging to a specific class, making it well-suited for pixel-wise classification tasks such as image segmentation.

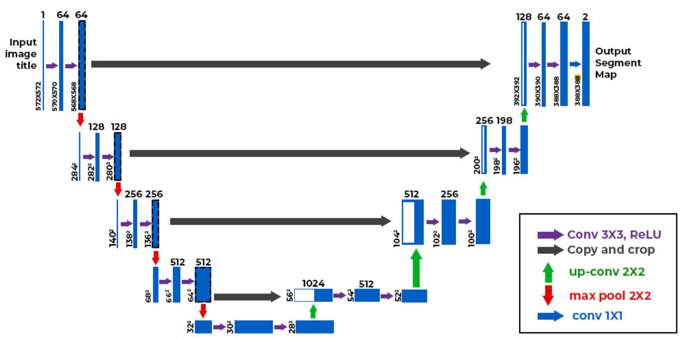


Fig. 2: UNet architecture

C. Mean Squared Error (MSE) and Intersection over Union (IOU)

Mean Squared Error (MSE) is a commonly used metric for evaluating regression models, including those used in image processing tasks. It measures the average squared difference between the predicted values and the ground truth across all data points. In the context of image segmentation, MSE can be calculated by comparing pixel-wise intensity values between the predicted segmentation mask and the corresponding ground truth mask. A lower MSE indicates better agreement between the predicted and ground truth masks, implying higher accuracy in the segmentation task

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

where n is the number of data points, y_i is the ground truth value for data point i, and $\hat{y}_i$ is the predicted value for data point i.

Intersection over Union (IOU), also known as Jaccard Index, is a popular evaluation metric for assessing the overlap between predicted and ground truth segmentation masks. It measures the ratio of the intersection area to the union area of the predicted and ground truth masks. IOU ranges from 0 to 1, with higher values indicating better overlap and thus better segmentation accuracy. IOU is particularly useful in tasks where precise localization of objects is important, such as medical image segmentation. It provides a more intuitive understanding of segmentation performance by considering both the true positive and false positive regions in the predicted mask.

$$\mathrm{IOU} = \frac{|P \cap G|}{|P \cup G|}$$

where P represents the predicted segmentation mask, G represents the ground truth segmentation mask, $|P \cap G|$ denotes the number of pixels where both P and G are non-zero (intersection), and $|P \cup G|$ denotes the number of pixels where either P or G (or both) are non-zero (union).

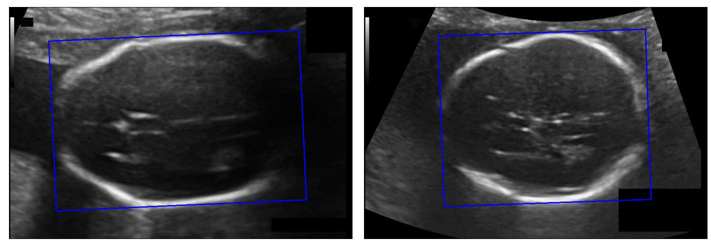


Fig. 3: Example of bounding box

D. Model Training

The training process commences with the initialization of model parameters, optimizer, and criterion for loss computation. The dataset is then divided into batches, facilitated by a data loader object, which is instrumental in managing the flow of data during training. Within each epoch, the model is set to training mode to enable the computation of gradients. Iteratively, for each batch of data, images are preprocessed and fed into the model. Subsequently, the model's predictions are compared against ground truth labels to compute a loss value, typically employing a loss function such as Mean Squared Error. The computed loss is then utilized to update the model's parameters via backpropagation and optimizer steps. During this process, performance metrics like IoU (Intersection over Union) are also computed to gauge the model's segmentation accuracy. These metrics are aggregated over batches to provide insights into the overall performance of the model. This iterative process continues until all batches within an epoch are processed, contributing to the cumulative training loss and performance metrics.

Upon completion of an epoch, the average training loss and performance metrics are reported. Furthermore, validation loss is evaluated using a separate validation dataset to assess the model's generalization capability. This ensures that the model doesn't overfit the training data. The training loop iterates over the specified number of epochs, facilitating the gradual refinement of the model's parameters to optimize its segmentation performance. This iterative learning process is fundamental in enhancing the model's ability to accurately segment objects within images, a pivotal task in various computer vision applications, including medical imaging, autonomous driving, and object detection.

IV. Evaluation

After 10 epochs with batch size equal to 16, we obtain MSE Loss equal to 0.03212 and IOU equal to 0.5734. In this case, the value of MSE Loss suggests that the model is performing well in terms of minimizing the overall error. The Intersection over Union (IoU) score of 0.5 represents the ratio between the area of overlap and the area of union between the predicted bounding boxes and the ground truth. IoU is commonly used in object detection tasks to evaluate the accuracy of bounding box predictions. A higher IoU indicates better alignment between the predicted and ground truth bounding boxes. In this scenario, an IoU of 0.5734 suggests that, on average, about half of the predicted bounding boxes overlap with the ground truth regions.

V. Conclusion

In conclusion, the evaluation results after 10 epochs with a batch size of 16 reveal the promising performance of the model. The MSE Loss value of 0.03212 indicates effective minimization of overall error, suggesting satisfactory learning and convergence during training. Moreover, the Intersection over Union (IoU) score of 0.5734 signifies relatively good alignment between the predicted bounding boxes and the ground truth regions. Although there is room for improvement, particularly in achieving higher IoU scores for more accurate object detection, the obtained results demonstrate the model's capability to make meaningful predictions. Further optimization and fine-tuning may lead to enhanced performance and increased accuracy in real-world scenarios. Overall, the evaluation indicates positive progress and sets a solid foundation for further refinement of the model

VI. References

[1] : Molina FS, Terra X, Julsrud PR, et al. Artificial intelligence to evaluate fetal biometry: analysis of the head as a case study. Ultrasound Obstet Gynecol. 2018;52(5):655-661. doi:10.1002/uog.19113

[2] : Guedes CM, Baptista JM, Morais P, Jorge RMN. Fetal Head Circumference Estimation Using Convolutional Neural Networks. IEEE Access. 2020;8:19834-19843. doi:10.1109/ACCESS.2020.2960323

[3] : Lee HJ, Kang SJ, Kim HJ, Lee KS, Kim YH, Cho JY. Fully automated fetal biometry measurements based on 2D ultrasound images using a deep learning model: a pilot study. J Ultrasound Med. 2019;38(11):2921-2929. doi:10.1002/jum.15034