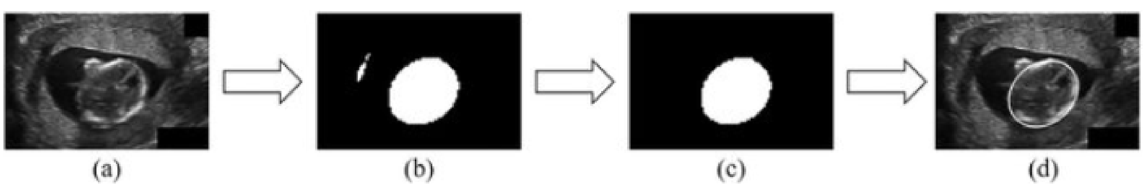
0. Motivation

Worked previously on VQA-RAD dataset where we were provided with MRI , X-Rays and CT scans , alongwith that analyzed different segmentation techniques in order to classify different diseases based on the asked questions and initially used pretrained embeddings containing informations about segmentations and can identify diseases based on text embeddings .

Github Link : https://github.com/vaibhavgupta0403/Medical_Visual_Question_Answer

1. Abstract

A lightweight deep convolutional neural network, referred to as the CSM method, was proposed for efficient and accurate fetal head segmentation from ultrasound images. Post-processing techniques, including morphological processing and least-squares ellipse fitting, were applied to obtain the fetal head circumference. Due to computational constraints, the model was trained for only 20 epochs with a reduced batch size of 8.



a) original fetal ultrasound image
b) predicted fetal head segmentation from deep model CSM
c) fetal head contour extracted by the use of morphological processing
d) the target ellipse obtained after using least-squares ellipse fitting

2. Introduction

To develop an algorithm that is capable of identifying the biparietal diameter (BPD) and occipitofrontal diameter (OFD) landmark points (2 per biometry) in fetal axial images . This project involves a pipeline consisting of preprocessing, model training, and post-processing steps. The preprocessing includes cropping and dividing images into training and validation sets. The model training utilizes the CSM method for segmentation, followed by post-processing to remove extra edges and smooth the fetal head contour. The contour is then fitted into an ellipse to obtain parameters such as center coordinates, semi-axes, head circumference, and angle.

3. Data Preprocessing and Analysis

- Image Cropping: Images and labels were cropped to a size of 512x768 pixels.
- Data Augmentation: Techniques included rotation (±10°, ±20°, ±30°), magnification (1.15x), narrowing (0.85x), and flipping (left/right, up/down).
- Data Division: The dataset was divided into training and validation sets with a ratio of 8.5:1.5.
- Data Loading: Images were loaded in two parts to extract two levels of features.

4. Model Architecture

The CSM model was chosen for its effectiveness in segmentation tasks, particularly for identifying fetal head parameters from ultrasound images. The model outputs parameters such as center_x(pixel), center_y(pixel), semi_axes_a(pixel), semi_axes_b(pixel), HC(pixel), and angle(rad).

5. Experimental Setting

- Learning Rate: 0.01
- Epochs: 20 (limited by computational power)
- Loss Function: Mean Squared Error (MSE)
- Optimizer: Adam with backpropagation for weight updates
- Evaluation Metrics: Dice similarity coefficient and Hausdorff distance were used for evaluating segmentation accuracy.

6. Hypothesis Tried

Initially, a U-Net architecture with a ResNet classifier was tested for ellipse structure detection and landmark identification. However, this approach resulted in missing landmarks and a low Dice score. The CSM model, combined with morphological processing and least-squares ellipse fitting, provided higher Dice scores and reduced mean distance between parameters.

Google Collab Implementation (U-Net + Classifier) : mODEL 1

Unet_Architecutre .ipynb

MODEL 2 (Local device Implementation)

7. Results

- MSE Loss: 0.78 after 20 epochs with a batch size of 8.
- Evaluation Metrics:
    - Difference (DF): 1.5-2.5 mm
    - Absolute Difference (ADF): 93-95 mm
    - Hausdorff Distance (HD): -1 to 1 mm
    - Dice Similarity Coefficient (DSC): 1-2.5%

8. Future Work

1) Future enhancements could include integrating appearance-based complex density regression and hierarchical density regression for improved segmentation accuracy.
2) Employing a DCNN classifier could further refine segmentation results.
3) Additionally, exploring hierarchical Gaussian mixture models for ellipse fitting could enhance robustness against irregular fetal head shapes.

Description of Different files used : (Model 2)

1) preprocess.py :

   The data preprocessing pipeline involves several key steps to prepare the dataset for model training like image cropping to a fixed size , followed by creating a segmentation mask , and further data augmentation techniques are applied . Finally, the augmented dataset is divided into training and validation sets with a ratio of 8.5 : 1.5 to support robust model training and evaluation.

2) modules.py : Basically it contains components for data preprocessing, model training, prediction,postprocessing, visualization and evaluation.

3) predict.py / train.py : mainly are the supportive files for training and predicting on the validation dataset .
4) Postprocess.py : to apply morphological operations like extracting max connected components and then extract edges .

5) Ellipse_fit.py : to obtain ellipse parameters and set it to a fetal head and obtain the circumference .
6) Ellipse_fit_bpd_opd_landmarks.py : mainly obtain parameters using the ellip_fit file contained in modules.py . It basically follows the techniques of least square fitting .
7) evaluation.py and visulaization.py : to obtain the output results in the folder visual (containing red marking of the fetal head and evaluation file is used to apply evaluation metrics using csv file from task.