

MOHAMED BIN ZAYED UNIVERSITY OF ARTIFICIAL INTELLIGENCE

## Background

- length (CRL) • Inaccurate crown-rump can lead to incorrect measurement gestation age (GA) calculation, resulting in a wrong assessment of fetal growth.
- either • CRL measurements can be obtained through manually or segmentation-based algorithms.
- The quality of the segmentation-based algorithms needs to be checked for CRL measurement performance.

## Aim

- To segmentation quality verify automatically with a deep learning-based method called FUSQA.
- To demonstrate the importance of an automated fetal ultrasound image quality assessment approach on clinical a essential downstream task (accurate CRL measurement and GA estimation).

# Materials & Methods

- D<sub>A</sub>: 696 fetal ultrasound images (UKacquired)
- D<sub>B</sub>: 226 fetal ultrasound images (UAEacquired)
- A single CNN model used to estimate probability of being good the segmentation (Fig1).
- A set of altered masks from ground truth masks were generated (Fig2).

#### **FUSQA: Fetal Ultrasound Segmentation Quality Assessment** Sevim Cengiz, Ibrahim Almakky, Mohammad Yaqub Computer Vision Department, Mohamed bin Zayed University of Artificial Intelligence, Abu Dhabi, United Arab Emirates

## Proposed Model

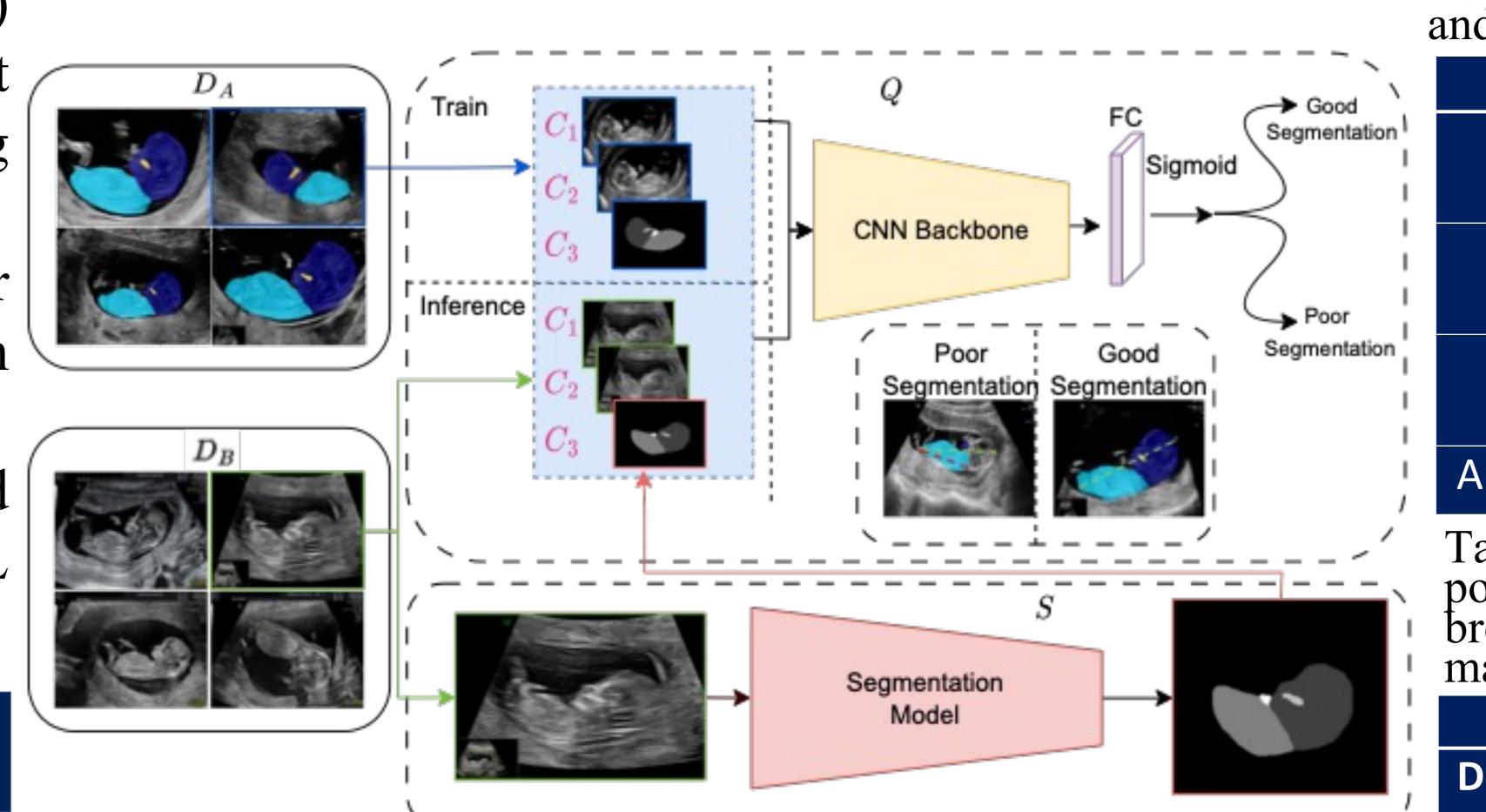


Fig1: The train and inference pipelines for FUSQA method using two datasets  $D_A$  and  $D_B$ . The bottom-right shows samples of good and bad segmentation masks and their impact on the CRL estimation.

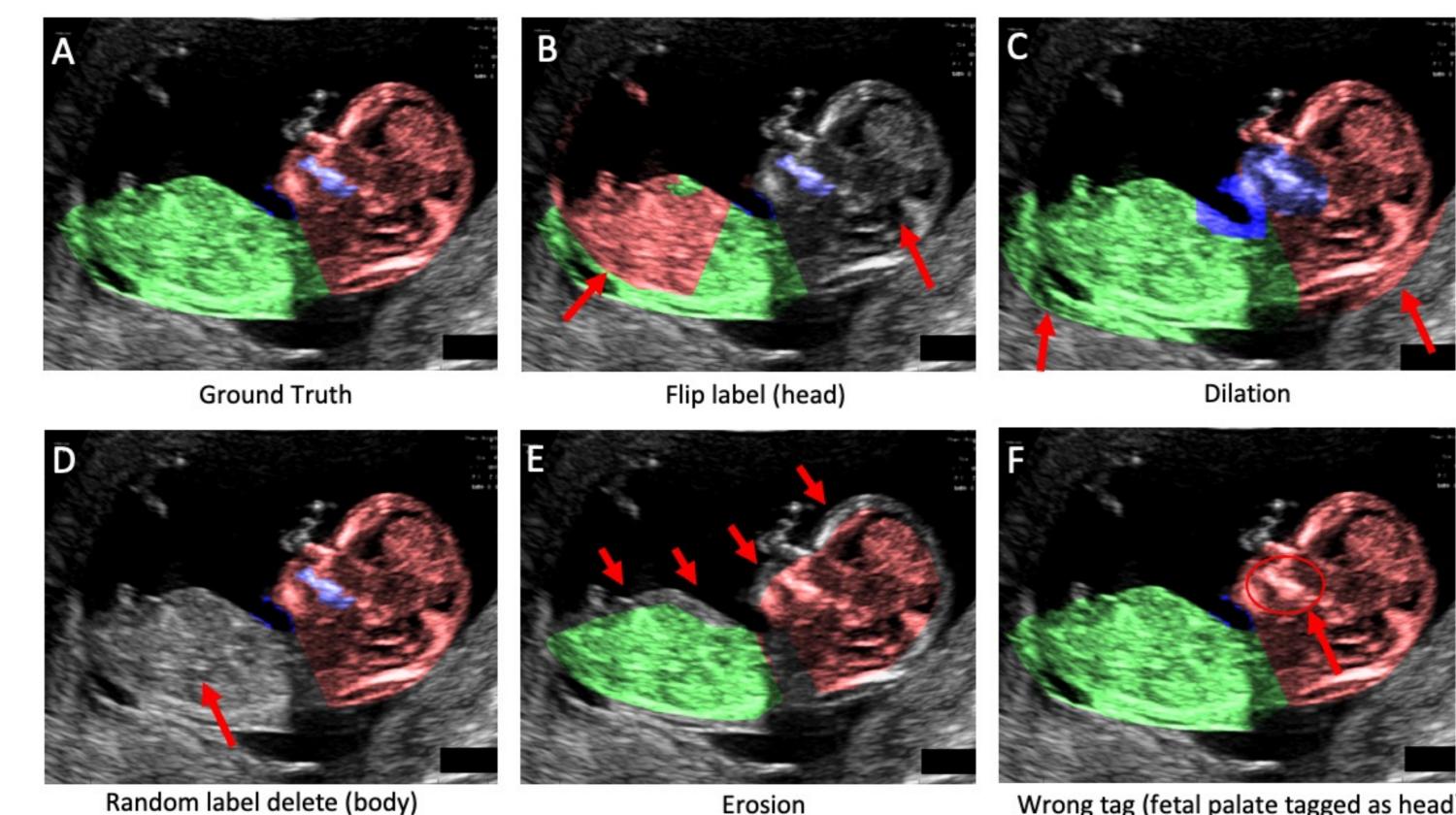


Fig2: An example ground truth segmentation mask (A) and altered poor segmentation masks from it with the following variants: flipping of the head (B), segmentation over-estimation (C), randomly selected label deletion (D), segmentation under-estimation (E), fetal palate • tagged as the head (F).

[1] Francesco Galati and Maria A. Zuluaga. Functional Imaging and Modeling of the Heart, Lecture Notes in Computer Science, pages 101–111, Cham, 2021. doi: 10.1007/978-3-030-78710-3 11.



Wrong tag (fetal palate tagged as head

and Single CNN models with different backbones.						
Model	Network	Precision	Recall	Acc.	F1 Score	
Siamese	ResNet 18	0.673	0.97	0.75	0.795	
	ResNet 50	0.5	1.0	0.5	0.66	
Synergic	ResNet 18	0.525	0.983	0.547	0.685	
	ResNet 50	0.746	0.87	0.787	0.803	
Proposed	ResNet 18	0.795	1.0	0.871	0.886	
	ResNet 50	0.804	0.982	0.902	0.87	
Anomaly Detection [1]	CAE	1.0	0.72	0.70	0.83	

Table 2: The mean CRL and GA estimation errors in predicted good and poor-quality segmentation masks on unseen images from  $(D_B)$  (Top). A breakdown of the compliance of predicted good and poor segmentation masks with FASP criteria on the dataset  $D_B$  (Bottom).

Downstream task on	
proposed model	
Downstream task on	
CAE	
Image Guidance	
Criteria	
	ŀ

CRL dif GA diff CRL dif GA diff Neutral Fetal Magnif Fetal face Horizontal Left calipe **Right calipe** Acceptan

### Conclusions

- We formulate the segmentation quality process an distinguish between estimation.
- different ultrasound machines. classification accuracy on an unseen dataset.



### Results

Table 1: The comparison on unseen  $D_{p}$  between the Siamese, Synergic,

Poor Seg.	Good Seg.
13.63	2.64
7.73	1.45
17.71	5.01
10.06	2.79
67.6%	79.7%
64.9%	93.6%
75%	99.1%
76%	99.1%
67.6%	100%
45.4%	85.2%
63.9%	95.4%
64.9%	96.3%
	13.63 7.73 17.71 10.06 67.6% 64.9% 64.9% 675% 65% 45.4% 63.9%

assessment automated classification task to good and quality poor segmentation masks for more accurate gestational age

We validate the performance of our proposed approach on two datasets we collect from two hospitals using

Our best-performing architecture achieved over 90%