UNIVERSITY OF BIRMINGHAM

# Cross-domain Ultrasound Classification

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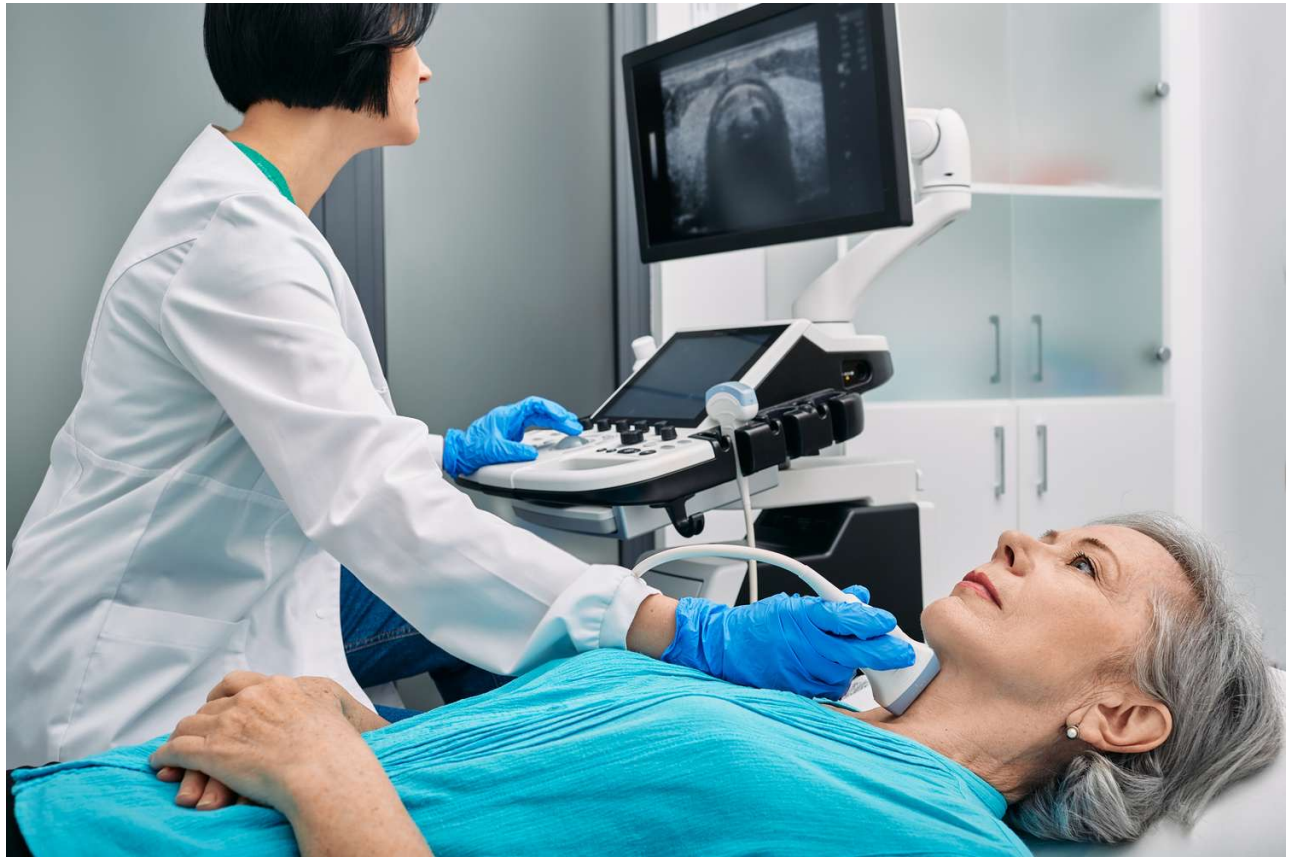
# Outline

- Ultrasound imaging
- Fetal ultrasound classification
- Domain shift in fetal ultrasound screening
- Cross-domain fetal ultrasound classification

# Ultrasound imaging



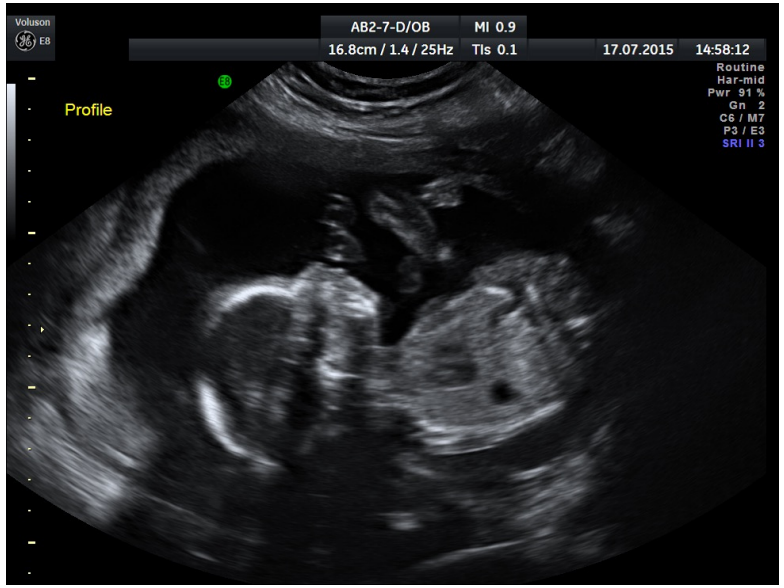
## Advantages:

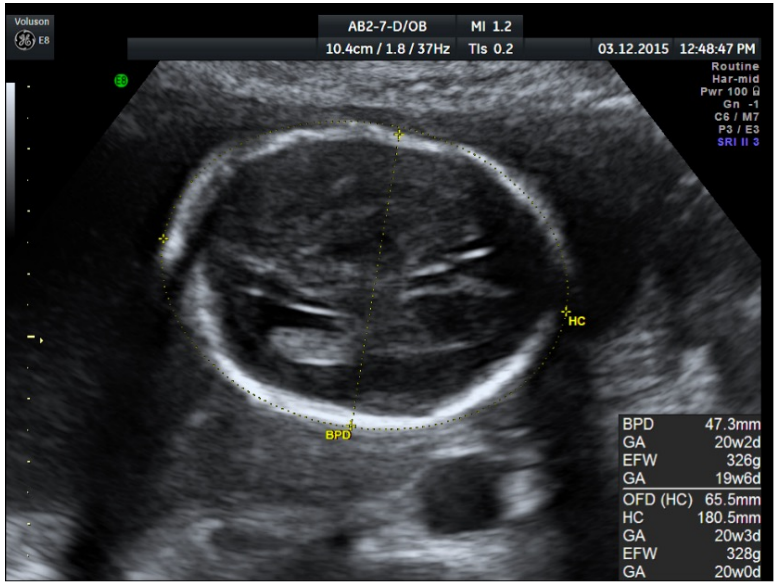
- Portability
- Low cost
- Real-time imaging capability
- No radiation exposure
- …

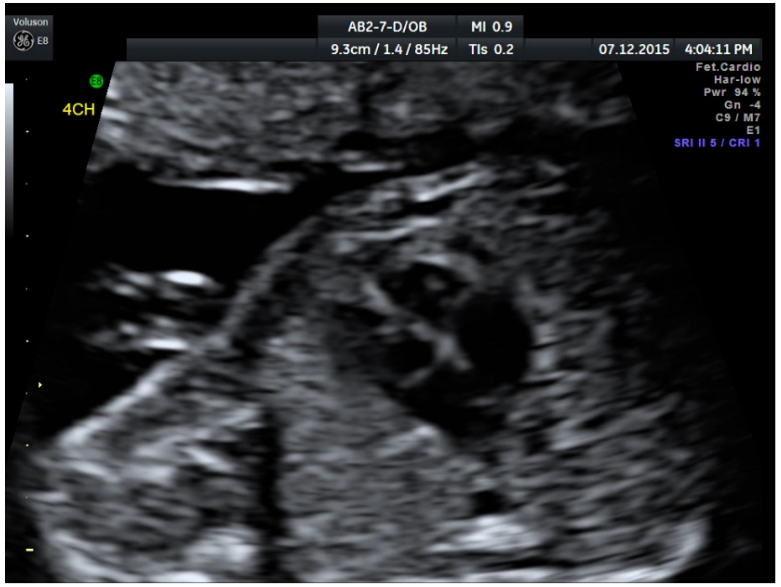
## Disadvantages:

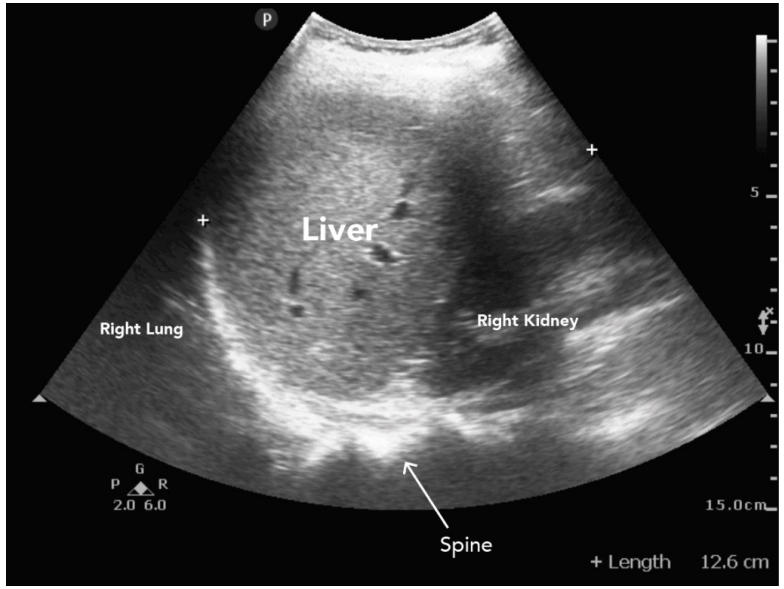
- Low image quality and details
- …

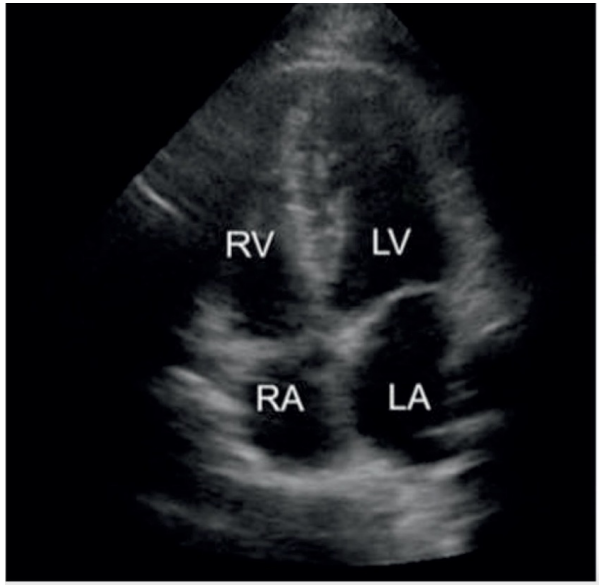
# Ultrasound imaging

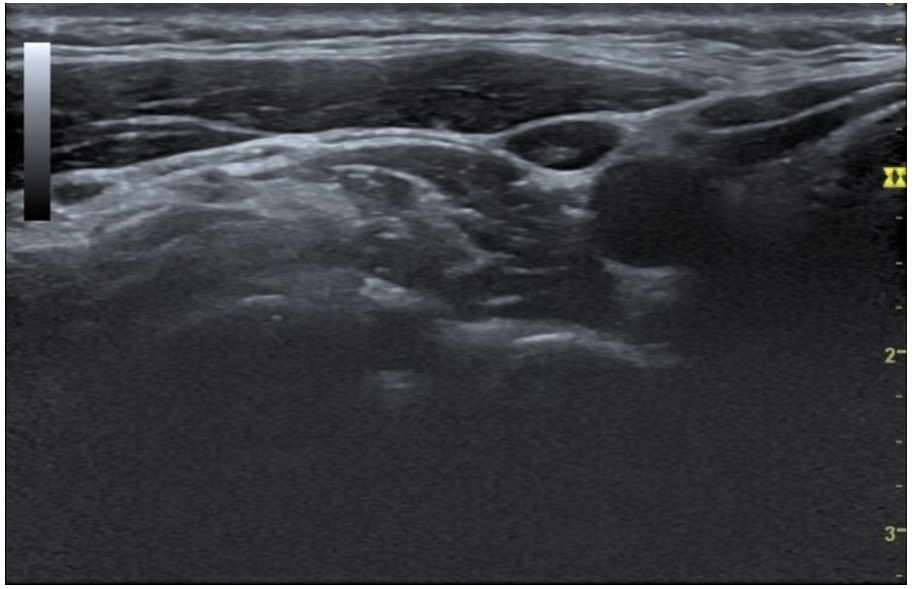


# Fetal ultrasound classification

| Area | Anatomies | |
|---|---|---|
| Head | Brain (cb.) | Brain view at the level of the cerebellum |
| | Brain (tv.) | Brain view at posterior horn of the ventricle |
| Facial Features | Lips | Coronal view of lips and nasal tip |
| Heart | 4CH | Four chamber view |
| | 3VV | Three vessel view |
| | RVOT | Right ventricular outflow tract |
| | LVOT | Left ventricular outflow tract |
| Abdominal content | Abdominal | Standard abdominal view at stomach level |
| | Kidneys | Axial kidneys view |
| Spine | Spine (sag.) | Sagittal spine view |
| | Spine (cor.) | Coronal spine view |
| Limb | Femur | Standard femur view |
| Others | Profile | Median facial profile |

Categories of scan planes required by NHS


a) Baumgartner, et al. SonoNet: Real-Time Detection and Localisation of Fetal Standard Scan Planes in Freehand Ultrasound. https://ieeexplore.ieee.org/abstract/document/7974824

b) Sarker, et al. COMFormer: Classification of Maternal–Fetal and Brain Anatomy Using a Residual Cross-Covariance Attention Guided Transformer in Ultrasound. https://ieeexplore.ieee.org/abstract/document/10239175

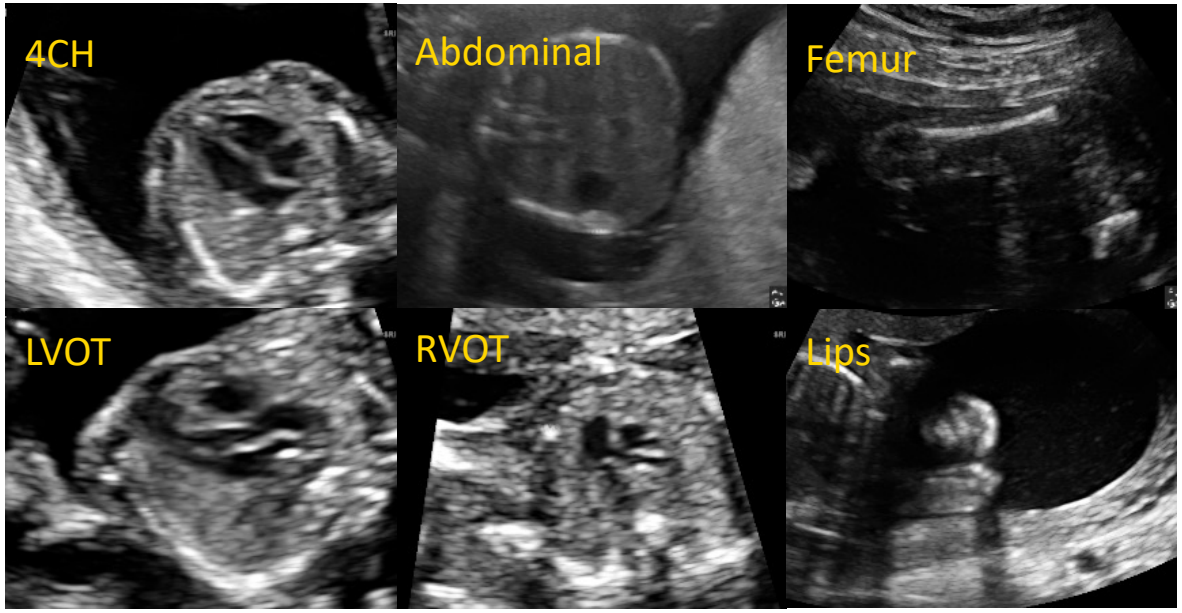
c) Burgos-Artizzu, et al. Evaluation of deep convolutional neural networks for automatic classification of common maternal fetal ultrasound planes. https://www.nature.com/articles/s41598-020-67076-5

# Domain shift in ultrasound imaging

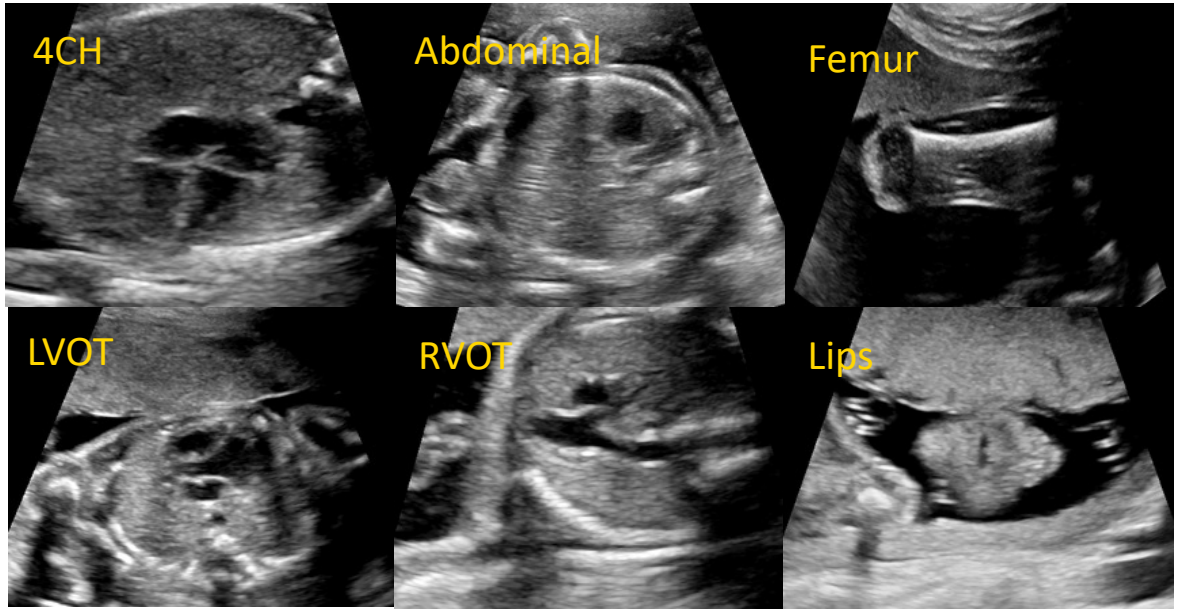
Different data distribution
with artifacts versus without artefacts

Different acquisition device

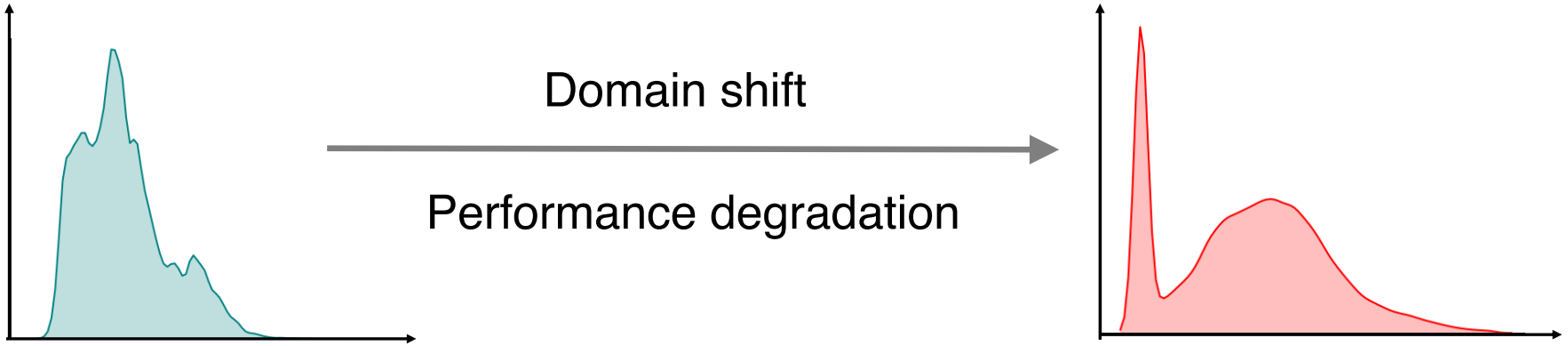
# Cross-device fetal ultrasound classification



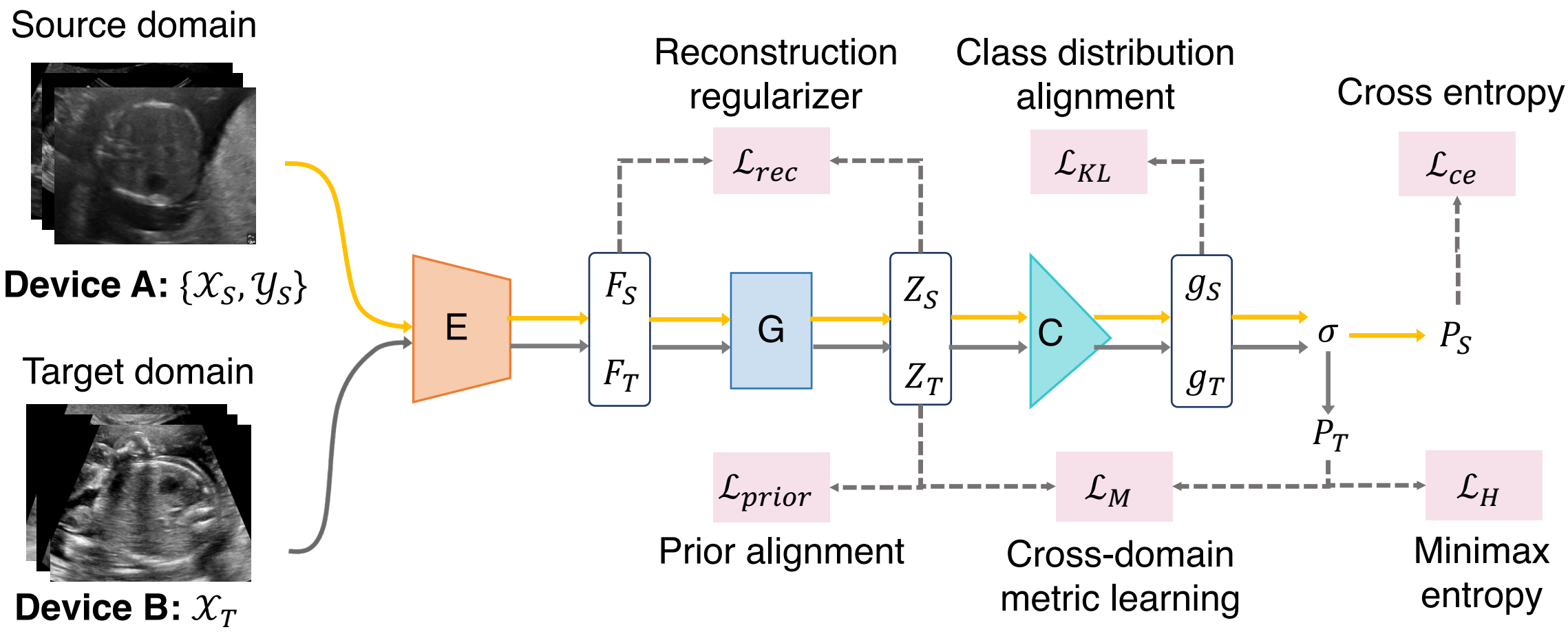

Device A: GE Voluson E8




Device B: Philips EPIQV7 G



# Cross-device fetal ultrasound classification (model training)




Statistic Distribution

E Encoder

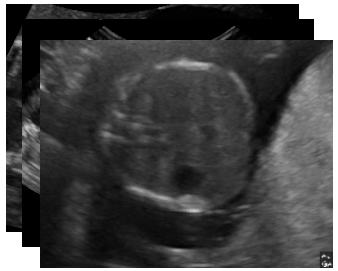
G Gaussian embedding

C Classifier

$\sigma$ Softmax

# Cross-device fetal ultrasound classification (model test)

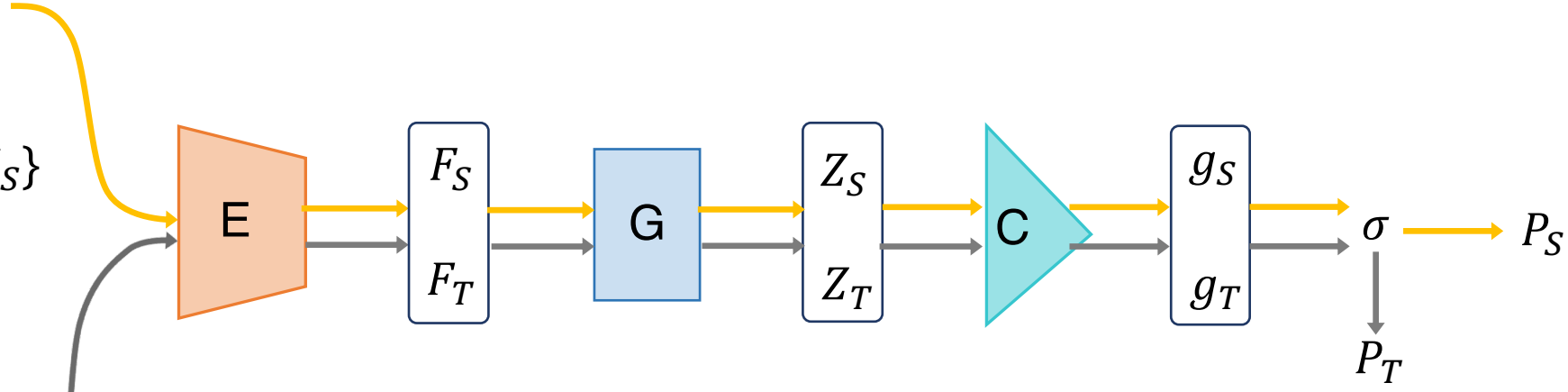
Source domain



**Device A:** $\{\mathcal{X}_S, \mathcal{Y}_S\}$

Target domain

**Device B:** $\mathcal{X}_T$




E Encoder

G Gaussian embedding

C Classifier

$\sigma$ Softmax

# Results

| Method | Source domain: Device A | | | Target domain: Device B | | |
|---|---|---|---|---|---|---|
| | F1-score | Recall | Precision | F1-score | Recall | Precision |
| Source only | 0.8782 | 0.8800 | 0.8786 | 0.2455 | 0.3400 | 0.3070 |
| ADDA | 0.8841 | 0.8850 | 0.8860 | 0.1377 | 0.2050 | 0.1623 |
| DANN | 0.8321 | 0.8350 | 0.8564 | 0.3390 | 0.3650 | 0.3756 |
| MME | 0.8876 | 0.8900 | 0.8914 | 0.4398 | 0.5133 | 0.4565 |
| Ours | 0.8990 | 0.9000 | 0.9027 | 0.7713 | 0.7717 | 0.7874 |

$$F1 = \frac{TP}{TP + \frac{1}{2}(FP + FN)}$$

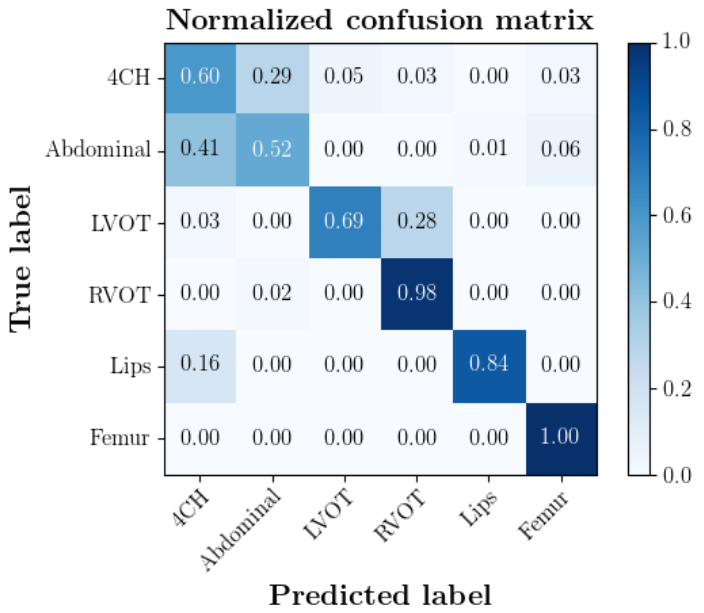
$$Recall = \frac{TP}{TP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

TP: True positives

FP: False positives

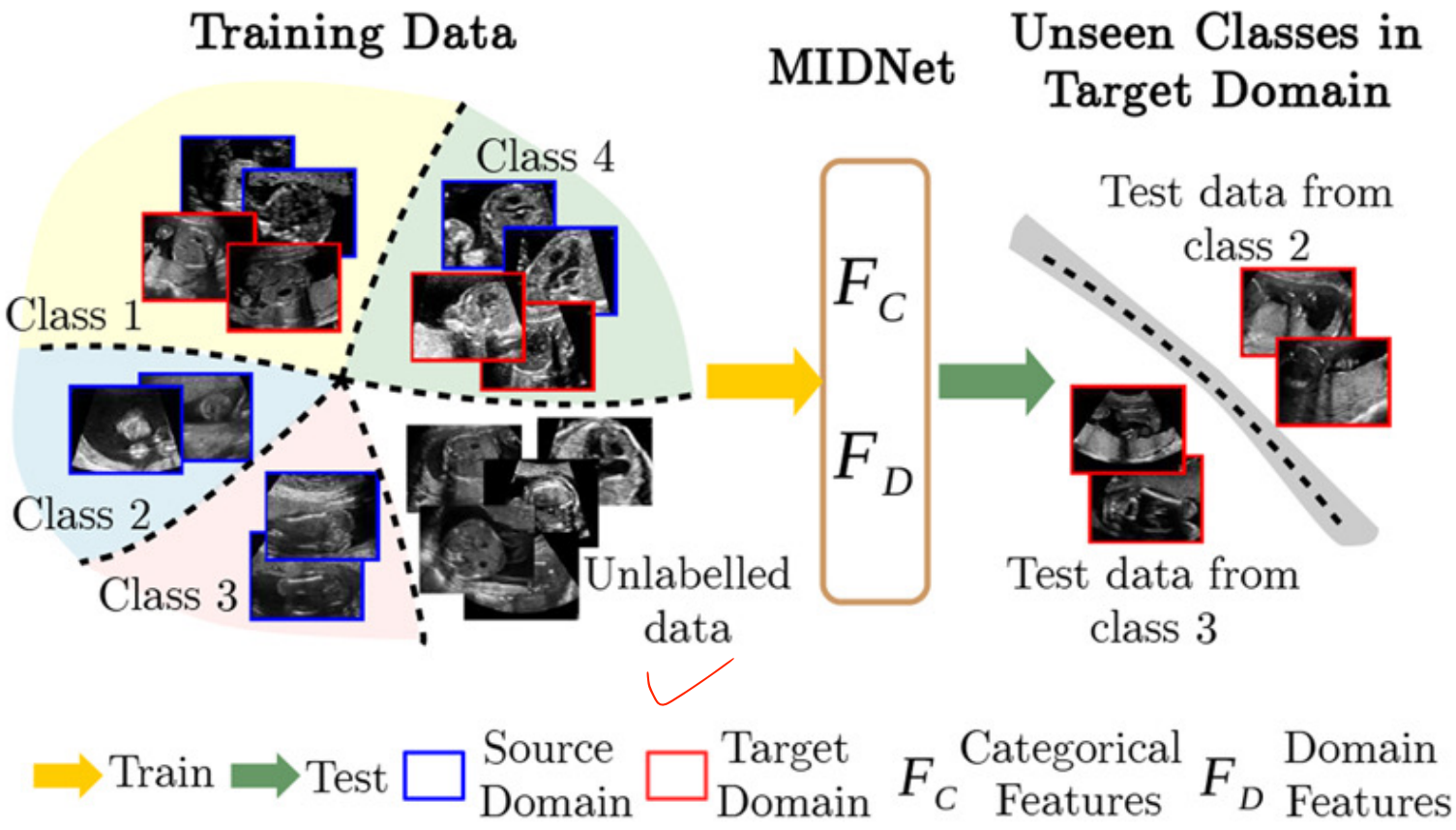
FN: False negatives



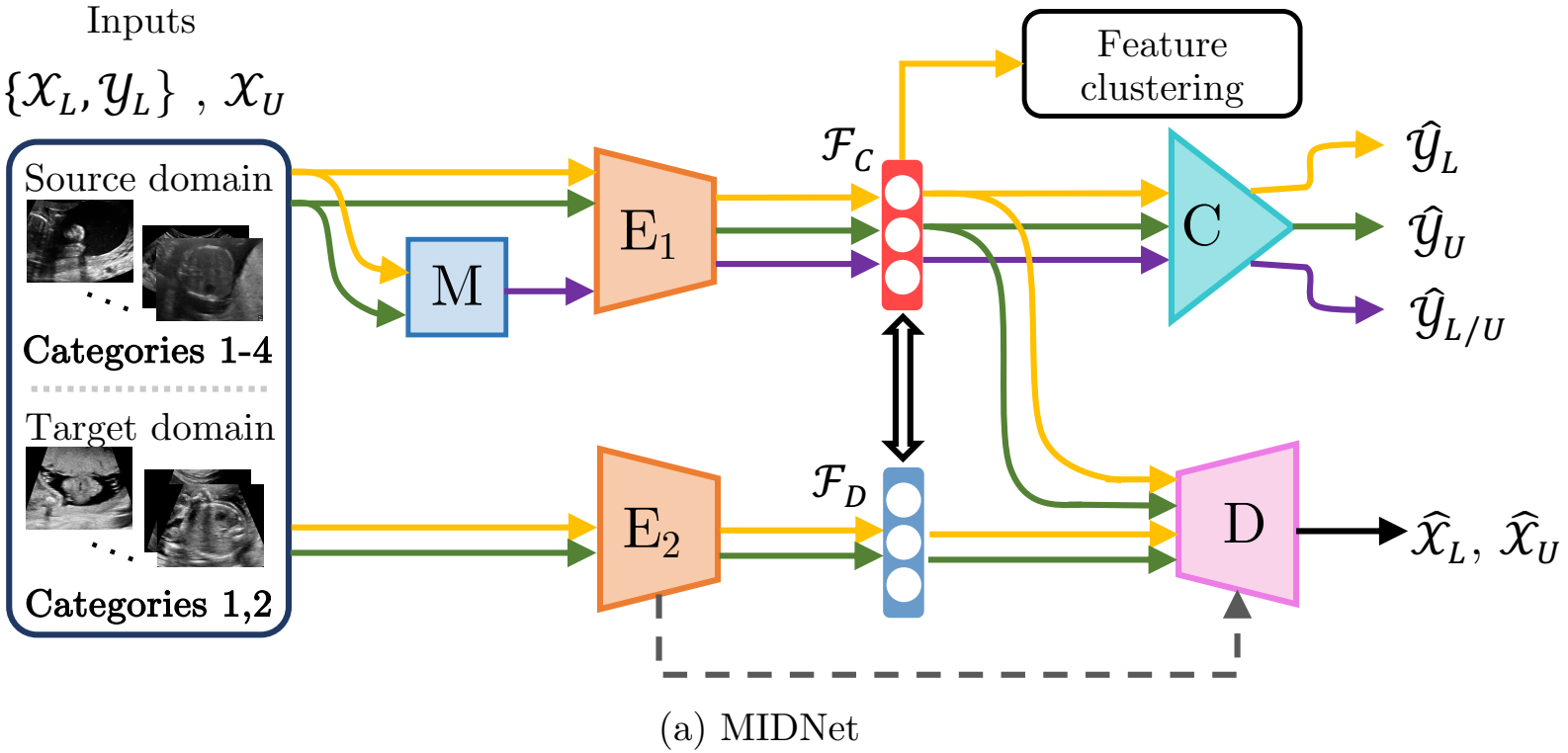
# One step further

## How about different categories in different domains?

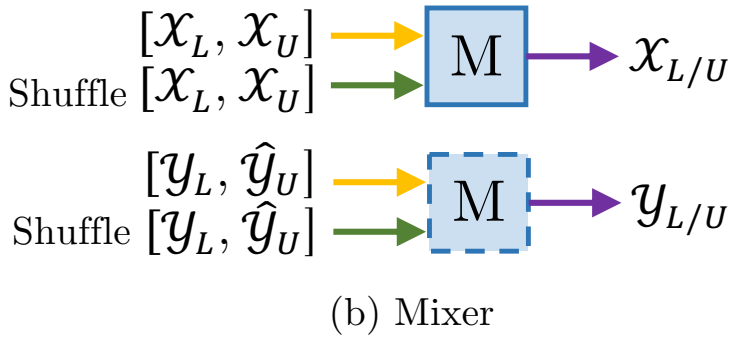
Semi-supervised



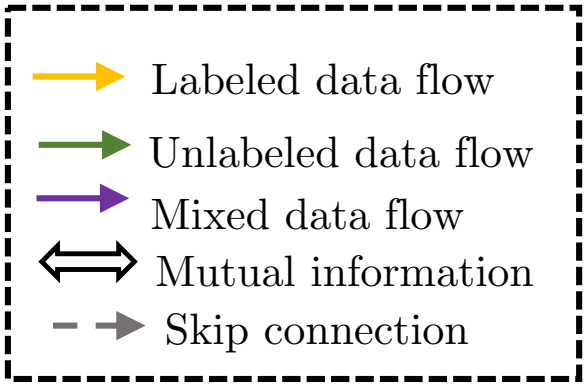
# Model training

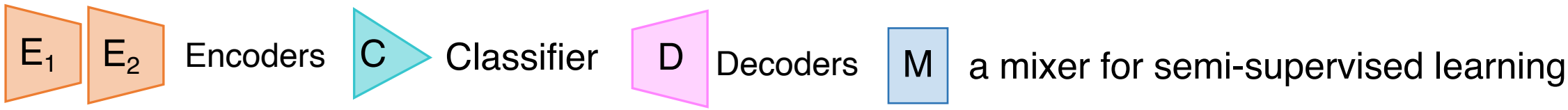



(a) MIDNet




(b) Mixer



# Results

| Methods | $T^{New}_{Target}$ | | |
|---|---|---|---|
| | F1-score | Recall | Precision |
| Source only | 0.6742 | 0.7050 | 0.6899 |
| VGG [84] | 0.7039 | 0.7250 | 0.7011 |
| Res-VGG [84, 10] | 0.6880 | 0.6300 | 0.8728 |
| Two-step-fair [23] | 0.7491 | 0.7400 | 0.7644 |
| Two-step-Unfair [23] | 0.6069 | 0.6150 | 0.6013 |
| Multi-task [254] | 0.7522 | 0.7800 | 0.7955 |
| DANN [19] | 0.5611 | 0.5050 | 0.7784 |
| MME [25] | 0.4293 | 0.3600 | 0.9595 |
| MIDNet | **0.8383** | **0.8600** | 0.8497 |