TWO-VIEW LEFT VENTRICULAR SEGMENTATION AND EJECTION FRACTION ESTIMATION IN 2D ECHOCARDIOGRAMS

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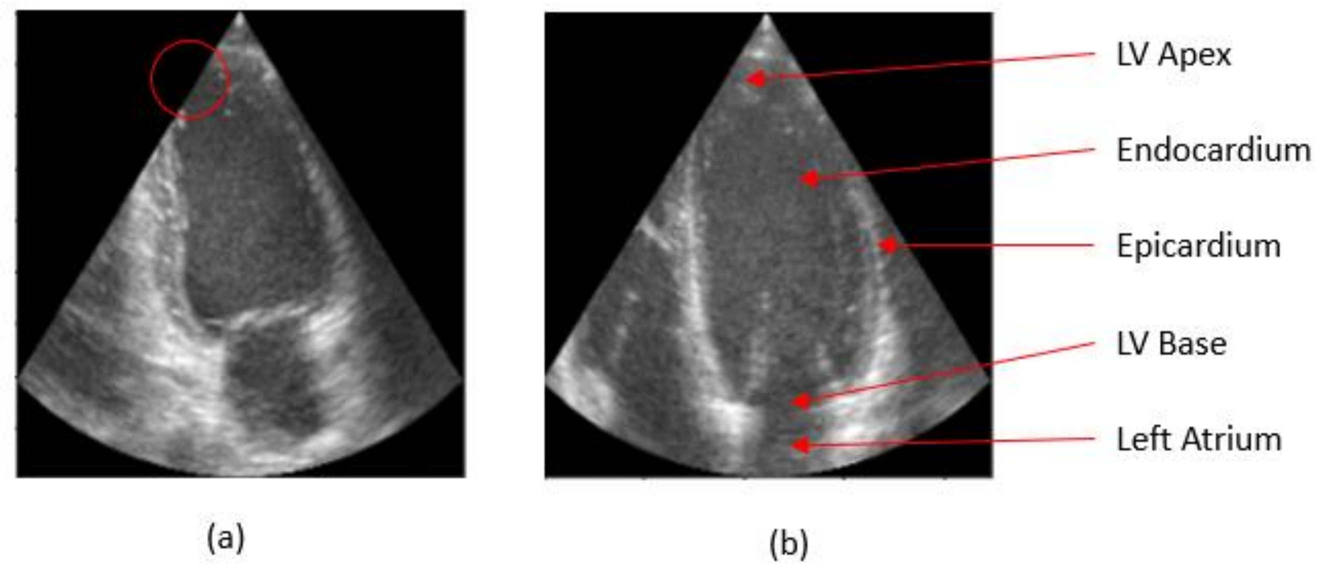
Challenges in Echocardiography

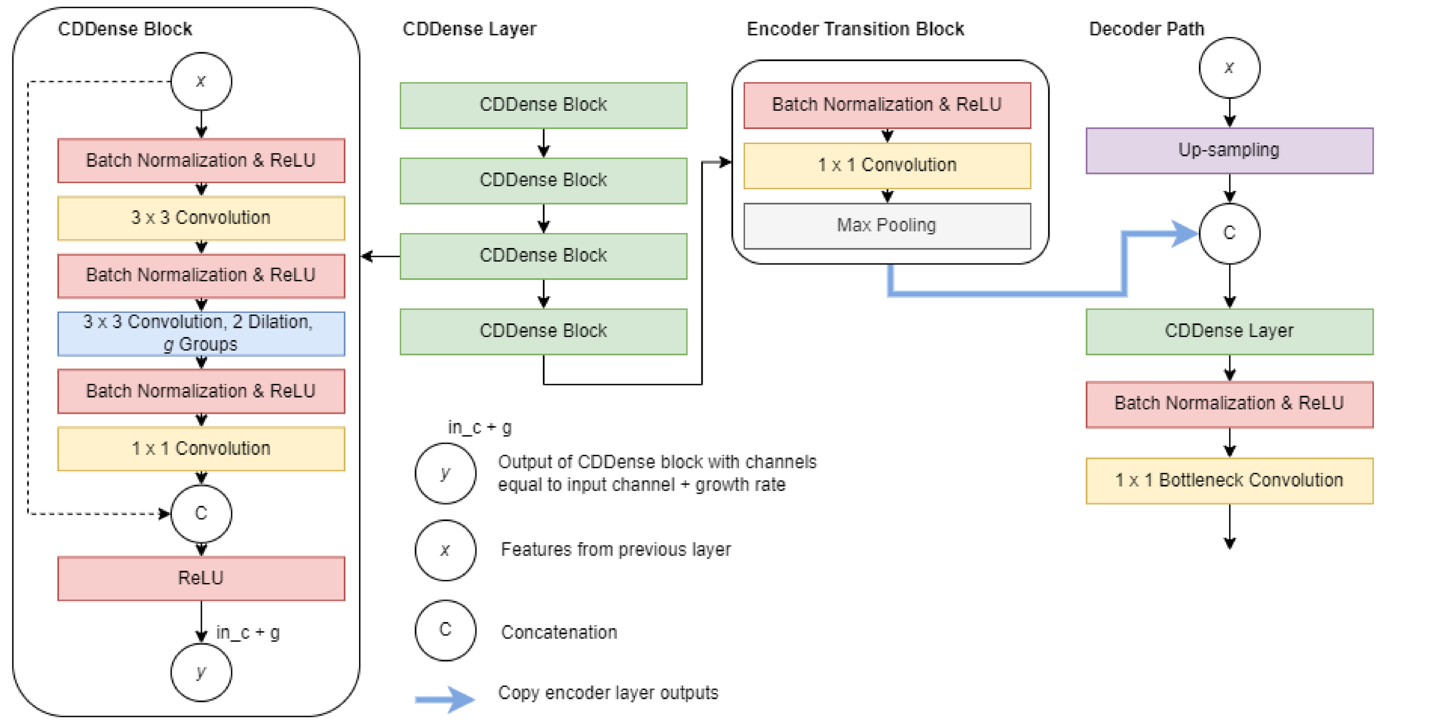


- Current methods for analysis are labor-intensive, time-consuming, and require high-level of skills.
- Frames are often low-quality and low-contrast.
- Estimation of ejection fraction (EF) suffers from high inter-observer variability.

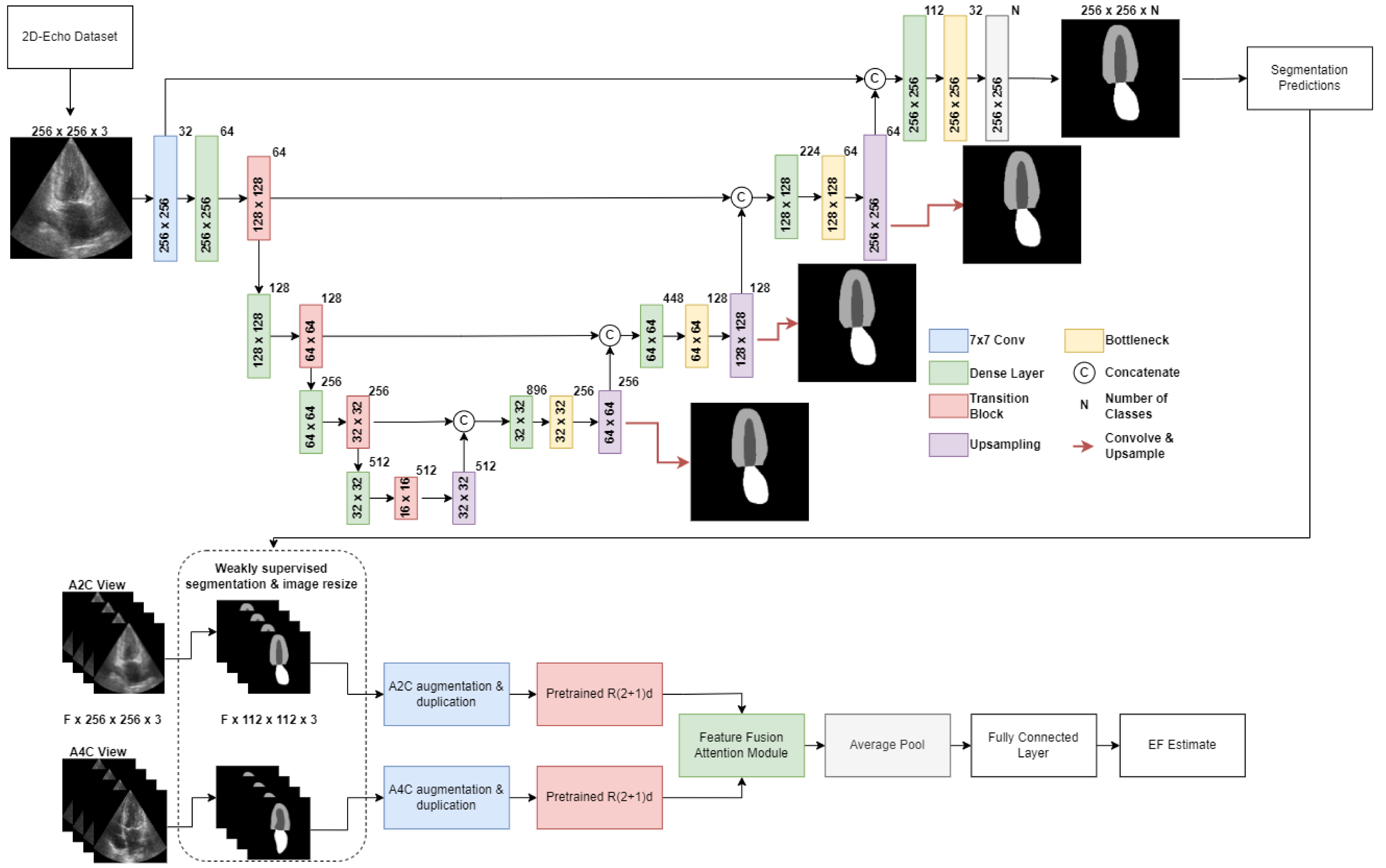
Contributions

- Developed a fast and accurate segmentation model.
- Developed a multi-view EF estimation model.
- Evaluated that segmentation is necessary for EF estimation in noisy and low-quality frames.
- First full-deep learning approach to achieve state-of-the-art (SOTA) performance against Modified Simpson's Rule.

Schematic of Segmentation Model



Proposed CDDenseUnet (top) and TC-R(2+1)d (bottom)



Contour Examples

Sample prediction contours (blue) against ground-truth (red):

- Results show that our segmentation network accurately predicts contours even for sub-optimal frames

Segmentation Results (Endocardium)

Model	ED ↑ Dice Score	ED ↓ MAD (mm)	ED ↓ HD (mm)	ES ↑ Dice Score	ES ↓ MAD (mm)	ES ↓ HD (mm)	Inference Time (s)
SRF [3]	0.895 ± 0.074	2.8 ± 3.6	11.2 ± 10.2	0.848 ± 0.137	3.6 ± 7.8	11.6 ± 13.6	-
BEASM-fully [3]	0.879 ± 0.065	3.3 ± 1.8	9.2 ± 4.9	0.826 ± 0.137	3.8 ± 2.1	9.9 ± 5.1	-
BEASM-semi [3]	0.920 ± 0.039	2.2 ± 1.2	6.0 ± 2.4	0.861 ± 0.070	3.1 ± 1.6	7.7 ± 3.2	-
Unet1 [3]	0.934 ± 0.042	1.7 ± 1.0	5.5 ± 2.9	0.905 ± 0.063	1.8 ± 1.3	5.7 ± 3.7	0.090[a]
Unet2 [3]	0.939 ± 0.043	1.6 ± 1.3	5.3 ± 3.6	0.916 ± 0.061	1.6 ± 1.6	5.5 ± 3.8	0.140[a]
ACNN [3]	0.932 ± 0.034	1.7 ± 0.9	5.8 ± 3.1	0.903 ± 0.059	1.9 ± 1.1	6.0 ± 3.9	-
SHG [3]	0.934 ± 0.034	1.7 ± 0.9	5.6 ± 2.8	0.906 ± 0.057	1.8 ± 1.1	5.8 ± 3.8	-
Unet++ [3]	0.927 ± 0.046	1.8 ± 1.1	6.5 ± 3.9	0.904 ± 0.060	1.8 ± 1.0	6.3 ± 4.2	-
ResDUnet [1]	0.951 ± 0.030	1.4 ± 1.2	4.5 ± 1.2	-	-	-	-
PLANet [4]	0.951 ± 0.018	1.3 ± 0.5	**4.2 ± 1.4**	0.931 ± 0.032	1.4 ± 0.6	**4.3 ± 1.5**	0.016[b]
CDDenseUnet (ours)	**0.952 ± 0.003**	**1.2 ± 0.1**	4.4 ± 0.3	**0.931 ± 0.003**	**1.2 ± 0.1**	4.4 ± 0.4	**0.015**[c]

**Results from the experiments of Leclerc* et al. *[3]*
[a]Tesla M60, [b]Titan V, [c]Tesla P100

EF Estimation Results

Technique	Observer/Model	↑ Correlation	bias ± σ	↓ MAE (%)	↓ RMSE (%)	↑ R^2
Cardiologists	O1a vs O2 (*inter*-observer) [3]	0.801	-9.1 ± 8.1	10.0	-	-
	O1a vs O3 (*inter*-observer) [3]	0.646	-12.6 ± 10.0	13.4	-	-
	O2 vs O3 (*inter*-observer) [3]	0.569	3.5 ± 11.0	8.5	-	-
	O1a vs O1b (*intra*-observer) [3]	0.896	-2.3 ± 5.7	**0.9**	-	-
Non-deep learning segmentation + Simpson's Rule	SRF [3]	0.465	-11.5 ± 15.4	12.8	-	-
	BEASM-fully [3]	0.731	-9.8 ± 8.3	10.7	-	-
	BEASM-semi [3]	0.790	-9.4 ± 7.2	10.0	-	-
Deep learning segmentation + Simpson's Rule	Unet1 [3]	0.791	-0.5 ± 7.7	5.6	-	-
	Unet2 [3]	0.823	-1.0 ± 7.1	5.3	-	-
	ACNN [3]	0.799	-0.8 ± 7.5	5.7	-	-
	SHG [3]	0.770	-1.4 ± 7.8	5.7	-	-
	Unet++ [3]	0.789	-1.8 ± 7.7	5.6	-	-
	Automated EF [6]	-	1.8 ± 8.9	6.7	-	-
	PLANet [4]	0.882	0.6 ± 5.8	-	-	-
Actual frames + action recognition	R(2+1)d (A4C-only)[a]	0.705	-0.3 ± 8.4	6.7	8.5	0.428
	Dual-View EF [2]	0.381	-	8.0	10.0	0.201
	TC-R(2+1)d (ours) - concatenate[b]	0.777	-0.5 ± 7.4	5.9	7.6	0.535
Ours	TC-R(2+1)d (ours)	**0.903**	-0.8 ± 4.9	**3.8**	**5.0**	**0.792**

[a]Similar to EchoNet-Dynamic [5].
[b]Similar to Dual-View EF [2].

Conclusion

- Proposed a framework designed to tackle challenges in echocardiography.
- CDDenseUnet and TC-R(2+1)d outperforms current SOTA methods while achieving faster inference time reaching dice and MAE scores of 95.2% and 3.8%, respectively.
- The use of two-view and fully-segmented echocardiograms yielded superior results.

REFERENCES:

[1] Alyaa Amer, Xujiong Ye, and Faraz Janan. Resdunet: A deep learning-based left ventricle segmentation method for echocardiography. IEEE Access, 9:159755–159763, 2021.
[2] Delaram Behnami, Zhibin Liao, Hany Younan Azer Girgis, Christina Luong, Robert Rohling, Kenneth Gin, Teresa Tsang, and Purang Abolmaesumi. Dual-View Joint Estimation of Left Ventricular Ejection Fraction with Uncertainty Modelling in Echocardiograms, pages 696–704. 10 2019.
[3] Sarah Leclerc, Erik Smistad, Joao Pedrosa, Andreas Ostvik, Frederic Cervenansky, Florian Espinosa, Torvald Espeland, Erik Berg, Pierre-Marc Jodoin, T. Grenier, Carole Lartizien, Jan Drhooge, Lasse Løvstakken, and Olivier Bernard. Deep learning for segmentation using an open large-scale dataset in 2d echocardiography. IEEE Transactions on Medical Imaging, PP:1–1, 02 2019.
[4] Fei Liu, Kun Wang, Dan Liu, Xin Yang, and Jie Tian. Deep pyramid local attention neural network for cardiac structure segmentation in two-dimensional echocardiography. Medical Image Analysis, 67:101873, 01 2021.
[5] David Ouyang, Bryan He, Amirata Ghorbani, Neal Yuan, Joseph Ebinger, Curtis Langlotz, Paul Heidenreich, Robert Harrington, David Liang, Euan Ashley, and James Zou. Video-based ai for beat-to-beat assessment of cardiac function. Nature, 580, 04 2020.
[6] Erik Smistad, Olivier Bernard, Bjørnar Grenne, Lasse Løvstakken, Andreas Ostvik, Ivar Salte, Daniela Melichova, Thuy Mi Nguyen, Kristina Haugaa, Harald Brunvand, Thor Edvardsen, and Sarah Leclerc. Real-time automatic ejection fraction and foreshortening detection using deep learning. IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control, PP:1–1, 03 2020.