ADVANCED COMPUTING USER DAY

1D-CNNs for arterial blood pressure-based cardiac output estimation

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Hemodynamic instability in the ICU

~1 in 5 patients in the ICU become unstable[1]

Data overload and limited time available

"Develop AI-based decision support systems to prevent hemodynamic deterioration in ICU patients"

[1] Rahman et al., *Critical Care* 25, 1-9 (2021)

Predict hemodynamic deterioration

- Create a time window for proactive intervention

Extract and process the most important information

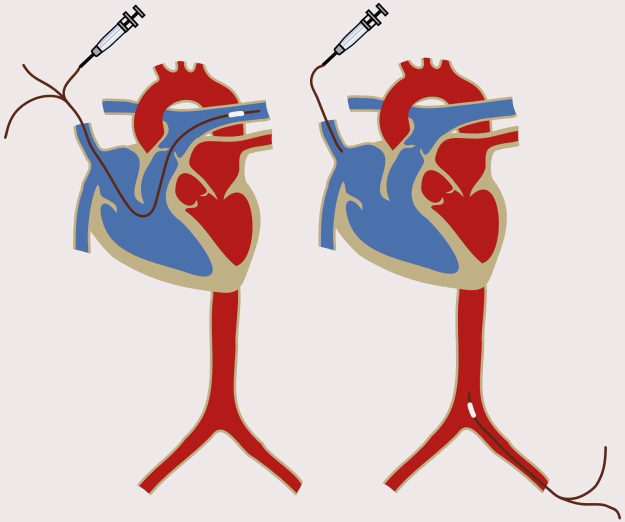
- Counter information overload

Derive Cardiac Output (CO)

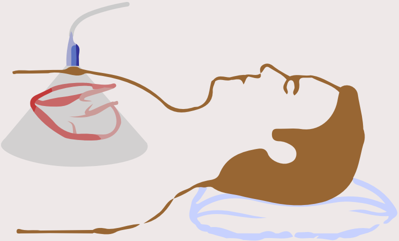
- Use underutilized patient monitor waveforms, arterial blood pressure (ABP)

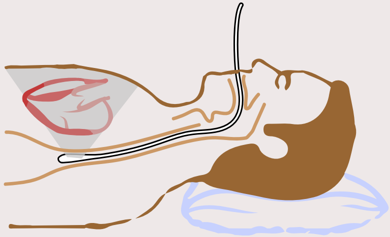
Cardiac Output: Limitations current methods

1. Thermodilution



2. Ultrasound

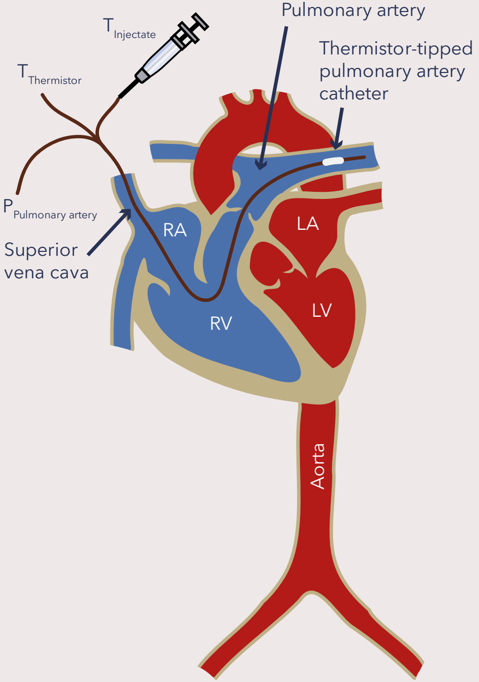




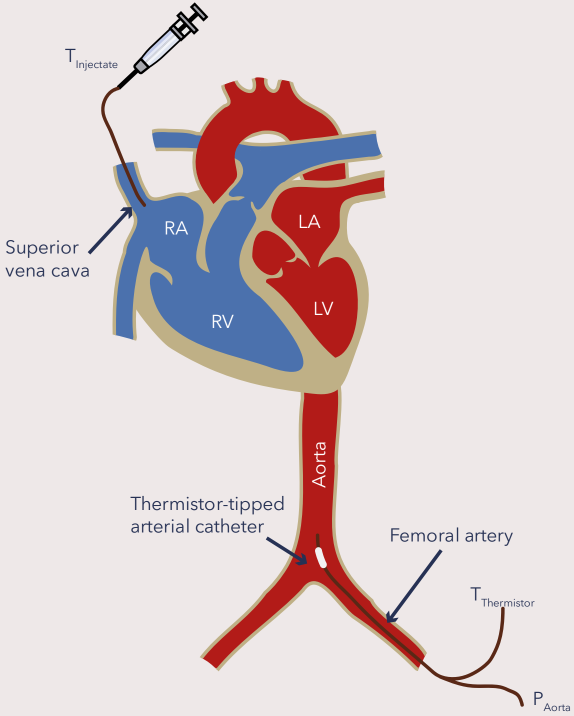
3. APCO devices

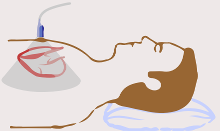
Cardiac Output: Thermodilution

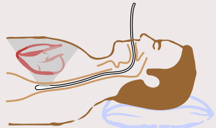
A. Pulmonary artery thermodilution



B. Transpulmonary thermodilution

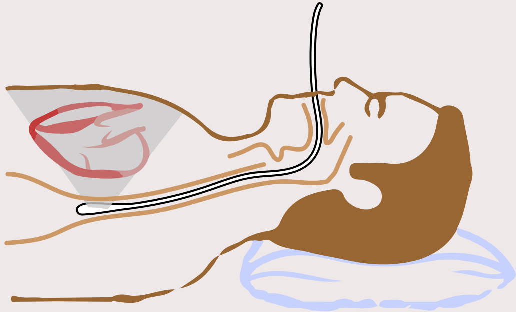




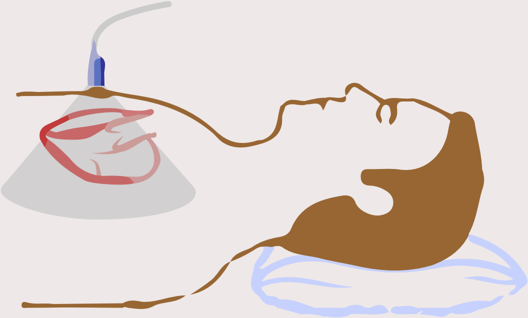


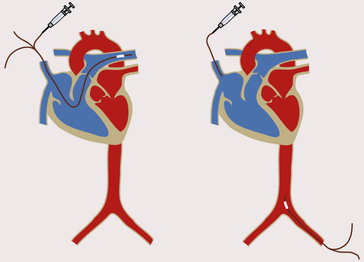
Cardiac Output: Ultrasound

A. Transesophageal echo



B. Transthoracic echo

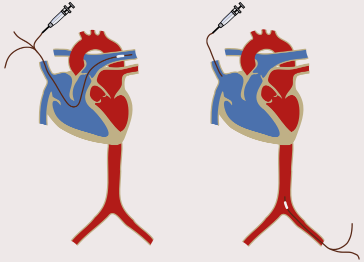


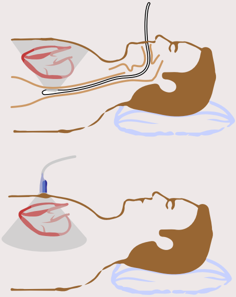


Cardiac Output: APCO devices

A. Edwards FloTrac™ system

B. Edwards ClearSight™ system

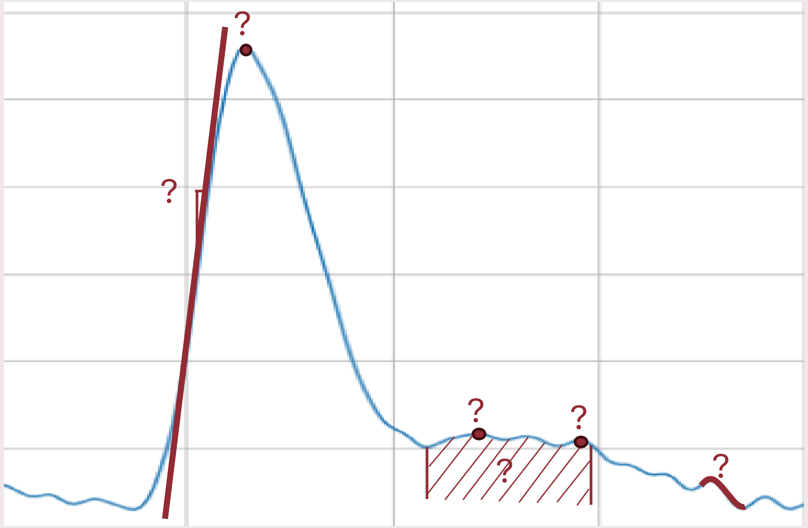




Cardiac Output: Machine learning approach

Complex signal with ‘hidden’ features that cannot be captured with simple algorithms

Deep learning can efficiently learn representations by encoding data into ‘self-learned’ features



Original Paper

Development and Validation of an Arterial Pressure-Based Cardiac Output Algorithm Using a Convolutional Neural Network: Retrospective Study Based on Prospective Regi

Hyun-Lim Yang[1,2], PhD; Chul
Shim[5], BSc;
ublic of Korea
of Korea
University College of Medicine, Seoul, Republic of Korea
of Science and Technology, Daejeon, Republic of Korea
Communication Engineering, Daegu Gyeongbuk Institute of Science & Technology (DGIST), Daegu, Republic of

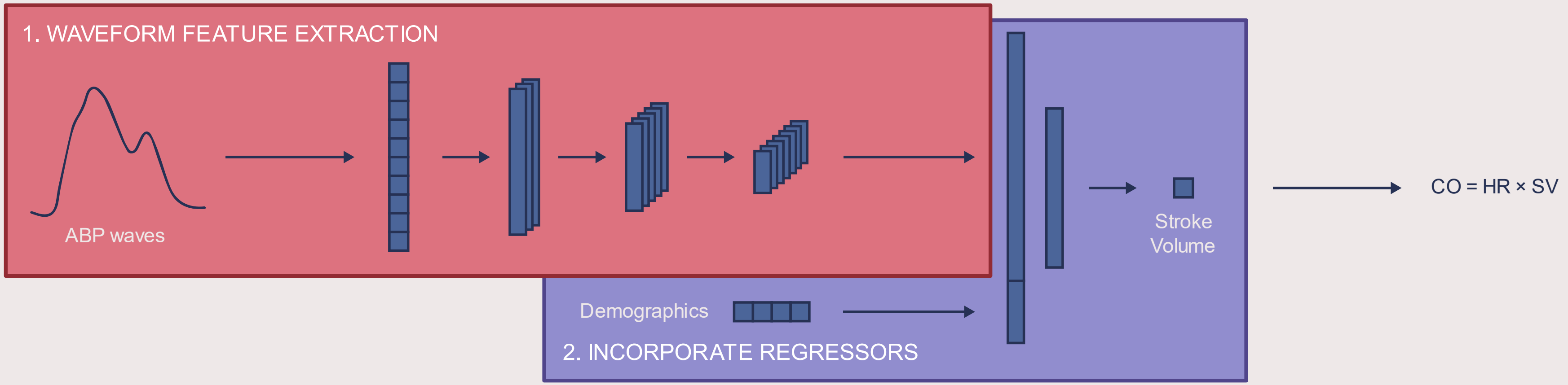
1. "Better performance than FloTrac (Edwards) device"
2. "Absolute error of 14.5 mL compared to golden standard PAC"
3. "Absolute percentage error of 20.5 percent"

[2] Yang et al., *JMIR Medical Informatics* 9(8), e24762 (2021)

APCONet

Principle: 1D-CNNs extract latent CO features

20sec 100Hz ABP signal represented as a 1D ‘image’: $(2000 * 1 \text{ pixels})$



Data required:

- ABP waveforms, demographics (age, sex, height, weight)
- Stroke Volume measurements

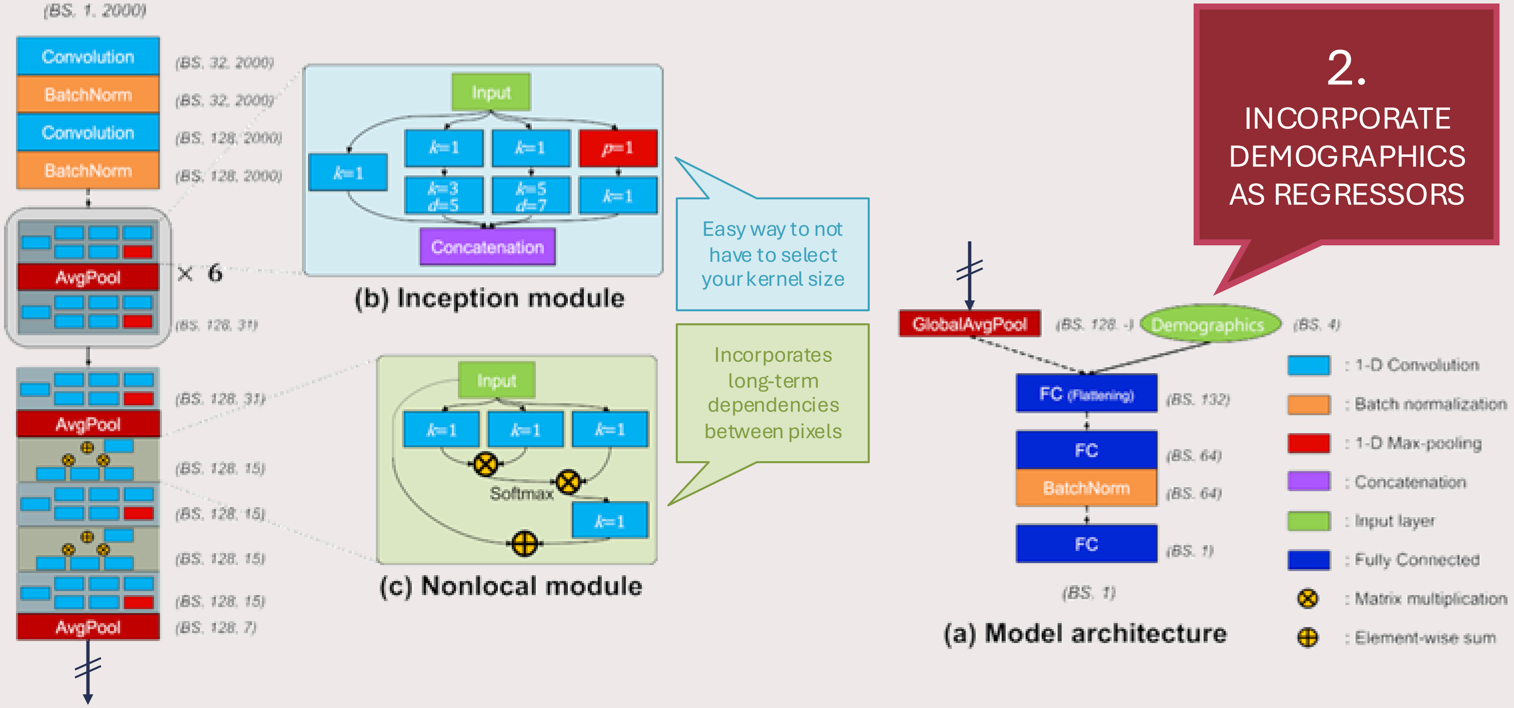
Sliding window approach samples ABP and SV every 2 seconds (continuous)

APCONet

Network structure: Two distinct parts

1.
WAVEFORM FEATURE EXTRACTION

2.
INCORPORATE DEMOGRAPHICS AS REGRESSORS



Easy way to not have to select your kernel size

Incorporates long-term dependencies between pixels

[2] Yang et al., *JMIR Medical Informatics* 9(8), e24762 (2021)

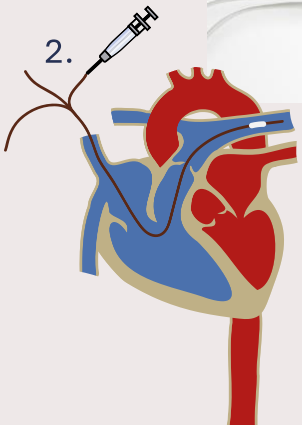
APCONet

Dataset: Two measurement modalities for *transfer learning*

- Operating room of Seoul National University Hospital, South Korea
  - Like our ICU patients, patients are highly unstable! ✓

1. Pretraining on SV values from ***FloTrac***
   - VitalDB dataset: https://vitaldb.net/dataset/
   - 5.8M samples from 900 patients
2. Finetuning on SV values from ***PAC catheter***
   - Dataset from GitHub[2]
   - 368k samples from 400 patients

2.

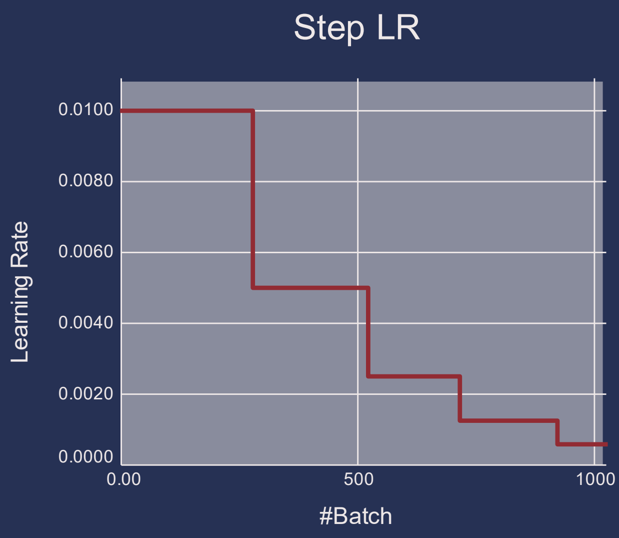


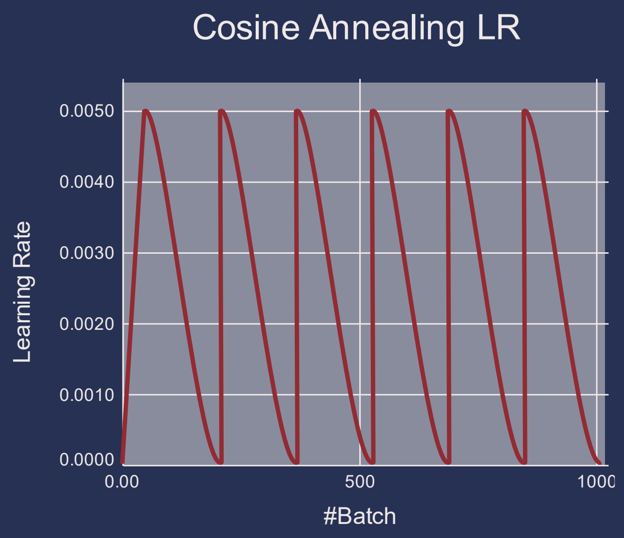
[2] Yang et al., *JMIR Medical Informatics* 9(8), e24762 (2021)

Manual hyperparameter tuning

1. Weight decay: 0.5 ↓ 0.1

2. Learning rate decay scheme:





Finetuned Deep Learning (DL) model predictions vs PAC data

Performance on test dataset

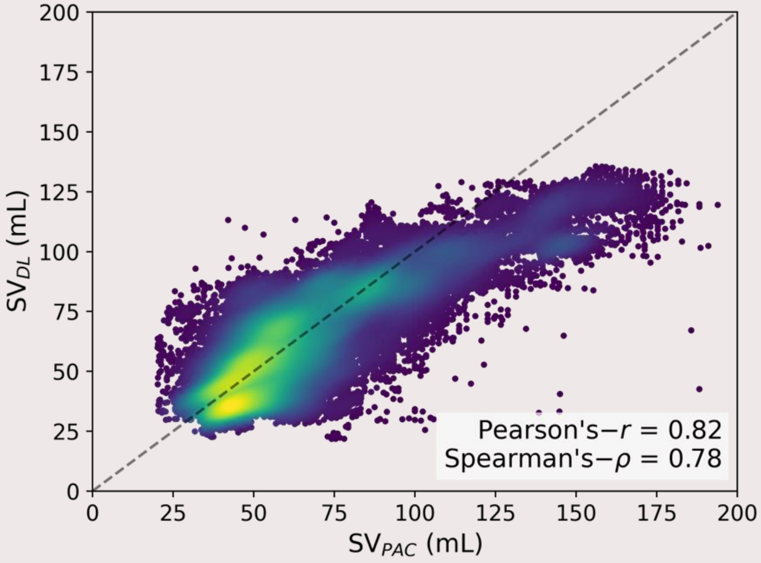
Measure	Yang et al. (reproduced)	New model
Error, mean (SD)	-4.2 (17.6)	**-2.7 (15.8)**
Absolute error, mean (SD)	13.9 (11.6)	**11.7 (11.0)**
Percentage error, mean (SD)	**-0.9** (27.7)	1.6 **(24.0)**
Absolute Percentage Error, mean (SD)	20.7 (18.4)	**17.1 (17.0)**

(97 patients, n=38155)

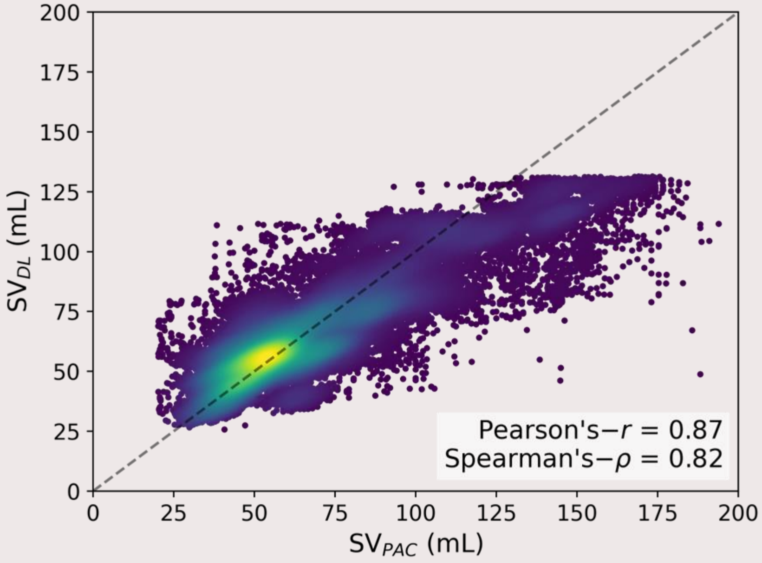
Finetuned Deep Learning (DL) model predictions vs PAC data

Scatterplots

Yang et. al. (reproduced)



New model

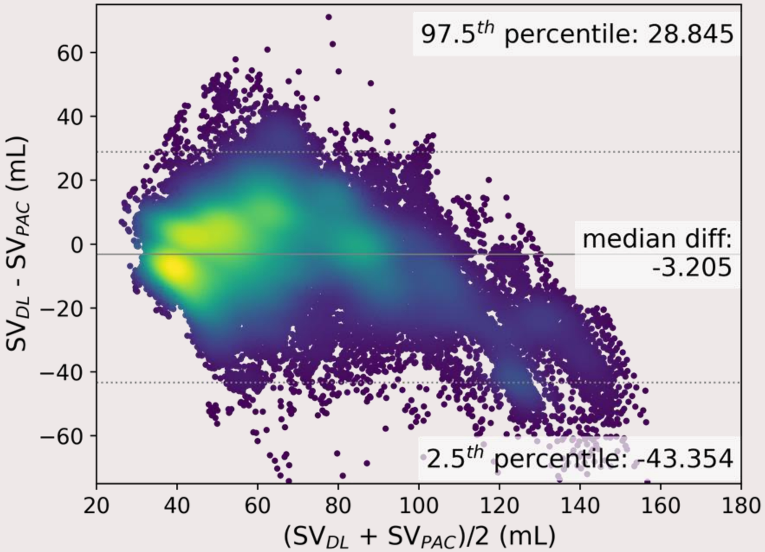


(97 patients, n=38155)

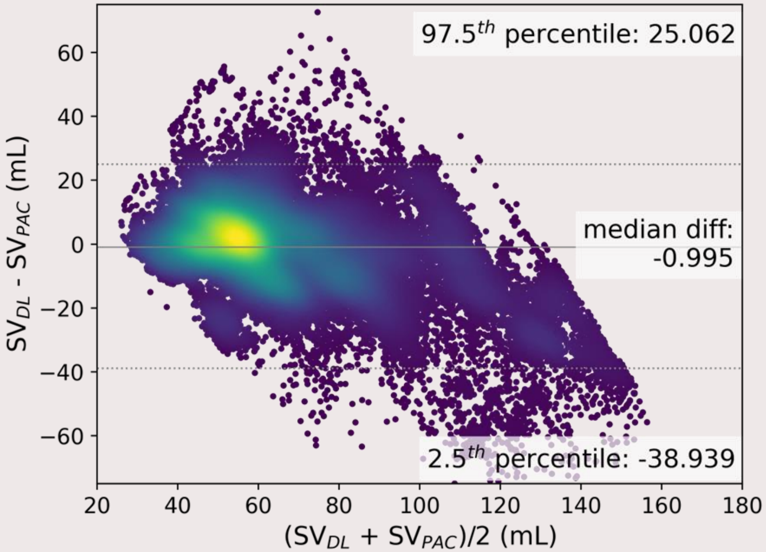
Finetuned Deep Learning (DL) model predictions vs PAC data

Bland Altman plots

Yang et. al. (reproduced)



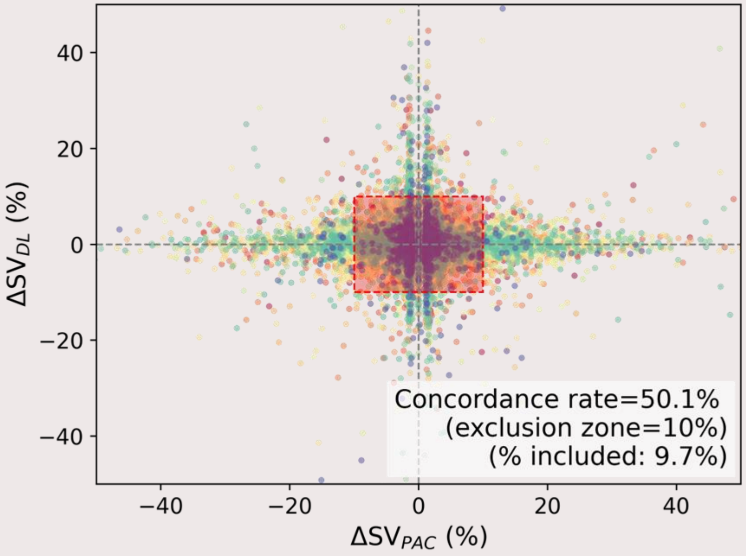
New model



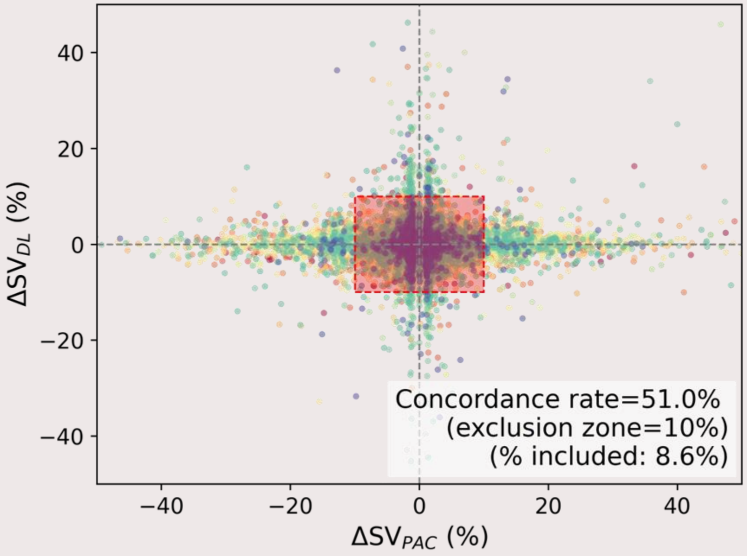
(97 patients, n=38155)

Finetuned model vs PAC data
Four-Quadrant plots

Yang et. al. (reproduced)



New model



Challenges with Deep Learning

Explainability in the clinic (black box)

End-to-end deep learning is computationally expensive

- Encode wave signals separate from prediction task

Next steps

Further model development

Try different network structures

- New encoder structures
- Add prior/domain knowledge by adding more regressors
  - e.g. waveform morphological features

Predict SV rate of change

- More clinically relevant than absolute values

Ensemble learning: Add more waveform signals as parallel networks

- CVP
- ECG
- etc.

Next steps

External validation

Validate or finetune models on:

- MIMIC-III database ICU data
    - Pulmonary artery thermodilution CO
- Local Catharina Hospital ICU data
    - Transpulmonary thermodilution CO
    - Transthoracic ultrasound CO

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Thank you!

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