Deep Learning Regression of Cardiac Phase on Real-Time MRI

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AiDA lab

Financial Disclosures

- **Albert Hsiao** has financial Interest/affiliation with the listed organizations:
  - Ownership/Founder, Major stock Share holder/Equity Intellectual Property Rights at Arterys, Inc (acquired by Tempus)
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Motivation

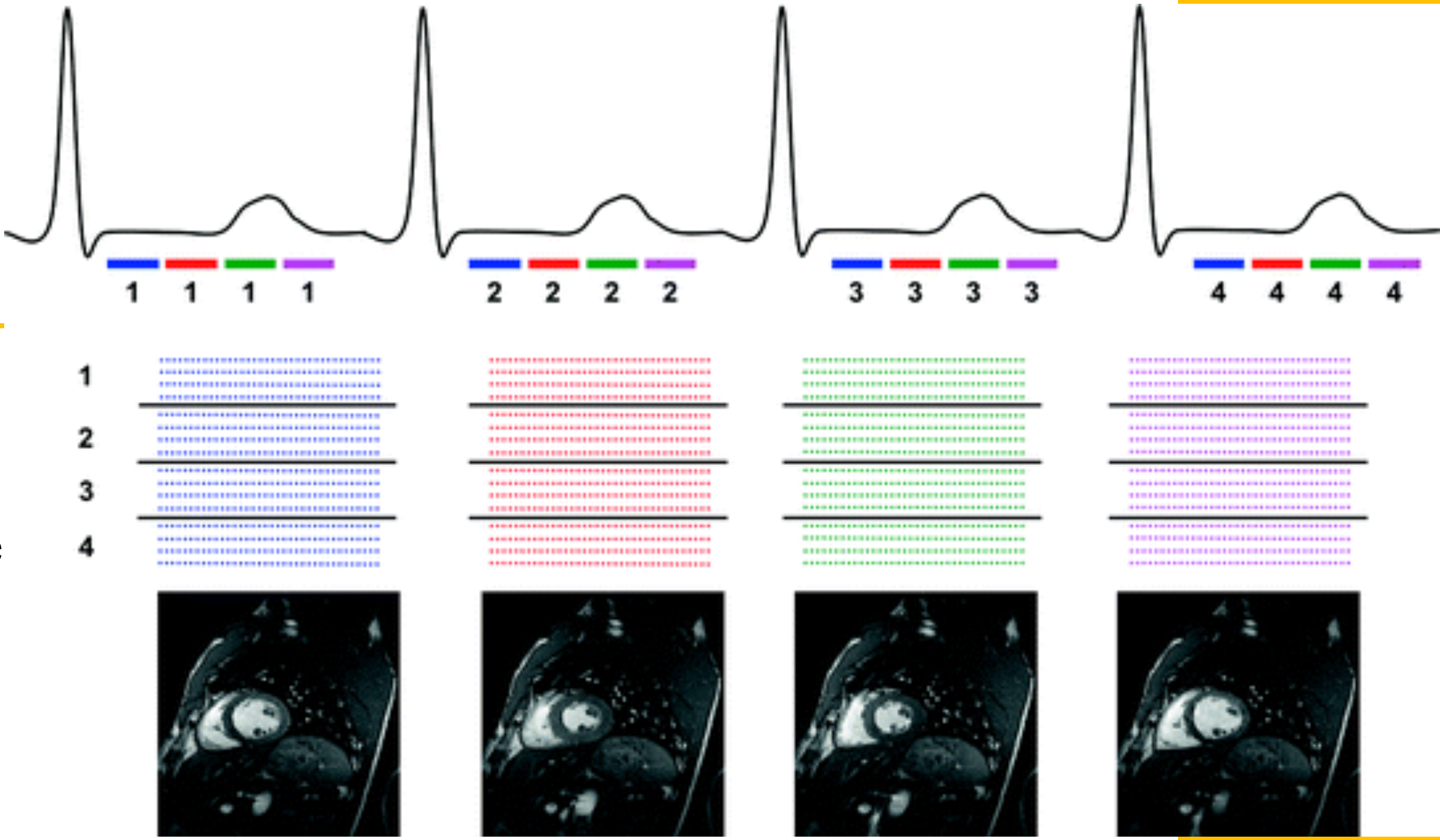


Figure from: [1] Muthurangu, Vivek, and Steven Dymarkowski. "Cardiac MRI physics." Clinical Cardiac MRI (2012): 1-30.

- **Cine steady-state free-precession (SSFP)** is the backbone of cardiovascular MRI and used for quantitative assessment of left ventricular structure and function.
- **Cine SSFP requires** electrocardiogram (ECG) recorded over multiple heartbeats with breath-holds.
- **ECG-gating** is used to concatenate images over multiple RR-intervals which obscures quantification of beat-to-beat variations and is vulnerable to artifacts.

Real-time (RT) SSFP, performed without ECG-gating or breath-holding, has the potential **to address** Cine SSFP **limitations** in arrhythmia.

RT SSFP for quantitative analysis of cardiac function is **not clinically-feasible**.

Cardiac phases must be identified from the RT SSFP images at the first place.

Applying analytical models developed for the standard Cine SSFP is not possible otherwise as they perform on individual R-R intervals depending on labeled cardiac phases.

Labor-intensive and time consuming

Cine SSFP **RT SSFP**

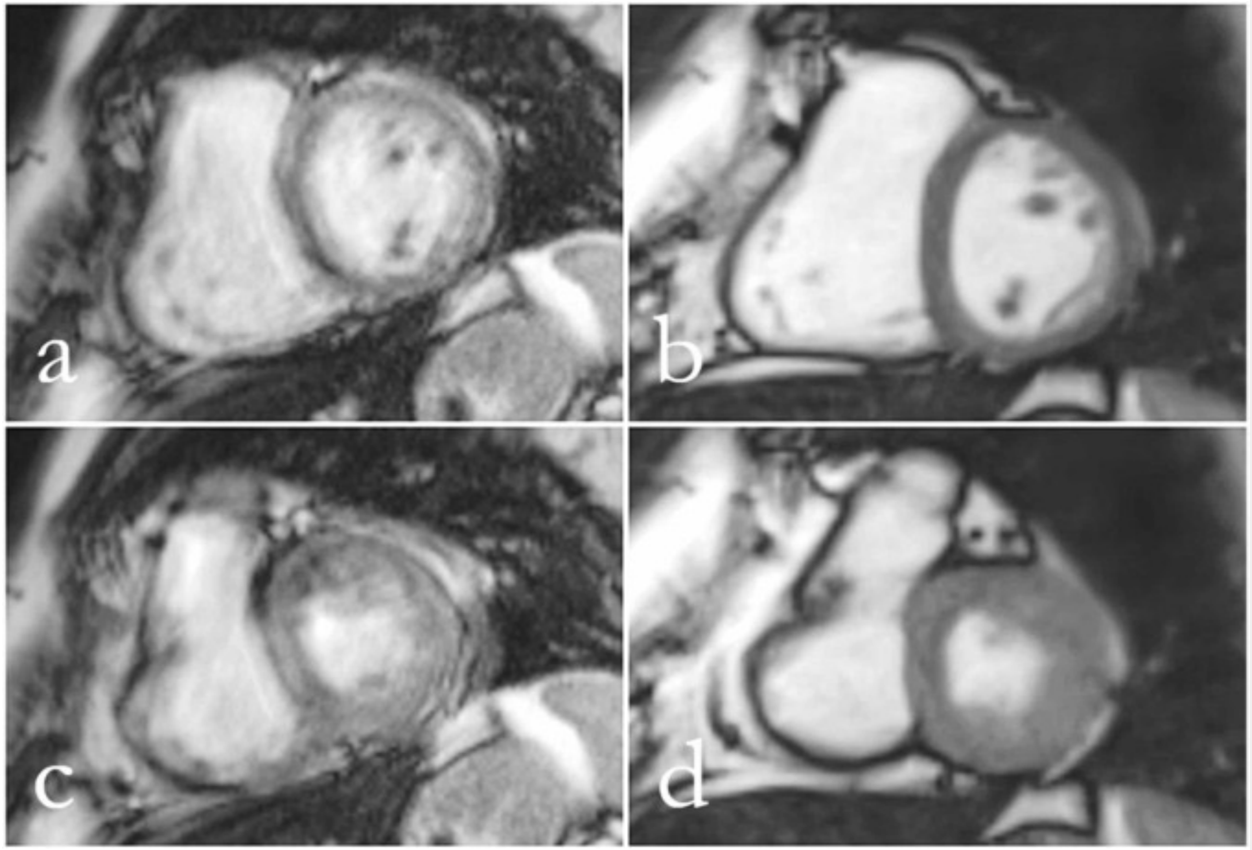
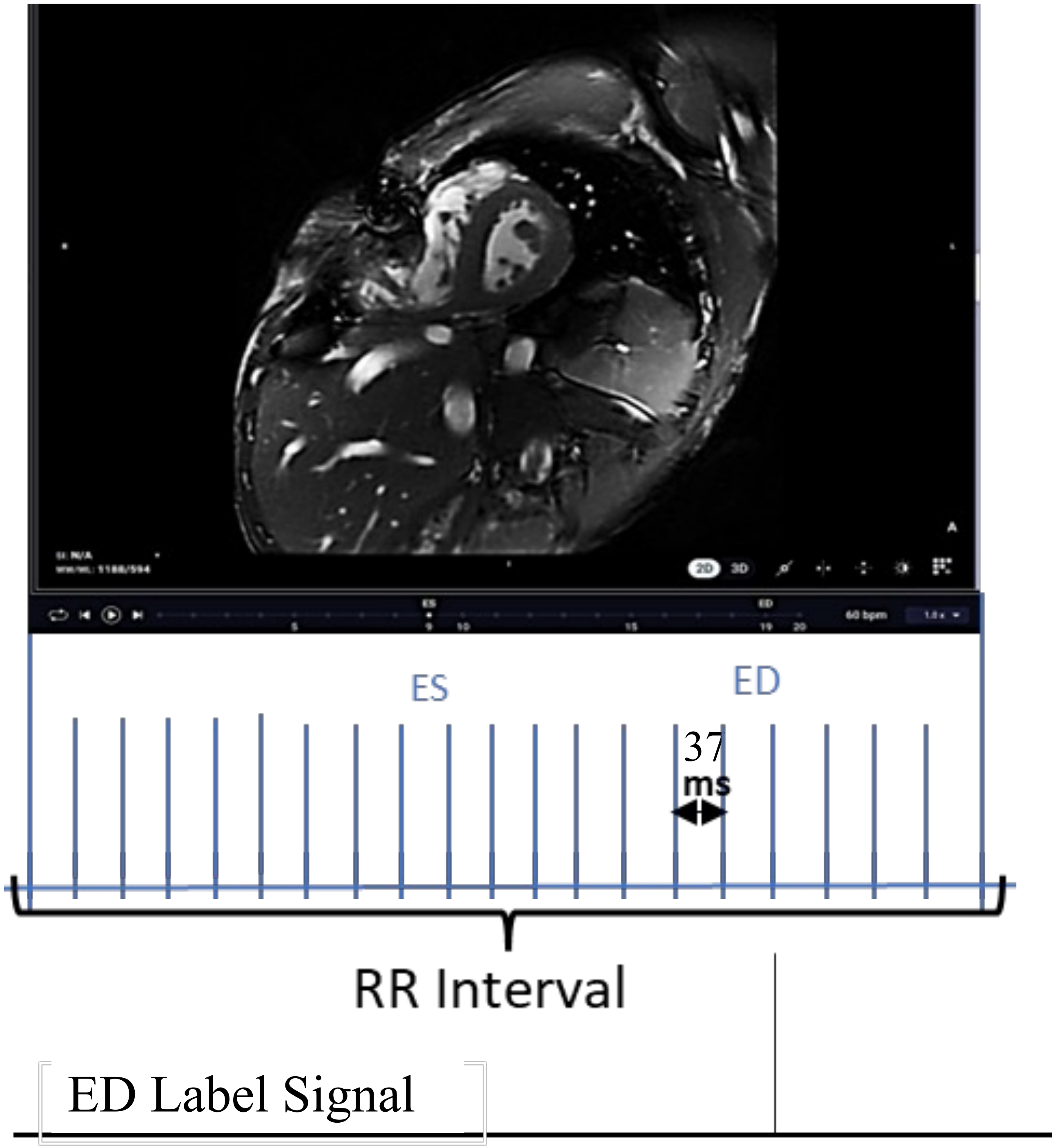


Figure from: [2] Laubrock, Kerstin, et al. "Imaging of arrhythmia: Real-time cardiac magnetic resonance imaging in atrial fibrillation." European Journal of Radiology Open 9 (2022): 100404.

Proposed Solution

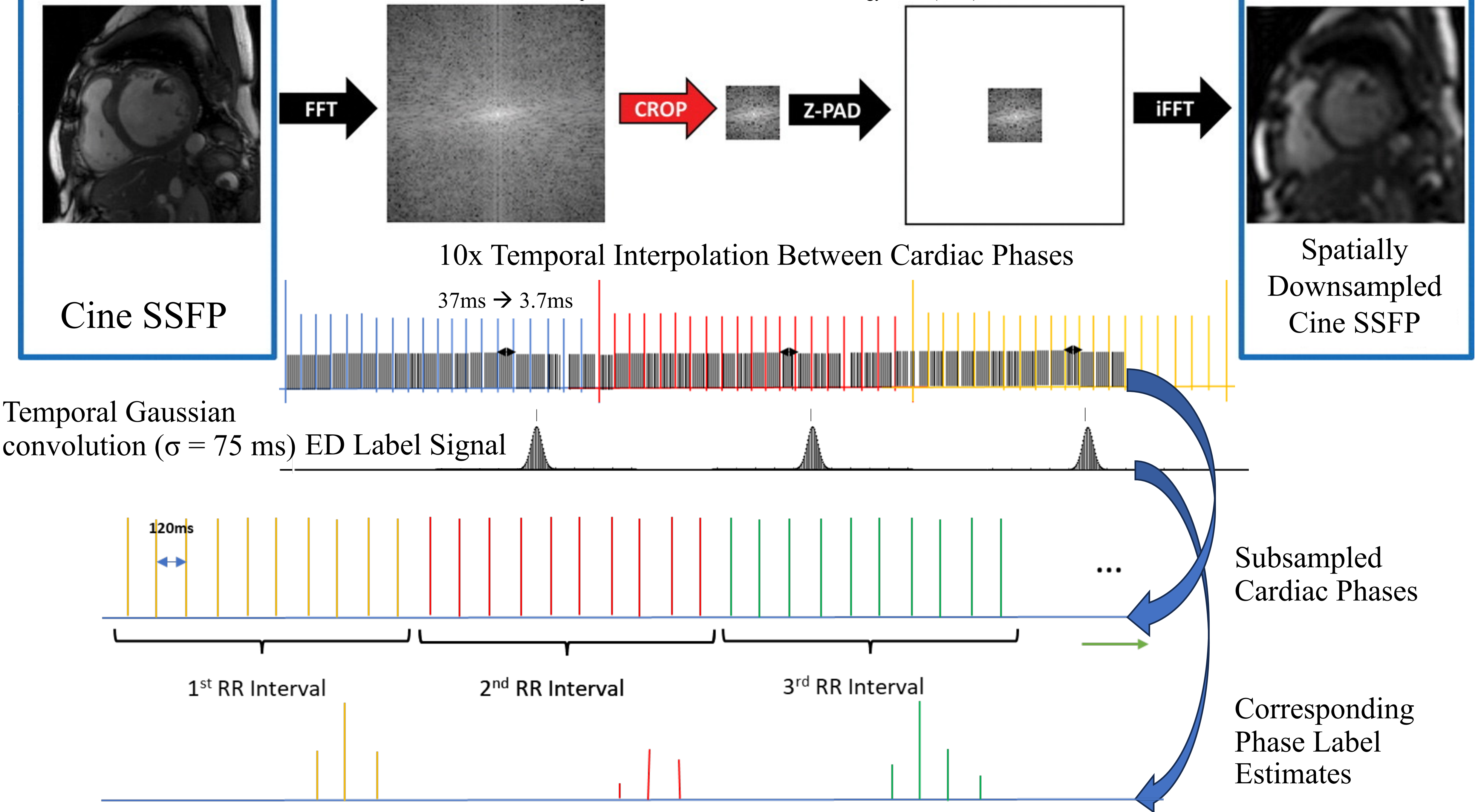
We propose a **semi-supervised deep learning (DL)** strategy to automatically identify **end-diastolic (ED)** and **end-systolic (ES)** cardiac phases from each slice of RT SSFP image series across the entire LV volume



241 patients with short-axis cine SSFP

- 20 cardiac phases in each cine series
- Temporal Steps: 37 ± 12.5 ms
- Labeled cardiac phases

Figure from: [3] Masutani, Evan M., Naeim Bahrami, and Albert Hsiao. "Deep learning single-frame and multiframe super-resolution for cardiac MRI." Radiology 295.3 (2020): 552-561.

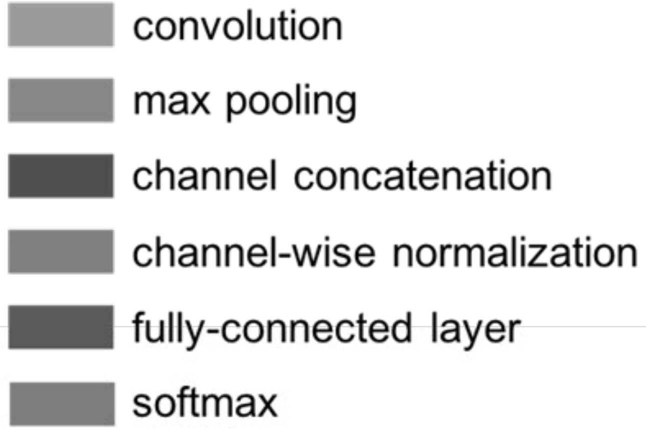


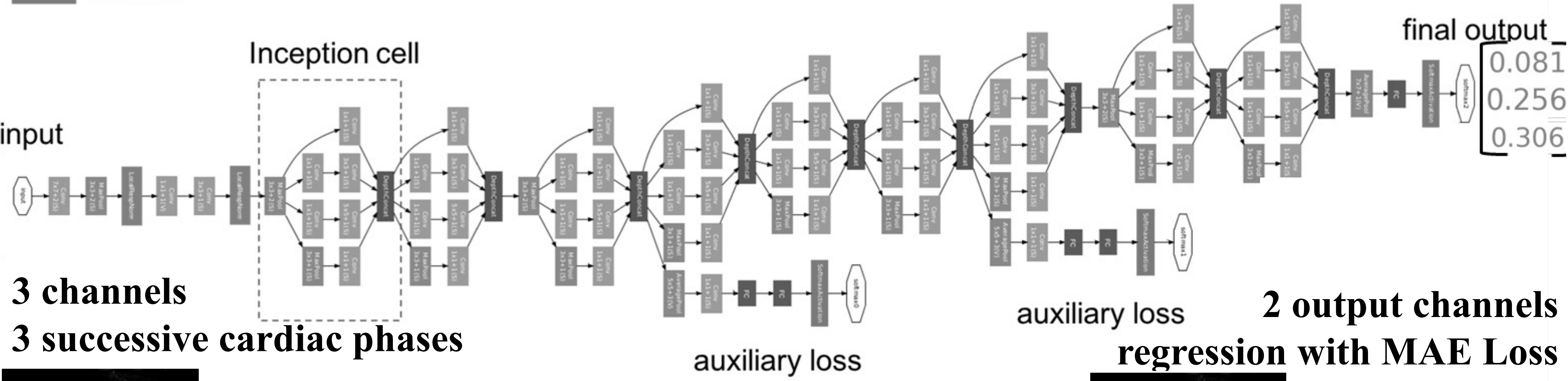
Xception Model Pretrained on ImageNet

22.9M parameters to train

[4] Chollet, François. "Xception: Deep learning with depthwise separable convolutions." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.

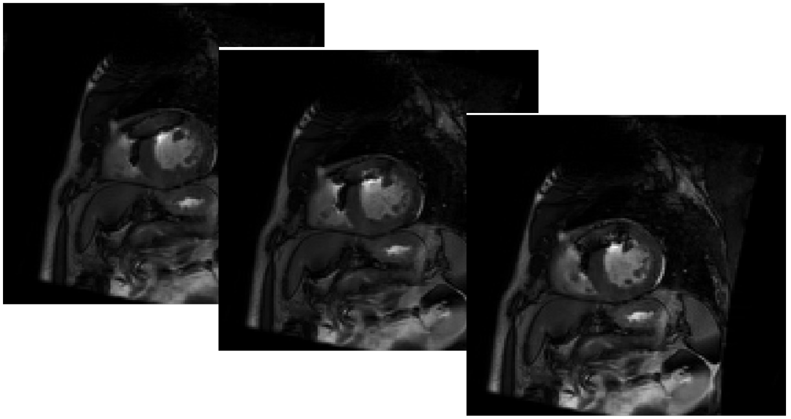
Figure modified from: [5] Szegedy, Christian, et al. "Going deeper with convolutions." Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.





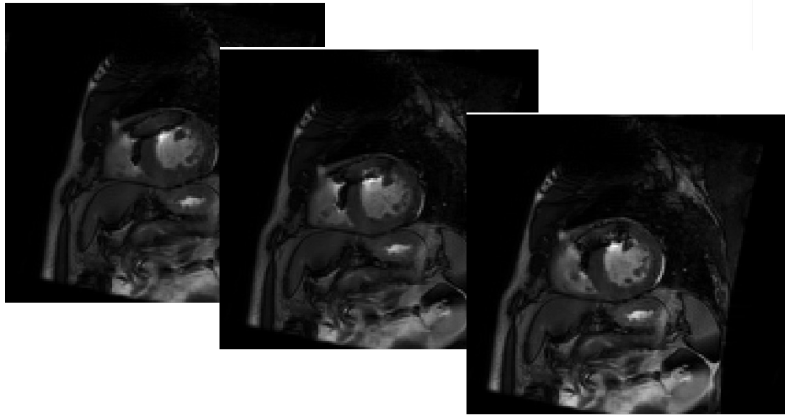
3 channels

3 successive cardiac phases



2 output channels

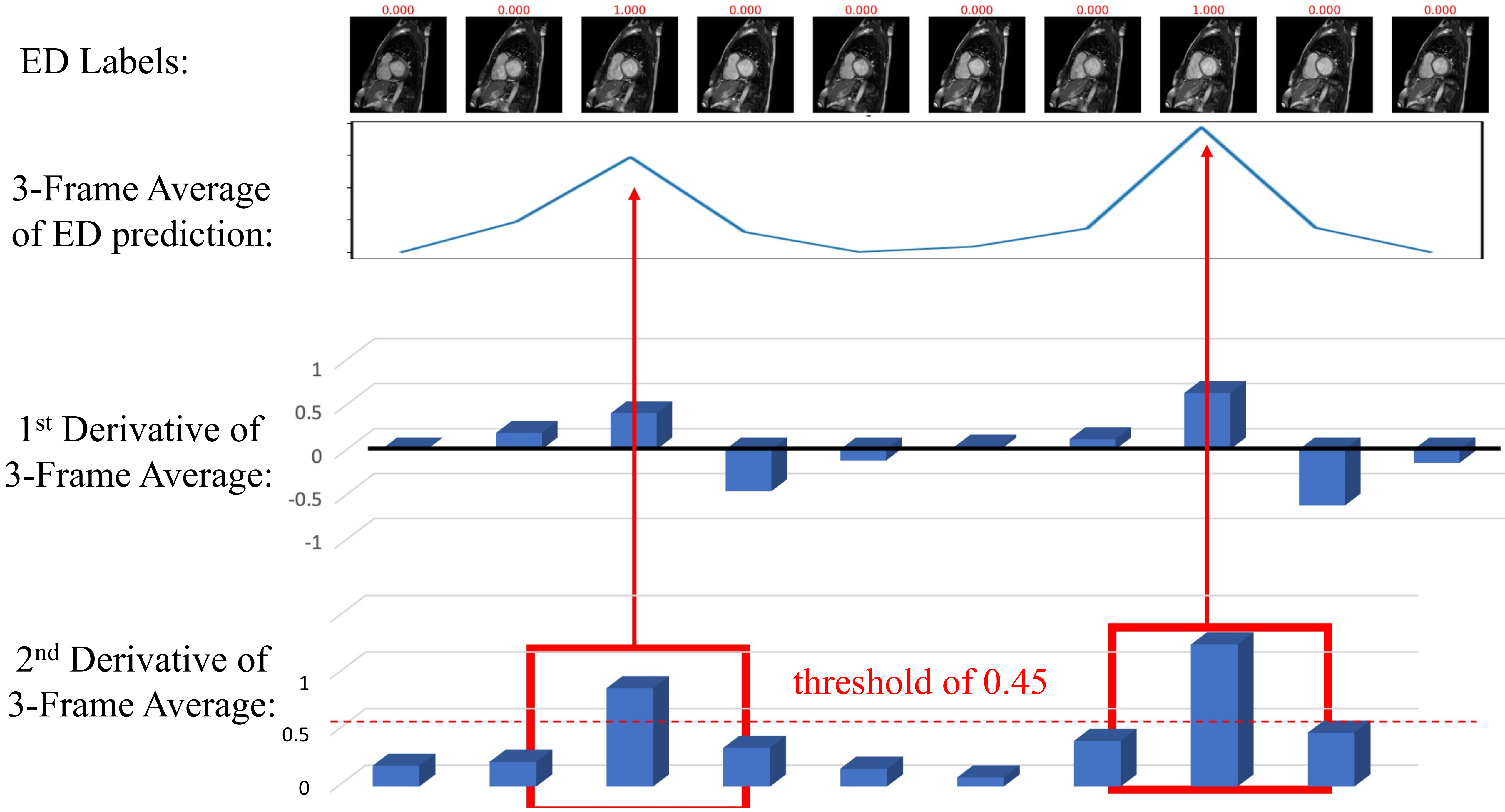
regression with MAE Loss



Training Parameters

PREPROCESSING	View Standardization Histogram Matching [0,1] Normalization
AUGMENTATION	Changing Starting point Negative Cropping (zoom out) Temporal Step (120 – 240 ms)
LOSS FUNCTION	Mean Absolute Error()
BATCH SIZE	48
EPOCHS	120

Data	Train (80%)	Validation (10%)	Test (10%)
Short-Axis Cine SSFP			
Patients (n = 241)	193	24	24
Cardiac Phases (n = 4,820)	3,860	480	480
Spatiotemporally Downsampled Short-Axis Cine SSFP			
Cardiac Phases (n = 482,000)	386,000	48,000	48,000

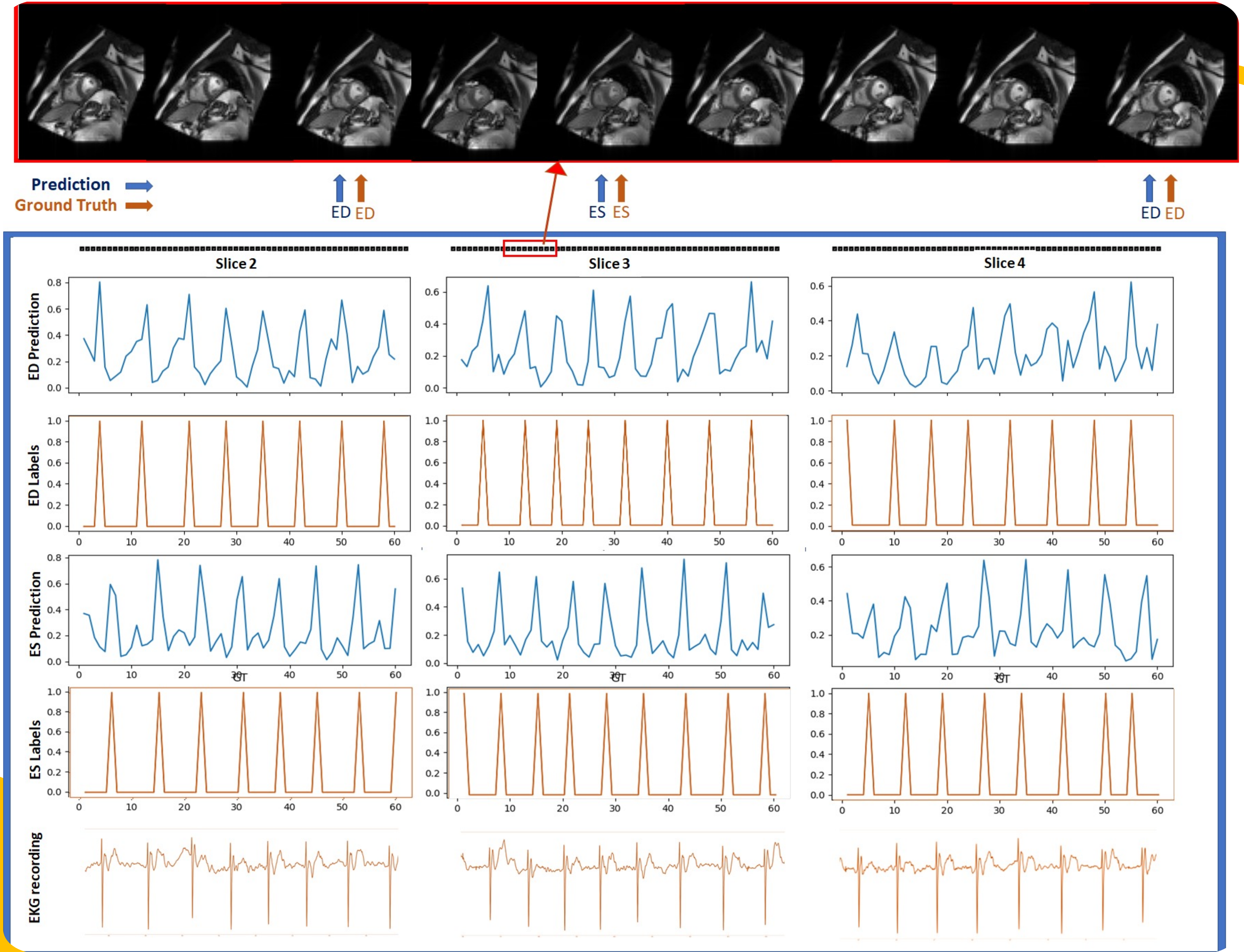

ED Labels:
0.000
0.000
1.000
0.000
0.000
0.000
0.000
1.000
0.000
0.000
3-Frame Average of ED prediction:
1st Derivative of 3-Frame Average:
1
0.5
0
-0.5
-1
2nd Derivative of 3-Frame Average:
threshold of 0.45
1
0.5
0

Cardiac Phase (Frame) Distance of 0 (Delay = 0 ms)

	ED	ES
Accuracy	0.905	0.877
Recall	0.8238	0.739

Cardiac Phase (Frame) Distance of 1 (Delay = 120 – 240 ms)

	ED	ES
Accuracy	0.96	0.957
Recall	1.00	0.984



Prediction
Ground Truth
ED ED
ES ES
ED ED
Slice 2
Slice 3
Slice 4
ED Prediction
ED Labels
ES Prediction
GT
ES Labels
EKG recording

Conclusions

- Deep-learning enables automatic cardiac phase estimation of End Diastole (ED) and End Systole (ES) from downsampled cine steady-state free-precession (SSFP) MRI within 0-1 frame distance
- This model is a translatable toward ED and ES identification from Real-time SSFP

Thank You for Listening

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