AI for CMR Postprocessing

- Is the Problem Solved?

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May 5, 2022

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- No conflict to declare

Outline

- CMR post-processing
- State of the art
- Is the problem solved?
- Where remain the problems?
- Know what you do not know

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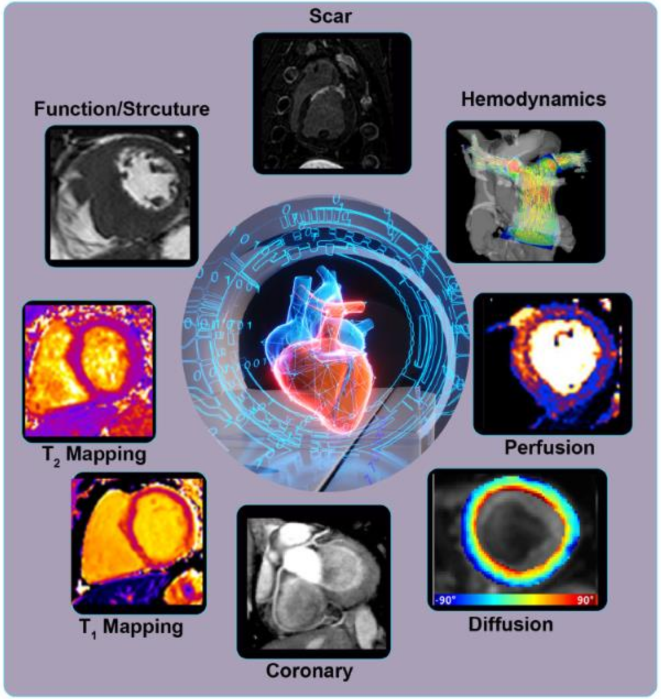
Cardiovascular Magnetic Resonance

- **CMR is a highly versatile imaging modality for heart**
  - Structure
  - Function
  - Mechanics
  - Tissue
  - Flow
  - …



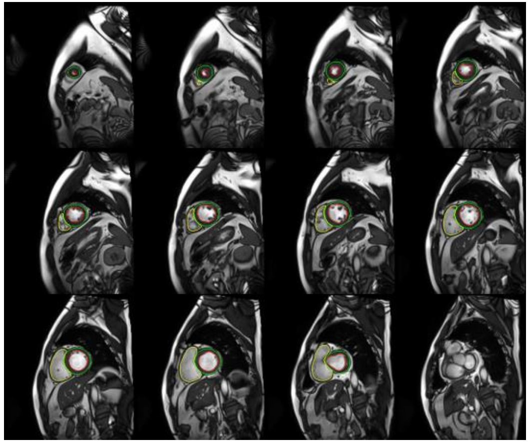
Guo et al. JMRI 2021

- **Comprehensive spectrum**

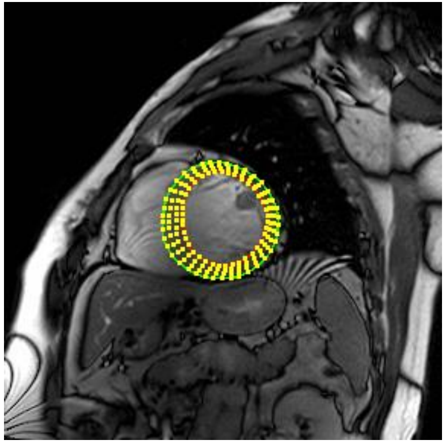
CMR Postprocessing

- CMR sequences demand dedicated postprocessing

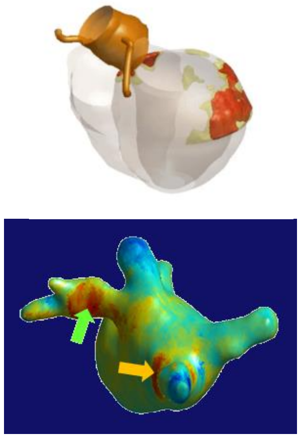
function



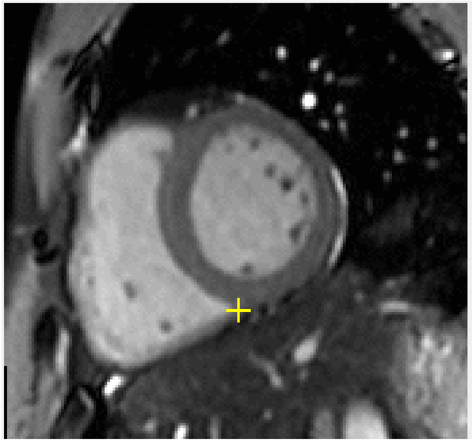
strain



scar



mapping



CMR Postprocessing

- **Postprocessing of CMR used to be difficult**
  - Manual:

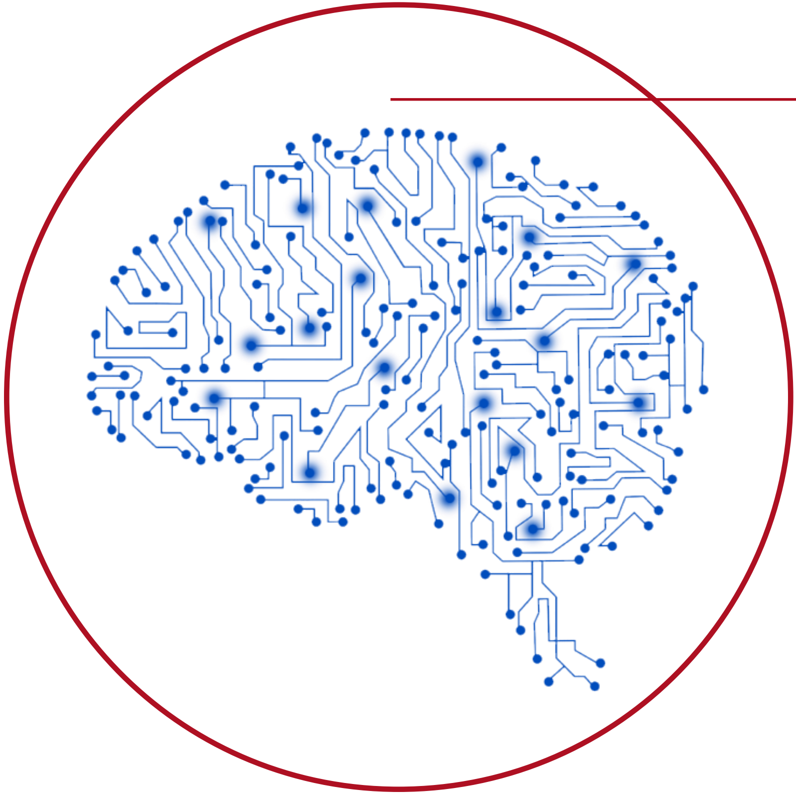
    Time consuming, labor intensive
  - Automatic:

    Difficult to model due to the high variability of data

    Hard to balance the bias-variance tradeoff

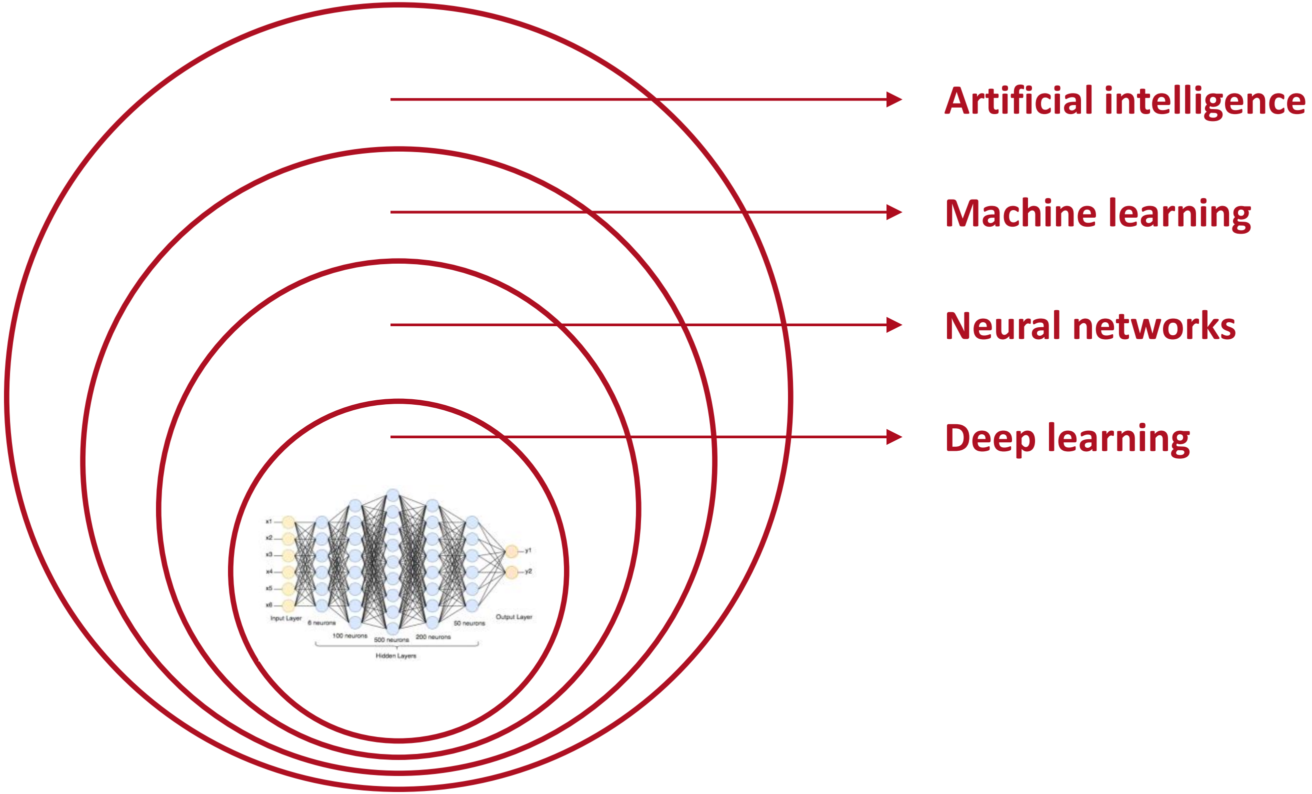
… before the deep learning era

AI for CMR Postprocessing



Artificial intelligence

AI for CMR Postprocessing



AI for CMR Postprocessing

- **Deep learning is creating new frontiers in CMR postprocessing**

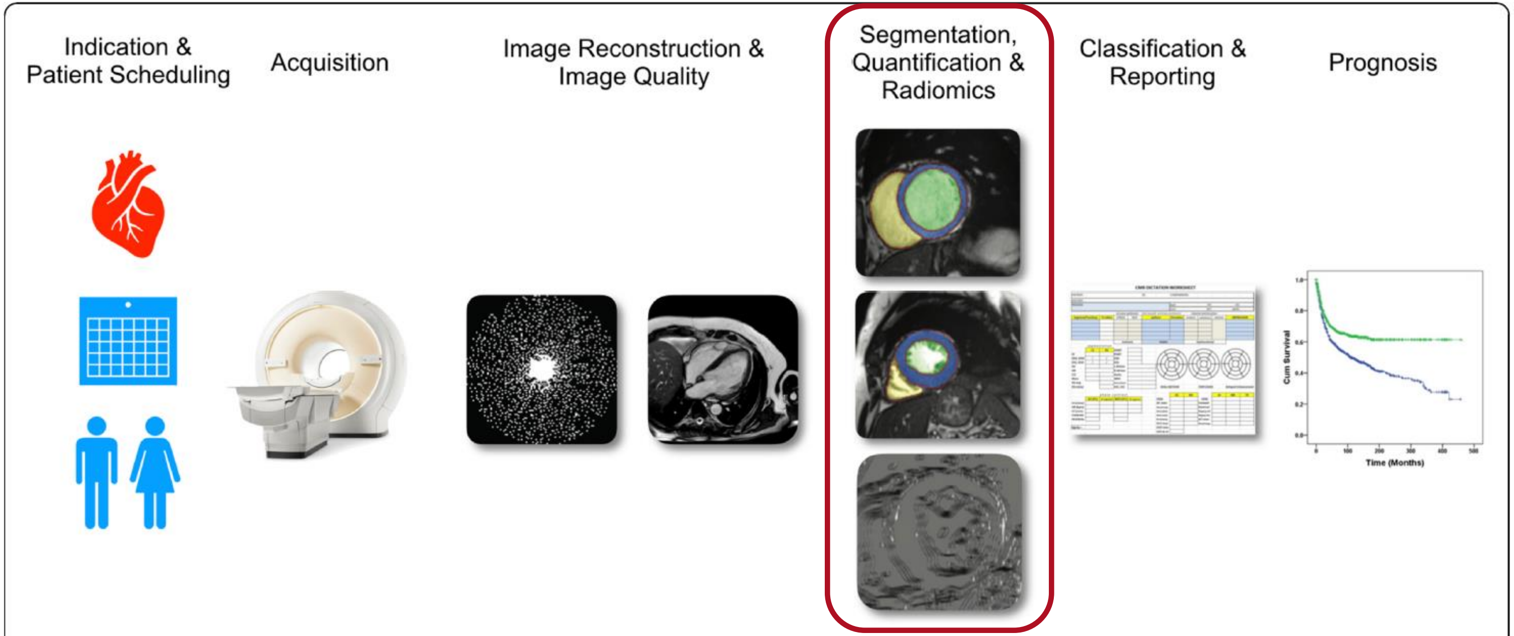


Fig. 2 Machine learning will impact all aspects of cardiovascular magnetic resonance imaging from patient scheduling to image analysis and prognosis

Leiner et al. JCMR 2019

AI for CMR Postprocessing

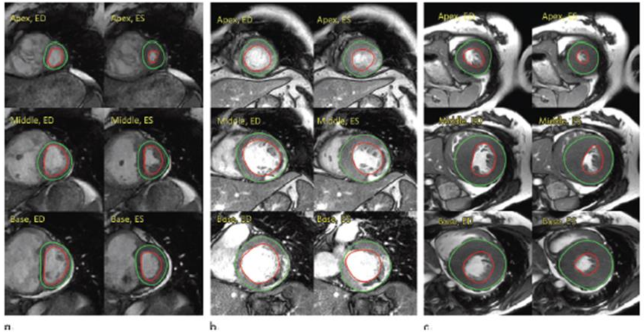
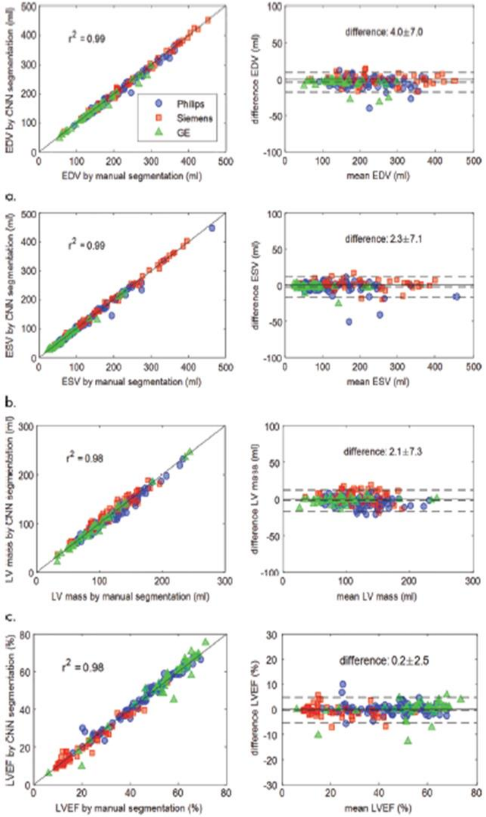


Figure 4: Examples of automated left ventricular segmentation from convolutional neural network. Six images are shown for each example. Apical, middle, and basal sections are shown at end-diastolic (*ED*) and end-systolic (*ES*) phases. **(a)** Data set 4. Image obtained at 1.5 T (HDxt; GE Medical Systems, Waukesha, Wis) in patient with pulmonary hypertension. **(b)** Data set 4. Images obtained at 1.5 T (HDxt, GE Medical Systems) in patient with ischemic cardiomyopathy after intravenous administration of gadolinium chelate. **(c)** Data set 4. Images obtained at 3.0 T (Discovery, GE Medical Systems) in patient with hypertrophic cardiomyopathy.



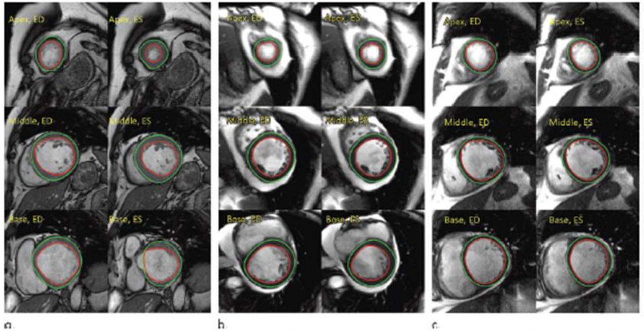
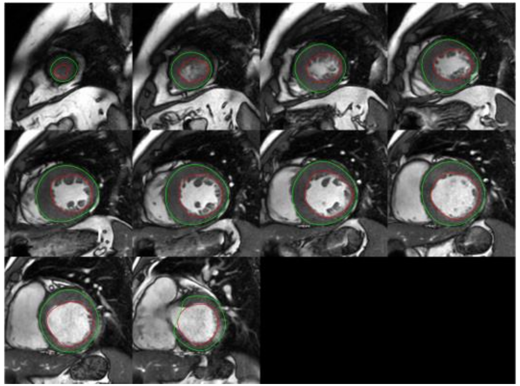
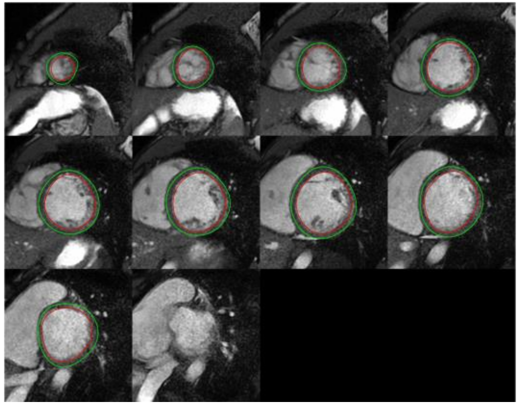


Figure 3: Examples of automated left ventricular segmentation from convolutional neural network. Apical, middle, and basal sections are shown at end-diastolic (*ED*) and end-systolic (*ES*) phases. **(a)** Data set 1. Images obtained at 1.5 T (Intera; Philips Medical Systems, Best, the Netherlands) in patient with ischemic cardiomyopathy. **(b)** Data set 2. Images obtained at 1.5 T (Ingenia, Philips) in patient with ischemic cardiomyopathy. **(c)** Data set 3. Images obtained at 1.5 T (Avanto; Siemens Medical Solutions, Erlangen, Germany) in patient with dilated cardiomyopathy.

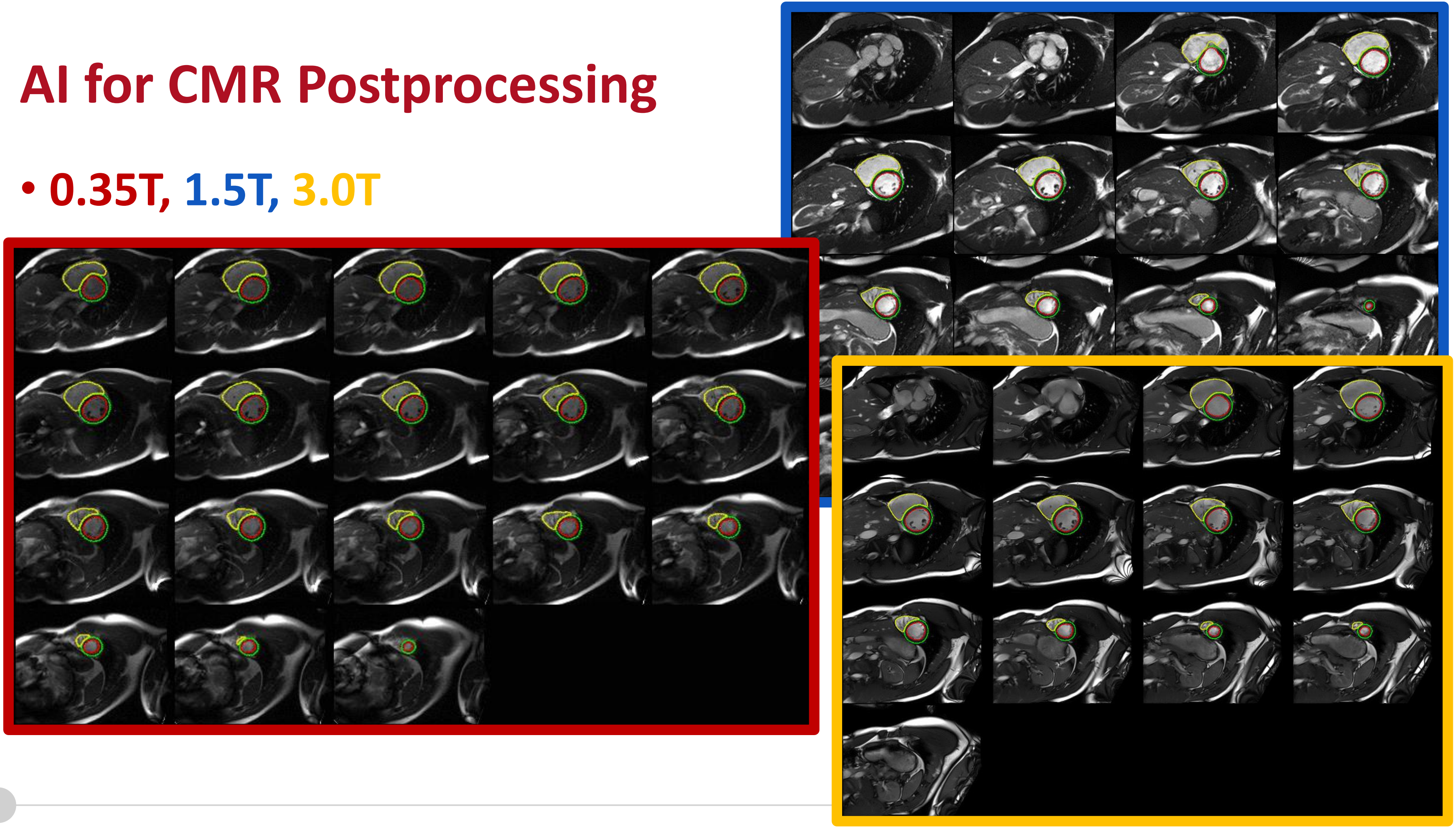




Tao et al. Radiology 2019

AI for CMR Postprocessing

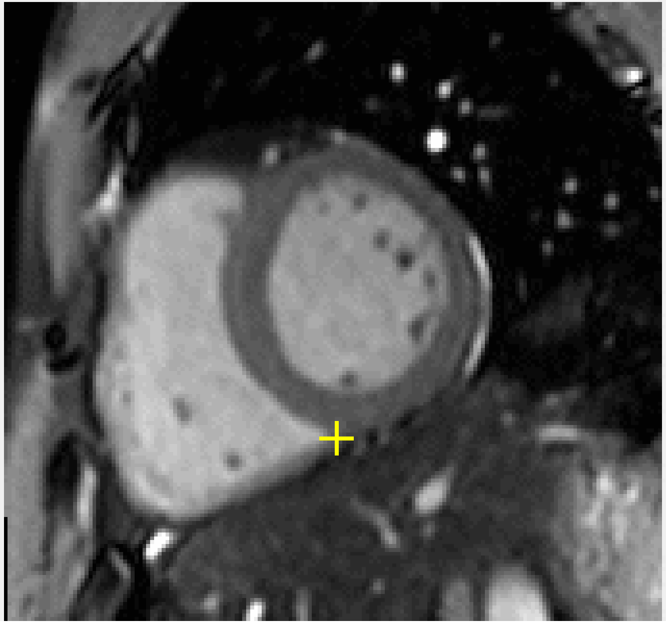
- 0.35T, 1.5T, 3.0T



AI for CMR Postprocessing

original

motion-corrected



Tao Q et al. JMRI 2018

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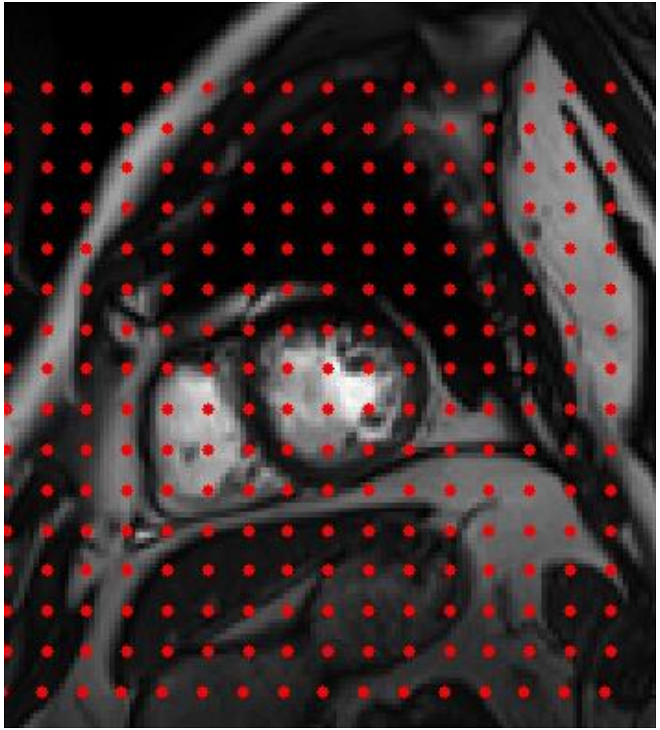
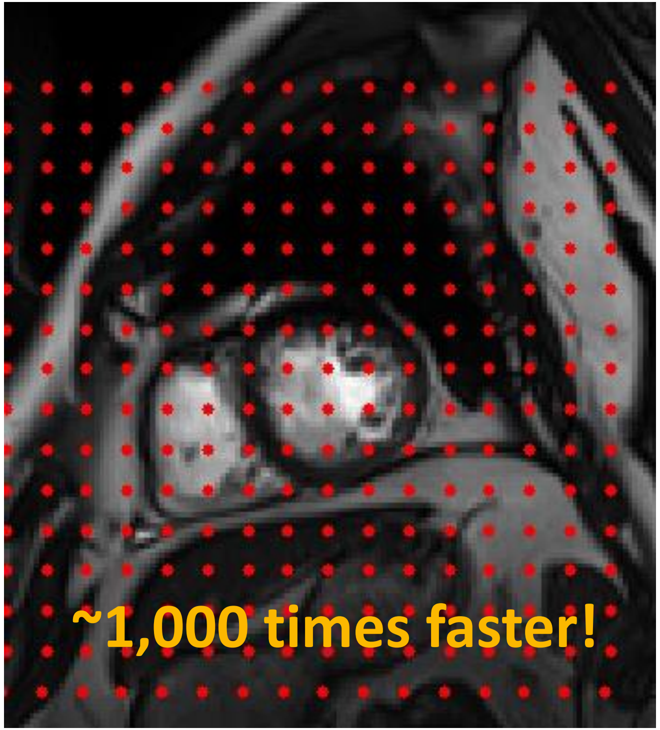
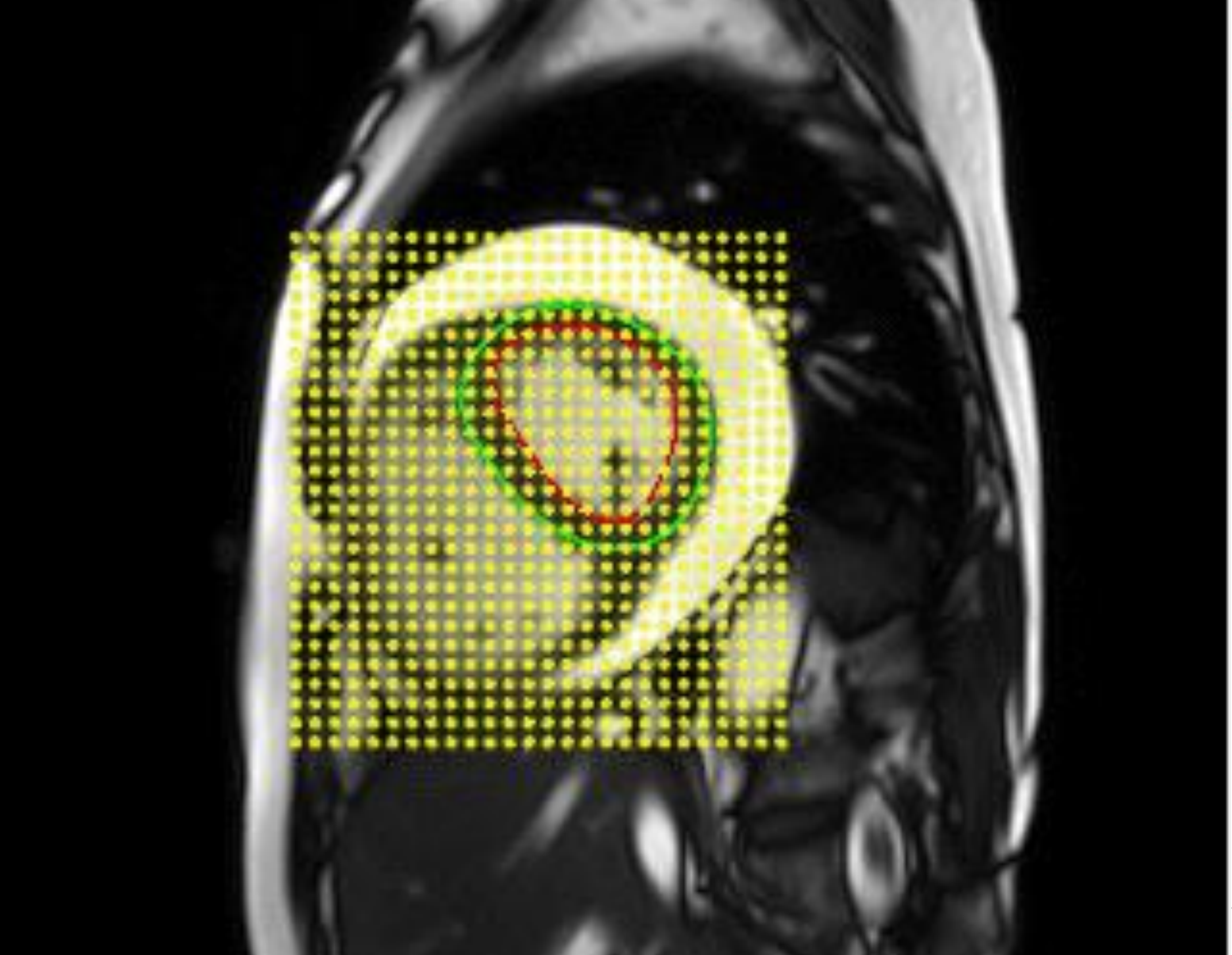
Registration



Deep learning



Qiao et al. Medical Physics 2020



AI for CMR Postprocessing:

State of the Art

- **Fruitful outcome of scientific research**

- **Timely industrial development**

Outline

- CMR post-processing
- State of the art
- **Is the problem solved?**
- **Where remain the problems?**
- Know what you do not know

Is the Problem Solved?

2514 IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 37, NO. 11, NOVEMBER 2018

Deep Learning Techniques for Automatic MRI Cardiac Multi-Structures Segmentation and Diagnosis: Is the Problem Solved?

Olivier Bernard, Alain Lalande, Clement Zotti, Frederick Cervenansky, Xin Yang, Pheng-Ann Heng, Irem Cetin, Karim Lekadir, Oscar Camara, Miguel Angel Gonzalez Ballester, Gerard Sanroma, Sandy Napel, Steffen Petersen, Georgios Tziritas, Elias Grinias, Mahendra Khened, Varghese Alex Kollerathu, Ganapathy Krishnamurthi, Marc-Michel Rohé, Xavier Pennec, Maxime Sermesant, Fabian Isensee, Paul Jäger, Klaus H. Maier-Hein, Peter M. Full, Ivo Wolf, Sandy Engelhardt, Christian F. Baumgartner, Lisa M. Koch, Jelmer M. Wolterink, Ivana Išgum, Yeonggul Jang, Yoonmi Hong, Jay Patravali, Shubham Jain, Olivier Humbert, and Pierre-Marc Jodoin

Is the Problem Solved?

- **Conclusions:**
  - Well, almost
  - Critical cases remain
    - Base
    - Apex
    - RV?
    - New acquisition settings with unknown distribution?

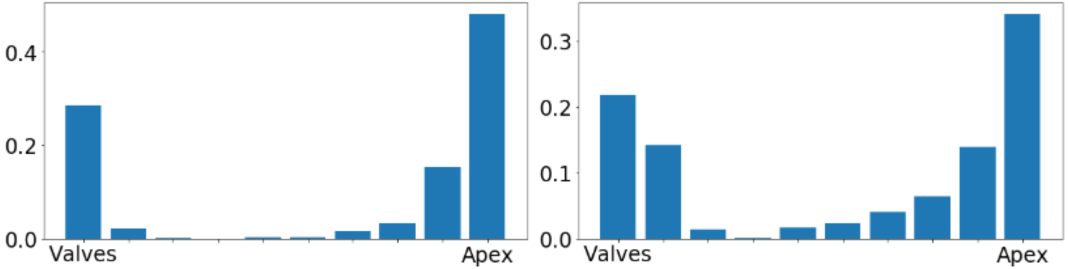


Fig. 3. Histogram of degenerated slices ED (left), and ES (right).

Is the Problem Solved?

- **Further improved algorithms for CMR postprocessing**
  - Network architecture
  - Dataset curation
  - Augmentation

→ Improved accuracy and generalizability

Is the Problem Solved?

- **Further improved algorithms for CMR postprocessing**
  - Network architecture
  - Dataset curation
  - Augmentation

→ Improved accuracy and generalizability

- **However, “corner cases” cannot be avoided**
  - Imaging parameters
  - Artefacts
  - Abnormalities

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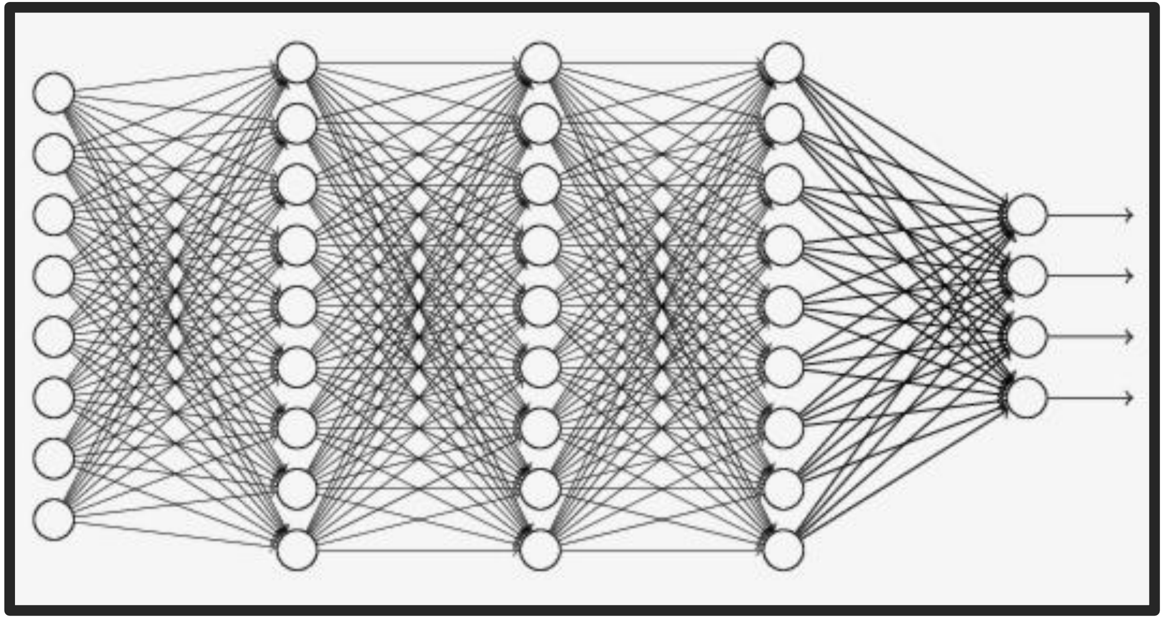
- **Know what you do not know**

“Black Box” Deep Learning

- **Difficulty to explain and control the “black box”**



Uncertainty in Deep Learning

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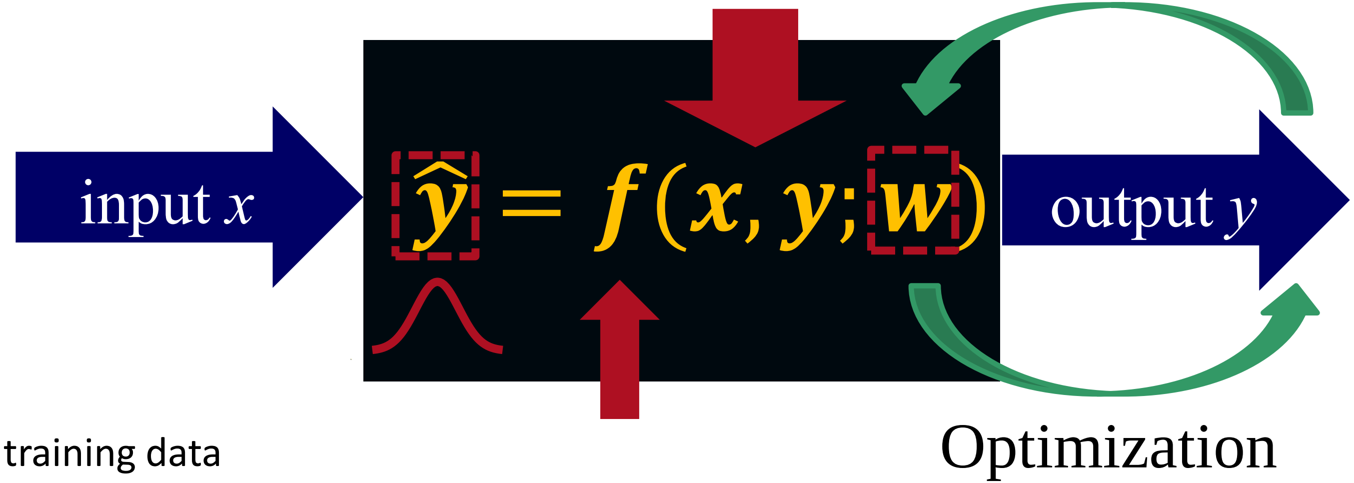

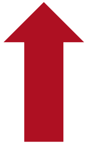

x, y are training data

$f(\cdot)$ is function class

w is parameter

$\hat{y}$ is test-time prediction

Uncertainty in Deep Learning

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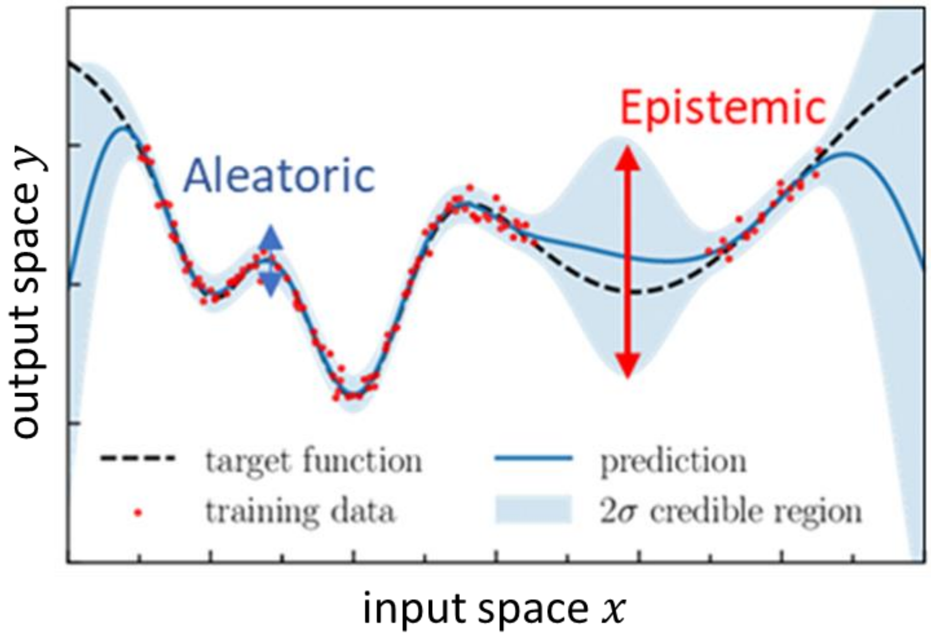
- Task complexity → Aleaotric
- Training data
- Network architecture
- Optimization procedure

Epistemic

Uncertainty in Deep Learning



LIKELIHOOD
The probability of "B" being True, given "A" is True

PRIOR
The probability "A" being True. This is the knowledge.

$$P(A|B) = \frac{P(B|A).P(A)}{P(B)}$$

POSTERIOR
The probability of "A" being True, given "B" is True

MARGINALIZATION
The probability "B" being True.

Bayesian Uncertainty

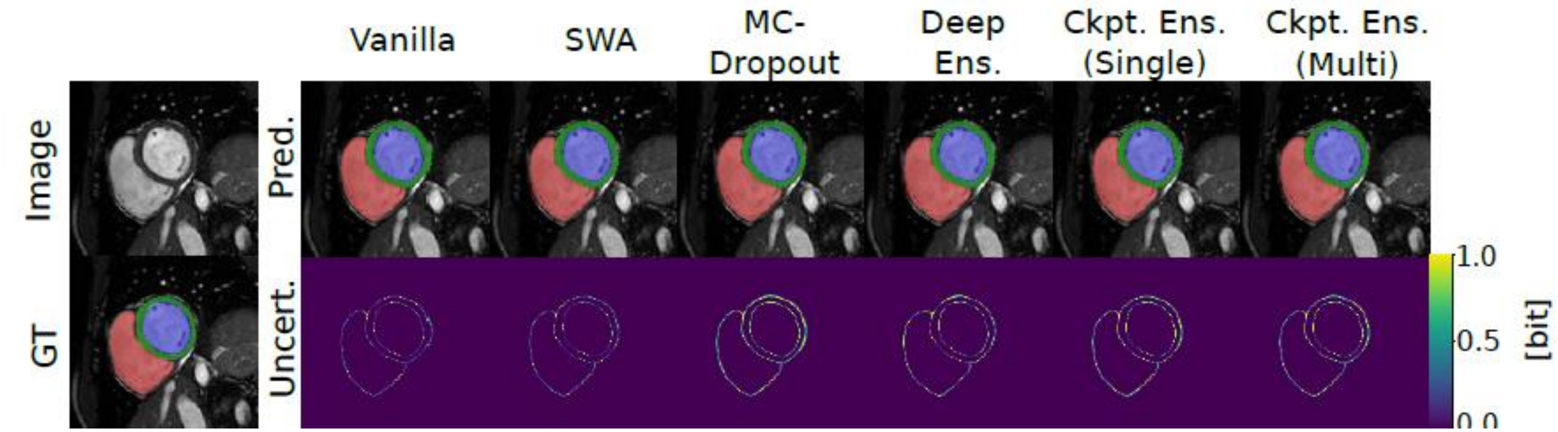
- There can be many solutions of the neural network to a curated dataset

- The optimal solution from the current dataset D

$$p(\mathbf{y}^*|\mathbf{x}^*, \mathcal{D}) = \int p(\mathbf{y}^*|\mathbf{x}^*, \mathbf{w}) \boxed{p(\mathbf{w}|\mathcal{D})\ d\mathbf{w}}$$

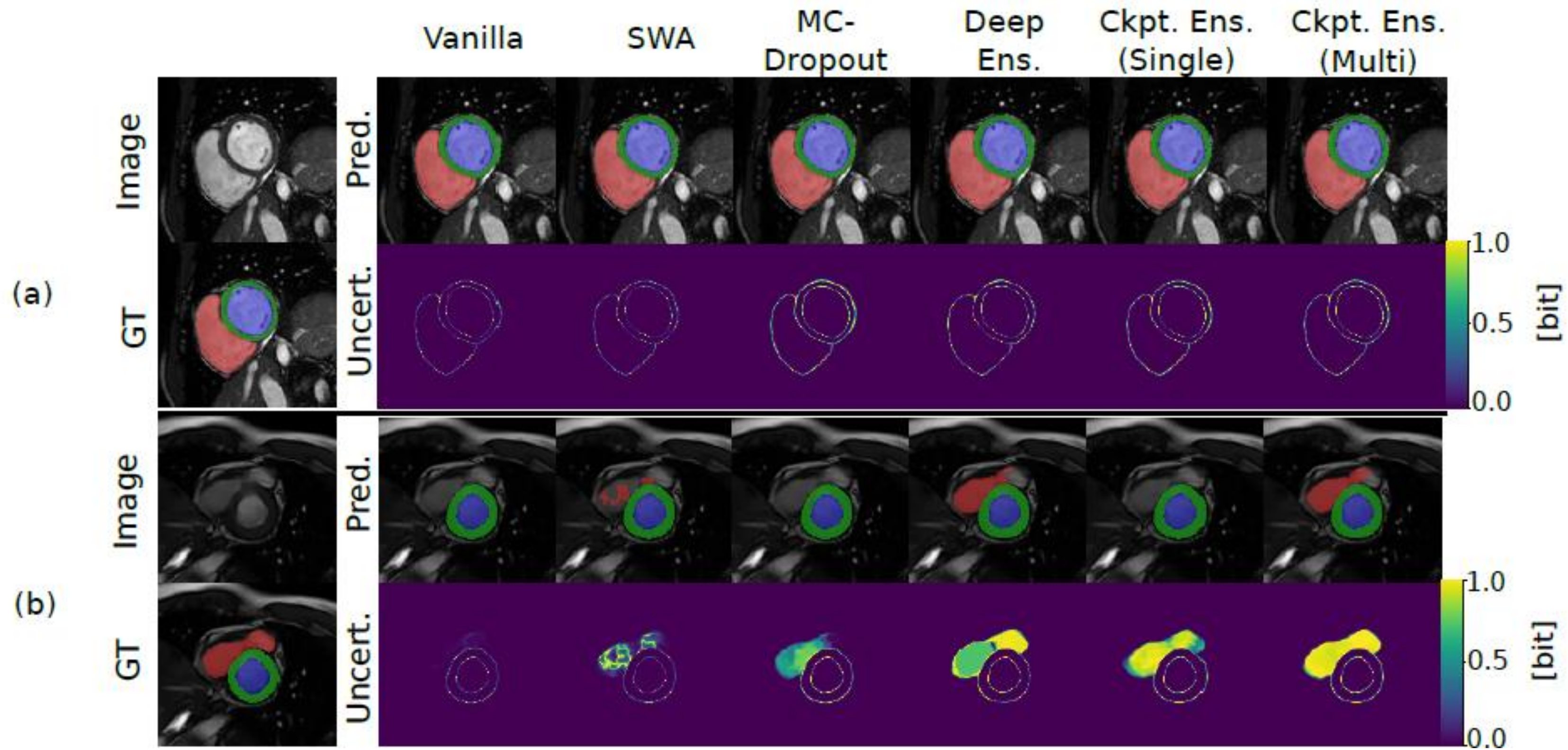
Uncertainty in Deep Learning

(a)



Unpublished data

Uncertainty in Deep Learning



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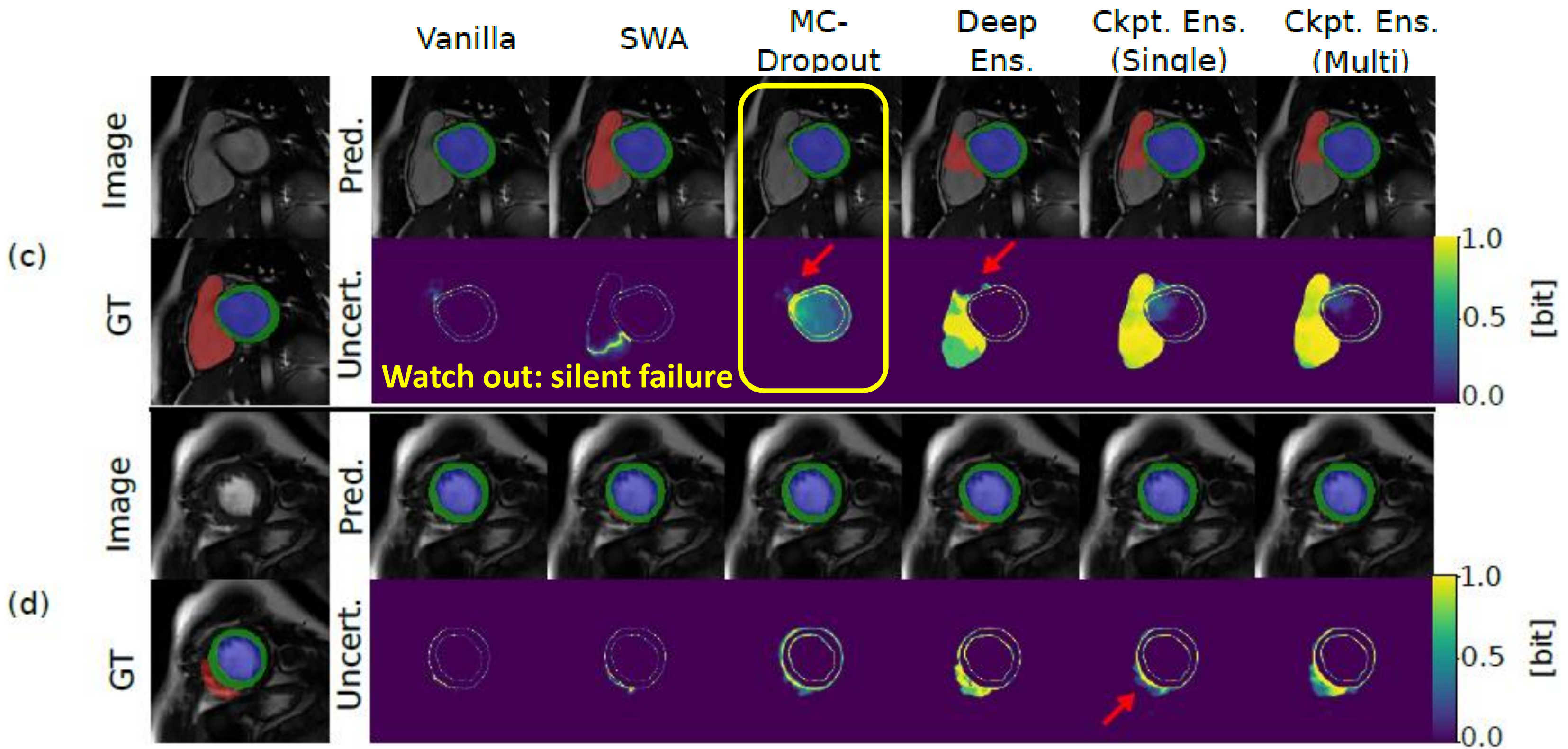

Unpublished data

Uncertainty in Deep Learning

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- **Quantitative evaluation**
- **The Bayesian framework**
  - Better calibration
  - Improved performance
- **Extends to other tasks**

Table 1. Dice coefficients on ID and OOD test sets.

Method	ACDC Validation (ID)			M&M Vendor A (OOD)			M&M Vendor B (OOD)		
	RV	MYO	LV	RV	MYO	LV	RV	MYO	LV
Vanilla	0.911 ±0.052	0.904 ±0.026	0.944 ±0.035	0.830 ±0.119	0.810 ±0.043	0.897 ±0.063	0.878 ±0.077	0.844 ±0.054	0.894 ±0.076
SWA	0.913 ±0.054	0.910 ±0.023	0.948 ±0.033	0.856 ±0.093	0.808 ±0.041	0.896 ±0.061	0.879 ±0.067	0.845 ±0.050	0.897 ±0.069
MC-Dropout	0.906 ±0.061	0.901 ±0.028	0.940 ±0.043	0.810 ±0.146	0.810 ±0.049	0.896 ±0.066	0.880 ±0.079	0.844 ±0.058	0.891 ±0.081
Deep Ens.	0.915 ±0.051	0.912 ±0.023	**0.951** ±0.029	**0.857** ±0.089	0.816 ±0.041	0.902 ±0.062	**0.885** ±0.068	0.849 ±0.047	0.897 ±0.064
Ckpt. Ens. (Single)	**0.919** ±0.051	0.912 ±0.022	**0.951** ±0.032	0.851 ±0.100	0.816 ±0.041	0.902 ±0.061	0.883 ±0.070	0.850 ±0.048	**0.901** ±0.065
Ckpt. Ens. (Multi)	0.918 ±0.051	**0.913** ±0.024	**0.951** ±0.031	0.852 ±0.105	**0.818** ±0.043	**0.905** ±0.060	**0.885** ±0.069	**0.851** ±0.050	0.899 ±0.071

Table 2. ECE (%) on ID and OOD test sets.

Methods	ACDC Validation (ID)	M&M Vendor A (OOD)	M&M Vendor B (OOD)
Vanilla	2.56	4.34	3.79
Temp. Scaling	2.18	3.91	3.46
SWA	2.39	4.07	3.70
MC-Dropout	1.70	3.41	2.95
Deep Ens.	1.63	3.16	2.85
Ckpt. Ens. (Single)	**1.25**	2.83	2.69
Ckpt. Ens. (Multi)	**1.25**	**2.75**	**2.61**

Unpublished data

Uncertainty in Deep Learning

- **Know what you do not know**
  - By analyzing the uncertainties related to the learning process

- **Solve the problem even better**
  - More accurate analysis (theoretically guaranteed)
  - More reliable quality control

Conclusions

- **AI for CMR postprocessing is close to a "solved problem"**

- **..., however, there are always cases where it cannot be absolutely *certain***

- **In cases of *uncertainty*, let the experts know!**

Acknowledgement

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Thank you

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