SIEMENS Healthineers

Intelligence Artificielle

De l'imagerie médicale au jumeau numérique

Tommaso Mansi, with contributions from Siemens colleagues and clinical collaborators

Who we are

€13.8bn
Revenue[1)]

Market leader
in majority of businesses

>70
countries with direct presence

>48,000
highly skilled employees

18,000+
patents IP base

~240,000
patient touch points every hour

Access to care for
~1.3bn people
in developing countries

>70%
of critical clinical decisions are influenced by the type of technology we provide[2)]

~600,000
installed base

>90%
of global top 100 providers partner with us

1) Revenue P10 FY 2017 (not acc. to IFRS 15)
2) AdvaMedDX, “A Policy Primer on Diagnostics”, June 2011, p. 3

Innovation is our main driver

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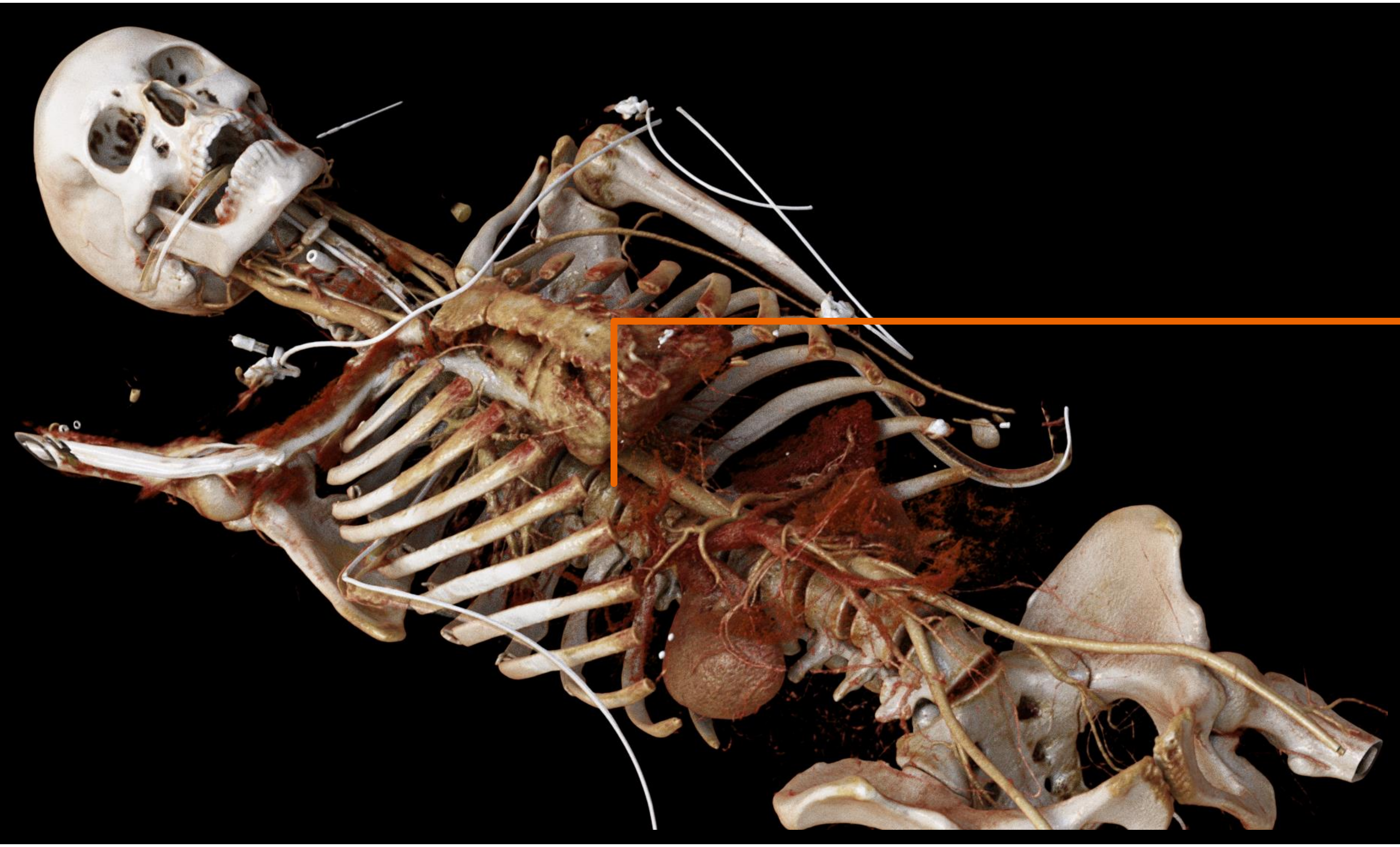
MRI 1980

MRI today – Tractography of a healthy volunteer

The concepts and information presented in this slide deck are based on research results that are not commercially available

Data courtesy of CUBRIC, UK

Trauma case – CT Cinematic Rendering



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Data courtesy of Vancouver General Hospital, Vancouver, Canada

Artificial intelligence and importance of Big Data – Run-time classification error

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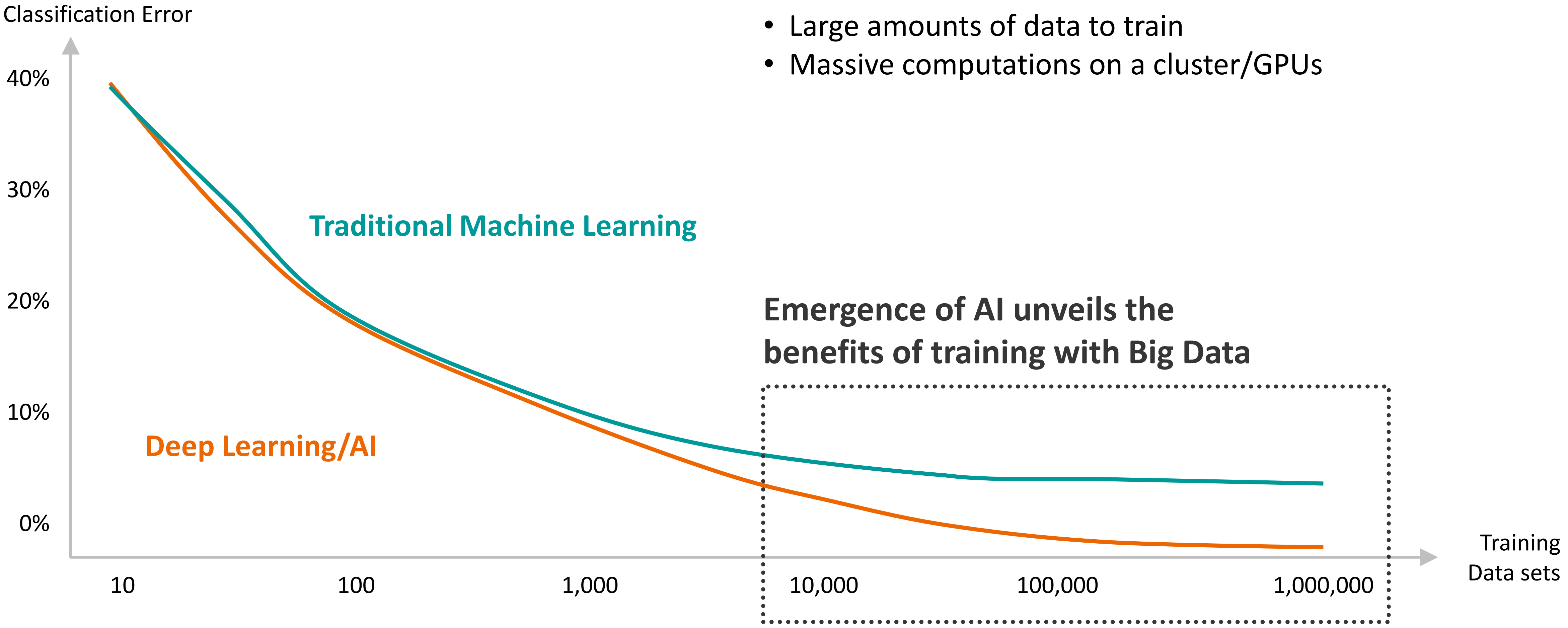

- Large amounts of data to train
- Massive computations on a cluster/GPUs

Emergence of AI unveils the benefits of training with Big Data

Hierarchy of AI systems

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Integration, access, complexity

Patient Cohort	• Population health management, Process optimization • Outcome analysis, quality care, meaningful use
Patient Centric	• Digital Twin • Predict, plan, prescribe
Reading/Reporting/Guidance	• Measure and quantify • Detect, diagnose and guide
Scanner/Instrument	• Workflow automation • Reconstruction, advanced physics

AI drives healthcare digitalization

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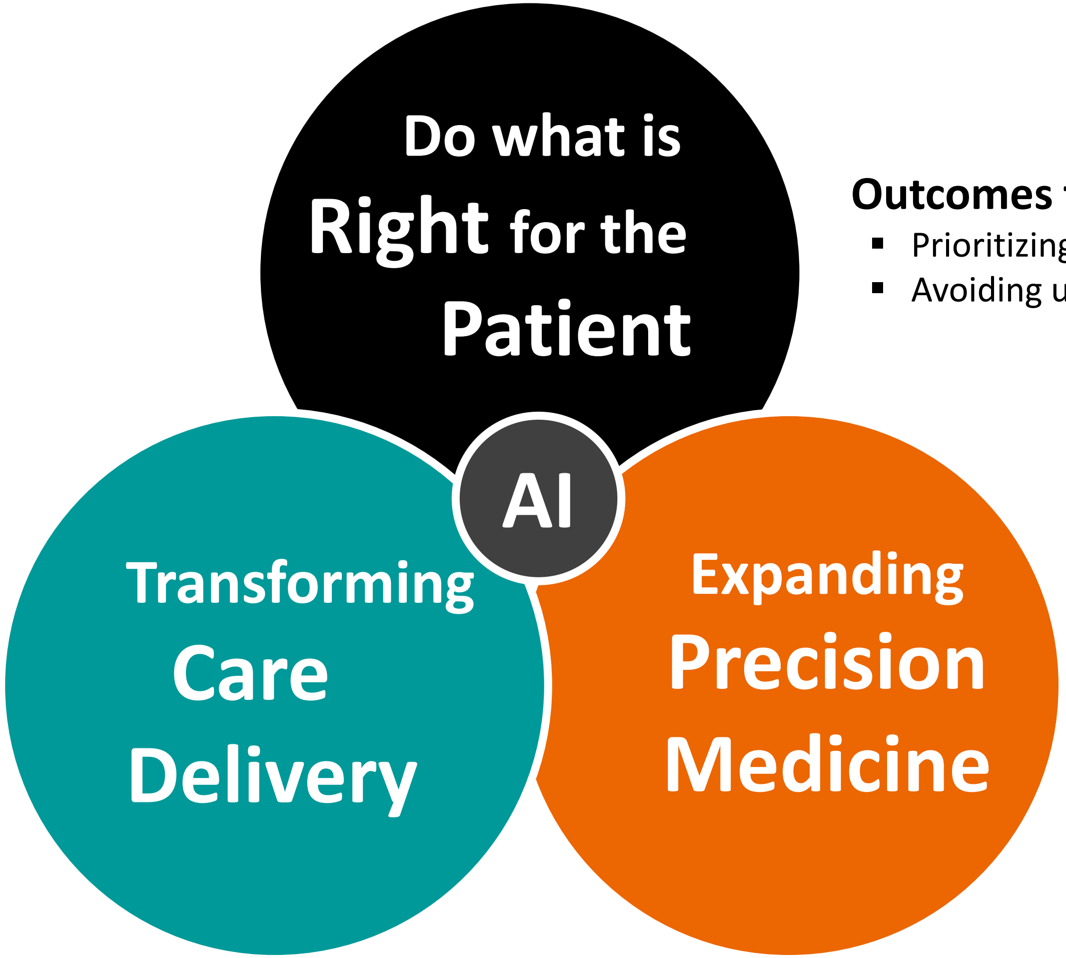
Outcomes that matter to patients
- Prioritizing complex/acute cases
- Avoiding unnecessary interventions



Efficiency and productivity
- Increased productivity through assistance in automation
- Clinical operation optimization

Quality of care
- Patient and risk stratification
- Outcome optimization

First patient positioning system powered by AI
The FAST integrated workflow with FAST 3D camera

AI

Input

Color Image Data
3D Depth Image Data
Infrared Image Data

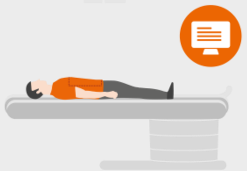
Based on deep learning algorithms, the following are possible

- Landmark detection
- Range detection based on protocol input
- Range adaption to user changes over time
- Isocenter positioning
- Patient direction analysis

Output

Right dose modulation with **FAST Isocentering**

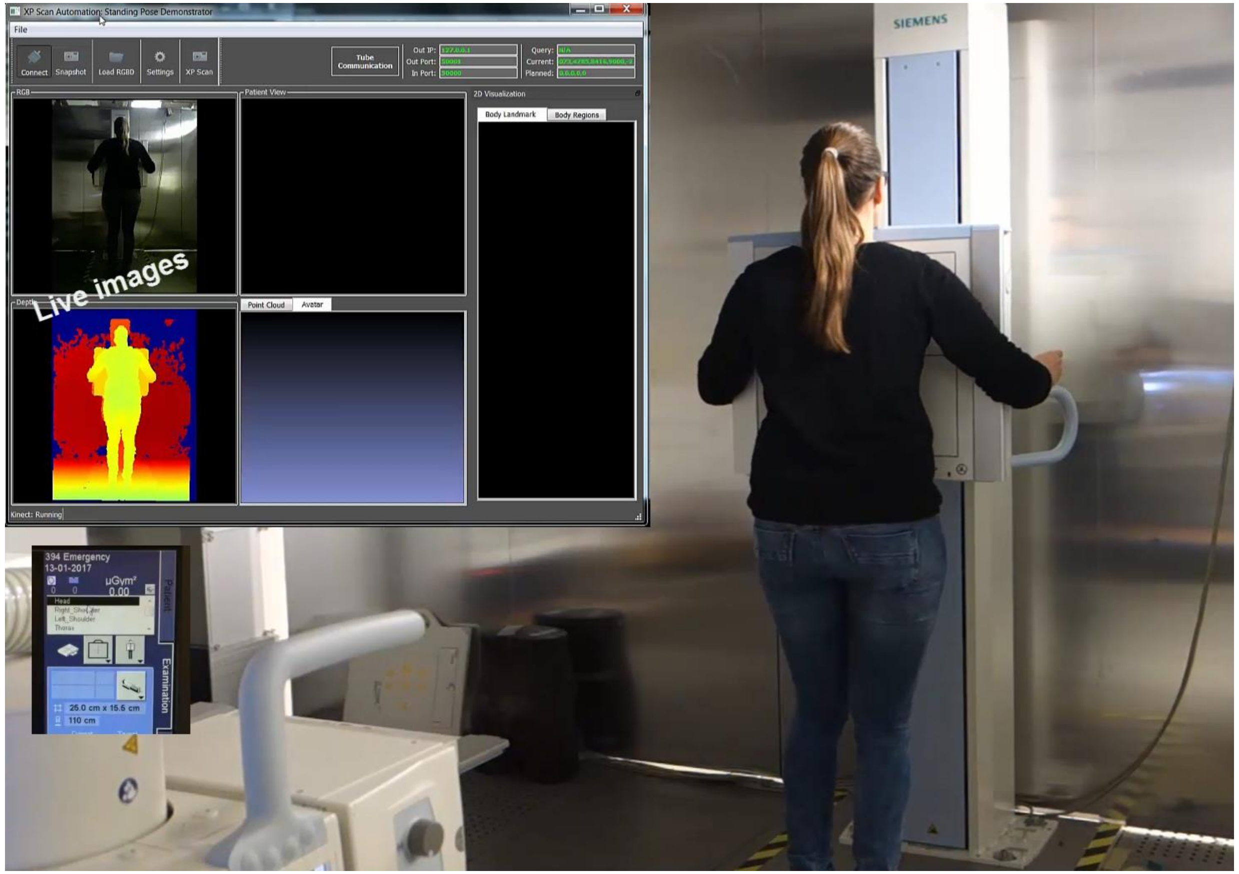
Right scan direction with **FAST Direction**



Correct and complete body region with **FAST Range**

Teixeira et al, Generating Synthetic X-ray Images of a Person from Surface Geometry, IEEE CVPR 2018

Smart X-Ray tube



Automatic positioning of tube

- 3D camera
- Patient landmarks
- 3D avatar trained on thousands of human body poses and shapes
- 3D location of mobile detector

Video

- Real-time avatar building
- Scanning of Head, Shoulder, Thorax, Abdomen, Right Hip
- Automatic collimation

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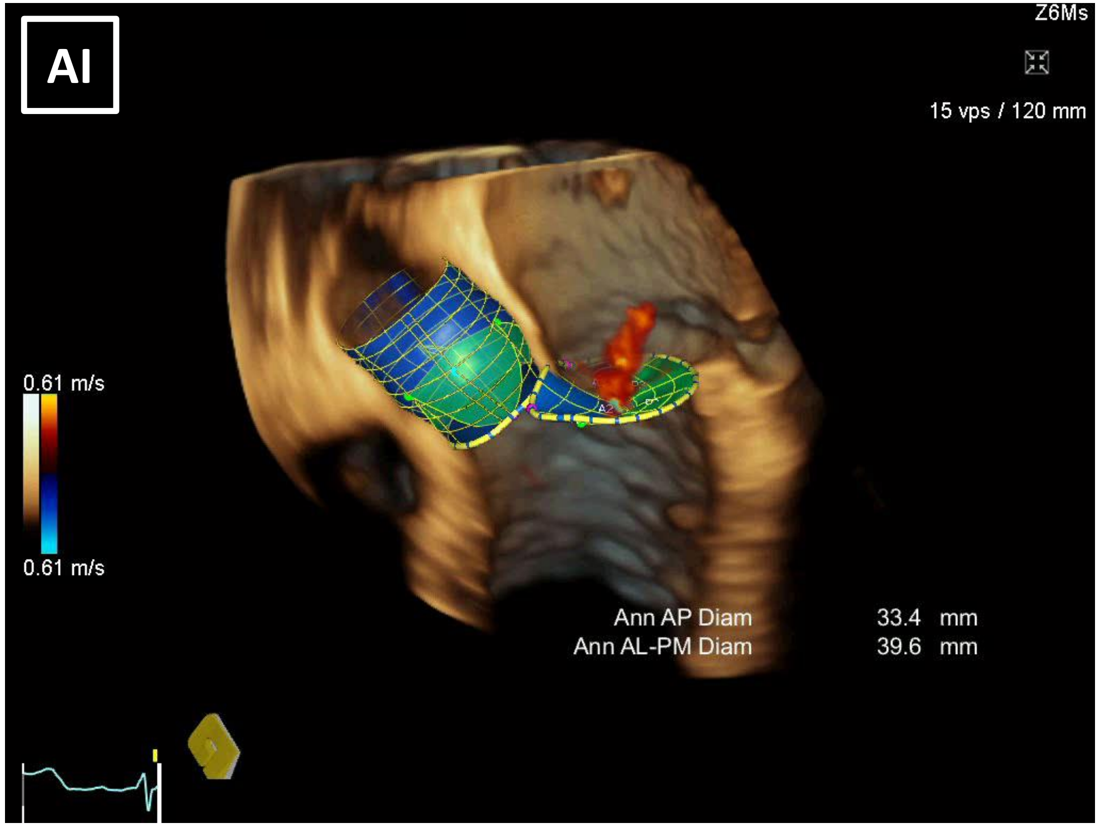
Volume, real-time 3D transesophageal echocardiography with 3D+t valve analysis



eSieValves^{TM} Analysis

Personalized Assessment of Cardiac Valves within seconds

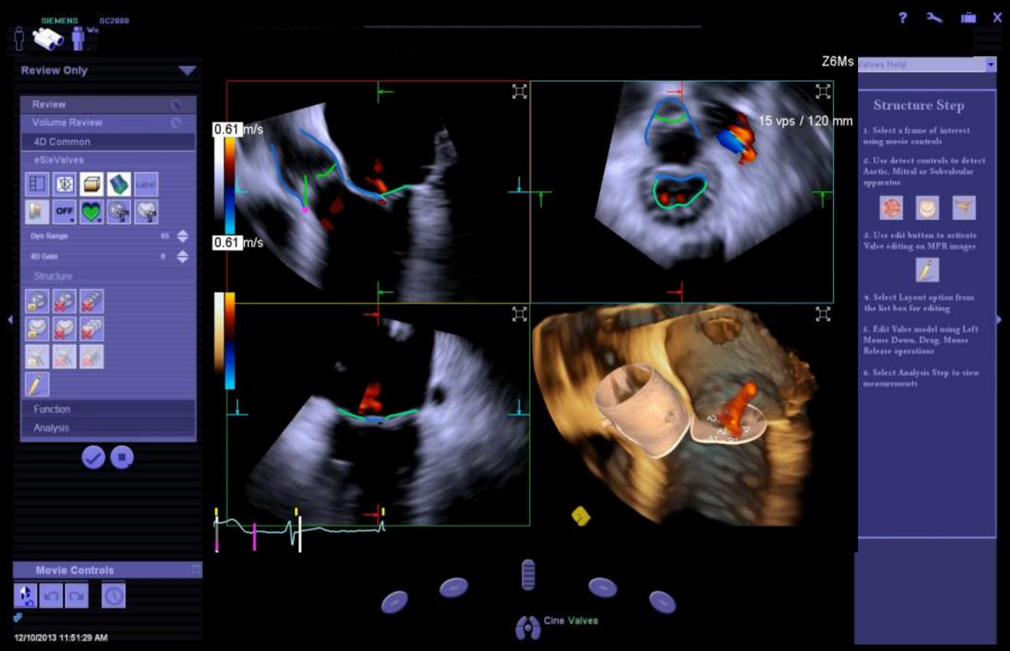
Visualization of anatomy, landmarks, and associated measurements in 3D

S. Grbic, et al., Personalized Mitral Valve Closure Computation and Uncertainty Analysis from 3D Echocardiography, Medical Image Analysis, 2016

Data Courtesy of Piedmont Heart Institute, Atlanta GA

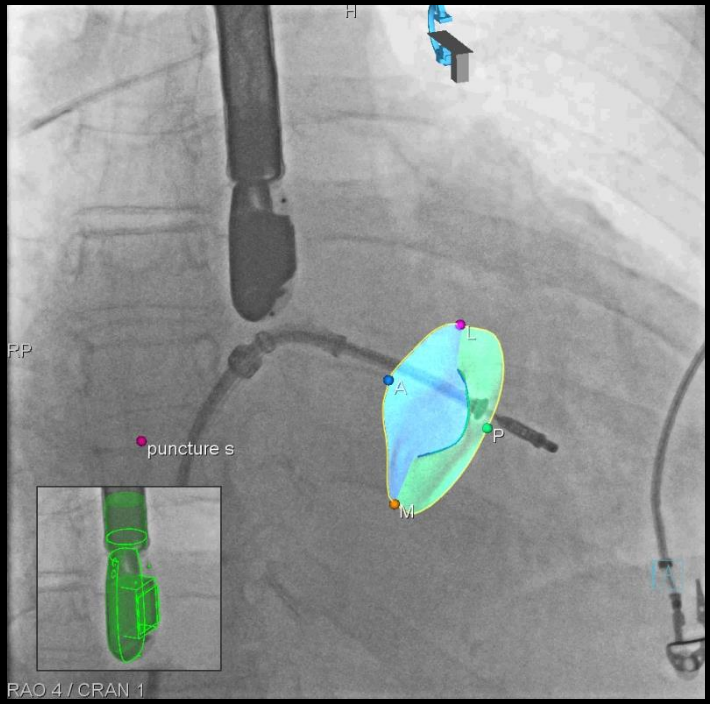
Image fusion through deep reinforcement learning

Transesophageal Echocardiography



Visualize and quantify valve anatomy

Xray-Echo Fusion



Real-Time valve model overlay

TrueFusion represents a workflow consisting of syngo TrueFusion and TrueFusion echo-fluoro guidance

Image courtesy University Hospital Bonn, Germany

Behind the scene: a broad family of deep learning-based agents for medical image analysis

Body marker detection

Multi-Scale Deep Reinforcement Learning

Organ contouring

Deep Adversarial Image-2-Image Network

Tissue characterization

Deep Dense Feature Pyramid Network

Image registration

Deep Variational Image-2-Image Registration Network

Next generation image parsing using multi-scale deep-reinforcement learning

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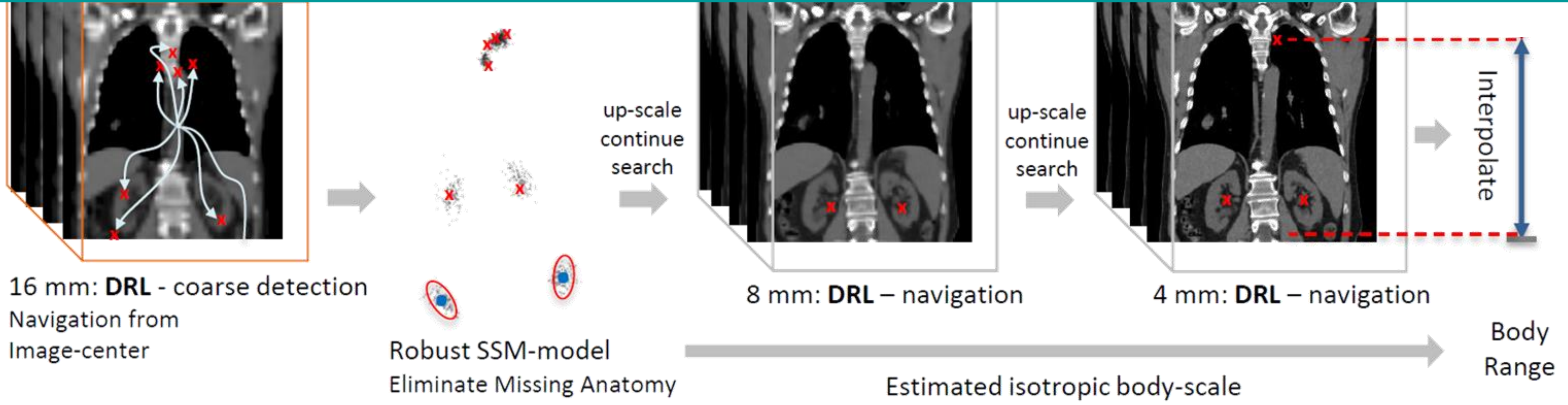
Artificial agent trained on how to search for multiple body markers in 3D images

Validated on **2305 CT volumes**
Focus on robustness: **No failures**

Real time speed: 0.8s
Superior (+20-30%) other deep learning pipelines



Ghesu et al. *"Multi-scale deep reinforcement learning for real-time 3D-landmark detection in CT scans."* TPAMI 2019

Organ contouring for radiation therapy

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30+ organs / anatomies at risk

Trained on 4.5M images

Head
- Brain

Chest
- Ribs
- Aorta
- Heart
- Spinal cord
- Sternum
- Esophagus
- Right breast
- Left breast
- Right inf. lung
- Right mid. lung
- Right sup. lung
- Left inf. lung
- Left sup. lung

Abdomen and pelvis
- Bladder
- Prostate
- Liver
- Spleen
- Right kidney
- Left kidney
- Rectum
- Right fem. head
- Left fem. head
- Bowel bag

Whole body
- Skeleton
- Body

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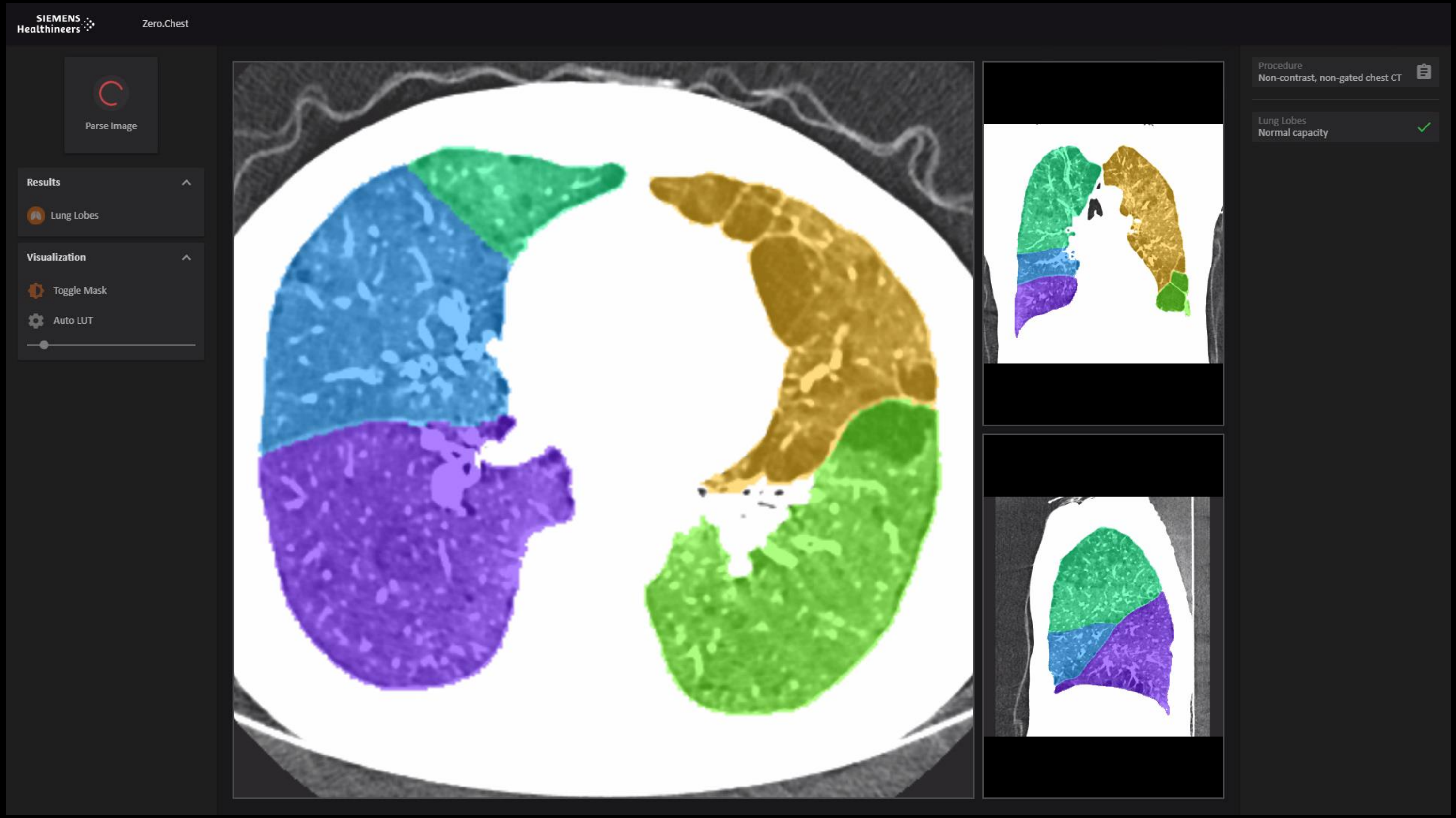
AI can help reading chest imaging faster
Non-contrast, non-gated chest CT

AI agents populate table of measurements and findings



Parsing lung lobes
Normal capacity

Scanning for lung nodules
Upper right lobe, solid, 8x4mm

Emphysema?
Substantial: Paraceptal, centrilobular

Airways
Normal

Low bone mineral density?
Normal density

Scanning for vertebra fractures
T6, mild
T8, mild

Cardiomegaly?
Normal heart size

Coronary calcium burden?
Proximal LAD severe

Aorta aneurysm, aorta stenosis?
Normal diameters

Aorta plaque burden
Diffused, mild severity

Fleischner guidelines: High risk

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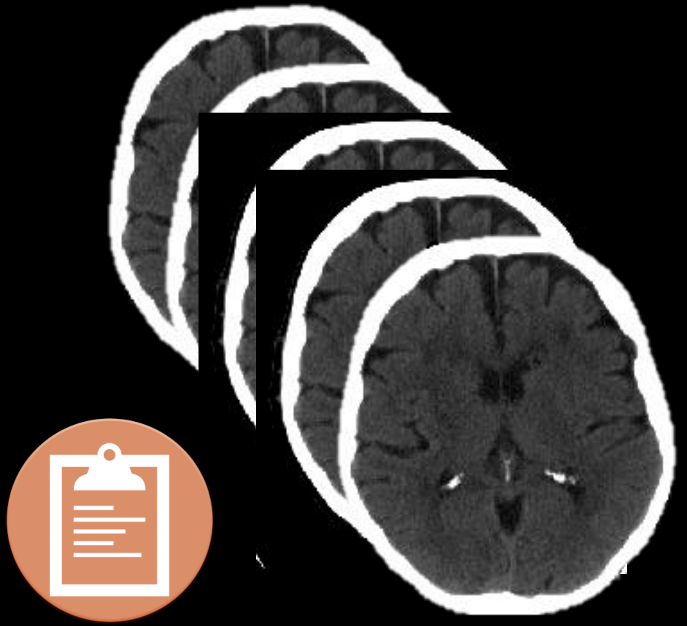
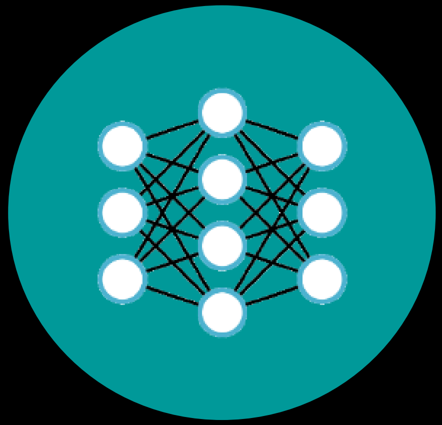
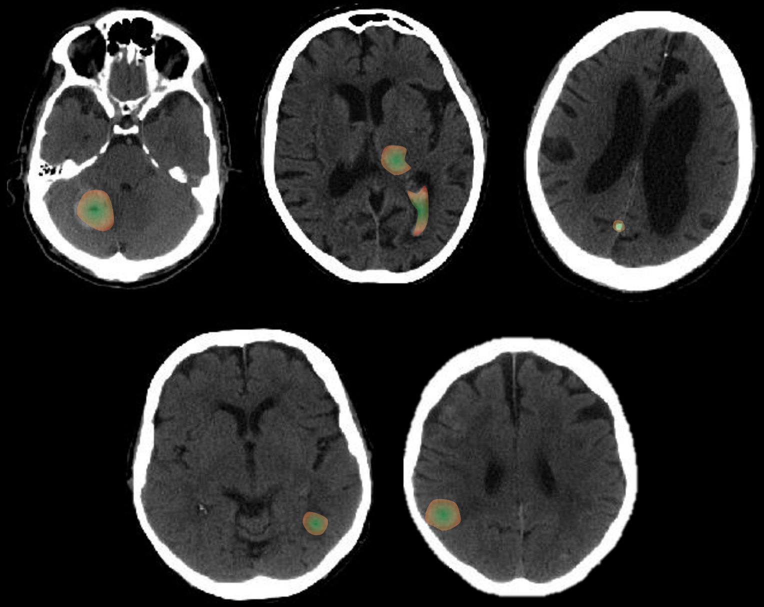
Learning to detect brain hemorrhage



Non-Contrast Head CT and Radiology Reports



AI system trained on 100,000 images



Hemorrhage Detection: Cerebellar, Basal Ganglia, Gyral, Left Occipito-Temporal Lobe, Right Lateral Parietal Lobe

Source: Data courtesy of Northwell Health

The concepts and information presented in this slide deck are based on research results that are not commercially available

Improved Hemorrhage Detection on Non-Contrast Head CT Using a Robust Artificial Intelligence Pipeline, ASNR 2018

Artificial Intelligence technology assists prostate cancer risk assessment and supports reporting

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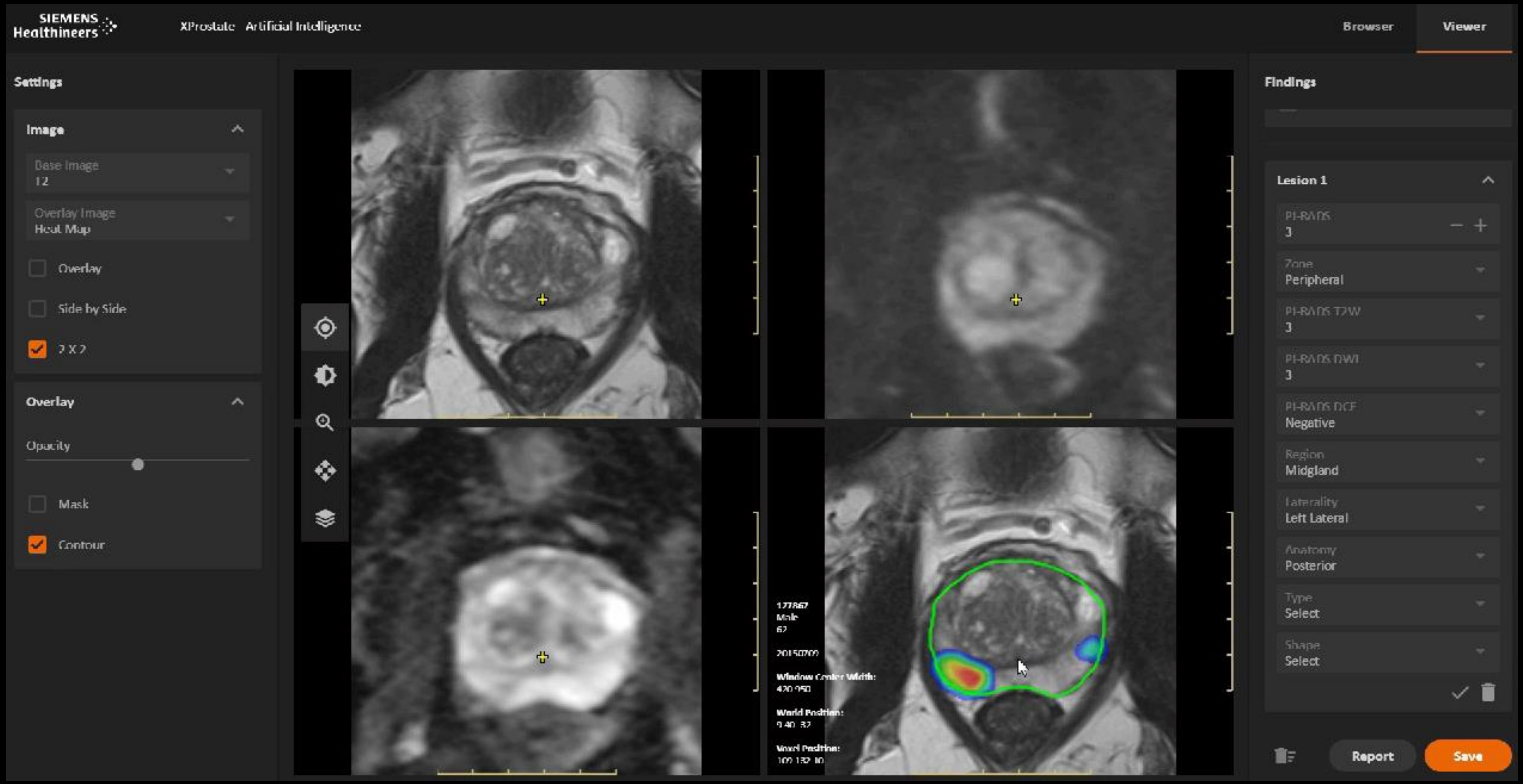


Cross-validation on 1,000 cases
AUC = 93%, per slice

The concepts and information presented in this slide deck are based on research results that are not commercially available

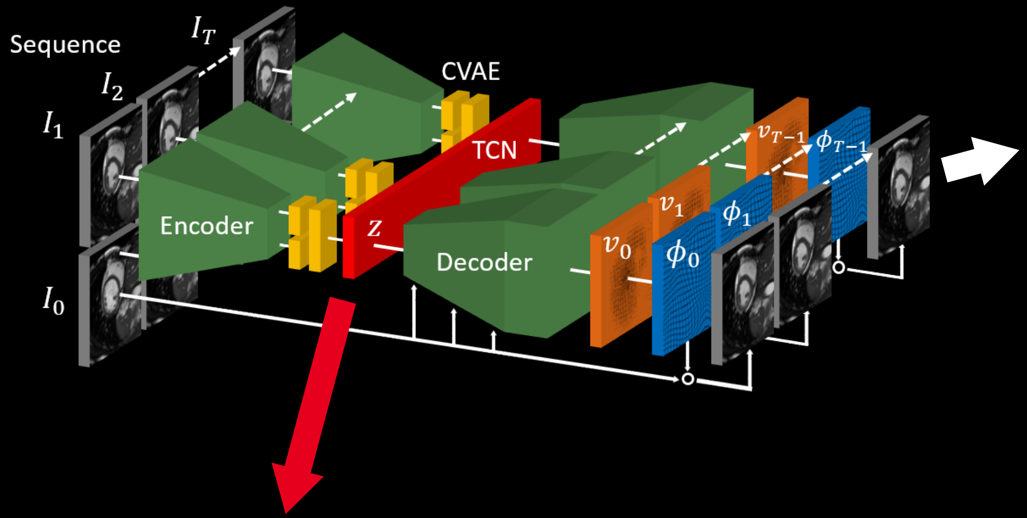
mpMRI Prostate AI integrates

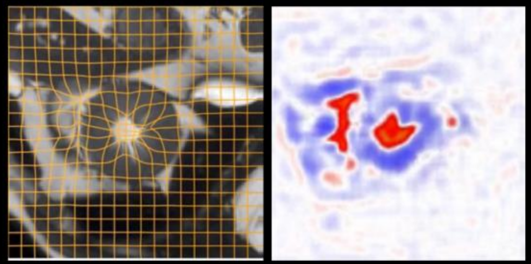
- Anatomical info (T2-weighted)
- Functional info (DWI high B, DWI ADC)

2 lesions identified. Are the lesions organ confined?

- Prostate segmentation map
- Select lesion based on heat map
- Auto-populate PI_RADS scores
- Check scores
- Identify index lesion
- Create report

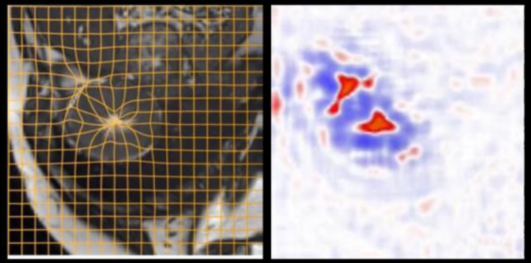
Learning probabilistic models of organ motion

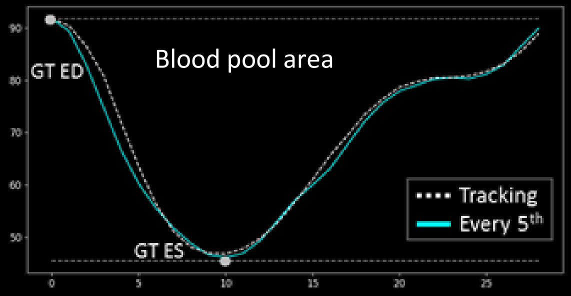




Diffeomorphic organ tracking for motion analysis

AI-based temporal interpolation





Motion interpolated between every 5th frames resulted in no significant differences with original sequence

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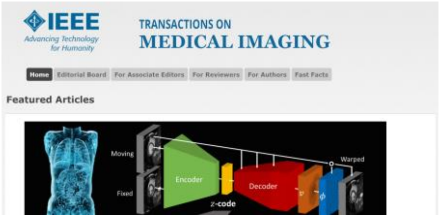
Temporal CVAE to learn motion model directly from data

- Trained on 750,000 sequences (234 subjects)
- Improved accuracy and temporal consistency compared to AI-based pair-wise registration



Inria

Krebs, Julian, et al. "Learning a probabilistic model for diffeomorphic registration." IEEE TMI 2019.

AI-Pathway Companion
Patient health management across multi-clinical pathways

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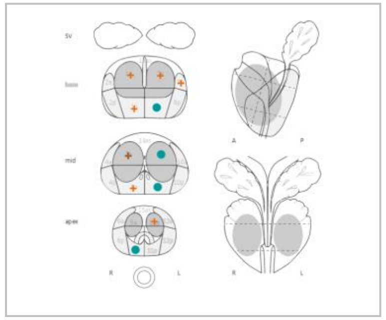
Prostate cancer

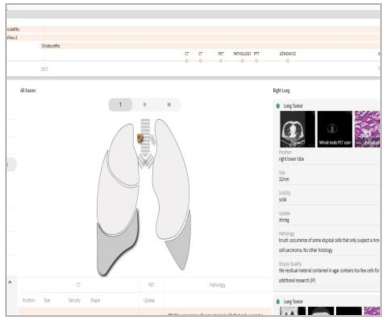
Lung cancer

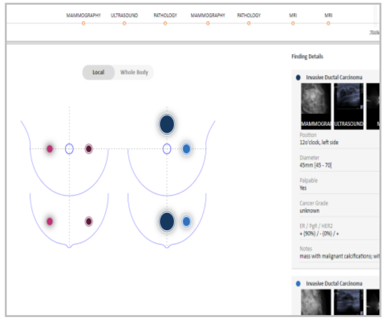
Breast cancer

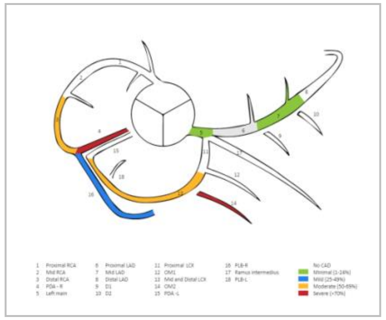
Coronary artery disease

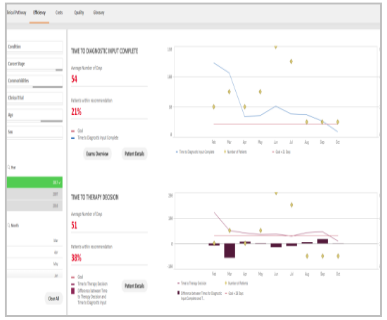
Analytics KPIs



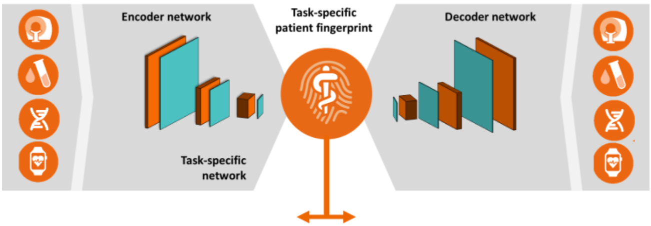








Combine multi-modal patient data into a **task-specific fingerprint**



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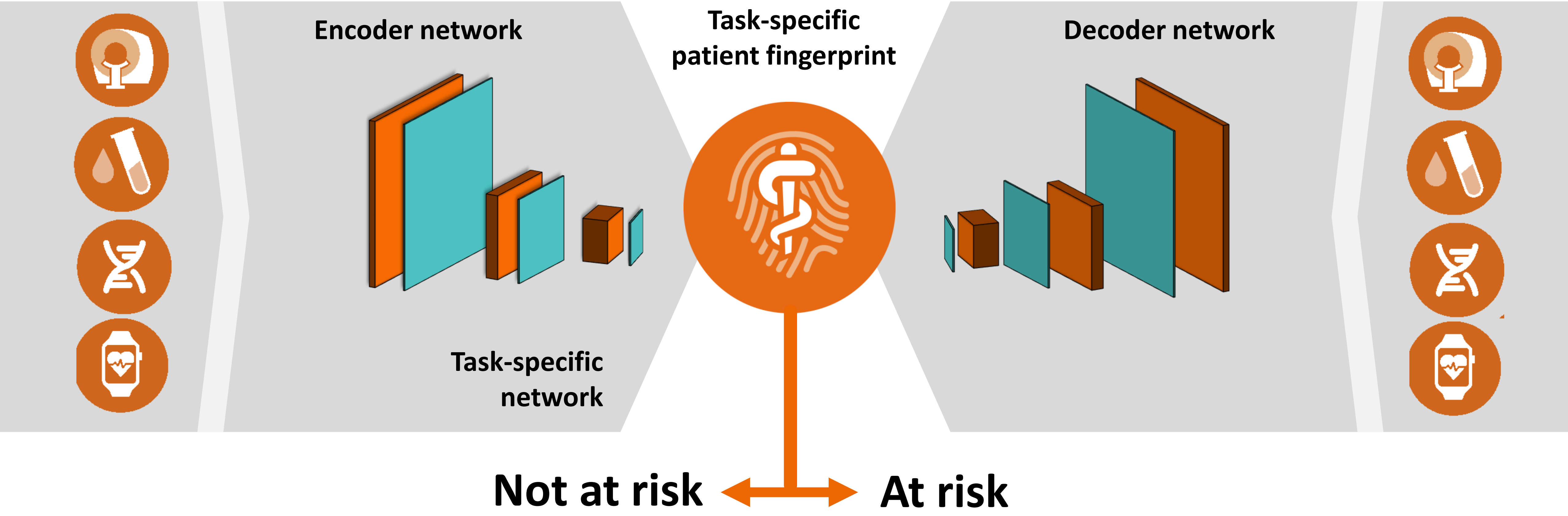
DeepReasoner: Multitask deep network for prediction and risk assessment

Combine multi-modal patient data into a **task-specific fingerprint**



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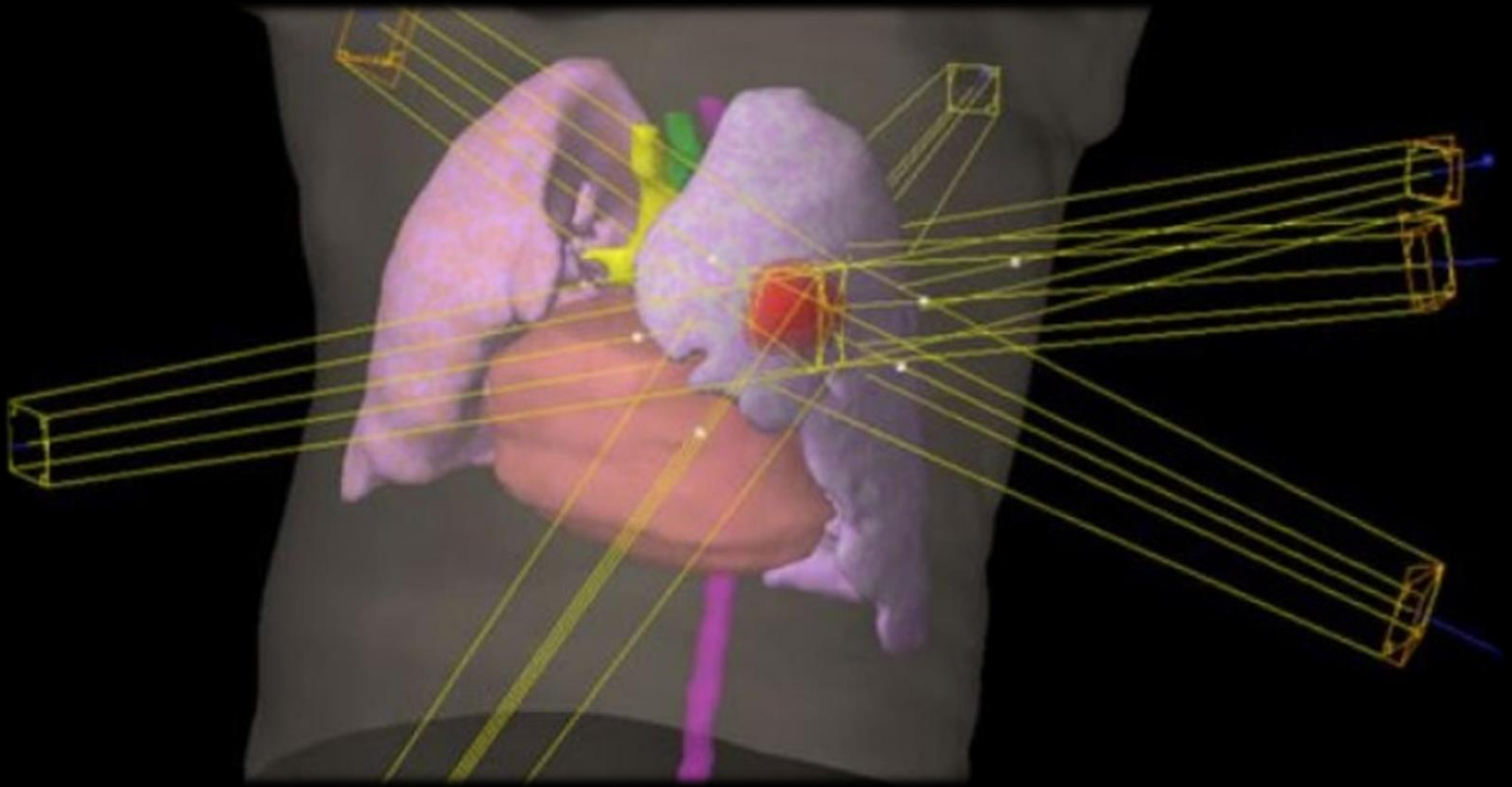
Predicting outcome of stereotactic body radio-therapy (SBRT) for lung cancer



Can Deep Reasoner differentiate patients with different response patterns?

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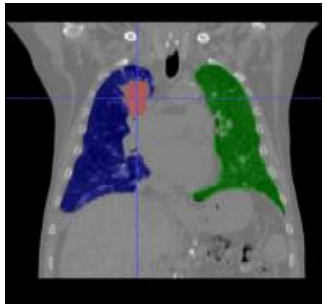
DeepReasoner-based radiomics for SBRT outcome prediction

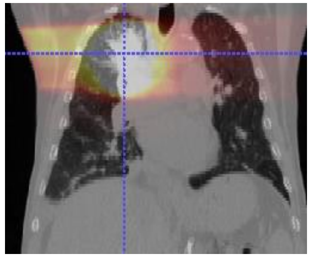
Diagnosis and planning

Imaging



EHR

Treatment Parameters



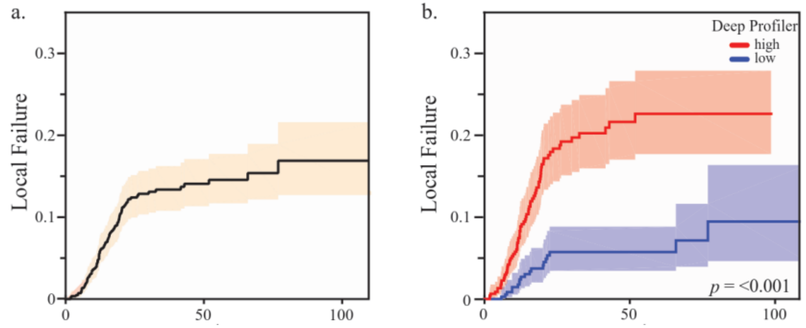
Learn fingerprint to differentiate responder and non-responder groups

Risk score

AI trained on dataset of 1,000 cases

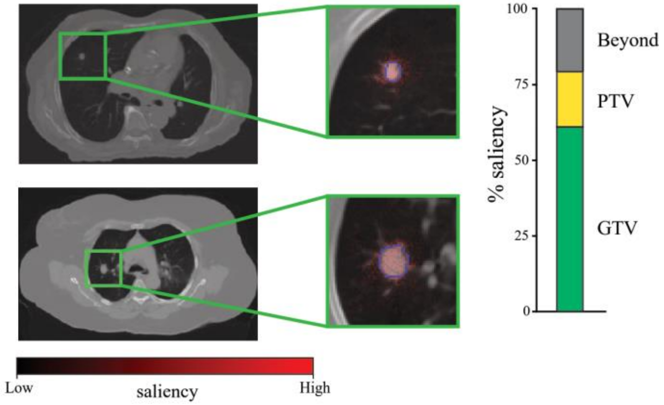
Probability of local failure after SBRT

Reduced local failure rate by 45% in favorable sub-group



No stratification

Deep reasoner stratification



Source: Data courtesy of Cleveland Clinic

The concepts and information presented in this slide deck are based on research results that are not commercially available

What if we could create a digital twin of the patient's heart?

- **Multiscale, Personalized Physiological Model of the patient's heart**
- Similar dimensions, electrical signal activation, muscle contraction, ejection fraction, pressure dynamics
- Mechanistic and statistical modeling
- Model is under our control
- **Potential to test and prescribe best therapy for the patient**

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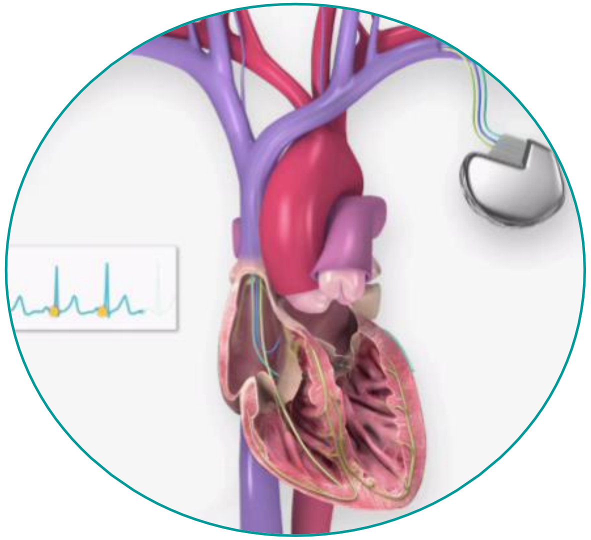
Application of the digital twin: How to maximize chance of response to Cardiac Resynchronization Therapy?

2-3 hours per procedure



150,000 patients/year

30-50% non-responders

High demand to optimize lead location and personalize stimulation delays

Numbers for USA Market – 2013 ESC Guidelines CRT: Lopez-Sendon, Medicographia, 2011
Market Intel Reports, 2016; Mathilda et al., Circulation, 2017

VirtualHeart: A digital twin of a patient's heart to support EP interventions

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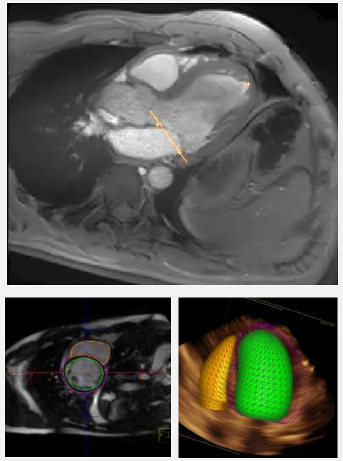
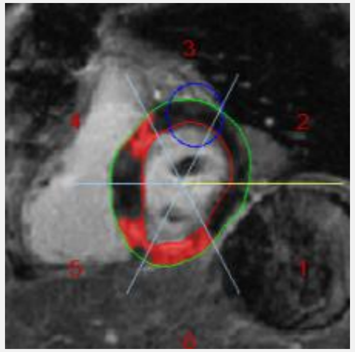
Model anatomy from images

Ejection Fraction, Stroke Volume



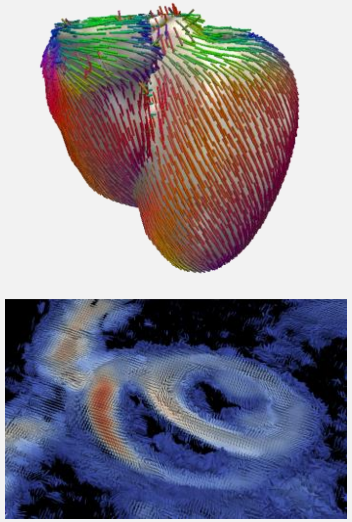
Quantify tissue substrate

Scar burden, healing tissue



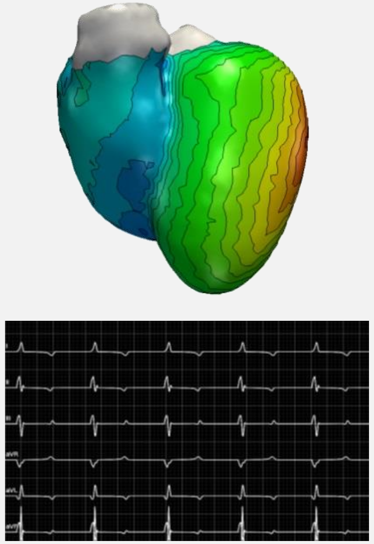
Model myocardium fibers

Fiber strain



Estimate cardiac electrophysiology

QRS duration, morphology



Patient-specific cardiac electromechanics

Stiffness, Stress

Model anatomy → **Fuse multi-source information** → **Compute physiology** → **Virtual test for therapy optimization**

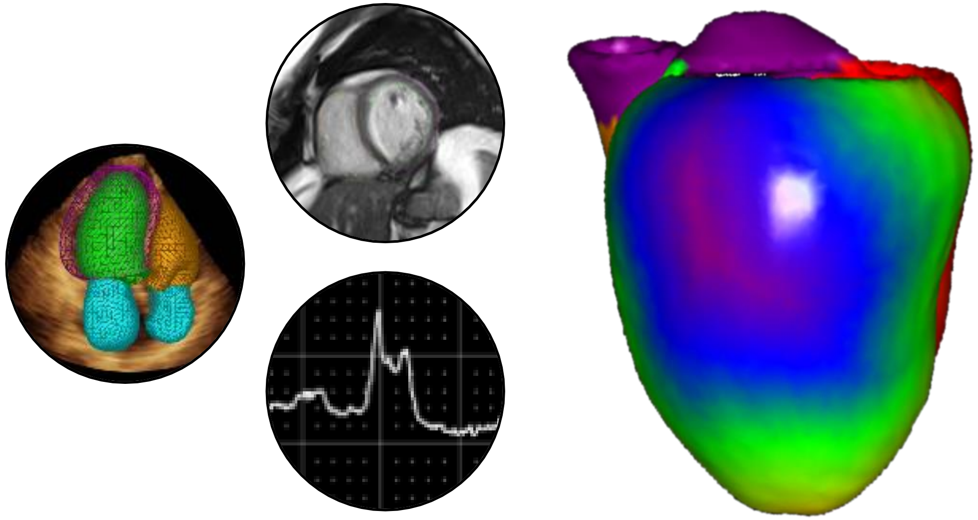
The concepts and information presented in this slide deck are based on research results that are not commercially available

Neumann et al., "A self-taught artificial agent for multi-physics computational model personalization", MedIA 2016

Continuously updated digital twin for guidance of left ventricle lead implant

Before the intervention

Patient’s digital twin is created to assess best LV lead positions in terms of electrophysiology response



During the intervention

The model is updated with interventional measurements (ECG, sensed delays), as the intervention proceeded

Observed changes in QRS duration accurately predicted by the model

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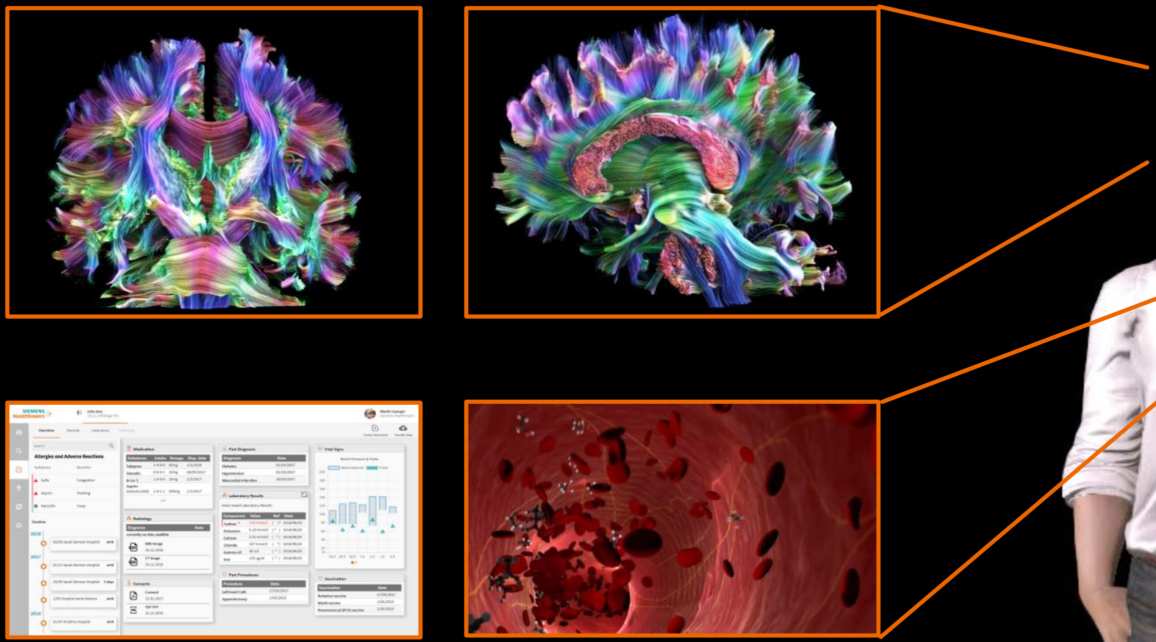
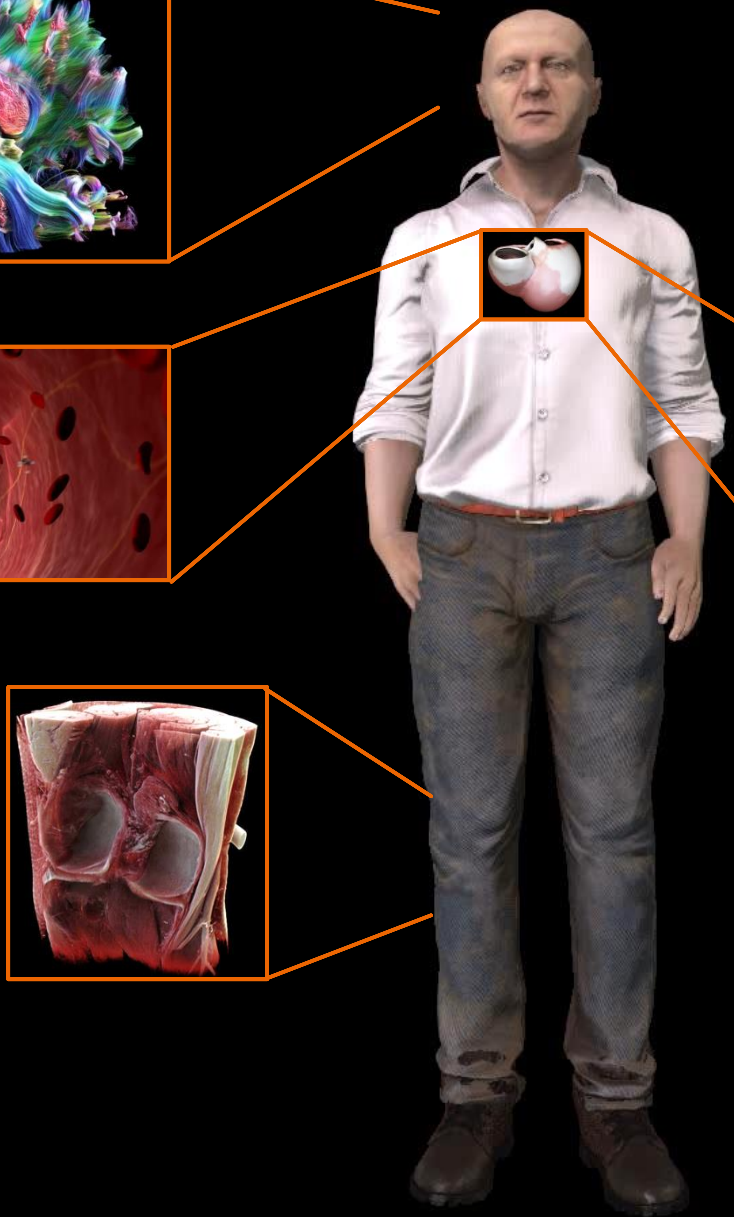
Evaluation performed at IHU Bordeaux, Dr. Ritter and Dr. Lafitte; Data courtesy of IHU Bordeaux





Digital twin –

lifelong, personalized physiological model updated with each scan, exam

Person-centric prevention and holistic treatment

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Thank you for your attention

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