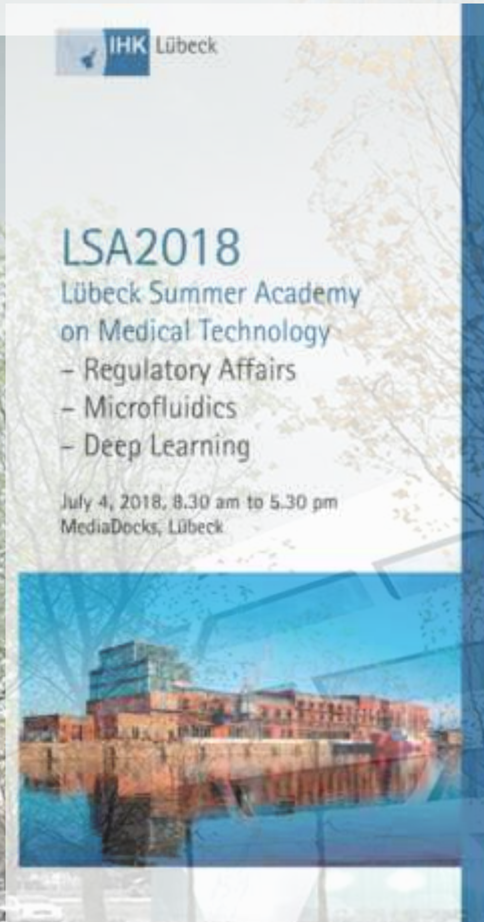
WHY DEEP LEARNING WILL NOT REPLACE RADIOLOGISTS

HORST HAHN, FRAUNHOFER MEVIS & JACOBS UNIVERSITY, BREMEN

4 JUL 2018, LSA, MEDIA DOCKS, LÜBECK



Fraunhofer MEVIS
„Werkstatt der Digitalen Medizin“
Gebäudefertigstellung 2020

THE DISRUPTIVE DOZEN

World Medical Innovation Forum, Boston

2016 Disruptive Dozen | CANCER

Below is our Disruptive Dozen for 2016, guided through the nomination and selection-ranking process by our committee, each earning scores along the way.

We present them to you in order of their rank after the final voting was completed.

The medical professionals listed below, experts in oncology, were each paired with a specific disruptive innovation.

At the Forum presentation, each expert explained its potential impact on cancer in the decade ahead.

1 | Cellular Immunotherapy

Marcela Maus, MD, PhD
Director of Cellular Immunotherapy, MGH, Assistant Professor, Harvard Medical School

2 | Immune Modulators (Checkpoint Inhibitors) and Vaccines

Antonio Chiocca, MD, PhD
Chairman, Neurosurgery, BWH, Professor of Surgery, Harvard Medical School

3 | Liquid Biopsy for Oncology

Shyamala Maheswaran, PhD
Associate in Molecular Biology, Surgery, MGH, Associate Professor, Surgery, Harvard Medical School

4 | Machine Learning and Computational Biology to Transform Cancer Care

James Brink, MD
Radiologist-in-Chief, MGH, Juan M. Taveras Professor of Radiology, Harvard Medical School

5 | Epigenetics and Cancer Treatment

Johnathan Whetstine, PhD
Tepper Family MGH Research Scholar, Associate Professor of Medicine, Harvard Medical School

6 | The Microbiome and Cancer

Lynn Bry, MD, PhD
Associate Professor of Pathology, Director, Massachusetts Host-Microbiome Center and Crimson Core, Dept. Pathology, BWH

7 | CRISPR: Genome Editing and Cancer

Keith Joung, MD, PhD
Associate Pathologist, Associate Chief for Research, The Jim and Ann Orr MGH Research Scholar, MGH, Professor of Pathology, Harvard Medical School

8 | Single-Cell Molecular Profiling

Carl Novina, MD, PhD
Cancer Immunology, DFCI, Associate Professor, Microbiology and Immunobiology, Harvard Medical School

9 | mHealth and Cancer Care

Ann Partridge, MD
Director, Adult Survivorship Program, Program for Young Women with Breast Cancer, DFCI, Associate Professor of Medicine, Harvard Medical School

10 | Patient-Specific Research to Enable Efficient Drug Development

Jeffrey Engelman, MD, PhD
Director, Center for Thoracic Cancers, MGH Cancer Center, Associate Professor of Medicine, Harvard Medical School

11 | Redefining Value in Cancer Care

Tim Ferris, MD
Senior Vice President of Population Health Management, PHS

12 | Nanotechnology and Cancer Treatment

Omid Farokhzad, MD
Physician-scientist, Anesthesiology, BWH, Associate Professor, Harvard Medical School

WORLD MEDICAL INNOVATION FORUM™

4

Machine Learning and Computational Biology to Transform Cancer Care

The accelerating field of precision medicine includes all of those diagnostics and treatments targeted to the needs of individual patients on the basis of their genetic, biomarker or physical characteristics that distinguish one patient from another with similar clinical presentations.

In recent years, great progress has been made in recording an individual's state of health, right down to the molecular level of gene activity. However, the ultimate goal of using this information for precision medicine has remained largely unfulfilled when it comes to cancer care.

With all of the reams of data available from a patient's full genome sequencing, the thousands of pages of critically important background information from medical journals and with the doubling of overall medical information every five years, most cancer researchers and clinicians can't keep up with this avalanche of information and derive maximum value from it. Unfortunately, it's the patient with cancer who ultimately misses out on crucial information that may be pertinent to their care and, many times, has to then settle for a one-size-fits-all cancer treatment and hope for the best.

This is where computational biology, which involves the development and using of tools to analyze and model biological data and systems, along with machine learning, which is the ability of computers to learn without being explicitly programmed, can revolutionize personalized medicine and make cancer diagnoses more accurate.

To understand the cause of cancer and to develop more effective methods of prevention, detection and treatment, clinicians and researchers need access to rich molecular and clinical data sets. The good news is that over the next few years, technology will be revolutionizing the understanding and treatment of diseases, especially cancer. By gathering the latest information from the patient's biology, and combining that with trillions of data points from tens of thousands of other cancer patients, individualized patient-specific cancer treatment options can then be created in days, and sometimes in just a matter of minutes.

Thanks to the latest machine learning algorithms and bioscience advancements, future advances in cancer diagnosis and treatment will be based on DNA mutations, not simply the location of the cancer in a person's body. Using supercomputers, researchers will be able to quickly examine specific genes in pathology samples, note the type and location of the cancer, the grade and size of the tumor, review all of the proteins, metabolites, and lipids, and then compare them all, taking into account demographics, age and gender. After subjecting this to a mathematic algorithm that uses machine learning to compare the many associations and correlations, a more precise and targeted treatment plan can then be developed.

In just a few years, experts envision that these targeted cancer treatment plans will be available within the span of 24 hours. This, of course, will represent the true value of machine learning and computational biology. Human intelligence and medical experience is not being replaced by the gathering and distillation of this statistical data, but rather it's being augmented and enhanced by it, which allows researchers and clinicians to be better at what they do.

Leading U.S. and European research institutes in machine learning and statistical genetics are now working together to develop techniques for robust biomarker discovery and elucidation of the causal mechanisms governing cancer and its progression. Ultimately, this treasure trove of information will be added to data banks and help cancer researchers from across the world mine and glean insights from the gigantic amounts of data in order to truly progress in the fight against cancer. \\

2017 Disruptive Dozen
CARDIOVASCULAR

Below is our Disruptive Dozen for 2017, which was guided through the nomination and selection-ranking process by our committee, each earning scores along the way.

We present these disruptors to you in order of their rank after the final committee voting was completed.

The medical professionals listed below, experts in cardiovascular and cardiometabolic disease, were each paired with a specific disruptive innovation.

At the Forum presentation, each expert explained its potential impact on cardiovascular and cardiometabolic disease in the decade ahead.

1 | **Quantitative Molecular Imaging for Cardiovascular Phenotypes**
Marcelo DiCarli, MD
Brigham and Women's Hospital

2 | **Harnessing Big Data and Deep Learning for Clinical Decision Support**
Christian Ruff, MD
Brigham and Women's Hospital

3 | **Targeting Inflammation in Cardiovascular Disease**
Matthias Nahrendorf, MD, PhD
Massachusetts General Hospital

4 | **Adopting the Orphans of Heart Disease**
David Milan, MD
Massachusetts General Hospital

5 | **Power Play: The Future of Implantable Cardiac Devices**
Christine Albert, MD
Brigham and Women's Hospital

6 | **Understanding Why Exercise Works for Just About Everything**
Gregory Lewis, MD
Massachusetts General Hospital

7 | **Less is More: Minimalist Mitral Valve Repair**
Prem Shekar, MD
Brigham and Women's Hospital

8 | **Finding Cancer Therapies without Cardiotoxicity**
Anju Nohria, MD
Brigham and Women's Hospital

9 | **Expanding the Pool of Organs for Transplant**
Joren Madsen, MD, DPhil
Massachusetts General Hospital

10 | **Breaking the Code: Diagnostic and Therapeutic Potential of RNA**
Saumya Das, MD, PhD
Massachusetts General Hospital

11 | **Nanotechnologies for Cardiac Diagnosis and Treatment**
Natalie Artzi, PhD
Brigham and Women's Hospital
Contributor: Jeffrey Karp, PhD, Brigham and Women's Hospital

12 | **Aging and Heart Disease: Can We Reverse the Process?**
Jason Roh, MD
Massachusetts General Hospital

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Harnessing Big Data and Deep Learning for Clinical Decision Support

A single patient can generate considerable meaningful pieces of data based on information gleaned from the 20,000 to 30,000 genes in the human genome. Multiplying so much data by tens of thousands of patients with heart disease and other ailments results in "big data." Big data implies large volume and complexity, such that advanced mathematics and high-performance computers are needed to make sense of it.

With all of the reams of electronic health data now available from patients, the thousands of pages of critically important background information from medical journals, and with the doubling of overall medical information every five years, most heart researchers and clinicians can't keep up with this avalanche of information and derive maximum value from it.

This is where computational biology, which involves the development and use of tools to analyze and model biological data and systems, along with deep learning, which is the ability of computers to learn without being explicitly programmed, can revolutionize personalized medicine and, over the course of the next decade, make heart diagnoses more accurate.

Computational biology offers the promise of finding novel associations in the vast sea of data that underlie important mechanisms of disease and can help uncover potential targets for treatment that would remain hidden to even the most expert investigator.

Doctors can't manage what they can't measure, which is why to better understand the cause of heart disease and develop more effective methods of prevention, detection, and treatment, clinicians and researchers are being provided access to rich molecular and clinical data sets. The use of electronic information is changing rapidly and over the next few years technology will be revolutionizing the understanding and treatment of diseases, especially heart disease. By gathering the latest information from the patient's biology, and combining that with trillions of data points from tens of thousands of other heart patients, individualized patient-specific treatment options can then be created in days, and oftentimes in just a matter of minutes.

Over the next decade, the use of big data from the oceans of electronic medical health records that has been sorted, reviewed, analyzed, and stored will help researchers and doctors better understand the root causes of heart disease.

The potential for big data analytics to improve cardiovascular quality of care and patient outcomes is enormous, thanks especially to two ongoing studies. A $75 million five-year study launched by Boston investigators and a team of international collaborators has begun gathering extensive health information from volunteers whose contributions will potentially provide new insights as to what marks the transition from a healthy heart to one on the road to serious disease.

While much has been learned in the past two decades about coronary disease—lesion formation, inflammation, plaque rupture, thrombosis, and heart attack—very little is known about the initial stages of the disease, where it may initiate in the body, and how it progresses. This novel study promises to provide those answers.

Another heart study, this an ambitious one spearheaded by investigators in San Francisco, is expected to enroll up to one million participants worldwide who will be using smartphones, mobile health apps, and other technology to relay information about their heart health.

After sorting through this big data and analyzing the wealth of information, the Boston and San Francisco researchers hope to be able to reduce deaths due to heart disease by using the accumulated data to create better ways to predict the occurrence and progression of heart disease.

This is where deep learning will turn this vision into reality by using patient data for improved and robust biomarker discovery, enhanced disease diagnosis, prognosis, and prediction of therapy outcomes. This form of artificial intelligence uses computer algorithms to identify patterns in large data sets, and can continuously improve with additional data.

The use of electronic health information is changing rapidly, and over the next decade it's clear that big data and deep learning will play an ever increasingly important role in the care of the heart, particularly when quality data is available for individual patient. \\

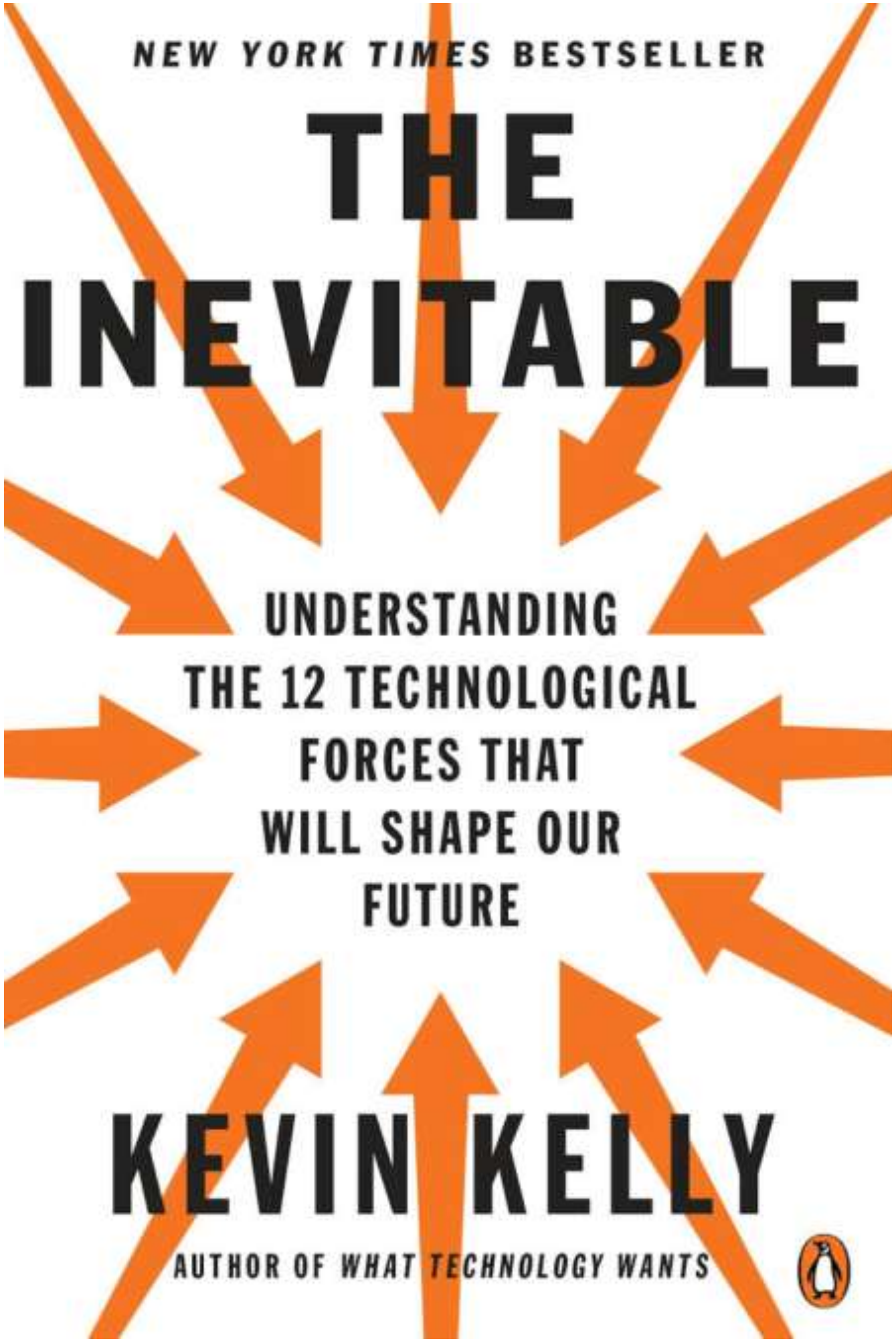
"...Star Wars technology in a Flintstones health care system."

conte

90 Jahre ist ein gutes Alter, um mit der Arbeit aufzuhören – im Prinzip.

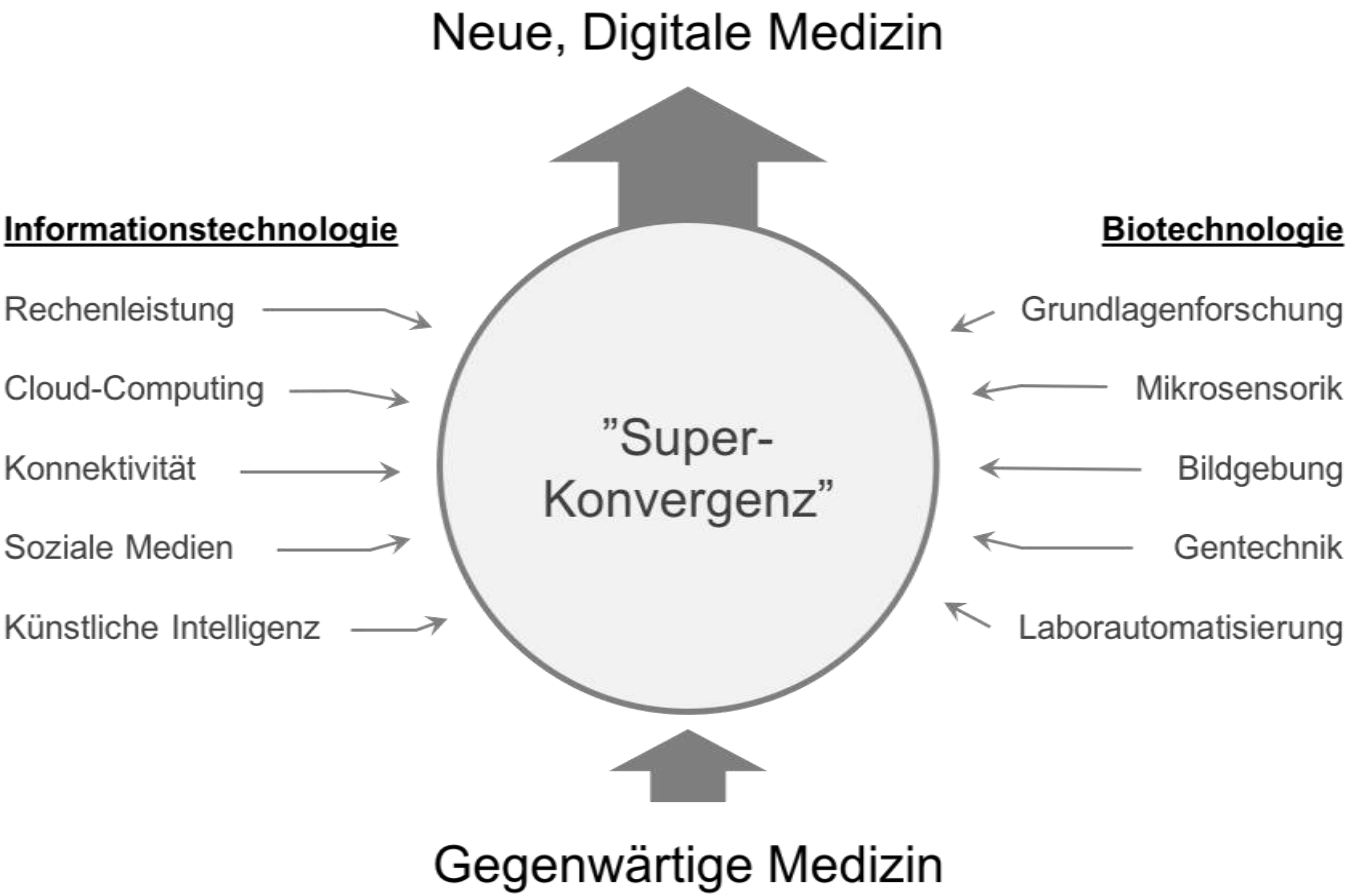
Wenn man alles verwirklichen würde, was medizinisch möglich wäre, würde unser gesamtes Bruttosozialprodukt aufgebraucht.
Es könnte nichts mehr außer „Gesundheit“ finanziert werden.
Schon heute findet in Wahrheit eine verdeckte Rationierung oder auch eine offene Priorisierung statt.

Prof. Dr. med. Fritz Beske, MPH



"We are morphing so fast that our ability to invent new things outpaces the rate we can civilize them."

The Inevitable, Kevin Kelly, 2016



Hahn & Schreiber, 2017
(adapted from Topol, 2011)

THE DIAGNOSTIC DILEMMA

How Doctors are Drowning in Complexity

THE DIAGNOSTIC DILEMMA

…resulting in complexity, cost and new sources of error

quality: new modalities, biomarkers, risk models, therapies, stratification, etc.

individualized
interdisciplinary
highest quality
cost-efficient
participative
predictive
…

safety and efficiency: *reduce complexity, standardized procedures, evidence based, …*

Medical (R)Evolution: *Deepened understanding of metabolic pathways resulting in a vast number of subtypes*
„Orphanization of Disease“

Automation in Medical Imaging (AMI)

addressing the tasks
that doctors don't like!

… and those tasks
they aren't able to do.

automation in medical imaging

Radboudumc

Fraunhofer MEVIS

ON THE LACK OF INTEGRATION

Between Precision and Simplicity

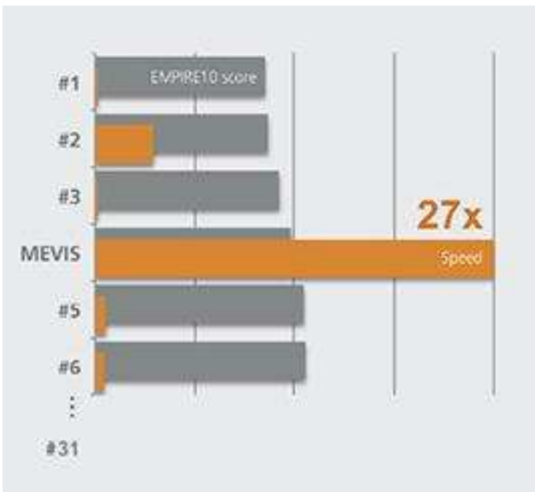
„Screening" = Find the N relevant differences
(N: unknown)

Why do we like solving these side-by-side pictures?
…because we are not particularly good in it.

Deformable Lung CT Registration (3D/4D)

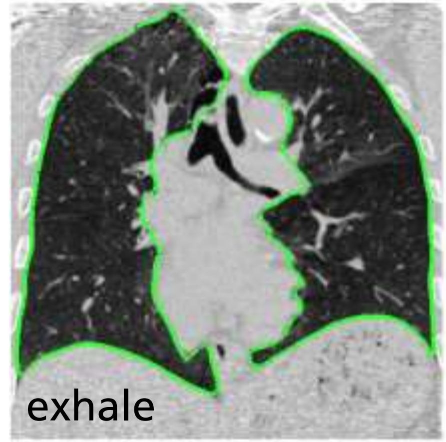
Validation:

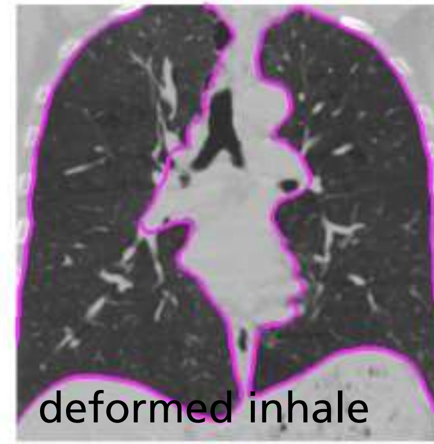
- MICCAI Grand Challenge EMPIRE, DIRLab Benchmark



- Successfully used in > 1000 cases

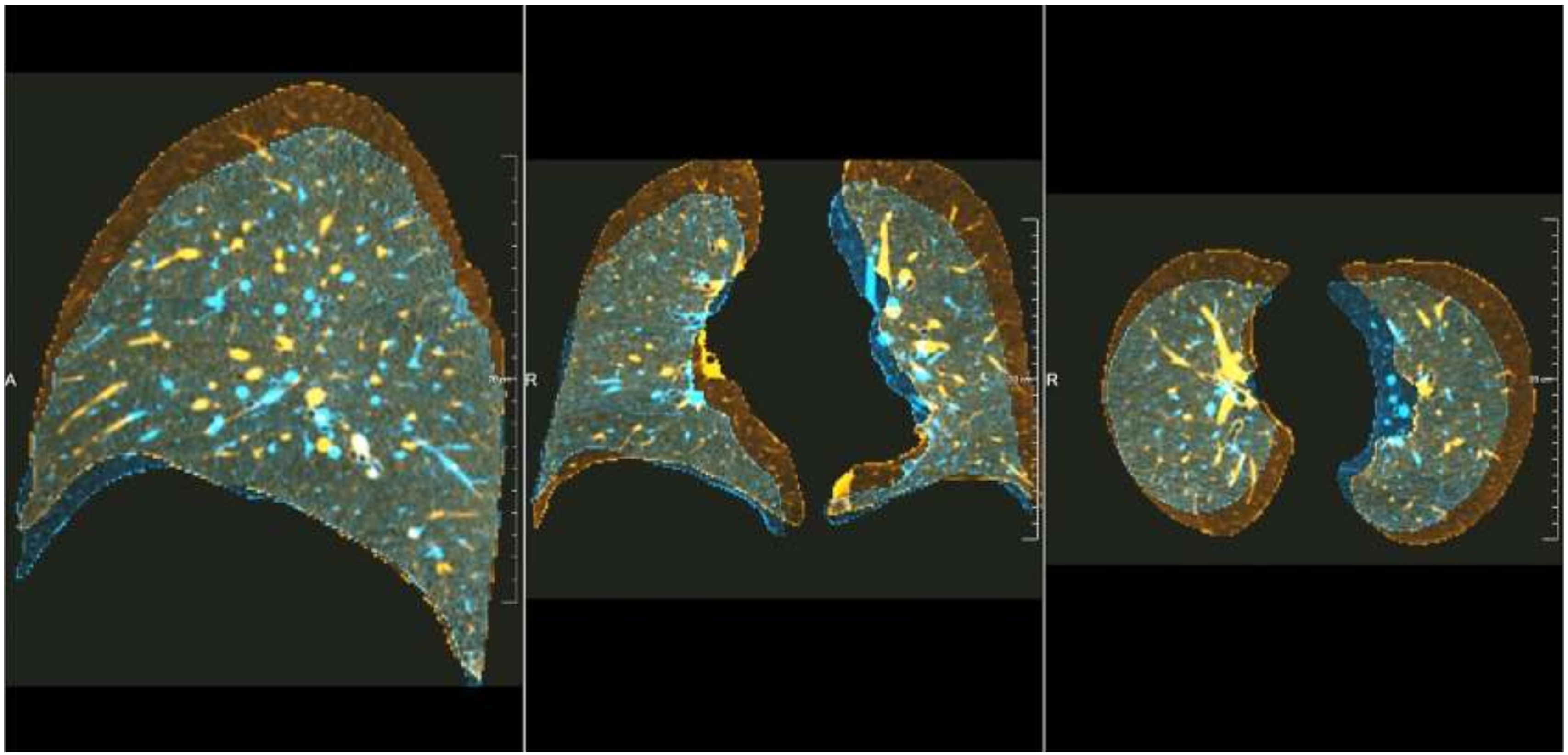
Solution ready for product delivery





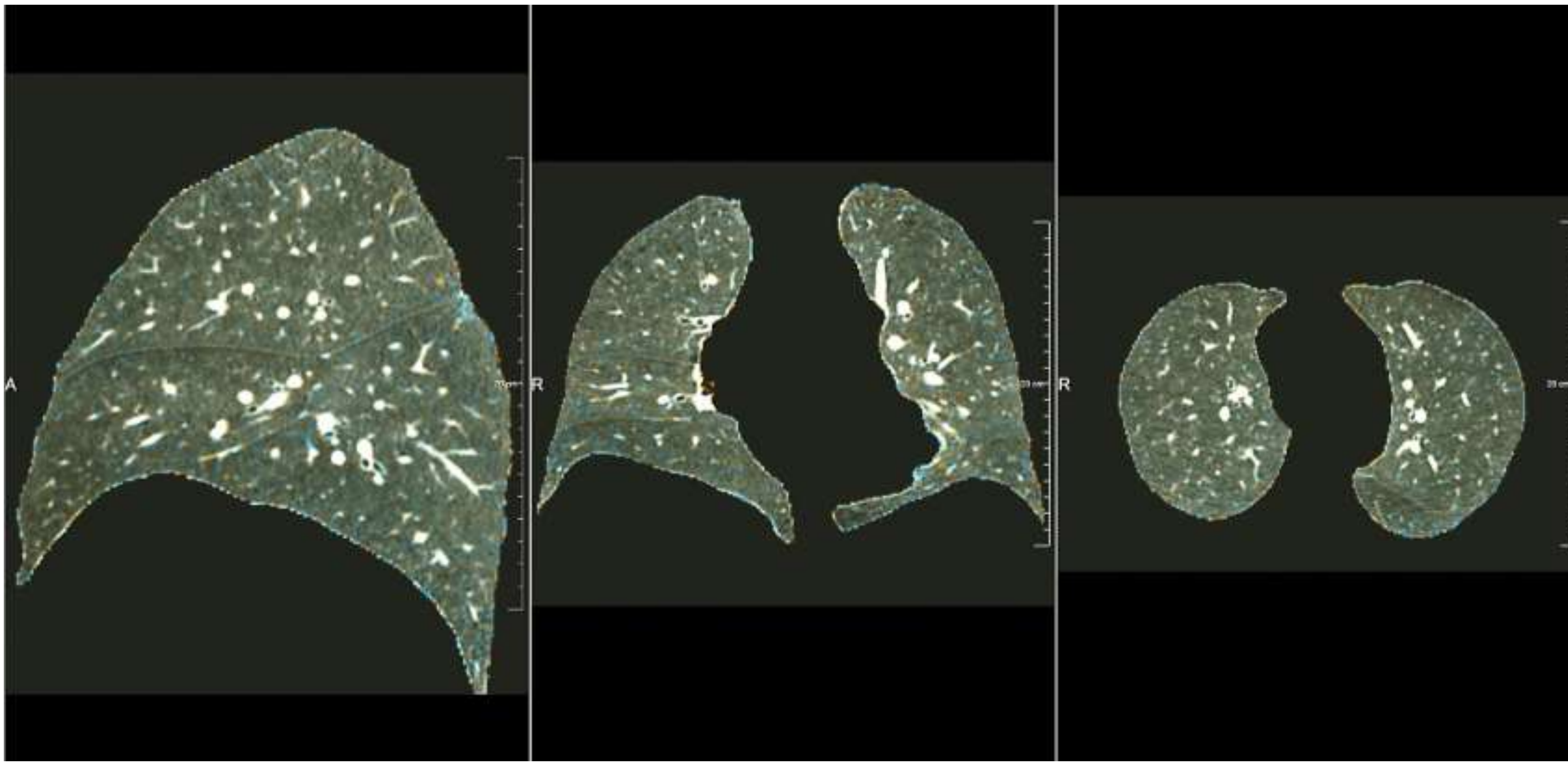
J. Ruehaak et al.

Inhale/Exhale Scans – Without Registration

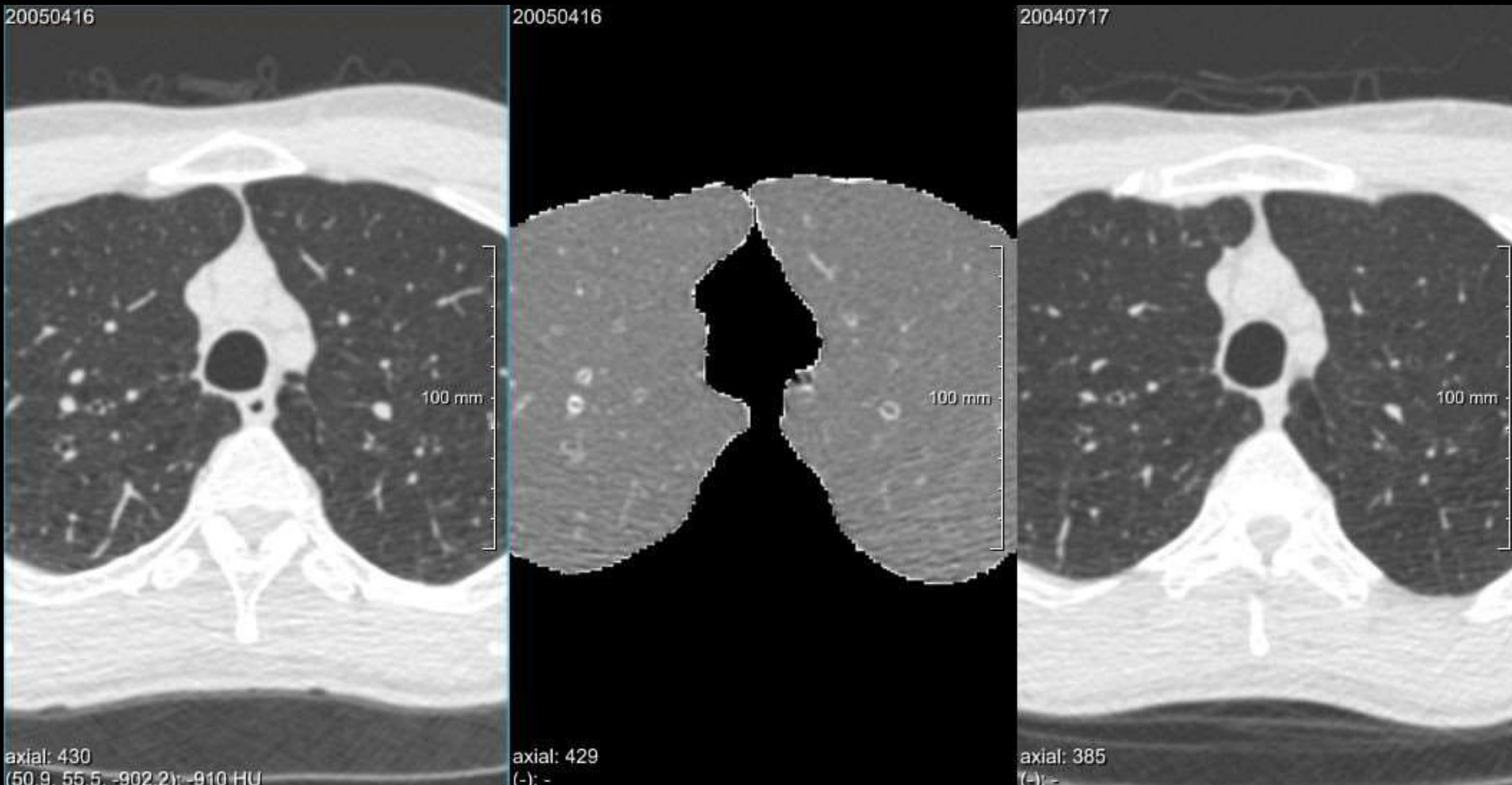


J. Ruehaak et al.

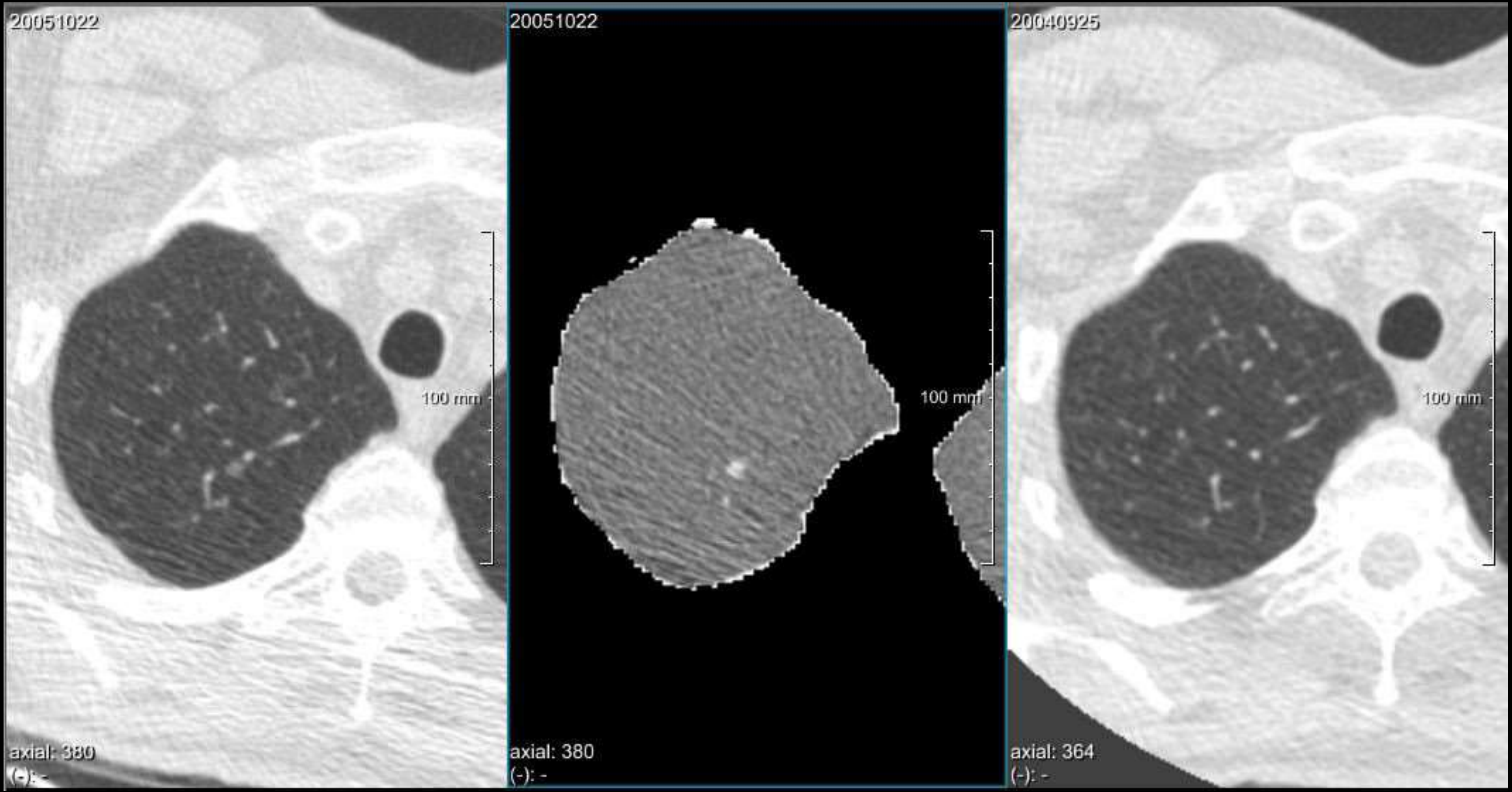
Inhale/Exhale Scans – With GDREG



EXAMPLE: ENLARGED VESSELS

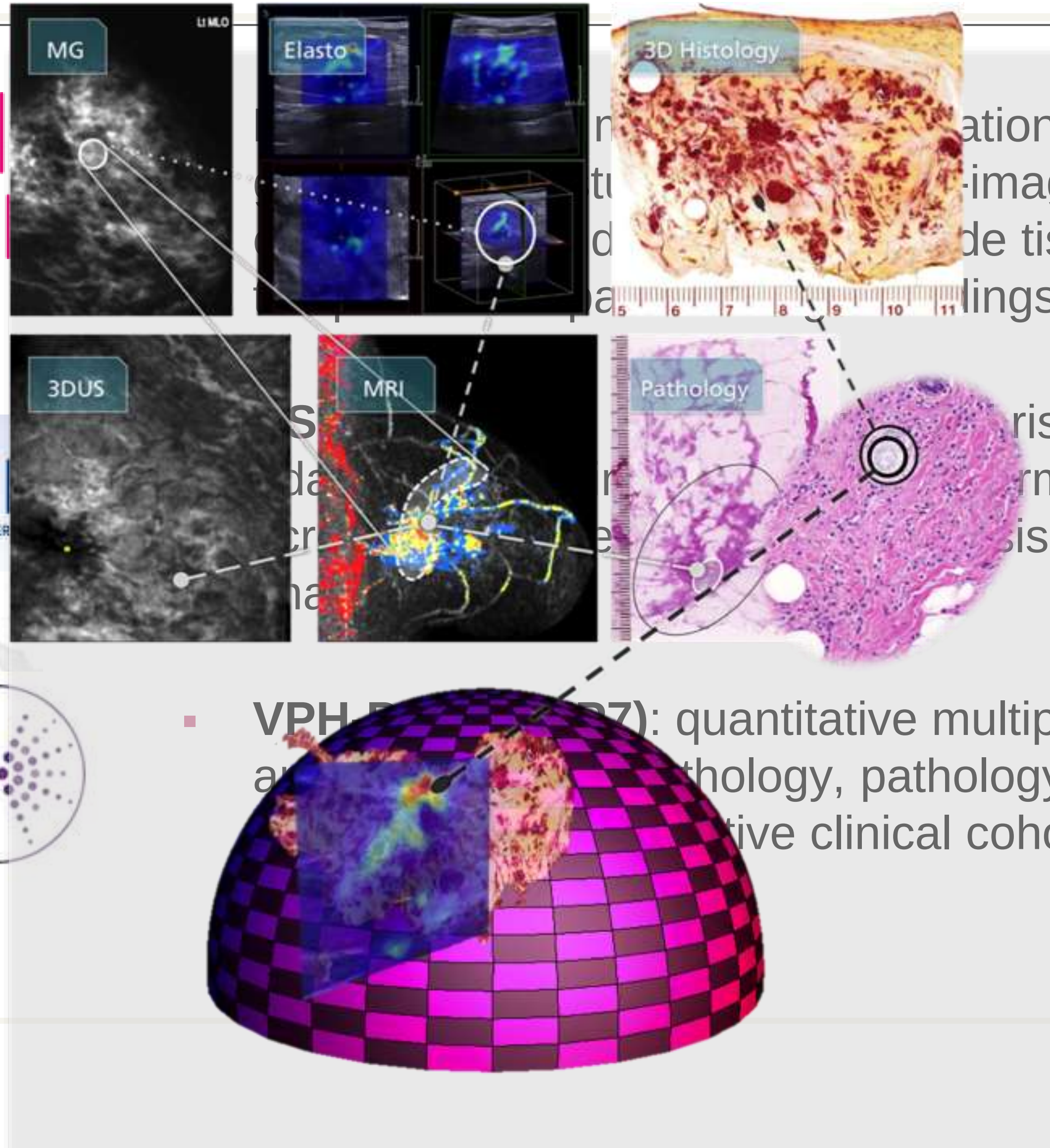


EXAMPLE: NEW TUMOR IN FOLLOW-UP



Example: Integrated Breast Care

Virtual Physiological Human and Healthcare (FP7)



ation, hypothesis
-imaging
de tissue bank),
lings

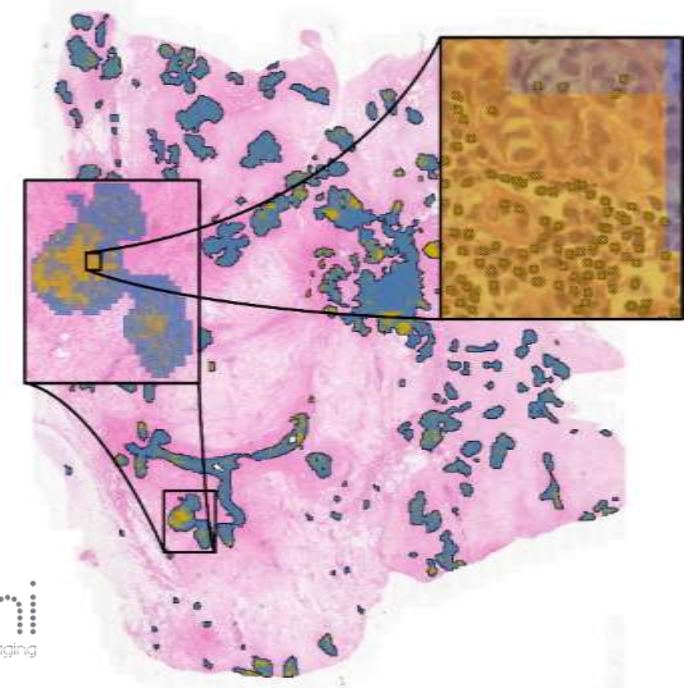
risk based
rmediate risk
is, temporal

- **VPH-P...(FP7)**: quantitative multiparametric
thology, pathology-radiology
tive clinical cohort

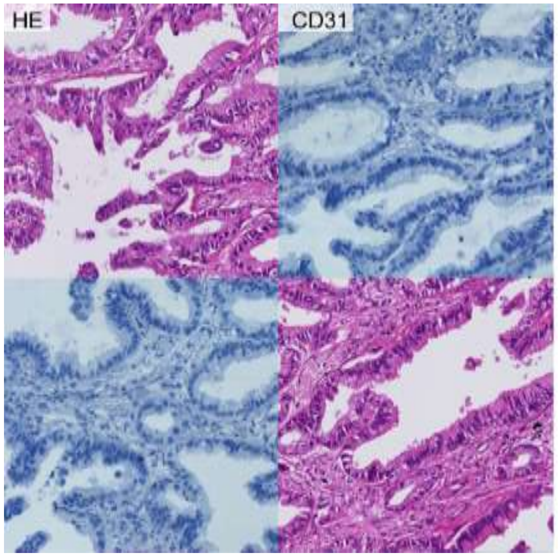
Specific Solution Components

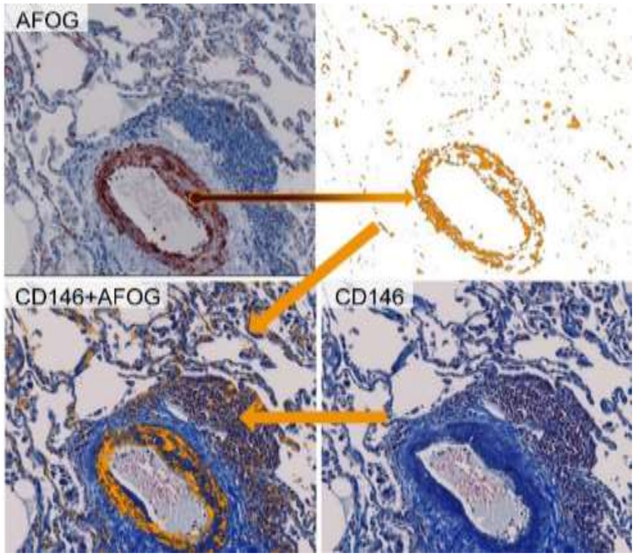
Quantitative Pathology

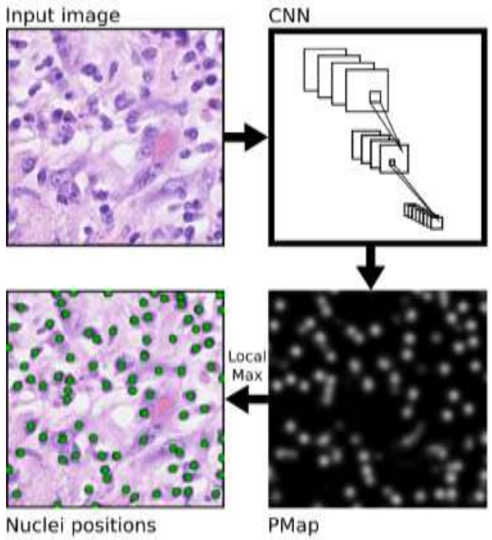
- Combination of two key technologies:
  - Automated tissue characterization
  - Virtual multistaining



ami
automation in medical imaging

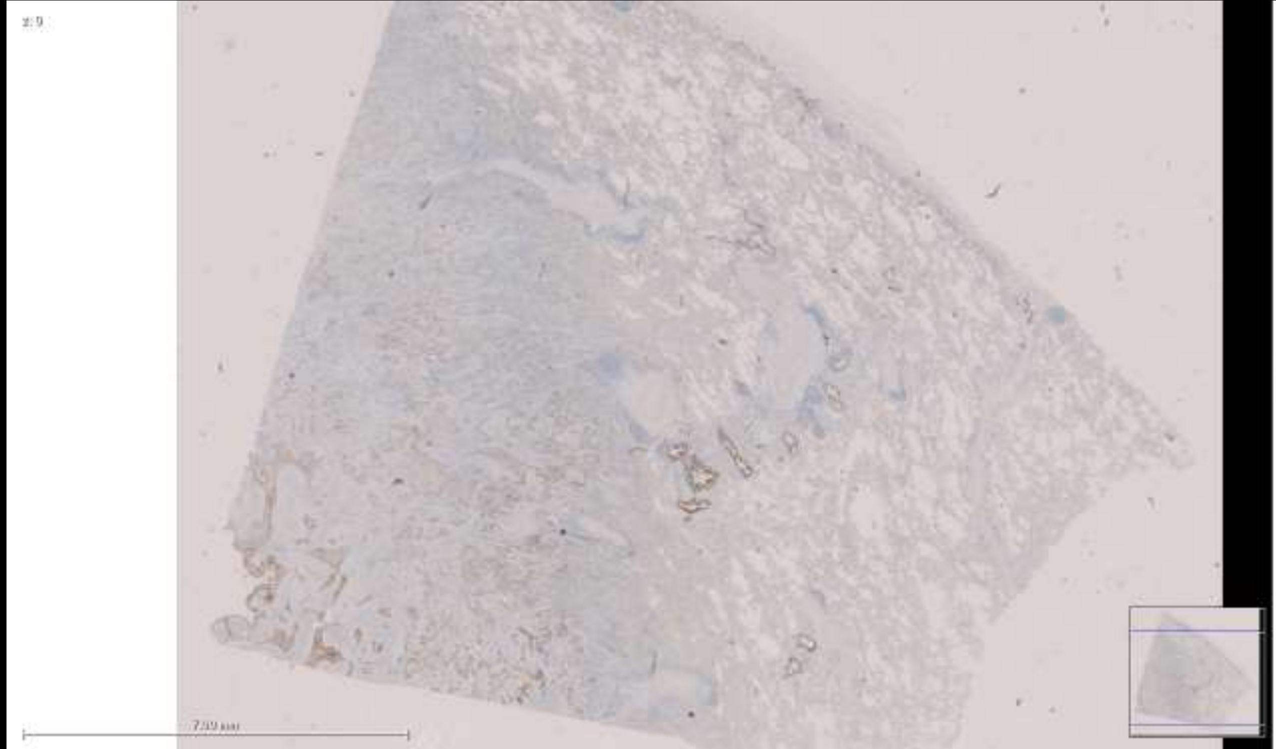


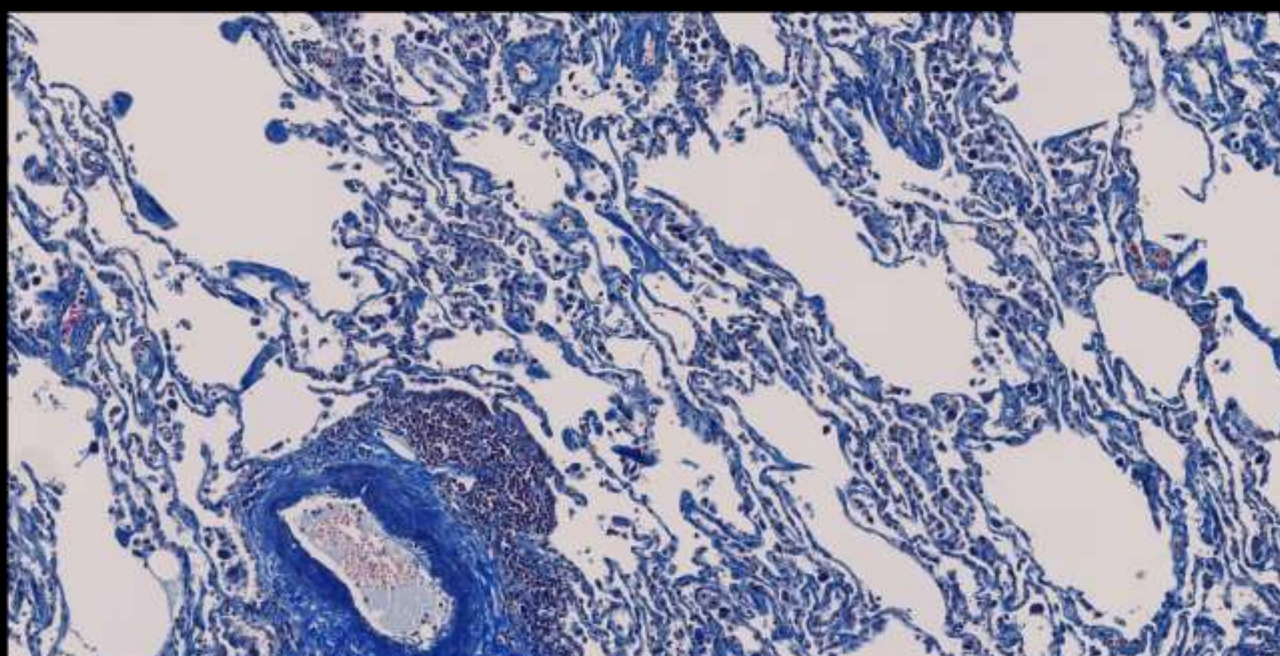




Fraunhofer


J. van der Laak, Nijmegen
Radboudumc



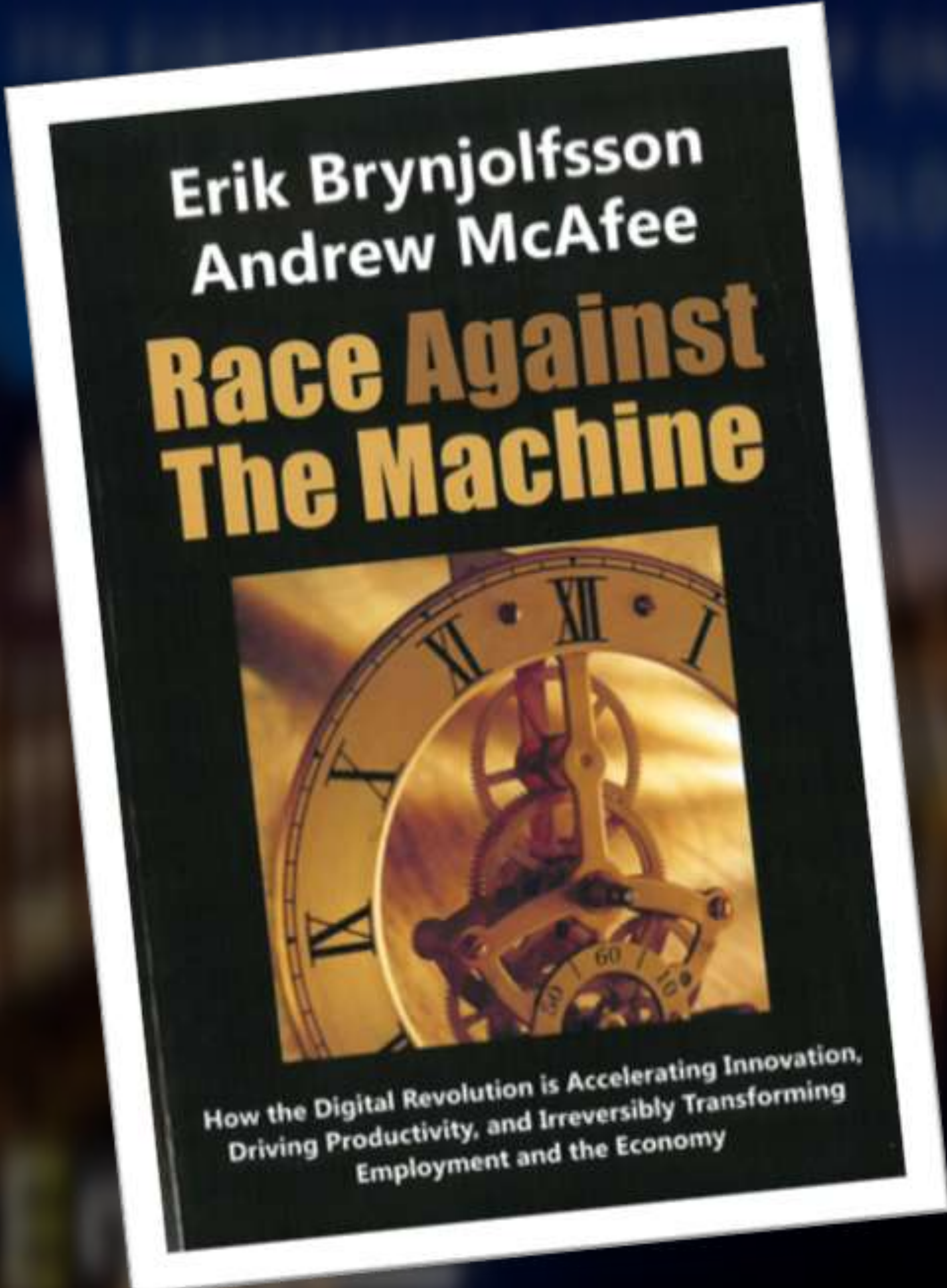


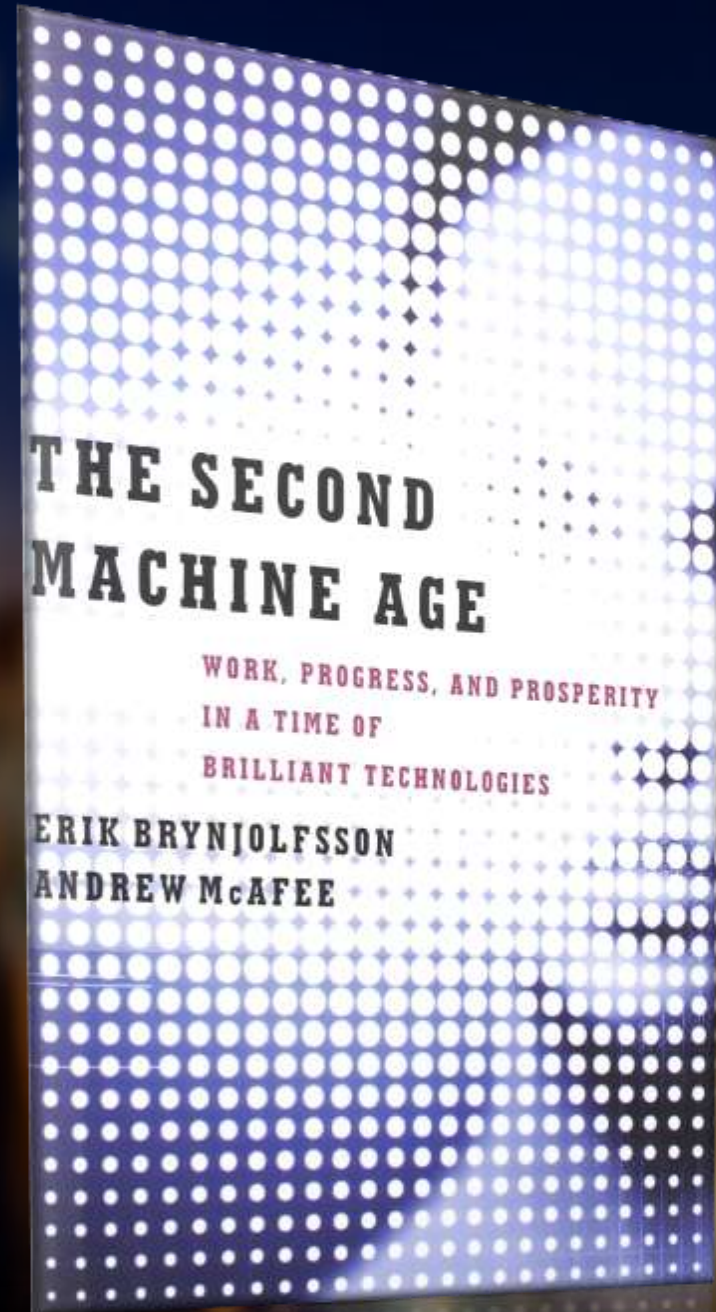
J. Lotz et al., Lübeck

Fraunhofer
MEVIS

ON HUMAN-COMPUTER TEAMS

Why Asking the Replacement Question is Wrong


Erik Brynjolfsson
Andrew McAfee
Race Against The Machine
How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy


THE SECOND MACHINE AGE
WORK, PROGRESS, AND PROSPERITY IN A TIME OF BRILLIANT TECHNOLOGIES
ERIK BRYNJOLFSSON
ANDREW McAFEE

Geoff Hinton, 2016, Source: YouTube

Geoff Hinton comments on radiology and deep learning at the 2016 Machine Learning and Market for Intelligence Conference in Toronto

Geoff Hinton, 2016

„ Let me start by just saying a few things that seem obvious.
I think if you work as a radiologist, you are like the coyote that's already over the edge of the cliff but hasn't yet looked down, so he doesn't realize that there is no ground underneath him.

„ People should stop training radiologists now.
It's just completely obvious that within five years, deep learning is going to be better than radiologists, cause it's gonna obtain a lot more experience.
It might be ten years, but we've got plenty of radiologists already. ...

„ There's goona be thousands of applications of the deep learning technology we currently have, ...

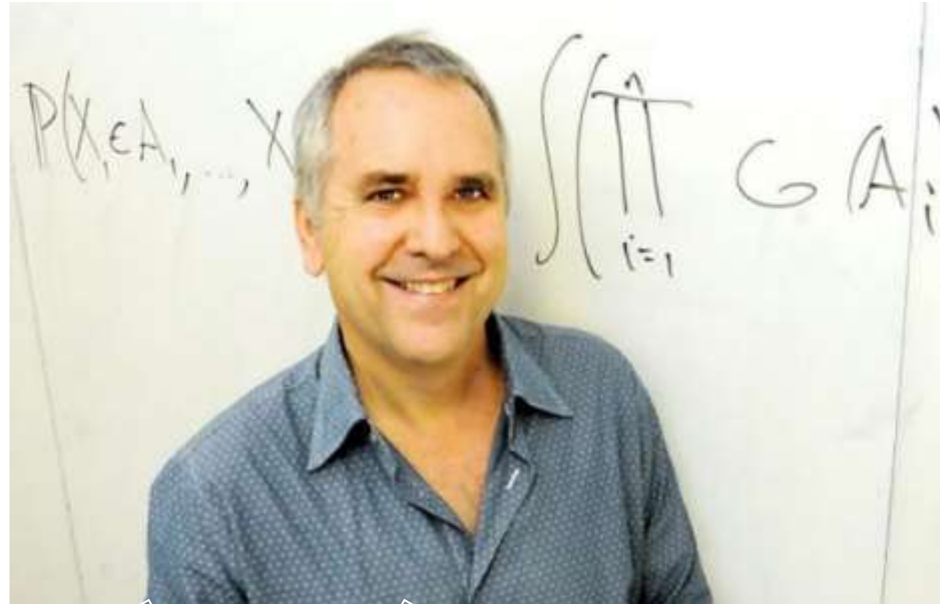
„ Take any old problem, where you have to predict something, and you have a lot of data, and deep learning is probably gonna make it work better than the existing techniques. "

Geoff Hinton comments on radiology and deep learning at the 2016 Machine Learning and Market for Intelligence Conference in Toronto

Annual Conference on Neural Information Processing Systems (NIPS) 2014, Montréal

FATHERS OF DEEP LEARNING

GEOFFREY HINTON
*1947, U TORONTO & GOOGLE

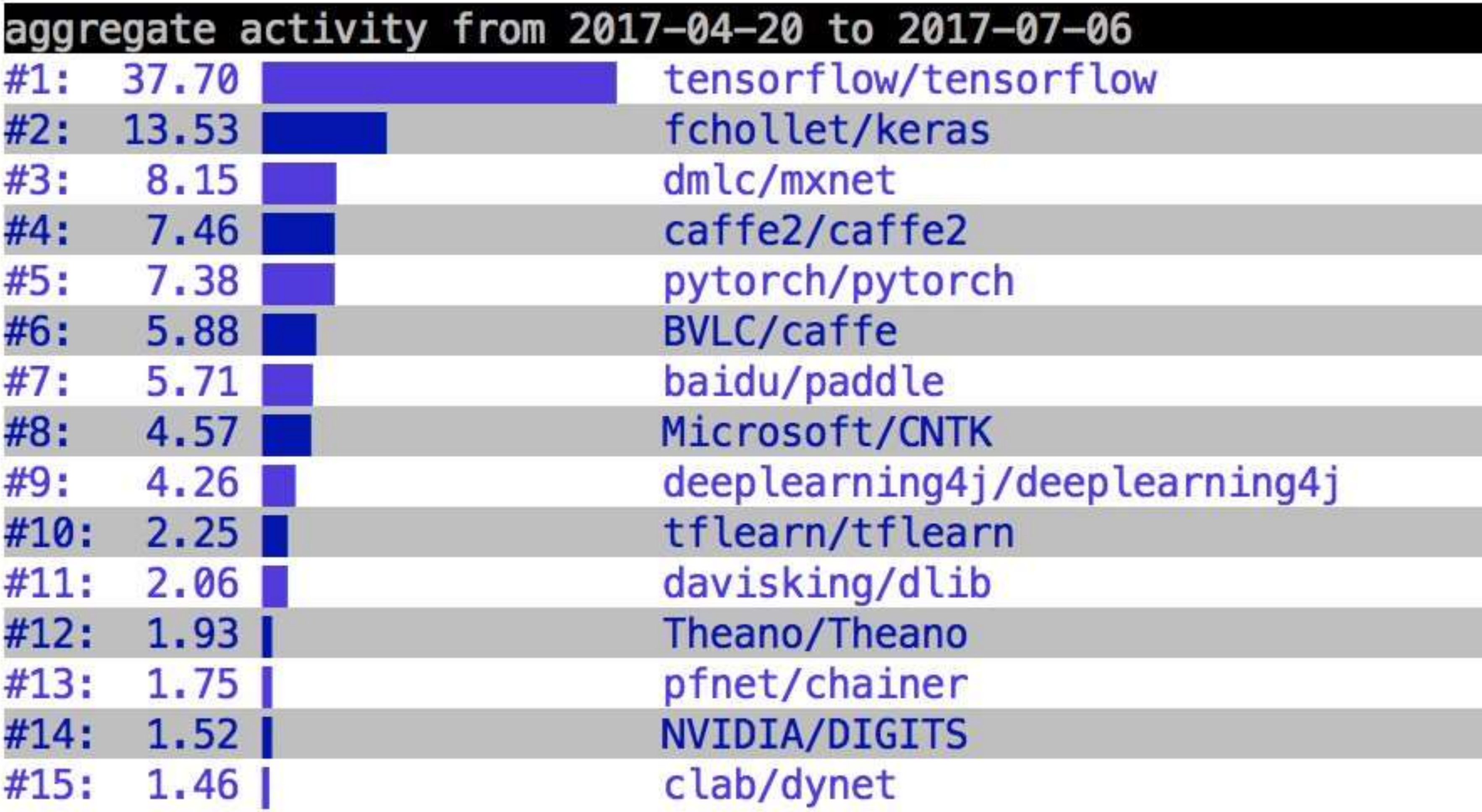


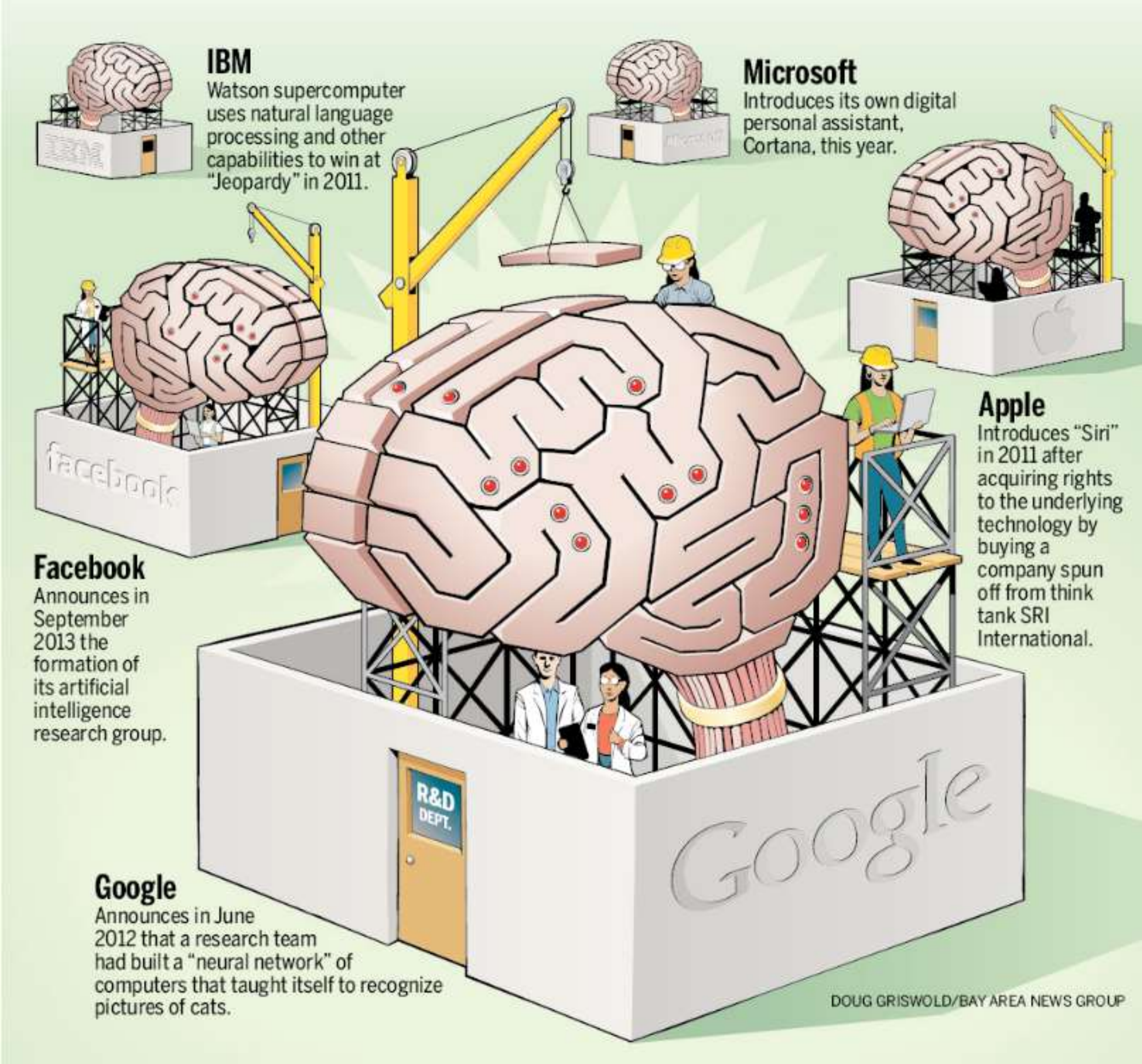
MICHAEL JORDAN
*1956, U CALIFORNIA, BERKELY

YANN LECUNN
*1960, DIRECTOR OF AI RES., FACEBOOK

YOSHUA BENGIO
*1964, HEAD OF MILA, U MONTRÉAL

ANDREW NG
*1976, VP & CHIEF SCIENTIST, BAIDU


aggregate activity from 2017-04-20 to 2017-07-06
#1: 37.70 tensorflow/tensorflow
#2: 13.53 fchollet/keras
#3: 8.15 dmlc/mxnet
#4: 7.46 caffe2/caffe2
#5: 7.38 pytorch/pytorch
#6: 5.88 BVLC/caffe
#7: 5.71 baidu/paddle
#8: 4.57 Microsoft/CNTK
#9: 4.26 deeplearning4j/deeplearning4j
#10: 2.25 tflearn/tflearn
#11: 2.06 davisking/dlib
#12: 1.93 Theano/Theano
#13: 1.75 pfnet/chainer
#14: 1.52 NVIDIA/DIGITS
#15: 1.46 clab/dynet

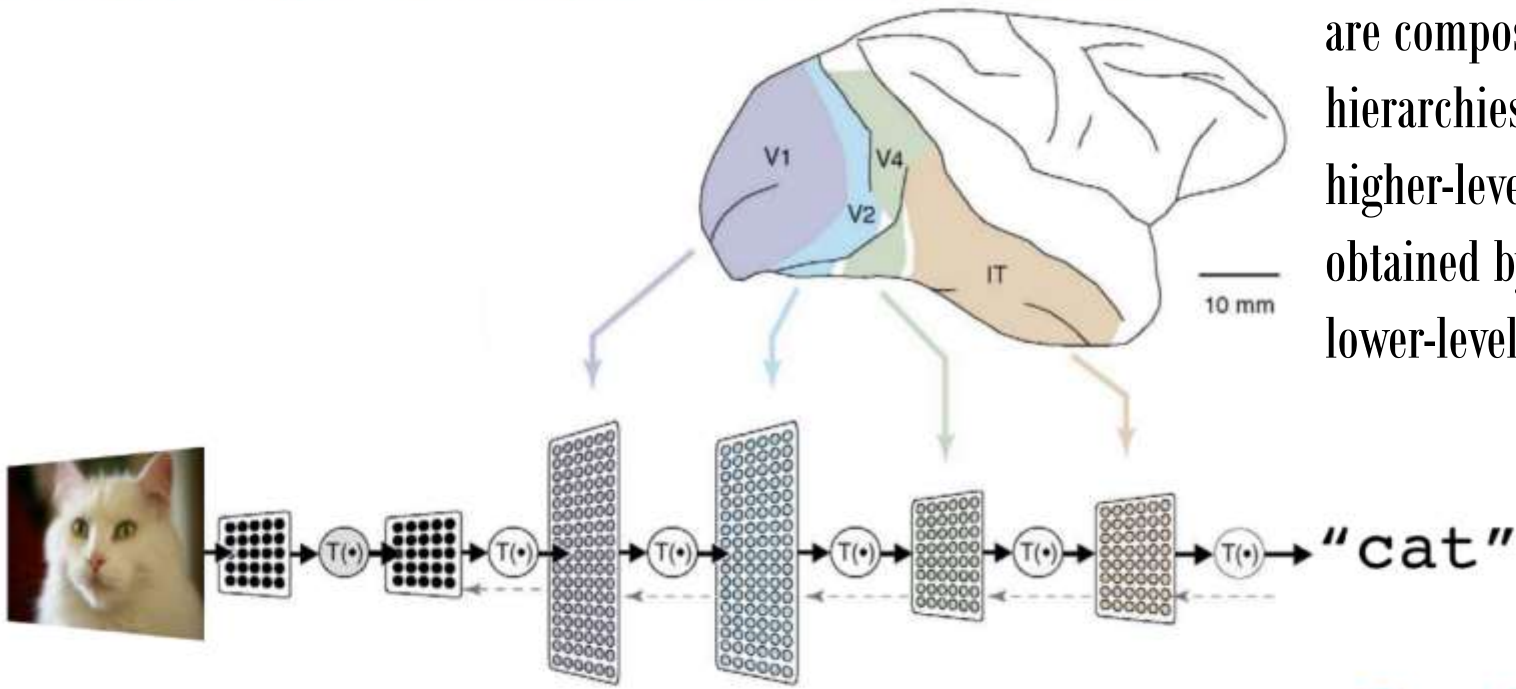


IBM
Watson supercomputer uses natural language processing and other capabilities to win at "Jeopardy" in 2011.
Microsoft
Introduces its own digital personal assistant, Cortana, this year.
Apple
Introduces "Siri" in 2011 after acquiring rights to the underlying technology by buying a company spun off from think tank SRI International.
Facebook
Announces in September 2013 the formation of its artificial intelligence research group.
Google
Announces in June 2012 that a research team had built a "neural network" of computers that taught itself to recognize pictures of cats.
IBM
facebook
R&D DEPT.
Google
DOUG GRISWOLD/BAY AREA NEWS GROUP

What is Deep Learning?

- Loosely inspired by what (little) we know about the biological brain.
- Higher layers form higher levels of abstraction

Deep neural networks exploit the property that many natural signals are compositional hierarchies, in which higher-level features are obtained by composing lower-level ones



Jeff Dean, Google

Google

Anything humans can do within 0.1 sec, the right 10-layer network can do, too.

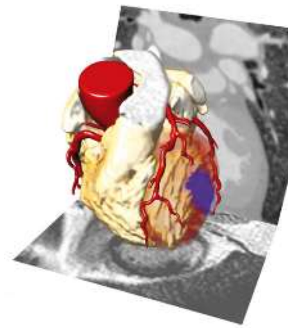
Jeff Dean, Google, 2014

Anything humans can do within 1 sec, deep learning can do, too.

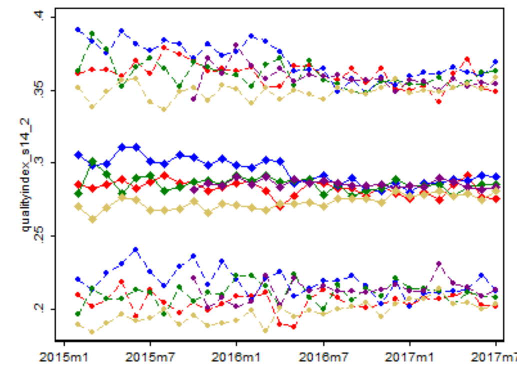
Andrew Ng, Baidu, 2017

Specific Solution Components

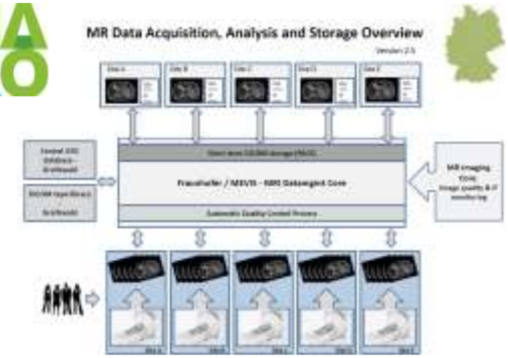
Ongoing Platform Developments



- DRG Radiomics Platform
  - initiated by the executive board *Radiomics and Big Data* of the German Roentgen Society (DRG)
  - pilot project on prediction of outcomes for patients with acute myocarditis



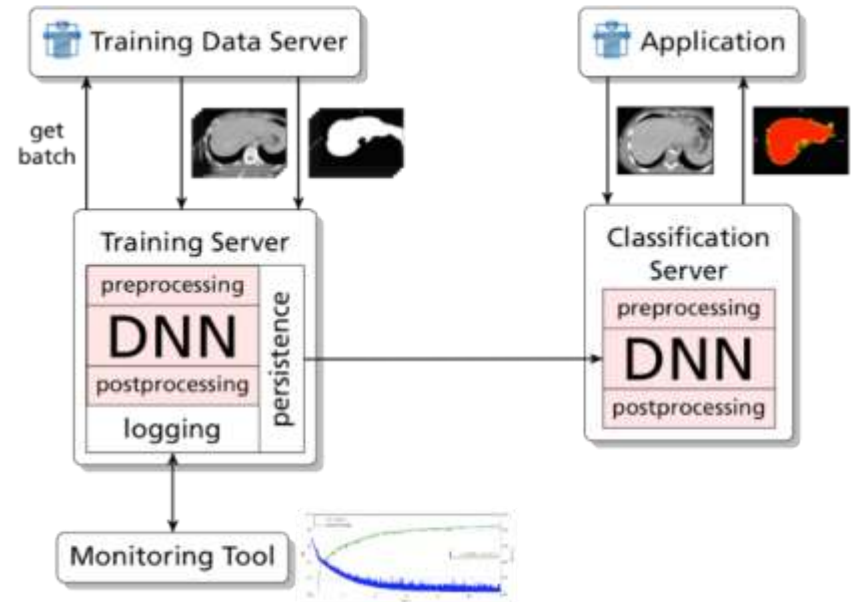
- NaKo Incidental Findings Reading Platform
  - collaborative reading and research tool
  - approx. 30,000 volunteers with whole body MRI
  - including Automated Quality Assessment (AQUA)

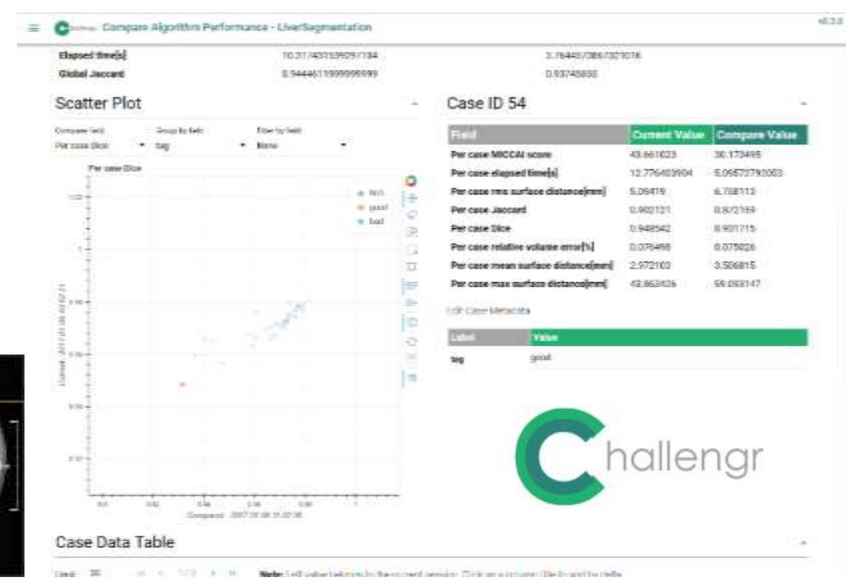


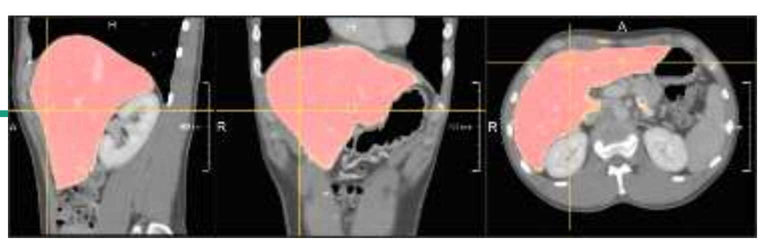
Fraunhofer

Deep Learning for Pattern Recognition and Development of Imaging Biomarkers

- Deep learning (DL) for pattern recognition
  - Automatic segmentation of annotated structures
  - Prediction of clinical categories and parameters from image data
  - Prediction of clinical categories and parameters from image data with corresponding clinical data
- Comparison of DL results and Radiomics features with framework for algorithm validation *ChallengR*

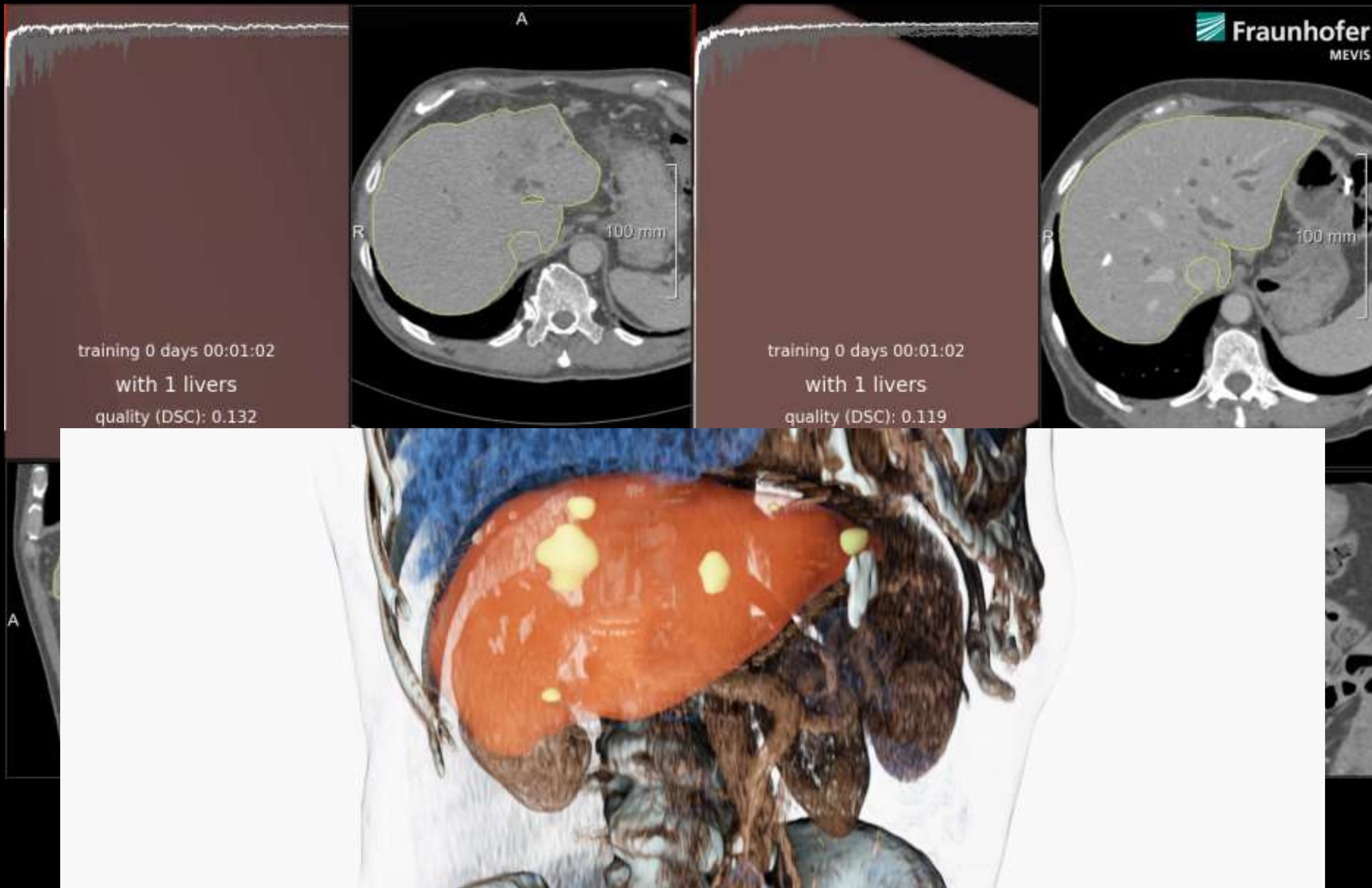




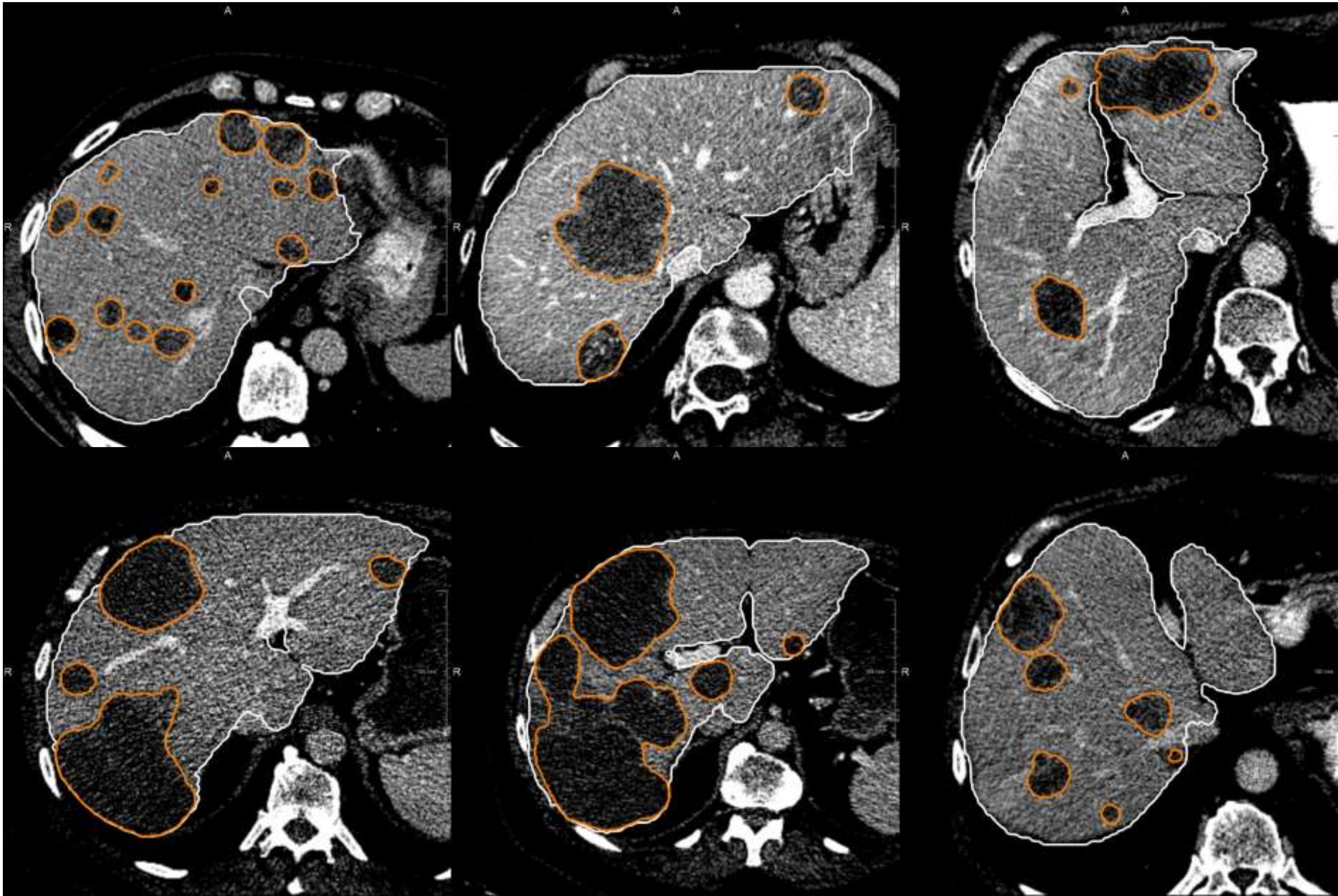


Neural network based automatic liver and liver tumor segmentation

Grzegorz Chlebus, Hans Meine, et al.



Examples



LiTS Results @ MICCAI 2017

- Tumor segmentation
  - Dice per case: 0.68
  - Precision at > 0% overlap: 0.72
  - Recall at > 0% overlap: 0.57

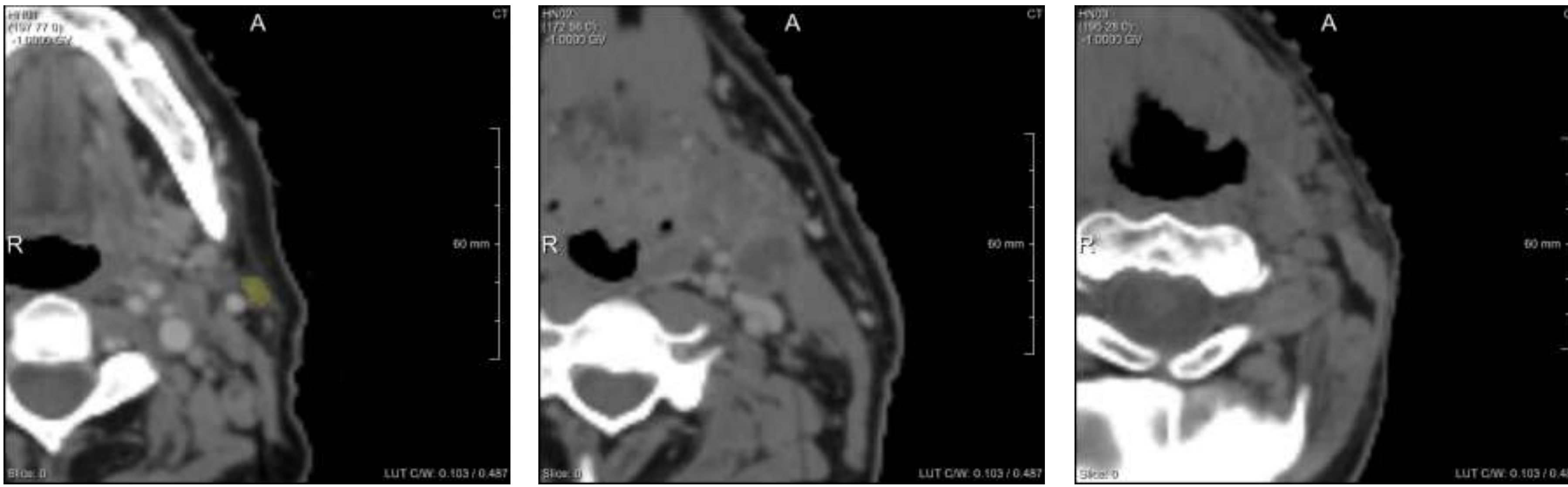
Lesion												
#	User	Entries	Date of Last Entry	Dice per case ▲	Dice global ▲	VOE ▲	RVD ▲	ASSD ▲	MSD ▲	RMSD ▲	Precision at 50% overlap ▲	Recall at 50% overlap ▲
1	leHealth	20	08/04/17	0.7020 (1)	0.7940 (5)	0.394 (11)	5.921 (18)	1.189 (12)	6.682 (5)	1.726 (8)	0.156 (14)	0.437 (3)
2	hchen	12	08/04/17	0.6860 (2)	0.8290 (1)	0.356 (3)	5.164 (17)	1.073 (5)	6.055 (1)	1.562 (2)	0.409 (4)	0.408 (4)
3	hans.meine	7	07/30/17	0.6760 (3)	0.7960 (4)	0.383 (10)	0.464 (12)	1.143 (8)	7.322 (12)	1.728 (9)	0.496 (2)	0.397 (5)

- Liver segmentation
  - Dice per case: 0.96
  - Relative volume difference: -0.4%

RADIOTHERAPY PLANNING

Methodological Evaluation of 2D and 3D U-Nets on the Parotid Gland Segmentation Problem

- Good results can already be achieved without much fine-tuning
- First results after only two weeks work of one person



Hänsch A, Schwier M, Gass T, Morgasz T, Haas B, Klein J, ***Hahn HK*** *(2018) Comparison of different deep learning approaches for parotid gland segmentation from CT images. SPIE Proceedings Vol. 10575: Medical Imaging 2018: Computer-Aided Diagnosis*

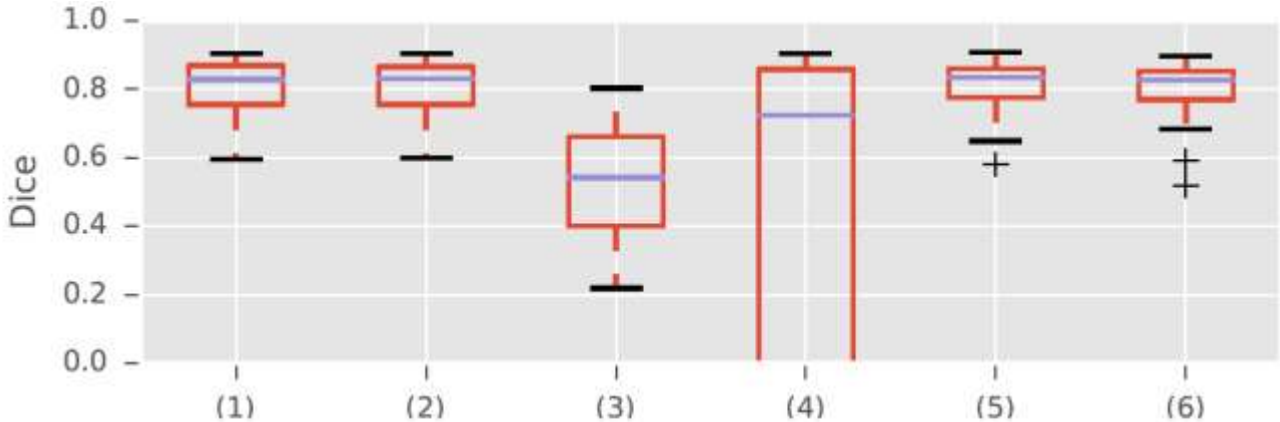


Figure 1. Dice score on 40 test cases using different classification approaches. (1-4): 2D U-Net trained on axial slices with evaluation (1) only on an ROI around the target structure before post-processing (PP) by selection of the largest connected component, (2) on ROI after PP, (3) on the full volume before PP, (4) on the full volume after PP; (5): 2D U-Net ensemble evaluated on the full volume after PP; (6): 3D U-Net evaluated on the full volume after PP.

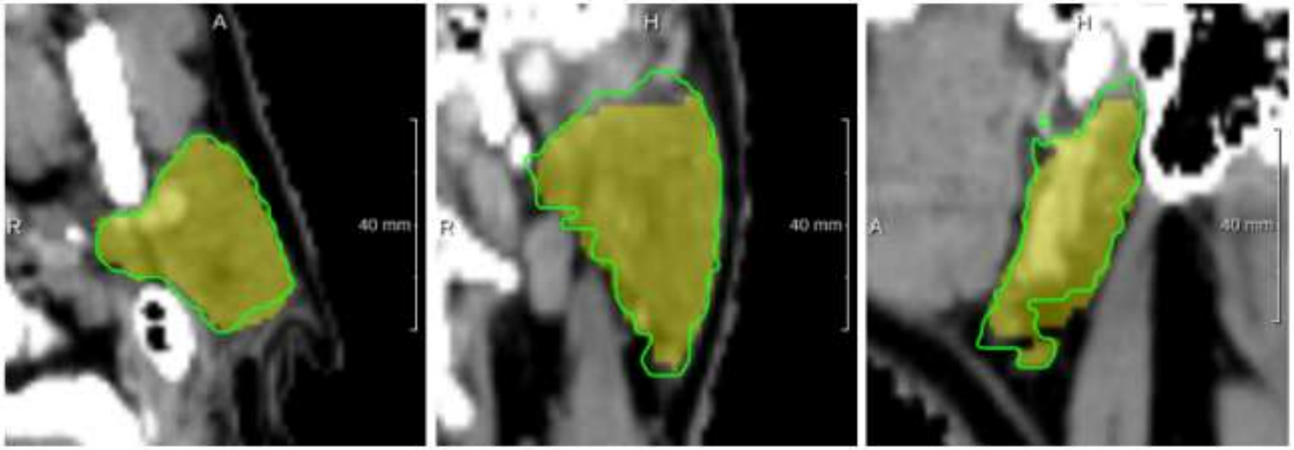


Figure 2. Exemplary test case in axial, coronal and sagittal view (left to right). The reference contour of the left parotid gland is shown in green, the segmentation by the 2D U-Net ensemble (Dice 0.91) as yellow overlay.

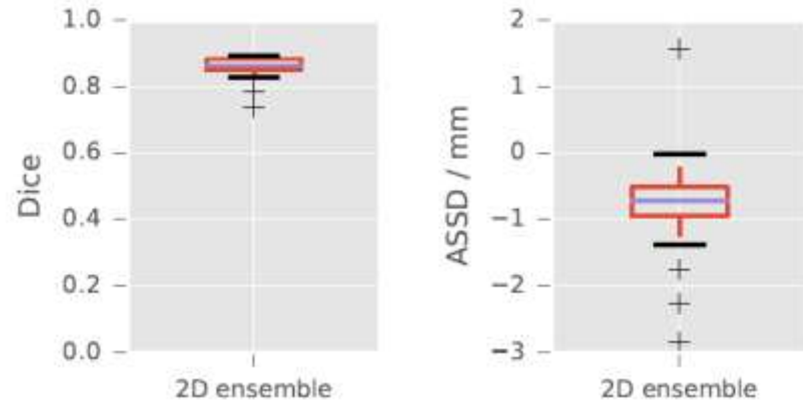


Figure 3. Quantitative results on the MICCAI Head and Neck Auto-Segmentation Challenge (off-site and on-site) test data. Left: Dice score on all test cases; right: average signed surface distance (ASSD) in mm.

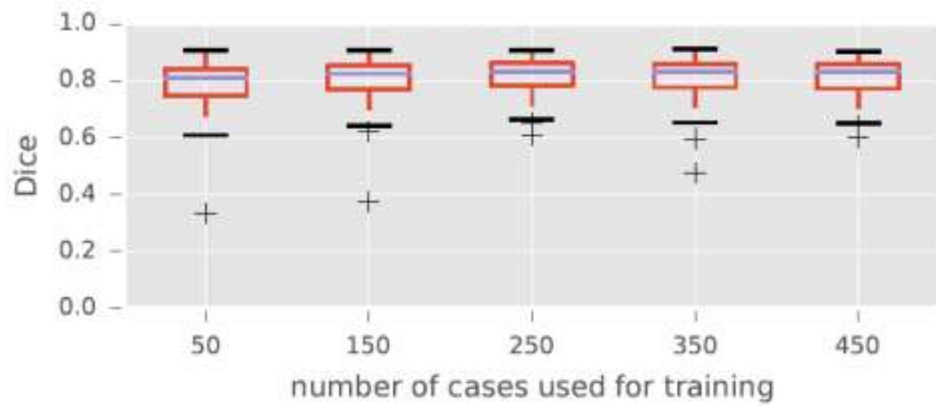


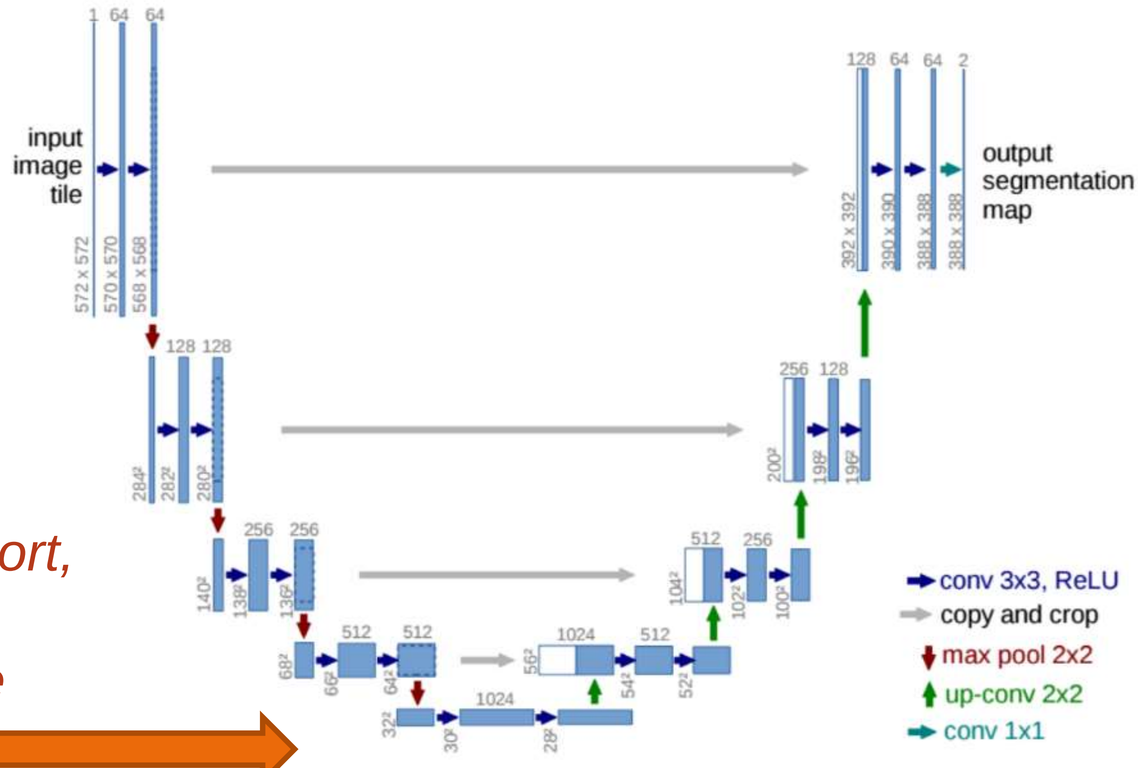
Figure 4. Box plot of the Dice scores on 40 test cases with the 2D U-Net ensemble when varying the number of training samples.

*Hänsch A, Schwier M, Gass T, Morgasz T, Haas B, Klein J, **Hahn HK** (2018) Comparison of different deep learning approaches for parotid gland segmentation from CT images. SPIE Proceedings Vol. 10575: Medical Imaging 2018: Computer-Aided Diagnosis*

U-nets for Image Segmentation

(O. Ronneberger et al.)

special variant of deep neural networks
combining the ***"what"*** and the ***"where"***



for decision support, add non-imaging information to the „what" level

Fig. 1. U-net architecture (example for 32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations.

CONCRETE SOLUTION APPROACHES

How Can We Accelerate Value Generation Together?

Radiomics for Radiologists, Bremen, June 15-17, 2016

- Organisation: Ron Kikinis mit Unterstützung der DFG (Dr. Christian Renner) und in Kooperation mit der Deutschen Röntgengesellschaft e.V. (Prof. Stefan Schönberg) und der Konferenz der Lehrstuhlinhaber in der Radiologie (Prof. Gabriele Krombach)
- Teilnehmer (insgesamt 32):
  - Algorithmen/Technologie: Fraunhofer MEVIS, Harvard Medical School, Radboud Universität, DKFZ, TUM
  - Radiologie: Radboud Universität, UMM, LMU, Heidelberg, Charité Berlin, Frankfurt, Köln, Giessen, Ulm, Lübeck, Münster, Tübingen

Fraunhofer MEVIS

Radiomics for Radiologist, Bremen, June 15-17, 2016

Es wurde ktiv
rekrutiert

Beispiele:

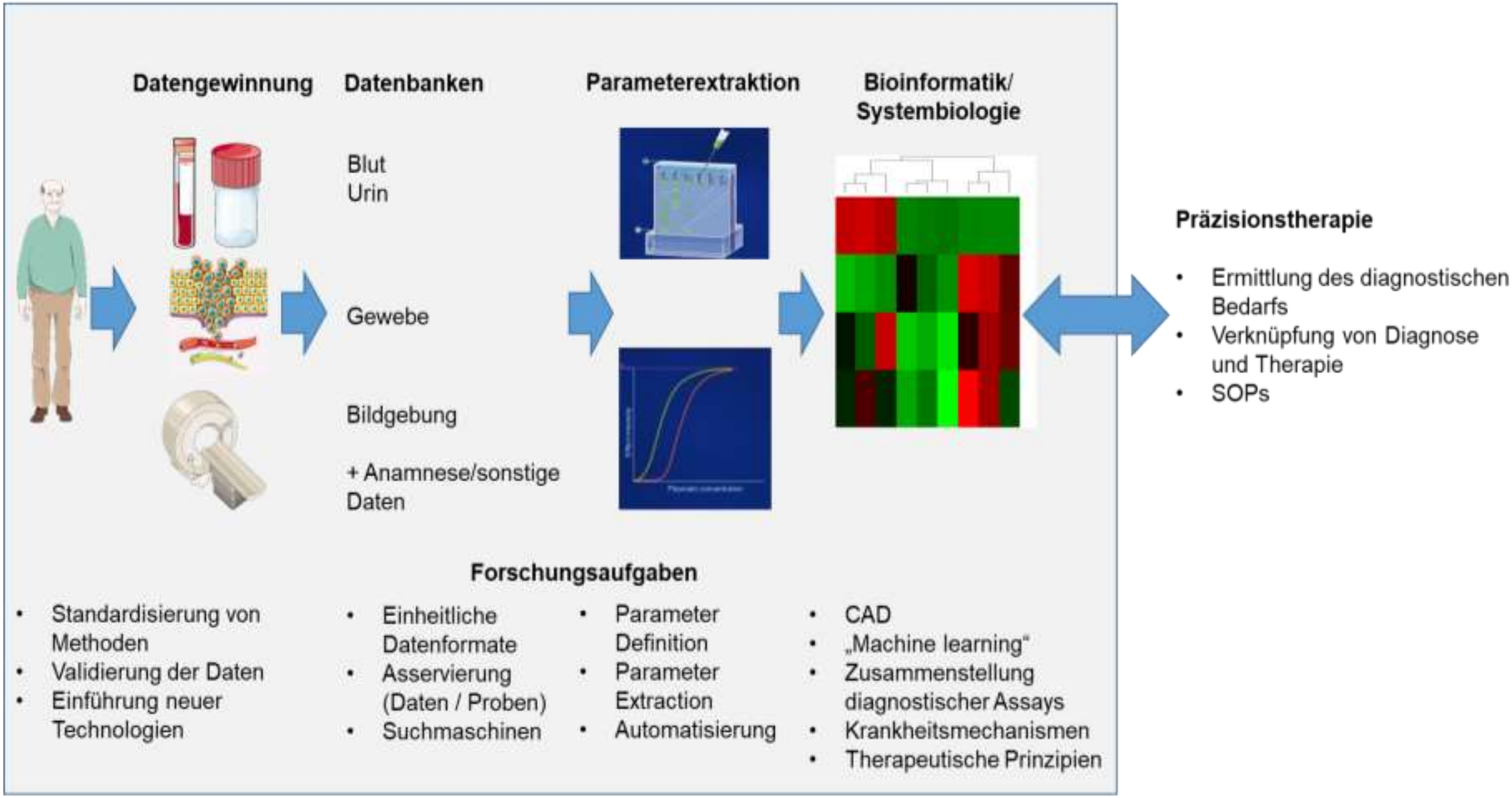
- Uni Gi olic
  pulmo
- Univer
- LMU M er
- Uni Lü
- Uni Ul zinomen,
  Jochen
- Uni Fra rt Strauß
- Uni Kö
- Prostat n), David
  Bonek

Joint Methodology for all Clinical Subprojects “V-K-D-T”

1. Define clearly the **clinical question and expected advantage (value)**.
2. Refer precisely to the respective **physiopathology and/or molecular biology (knowledge)**.
3. Define the **data and modalities, protocols and/or sequences**, which will be sufficient for the intended radiomics approach and at the same time feasible on a larger scale **(data)**.
4. Define clearly those **specific endpoints** that should be correlated to the acquired complex imaging and additional data **(target)**.

Comprehensive Diagnostic Center Aachen (CDCA)

UNIKLINIK RWTHAACHEN



adapted from: Kiessling F. The changing face of cancer diagnosis: From computational image analysis to systems biology. Eur Radiol. 2018 Feb 27. [Epub ahead of print]

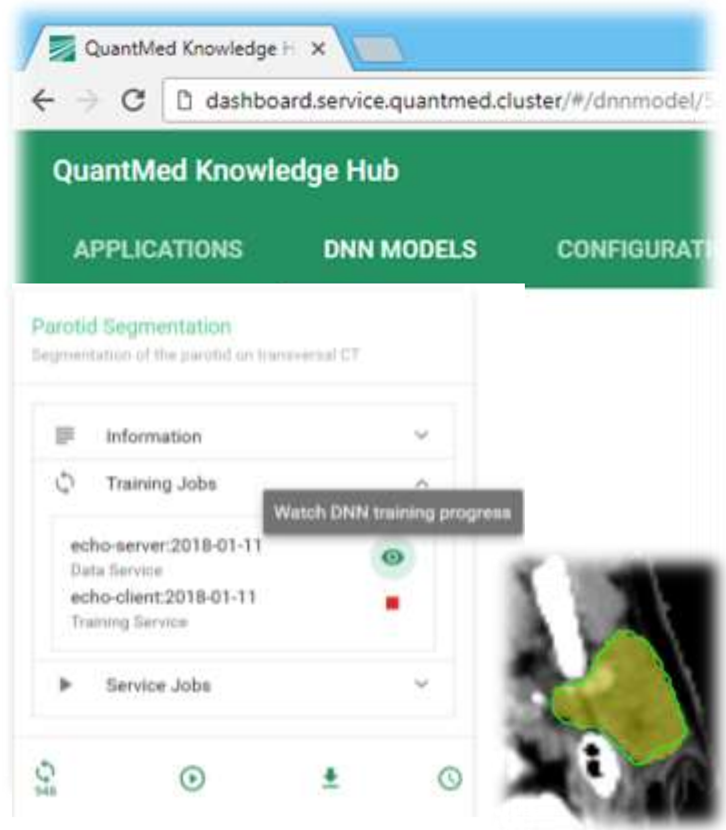
Fraunhofer MEVIS

Web-Based Distributed DNN Training
coupled with AppStore concept

- Set up of **QuantMed cluster:** distributed system of
  machines that can host different services and which process training jobs for **deep learning**.

- **Easy data preparation**: One click solution .mlab → Docker
  Can then be selected as data preparation service in DNN
  training UI.

- Clinical raw data remains within the firewall of the supplying device and is analyzed on-site in a so-called **QuantMed node**.



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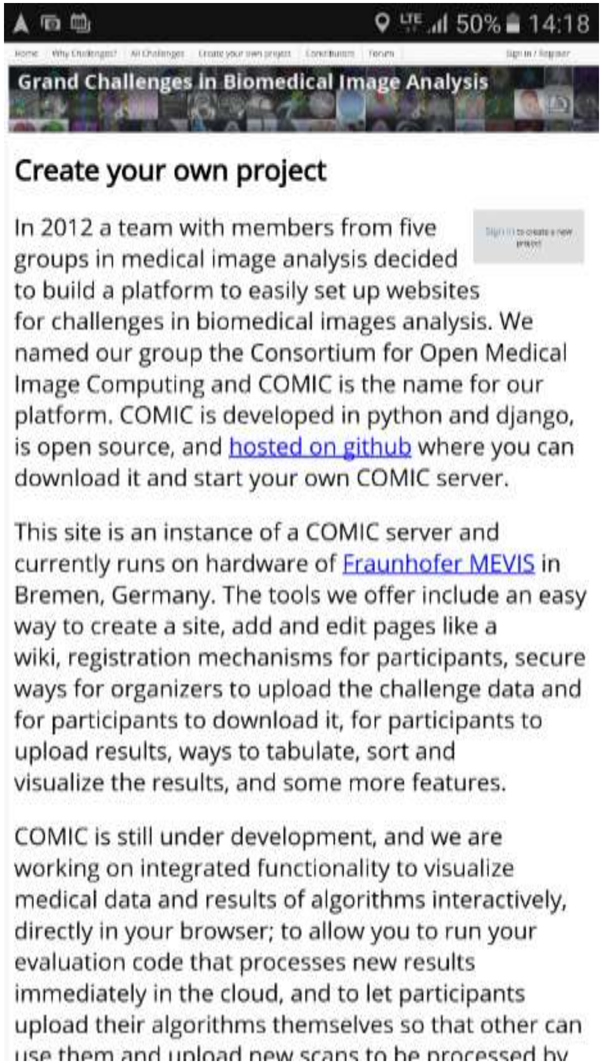
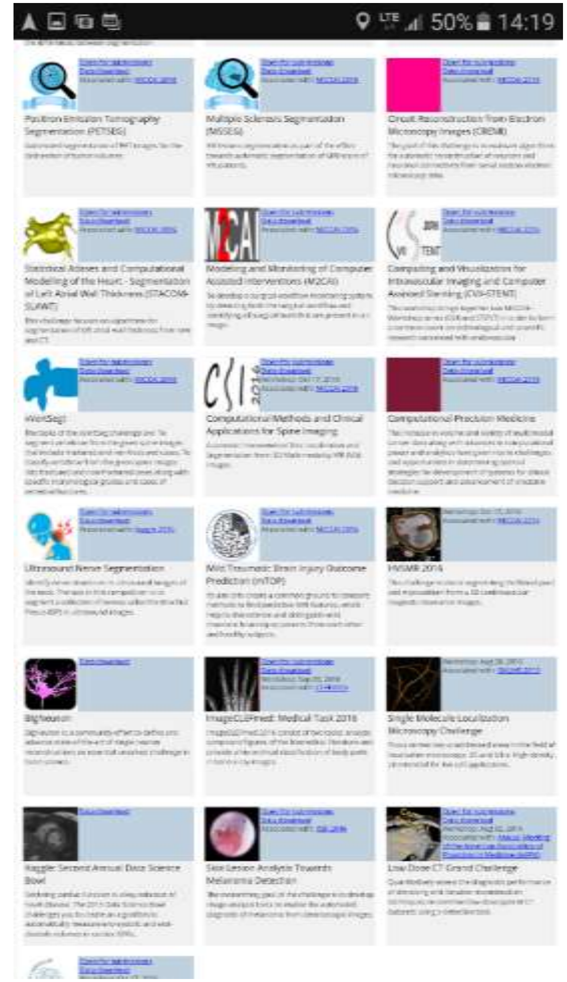
COMIC – Consortium for Open Medical Image Computing





diag automation in medical imaging

Radboudumc

Fraunhofer MEVIS

MEVIS „Werkstatt der Digitalen Medizin“ (2020)

SciCom & Young Researchers: Responsible Research and Innovation

Nerdy is the new awesome!

Raising awareness about how the digital transformation influences healthcare
by engaging the public into new possibilities that
emerge from innovative R&D.

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