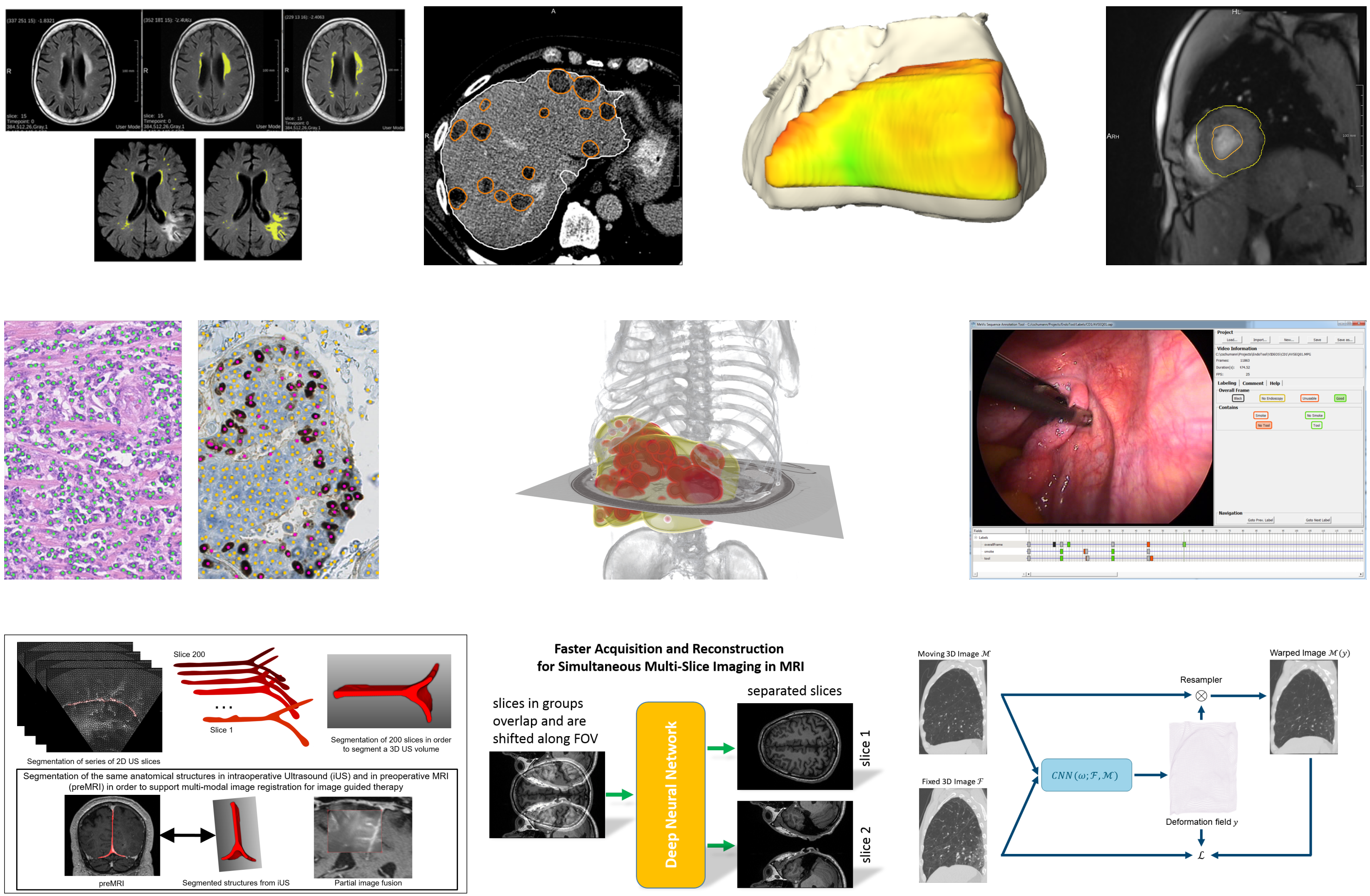
# KI in der Radiologie: aktuelle Forschungsthemen

Grzegorz Chlebus

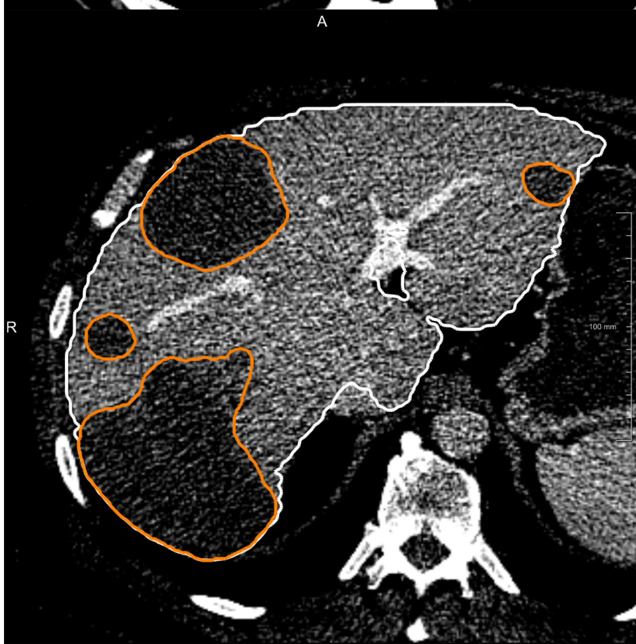
04.07.2019 DICOM-Treffen

# Wie kann KI Medizin helfen?

- Detektion
  - Ist eine Pathologie da?
- Klassifikation
  - Was für eine Pathologie ist das?
- Segmentierung
  - Wie groß ist ein Organ?
- Prädiktion
  - Wird der Patient in 12 Monaten Krebs bekommen?


Slice 200
...
Slice 1
Segmentation of 200 slices in order to segment a 3D US volume
Segmentation of series of 2D US slices
Segmentation of the same anatomical structures in intraoperative Ultrasound (iUS) and in preoperative MRI (preMRI) in order to support multi-modal image registration for image guided therapy
preMRI
Segmented structures from iUS
Partial image fusion
Faster Acquisition and Reconstruction
for Simultaneous Multi-Slice Imaging in MRI
slices in groups
overlap and are
shifted along FOV
Deep Neural Network
separated slices
slice 1
slice 2
Moving 3D Image $\mathcal{M}$
Fixed 3D Image $\mathcal{F}$
$CNN(\omega; \mathcal{F}, \mathcal{M})$
Resampler
Deformation field $y$
Warped Image $\mathcal{M}(y)$
$\mathcal{L}$

# Automatische Leber- und Tumor-Segmentierung


www.nature.com/scientificreports

3rd place at the LiTS challenge

SCIENTIFIC REPORTS

OPEN

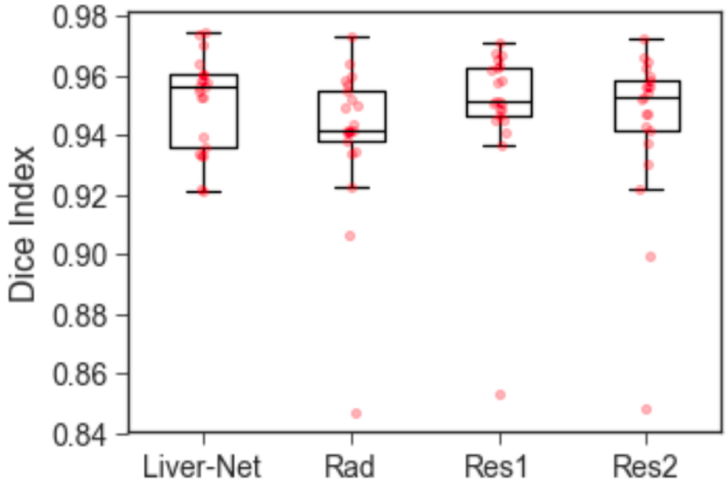
## Automatic liver tumor segmentation in CT with fully convolutional neural networks and object-based postprocessing

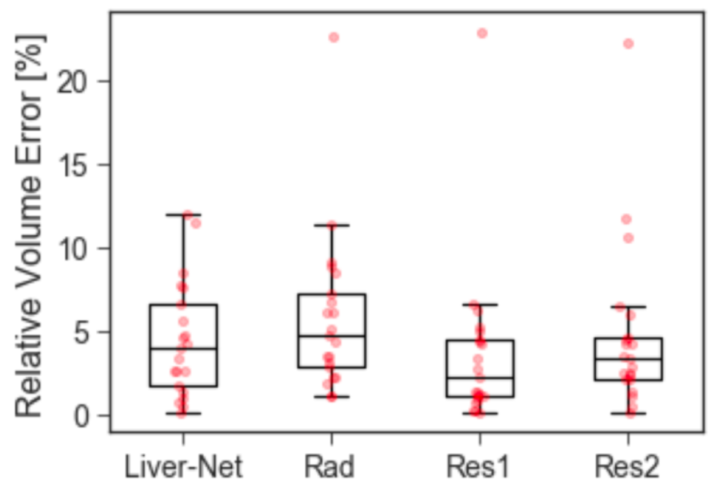
Received: 16 July 2018
Accepted: 6 October 2018
Published online: 19 October 2018

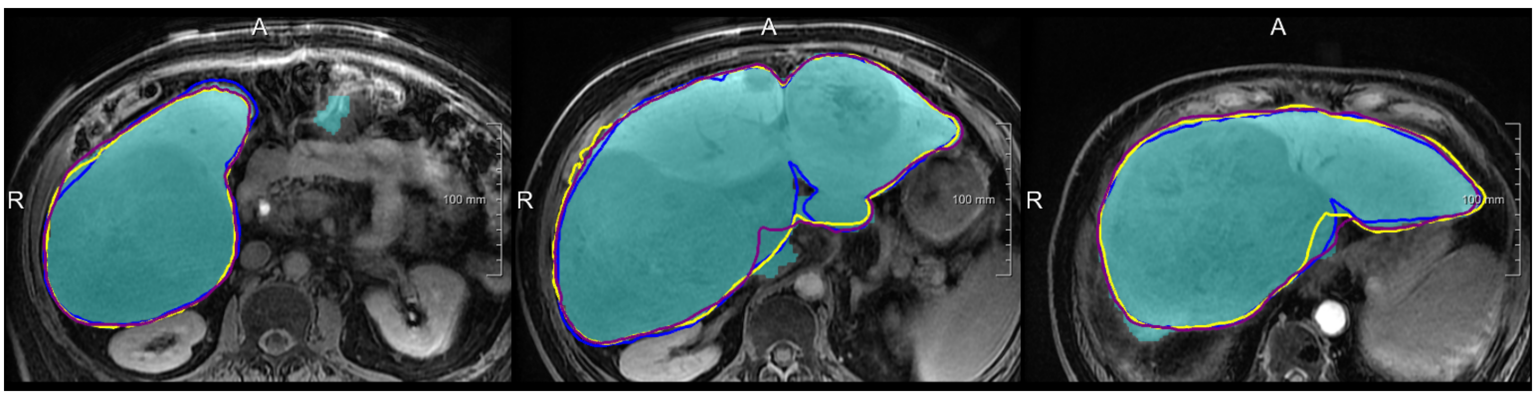
Grzegorz Chlebus[1], Andrea Schenk[1], Jan Hendrik Moltz[1], Bram van Ginneken[1,2], Horst Karl Hahn[1,3] & Hans Meine[1,4]

# MR Leber-Segmentierung

- Vergleich mit klinischen Nutzern




Chlebus G et al., “Reducing inter-observer variability and interaction time of MR liver volumetry by combining automatic CNN-based liver segmentation and manual corrections”, PLOS ONE 2019.

*“One of the biggest limitations of deep learning is that right now it requires really a lot of data, especially labeled data.”*

*“For interpretability I don’t think we even have the right definitions.”*

Ian Goodfellow im Gespräch mit
Lex Fridman (18.04.2019)

# Einschränkungen der KI

- KI Systeme brauchen große annotierte Datensätze

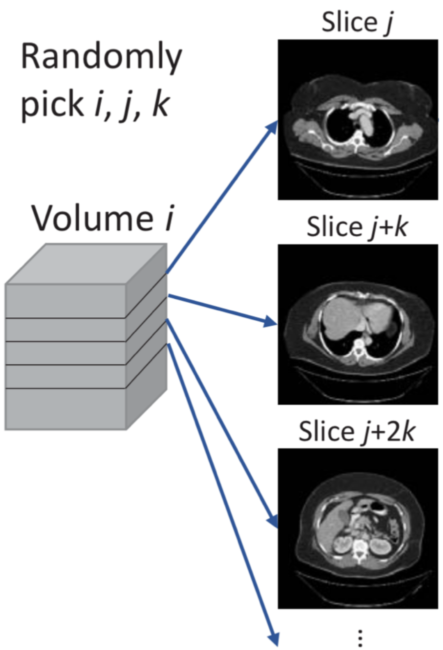
Unsupervised learning

- KI Systeme sind schwierig zu interpretieren

Bessere Tools notwendig

# Unsupervised learning

## Self-Supervised Body Regressor

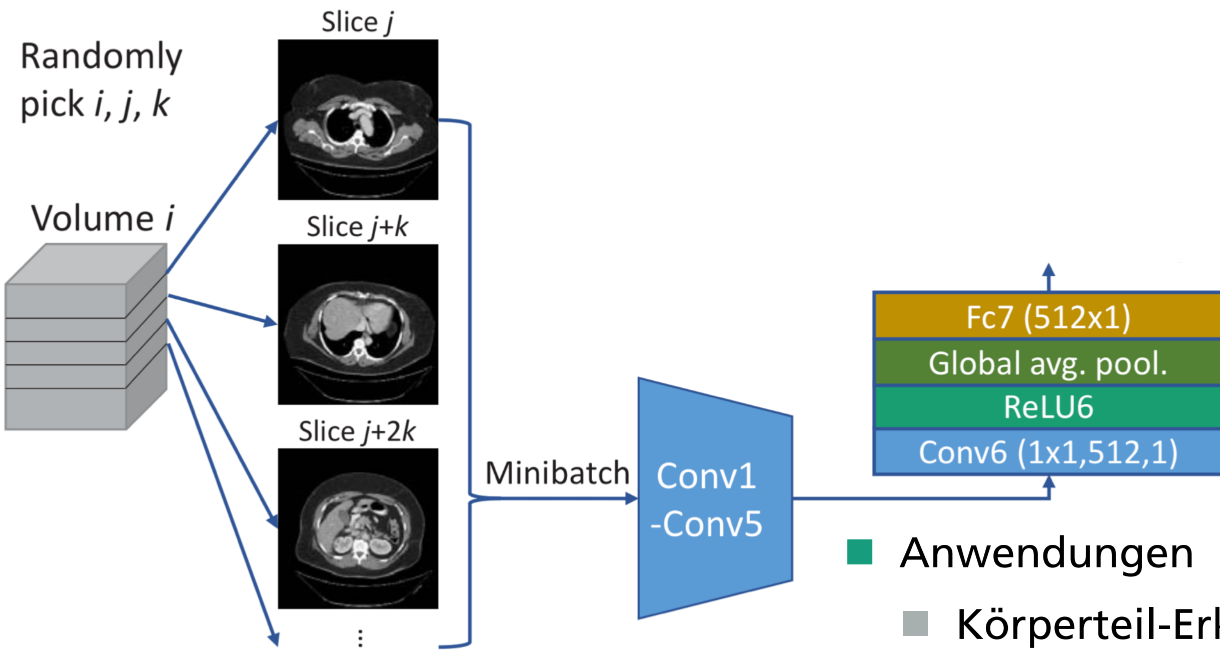



- Anwendungen
  - Körperteil-Erkennung
  - Ausrichtung der Bilder

Yan K, Lu L, Summers RM. Unsupervised body part regression via spatially self-ordering convolutional neural networks. 15th International Symposium on Biomedical Imaging (ISBI 2018).

# Unsupervised learning

## Self-Supervised Body Regressor

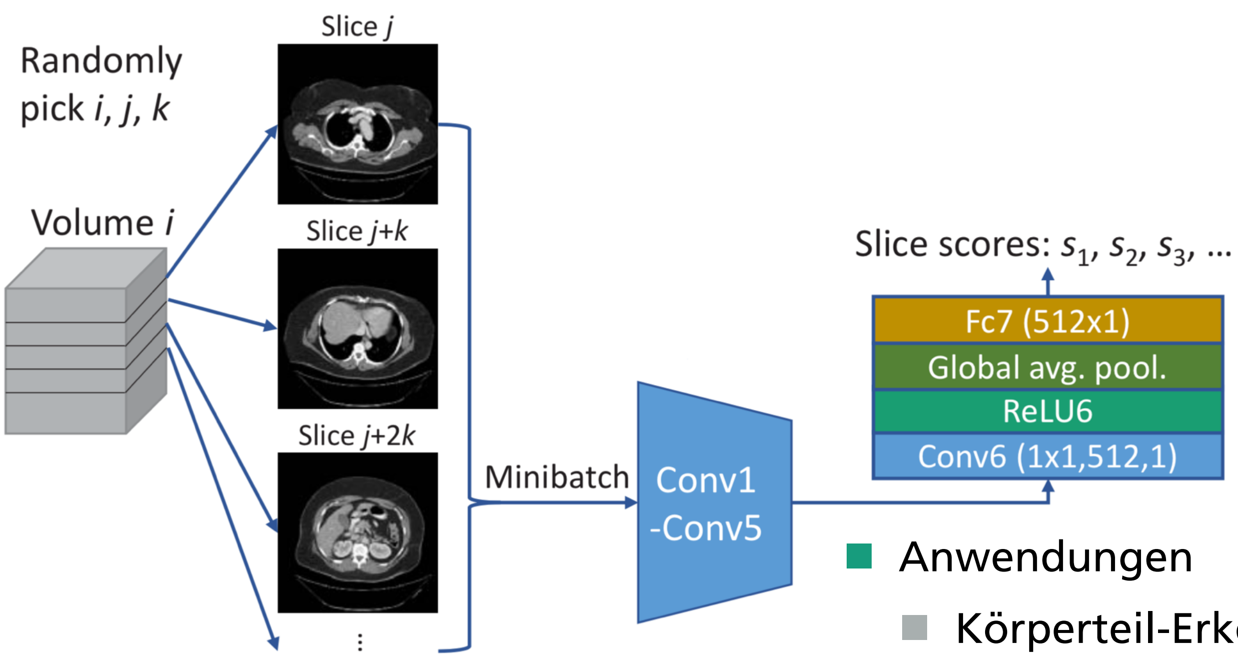



- Anwendungen
  - Körperteil-Erkennung
  - Ausrichtung der Bilder

Yan K, Lu L, Summers RM. Unsupervised body part regression via spatially self-ordering convolutional neural networks. 15th International Symposium on Biomedical Imaging (ISBI 2018).

# Unsupervised learning

## Self-Supervised Body Regressor

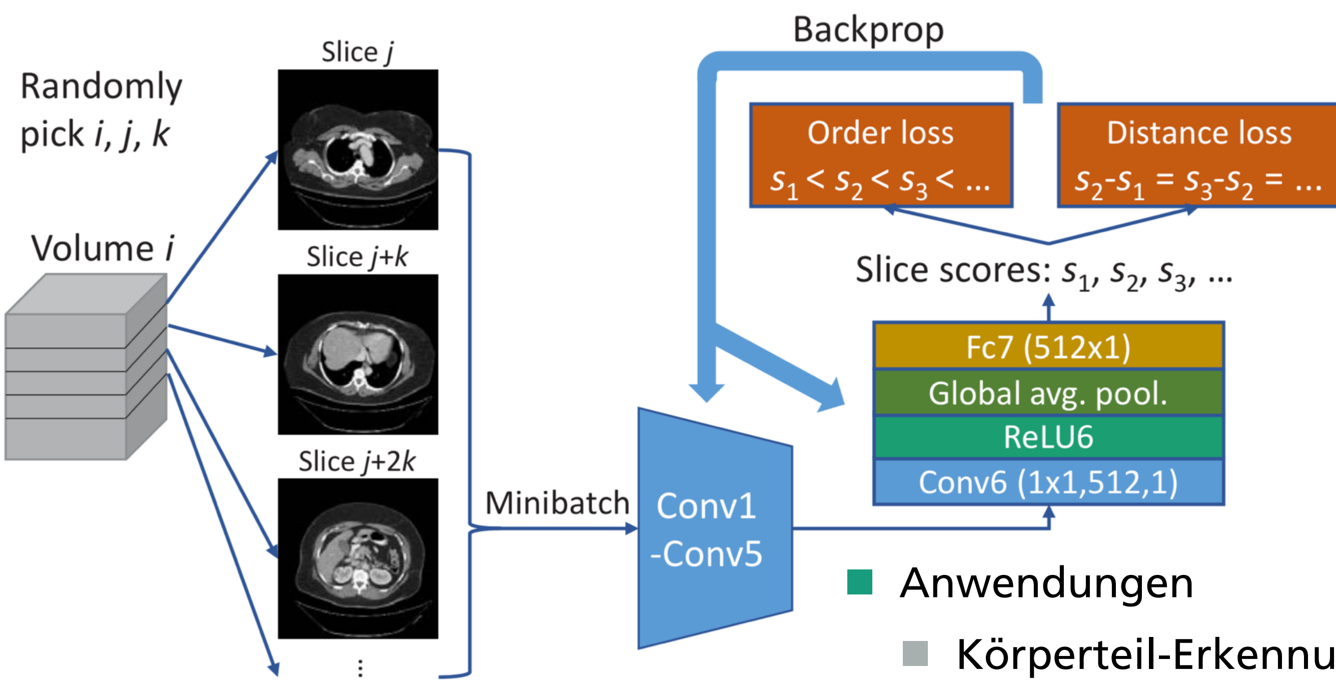



- Anwendungen
  - Körperteil-Erkennung
  - Ausrichtung der Bilder

Yan K, Lu L, Summers RM. Unsupervised body part regression via spatially self-ordering convolutional neural networks. 15th International Symposium on Biomedical Imaging (ISBI 2018).

# Unsupervised learning

## Self-Supervised Body Regressor

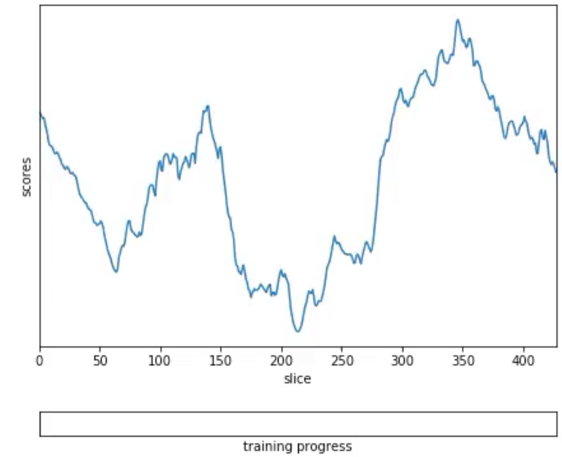


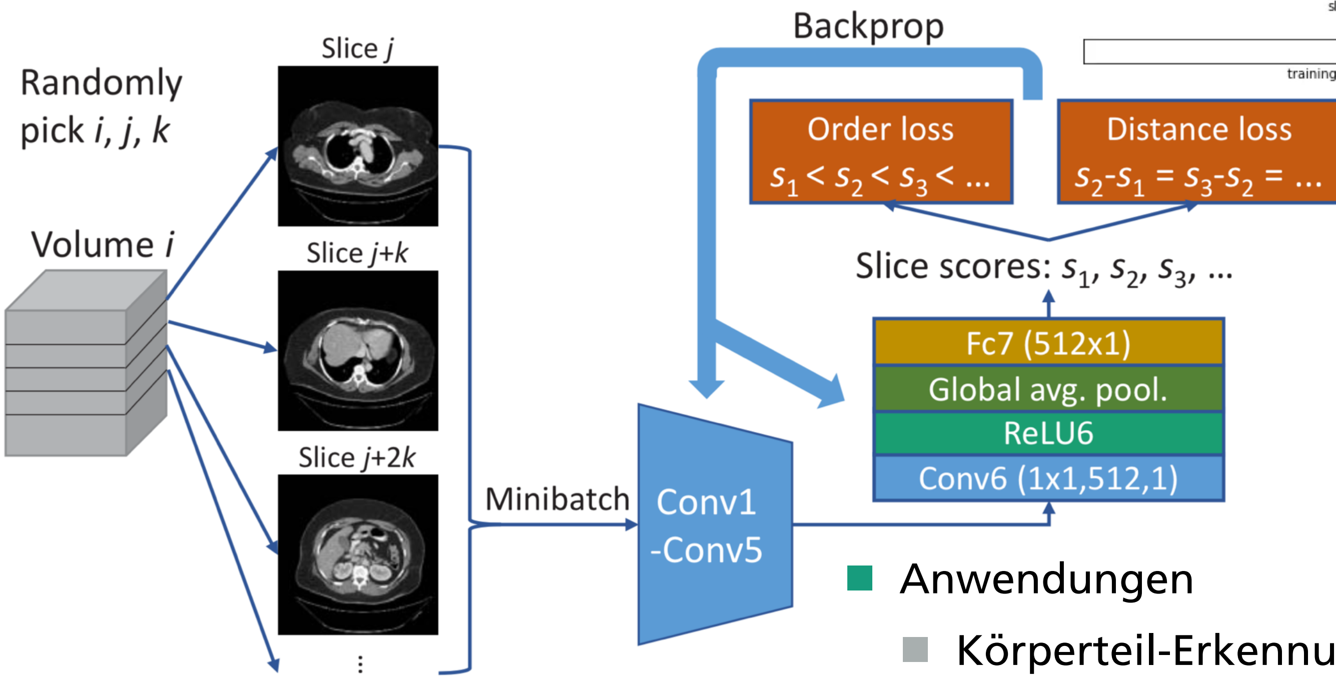

- Anwendungen
  - Körperteil-Erkennung
  - Ausrichtung der Bilder

Yan K, Lu L, Summers RM. Unsupervised body part regression via spatially self-ordering convolutional neural networks. 15th International Symposium on Biomedical Imaging (ISBI 2018).

# Unsupervised learning

Self-Supervised Body Regressor



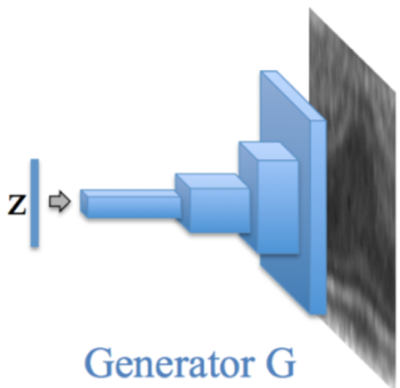

- Anwendungen
  - Körperteil-Erkennung
  - Ausrichtung der Bilder

Yan K, Lu L, Summers RM. Unsupervised body part regression via spatially self-ordering convolutional neural networks. 15th International Symposium on Biomedical Imaging (ISBI 2018).

# Unsupervised learning

## Anomaly detection

- Training auf nur gesunden Fällen

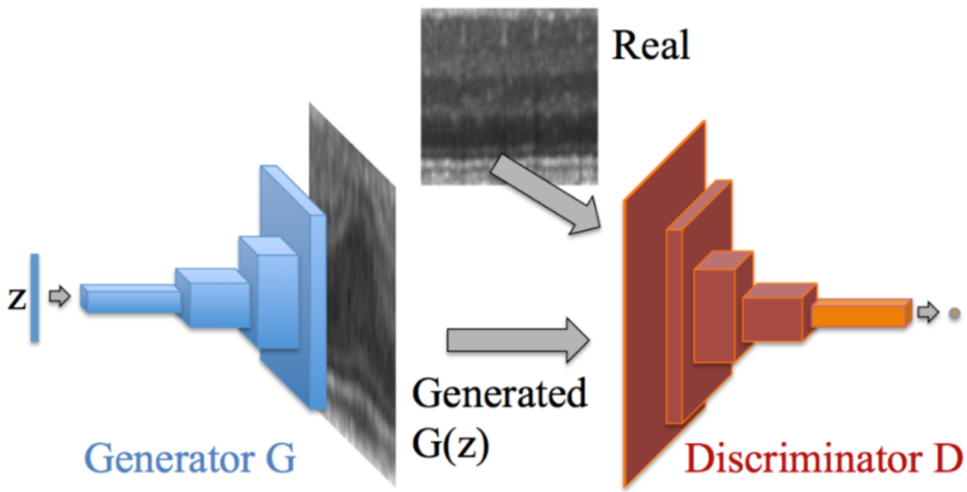



Schlegl, Thomas, et al. "Unsupervised anomaly detection with generative adversarial networks to guide marker discovery." International Conference on Information Processing in Medical Imaging. Springer, Cham, 2017.

# Unsupervised learning

## Anomaly detection

- Training auf nur gesunden Fällen

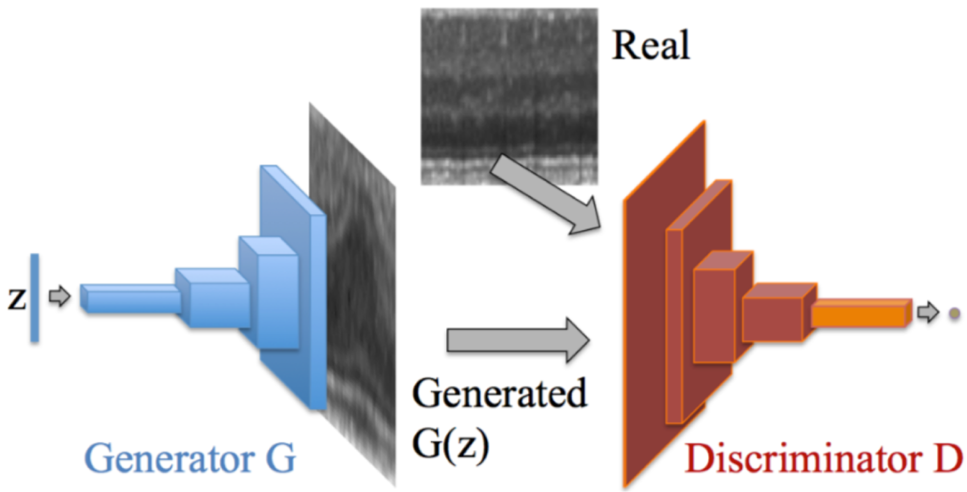


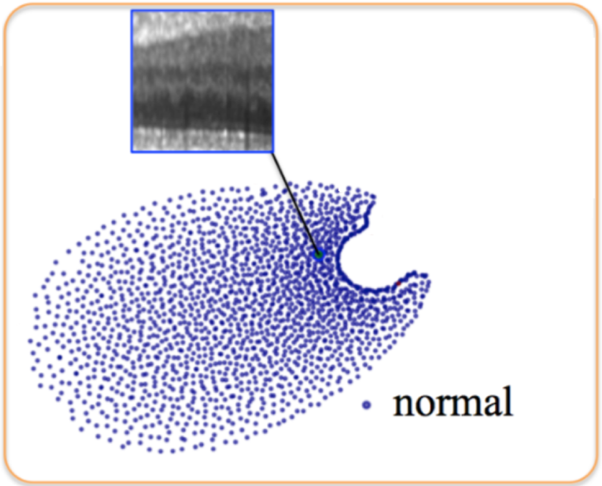

Schlegl, Thomas, et al. "Unsupervised anomaly detection with generative adversarial networks to guide marker discovery." International Conference on Information Processing in Medical Imaging. Springer, Cham, 2017.

# Unsupervised learning

## Anomaly detection

- Training auf nur gesunden Fällen



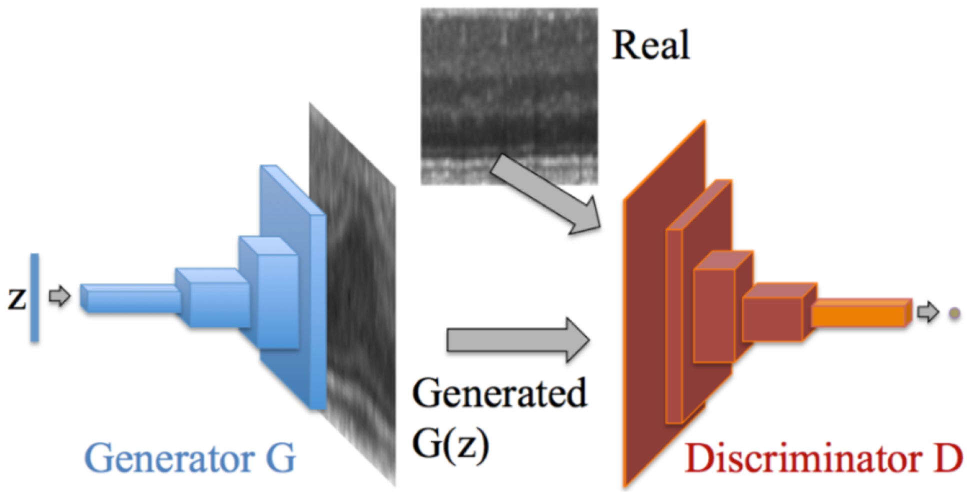



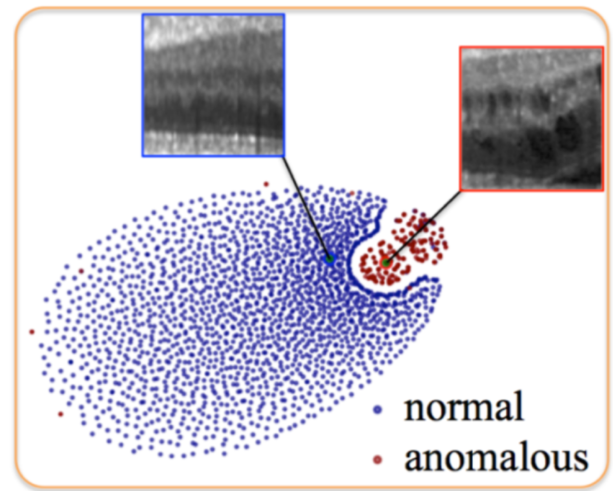

Schlegl, Thomas, et al. "Unsupervised anomaly detection with generative adversarial networks to guide marker discovery." International Conference on Information Processing in Medical Imaging. Springer, Cham, 2017.

# Unsupervised learning

## Anomaly detection

- Training auf nur gesunden Fällen

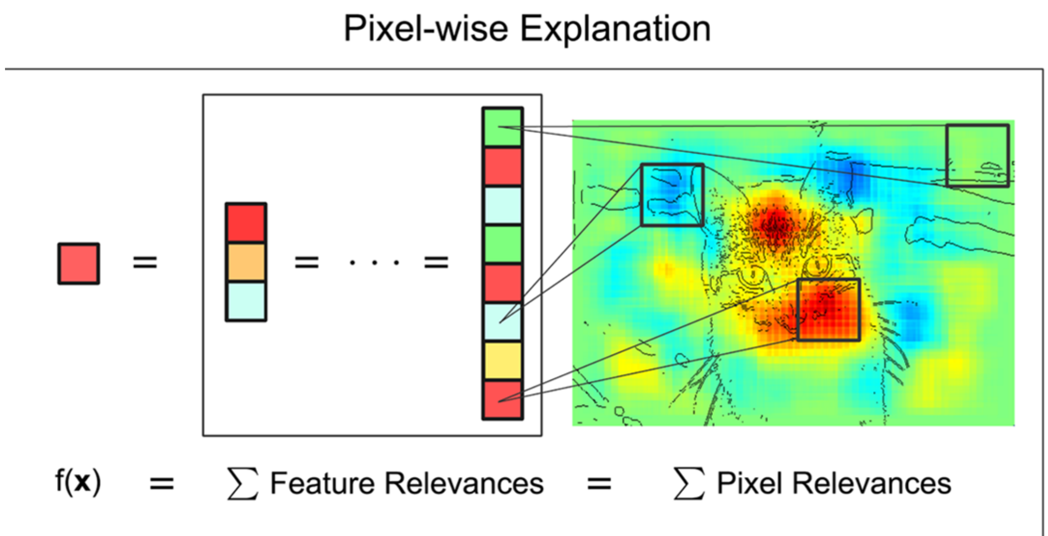



Schlegl, Thomas, et al. "Unsupervised anomaly detection with generative adversarial networks to guide marker discovery." International Conference on Information Processing in Medical Imaging. Springer, Cham, 2017.

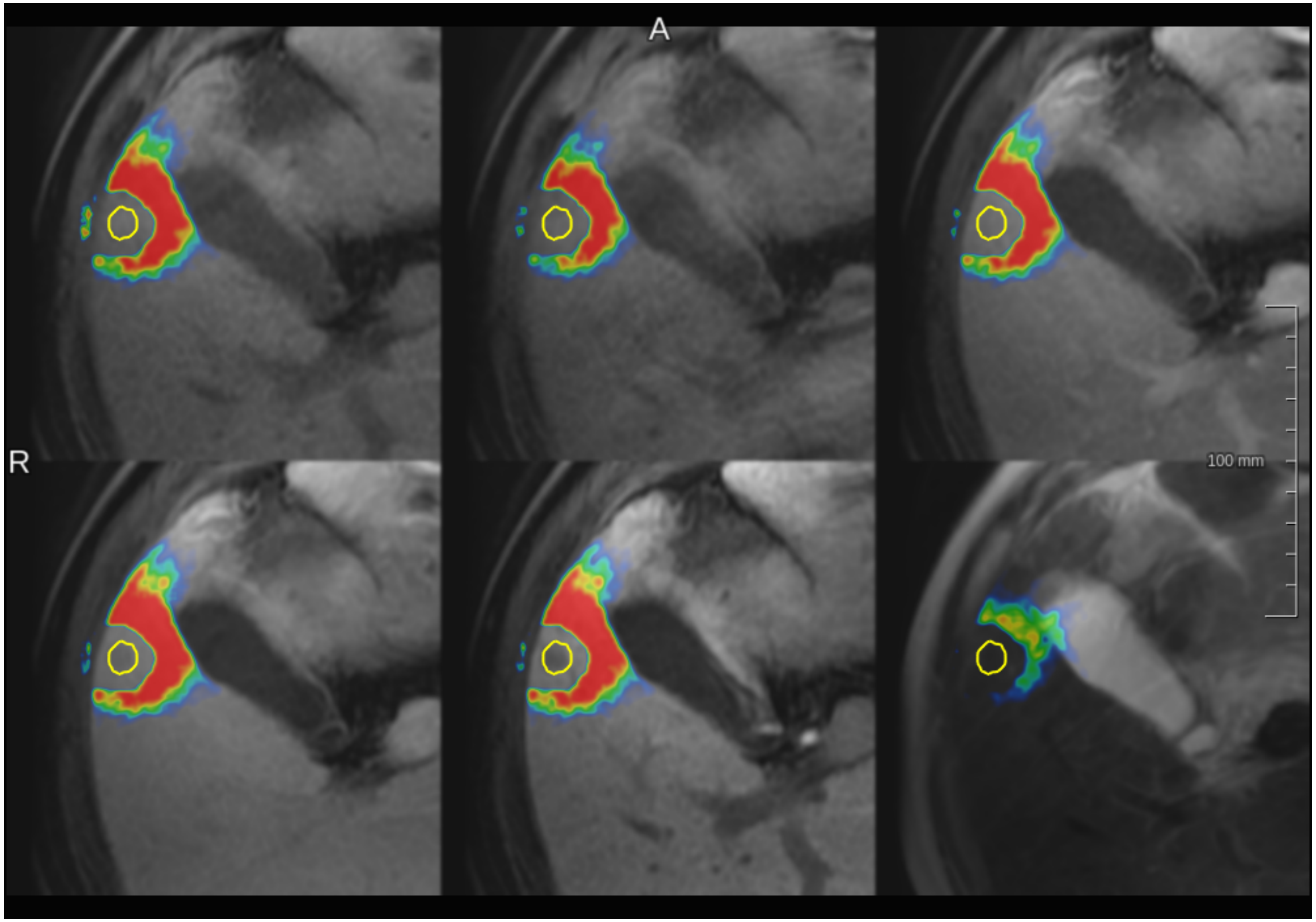
# Erklärbarkeit der KI

- Ansätze
  - Layer-wise relevance propagation




Bach S, Binder A, Montavon G, Klauschen F, Müller KR, Samek W. On pixel-wise explanations for non-linear classifier decisions by layer-wise relevance propagation. PloS one.

# Erklärbarkeit der KI



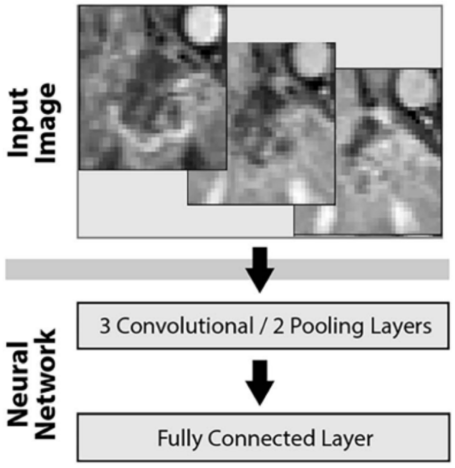

**Schwierig zu interpretieren**

Chlebus G et al. Relevance Analysis of MRI Sequences for Automatic Liver Tumor Segmentation. MIDL 2019.

# Erklärbarkeit der KI

## Interpretation durch radiologische Bild-Merkmale

- Klassifikationsmodell: 6 Läsion-Klassen

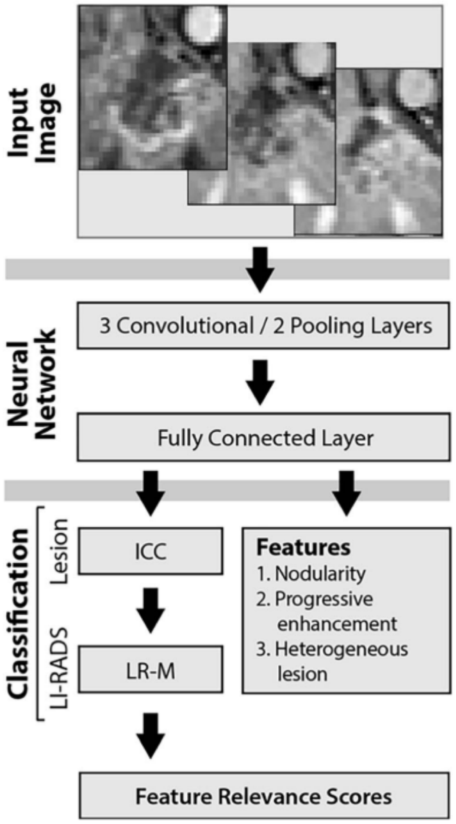



Wang CJ, Hamm CA, Savic LJ, Ferrante M, Schobert I, Schlachter T, Lin M, Weinreb JC, Duncan JS, Chapiro J, Letzen B. Deep learning for liver tumor diagnosis part II: convolutional neural network interpretation using radiologic imaging features. European radiology.

# Erklärbarkeit der KI

Interpretation durch radiologische Bild-Merkmale

- Klassifikationsmodell: 6 Läsion-Klassen
- Erklärbarkeit durch LI-RADS Features
  - Washout
  - Arterial phase enhancement
  - ...




Wang CJ, Hamm CA, Savic LJ, Ferrante M, Schobert I, Schlachter T, Lin M, Weinreb JC, Duncan JS, Chapiro J, Letzen B. Deep learning for liver tumor diagnosis part II: convolutional neural network interpretation using radiologic imaging features. European radiology.

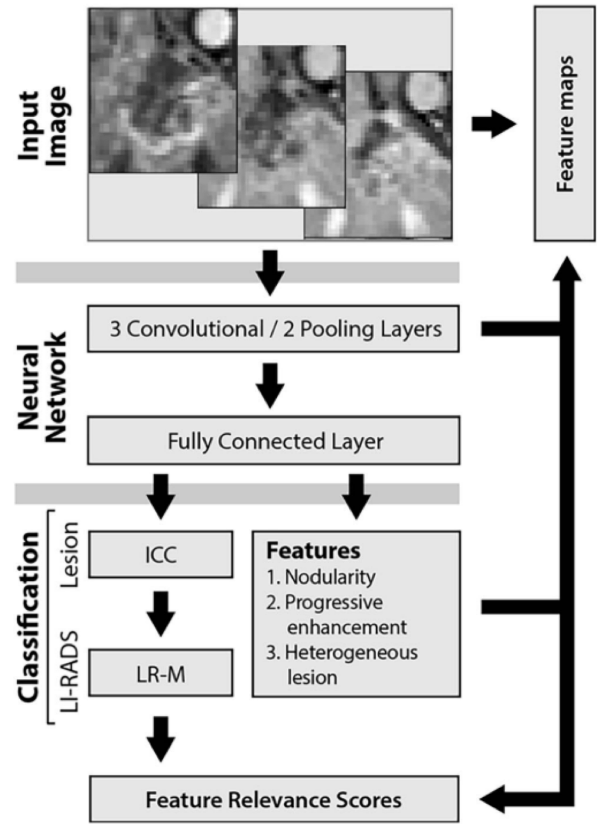
# Erklärbarkeit der KI

## Interpretation durch radiologische Bild-Merkmale

- Klassifikationsmodell: 6 Läsion-Klassen

- Erklärbarkeit durch LI-RADS Features
  - Washout
  - Arterial phase enhancement
  - ...

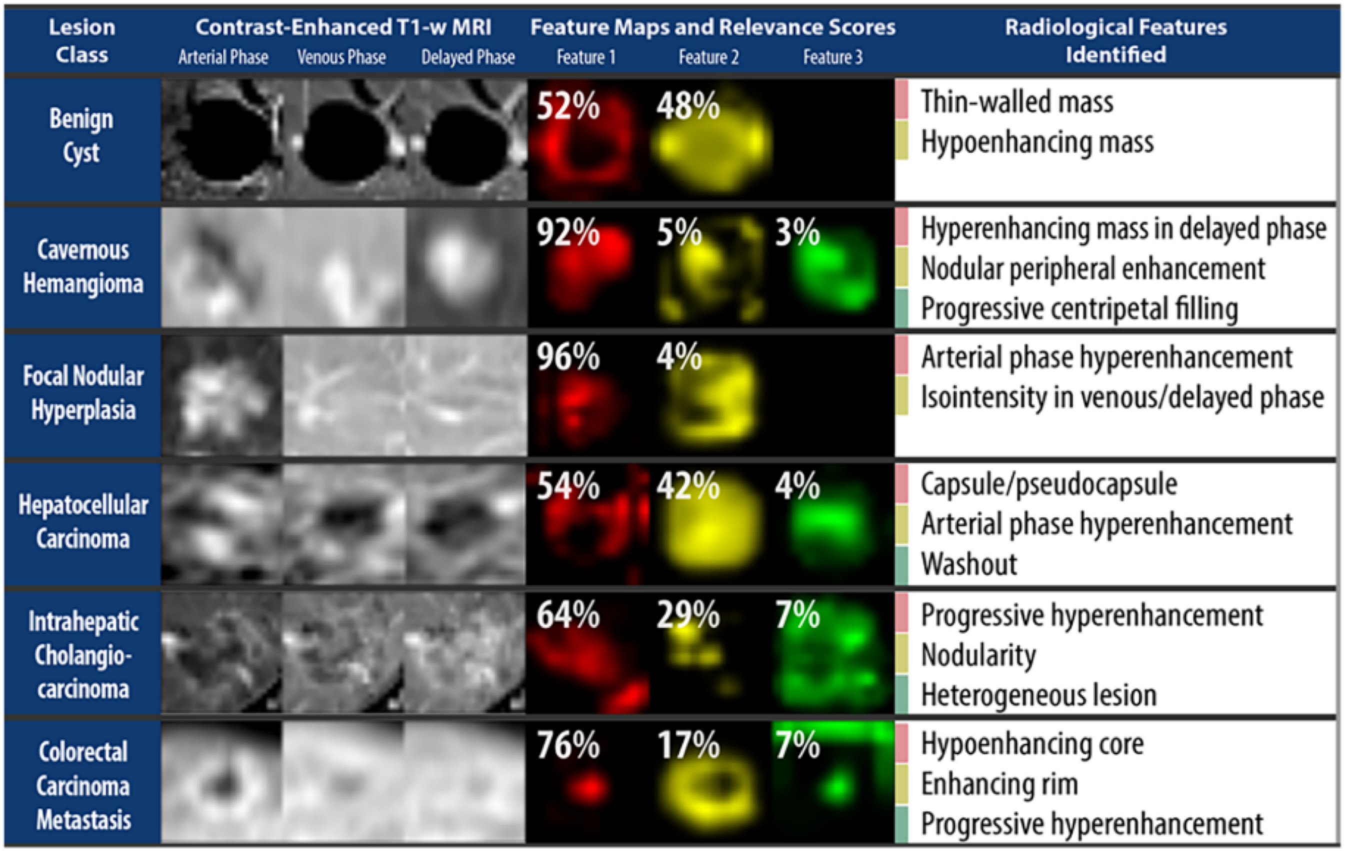
- Anhand von welchem Bild-Bereich wurde ein Feature gefunden?




Wang CJ, Hamm CA, Savic LJ, Ferrante M, Schobert I, Schlachter T, Lin M, Weinreb JC, Duncan JS, Chapiro J, Letzen B. Deep learning for liver tumor diagnosis part II: convolutional neural network interpretation using radiologic imaging features. European radiology.

# Explainable AI

## Interpretation using radiologic imaging features




Schwierig zu erkennen:

- Nodularity
- Central scars

Wang CJ, Hamm CA, Savic LJ, Ferrante M, Schobert I, Schlachter T, Lin M, Weinreb JC, Duncan JS, Chapiro J, Letzen B. Deep learning for liver tumor diagnosis part II: convolutional neural network interpretation using radiologic imaging features. European radiology.

# Weiterentwicklung der KI in der Radiologie

- Kollaboration zwischen Radiologen und KI-Forschern sehr wichtig


- Fraunhofer MEVIS ist an der Kollaboration aktiv beteiligt im Rahmen von
  - Forschungsprojekten z.B. STRIKE
  - Größeren Konsortien z.B. mit DRG

# Danke für Ihre Aufmerksamkeit ☺
# Fragen?