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P25

DiffErentiable TEmporal (DETECT) Loss for Liver Cancer Screening in 4D Dynamic Contrast-Enhanced MRI

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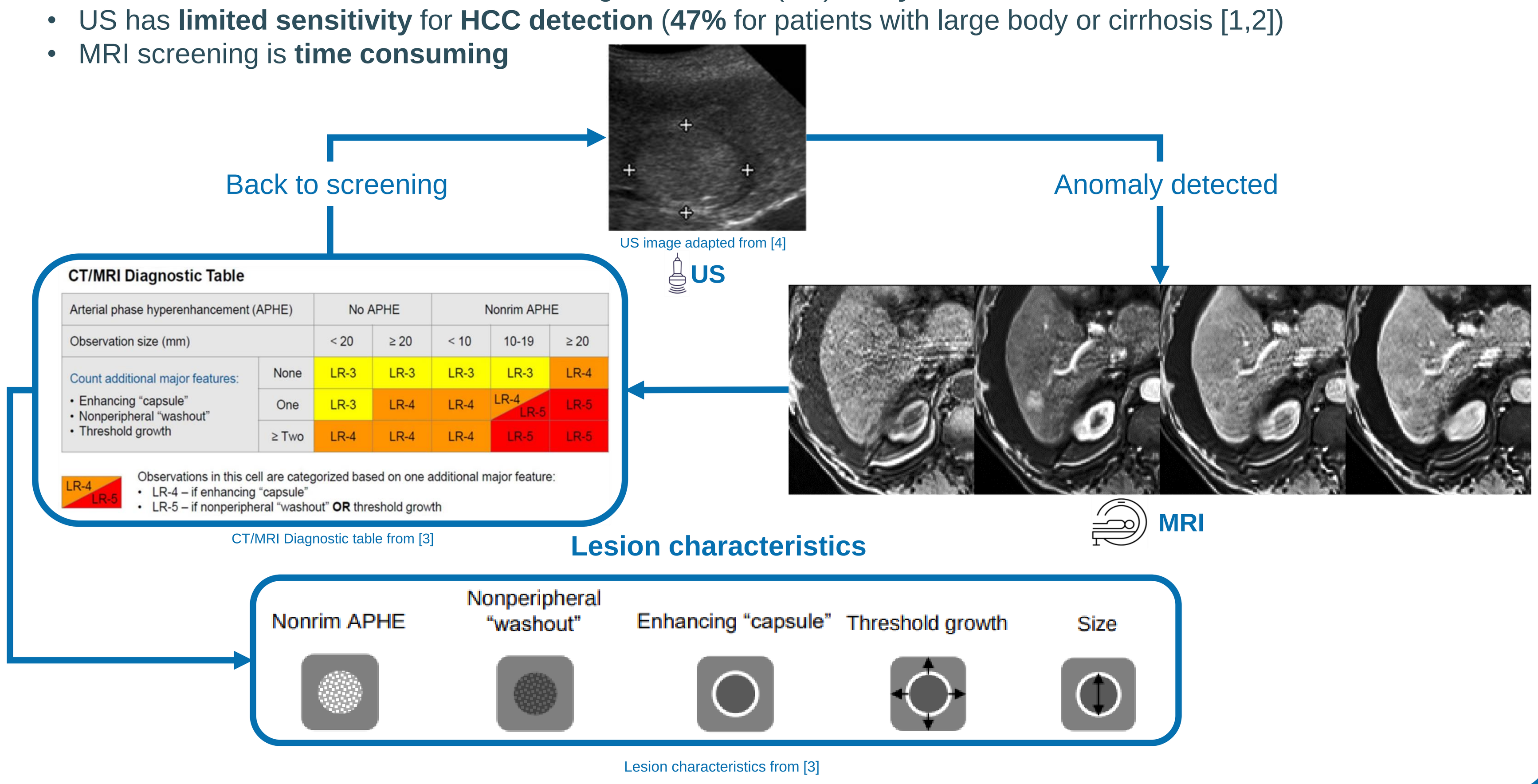
BACKGROUND

Hepatocellular Carcinoma (HCC) screening standard

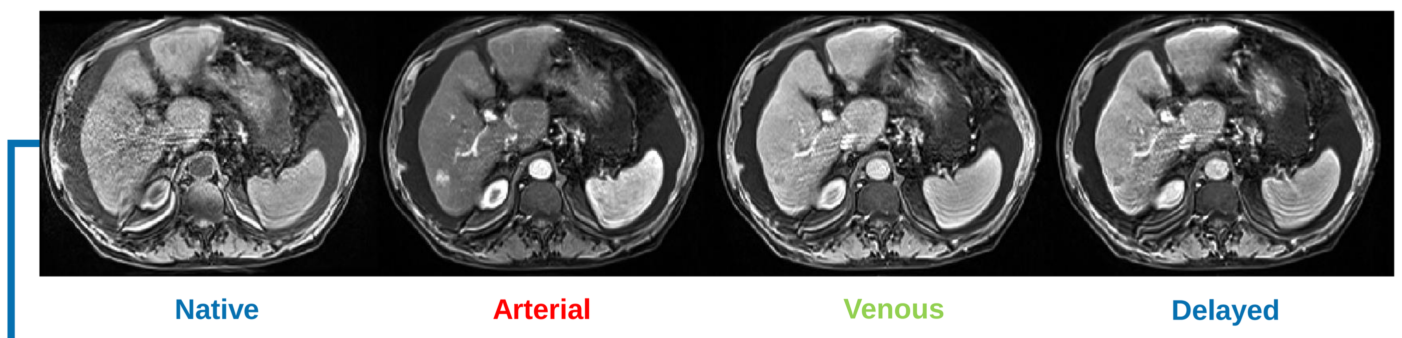
- Patients considered **at-risk of HCC** undergo ultrasound (US) **every 6 months**
- US has **limited sensitivity** for **HCC detection** (**47%** for patients with large body or cirrhosis [1,2])
- MRI screening is **time consuming**

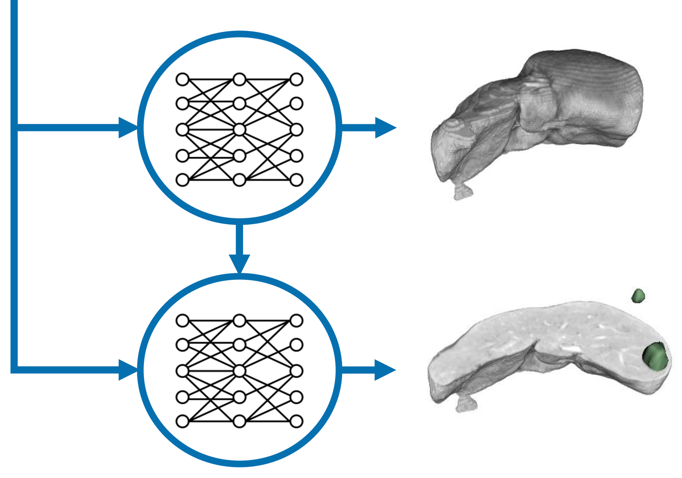


AIMS

Deep learning for HCC detection in 4D MRI

- **Dynamic Contrast-Enhanced (DCE) MRI** allows to diagnose HCC **without** the need for **biopsy**
- A deep learning algorithm can **support experts** in that screening task





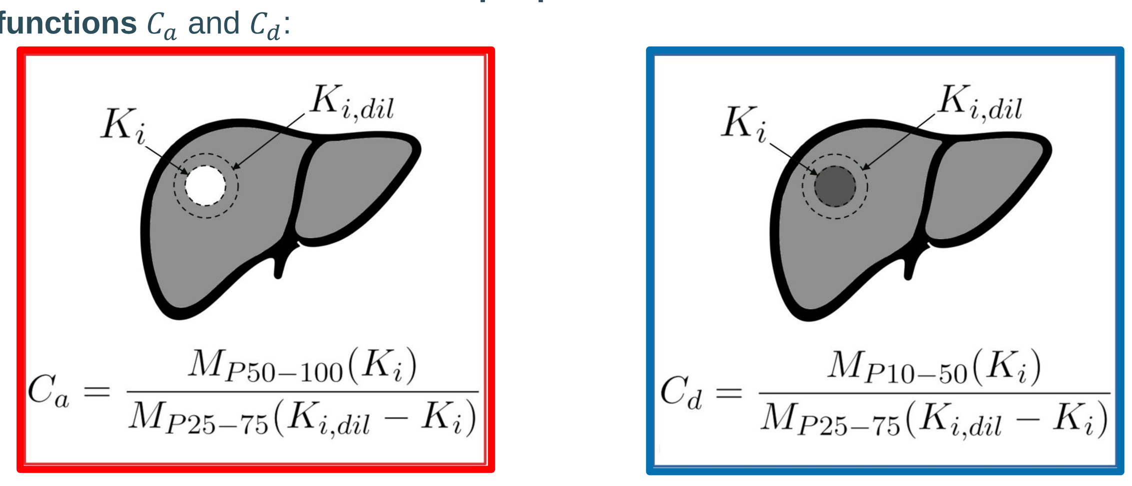
Objectives:

1. **Liver extraction**
   Training of a deep learning model to segment the liver from the DCE MRI to facilitate the task of HCC screening.
2. **HCC screening**
   Training of a deep learning model to segment and detect HCC lesions in extracted liver from DCE MRI.

METHODS

DiffErentiable Temporal (DETECT) Loss

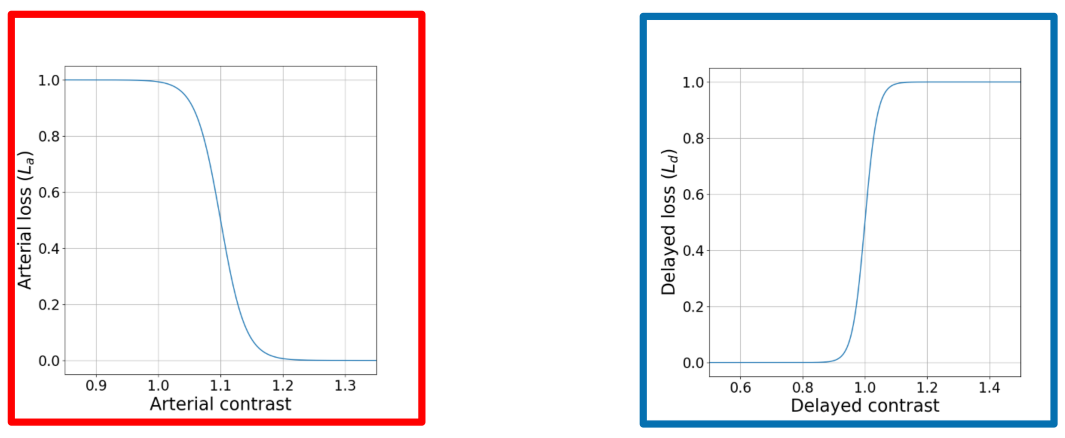
The lesion characteristics **Nonrim APHE** and **Nonperipheral «washout»** can be **translated** into arterial and delayed **contrasts functions** C_a and C_d:



$$C_a = \frac{M_{P50-100}(K_i)}{M_{P25-75}(K_{i,dil} - K_i)}$$

$$C_d = \frac{M_{P10-50}(K_i)}{M_{P25-75}(K_{i,dil} - K_i)}$$

Use of **sigmoids** to bound C_a and C_d between 0 and 1:



A **temporal loss** L_T is created by a weighted sum of the contrast losses L_a and L_d :

$$L_T = \gamma \cdot L_a + \delta \cdot L_d$$

The final **DETECT** loss consists in the combination of the temporal loss L_T and a Tversky loss L_{Seg} :

$$L_{\mathrm{DETECT}} = \frac{1}{Z}\sum_{b=1}^{B}\sum_{i=1}^{N}(1-\lambda)\cdot L_{\mathrm{T,b}}(I, K_{\hat{M}_i}) + \lambda \cdot L_{Seg,b}$$

The L_{Seg} loss part helps the model to **generate candidate lesion**, and the L_T loss is used to **detect temporal malignancy** patterns, with a balance governed by λ.

Post-Processing

- **Gaussian blurring** of probability maps
- **Dilation and erosion** of probability maps
- **Gaussian weighting** of patch predictions
- **Test-time augmentation** to improve prediction reliability
- **Local temperature scaling** to calibrate probability maps
- **Ensembling** for test dataset predictions

RESULTS

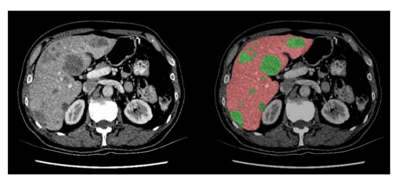
Datasets

Data split	Training and validation sets	Internal screening test set	Internal pre-surgery test set
HCC positive patients	65	14	39
HCC negative patients	-	82	-
Number of lesions	139	24	71
Lesions diameter (mm)	20.5+-11.8	23.5+-16.3	26.8+-14.0
LR-5	88	16	58
LR-4	23	4	4
LR-3	22	2	8

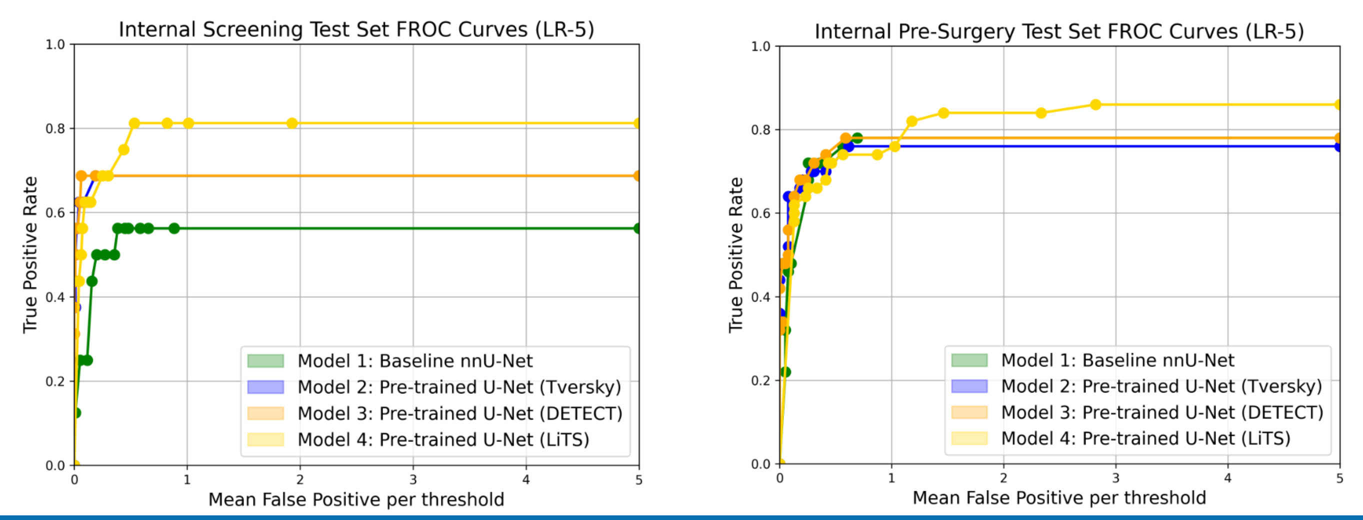
Experiments

1. **nnU-Net**
   The nnU-Net [5] is an **automated** deep learning **framework** for medical image segmentation offering state of the art performance with **limited manual intervention** needed.
2. **U-Net (Tversky)**
   Attention U-Net [6] trained with a Tversky loss function. **Penalty of false negatives and false positives** are governed by the **α** and **β** parameters and were set to 0.1 and 0.9 for the experiment.
3. **U-Net (DETECT)**
   Attention U-Net **pre-trained** with a Tversky loss and **fine-tuned** with our **DETECT** loss function with parameters δ=0.5, γ=0.5 and λ=0.
4. **U-Net (LiTS)**
   Attention U-Net **pre-trained** with a Tversky loss at the detection of lesions in **CT imaging** (LiTS dataset with 1022 annotated lesions [7]) and **fine-tuned** with our internal MRI dataset.

$$\mathrm{TI} = \frac{\mathrm{TP}}{\mathrm{TP} + \alpha\mathrm{FN} + \beta\mathrm{FP}}$$



Results



CONCLUSION

- The use of the **DETECT** loss fonction can improve the detection of **HCC lesions**
- When external data is available and a **higher** number of **false positives** is acceptable, a pre-trained model such as **U-Net (LiTS)** may be a more suitable option

REFERENCES

References: [1] Tzartzeva K et al., Gastroenterology 2018, [2] Kim SY, JAMA Oncol. 2017, [3] Chernyak V et al., Radiology, 2018, [4] Virmani J, Kumar V et al., J Digit Imaging 2013, [5] Isensee et al., Nat Methods 18 2021, [6] Oktay et al., 2018, [7] Patrick et al., Medical Image Analysis 2023

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