Supplementary Materials

Gd-EOB-DTPA-enhanced MRI radiological and deep learning radiomics models for predicting dual-phenotype hepatocellular carcinoma and patient prognosis

Manuscript Author:

Huilin Sun[1,#], Jingcheng Hu[2,#], Qian Wu[1,#], Tao Zhang[3], Mingzhan Du[4], Ximing Wang[1], Yan Yang[1], Chunhong Hu[1], Yixing Yu[1]

[1]Department of Radiology, The First Affiliated Hospital of Soochow University, Suzhou 215006, Jiangsu, China.

[2]Department of Endocrinology, The First Affiliated Hospital of Soochow University, Suzhou 215006, Jiangsu, China.

[3]Department of Radiology, Affiliated Nantong Hospital 3 of Nantong University, Nantong 226000, Jiangsu, China.

[4]Department of Pathology, The First Affiliated Hospital of Soochow University, Suzhou 215006, Jiangsu, China.

[#]Authors contributed equally.

Correspondence to: Dr. Yan Yang, Prof. Chunhong Hu, Prof. Yixing Yu, Department of Radiology, The First Affiliated Hospital of Soochow University, Suzhou 215006, Jiangsu, China. E-mail: yangyan892025@163.com; sdhuchunhong@sina.com; yuyixing@163.com

ORCID: Huilin Sun (0009-0005-5416-6318)

Supplementary Method 1 MR imaging acquisition

The specific machines included Simens Magnetom Skyra 3.0T MRI (Siemens, Germany), and Philips Medical Systems 3.0T MRI (Philips Netherlands) imaging system, a 16-channel phased array body coil. The detailed scanning sequences and parameters are shown in the tables below. Diffusion-Weighted Imaging (DWI) was acquired with b values of 0 and 800 s/mm2.Gd-EOB-DTPA (Bayer, Berlin, Germany) through the elbow vein (0.1 mL/kg body weight) was injected followed by 20 mL of 0.9% saline at a flow rate of 1 mL/s.Arterial phase,portal venous phase and hepatobiliary phase images were acquired at 20–30 s,60–70 s and 20 minutes after GD-EOB-DTPA after injection of the contrast agent, respectively.

The MRI scan sequences and parameters for Siemens Medical Systems 3.0T MRI

Sequence	Category	TR(ms)	TE(ms)	FOV (mm)	Thickness (mm)	Fat saturation	Breath-hold
T1WI in/ opposed phase	3D VIBE	4.11	2.47/1.24	400×400	3.5	No	Yes
T1WI-fs	3D VIBE	4.11	1.24	400×400	3.5	Yes	Yes
T2WI-fs	TSE	3000	82	400×400	6.5	Yes	Yes
DWI	Ep2d	5600	58	400×400	6.5	Yes	No
Contrast-enhanced							
T1WI-fs （AP）	3D VIBE	4.15	2.01	400×400	3.5	Yes	Yes
T1WI-fs （PP）	3D VIBE	4.15	2.01	400×400	3.5	Yes	Yes
T1WI-fs （HBP）	3D VIBE	4.15	2.01	400×400	3.5	Yes	Yes

Notes: FOV: field of view; 3D VIBE, a three-dimensional volume interpolated breath-hold examination; Ep2d, a two-dimensional echo-planar technique; fs, fat suppression; AP: arterial phase; PP: portal venous phase; HBP: hepatobiliary phase.

The MRI scan sequences and parameters for Philips Medical Systems 3.0T MRI

Sequence	Category	TR(ms)	TE(ms)	FOV (mm)	Thickness (mm)	Fat saturation	Breath-hold
T1WI in/ opposed phase	mDIXON	3.7	1.32	400×300	6	No	Yes
T1WI-fs	mDIXON	3.7	1.32	400×300	6	Yes	Yes
T2WI-fs	TSE	448	70	320×364	4		
DWI	DW EPI	1783	55	300×360	5	Yes	No
Contrast-enhanced							
T1WI-fs(AP)	mDIXON	3.8	1.4	400×300	3	Yes	Yes
T1WI-fs(AP)	mDIXON	3.8	1.4	400×300	3	Yes	Yes
T1WI-fs(HBP)	mDIXON	3.8	1.4	400×300	3	Yes	Yes

Notes: FOV: field of view; mDIXON:modified Dixon; fs, fat suppression; TSE, turbo spin-echo; DW EPI: Diffusion-Weighted Echo Planar Imaging;AP: arterial phase; PP: portal venous phase; HBP: hepatobiliary phase.

Supplementary Method 2 Detailed training parameters of 3D Swin Transformer

We fine-tuned 3D Swin Transformer models for extracting features from AP, PP, and HBP images, respectively. The models employed the “swin3d_s” architecture from the “torchvision.models.video” module in PyTorch 2.5.1 (https://github.com/pytorch/pytorch). We employed a partial fine-tuning strategy using the swin3d_s model. The model architecture consists of 4 hierarchical stages with patch merging layers between stages, followed by a LayerNorm and a classification head. (a) Frozen layers: Stages 1-3 and their associated PatchMerging layers, plus the patch embedding layer. These early and middle layers capture general spatiotemporal features (edges, textures, local patterns) that are largely transferable across domains. (b) Updated layers: The last stage (Stage 4, comprising 2 SwinTransformerBlocks), the final PatchMerging layer, the LayerNorm, and the classification head. These deeper layers capture task-specific high-level semantics and are the most beneficial to adapt to the target domain. A variety of empirically validated methodologies, such as data augmentation and progressive learning rate decay, were

systematically implemented during the training phase to effectively counteract potential overfitting tendencies. Data augmentation included Resized, ScaleIntensityRanged, RandFlipd, and RandAffined. In this study, the batch size was set to 16, the initial learning rate to 1e-4 for the classification head and 1e-5 for the fine-tuned backbone, with a StepLR scheduler decaying the learning rate by a factor of 0.1 every 7 epochs. To mitigate inter-class distribution disparities, we implemented focal loss as the core optimization objective. The architecture employed Adam optimizer, an adaptive optimization algorithm with automated learning rate modulation. The training epochs were 200-500. After the training phase concluded, the fine-tuned model weights were employed to derive discriminative feature embeddings from medical imaging datasets. Each VOI yielded 768 deep learning features.

Supplementary Method 3 Radiomics feature selection

Radiomics features was calculated on the original and pre-processed images using the wavelet,wavelet transform, square, square root, logarithm, Laplacian of Gaussian, gradient and exponential filters. Feature computation was performed at resampling voxel dimensions of 1 × 1 × 1mm3 and an intensity bin width of 25. Radiomics features were extracted from both the DPHCC and non-DPHCC on the AP, PP and HBP images, including first-order statistics, shape, and texture features. Texture features included gray level co-occurrence matrix (glcm), gray level run length matrix (glrlm), gray level size zone matrix (glszm), gray level dependence matrix (gldm), and neighboring gray tone difference matrix (ngtdm).

Supplementary Table 1 Selected Feature Numbers in the Constructed Models

Phase	Feature Type	Selected Feature Number
AP	Radiomics	24
	DL	14
	DLR	21
PP	Radiomics	3
	DL	12
	DLR	11
HBP	R	8
	DL	17
	DLR	6
CP	Radiomics	11
	DL	2
	DLR	7

AP=arterial phase; PP=portal venous phase; HBP=hepatobiliary phase; CP=combined phase; DL=deep learning; DLR=deep learning radiomics.

Supplementary Table 2

Selected Features of the Radiomics, DL and DLR Models in PP and CP

Model	Features	Coefficients
PP-radiomics	pp_exponential_gldm_DependenceVariance	0.52
	pp_wavelet-HLL_glcm_InverseVariance	-0.55
	pp_wavelet-HHL_glszm_SmallAreaLowGrayLevelEmphasis	0.74
PP-DL	pp_DL_feature_196	0.22
	pp_DL_feature_242	0.15
	pp_DL_feature_254	-0.25
	pp_DL_feature_279	-0.39
	pp_DL_feature_403	-0.09
	pp_DL_feature_452	-0.14
	pp_DL_feature_464	-0.31
	pp_DL_feature_578	0.32
	pp_DL_feature_603	0.22
	pp_DL_feature_605	-0.14
	pp_DL_feature_615	0.29
	pp_DL_feature_724	-1.02
PP-DLR	pp_exponential_gldm_DependenceVariance	0.51
	pp_square_gldm_DependenceVariance	0.32
	pp_wavelet-HLL_glcm_InverseVariance	-0.55
	pp_wavelet-HHL_gldm_LargeDependenceLowGrayLevelEmphasis	-0.02
	pp_wavelet-HHL_glszm_SmallAreaLowGrayLevelEmphasis	0.67
	pp_DL_feature_242	0.29
	pp_DL_feature_314	0.15
	pp_DL_feature_464	-0.08
	pp_DL_feature_605	-0.27
	pp_DL_feature_724	-1.04
	pp_DL_feature_735	-0.36
CP-radiomics	ap_exponential_glszm_SmallAreaLowGrayLevelEmphasis	0.23
	ap_wavelet-LHL_glcm_InverseVariance	-0.20
	pp_exponential_gldm_DependenceVariance	0.56
	pp_exponential_glrlm_ShortRunLowGrayLevelEmphasis	0.21
	pp_square_gldm_DependenceVariance	0.22
	pp_wavelet-LLH_glcm_ClusterTendency	0.26
	pp_wavelet-HLL_glcm_InverseVariance	-0.28
	pp_wavelet-HHL_glcm_MCC	-0.27
	pp_wavelet-HHL_gldm_LargeDependenceLowGrayLevelEmphasis	-0.07
	pp_wavelet-HHL_glszm_SmallAreaLowGrayLevelEmphasis	0.58
	pp_wavelet-HHH_glcm_Imc2	0.16
CP-DL	ap_DL_feature_9	0.36
	pp_DL_feature_724	-1.18
CP-DLR	ap_DL_feature_254	-0.39

pp_exponential_gldm_DependenceVariance	0.54
pp_exponential_glrlm_ShortRunLowGrayLevelEmphasis	0.23
pp_wavelet-HLL_glcm_InverseVariance	-0.40
pp_wavelet-HHL_glszm_SmallAreaLowGrayLevelEmphasis	0.56
pp_wavelet-HHH_glcm_Imc2	0.27
pp_DL_feature_724	-1.16

AP=arterial phase; PP=portal venous phase; CP=combined phase; DL=deep learning; DLR=deep learning radiomics.

Supplementary Table 3

Bootstrap feature selection stability analysis result of the PP-DLR model

Features	Selection Frequency (%)	Selection Rank
pp_exponential_gldm_DependenceVariance	84	1
pp_square_gldm_DependenceVariance	6	104
pp_wavelet-HLL_glcm_InverseVariance	36	5
pp_wavelet-HHL_gldm_LargeDependenceLowGrayLevelEmphasis	5	151
pp_wavelet-HHL_glszm_SmallAreaLowGrayLevelEmphasis	78.5	2
pp_DL_feature_242	25.5	11
pp_DL_feature_314	9.5	60
pp_DL_feature_464	16.5	25
pp_DL_feature_605	6.5	91
pp_DL_feature_724	70	3
pp_DL_feature_735	28	7

PP=portal venous phase; DL=deep learning; DLR=deep learning radiomics.