A Novel Computer-Aided Diagnostic System for Early Assessment of Hepatocellular Carcinoma

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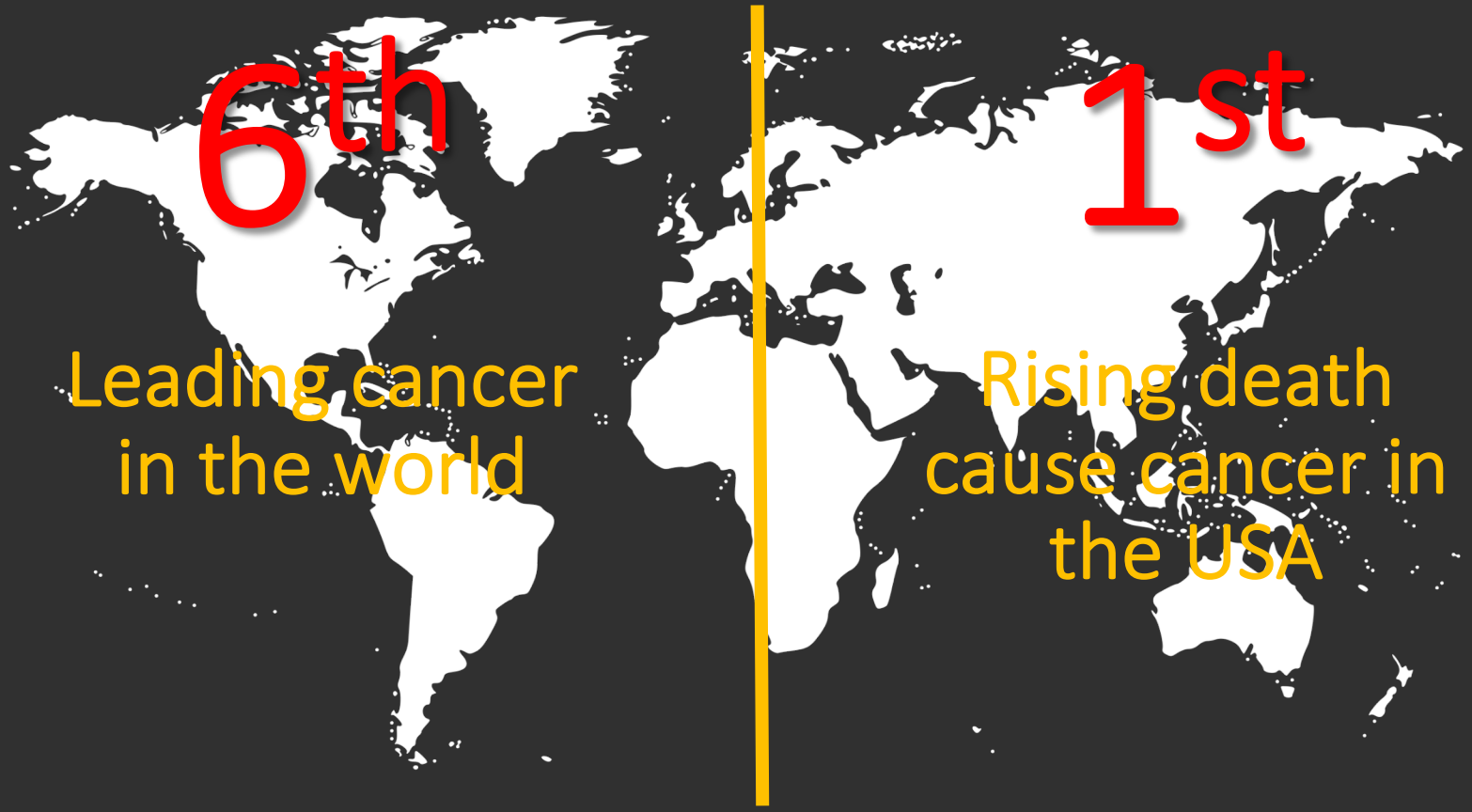
ICPR 2020

Research Motivations



The blue faery liver cancer association 2020

Research Motivations

Annual records:

- Worldwide : 800,000 new cases and 700,000 new deaths
- In the USA: 42,030 new cases and 31,780 deaths

At Global Averages:

1/5000 People

is in danger of contracting HCC

- HCC is a cancer arising from the liver cells.
- HCC is the most common primary liver disease, and its incidence is increasing.
- The prognosis of HCC is affected by its severity level when detected, as curative managements can be enough for early-stage HCC.
- Early assessment of liver cancer patients with HCC is of immense importance to provide the proper treatment plan.

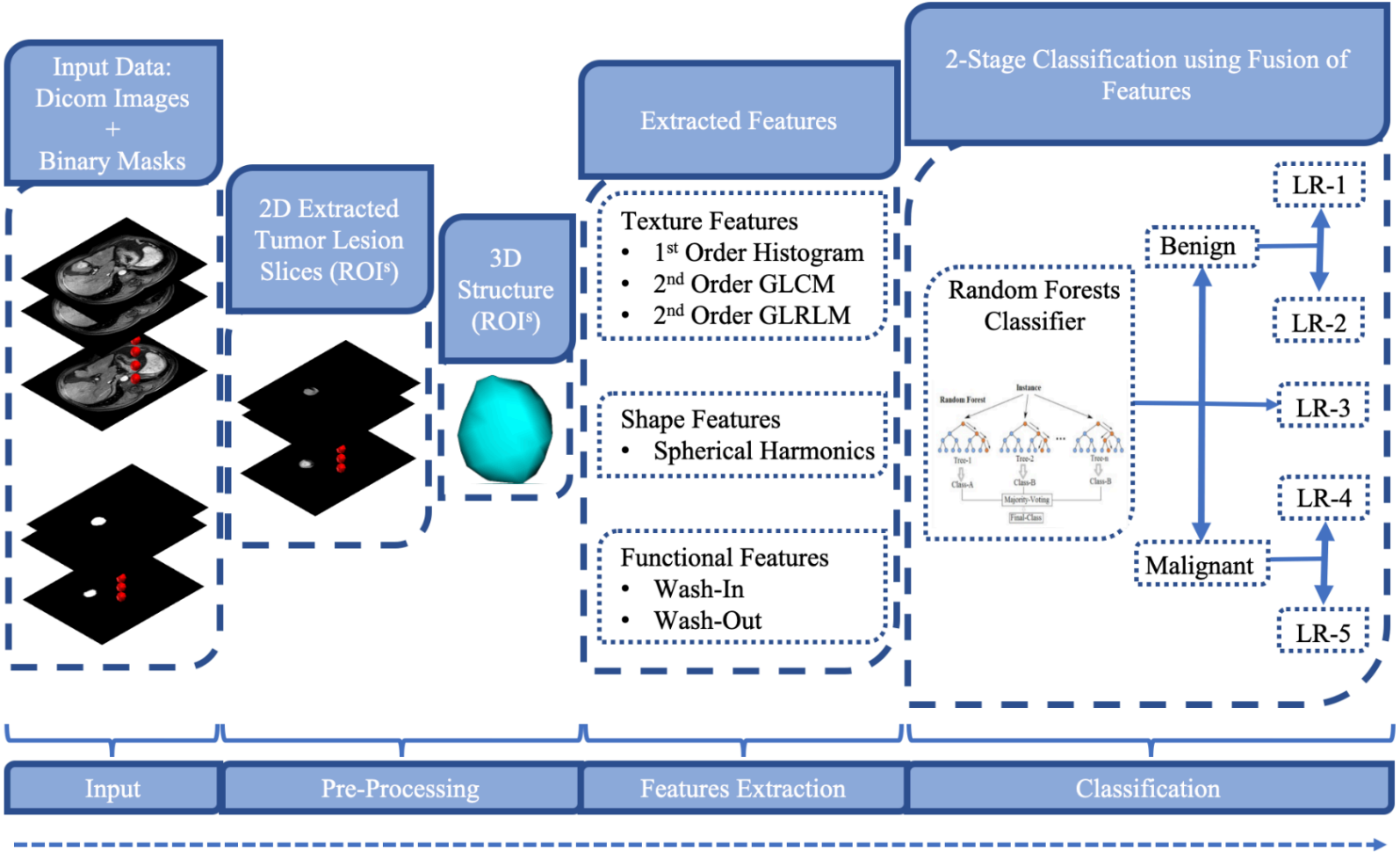
Current Diagnostic Tools & Limitations

- For HCC, a radiological diagnosis (LI-RADS) provides high diagnostic performance and is considered as the Gold-Standard, which makes the medical organizations depend only on highly-experienced radiologists for HCC diagnosis.

- Therefore, there is an urgent need for an **automated machine-learning based CAD system** to identify HCC and its grade to provide the proper treatment plan.

Liver Imaging Reporting and Data System (LI-RADS v2018)

Proposed Framework



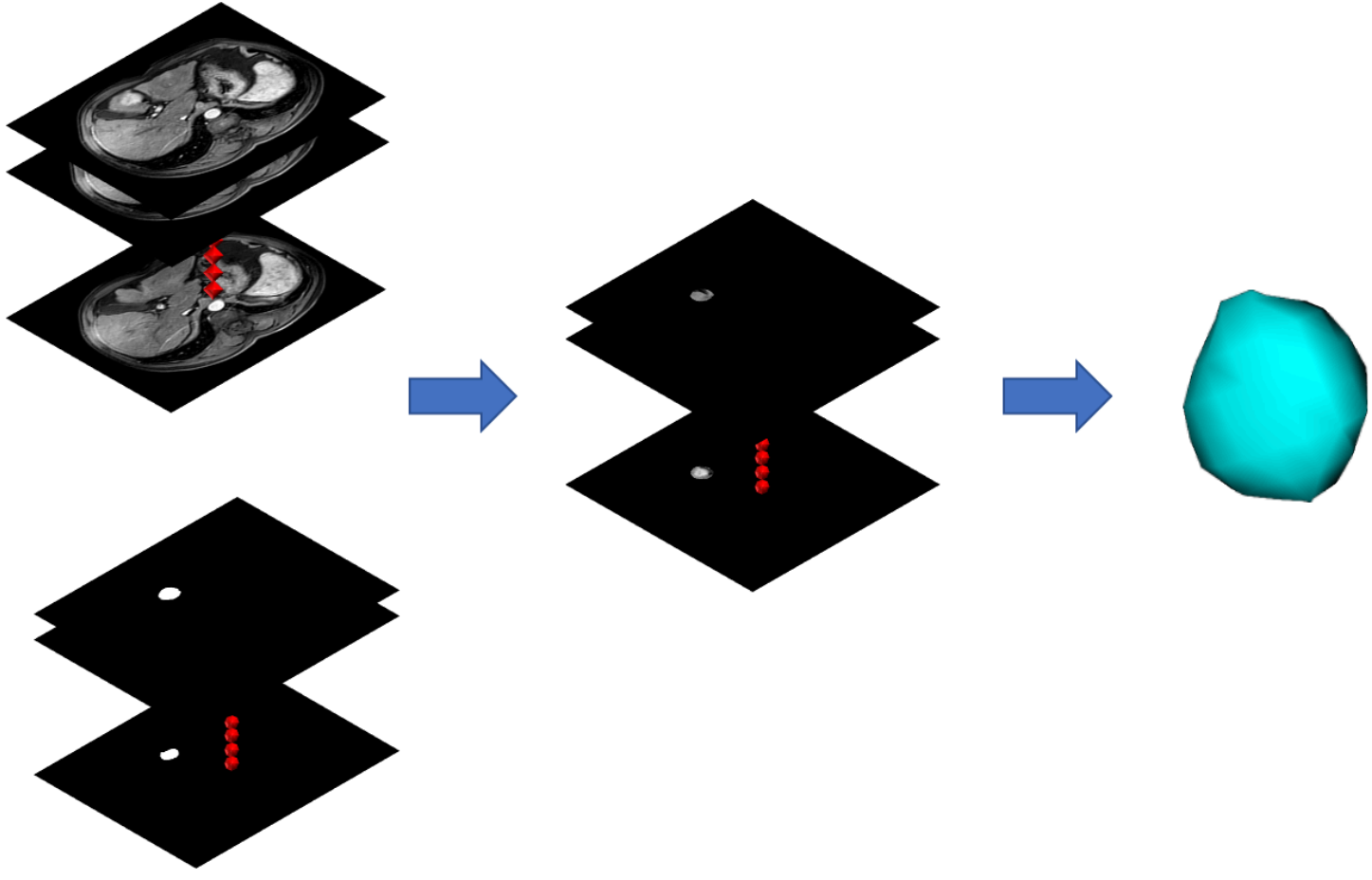
Input: CE-MRI Data Collection

- A total of 85 patients with high risk of developing HCC without history of loco-regional treatment plan, (M = 61 and F = 24), provided their consent to participate in this study.
- They averaged an age of (55.131 ± 7.12) ranging from 40 to 73 years old.
- 34 patients with benign tumors (LR-1 = 17 and LR-2 = 17), 17 with intermediate, and 34 with malignant tumors (LR-4 = 17 and LR-5 = 17)
- Acquisition parameters of MRI sequences are defined in the following Table:

Sequence	TR (msec.)	TE (msec.)	FOV (mm)	Matrix	Slice thickness (mm)	Slice gap (mm)	Flip angle
T2	>=445	26-28	230	160-144×240	6	3	NA
T2 SPAIR	2500-3000	80-100	230	144×144	6	3	NA
Dynamic GRE (THRIVE)	7.3	3.1	500	256×128	3	1	40

Acquisition parameters of MRI sequences. TR: repetition time; TE: echo time; FOV: field of view; SPAIR: spectral attenuated inversion recovery; GRE: gradient-recalled echo; THRIVE: T1-weighted, high-resolution isotropic volume examination.

Liver Tumor Preprocessing

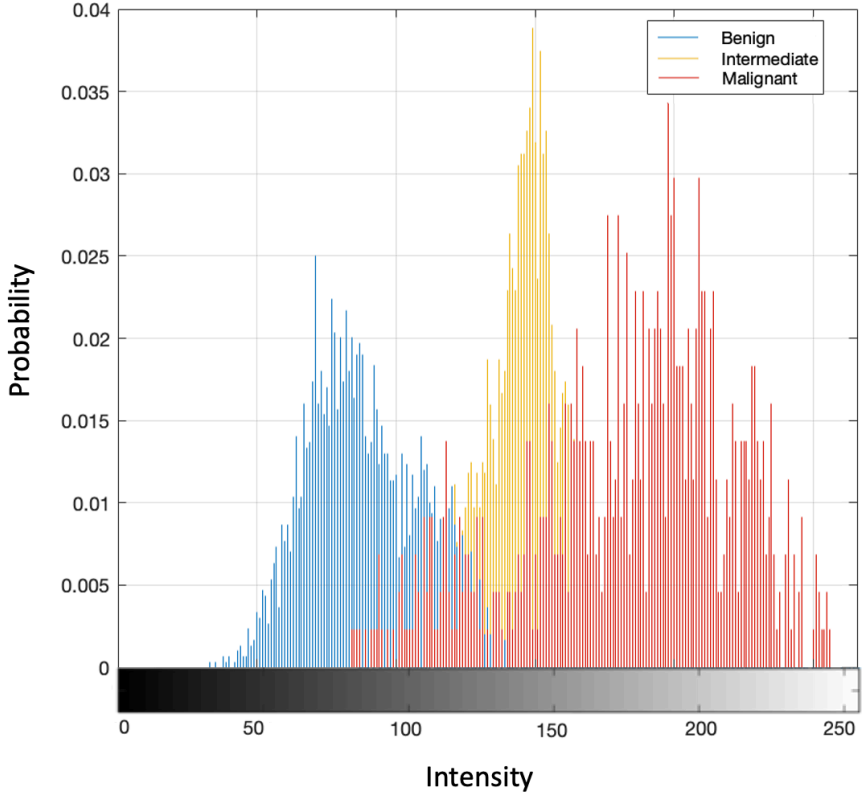


Features Extraction: Texture Features

1st Order Texture Features

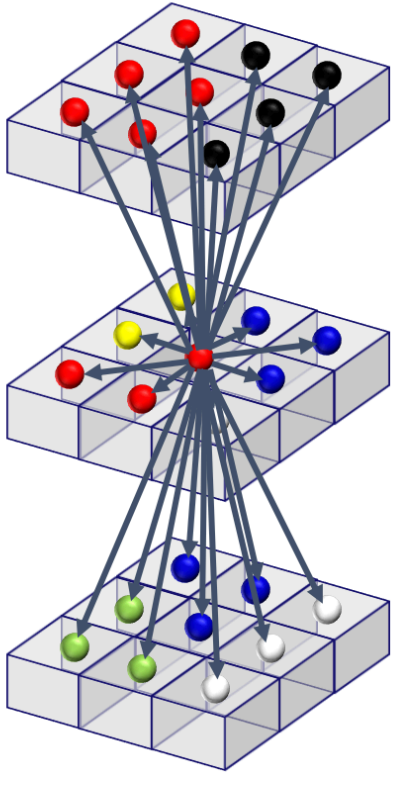
- Here, we extracted texture analysis features from the gray-level histogram of the four 3D constructed objects for each tumor lesion.

- The computed features are mean, variance, standard deviation, skewness, kurtosis, entropy, cumulative distribution function and gray-level percentiles.



Features Extraction: Texture Features (cont'd)

A 3*3*3 Section from an HCC Tumor 3D object



2nd Order GLCM

Update

GLCM of the HCC Tumor 3D object

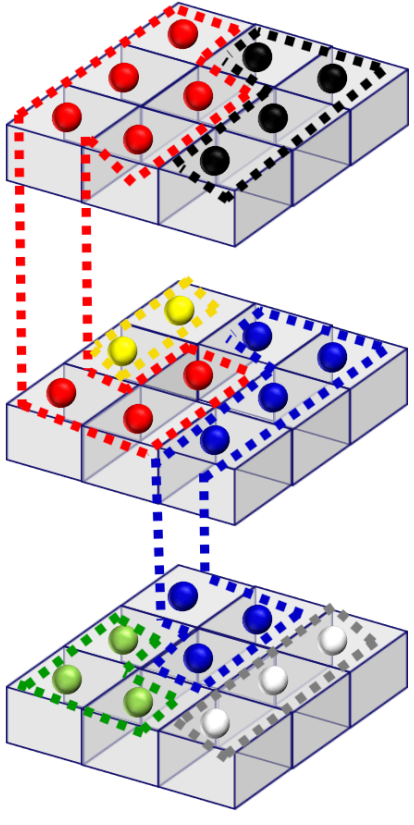
	+7+7	+4	+6	+3	+4	+2
	+4	+0	+0	+0	+0	+0
	+6	+0	+0	+0	+0	+0
	+3	+0	+0	+0	+0	+0
	+4	+0	+0	+0	+0	+0
	+2	+0	+0	+0	+0	+0

Represent different intensity levels

+value The value to be added to the GLCM cells

Features Extraction: Texture Features (cont'd)

A 3*3*3 Section from an HCC Tumor 3D object



2nd Order GLRLM

Update

GLRLM of the HCC Tumor 3D object

	1	2	3	4	5	6	7	8
●	+0	+0	+0	+0	+0	+0	+0	+1
●	+0	+0	+0	+1	+0	+0	+0	+0
●	+0	+0	+0	+0	+0	+0	+1	+0
●	+0	+0	+1	+0	+0	+0	+0	+0
●	+0	+0	+1	+0	+0	+0	+0	+0
●	+0	+1	+0	+0	+0	+0	+0	+0

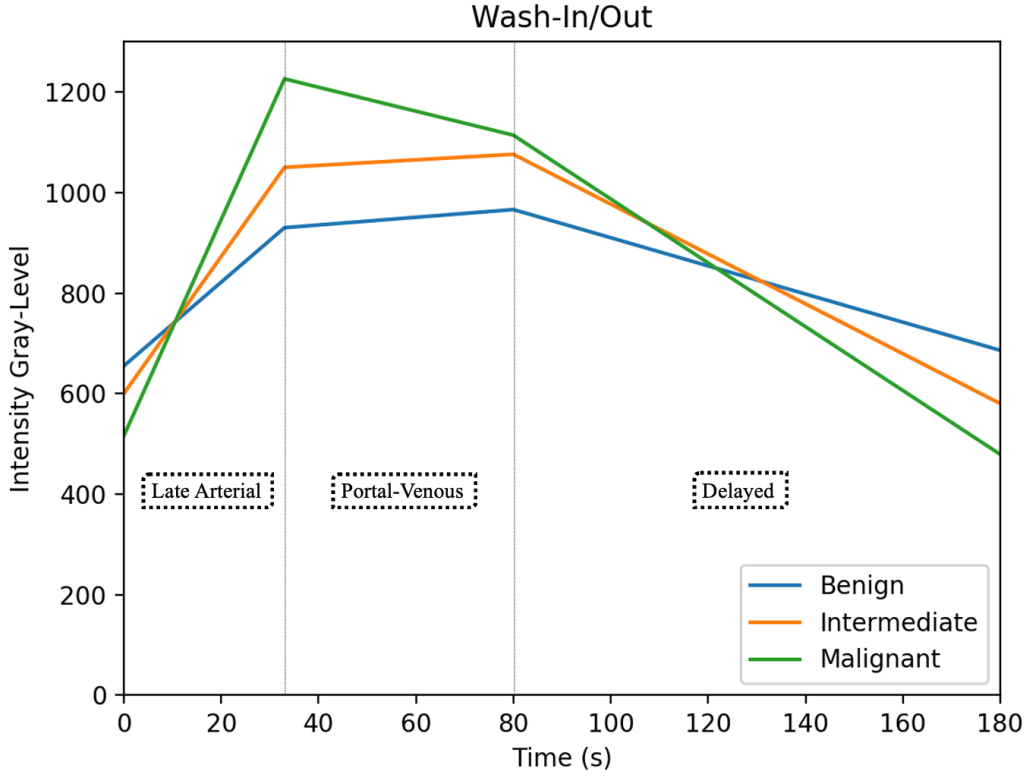
● ● ● ● ● ● Represent different intensity levels

1 2 3 4 5 6 7 8 Represent different Run Lengths

+value The value to be added to the GLRLM cells

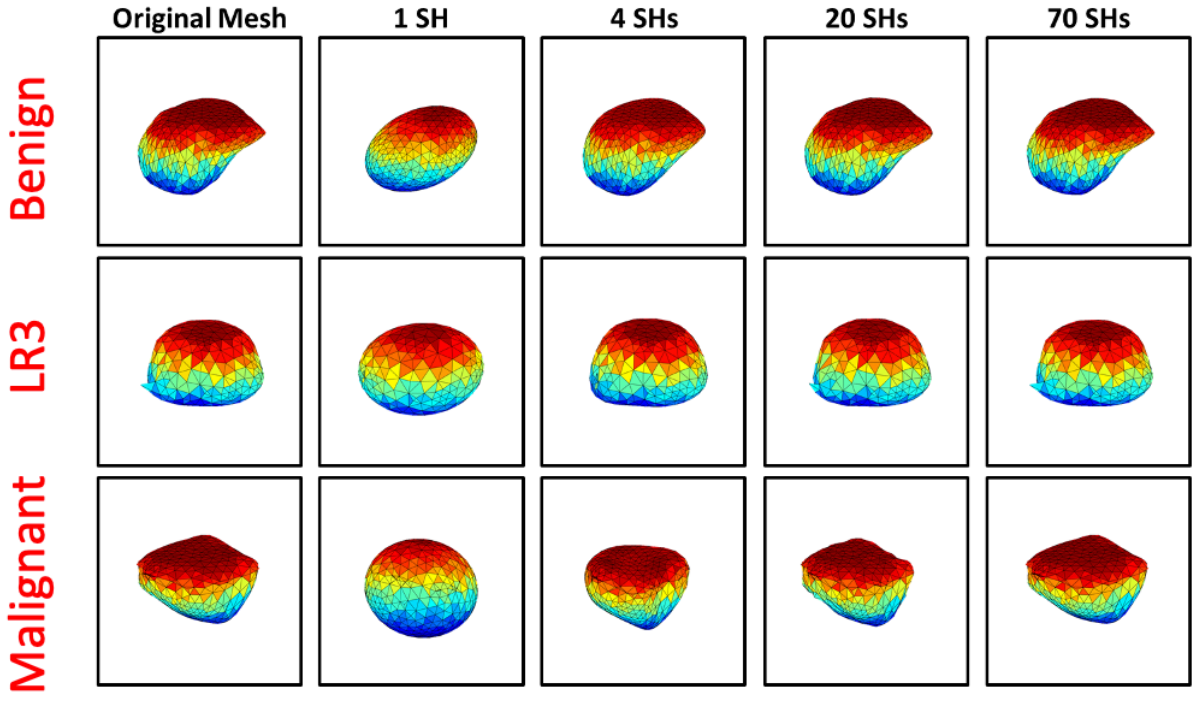
Features Extraction: Functional Features

➢Examine the functional hyperenhancement (wash-in) and hypo-intensity (wash-out) developed by the HCC regenerative progressive nodules.



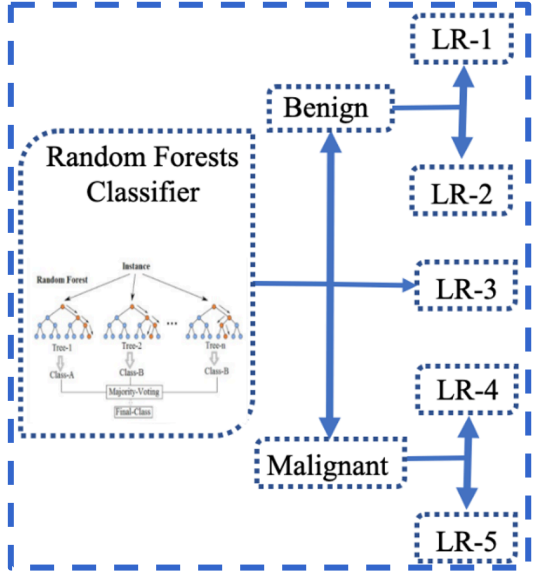
Features Extraction: Shape Features

➢In the proposed framework, we used the state-of-the-art spectral analysis employing spherical harmonics (SH) to extract shape features for diagnosing liver tumors.



Features Integration and Tumor Classification

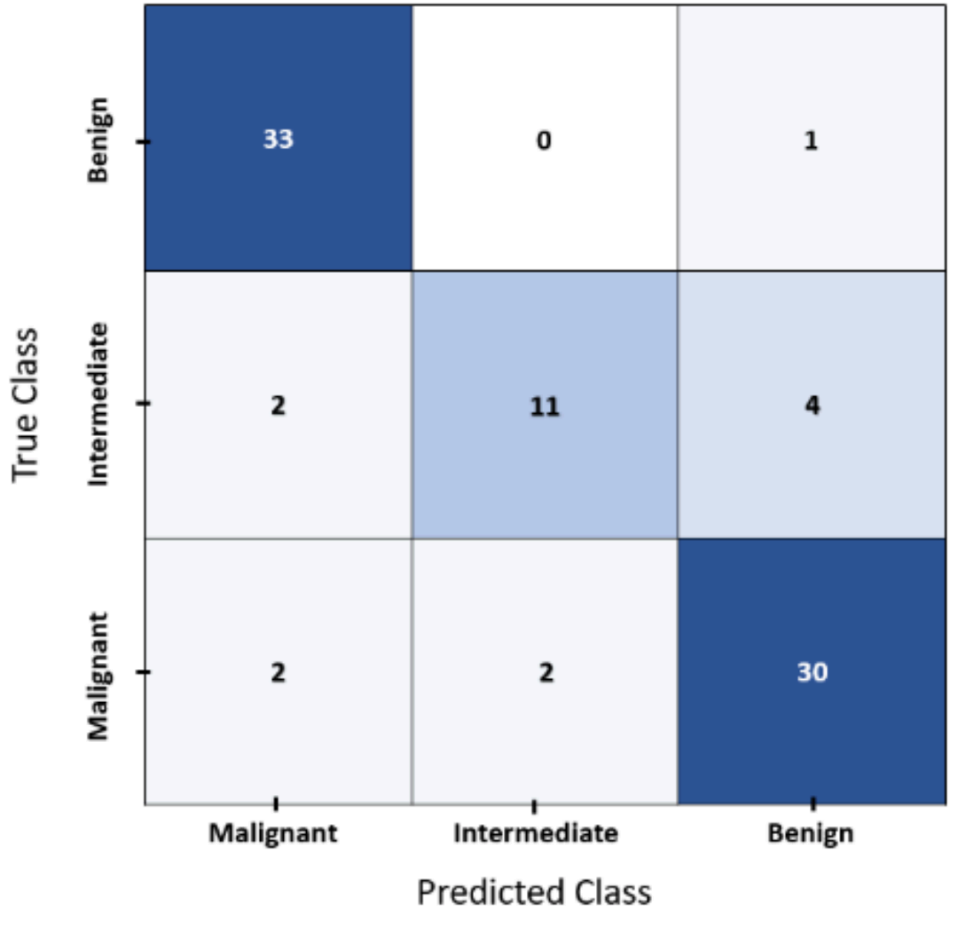
- First, we started assessing the classification performance using individual features.
- Then, we integrated all the extracted features by using concatenation methods obtaining combined features and employed ML classifiers towards the final diagnosis.



Diagnostic Results

Classifier	Approach	Accuracy	AUROC (+ve Class)			Correct Instances		
			B	LR3	M	B/34	LR3/17	M/34
RFs	**LOSO**	**87.1%**	**0.95**	**0.92**	**0.91**	**33**	**11**	**30**
	10-Fold	**85.9%**	**0.93**	**0.84**	**0.89**	**31**	**12**	**30**
	5-Fold	**81.2%**	**0.88**	**0.89**	**0.87**	**32**	**9**	**28**
KNN$_{Fine}$	LOSO	85.9%	0.91	0.85	0.90	31	13	29
	10-Fold	83.5%	0.91	0.82	0.86	30	10	30
	5-Fold	78.8%	0.88	0.74	0.84	31	9	27
SVM$_{Cub}$	LOSO	81.2%	0.89	0.82	0.84	30	12	27
	10-Fold	77.6%	0.85	0.73	0.87	29	9	28
	5-Fold	77.6%	0.85	0.73	0.87	29	9	28
SVM$_{Quad}$	LOSO	84.7%	0.94	0.89	0.89	31	11	30
	10-Fold	82.4%	0.93	0.81	0.85	31	12	27
	5-Fold	77.6%	0.89	0.80	0.85	29	9	28

Diagnostic Results



Diagnostic Results

Approach	Accuracy	AUROC	Correct Instances	
LR1 vs. LR2			**LR1/17**	**LR2/17**
LOSO	91.2%	0.95	14	17
10-Fold	88.2%	0.92	13	17
5-Fold	85.3%	0.90	12	17
LR4 vs. LR5			**LR4/17**	**LR5/17**
LOSO	85.3%	0.88	16	13
10-Fold	82.4%	0.83	15	13
5-Fold	82.4%	0.83	15	13

Summary

- The proposed HCC-CAD system has the ability to provide accurate grading for different hepatic observations according to the LI-RADS guidelines.
- Using the Random Forests classifier with a leave-one-out (LOSO) cross-validation, the developed CAD system achieved an 87.1% accuracy in distinguishing between malignant, intermediate and benign tumors (i.e., First stage classification).
- Using the same classifier and validation, the LR-1 lesions were classified from LR-2 benign lesions with 91.2% accuracy, while 85.3% accuracy was achieved differentiating between LR-4 and LR-5 malignant tumors (i.e., Second stage classification).

Future work

- We have already started to collect a larger subject cohort to optimize the performance of our system in distinguishing and grading multiple hepatic observations at the same classification stage.
- Hepatic observations with LR-M will be added to our dataset to enhance the diagnostic capabilities of our CAD system.
- Automatic segmentation is being developed to reduce the computational time and subjectivity.
- Applying deep learning techniques (e.g., Autoencoder and CNN).

Thank You
&
Questions

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