Comparison of Radiomic Machine and Deep learning Survival models in patients with Hepatocellular Carcinoma

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Shivabalan Kathavarayan Ramu, MBBS[1]; Anjali Byale, MBBS[2]; Aisvarya Sri, MD[3], Adithya Ajith, MD[3], Achintya Singh, MD[4]
[1]Mayo Clinic, Rochester; [2]UPMC McKeesport; [3]AIIMS; [4]MetroHealth Medical Center

Background

- Hepatocellular carcinoma (HCC) is the second major contributor to cancer-related mortality worldwide.
- Certain limitations of traditional imaging and report methods such as insufficient depth of imaging feature interpretations are big time drawbacks in th emanagemnt of HCC.
- The merging of AI with Radiomics help to enhance the precision in managing HCC.

Objectives

- To compare machine learning (ML) and deep learning (DL) approaches to predict survival outcome in patients with Hepatocellular Carcinoma (HCC).

Methods

- The clinical and image data of 82 patients were accessed from the TCGA-LIHC collection in The Cancer Imaging Archive (https://wiki.cancerimagingarchive.net/display/Public/TCGA-LIHC). Out of the total 97 subjects, patients with incomplete image sequences were excluded to finally include 39 patients. All of them had pathologically confirmed HCC without preoperative treatment.[2]
- All subjects included into this research underwent abdominal multiphasic dynamic contrast-enhanced CT with the multi-detector row CT (MDCT) units (GE LightSpeed QX/I, GE Healthcare, USA or Siemens Sensation 16, Siemens, Germany). Detailed imaging parameters are listed as follows: 120 kV, auto tube current, field of view (FOV): 320–500 mm× 320–500 mm, scanning matrix: 512 × 512, reconstruction kernel: standard, scan type: helical, slice thickness 5 mm, slice gap: 5 mm, reconstructed section thickness 2 mm.
- The arterial-phase (AP), venous-phase (VP) and delay-phase (DP) CT were performed at 30–35 s, 65–70 s and 150–180 s after intravenous injection of contrast enhanced agent (Ultravist 370, Bayer Schering Pharma, Berlin, German, Dose: 1.5 mL/kg, injection rate: 3.0 mL/s).

We delineated the following regions of interest (ROIs) and segmented them. by an opensource software, LIFEx (www.lifexsoft.org) [3](Figure 1). The ROIs were segmented in the venous-phase (VP) CT images and then the volume of interests were copied to the other phases.

1) Peritumoral 1 (first 2mm zone around the tumour)
2) Peritumoral 2 (second 2mm zone around the tumour)
3) Tumoral
4) paravertebral muscles L4, L5
5) Paravertebral muscles L1, L2, L3
6) Psoas muscle at the L1, L2 & L3 levels
7) rest of the psoas muscle.

The radiomics features were extracted from the segmented ROIs.

We evaluated the following models:
1) Cox proportional hazards model by componentwise likelihood-based boosting with step number 10 and penalty number 100,
2) Deephit: trains a neural network to learn the estimated joint distribution of survival time and event, while capturing the right-censored nature inherent in data. Analysis was done with frac 0.3, relu activation, 0.1 dropout, 100L epochs and a batch size of 32L,
3) Multitask logistic regression model with ranking based feature selection to predict survival using a logistic regression model and the parameters from each model are estimated simultaneously in the maximization of the joint likelihood function, and
4) Random survival forest with 1000 trees. Analyses were done in RStudio, and missing values were imputed using *missRanger* package.[1]

The data is split into 80 percent training and 20 precent validation. All models were 5-fold cross validated. Prediction statistics was calculated for each model developed

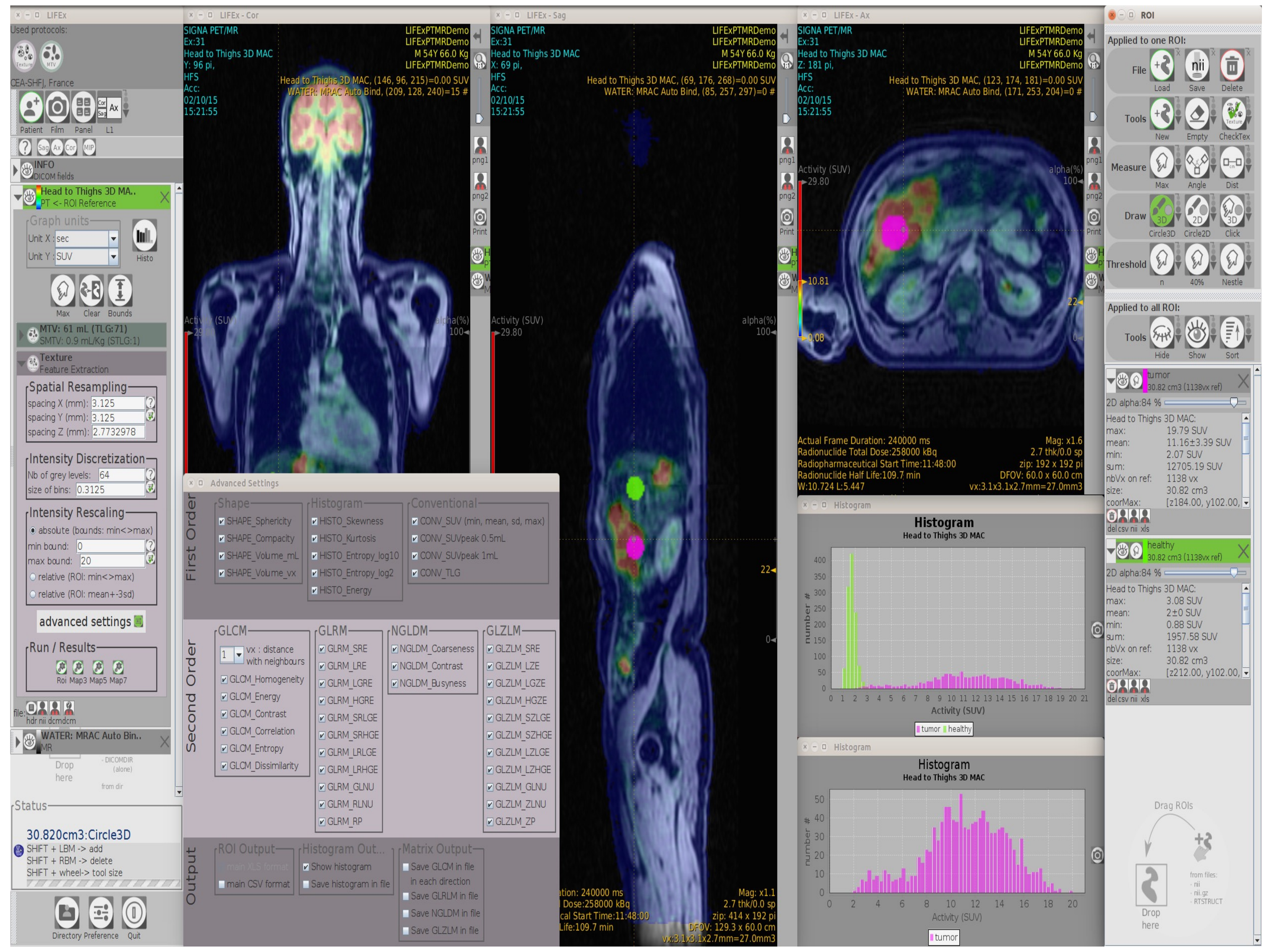
Results

- Out of the selected ML and DL models, Multitask logistic regression preformed the best in classifying all regions of interest.
- Amongst the regions of interest, paravertebral muscles and psoas muscles had higher discriminatory capacity than the actual tumour regions themselves.

Table 1. Comparison of performance metrics of the models.

S.No.	Model specification	AUC	C-index	AUC	C-index	AUC	C-index	AUC	C-index	AUC	C-index	AUC	C-index	AUC	C-index
Region of interest		1	1	2	2	3	3	4	4	5	5	6	6	7	7
1.	Cox boost	0.47	0.45	0.60	0.71	0.73	0.79	0.46	0.63	0.40	0.46	0.60	0.59	0.66	0.71
2.	Deep hit	0.47	0.45	0.60	0.71	0.73	0.79	0.46	0.63	0.40	0.46	0.60	0.59	0.66	0.71
3.	Multitask logistic regression	0.87	0.81	0.86	0.93	0.80	0.80	0.93	0.89	0.93	0.89	0.86	0.93	0.86	0.93
4.	Random survival forest	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5

Figure 1. LIFEX software showing the radiomics and the tumor delineation.



Discussion

- CT-derived radiomics were valuable for noninvasively assessing the survival and the paravertebral and psoas muscles have better predictive capacity to predict survivals apart from the tumour or peritumoral regions themselves.
- This is the first study to our knowledge to have shown that the paravertebral muscle radiomics can predict survival comparable to the tumoral radiomics in HCC patients.
- The MTLR model showed highest AUC amongst all the models.
- MTLR model showed highest AUC of prediction with paravertebral muscles at L1,2,3 levels (0.93) followed by peritumoral zone 1 of first 2mm around the tumor (0.87). This is higher than the accuracy shown by Feng et al who first reported that the combined intratumoral and peritumoral radiomics model derived from gadolinium-ethoxybenzyl-diethylenetriamine (Gd-EOB-DTPA)-enhanced MRI showed an AUC of 0.83 (95%CI: 0.71-0.95) in the validation cohort.[4]
- The biggest limitation to our study is the sample size. Hence, we came across the convergence issue. encountered a convergence issue while performing the machine learning analysis.

Conclusions

- Machine learning methods offered limited improvement over the Mayo Clinical risk score except for the Multitask logistic regression model in predicting PBC survival outcome at 1-year.

References

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