AI for classification and navigation of liver US in patients with HCC

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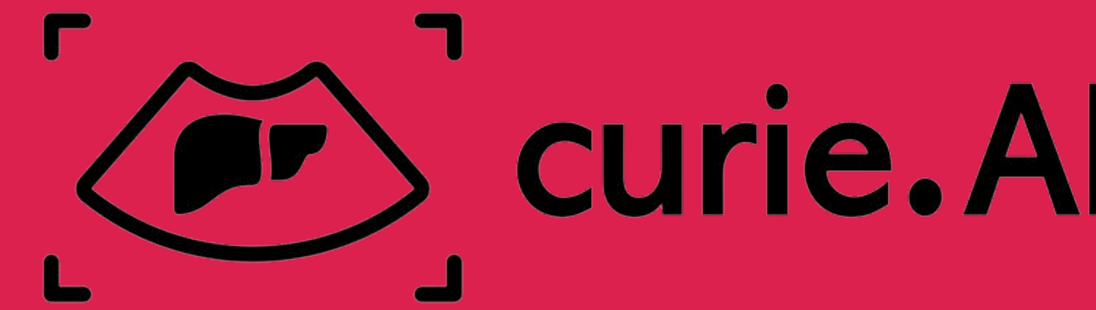


J. KLEPICH[1], R. MITCHELL[1], R. HARDY[1], S. HALL[1] and J. VILLAREAL[1]
1 University of California, Berkeley

1 Introduction

Deep learning methods have been used in medical imaging to aid in classification systems such as navigation systems for liver segmentation, feature extraction, and disease classification and to generate realistic medical images that could be used for training neural networks. Convolutional Neural Network (CNN) and two-phased Generative Adversarial Network (GAN) architectures have been used for the synthesis of images for improved classification of liver disease.

2 Aim

In this project, we build a pipeline in which real-time ultrasounds are processed via an object detection model to aid in ultrasound navigation. The object detection model identifies 10 different structures (organs, veins, and masses), including HCC. Sagittal and transverse views in which kidneys are detected are passed to subsequent models to detect the stage of liver steatosis or cirrhosis of the patient. The steatosis grade is a function of the echogenicity of liver/kidney ratio[1].

3 Method

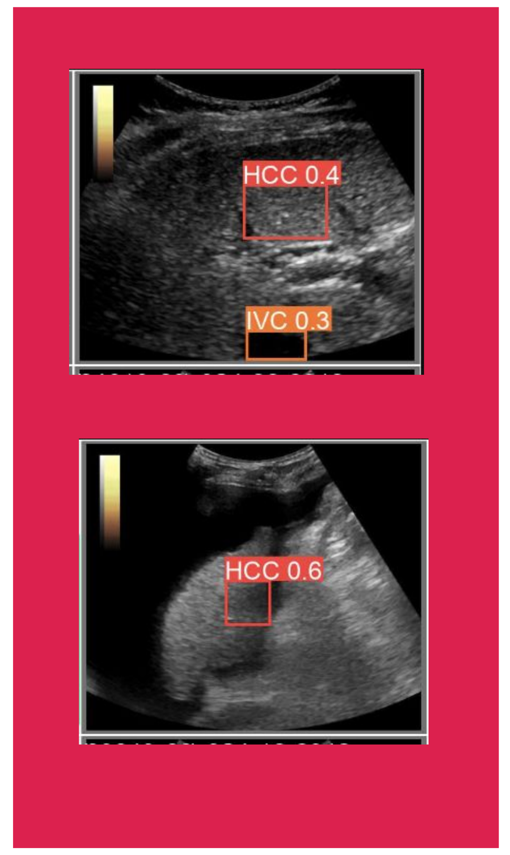
- We used the Eisenbrey, J., Lyshchik, A., & Wessner, C. (2021). Ultrasound data of a variety of liver masses [Data set] containing 197,000 images from 120 patients with different stages of liver disease and hepatocellular carcinoma HCC, as well as the dataset of B-mode liver ultrasounds acquired by the Department of Internal Medicine, Hypertension and Vascular Diseases at the Medical University of Warsaw, Poland.[2,3]
- The datasets were normalized based on the prevalence distribution of the disease in the US population and labeled manually using Roboflow.
- Training, validation, and testing splits ratios were 75%,17%, and 8%, respectively
- Three object detection models based on COCO, YOLOv8, and Robloflow 2.0 with preprocessing and augmentations were trained using patient-level splits to avoid data leakage. The classes detected are HCC, sagittal view (top/bottom), transverse view (left/right), kidney, kidney-medulla, hepatic vein, portal vein, and IVC.
- Views including kidneys were sent to a classifier to detect: normal, mild, moderate, or severe steatosis and cirrhosis.
- Synthetic Images to improve accuracy were generated using latent diffusion models conditioned on semantic maps, class-to-image, and text-to-image models.

4 Results

This study evaluated three object detection models for their performance detecting organs in ultrasound images. The models were based on COCO, YOLOv8, and Roboflow 2.0 architectures. We found that the YOLOv8 model performed the best for kidney detection, achieving a mean Average Precision (mAP) of 97.6.1% with a precision of 96% and recall of 85.2%.

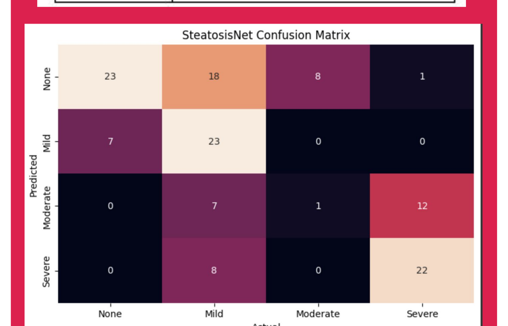
The YOLOv8 model was trained for up to 200 epochs using patient-level splits to avoid data leakage. The training dataset was normalized based on the prevalence distribution of the disease in the US population, and the images were labeled manually using Roboflow.

For steatosis grading, we used EfficientNet (Confusion Matrix), training for steatosis grade was labeled from a biopsy, which provides the percentage of hepatocytes with fatty infiltration. (None: 0%, Mild: 5% to 20%, Moderate: 25% to 50%, Severe: 50% to 100%)



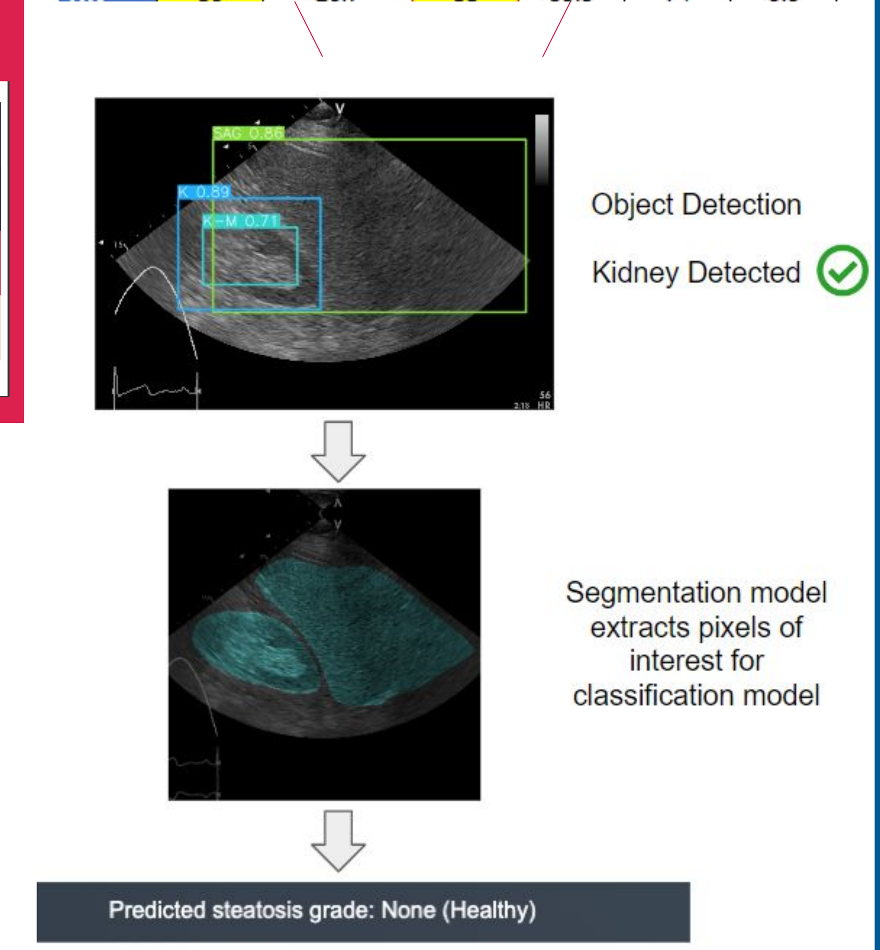
Detection of HCC with different probabilities associated with each finding. Other ROI are also detected in each frame.

Class	Description
HCC	Hepatocellular Carcinoma
LVR	Liver
PV	Portal Vein
HV	Hepatic Vein
IVC	Inferior Vena Cava
K	Kidney
K-M	Kidney Medulla
SAG	Saggital View
TRV	Transverse View
NO HCC	Mass identified as NON-HCC



If the object detection model detects a liver and kidney together in an image, the image is passed to the second part of the pipeline for steatosis grading.

	mAP					
	Robo_A v10	YOLOv8-v10	Robo_F v9	YOLOv8-v9	Robo_A v8	YOLOv8-v8
all	39	40.1	43	43.5	54	34.2
HCC	7	4.8	4	4.49	5	0.8
HV	11	6.6	2	7.49	1	0.8
IVC	14	16.1	10	33.9	11	14.8
K	58	90.0	78	92	71	87.1
K-M	88	97.6	82	92.8	94	99.5
LVR	40	43.0	NA	NA	NA	NA
PV	15	2.5	40	4.95	1	7.7
SAG	37	73.7	43	76.5	99	75.0
TRV	80	26.7	88	35.5	74	0.0



Model Type	mAP	Precision	Recall	Epochs	Augmentation	Dataset
Patient-level split						
Roboflow 2.0	53.8%	73.8%	48.4%	300	Grayscale, Saturation, Brightness	321 original images + 345 augmented. Steatosis + Cancer
COCO	20.5%	70.2%	45.3%	50		
YOLOv8	44%	65.2%	35.6%	200		
Image-level split						
YOLOv8	63.6%	71.8%	57.5%	25	Rotation: -20° and +20°	321 original images + 345 augmented. Steatosis + Cancer
Roboflow 2.0	93.1%	76.8%	90.8%	600	Rotation: -10° and +10°	
Roboflow 2.0	95.8%	91.4%	91.7%	600	Rotation: -20° and +20° Brightness, Contrast, Horizontal Flip	

5 Conclusion

We show that a classifier trained on a mixture of real and synthetic steatosis ultrasounds outperforms models trained only on real images. A pipeline using YOLOv8 or Roboflow 2.0 can be used as a navigation aid system, and an EfficientNet classifier can be helpful in the staging of liver steatosis/cirrhosis disease.

These findings indicate that ultrasound technicians, clinical imaging healthcare professionals, and diagnostic medical sonographers could be helped by artificial intelligence/deep learning models in their liver protocol navigation and selection of ROI, and as a reliable factor for grading fatty liver disease and detecting masses, with a probability of HCC.

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- Sarai Gonzalez Huezo, M.D.

7 References

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2. **Eisenbrey, J., Lyshchik, A., & Wessner, C. (2021).** Ultrasound data of a variety of liver masses [Data set]. The Cancer Imaging Archive.
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8 Contact Information

Dr. Joseph Klepich (jklepich@berkeley.edu)